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Determinants of Corporate Credit Spreads

by

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Abstract

This thesis examines determinants of the levels and movements in corporate bond yields in excess of comparable maturity Treasury yields. Three empirical techniques are used: a random walk, first differenced, and fixed effects models. We find that credit spreads are typically persistent over long periods of time, the effective federal funds rate moves inversely with credit spreads, and that crisis-era spreads are poorly described by random walks. These results both confirm and contradict prior findings, and have high explanatory power, capturing 67-87% of credit spread variation.

1. Introduction

The determinants of differences in yield between U.S. corporate bonds and U.S. Treasury debt, the credit spread, is important to issuers, investors, and economists alike. From an issuer's perspective, the choice to issue bonds and how that cost of capital will compare to that of U.S. government bonds and equity will influence capital structure decisions. Investors seek to allocate risk efficiently so as to achieve expected returns commensurate with the weight of investment risks. And economists seek to understand how corporate bonds impact the efficient allocation of capital across issuers, be they corporate, sovereign, or municipal.

The credit spread is positive due to the number of additional risks that corporate debt poses relative to Treasuries. As a result, their relative yields are thought to account for the risky nature of a corporate bond's yield. However, both existing theory and prior research are inconclusive regarding which factors predominately drive this spread. Although many factors have been identified, empirical evidence reveals that they have low explanatory power. Default risk is considered the preeminent risk as the primary risk associated with lending to a firm is that it might default on its obligation to bondholders. However, prior work demonstrates that this only plays a small role in determining spreads (Delianedis and Geske, 2001). Even on a historical basis spanning 150 years, it is observed that default and subsequent recovery rates in historical bankruptcies provide that bondholders are – on average – paid back nearly twice as much in corporate yield than losses burdened (Giesecke et. al. 2010). This evidence suggests that additional factors must also be at play even though prior work acknowledges the role of default.

Credit spreads are also studied for how issue-specific characteristics and investor preferences determine liquidity per se, and the role that these factors play in driving liquidity and spreads. It is well known that the $9.8 trillion bond market is broad – yet most outstanding bond issues trade almost never.[1] There are a number of characteristics associate with illiquidity and wider credit spreads, including issuance size, time since bond issuance, and credit quality (Helwege, Huang, and Wang, 2013; Houweling, Mentink, and Vorst, 2005). There is ample evidence that these concepts explain a greater portion of the corporate yield relative to U.S. debt obligations. Moreover, considerations such as market segmentation of investors and so-called "liquidity clientele effects" also determine liquidity due to bond buyer preferences. In this case, insurance companies will likely invest in certain bond issues expecting that other bondholders of the issue will have low asset turnover and be unlikely to trade prior to maturity (Mahanti et. al, 2008; Huang et. al, 2013). They will exchange liquidity in an issue in return for additional spread because they anticipate holding the bond for the long-term. This is another factor that must be considered in setting spreads in addition to issue characteristics.

Furthermore, bonds are generally traded through an over-the-counter (OTC) market structure, which generates greater costs for dealers and investors to transact bond trades and thus leads to larger spreads. Considerable prior work focuses on the additional search costs associated with the bond market, as most bonds trade infrequently and the ability to find the best price for a given bond is more difficult due to search costs. Thus, prior empirical work on the divergence of theoretical value

[1] $9.8 Trillion as of the2013Q4 release from the Securities Industry and Financial Markets (SIFMA) report on outstanding corporate bond issuance.

from trading prices illustrates this effect and points to the market structure's costs (Jankowitsch, Nashkikar, and Subrhahmanyam, 2011).

Moreover, tax effects and the differential tax treatment of corporate bonds versus other debt instruments in the credit universe demonstrate further controlling factors of credit spreads. Corporate interest is taxable, and investors are determined to consider alternative assets based on after-tax returns. As a result, there is evidence that state taxation of corporate interest and the lack thereof on Treasury coupons may drive yields higher on corporates relative to U.S. government bonds (Bodie, Kane, and Marcus, 2011). Moreover, analysis of the tax-exempt municipal bond market suggests that taxation plays a large role in driving corporate credit spreads wider (Wang, Wu, and Zhang, 2008).

Corporate bond spreads are also studied in how they react to contagion when a firm in one sector experiences financial distress and how that impacts trading prices of similar firms in the industry. Risks of similar firms - even if managed under different methods or differing levels of accounting health – are impacted due to their perceived correlation (Collin-Dufresne, Goldstein, and Helwege, 2010). This is the subject of a few studies that discuss and illustrate the way that new information is incorporated into bond yields.

To identify how spreads evolve over time and the impact of these risks in determining spreads, I use data on U.S. corporate bonds from 2005 through the third quarter of 2013. The observations that are examined in this paper are broken down into subsets based on interesting subdivisions. We break down summary statistics among the entire dataset, investment grade and high-yield, and financial and non-financial names. T-tests of the means reveal that these subsets are statistically discernible from one another across the board. Furthermore, we separate our dataset into three separate “regimes’ centered around the 2008 financial crisis when bond market liquidity was lower and spreads higher (Dick-Nielsen, Feldhutter, and Lando, 2012; Gilchrist and Zakrjsek, 2013). This period is studied separately from pre and post-crisis periods to identify how the crisis affected determinants of corporate spreads.

The empirical approach to corporate credit taken here draws on the evidence provided by past analysis and extends on prior models. We begin by testing the persistence of past values on current credit spreads with a random walk. This is extended to a ten value lagged random walk model, which is shown to account for a large portion of spread movement. A first differenced model is also applied to time-demean and further analyze credit spread determinants. Moreover, we approach credit spreads using a firm and year fixed effects model while controlling for a number of issue-specific and macroeconomic-based factors. All models are applied separately to individual time regimes, credit grades, and industry types to determine what drives spreads in different bond subsets.

Our results indicate that the random walk model outperforms the predictive and explanatory power of most of the other models, with the notable exception of our fixed-effects model during the pre-crisis regime. It is compelling that random walks can – over the entire dataset – explain nearly 80% of the variation in spreads. For the random walk model, most subsets are explained around 80% with the exception of the crisis period, which appears to be least fit by the model. However, differenced models don't explain more than 43% of spreads and fail to provide a comprehensive framework for spreads. Despite being empirically valid, the variable restrictions imposed by differenced models remove issue-specific data and remove explanatory power. The proposed fixed-effects models don't explain most of the subsets better than the random walk, but still provide insight on the significance of particular variables on spreads throughout different subtypes and periods.

The controlling variables' significances aren't all in line with prior evidence and provide tension relative to earlier work. While the TED spread, the difference between interbank rates and the Federal funds rate, is observed to be very significant throughout our study and positively correlate with corporate spreads, the federal funds rate is also statistically relevant, but reveals a negative relationship – at odds with prior conclusions. Furthermore, the addition of a dummy variable to control for premium bonds to control for jump-to-default risk is negatively correlated, when we anticipate a positive impact.

Generically, we produce models here that explain 67-80% of credit spreads, with one model working as high as 87.4%. The results here imply that corporate credit can be well explained by a combination of bond-specific and macroeconomic determinants relevant to the bond market. Our conclusions outperform prior literature in the ability to explain spreads – but most so over specific subsets. The limitations inherent in our research provide that our conclusions should be understood relative to the approach taken here in contrast to other pieces. However, the results revealed here can be accepted with confidence as basis for distinguishing what drives specific bond types over different time periods.

Chapter 2 presents a review of bond pricing and an examination of the conceptual structures that underlie bond valuation and the spreads that persist between corporate and government bonds. In Chapter 3 a review is presented of the specific risks that are intrinsic to and generated by the market structure of bond trading. These include default, liquidity, macroeconomic tax, and contagion effects on corporate bonds. The empirical methodology and dataset construction are reported in Chapters 4 and 5. Chapter 6 summarizes and interprets the empirical results, and Chapter 7 concludes.

2. Bond Pricing

2.1 Overview

Conventional portfolio theory demonstrates that measures of relative risk of assets provide the basis for asset allocations. In a no-arbitrage framework, economists believe that additional expected return can only be achieved by taking on additional risk – or more variance in the distribution of possible portfolio returns. The crux of these choices depends on the levels of U.S. Treasury bond yields, which are considered the risk-free rates of return. While they may fluctuate in value, this risk-free yield is guaranteed until maturity due to the common-held belief regarding the supreme credit quality of the U.S. government. It is relative to this rate that "risky" private sector assets such as corporate bonds and equities are judged by their expected returns in excess of the risk-free yield.[2]

Bullet corporate bonds are lending instruments that represent claims to the timely payment of interest on a regular basis and full repayment of principal of the bond at maturity.[3] A corporate bond is initially issued in the "primary market," where a large investment bank will purchase the bonds from the issuing firm, market them to investors, and distribute bonds. Following initial issuance and purchase by the firm's clients, the bonds are traded in the "secondary market." What is unique about trading bonds in the secondary market is that there is no centralized exchange, such as the New York Stock Exchange (NYSE) for equities. Rather, it is comprised of an

[2] From the corporation's perspective, the decision to raise capital via equity or debt is termed capital structure. This is analogous to the investor's decision regarding portfolio characteristics, and is discussed in Appendix A.

[3] Bullet meaning the traditionally most common type of bond that will provide regular payment of debt service until the ultimate repayment of principal at the maturity date of a given debt instrument. There are floating rate and zero-coupon bonds, but this discussion and later analysis is limited to bonds that will pay a fixed rate on a regular basis.

over-the-counter (OTC) market. Instead of organizing a centralized order book of buy and sell orders for the NYSE, bonds trade between two parties in a negotiated transaction between broker-dealer institutions and investors. Thus, the transactions are a result of various bargaining relationships between bond investors and different brokers. While there has been movement to some centralized bond trading platforms, it still remains an OTC driven market.

$$Price_t = \frac{C}{(1+i)} + \frac{C}{(1+i)^2} + \cdots + \frac{C}{(1+i)^n} + \frac{P}{(1+i)^n} \qquad [1]$$

As shown in Equation 1, a bond's price reflects the present discounted value of all payments that the borrower, the bond issuer, will make to the lender, the bondholder, over the lifetime of the bond. The majority of bonds that are issued will be of the bullet variety and will pay a fixed "coupon," typically on a semi-annual payment cycle. This is until the principal matures and the issuing firm pays s back bondholders.

At time of issuance the bond's coupon, *C*, is directly proportional to the then-prevailing market interest rate, *i*, although at subsequent dates the prevailing interest rate, *i*, may differ from the initial rate such that the bond's coupon may appear overly generous or inadequate. If the bond's coupon appears overly generous the bond is described as being a premium bond, and it would sell for a price in excess of the issue price, which is generally $100; when the coupon yield, the ratio of coupon to price, is less than current interest rates, the bond would be a discount bond and would sell for less than $100. At time of maturity, the bondholder is paid the principal or face value of the bond, which is typically $100. Thus, the bond's price is usually roughly $100, with deviations reflecting changes in bond, issuer, or market characteristics. The yield to maturity, the specific yield that is referenced throughout this paper, is the discount rate for all coupon payments and principal payment that will be set equal to the bond's price.

As a result, bond prices and yields will move inversely with one other. The lower the price a bond will trade at – ceteris paribus – the higher the yield that the bond's future cash flows will represent. Conversely, a higher price will reduce the interest rate at which these flows will be brought back to present value.

2.2 Risk Spreads, not Yields

The time value of money implications on corporate bond yields motivate studying their spreads to interest rates rather than their total yields. Corporate bond yields will be examined by analyzing the yield's difference in excess of a Treasury bond of comparable maturity. This spread strips out the basic "interest-rate risk" that government bond yields represent, because they lack any perceived risk of default.

It is interesting to note that while this work focuses only on U.S. corporates, European corporate bonds will also follow U.S. Treasury yields more closely than European sovereign rates (Van Landschoot, 2008). It is worth noting that recent bouts of political turmoil in the United States may bring into question the viability of the U.S. government bonds as the supposed risk-free asset.[4] This demonstrates the empirical suitability of U.S. Treasuries because of its demonstrated relationship with European corporate debt. As a result, this empirical analysis looks at the risk-free interest rate and the Treasury yield curve as one and the same.

[4] Since an initial congressional battle in August 2011, the U.S. Congress has experienced increasing brinkmanship approaching the federal debt limit that has almost forced a default on principal and interest payments by the government. This has been avoided thus far, but the prospect of a refusal to increase federal borrowings due to political gamesmanship may risk its risk-free status.

The corporate bond's spread is considered the risk premium, or the payment of additional yield that represents the amount that an investor requires to hold the bond while taking on risks beyond the risk-free rate. Elton et. al. (2001) observe that the biggest difference between corporate and Treasury debt is that Treasuries offer return without deviation, while corporates provide systematic exposure to different types of risk.

Theory will dictate that the risks that vary between government and corporate debt is the probability of default that firms represent – unlike the presumed zero credit risk of U.S. government claims. However, prior research suggests that characteristics and market structures of corporate bond trading will impact yield levels and provide evidence that investors look at more than fundamental probability of a firm's default.

The fundamental default risk that a given issuer may impose on its bondholders is a primary risk of corporate credit. The chance that a firm cannot make good on its promises to bondholders and be forced to cut debt principal or otherwise restructure debt is the fundamental risk to bond cash flows that bondholders otherwise expect to receive.

Prior empirical works show that issue-specific characteristics will impact the trading frequency and spreads of corporate bonds. Time since bond issuance and the original issue size is observed to impact secondary market liquidity on corporate credit spreads.

Liquidity Clientele Theory states that bond investors segment themselves based on heterogeneous preferences. For some bonds, this will limit liquidity after issuance. This effect is most observed in investment grade credit where insurance firms with long-term motivations will limit secondary market liquidity because they typically hold bonds until maturity.

OTC market structure and the search costs of finding buyers and sellers in a decentralized marketplace are also discussed further. This market set-up is unlike that in the equity market where a central order book is kept and buyers and sellers are matched. Rather, broker-dealers must maintain inventory and investors are forced to search for the best prices among the dealer community.

A number of macroeconomic indicators are also shown to drive corporate credit spreads. These include the TED spread, Effective Federal Funds Rate, Broker-Dealer Asset Base, and SP500 volatility. These are proven to correlate with spreads across the credit and business cycles.

