Popularity-based Asset Pricing: Empirical Studies of Credit Market Drivers

By:

Eugene Kwame Okyere-Yeboah

Supervisors:

Dr. Stephen Thomas

Dr. Andrew Clare

Submitted in partial fulfillment of the requirements

of the Degree of Doctor of Philosophy

Bayes Business School

City, University of London

August,2024

Declaration

I certify that the thesis I have presented for examination for the Ph.D. degree of the Bayes Business School, University of London, is solely my own work other than where I have clearly indicated that it is the work of others (in which case, the extent of any work carried out jointly by me and any other person is clearly identified in it). The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgment is made. This thesis may not be reproduced without my prior written consent. To the best of my belief, I warrant that this authorization does not infringe on any third party's rights.

Eugene Kwame Okyere-Yeboah

Dedications

To Mr. Harry Kwaku Mensah Okyere-Yeboah, Esq., my younger brother, who was my psychological twin. Given his compassionate disposition and intellectual prowess, he passed away at a young age without the opportunity to make a tremendous impact in this world. To my mother, Mrs. Comfort Jessica Okyere-Yeboah, a true woman of substance and a pillar of strength, and to my father, Mr. Joseph Kwame Okyere-Yeboah, the definition of a gentleman and my benchmark in all walks of life, though you have all transitioned from the physical to the spiritual world, I am sure you're looking from the heavens with tremendous pride and joy. I thank you for shaping me into becoming who I am. *And I will continue to pray for guidance as you have always encouraged me to do so. I do miss you all.*

I am, however, grateful to God to have my beloved remaining siblings, Vesta and Gilbert; in addition to being there for me, they have constantly reminded me of our ***journey.***

Moreover, to my wife, Muriel, and our children, Alistair and Eleanor: my shining lights and grit whenever the going gets tough. And, man! It has been tough! A road less traveled; ***but, as in life, it's always on the journey where one's character is shaped, not the destination. I hope to explain my thesis to them (our children) in the coming years as an inspiration for their future endeavors.***

Eugene Kwame Okyere-Yeboah

Acknowledgements

I want to thank my supervisors, Dr. Stephen Thomas and Dr. Andrew Clare, at Bayes Business School, University of London, for their continual valuable guidance and constructive feedback in shaping this thesis. The original mathematical framework for equities is attributed to Dr. Paul Kaplan, and it is with his permission that I can adapt it to corporate credits. I am indebted to Prof. Roger Ibbotson of Yale University School of Management for his precious time in having numerous conversations with me about the fundamental ideas behind PAPM, and for giving me insightful and constructive feedback. Also, to Mr. Thomas Idzorek and Dr. Paul Kaplan, of Morningstar, Inc., who are among the original authors of the PAPM framework.

Finally, but not least, I wish to extend my most profound appreciation to my friend and mentor, Dr. Con Keating for encouraging me to pursue this doctorate. Over the years, he has helped shape my ideas about the capital market and its linkage to global society.

Contents

List of Tables

List of Figures

List of Abbreviations

A	**Rating category A**
AA	**Rating category AA**
AAA	**Rating category AAA**
ADF	**Augmented Dickey-Fuller**
APT	**Arbitrage Pricing Theory**
Avg.	**Average**
BAML	**Bank of America Merrill Lynch**
BBB	**Rating category BBB**
BM	**Benchmark**
bps	**Basis points**
CAPM	**Capital Asset Pricing Model**
CDS	**Credit Default Swap**
DUR	**Duration**
e.g.	**for example**
EOY	**Eugene Okyere-Yeboah**
ES	**Expected Shortfall**
E	**Environmental**
S	**Social**
G	**Governance**
et al.	**and others**
EW	**Equal-weighted**
FF	**Fama and French**
HY	**High yield**
IG	**Investment grade**
MA	**Moving average**
MCW	**Market-capitalization weighted**
MF	**Multi-factor**
MPT	**Modern Portfolio Theory**

OAS	**Option-Adjusted Spread**
PAPM	**Popularity Asset Pricing Model**
PRI	**Principles for Responsible Investment**
RTG	**Rating**
SR	**Sharpe ratio**
SRI	**Sustainable and Responsible Investing**
S&P	**Standard and Poor's**
subIG	**sub Investment Grade**
t-stat	**t-statistic**
UN	**United Nations**
USD	**U.S. Dollar**
U.S.	**United States of America**
VaR	**Value-at-Risk**
VIX	**Volatility index**
Vol.	**Volatility**

Abstract

This thesis explores the fundamental role of pricing models in valuing securities within capital markets. It introduces the Popularity Asset Pricing Model (PAPM), a novel and generalized framework that builds on existing models like Capital Asset Pricing Model (CAPM), and Arbitrage Pricing Theory (APT) but addresses their restrictive and unrealistic assumptions. PAPM emphasizes the concept of popularity, which encapsulates preferences or tastes for certain characteristics, and how this influences asset pricing. By applying popularity to credit instruments, the thesis explains premiums and market anomalies through a framework where popularity affects the demand curve and, consequently, the premiums. This research demonstrates that time-varying risk premia are significantly influenced by market activity and financial risks, aligning with investor preferences. These preferences are in the form of risk and nonrisk characteristics of the asset being priced. The thesis bridges classical and behavioral finance by investigating how various preferences impact a company's credit risk premium, as measured by the credit default swap (CDS) spread.