Tax rates are also shown to influence corporate spreads due to the taxable nature of coupon payments. This is in contrast to both Treasury and municipal bonds. While differential tax treatment is shown to have weak evidence analyzing the former, the latter illustrates tax effects as a strong determinant of corporate spreads. Rational investors seek to maximize the equivalent taxable yield of their investments such that corporate bonds would pay a yield of r while municipal, or tax-exempt, bonds pay a yield of r_m. If an investor faced a marginal tax rate of τ, the investor would be satisfied with corporate bonds if and only if

$$r(1-\tau) \geq r_m, \qquad [2]$$

or

$$r \geq \frac{r_m}{(1-\tau)}. \qquad [2']$$

Thus, for example, a municipal bond that is tax-exempt and has a yield of 5% is essentially equivalent to a 8.33% yield on a taxable bond, assuming the investor faced a marginal income tax rate of 40%.[5]

Corporate credit also exhibits contagion effects in times of market-wide financial distress and isolated corporate bankruptcies. Contagion refers to the tendency of corporate bonds to show worse pricing in the presence of the default or increased distress of a similar corporate. This is likely due to perceived homogeneity of industry firms.

[5] The differences between yields on taxable and tax exempt bonds generally imply ex-post a statutory tax rate consistent with present day rates for high income individuals and corporations. According to Wang, Wu, and Zhang (2008), this coincidence is highly evident in municipal trading prices when controlling for liquidity. Because their sample period had lower tax rates, we use 40% as an approximation considering the expiration of Bush-era tax cuts.

3. Risk Factors of Corporate Credit – The Story behind Risk Premiums

Here, I outline the different risks that corporate credit holders take on in return for the premium yield relative to risk-free Treasury debt. Interest-rate risk will not be discussed further because corporate yields will only be examined as spreads to benchmark Treasuries. I will discuss literature encompassing fundamental default risk, bond-characteristic liquidity effects, liquidity clientele effects, market structure effects, macroeconomic factors, tax effects, and contagion.

3.1 Fundamental Default Risk

The primary risk that bond investors take is that of the future ability for the bond's issuers to make good on both principal and interest payments. Interestingly, prior work demonstrates that this doesn't drive the majority of the corporate yield premium. Delianedis and Geske (2001) find that most of the corporate credit spread is unexplained by the default component, implying that there is a large residual, so-called "non-default component" within corporate yields. They use the Black-Scholes-Merton contingent claims model (BSM) to estimate a firm's probability of default (see Appendix B for further details). This structural credit model calculates default probability by examining the theoretical probability of declared assets falling below the outstanding liabilities of the firm. Using options theory, they utilize the historical equity volatility on the issuing firm's stock to solve for the chance that a theoretical default will occur. Then, they examine how this default probability correlates with investment grade bond spreads. They find that a large non-default component exists because BSM explains only 5-22% of credit spreads, depending on rating level. However, their results do provide evidence that default risk accounts for greater portions of the credit spread for more speculatively rated credits. This provides a compelling baseline for further examination, and motivates separate analysis of investment grade and high-yield credits to identify the driving factors of corporate yield spreads. It may also imply a behavioral factor exists in that investment grade credits are considered relatively unlikely to default to the point that their spreads may be primarily driven by market-specific technical or liquidity aspects.

However, it is necessary to understand the limitations of this approach due to the purely structural analysis and lack of consideration for investors' perception of expected default risk. Delianedis and Geske (2001) find only the existence of a large residual of the corporate credit premium relative to their way of assessing corporate credit risk. While BSM theory does offer insight into credit default risk, the method bypasses specific structural components such as leverage, cash flows, and other metrics derived from financial statements. By contrast, other literature assumes the importance of these accounting metrics and corporate cash reserves in explaining default risk (e.g., Acharya, Davydenko, and Strebulaev, 2011). This literature hypothesizes that higher cash coincides with more conservative management due to default concerns, which will be an important part of this empirical work.

Perhaps the most widely used model to predict corporate bankruptcy is Altman's Z-Score model. This model computes a variable, *Z*, as a function of various financial statement derived metrics such that a score in a specific range has at least a 95% probability of predicting whether a firm would be bankrupt within the year. For example, scores less than 1.81 for manufacturers and 1.23 for non-manufacturers and private firms are consistent with a high likelihood of bankruptcy. The formula is estimated differently for manufacturing firms (Equation 3) and non-manufacturing and private firms (Equation 3'):

$$Z = 3.3\frac{EBIT}{Total\ assets} + 1.2\frac{Net\ working\ capital}{Total\ assets} + 1.0\frac{Sales}{Total\ assets} + .6\frac{Market\ value\ of\ equity}{Book\ value\ of\ debt} + 1.4\frac{Accumulated\ retained\ earnings}{Total\ assets} \quad [3]$$

and

$$Z = 1.05\frac{EBIT}{Total\ assets} + 6.56\frac{Net\ working\ capital}{Total\ assets} + 6.72\frac{Book\ value\ of\ equity}{Total\ liabilities} + 3.26\frac{Accumulated\ retained\ earnings}{Total\ assets}. \quad [3']$$

Altman's Z-score is used in much of the literature to proxy for bankruptcy risk (Ross, Westerfield, Jaffe, 2010).

Furthermore, the method does not take into account market-based perceptions of risk, and suggests that corporate yield premiums should only equal structural risk as opposed to risk judged by market participants. Much evidence shows that investor perceptions are based on both judgments of contagion risk and agencies' credit ratings on bond prices (Collin-Dufresne, Goldstein, and Helwege, 2010; Fracass, Petry, and Tate, 2013). Relative credit judgments that market participants have beyond the structural model proposed in the literature may suggest that their theory is with fault.

However, empirical work controlling for default risk using the Black-Scholes-Merton structural default risk or using historical loss rates both demonstrate that a large component of spreads is outside of the risk of nonpayment of bond principal and interest. Prior analyses have sought to explain what goes unexplained by default risk alone in explaining the yield premium of corporate bonds. Therefore, this analysis will focus on the other risks that drive the size of yield premiums.

3.2 Liquidity effects

In light of the large residual in credit spreads that is unexplained, we seek to examine what qualities of bonds and the bond market contribute to less liquidity, and, in turn, larger spreads. One major reason that is often considered is liquidity. Liquidity is the concept of how easily a financial instrument can be converted to cash in a timely fashion. Higher liquidity in an asset generally translates to many active buyers and sellers with transactions occurring at prices that are close to fair value. If a basic bond pricing formula such as Equation 1 were rewritten as

$$Price_t = f(Coupon, i, P, n), \quad [4]$$

then a complete model that included liquidity might read

$$Price_t = f(Coupon, i, P, n) + g(liquidity). \quad [4']$$

In a model such as Equation 4', the term $g(liquidity)$ would be expected to increase at a decreasing rate. Building off a model derived for equity pricing from Bodie, Kane and Marcus (2011), the term $g(liquidity)$ would be assumed to effectively incorporate three separate elements: the covariance of the liquidity of the focal bond with the aggregate market, the covariance of the return on the focal bond and the liquidity of the aggregate market, and the covariance of the liquidity of the focal bond with the return on the aggregate market.

Risk-free rates of return are typically judged by looking at the most recent issues of liquid Treasury bonds. These Treasury securities are frequently traded and are a standardized product in demand due to their perception as the safe-haven asset of choice. However, the corporate bond market has $9.8 trillion in outstanding issuance, with many bonds trading infrequently, if ever. This in turn creates a less liquid market and attracts investors that will trade less frequently and are more likely to hold issues until maturity.

To proxy for liquidity, equity and credit literature often relies on the Amihud liquidity measure, first put forth in his analysis of illiquid equities. His proxy for liquidity – a concept that is admitted to be “elusive” – is defined as an average ratio of daily total returns to trading volume (in total dollars) over a given year. This measure gives percentage price change relative to the day’s total trading flow, essentially measuring the price impact of day-to-day shifts in quantities exchanged.

Amihud also notes that float sizes of equities can impact liquidity, as a larger float will have a smaller effect for a given order flow and will typically have tighter bid-ask spreads (Amihud, 2002). This concept of liquidity also applies to corporate bond issue sizes (Helwege, Huang, and Wang 2013). This focus and usage in other literature make this an interesting look into a liquidity proxy. Though initially used to look at equity order flow and price changes, it has been applied to corporate credit spread analysis.

The liquidity measures used in this examination focus on bond characteristics and how they may translate to transaction prices at higher spreads.

3.2.1 Issue-Specific Characteristics

Houweling, Mentink, and Vorst (2005) find that liquidity accounts for 18-23 basis points (bps). They control for bond liquidity using multiple proxies: bond issuance size, listed, euro, on-the-run, age, missing prices, yield volatility, number of contributors, and yield dispersion.[6] These proxies are used to test the relative value of each proxy in analyzing corporate yield spreads. They find that each proxy except one is statistically significant in predicting yields, and demonstrate that all significant proxies are relevant but nearly identical to one another (Houweling, Mentink, and Vorst, 2005).

Moreover, Helwege, Huang, and Wang (2013) come to similar conclusions regarding characteristics and corporate credit spreads. Using a similar approach, they run multiple regressions using different proxies for liquidity, which include trading frequency, issuance size, age, and volatility. Their empirical approach uses these characteristics to analyze returns to less liquid bonds paired with bonds issued by same firm and comparable qualities. By estimating bid-offer spreads from the dealer community, they tease out how costly transactions are in the open market in looking at the liquidity of these bonds. Their analysis suggests the value of controlling for firm-specific effects. This approach isolates issuer-specific effects and tests differences among bonds by the same issuer. These make their empirical conclusions more robust and demonstrate that liquidity qualities impact spreads similarly across bonds when controlling for different firms.

While they find statistically significant effects of liquidity on spreads, they posit that their proxies may pick up on credit components in high-yield corporate bonds – implying that the liquidity and credit risks differ across credit qualities. They analyze bond pairs issued by the same firm – effectively isolating firm specific effects of corporate bond prices (Helwege, Huang, and Wang, 2013). They find statistically

[6] Yield Volatility: historical trading volatility; Number of Contributors: number of dealers providing quotes for a given bond; Yield Dispersion: dispersion of yield quotes on a given day for a bond.

significant liquidity effects, but notice that these effects are highly correlated with credit quality. Much literature has found significant variations between investment grade and high-yield credits. This finding promotes the theory that speculative grade credits demonstrate idiosyncratic liquidity effects. This may reveal an interactive effect between credit quality and bond liquidity. These findings demonstrate the need to analyze credit grades separately to estimate what drives spreads in each subgroup.

3.2.2 Liquidity Clientele

Further analysis demonstrates a "liquidity clientele effect" that impacts corporate credit spreads. This effect is defined as the observation that bond markets are segmented across maturities, liquidity preferences, and credit quality and that each characteristic will impact the collection of investors buying particular bonds (Huang et. al, 2013). In their work, they examine how this affects investor segments that will demand certain bonds and impact secondary market liquidity. Their claim rests on the idea that different bond characteristics such as credit quality and maturity will drive subsequent trading levels. They look at the Mergent insurance firm holdings dataset to analyze how their preferences affect bond spreads. This is because insurance firms tend to hold bonds until maturity and do not routinely turn over portfolio assets (Huang et. al, 2013; Mahanti et. al, 2008; Huang et. al, 2013). Examining insurance portfolio data and illiquidity measures, they find that different insurance companies hold varying levels of liquidity in their portfolios. They find that these differences in portfolio allocations are statistically significant, and signify that each firm has distinct preferences that impact bond trading spreads. This idea first comes from Amihud and Mendelson (1986), who demonstrate that exogenous preferences of different investors shape attitudes toward bonds based on the bond buyers' liquidity needs after purchase. Beyond liquidity preference, they expand on this theory by looking at the "amortized trading costs" that impact investors with different liquidity timelines. Their examination finds that investors with long-term horizons will prefer less liquid securities due to higher trading costs being amortized over a longer timeline (Huang et. al 2013).

Liquidity clientele also reveals major differences between high-yield and investment grade corporate bonds. The observed preferences of insurance companies don't play a role in the high-yield space, which is unlike the effect observed in the investment grade market. They note an estimate that insurance firms hold only 8% percent of outstanding high-yield debt (Ellul, Jotikasthira, and Lundblad, 2011). Therefore, they conclude that insurers' liquidity preferences don't impact high-yield, because they are not the "marginal investor[s]" for this credit grade (Huang et. al., 2013). Therefore, we see that insurance portfolios are likely investors of less liquid, but higher quality bonds.[7] This finding suggests that the market microstructures for lower credit quality bonds are more reliant on the liquidity of their investor bases and may need to be modeled differently. This provides further evidence of microstructure differences between investment and speculative grade bonds than issue-characteristic liquidity.

In addition to analysis of clientele preferences in the context of insurance firms, analysis of bond price data from custodian banks further looks at how broker-dealer client holdings and turnover impact bond issue liquidity. Mahanti et. al. (2008)

[7] The authors also discuss insurance regulation of risky assets, which is believed to reduce willingness to invest in high-yield bonds.

examine the turnover of the clients of State Street's custodian bank, one of the largest asset custodians for institutional investors. They construct a latent liquidity proxy that uses the turnover for each client as proxy for that client's willingness to trade in and out of positions on a frequent basis. This idea of "latent liquidity" is defined for a certain bond as "the aggregate weighted-average level of turnover" for each fund holding a given bond. The theory is that if a specific bond is held by many portfolios that are likely to turnover, then that bond will be traded more frequently and will require fewer search costs on the part of dealers to source that bond. Conversely, insurance firms – as discussed earlier – have lower turnover and their holdings are less liquid. The authors find that their approach better explains credit spreads than controlling for characteristics such as age, coupon, rating, issuer size, and issue size (Mahanti et. al, 2008). This weakens our discussion in the prior section on the statistical power of these corporate bond characteristics. It does, however, strengthen the argument regarding the segmentation of corporate credit markets and the associated reduced liquidity for bonds that are traded less frequently by institutional clients with lower asset turnover.

The market for defaulted corporate bonds further illustrates the limits of liquidity, as only limited numbers of investors are willing to buy defaulted debt. Analyzing the 2008 financial crisis and trading activity in defaulted corporates, Han and Wang (2013) find that crisis supply shocks in the defaulted debt segment drive wider bid-offer spreads and contribute to illiquidity. This reinforces the general finding that riskier bonds are less liquid. Demand for defaulted debt is typically limited to specialized hedge funds that concentrate on this market segment, which is part of why this segment is illiquid. This coincides with earlier discussion of investor segmentation into their preferred credit spaces and penchant for secondary market liquidity. The distressed segment further highlights the importance that clientele segments have on corporate credit markets.

3.2.3 Liquidity Risks in OTC Markets

The over the counter structure of bond trading makes the market more sensitive to price shocks and financial distress, particularly that of broker-dealers. While stocks are traded very frequently and are fairly easy to buy or sell on any day, bonds are very different. One major difference between liquid equity trading and that of bonds is the market center versus the over-the-counter structure. While there has been movement to trading over electronic exchanges, most bond trading is still dominated by registered broker-dealers that facilitate liquidity through OTC transactions. This process is inevitably more costly due to the greater search, transaction, and inventory costs. These costs are also a result of the large market share associated with "buy and hold" investors such as insurance firms (Huang et. al., 2013). Furthermore, other empirical work focuses on the market-maker distress during 2008 that corresponds with wider credit spreads and less bond liquidity.

The literature finds that the particular distress experienced by Lehman Brothers and Bear Stearns impacted corporate credit more generally due to the firms' large presences in the fixed income markets (Dick-Nielsen, Peter Feldhutter, and Lando 2012).[8] The paper also cites the relative illiquidity in the OTC market environment during the 2008 financial crisis. They see these conditions as

[8] Both of these firms experienced severe financial distress in 2008. As a result, Bear was taken over by J.P. Morgan at a highly discounted price, and Lehman filed for bankruptcy in September.

contributing to the less orderly price discovery observed during the crisis, which caused further problems in valuing assets behind money market funds and portfolio valuation of housing related assets.[9] Because trading is concentrated with large broker-dealers, when there is market-wide uncertainty and firm-specific distress, then when a few broker-dealers suddenly and unexpectedly cannot supply liquidity prices drop and spreads climb. It seems that broker-dealer distress, particularly at the same time as market wide panic, can impact the mechanics of an orderly OTC market, and thus, adversely affect credit spreads.[10]

Feldhutter (2011) demonstrates the response of pricing during periods of intense selling pressure on bond prices and how the format of the market can cause periods of transactions at discounted prices to "fair value". The work discusses the typical difference between sophisticated and less sophisticated – typically retail – investors in the bond market. While large bond market participants such as insurance companies or institutional money managers often trade in large size and are more willing to search among dealers for the best price, smaller traders often will not search as much. Therefore, the expectation is that investors managing smaller asset bases are bid lower prices (larger spreads) when selling bonds to dealers and offered higher prices (lower spreads) when buying bonds. This also illustrates the overall importance of bargaining power in an OTC market when working with bond dealers. Feldhutter concludes that when bargaining power disappears due to credit events or

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[9] It is widely known that the contagion issues surrounding property values, mortgage delinquencies, and associated swaps and collateralized debt obligations caused trading volumes to dry up due to lack of appetite and limited knowledge regarding the risk that these securities represented.

[10] Credit default swaps (CDS) are used as a form of insurance for this sort of situation. Please see Appendix D for a discussion of how CDS are used to mitigate liquidity risks.

periods of overall illiquidity (like the 2008 credit market turmoil) that worse pricing ensues – despite any previously advantageous bargaining positions.

Moreover, inventory costs and the rising cost of capital for financial firms during the crisis further impacted corporate credit spreads and provided worse prices and higher spreads for market participants. Friewald, Jankowitsch, and Subrahanyam (2011) study bond trading surrounding the financial crisis to find that specific events impact broker-dealer liquidity provision such as the GM/Ford credit downgrades, and the subprime crisis.[11] They hypothesize that during these times of acute crisis that broker-dealers will find themselves with more binding capital constraints, thus reducing their ability to provide liquidity efficiently. In addition, the authors prove that a flight to more liquid assets because of market uncertainty will negatively impact less liquid bond issues.

It is difficult to empirically control for the different search and inventory costs borne by dealers and investors due to multiple confounding factors. However, there is evidence that these measures correspond with indicators of OTC market illiquidity. Jankowitsch, Nashkikar, and Subrhahmanyam (2011) examine differences between TRACE transaction prices and those from a Markit database on the same securities. While the former represents actual transactions, the latter is collected by survey from broker-dealer traders who will typically mark their own positions based on the price data that they release to Markit. This, the authors argue, will therefore be representative of fair value for these securities. They produce a theoretical model that dictates only search and inventory costs will determine the dispersion between Markit

[11] Only GM required a federal "Auto Bailout" during this period. While Ford's credit quality does come into question, it isn't forced to restructure debt obligations or rely on government assistance.

data and prices observed in transactions. This approach is interesting in that it seeks to measure illiquidity not based on bond-specific characteristics and specific periods of generic distress, but rather by differences in theoretical value and transaction prices. Furthermore, the empirical work finds that the systematic dispersion of bond trades from Markit prices is significantly correlated with bond characteristics that are mentioned in Chapter 3.2.1. Specifically, they find that amount issued, maturity, age, rating, bid-ask spreads, and trading volume correlate with dispersion of bond prices (2013). This indicates that controlling for issue characteristics and trading history will capture characteristics of bond market structure.

Additionally, they observe that the mean dispersion in their research is 49.94 bps, with standard deviation of 63.6 bps (2013). This indicates a wide degree of dispersion between surveyed Markit prices and bond trades, therefore revealing a highly illiquid market. Theoretically, a more liquid bond market would have to trade more closely around "fair" value and thus this spread would be close to zero. While this may be the case, it is worth noting that this may indicate inaccuracies or biases in the Markit data. Traders may be unwilling to accept that their holdings are worth less than transaction data may represent, or may be biased in that they closed a position that would have become more profitable if held further. Conversely, even if these biases could be observed from the academic's perspective, it is even more complex to know if there's other unknown information at work that would distort these conclusions further.

Ostensibly, bond market transaction costs and OTC trading create an additional consideration for an empirical analysis of credit spreads. As a result, the decision to control for characteristics that will increase search and inventory costs will be included to further strengthen the models to be discussed later.

3.3 Macroeconomic Factors

Furthermore, macroeconomic factors also affect spreads, as the general economy's performance can impact the ability of companies to continue as going concerns and avoid default. First, just as the capital asset pricing model (CAPM) shows that equity returns are related to aggregate equity market premiums, debt spreads relate to aggregate debt market conditions. There is evidence that cross-asset correlation between stocks and bonds can help control for credit spreads (Van Landschoot 2008; Acharya, Amihud, and Bharath, 2012). These include both single stock and market index volatility as controls that will positively relate to spreads.

Moreover, Chen et. al. (2013) find that spread characteristics and liquidity vary across the business cycle, and credit performance fluctuates with general economic performance. Only difference being that this analysis focuses on issues with five or fewer years left to maturity, due to the analysis focusing on Bond-CDS spreads. Acharya, Amihud, and Bharath (2012) identify additional market-based indicators of general financial distress and credit conditions to include in such analyses. They control for general macroeconomic distress using multiple rate spreads, including the TED spread (defined in Chapter 4) and growth in broker-dealer assets. The first is a good indicator of adverse financial and economic conditions and will also be useful in identifying contagion risks, as is discussed later. Growth in dealer assets will also proxy with increasing optimism and improving business conditions as dealers are unlikely to increase inventory unless they expect higher demand, and should thus lead to tighter credit spreads. However, it is necessary to question whether changes in dealer assets will have an effect on liquidity as higher dealer assets might only reflect a greater willingness of firms to hold inventory rather than higher levels of client transactions.

3.4 Tax Effects

Other empirical work suggests that the differential tax treatment of fixed-income instruments drives wider corporate credit spreads. U.S. government bonds and U.S. corporates differ in that Treasury interest isn't subject to state income taxes while corporate coupons are. However, there is only weak evidence from empirical analysis of CDS spreads that taxes will drive spreads higher (Longstaff, Mithal, and Neis, 2005). The authors question both the economic significance and the strength of the empirical support for the statistically significant relationship they observe between coupons and credit spreads. Although they find that coupons are positively related to corporate spreads to Treasuries, they also find a relationship to corporate spreads relative to benchmark, highly rated corporate bonds. Because there aren't differential tax rates between benchmark corporates and other corporate bonds, the differences in coupon levels should not remain significant. These results imply that higher coupon bonds have some other unfavorable characteristics such as lower credit quality or less liquidity that would make coupons relate to relative differences in corporate yields (Longstaff, Mithal, and Neis, 2005).

However, the tax-exempt municipal credit market offers evidence that variation in tax treatment will affect bond spreads. Recent findings demonstrate that municipal yields remain significantly lower relative to corporate issues due to tax considerations and drive taxable yields higher (or municipals lower) to adjust. It is a long maintained subsidy for local and state governments to issue debt that exempts investors from taxes on the payment of interest, thus allowing bonds to be marketed at a lower interest cost to the municipality (Wang, Wu, and Zhang, 2008). This is consistent with the aim of making municipal interest payments tax exempt to reduce municipality and state borrowing costs – by exempting interest taxation, rates investors demand and states can pay will be lower. This also affects demand for muni debt. Due to tax-exemption and the reduced yields relative to pre-tax corporate yields, tax-advantaged clientele including pension funds and life insurance companies will not benefit and participate in the municipal bond market.

Most of the appetite for muni risk comes from individual investors and their proxies (mutual funds, exchange-traded funds) looking to decrease tax burdens while investing in a historically safe asset class.[12] [13] This result is consistent with the liquidity clientele theory discussed earlier, and further points to the effect that investor preferences have on bond liquidity (Huang et. al., 2013). If a pension fund is already exempt, they can take a corporate yield tax-free instead of accepting lower yields that are priced to attract investors subject to income taxes. Compared to the municipals market, it seems that corporate credit will offer relatively more yield due to tax effects.

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[12] The Federal Reserve notes in a 2012 publication that Moody's reports only 71 defaults from 1970 to 2011. The Fed goes on to claim that unrated muni credits are historically 36 times more likely to default than what Moody's says, but the emphasis in this literature is on rated bonds.

[13] Historically, municipal bond defaults occur less often than their corporate counterparts. In recent years, more questions about municipal credit quality have been raised, fueled in part by record-setting bankruptcies including that of Detroit in July 2013.

3.5 Contagion

Furthermore, corporate bond market contagion may affect the liquidity of related companies. This stems from perceptions of homogeneity of companies within an industry. Importantly, the impact of sudden events contributes to corporate bond trading and highlights the effect of deteriorating credit quality on bond liquidity and in liquidity of related issuers' bonds.

Major, unanticipated news events can dramatically affect the credit quality of a particular corporate and cause a "jump-to-default" outside of what is expected in conventional credit analysis. Collin-Dufresne, Goldstein, and Helwege (2010) postulate that some of the extra spread on corporates comes from the inherent contagion risk of unexpected developments in credit quality. Instead of a gradual reduction in credit quality, a premium yield will "price in" the low probability of an unexpected, acute shock that could damage credit quality.

Interestingly, Collin-Dufresne, Goldstein, and Helwege (2010) provide support for analyzing bond prices relative to par value to control for credit contagion effects. Due to the risks studied in their literature, investors find it necessary to consider the possibility that imminent default may occur to any given bond. The price that is paid would impact the relative recovery rate. One bond purchased at a premium to its principal payment at maturity is disadvantaged to one at a discount. It seems that by using their literature to introduce a variable related to premium pricing that we can extend prior models and take another look at the jump-to-default risk that corporate credit contains.

There is also work that reveals how specific periods of market-wide distress can cause illiquidity, especially that surrounding the 2008 financial crisis. Dick-Nielsen, Feldhutter, and Lando (2012) find that bonds underwritten by Bear Stearns and Lehman while under distress traded with relatively less liquidity and larger credit spreads.[14] These extreme examples in 2008 illustrate a more extraordinary event. In this case, there is not only contagion risk surrounding the fate of major financial firms, but also contagion, illiquidity, and credit spread widening due to financial distress of U.S. broker-dealers. This, as these empirical pieces provide, demonstrates how the deterioration of investment bank credit quality can ripple through the bond market to decrease liquidity and widen bid-offer spreads.

Bai et. al. (2013) introduce analysis that shows cross-credit correlation can be a "contagious" response to a related-firms' credit event, and may be a greater risk than actual default risk. They examine days where credit events occur to specific corporates and cause market contagion putting downward pressure on related investment grade bonds (Bai et. al., 2013). This evidence suggests that there is a high degree of perceived correlation among credits, even of the investment grade quality, and will impact trading prices of other bonds despite the remote possibility of immediate default.[15] This confirms prior findings regarding contagion risks and market-wide responses to largely isolated credit events.

[14] Underwriting is the process of investment banks pricing, purchasing, and marketing new issues to clients. The banks will also play a role in making markets in the new issue immediately after issuance.
[15] Typically, bonds will be downgraded from investment grade to high-yield, and slowly move toward default. Investment grade bonds don't usually default unexpectedly without being downgraded.

Examination of implied recovery rates of distressed corporate bonds demonstrate that higher yields come from less liquidity in the thinner market segment defaulted bonds. Similar to Han and Wang (2013), Jankowitsch, Nagler, and Subrahmanyam (2013) explore trading activity surrounding corporate defaults. They reveal that the limited clientele willing to buy distressed debt in conjunction with widespread distaste for holding defaulted debt leads to extreme downward pressure on prices, with this decline leveling off in activity and volatility within 30 days. During this time, wider spreads are observed, and they find that liquidity varies inversely with short-term rates, outstanding credit default swaps (CDS) that are physically deliverable, and other macroeconomic variables (see more on CDS in Appendix C).[16] They also cite that general market contagion and broker-dealer distress will widen spreads due to decreased willingness to take on riskier bonds. Their study of the microstructure of trading demonstrates that factors outside of bond characteristics will affect trading activity and liquidity for defaulted bonds.

3.6 Limitation of Study – Optionality and Note type

This analysis is limited to the empirical testing of “straight bonds” or those without any optionality, complexity. With that, bonds with callable, puttable, and sinking fund provisions will be struck from the observed data, which is in line with prior practice examining high-yield and investment grade debt (Delianedis and Geske, 2001; Helwege, Huang, Wang 2013). This is because of the valuation and greater uncertainty regarding the maturity and credit risk considerations of additional bond covenants. In examining defaulted corporate bonds, they find no difference due

[16] The phrase “physically deliverable” simply means that the exchange in the swap agreement requires that the party who buys protection transfers the bond referenced in the contract to the protection seller. This is as opposed to a cash settlement of the contract.

to their focus on recovery rates rather than issues such as reinvestment risk and yields.[17] Because this exploration will not include defaulted debt, it would make sense that the approach taken here would differ from approaches to distressed instruments due to the non-negligible differences seen in analyzing bonds with optionality.

[17] Bonds with optionality such as those with call dates prior to maturity benefit issuers by letting them buy back the bonds and refinance at a lower rate – this inevitably would hurt bondholders as they would be forced to reinvest at a lower interest rate.

4. Empirical Approach

This section will outline the various models that will be applied to the bond dataset. A variety of econometric techniques are used to examine determinants of bond spreads: a random walk with multiple lags, a time differenced model, and a model with multiple types of fixed effects. Several variants of each model are examined such as with and without a squared term for years to maturity to capture potential non-linear effects of explanatory variables.

4.1 Random Walk

It will be necessary to test for whether corporate credit spreads follow a random walk – or some other autoregressive process. I will begin this exploration by analyzing spread movements with a random walk regression, as it may be possible that the majority of credit spread movement follows this time-persistent model. This is consistent with the evidence shown in Chapter 3 that identifiable risks may hold high theoretical power, yet have weak empirical power.

Standard ordinary least squares (OLS) regression analysis relies on assumptions regarding the process that determines the movement of the estimated variable. In the case of time-series data, classical linear model assumptions require that observations of the estimated outcome are independent – or at most weakly dependent – from period to period. In a random walk model, this isn't the case; rather, values in one period are highly dependent on values in prior periods. Changes from period to period are considered random shocks centered around a mean of zero – implying that the best estimate of next period's value is that of the current period.

In this case, a random walk is a fitting baseline approach that will first examine whether credit spreads follow a random walk subject to persistence across time and random movement. This will give basis to whether our given variables can outperform a simple model of credit spreads meandering through time with inherent randomness that will be most closely approximated by the previous period's spread. The random walk movement will be looked at without a constant to see how the coefficients represent the time-persistence of previous values on a given day's spread. We will also regress further lags on the current model until the statistical significance of the lags no longer exists. This will show how persistent spreads are from trading day to trading day for each bond. This is consistent with the recommendations of Campbell and Perron (1991). This is represented by Equation 5:

$$spread_t = \alpha * spread_{t-1} + \cdots + spread_{t-n} + \varepsilon_t. \quad [5]$$

In looking at corporate yields, their spreads to the relevant risk-free rate will be considered using only the spread to benchmark U.S. Treasury rates. We label the independent variable throughout *spread.* These credit spreads will be calculated by subtracting corporate bond yields from the closest maturity, on-the-run (most liquid) U.S. government bonds. This seems like a reasonable way to interpret the risk-free rate and is consistent with prior literature (Dick-Nielsen, Feldhutter, and Lando, 2012). Other research suggests that that we rely on Treasury swap data, instead we look at U.S. government bond yields, which is most commonly used.

4.2 First differenced model

Much prior research suggests that credit spread time-series are non-stationary, which will inherently corrupt a non-transformed OLS regression of the credit spreads.

This is because for OLS to be the best linear unbiased estimator each variable must be a normally distributed random variable and be time independent. However, if we difference spreads over time, we may estimate a model with OLS and analyze the components impacts without bias and violation of OLS assumptions. The model will be estimated in the form of differenced variables where $spread_{it} = spread_t - spread_{t-1}$ from Equation [5]. Thus, the basic model is now:

$$spread_{it} = \beta_0 + \beta_1 matur_{it} + \beta_2 fedrate_{it} + \beta_3 ted_{it} + \beta_4 eqvol_{it} + \varepsilon_{it} \qquad [6]$$

This model doesn't include all of the variables that are included in our final model due to the nature of differenced models. Because the equation models only differences across time, all the control variables must also vary across time. A concept such as issuance size or coupon doesn't vary with time, and thus cannot be included in this model. This is a major limitation of this model, but it may still be an effective approach to explore which variables that move day-to-day best influence changes in corporate credit spreads. Furthermore, this model forces us to omit age due to the collinearity between the difference in bond age and years to maturity.[18] While prior empirical work emphasizes that both of these elements affect bond spreads, we must eliminate one to follow empirical theory.

Another issue with our differenced models is that the variables are more focused on general, macro-based trends than intuition and prior credit literature expects. We still believe in the importance of this model due to its empirical relevance. While it may not be the most valid model in terms of drawing from

[18] The sum of these two variables is always constant for a given bond.

previous evidence, it is untested in our references, but still expresses a valid and accepted form of time-demeaning series that may contain unit roots.

Four independent variables are used in this round of analysis. The first variable, *matur*, reveals the combined effect of reduced maturity and increased bond age as the bond's spread changes over time. This variable provides insight as to whether the force of age or declining years to maturity more significantly impacts spreads. We would expect that maturity would be systematically related to credit spreads due to the increased uncertainty surrounding longer-term bonds. In addition, more mature bonds attract higher levels of insurance market participation as this clientele prefers to buy and hold assets, and thus is less concerned with liquidity (see Chapter 3 for more details). Also, evidence of strong liquidity effects impacting short-term debt will later motivate the inclusion of an additional squared term for years to maturity. This will test for a non-linear relationship across credit spreads and maturity.

Second, macroeconomic conditions and the impact of the credit/business cycle will be captured by drawing on interest rate and economic data. Relevant literature (e.g. Chen et. al, 2013) suggests that macro conditions will affect the level of spreads throughout the credit cycle – lower short-term rates coincide with looser credit and a "frothier" credit environment. As near-term rates are higher, that will more likely determine tightening credit conditions such that spreads may grow larger relative to the risk-free rate.

The effective funds rate, *fedrate*, will also control for short-term market liquidity and proxy for monetary policy actions. While the Federal Reserve influences this rate, the effective rate varies more based on daily changes in available credit and willingness for banks to lend to one another. We use the effective rate because it is not only consistent with prior research, but also allows for our Post-Crisis Period to include the variable. As targeted rates have been 0-25 bps since 2009, it would be impossible to use the variable without relying on the effective rates measure. The most frequent data from the Federal Reserve is taken, and any missing trading days of data are filled in with the most recent value.

Third, the TED spread will be a good proxy for macroeconomic and credit conditions and is a measure of aggregate market liquidity. The spread is defined as the three-month London Interbank Offered Rate (LIBOR) minus the three-month Treasury bill rate. LIBOR is a number based on reports from banks' uncollateralized bank lending rates. Thus, the TED represents the difference in short-term and U.S. government borrowing rates. This figure correlates with market contagion and points to flight to quality that will measure willingness of market participants to take on short-term risk relative to the short-term bill rate. A tighter TED spread indicates generic willingness of market participants to take on risk, thus the spread should positively correlate with greater credit spreads and more risk aversion.

Both the TED and effective Fed funds rate will be transformed from yield percent to basis points. Thus, a 0.15% effective rate will be expressed as 15. These variables' estimated coefficients will correspond with the linear relationship with credit spreads if they increase by a basis point.

Citing evidence that broader equity market volatility will affect corporate spreads, we will control for this by using rolling 60 day equity volatility of the SP500

U.S. (Acharya, Amihud, Bharath, 2011) stock market index, *eqvol*). The market capitalization weighted index of 500 major corporations should provide a good measure of market distress and investor uncertainty that will likely have a positive effect on credit spreads, and correlate with credit widening. While both markets respond differently to new data points and events, equity market volatility is shown to correlate with higher spreads and bond market stress. By including a measure of volatility over 60 days we are effectively allowing three months of trading activity to influence bond prices. This is appropriate as it is well known that equity markets are efficient both in aggregate and relative to the bond markets. Thus, including this variable insures that bond spreads are changing due to characteristics in corporate debt, not due to changes in equity market activity.

4.3 Fixed effects modeling

In line with prior findings, fixed effects modeling will be included in our modeling of corporate credits (Helwege, Huang, and Wang, 2013). Fixed effects will allow our analysis to hold effects of different issuers' bonds constant, and remove the effect of specific issuers. By holding these effects constant, we can better identify how default, liquidity, and other aspects most affect bond prices.

The fixed-effects model that will be used for this analysis control for both firm and year effects for each of the bonds that are being examined. There are two ways to approach this type of effect: separate fixed effects and interactive fixed effects. We begin with interactive firm-year fixed effects on the theory that each bond from a particular issuer trading in a year will have a common risk of default or credit event.[19] This model is similar to the approach that is first discussed by Graham, Li, and Qui (2011), where they examine executive compensation by fixing manager-specific, employer, and time effects. Given certain unobservable traits that may be specific to certain issuers, including different balance sheet conditions, credit quality perceptions, and reputation, this fixed-effects model would help account for these differences among issuers and add-value to this analysis.

However, it turns out that many of the bond issuers vary little from year to year during the period examined herein. As a result, many of these issuer-year fixed effects are collinear and are dropped from the model. Accordingly, the analysis reported herein uses the more conventional separate fixed effects for issuer and year. This is consistent with the conventions in the literature (e.g., Helwege, Huang, and Wang, 2013). We report for robustness that all results reported herein are qualitatively similar to those obtained using the interactive fixed effects. While it may be preferable to use more specific variables to account for the effects of issuer characteristics or events in a particular calendar year, this approach will provide insight on how bond and issuance specific characteristics for the same issuer provide for different yields across a firm’s term structure of interest rates.

Standard errors will be clustered within each issuer due to firm-specific differences that may persist from period to period. Throughout time, each firm has characteristics that change minimally from year to year, consistent with the fact that this dataset includes only senior debt that is not illiquid. Thus, there is a level of serial

[19] It is worth reiterating that because this study is restricted to senior notes, each bond by each issuer will receive the same seniority in the case of default. Since subordinated notes would expect lower recovery rates, their inclusion would require additional controls for this type of model.

correlation and heteroscedasticity that can be controlled for by clustering standard errors.

The fixed effects model is in the form of:

$$spread_{it} = \beta_0 + \beta_1 matur_{it} + \beta_5 age_{it} + \beta_3 fedrate_{it} + dprem_{it} + \beta_5 age_{it} + \beta_6 issuesize_{ot} + \beta_7 \beta_2 ted_{it} \beta_8 bdassets_{it} \beta_4 + eqvol_{it} + \gamma_i + \delta_t + \varepsilon_{it} \; . \quad [7]$$

We will rely on multiple concepts to analyze the effect that certain bond characteristics will have on bond liquidity and corporate spreads. The dependent variable, *spread*, is as defined in Chapter 4.1, and the first four independent variables – *matur, fedrate, ted and eqvol* – are as defined in Chapter 4.2. The remaining four independent variables are now explained.

First, *age*, or the time since the bond was issued is included to capture both changes in a bond's quality over its lifespan and the possibility of changes in the firm's financial performance over its lifecycle. Prior research suggests that this is a reliable indicator, and is observed to positively correlate with credit spreads (Helwege, Huang, and Wang, 2013, Houweling, Mentink, and Vorst, 2005). This is due to the declining liquidity of older bond issues and the impact buy and hold investors have on secondary market liquidity.

Furthermore, bond issuance size, *issuesize*, will be used to control for issue characteristics that impact liquidity. We expect this to be negatively correlated with credit spreads, because a larger issue size would correlate with more trades due to a greater outstanding amount of bonds (as in Houweling, Mentink, and Vorst, 2005, and Helwege, Huang, and Wang, 2013).

Third, price data will also allow us to use a dummy variable, *dpremium,* to control for bonds trading at a premium to par value. A dummy variable is generated equal to "1" if the bond is trading over 100, and equal to "0" if not. Corporate bonds typically have a face value of $100 and subsequently trade in a narrow range around $100. This metric will be used to proxy for the additional risk implied by purchasing the bond at a price greater than face – that is, if an investor purchases a bond at 104 today due to today's prevailing interest rates, if default happens tomorrow, the most that the holder could claim is 100. This coincides with earlier research findings, and will be used to proxy for spread drivers outside generic default risk. This addition is drawn from literature on jump-to-default-risk in that this additional risk may be recognized and provides greater yield spread – all else equal – than otherwise would be required. Spreads may very well change based on this due to the possibility of a firm's imminent, yet unknown, chance of triggering bankruptcy.

Finally, broker-dealer credit market assets, *bdassets*, will measure balance sheet expansion by market makers. This data is reported quarterly and is expected to negatively correlate with corporate yield spreads. Growth in dealer assets should indicate more competitive bond pricing by market makers, and decreases in corporate credit spreads. While this is only a quarterly statistic, its inclusion is deemed valuable and represents an empirical extension that comes from the broker-dealer perspective rather than that of the issuer or investor. Because this study uses daily data on bond trades, we will use the prevailing quarterly data for all days in the quarter, in line with prior work (e.g., Acharya, Amihud, and Bharath, 2011).

5. Dataset

The reviewed literature provides a strong foundation for this analysis of corporate bond spreads. Prior academic research suggests that significant non-default components exist and can be measured, but there remains tension as to how to measure liquidity, the exact nature of its role in market operations, and the exact manner by which it affects corporate credit spreads. This section outlines first how the dataset is created, how the time period is broken up for analysis based on market events and trends, and then broad and subset summary statistics are discussed.

5.1 Creation of Dataset

Indicative bond data is drawn from Citi's proprietary Yield Book data for issue characteristics such as issue size and issuance date. I analyze bonds that trade between 2005 and the end of the third quarter of 2013. These periods will entirely include pricing during periods following the implementation of the FINRA's introduction of the TRACE system in 2005 to publish trading size and prices. As this dissemination of bond trades is meant to promote transparency, our approach focuses only on TRACE era data consistent with prior literature. This dataset ends in the third quarter of 2013 as that was the most recent data available when this research began.

This analysis is limited to U.S. issued, U.S. dollar denominated corporate bonds that are found on TRACE and have non-missing data from Yield Book. Each bond issuance has a unique identifier, known as a CUSIP.

Bond pricing and yield data is drawn from the Financial Industry's National Regulatory Authority's (FINRA) TRACE database, which contains all trading data for public price disseminations for fixed income securities. Pricing frequency will vary with genuine transaction data, but we eliminate all trades that are less than or equal to $100,000 in face value to eliminate retail trades (Dick-Nielsen, Peter Feldhutter, and Lando, 2012). There is precedent for removing trades below $500,000 in face value traded, but most of the work adheres to the $100,000 threshold; thus, we follow prior consensus in our approach.[20]

The data is then collapsed to yield an average price and yield for each day each bond issue trades. That is, we are not examining potential intraday movements, and prefer to focus on the day to day changes in yields when corporate credit trades. This is consistent with the reviewed literature that doesn't look at intraday trading. The resultant dataset will not be balanced across time to allow the most observations to be included.

Next, we look at the TRACE Master File and limit the file to corporate, fixed coupon securities. We also remove private placement securities, and medium term notes, a process which is in line with all prior literature. We also invoke elimination of subordinated notes in an effort to control for differences in capital structure decisions and the further effects that they may have on credit spreads.[21]

We winsorize price and yield data by removing the top and bottom percentile of bonds. In addition, those bonds that change by more than 20% in value between trading days are removed from the dataset. We take the CUSIPs that are now left

[20] Recall that corporate bonds are generally priced about $100. Thus, trades of $100,000 correspond to roughly 1,000 bonds being traded. Due to the fact that institutional traders rarely engage in such small transactions, these are excluded.

[21] See Appendix A for further detail on capital structure, subordination, and bondholder recovery.

from the TRACE files and use them to pull in Yield Book's Indicative Data. The trading data is then merged with the Indicative dataset and the scrubbed Master File.

We download constant maturity Treasury yield data from the Federal Reserve of St. Louis FRED and use them to create yield spreads by subtracting the closest maturity government security from the each corporate yield. We use the 3 month, 6 month, 1 year, 2 year, 5 year, 7 year, 10 year, and 30 year yields. To create a 30 year rate for periods when no 30 year securities are issued, we interpolate values by looking at the 10 and 30 year yields for prior to February 9, 2006.

We eliminate callable corporate bonds, which is in line with all prior research on non-defaulted corporate bond issues. Issues flagged as puttable or with a sinking fund are also removed from our observations. Bond optionality confounds what bond spreads imply regarding default risk and liquidity. As a result, prior research strikes them out of datasets to best understand bonds sans optionality, as discussed earlier in Chapter 3.6.

Observations missing yield or spread data at this point are also eliminated. We also remove any securities that are flagged as "InDefault" by Yield Book. Bonds are also eliminated that are marked are sovereign-sponsored and potentially indicate issuers who are backed by non-U.S. government credit.[22] Elimination of all of these elements shrinks our observation base to 179,895, a loss of 737,139 observations from our set.

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[22] An example of a sovereign backed issuer is the Svensk Bank, which is backed by the Swedish government.

5.2 Subsets of Data

The data can be analyzed in aggregate. However, I plan on breaking down this analysis into three separate time periods demarcated by the 2008 financial crisis. The period that began in 2007 and ended in the first quarter of 2009 will be considered the "Crisis Regime". We begin in 2007 due to the growing worries regarding increasing foreclosures and portents of wreckage to come in the U.S housing and mortgage markets. The crisis regime is characterized by aggressive Fed policy that impacts different industry spreads differently (Gilchrist and Zakrajsek, 2013). We mark the end of this period around when U.S. equity markets recover and general financial distress begins to recede following multiple bailout equity injections (TARP), and asset purchasing measures conducted by U.S. authorities. [23][24]

Thus, the first period covers the years 2005 and 2006 and is labeled the "Pre-Crisis Regime." Finally, the period from the second quarter of 2009 through the third quarter of 2013 is labeled the "Post-Crisis Regime." The breakdown of these periods will allow us to examine any difference that may exist in terms of what drives credit spreads during periods characterized by vastly different events, Fed policies, levels of financial distress, and popular perceptions of asset valuations. Later, I will present summary statistics and t-tests of the means to illustrate the marked differences between periods and further motivate the study of the different time regimes.

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[23] The Troubled Asset Relief Program (TARP) was initially constructed to purchase toxic assets related to housing distress that were illiquid and virtually didn't trade because of widening bid-ask spreads. This program was converted into a plan to reinforce support of major commercial and investment banks in the form of capital injections that gave the U.S. government non-voting interests in the companies.

[24] The Federal Reserve began multiple Troubled Asset and illiquid asset programs in addition to its lowering of the funds target rate that were aimed at supporting mortgage markets and money market funds.

The data will also be split according to two additional filters. First, I conduct separate analyses of high-yield versus investment grade bonds due to the liquidity clientele differences, default risks, and findings from prior research (as discussed in Chapter 3). Second, there will be separate analyses of bonds issued by financial and nonfinancial firms. Separation of industry is motivated by the distinctions observed in prior literature (Gilchrist and Zakrajsek, 2013). Separating credits should minimize error and allow for a side-by-side comparison of results that will further inform our conclusions and direction for future analyses.

5.3 Univariate Data

The initial dataset indicates a high degree of dispersion among the yields and yield spreads. I decide to remove any bonds that are unrated by both Moody's and Standard and Poors (S&P) agencies in line with observation s made in prior research (Kim and Stock, 2011). Prior to their elimination the mean spread was 323 basis points (bps) with a standard deviation of 2,131 bps; afterward the mean and standard deviation were 283 and 400 bps, respectively. This transformation indicates that there unrated debt issues are much different from rated ones in the levels that they trade relative to comparable Treasuries.

The dataset continues to have unrealistic price data, with a minimum of 0 and a max of 318. Recall, corporate bonds have a face value of $100. Bonds that are not in default typically trade within 20-30 points of par value. These statistics indicate that the bonds with prices very different from $100, such as those with prices greater than $150, are likely convertible notes as they have fairly low coupons, yet trade at high prices and yields that appear to not indicate a typical straight bond.[25] With this logic, we strike out all bonds trading over \$150 from the sample. We also remove all bonds trading below \$0, which is the sample's minimum. It intuitively doesn't make sense to examine any bond with a non-positive price. Thus, we set the minimum price at \$1 and eliminate all prices below this threshold. Extreme values remained in the dataset and appeared hard to explain. Accordingly, we invoke the Central Limit Theorem to winsorize our data and eliminate spread observations outside of three standard deviations of the mean, which removes spreads that exceed 1,683.83 bps.

We also restrict our examination to CUSIPs that have more than 45 trading days. The first reason is that any bonds that are traded that infrequently over the studied time period are most likely trading due to material credit events occurring that spurs further trading. As a result, these time series don't qualify as unit roots as their trading is correlated with actual events, and not simply random fluctuation of prices. Selling in these less liquids bonds would most likely indicate that there is a material change in the value or perceived quality of the bond. Obviously there may be some need for a trade if investors need to raise cash or reduce risk exposure. However, we might expect that these less frequently traded issues will likely trade on a non-random basis. Because the empirical approach we take is based on removing the persistence of unit roots to determine credit spreads, it is necessary to restrict our study to those time-series, which theoretically stand as time-persistent, random processes. Furthermore, the Stata function of choice to test the hypothesis of a unit root,

[25] A convertible bond is one that has equity, bond, and option elements. It is not a focus of this study, however, the data we draw from doesn't have a straightforward way of eliminating convertibles. In this case, outlier characteristics that aren't indicative of regular bonds help remove these notes.

xtunitroot, requires more than 45 observations per CUSIP. As a result, both theory and computing limitations give solid basis to restrict less-observed bond spreads. This test rejects the null hypothesis that all 427 of the bonds examined have unit roots, and accepts the alternative that at least one panel is stationary. However, this is a weak result that leaves open the possibility that most of the bonds follow a random walk. Therefore, we continue to begin our analysis with a random walk to test which subsets may contain a unit root.

Removing these outliers and tightening our observation sample leaves us with 157,345 observations of CUSIP trading days. Our summary statistics indicate that the average spread is 235 bps with a standard deviation of 178 bps (Summary Statistics: Column 1).[26] The data is skewed toward newer issues, with an average bond age of 3 years, but with a standard deviation of also 3 years. This indicates that the included bonds are younger and a likely more liquid dataset that would be expected to have yields tighter to comparable.

We then further break down our sample into investment grade and high yield notes. Our dataset is more concentrated in high-grade credits, with 145,996 observations in investment grade, over 10 times as many speculative grade credits in the sample (Columns 2, 3). The high ratio of investment grades may reflect our decision to include only more liquid bonds, consistent with the clientele hypothesis discussed in Chapter 3.2.2. The outcome of the summary statistics appears as expected with average high-yield credit spreads over 300 bps greater than that of the high-grade variety.

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[26] See Appendix E, Figures 1 and 2 for visuals of price and spread distributions.

However, it is notable that both categories have a wide degree of dispersion relative to their subset averages, as both have relatively high standard deviations. We complete t-test of the means between the two samples to test whether their properties signal unique subsets of our dataset. This demonstrates whether each group represents a sample from a statistically different population. In this case, the test reveals that each of the sub-sets is statistically different from one another across the data and that we can distinguish the higher quality from lower quality credits with a statistical basis. This confirms prior findings and the intuition that motivates analyzing each subset separately.

We continue to breakdown the sample into our three distinct regimes and examine what clear differences persist between them. 2005-2006 demonstrates much tighter spreads to risk-free securities than during the crisis period, with an average of 128 for 2005-2006 and 278 for 2007-2009Q1 (Columns 6, 7). The pre-crisis period also demonstrates much less dispersion, with standard deviation of 94, much less than the crisis (206) and post-crisis (173) numbers. The minimum and maximum spreads are also much different for each respective period. This exemplifies what we might expect regarding the more volatile spreads discussed in crisis-era literature. The t-tests show that these periods are statistically distinct and represent time regimes where bond trading and prices are different from factors in the other two periods. This clarifies what the literature informs us of the difference in bond trading during the crisis and the apparent resolution of turmoil following it (Dick-Nielsen, Feldhutter, and Lando, 2011; Gilchrist and Zakrajsek, 2013). The larger standard deviations likely indicate evidence observed in earlier studies regarding flight to quality effects in the highest rated corporate issues, and widening in spreads of the riskiest levels of debt.

Furthermore, the post-crisis period illustrates a subsample with smaller credit spreads, which indicates an overall improvement in perceptions of corporate credit following the recession (Column 8). This period also illustrates the highest average price, at 106, while the two earlier periods were 100 and 96. This demonstrates an increasing level of premium bonds, which would be expected in a declining interest rate regime due to Federal Reserve easing policies. The unusually low rates of this period are also observed in the yield and spread data. Corporate yields in our sample average 5%, which is significantly lower than the two prior periods.

Observations are then further broken down into financial and non-financial bonds. The summary statistics reveal 109,006 observations are of financial issues, more than twice as many as the 48,339 observations of non-financial bond trading observations (Columns 4,5). The average spreads are very close, financial and non-financial averages are 247 and 207 respectively. The t-tests reveal that these samples are statistically discernible, and that financials appear to be distinct from non-financial issuers. It is interesting that financial spreads are significantly wider – which might be a result of the period being studied. There is evidence that corporate credit concerns for banks are not resolved as quickly in empirical evidence surrounding the crisis (Gilchrist and Zakrajsek, 2013). Financial debt is also a year younger and has five years fewer left until maturity. That is, most financial debt has shorter maturity at time of issuance and was issued more recently.

6. Results

6.1 Random Walk

This first model is used to examine whether bond spreads are best predicted by past levels. The initial random walk with one lag for each bond indicates that credit spreads move along a random walk, with the lag being strongly statistically significant and persistent with an estimated coefficient of 0.815 (standard error of 0.001) (Table 1). This indicates a high level of persistence from period to period. The R^2 of that model indicates that 67% of the variation in credit spreads can be explained through the prior period's spread.

In line with (Campbell and Perron, 1991), we include additional lags until the last included lag is statistically significant. Thus, we present an expanded model that has ten lags (Table 1), which explains 79% of credit spreads. Interestingly, each lag remains both positive in sign and highly statistically significant (at the 1% level) even as more lags are included. The random walk of the entire dataset tells a story of persistent spreads. If a bond had traded daily, this would imply prices persist through two trading weeks. However, Chatrath et. al. (2012) note that the average corporate bond trades only on 20% of trading days.[27] Thus, these results indicate long-term stability of corporate bond yields. These results also imply that bonds are likely to change only when there are shocks to how the markets operate or how investors perceive the firm. Accordingly, we proceed by first examining whether bond spreads are similarly persistent in other subsets of the data and then by trying to identify possible causes of changes in the observed spreads.

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[27] This study examines TRACE data from 2007-2010.

As more lags are added to the model, the estimated coefficients drop sharply in magnitude while the standard errors remain nearly constant and all coefficients remain highly statistically significant. We examine the adjusted R^2 to identify whether the additional covariates have increased the explanatory power of the model as a whole. The observed upward trend in adjusted R^2 demonstrates increasing explanatory power in the variation of spreads. This effect diminishes as more lags are added to the analysis (see Table 1).

We continue analyzing the random walk nature of corporate credit spreads for each of the significant subsets that were described earlier in Chapter 5.2. First, separate analyses are conducted of investment grade and high yield credits. This is done to motivate further analysis of the precise impact that credit quality grouping has on bonds. The first random walk (Column 1 of Table 2) generates a highly statistically significant estimated coefficient for the high-yield grade dummy that is substantially larger than all other coefficients combined: 16.336 (s.e., 1.473). This is indicative of profound differences between the two divisions of credit grades.

I next conduct separate analyses of investment grade and high yield credits (Columns 2 and 3 of Table 2). Given that investment grade and high yield credits differ markedly across the board (see Summary Statistics) it is possible that the same set of independent variables would hold markedly different explanatory power in analyzing the observed variation in spreads. In line with this hypothesis, we find that analysis of only investment grade bonds explains 79% of spreads, but modeling high-yield bonds describes 81% of spreads. This is most interesting as even the most frequently traded high-yield bonds trade on fewer days per year than the most liquid investment grade issues (Chatrath et. al, 2012). These ten lags, thus, most likely represent spreads recorded over a longer time horizon – thus indicating that “stale” prices are still informative.

Secondly, separate analysis of financial and non-financial credit spreads reveals a similar high level of persistence and explanatory power (Columns 4 and 5 of Table 2). Both financial and non-financial spread models describe ~79% of credit spreads in each subset. While all the estimated coefficients are highly statistically significant in both models, it is interesting to note that the standard errors for non-financial lags are slightly higher than those in the financial model at 0.005 and 0.003, respectively.

Finally, it is possible that the financial crisis transformed the pricing structure for bonds. Accordingly, I now report results from different time periods. While the pre-crisis period explains 81% of spread variation and post-crisis explains 85%, the crisis model only can account for 67% of credit spreads. This reveals that the crisis period exhibits much less persistence in spreads across trading days. This is consistent with either other variables carrying higher explanatory power at this time or changes in the behavior of market participants (e.g., longer-term investors that suddenly face liquidity constraints may sell at discounts).

Overall, it seems that corporate credit spreads can be well approximated by their previous value. The results confirm that all subsets except the crisis period exhibit persistent trends that explain upward of 78% of the observed credit spreads. This confirms our earlier results of the meandering movement in corporate credit and will provide a reference baseline against which we can judge the results of later models.

6.2 First Differenced Models

We continue to examine credit spreads by looking at how differences from period to period impact changes in spreads over time. The first differenced models remove bias induced by the fact that many of the explanatory variables are extremely time-persistent. Differencing variables will remove this bias from the OLS regression. Because many variables that are observed to correlate with spreads do not vary across time, elements such as issue size cannot be accounted for. Instead, this model is based mostly on changes in broad market-based variables.

The results show that all variables are extremely statistically significant at the 1% significance level, but the total model provides a poorer fit of spread variation and reveals unexpected results. The results show that most subset credit spreads are positively correlated with older, shorter maturity bonds in all subsets except for the pre-crisis period (see Table 3). This is consistent with our expectations as older bonds are observed to contribute to less liquidity, and other analysis reveals that short-term bonds have decreased liquidity (Houewling, Mentink, and Vorst, 2011; Bai et. al. 2013). The largest economic significance is observed during the crisis period, which is also consistent with prior work (Dick-Nielsen, Feldhutter, and Lando, 2011).

Interestingly, the results indicate that corporate credit spreads negatively correlate with the Fed funds rate across each subset. This reveals that tighter (looser) short-term borrowing rates between banks are associated with smaller (larger) spreads. This is inconsistent with prior work claiming the opposite effect (Acharya, Amihud, and Bharath, 2012). We see the strongest relationship in crisis-era spreads at -0.633. This makes sense as spreads widened generally at a time when the target rate was cut aggressively in response to burgeoning turmoil (Gilchrist and Zakrajsek, 2013).

However, credit spreads are positively correlated with the TED spread, which is in line with prior findings. The strongest relationship is seen in the high-yield bond subset, where the spread increases by an estimated 1.426 bps for every additional basis point in TED. This suggests a high degree of sensitivity within the subset. Conversely, the TED has a smaller estimated effect during the crisis period, as the estimated coefficient shrinks to 0.656. The crisis era relationship seems at odds with prior findings regarding the high degree of risk aversion and flight to quality experienced during 2008. This may be due to flight to quality being statistically more attributed to differences in bond age or another indicator of bond liquidity.

Although equity volatility positively explains the observed variation in credit spreads across the board, it is not economically significant. We note that the magnitude of this variable is largest in the high-yield subset, which is supported by evidence of high-yield credits behaving more like equity across time (Delianedis and Geske, 2001). However, this effect is not too economically significant, as rolling 60 day, annualized volatility increases spreads at most by 0.106 bps. This is hardly a powerful effect, which contrasts with prior findings (Acharya, Amihud, and Bharath, 2012).

Each subset is modeled with significantly less fit than was observed in the random walk models. The models fit 31- 47% of spreads. This indicates either that there is greater variation in the observed values of the dependent variable or that there may be omitted variables. As the dependent variable is effectively the same as was used in the random walk model, I conclude that the low quality of fit indicates that important variables were omitted due to the impact of first differencing all variables (see Chapter 4). The best-fit subset is the crisis period, which coincides with the greater impact of macroeconomic events that dominate the differenced model (Acharya, Amihud, and Bharath, 2012). This is consistent with the idea that during stable economic regimes such as the pre- and post-crisis periods, bond spreads should respond primarily to issuer- and bond-specific characteristics. However, as these issuer- and bond-specific characteristics tend to be time invariant, they were all omitted from this round of analysis. Another interesting result is that financial spreads are significantly better modeled than non-financial spreads, explaining 44% and 31% of variation, respectively. This is also a compelling result that is unpredicted by prior evidence but is consistent with the fact that financial firms faced greater variation in operating performance and market conditions during the period examined in this thesis.

6.3 Fixed effects model

The full regression table (see Table 4) reports the results from the fixed-effect estimation of each of the seven sub-samples based on bond rating, whether the issuer is a financial firm, and the time period. First, across the board the estimated coefficients of the macroeconomic explanatory variables are consistently statistically significant in nearly all models while that is not true of the bond-specific characteristics. Second, the fixed-effects models explain between 67% and 87% of the variation in corporate credit spreads according to R^2. The pre-crisis time-regime is best described by the model (Column 5 of Table 4), with the rest of the models describe 67 - 76% of spreads. This is a compelling result in that some of these fixed-effect models now outperform the random walk of ten lags in their ability to explain credit spreads.

The variable *years*, which captures years until maturity, is statistically significant in all subsamples except that of non-financial issues (Column 4). However, the observed relationship is negative in all cases except during the pre-crisis period, which diverges from prior findings that spreads are larger for longer-term bonds (Houweling, Mentink, and Vorst, 2005). The largest magnitude is high-yield, which is -5.051, indicating that one more year until maturity correlates with 5 fewer bps. The difference between the results reported here and those found previously by Houweling et al. may reflect the usage of a larger dataset indicative of actual trades, which is unlike the dataset available to them.

Bond age is highly significant in explaining high-yield, financial, and crisis-era spreads. The result from the high-yield subset implies there is much less liquidity coming from bond age, and shows the additional illiquidity that corresponds with lower credit grades (Helwege, Huang, and Wang, 2013). The high degree of impact in crisis-era spreads confirms prior findings that show much less bond liquidity during the crisis period (Dick-Nielsen, Feldhutter, and Lando, 2012). This may also explain the greater impact on financial firms, which were generally more affected by the crisis than non-financial firms.

Issue size yields a complementary interpretation as it is only significant in the high-yield sub-sample. In this sub-sample, the estimated effect of an additional 100 million in issuance is a 16.8 bps tightening of credit spreads. This shows the relative importance of issue-specific liquidity for speculative grade credit.

The premium dummy variable is highly statistically significant in all subsets of the data, although it is slightly less significant in the pre-crisis period. However, the estimates show a negative relationship with bond spreads which implies that bonds trading over par don't require additional spread to compensate investors for the potential jump-to-default risk. This is at odds with the literature with which this variable is based on (Collin-Dufresne, Goldstein, and Helwege, 2010).

Consistent with basic bond pricing theory such as was shown in Equation 1, the bond coupon is one of the most significant explanatory variables. The bond coupon is consistently significant at the 1% level. All coefficients are positively correlated with credit spreads, which is indicative of a tax effect (Wang, Wu, and Zhang, 2008). The largest estimate is that for the crisis period at 31, and the smallest is 23. We note that this is the largest of the positive estimated coefficients meaning that higher coupon bonds may indicate that a bond also has other less desirable characteristics, as prior literature suggests. Thus, it is unclear whether this is the true effect of the bond coupon per se or rather captures both that effect and the impact of omitted variables that are correlated with bond coupons.

Moreover, the results reveal that each subset of the data is significantly affected by equity market volatility, with the impact of volatility greatest among the high-yield bonds. Volatility is associated with increased credit spreads during and after the financial crisis, which largely confirms prior findings (Acharya, Amihud, and Bharath, 2012).

The TED spread positively impacts all spreads in a statistically discernible manner, consistent with prior results (Acharya, Amihud, and Bharath, 2012). The strongest observed relationship is found in the post-crisis period, when an additional bp in the TED will increase spreads by over 2 bps. Furthermore, the impact of TED is smallest in the pre-crisis period when the estimated coefficient is 0.178. High-yield appears to be more affected by TED than investment-grade bonds, which suggests high-yield bonds are more susceptible to market-wide distress, as seen in prior work (Chatrath et. al, 2012).

Broker-dealer asset size is positive and statistically significant for most subsets. However, this relationship is surprising in light of past results (Acharya, Amihud, and Bharath, 2012). The value of broker-dealer assets has fluctuated a lot in recent years from a high in 2008 of nearly $900 billion, which is the period analyzed in Acharya et al. (2012) to $475-$500 bn in more recent periods. As a result, the dataset analyzed herein includes greater volatility in the variable and thus it is not surprising that our estimated coefficient differs sharply in interpretation. For example, the results found in this paper indicate that a $100 billion increase would imply 11.6 more basis points in spread (see Figure 3, Appendix E).

6.4 Fixed Effects model with Nonlinearity in *Years*

Because of the surprising result of *years* (discussed in Chapter 6.3), we revisit the literature to understand this result. There is evidence of unusual short-term liquidity effects in short-maturity bonds that lead to increased credit spreads (Bai et.

al., 2013). This implies that the years until maturity may have a varying, non-linear impact. As a result, we add another term to the model, *sqyears* or the squared value of years, to address this possibility and then re-estimate each model (see Table 5). The R^2 improves for both the investment grade and high-yield subsets, but decreases for both the financial and non-financial spread groups. The three time regimes have very similar quality of fit measures that are, at most, 0.1 percentage points lower than obtained previously.

Years to maturity remains statistically discernible only for financial and crisis-era spreads, but non-financial spreads are now highly statistically significant (at the 1% level) after previously being insignificant at all conventional levels of statistical significance. It is only for these three subset models that the squared value of years is statistically significant. The results indicate that in these three models maturity has a large negative coefficient while the squared value of maturity has a small positive coefficient, which reveals that the effect of maturity from 0-31 years remains negative. This continues to be at odds with prior work (Houweling, Mentink, and Vorst, 2005).

The addition of the new term changes the statistical and economic significance of bond age in the model. Age drops out of high-yield and financial credit spreads as being statistically discernible. The magnitude of the coefficient changes negligibly from 8.388 in the baseline model (Column 6 of Table 4) to 7.770 (Column 6 of Table 5). However, there is a difference in the high-grade subset as spreads were previously unrelated to bond age and are now weakly related.

The premium dummy variable remains significant, but at different magnitudes across the various subsets. It continues to be negatively correlated with spreads, but the standard errors are consistently larger than was observed previously. The coefficients for bond coupons remain positive and statistically significant, and are similar in magnitude to prior estimates.

Issue size is no longer significant for high-yield spreads, but is now highly statistically significant in the non-financial credit sub-sample. Equity volatility remains significant, but coefficients still are too small to be considered relevant to spread determination. Broker assets are also similarly significant, but notably drop out of both pre-crisis and non-financial models.

Altogether these results suggest that the addition of the non-linear term may improve the aggregate explanatory power of the model as was shown in the increased R^2s reported in Table 5 vs. Table 4. However, this additional variable had inconsistent effects across the models as other variables changed markedly in interpretation.

7. Conclusion

The results of this analysis provide evidence that credit spreads are highly dependent on past values. This is a powerful observation due to the infrequency of trading days (Chatrath et. al., 2012). The fixed-effect models show variations in the quality of fit, but can describe most of the observed variation in bond spreads, improving significantly on similar work reviewed in this thesis (e.g., Helwege, Huang, and Wang). However, the variables controlling for issue-specific liquidity demonstrate limited evidence that age and issuance size statistically impact credit spreads. Instead, economically and statistically significant relationships between spreads and macroeconomic variables are observed nearly across the board.

Analysis of the three separate time periods shows that the crisis period was markedly different from the years before and after. Consistent with the stylized finding that the crisis period was characterized by greater macro volatility and changes in liquidity preferences of market participants, the set of independent variables examined in this thesis were both individually and jointly less able to explain the observed variation in credit spreads. Nonetheless, the fixed effects model was able to explain roughly 72% of the observed variation in spreads during the crisis period.

These results suggest that investors should prefer to add riskier bonds to their portfolios during periods of macroeconomic distress when spreads will likely be larger than inherent default risk would imply. From the issuer side, these results suggest that corporates should have excess liquidity that will allow them to postpone borrowing past periods of generic market distress. Corporations therefore would benefit from reduced cash outlays through share buybacks or dividend payouts, which is consistent with theories regarding corporate capital structure.

It is possible that additional measures could be used to strengthen the conclusions observed here. For example, adding different controls for credit risk using credit grades, Z-scores, or BSM may give more robust results than using firm and year fixed-effects. However, Baghai, Servaes and Tamayo (2014) find that although average bond ratings have dropped three notches over the period 1985 to 2009, the spreads on the bonds with reduced ratings are actually lower than those of unaffected bonds. This suggests that firms and capital markets believe the rating changes, which reflect increased conservatism on the part of the ratings agencies, are unwarranted.

We must also acknowledge the manner with which credit spread data is examined here. Credit spreads are produced without specific controls for the yield curve slope, as was done in other prior work (e.g., Acharya, Amihud, and Bharath 2012; Chatrath et. al., 2012). By producing spreads using only constant maturity, on the run Treasury yields at specific points in the yield curve, we may have results that are dependent on the fixed points of this data production. Additionally, it may be that relying on Treasury swap data – as some works suggest – is an overall better proxy for the risk-free rate for another analysis than liquid Treasury bonds (Dick-Nielsen, Feldhutter, and Lando, 2012). That is, the dependent variable used here may have been estimated with error. If that is the case, then the error term will hold additional explanatory power triggering a reduction in the quality of fit for the whole model and lead to larger standard errors for all estimated coefficients.

Despite these limitations, the results found in this thesis provide interesting results for further exploration. TRACE data has only been collected since 2005, which is a relatively short period of time, and more data will be made public and available to economists in subsequent years. As more trade data is available, it will be possible to obtain a clearer understanding of how investment grade and high yield credits or financial and non-financial credits differ. Moreover, just as analysis in this thesis, consistent with much of the literature, used only inter-day data, it is possible that results might differ if intra-day trading data was used instead. Chatrath et al. (2012) found that even as most bonds do not trade daily, when bonds do trade, they tend to be traded multiple times on that day. Thus, using the intra-day data may yield additional insights into determinants of bond spreads.

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Summary Statistics by Subset

	Full		Investment Grade		High-Yield		Financial		Non-Financial		Pre-Crisis		Crisis		Post-Crisis	
	Mean	Standard Deviation														
Price	104	11	104	10	94	14	102	10	107	13	100	12	96	10	106	10
Yield	5	2	5	2	8	3	5	2	5	2	6	1	7	2	5	2
Spread	235	178	212	144	520	288	247	177	207	179	128	96	278	206	235	173
Coupon	6	1	6	1	7	1	6	1	6	2	6	1	6	1	6	1
Years	10	8	10	8	10	7	9	7	14	9	15	8	13	8	9	8
Age	3	3	2	2	4	4	2	2	3	3	3	3	2	3	3	3
N	157,345		145,996		11,349		109,006		48,339		11,564		28,841		116,940	

Regression Tables

Table: 1 Random Walk Lag Analysis

	(1) One Lag	(2) Two Lags	(3) Seven Lags	(4) Eight Lags	(5) Nine Lags	(6) Ten Lags
rwalk1	0.812***	0.446***	0.140***	0.123***	0.108***	0.098***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
rwalk2		0.450***	0.142***	0.125***	0.112***	0.102***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
rwalk3			0.140***	0.124***	0.109***	0.100***
			(0.002)	(0.002)	(0.003)	(0.003)
rwalk4			0.135***	0.119***	0.106***	0.096***
			(0.002)	(0.003)	(0.003)	(0.003)
rwalk5			0.132***	0.115***	0.101***	0.092***
			(0.002)	(0.003)	(0.003)	(0.003)
rwalk6			0.143***	0.125***	0.111***	0.101***
			(0.002)	(0.002)	(0.003)	(0.003)
rwalk7			0.135***	0.117***	0.103***	0.093***
			(0.002)	(0.002)	(0.003)	(0.003)
rwalk8				0.123***	0.109***	0.099***
				(0.002)	(0.003)	(0.003)
rwalk9					0.116***	0.106***
					(0.003)	(0.003)
rwalk10						0.091***
						(0.003)
N	161188	160761	158626	158199	157772	157345
R-sq	0.660	0.729	0.785	0.788	0.791	0.793
adj. R-sq	0.660	0.729	0.785	0.788	0.791	0.793

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01

Table 2: Random Walk by Subset

	(1) Full w/dummy	(2) Inv. Grade	(3) High-Yield	(4) Financial	(5) Non-Fin	(6) Pre-Crisis	(7) Crisis	(8) Post-Crisis
Lag 1	0.097***	0.097***	0.102***	0.096***	0.104***	0.064***	0.104***	0.096***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 2	0.101***	0.102***	0.102***	0.098***	0.114***	0.054***	0.109***	0.104***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 3	0.099***	0.097***	0.109***	0.103***	0.092***	0.059***	0.119***	0.098***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 4	0.095***	0.094***	0.101***	0.096***	0.094***	0.059***	0.094***	0.100***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 5	0.091***	0.093***	0.089***	0.094***	0.086***	0.053***	0.092***	0.098***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 6	0.100***	0.096***	0.115***	0.102***	0.099***	0.072***	0.112***	0.099***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 7	0.092***	0.097***	0.080***	0.092***	0.096***	0.058***	0.097***	0.095***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 8	0.098***	0.101***	0.092***	0.099***	0.096***	0.058***	0.106***	0.100***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 9	0.105***	0.106***	0.105***	0.106***	0.105***	0.055***	0.124***	0.107***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
Lag 10	0.090***	0.092***	0.086***	0.091***	0.091***	0.056***	0.094***	0.094***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.005)	(0.004)	(0.008)	(0.003)
HY Dummy	16.336***							
	(1.473)							
Observations	157345	145996	11349	109006	48339	11564	28841	116940
R-squared	0.793	0.785	0.812	0.793	0.792	0.805	0.671	0.846
Adjusted R-squared	0.793	0.785	0.812	0.793	0.792	0.805	0.671	0.846

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01

Table 3: First-Differenced OLS Subset Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inv. Grade	High-Yield	Financial	Non-Fin	Pre-Crisis	Crisis	Post-Crisis
Time Diff	8.985***	17.197***	9.991***	11.175***	-10.337***	21.983***	11.988***
	(0.264)	(1.980)	(0.354)	(0.494)	(0.692)	(0.923)	(0.341)
Fed Diff	-0.443***	-1.026***	-0.595***	-0.379***	-0.260***	-0.633***	-0.563***
	(0.003)	(0.018)	(0.004)	(0.005)	(0.006)	(0.007)	(0.004)
TED Diff	0.959***	1.426***	1.065***	0.883***	1.187***	0.656***	1.154***
	(0.005)	(0.044)	(0.007)	(0.009)	(0.022)	(0.012)	(0.009)
Vol Diff	0.058***	0.106***	0.075***	0.034***	0.011***	0.047***	0.074***
	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Constant	-0.012	-0.003	0.000	-0.022	0.239	33.064***	-0.129
	(0.319)	(2.443)	(0.418)	(0.628)	(1.703)	(1.317)	(0.407)
Observations	149355	11785	111602	49538	11822	29305	120013
R-squared	0.413	0.412	0.438	0.306	0.362	0.474	0.353
Adjusted R-squared	0.413	0.412	0.438	0.306	0.362	0.474	0.353

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01

Table 4: Fixed Effects Subset Models

	(1) Inv. Grade	(2) High-Yield	(3) Financial	(4) Non-Fin	(5) Pre-Crisis	(6) Crisis	(7) Post-Crisis
Years	-1.143***	-5.051**	-2.141***	0.033	1.225***	-1.356***	-1.331**
	(0.410)	(2.308)	(0.466)	(0.426)	(0.351)	(0.319)	(0.539)
Bond Age	1.042	4.802***	1.965**	1.987	-1.889	8.388***	0.854
	(1.122)	(1.710)	(0.834)	(1.595)	(1.322)	(1.818)	(0.876)
Issue Size	0.002	-0.168***	-0.001	-0.004	-0.001	-0.000	-0.002
	(0.002)	(0.026)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
Premium Dummy	-84.130***	-173.120***	-103.633***	-80.753***	-28.392**	-63.144***	-95.970***
	(10.790)	(25.654)	(19.707)	(14.672)	(10.912)	(9.866)	(18.756)
Coupon	25.870***	24.206***	23.809***	25.179***	19.863***	31.096***	23.064***
	(2.726)	(6.800)	(2.393)	(3.455)	(7.095)	(6.476)	(2.292)
Fed Rate	-0.304***	-0.866***	-0.408***	-0.280***	-0.013	-0.678***	-1.076**
	(0.064)	(0.234)	(0.128)	(0.064)	(0.064)	(0.080)	(0.515)
TED	0.910***	1.539***	1.044***	0.707***	0.178**	0.494***	2.085***
	(0.076)	(0.212)	(0.070)	(0.097)	(0.070)	(0.073)	(0.245)
B-D Assets	0.116***	-0.076	0.129***	0.117***	0.095	0.062***	0.091*
	(0.024)	(0.117)	(0.036)	(0.029)	(0.079)	(0.019)	(0.047)
SP500 Vol	0.049***	0.072***	0.059***	0.029***	-0.004***	0.014***	0.046***
	(0.005)	(0.015)	(0.004)	(0.005)	(0.001)	(0.003)	(0.005)
Constant	172.885***	413.172***	-7.515	192.862***	144.633**	266.902***	299.176***
	(46.083)	(142.099)	(77.620)	(38.256)	(65.235)	(63.517)	(47.421)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149755	11836	111910	49681	11860	29367	120364
R-squared	0.683	0.671	0.712	0.724	0.871	0.724	0.755
Adjusted R-squared	0.682	0.670	0.712	0.724	0.871	0.723	0.755

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01

Table 5: Fixed-Effects w/Squared Term

	(1) Inv. Grade	(2) High-Yield	(3) Financial	(4) Non-Fin	(5) Pre-Crisis	(6) Crisis	(7) Post-Crisis
Years	-6.070	-4.237	-5.129**	-30.782***	3.625	-10.942***	-3.686
	(3.850)	(4.368)	(2.298)	(9.636)	(3.256)	(3.662)	(2.392)
Years^2	0.115	0.118	0.114*	0.791**	-0.063	0.256***	0.069
	(0.103)	(0.115)	(0.060)	(0.284)	(0.081)	(0.096)	(0.063)
Bond Age	1.482*	1.973	0.680	2.676	-2.065	7.770***	0.630
	(0.815)	(1.580)	(1.078)	(1.943)	(1.338)	(1.858)	(0.767)
Issue Size	-0.001	-0.005	0.002	-0.183***	-0.001	0.001	-0.002
	(0.004)	(0.004)	(0.003)	(0.029)	(0.002)	(0.003)	(0.004)
Premium Dummy	-105.269***	-82.309***	-85.959***	-176.065***	-28.607**	-64.292***	-97.166***
	(20.589)	(15.469)	(11.227)	(22.245)	(10.862)	(10.444)	(19.500)
Coupon	25.489***	26.849***	27.724***	29.727***	19.335**	35.034***	24.031***
	(3.304)	(4.182)	(3.467)	(7.334)	(8.194)	(7.436)	(2.506)
Fed Rate	-0.404***	-0.278***	-0.300***	-0.879***	-0.013	-0.668***	-1.077**
	(0.124)	(0.064)	(0.064)	(0.222)	(0.064)	(0.080)	(0.512)
TED	1.041***	0.703***	0.907***	1.514***	0.182**	0.491***	2.079***
	(0.070)	(0.097)	(0.076)	(0.214)	(0.069)	(0.073)	(0.246)
B-D Assets	0.129***	0.116***	0.116***	-0.060	0.099	0.059***	0.090*
	(0.035)	(0.029)	(0.024)	(0.110)	(0.076)	(0.019)	(0.047)
SP500 Vol	0.058***	0.029***	0.048***	0.072***	-0.004***	0.014***	0.045***
	(0.004)	(0.005)	(0.005)	(0.015)	(0.001)	(0.002)	(0.005)
Constant	7.029	220.929***	184.028***	609.673***	125.193**	334.310***	315.264***
	(85.679)	(36.106)	(42.389)	(177.781)	(51.902)	(83.221)	(37.841)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111910	49681	149755	11836	11860	29367	120364
R-squared	0.713	0.725	0.683	0.680	0.871	0.725	0.756
Adjusted R-squared	0.713	0.724	0.683	0.679	0.871	0.724	0.755

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01

Appendix A: Capital Structure and Firm Financing Decisions

A.1 Capital Structure

Firms have financial assets that are backed by sources of capital. The sources of capital are either sales of ownership stakes in the firm, equity, or issuances of liabilities, debt. In the case of financial distress or default on outstanding debts, firms have capital structures that will prioritize the rights of lenders over equity owners. While creditors are only entitled to periodic coupons and repayment of principal, shareholders have the rights of ownership and the residual profits of the operating firm. This represents a greater intrinsic risk to equity investments, and will tend to cost more due to its relative subordination in a firm's capital structure.

In addition, debt is tax-advantaged relative to equity issuance. Interest payments are written off a firm's profit before being subject to taxation. Thus, a firm's debt will provide a "tax shield" to its shareholders while increasing the firm's leverage. Modigliani and Miller (1963) state that continually adding debt will also increase the firm's equity cost of capital. At some point, the additional cost of equity capital will outweigh the advantage of adding more debt for its tax-advantages (Ross, Westerfeld, and Jaffe, 2010).

In addition, large potential costs of financial distress promote more conservative capital structures among firms. According to Almeida and Philippon (2005), a greater marginal tax burden will improve the tax shield, but will – after a certain point of indebtedness – leave the firm's solvency vulnerable to the business cycle. Thus, while managers may be incentivized to add debt to improve shareholder value, there are future distress costs that may lead to bankruptcy.

A.2 Default, Bankruptcy, and Firm distress

Credit events that could hurt bondholder recoveries fall into a variety of different categories. In examining distressed bond trading, Han and Wang (2013) categorize credit distress into bankruptcy filings, distressed exchanges, receivership, and missed payments of principal or interest on debt. This paper generalizes these into bond “default” events. All of these events are considered defaults where a lender is in risk of not being paid the full future stream of coupon payments and principal repayment at maturity.

There are two types of bankruptcy filings relevant to this analysis. Chapter 11 bankruptcy proceedings protect the company from having to service debt while trying to restructure debt obligations and continue business operations. Chapter 7 bankruptcies, which occur much less frequently, will liquidate all of the assets of the firm and provide distributions to those with claims to the firm. Traditional capital structures will maintain priorities for lenders and subordinate rights to the shareholders. There also may be different levels of bondholders with some bondholders subordinated in the capital structure and rights to bankruptcy recovery. In contrast, distressed exchanges are when firms offer creditors cheaper bonds in exchange for their current debt holdings. This specific process is outside the realm of this exploration, but does present impairment of bondholder interests.

Receivership is a process following bankruptcy where a trustee, or receiver, is put in charge of the assets in distress and helps liquidate them to approved creditors. Typically, it is a state-controlled action taken in the wake of a bank or insurance company failure. Congress and state governments approve and use this procedure in a variety of ways to ensure orderly resolution of insolvent firms.

The upshot of credit default events is that they usually impair bondholder principal value and interest payments. There is much legal precedent and procedure that surrounds that details of who gets paid back in which amounts. However, these intricacies are beyond the scope of this examination.

Appendix B: Black-Scholes-Merton Diffusion Based Option Default Model (from Delianedis and Geske, 2001)

Black-Scholes-Merton option theory states the price for a given option is based on known factors such as the current stock price, option strike price, risk-free interest rate, and time until expiration. The solution – or unknown – to this formula is the “implied volatility” of an option. This figure states the annualized volatility of the firm’s stock price such that the price of the option is fairly valued based on the current price and distribution of future values. A more volatile stock will make options further out-of-the-money more valuable, as a stock that moves around more is more likely to make an out-of-the-money option worth something at expiration. While initially developed to understand option pricing, it is extended to discuss the probability of a firm’s default.

For studying corporate default, the authors look at a model used for corporate default diffusion processes. They estimate the “volatility” of a firm’s assets by using an issuing firm’s equity volatility. They estimate a zero coupon bond as representing the firm’s liabilities and use its balance sheet assets to estimate using volatility the likelihood that assets will fall below liabilities, thus trigger a theoretical default. By incorporating BSM into a model that a firm’s value is a function of its equity, future dividend payouts, interest payments, and debt principal, they construct a system of two equations. The first:

$$S(V,\sigma_v,T) = VN(d_1) - P(t,T)M\,N(d1-\sigma_v\sqrt{T}) + \frac{D}{D+I}\left[V - V\,N(k_1) + P(t,T)(D+I)N(k1-\sigma_v\sqrt{T})\right]$$

is a function relating BSM variables to its equity value that is then solved for V, its firm value. Then, the second equation solves for annualized volatility:

$$\sigma_s = Std\left(\frac{dS}{S}\right) = \frac{V}{S} S_V \sigma_V = \frac{\sigma_V V}{S}\left(N(d1) + \frac{D}{D+I}(1 - N(k1))\right)$$

Values for *V* and σ are then used to calculate the probability of a firm's default based on its outstanding liabilities and assets.

Appendix C: Historical Analysis

A 150 year historical analysis of default rates provides significant evidence that – generally – bondholders are paid more yield than past defaults and recovery rates would imply. This literature examines the historical default rates and corporate recovery rates following bankruptcies to find how yields compare to average bondholder losses (Giesecke et. al, 2011). First, the literature points to the nature of high default periods being infrequent and coincident with recessions. However, it is worth noting that the period it analyzes covers the second half of the 19th Century. This era sees unusually high default rates on corporate debts during a time of railroad industry distress. Railroad defaults accounted for 36% of par value of the total market in some years – default rates that haven't been observed as high since (see Figures 1, 2).

Another finding is that default losses – recovery rates times default rates – do not drive credit spreads, indicating that credit risk premiums don't move with time-specific changes in default rates. They find that over the examined period that investors have demanded – on average – twice the yield required to match bond losses (Giesecke et. al, 2011). This indicates that a large component of credit spreads is attributable to elements outside of default losses. They also examine how changes in bankruptcy law may affect differences in credit valuation and expected recovery rates (Giesecke et. al, 2011). While outside the scope of this examination, these additional insights further suggest that the degree of recovery and legal changes will affect perceptions of credit quality and expected default losses.

Empirical research on high yield issuers and the effect of lower credit quality on default rates presents evidence that while bond defaults may typically be low, the high-yield sector may present more volatile outcomes. Helwege and Kleiman (1996) look at year-to-year changes in speculative grade default rates. For many decades, so-called “fallen angels” or investment grade quality firms that have declined in quality have dominated the high-yield market. The addition of direct issuance into the high-yield space has presented more data on how these bond issues perform over time. They conclude that certain space-specific elements, including periods where some industrial sectors have a large (>5%) place in it. Sector concentration and the speculative grade market’s increased correlation with countercyclical economic factors explain why speculative grade defaults rates are volatile. Because different credit-sector specific issues affect the high-yield market, it is tougher to generalize whether high-yield bond investors are being paid enough, unlike Giesecke et. al.’s conclusion.

Figure 1: Historical U.S. Corporate Bond Default Rates 1866-2008: from Giesecke et. al. 2011

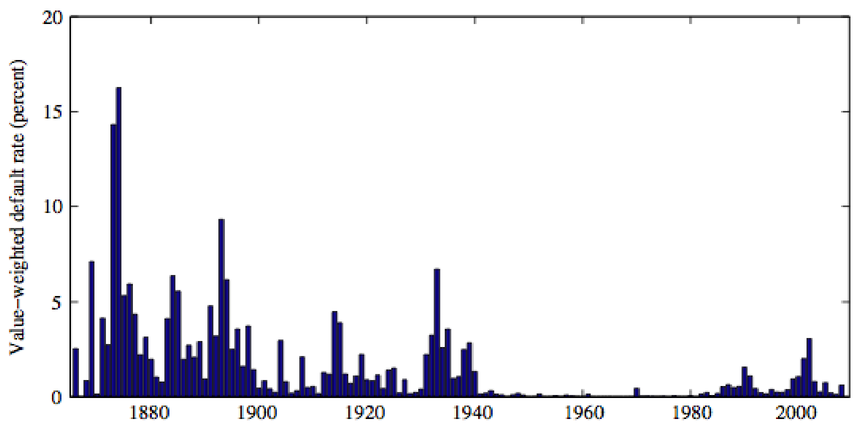

Fig. 1. Historical default rates. This graph plots the annual value-weighted percentage default rates for bonds issued by U.S. domestic nonfinancial firms for the 1866–2008 period.

Figure 2: Histogram of U.S. Value-Weighted Defaults: from Giesecke et. al. 2011

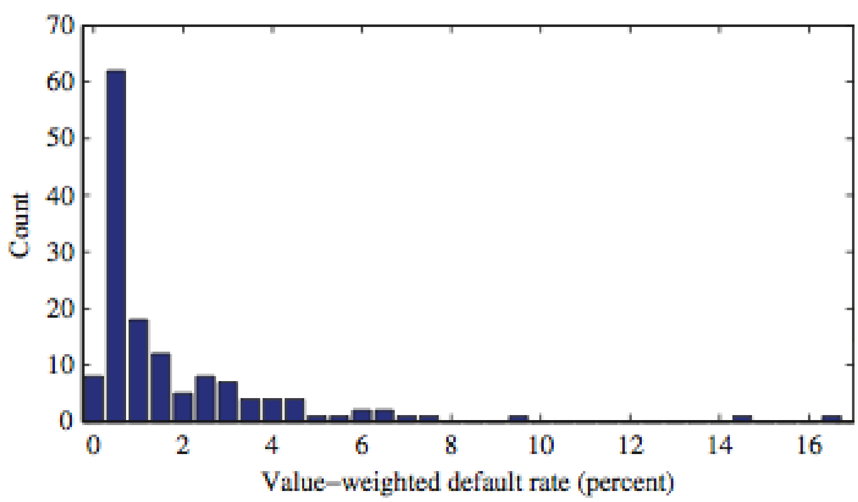

Fig. 2. Histogram of historical default rates. This figure shows the histogram of annual value-weighted percentage default rates for bonds issued by U.S. domestic nonfinancial firms for the 1866–2008 period.

Appendix D: Bond Liquidity and CDS

The existence and growth of the credit default swap (CDS) market also demonstrates that corporate bond spreads exceed perceptions of corporate credit risk. CDS contracts are swap agreements meant for one party to assume credit risk of a given debt-issuing corporation over an agreed time period in return for an annual premium from its swap counterparty. Similar to insurance, if the corporation enters default during the terms of the agreement, the party paying the premium in return for credit protection receives a payout. Unlike insurance, however, the party paying for the credit protection doesn't have to actually be a creditor of the issuing firm and can use the swap agreements for "speculation." In this case, an investor can gain risk exposure to a corporate through both a traditional corporate bond and by selling credit protection on an issuer. The latter case would gain exposure without any interest rate risk. CDS contract premiums relate to the perceived default risk of a particular corporate over a specific time period, thus providing a good market-based proxy for what corporate risk premiums should be. This is because, in theory, we would expect that CDS premiums would equal the risk premium of corporate bonds, as the yield premium to treasuries should be equal or less than the swap market's premium (Longstaff, Mithal, and Neis 2005). This is due to the additional counterparty risk contained in a CDS contract, the risk that in the event of corporate default that the counterparty to the swap is entered with may not be able to payout for credit losses. [28] They expected to find that the difference between the corporate bond's yield and its

[28] Yet, it should be noted that neither party to the derivative must hold the bond. They may both be speculative parties to the credit default swap.

corresponding CDS spread would equal the risk-free treasury rate over the given contract and bond's maturity.

However, empirical work demonstrates that this isn't the case. The difference between CDS premiums and corporate bond yields implies an economically significant level of difference that suggests a significant non-default component of bond spreads (Longstaff, Mithal, and Neis 2005). This suggests that the traders who examine both markets consider other components in assessing value and continue to promote the existence of a non-default component.

Interestingly, CDS analysis confirms what much prior literature says about the importance of liquidity, but may indicate an even greater effect than bond characteristics. CDS evidence finds that the liquidity component may be as high as 100bps, indicating a much larger effect than conclusions discussed in Chapter 3.1. These studies, while having the conclusion that bond characteristics and trading activity cause greater illiquidity and volatility in spreads, discern different levels of liquidity seen in corporate spreads.

Analysis that combines aspects of bond-specific liquidity and default concerns in CDS spreads finds that liquidity and credit quality are not separate elements and correlate and interact with one another in determining spreads. Chen et. al (2013) introduce liquidity factors that vary with structural credit models, which imply that liquidity and default effects fluctuate with the business cycle . This is consistent with bond-characteristics discussed in Chapter 3 regarding the correlation of credit quality with secondary market liquidity.

Appendix E: Additional Figures

Figure 1: Histogram of Bond Prices

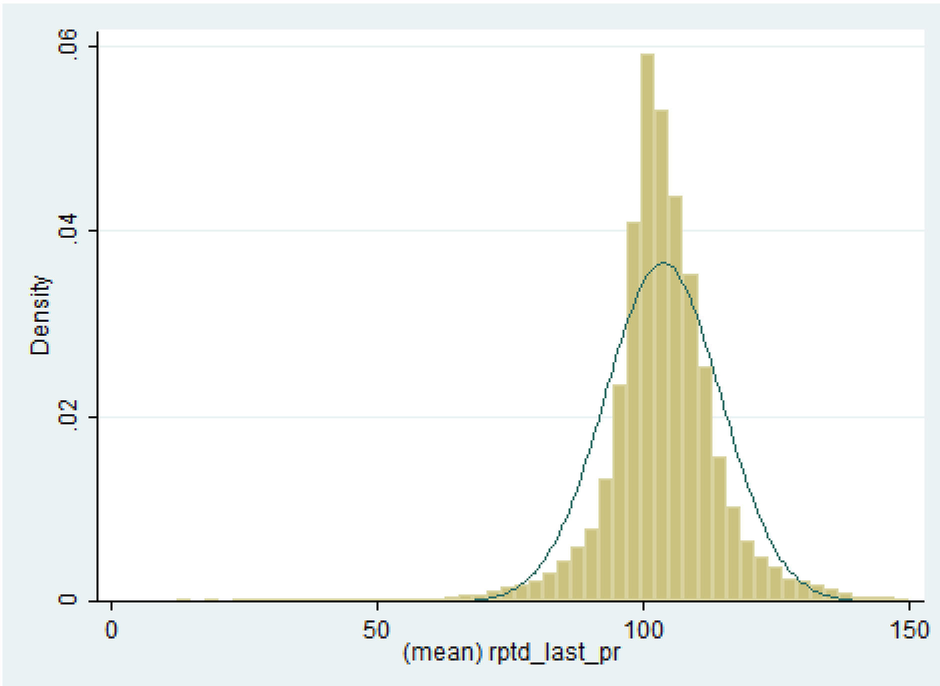

Figure 2: Histogram of Bond Spreads

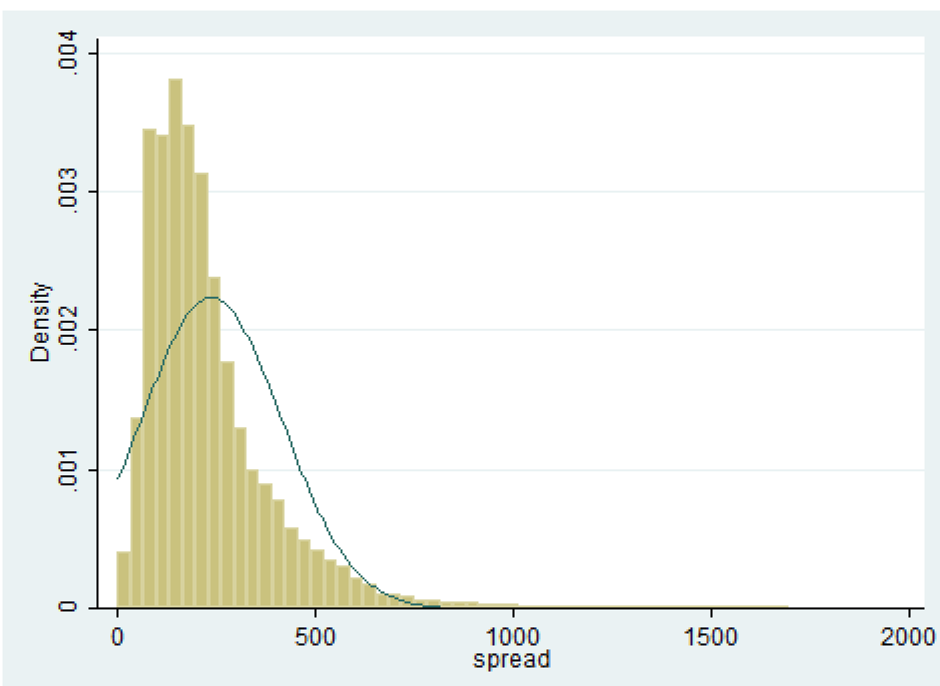

Figure 3: Graph of Broker-Dealer Assets since 2005