In the first paper, I have examined the fundamental research question concerning the preferences of macroeconomic variables on corporate credit risk premiums and, therefore, returns. I applied the SBBI dataset [1], a set of macroeconomic risk premiums to the popularity framework to illustrate the effect of their popularity as the drivers of corporate credit returns via the changes in CDS spreads.

In the second paper, I explored the research question concerned with the preferences of ESG scores, resulting in a relationship between corporate credit returns and equity returns of the same capital structure. Specifically, I investigated how popularity relates to socially responsible or ESG (environmental, social, and governance) investing. The popularity of companies with favorable ESG rankings increases the demand for their bonds, driving prices higher. The reverse is true of "sin" firms with low ESG scores. Predictably, the result is that companies with low ESG scores outperform those with high ESG scores.

[1] The Stocks, Bonds, Bills, and Inflation (SBBI) dataset is monthly data that includes total returns and yields of most of the major U.S asset classes

The third paper examined the research question of whether the preference for ESG scores, within the theoretical framework of PAPM, impacts credit portfolios' tail risk (expected shortfall). Thus, I investigate how the popularity of ESG and its pillars impact the tail risk of credit portfolios. It turns out that in the short-term (i.e., via expected loss), there is no impact on the popularity of ESG; there is a strong positive relation between the popularity of ESG score and the tail-risk (defined as expected shortfall).

Chapter 1

Introduction

1.1 Introduction

Finance is a distinctive field that closely examines human behavior, encompassing perceptions, expectations, and reactions. Market participants frequently need precise knowledge of their investments' true value or price. Within a free-market system, the collective beliefs of individual participants, which are continually evolving, drive price discovery. By definition, capital markets are influenced by perception and shifts in perception, occasionally punctuated by rational or irrational expectations. A model needs to be developed to forecast these prices. The existing models, central to almost every aspect of finance, estimate expected returns, valuation, portfolio formation, and cost of capital analysis. In this thesis paper, I introduce a novel framework, the Popularity Asset Pricing Model (PAPM); like its predecessor, the Capital Asset Pricing Model (CAPM), both follow the market equilibrium system or model by aggregating the collective beliefs (supply and demand) of individual participants taste/preferences for certain characteristics or factors, these factors can be a risk ***(unpopular)*** and non-risk ***(popular or unpopular)***. In other words, the PAPM posits that the primary drivers of price factors stem from investors' collective preferences and tastes. This model offers a framework for identifying and comprehending the factors that are priced in the market. In contrast to the APT, which focuses on macroeconomic factors affecting returns, assuming markets are efficient and arbitrage opportunities are quickly eliminated. PAPM incorporates investor behavior and preferences into asset pricing, acknowledging that popularity and subjective preferences can cause deviations from what traditional models might predict. The PAPM considers not just traditional risk factors but also how popular an asset is among investors. Assets that are more popular (desirable) might be overpriced and offer lower expected returns, while less popular (undesirable) assets might be underpriced and offer higher expected returns. Investors can use the PAPM to better understand the drivers of asset returns beyond traditional risk factors. By identifying and measuring popularity loadings, they can make more informed investment decisions, potentially identifying mispriced assets based on their popularity characteristics.

In the PAPM, the expected return of an asset is influenced not only by traditional risk factors but also by how popular the asset is. An asset with a high popularity loading on a desirable characteristic (e.g., high ESG rating/score) may have a lower expected return because it is more in demand and investors are willing to accept lower returns for holding it. Conversely, an asset with a high loading on a less popular characteristic may have a higher expected return to compensate for its lack of desirability.

The Capital Asset Pricing Model (CAPM) and the Popularity Asset Pricing Model (PAPM) are both single-period models. However, as collective investor preferences evolve over time, so too should the characteristics that are priced in the market, leading to time-varying factors with time-varying premiums. For instance, investor preferences in 1950 likely differed from those in 2000, and they will likely continue to evolve by 2050. While some aggregate preferences may persist in both direction and magnitude, others are expected to change over time. This concept aligns with Andrew Lo's framework in his book Adaptive Markets (Lo, 2017), where he argues that markets evolve in response to changing economic, behavioral, and technological circumstances, leading to shifting premiums over time. From a PAPM perspective, the root source of asset prices is the evolving views and preferences of the investing public. Consequently, the factors that are most likely to be priced in the market are those related to the most common and strongly held investor preferences at any given time. This dynamic approach underscores the importance of understanding how investor preferences shift and how these shifts influence the factors that drive asset pricing.
Table 1.1 contains the results of a series of thought experiments in which we attempt to identify the most common investor preferences and then identify the expected corresponding priced factor / expected return premium. This type of thought experiment is similar in spirit to Aghassi et al. (2023), which in the context of factor investing asks the question, "Who Is on the Other Side?"

Table 1.1 may show a form of lookback bias, but the underlying hypothesis and theory remain robust. The influence of investor preferences on asset prices is well-documented through the Popularity Asset Pricing Model (PAPM), as discussed by Idzorek, Kaplan, and Ibbotson (2021, 2023)[95]. It's crucial for investors and mar-

Table 1.1: Investor Tastes and Corresponding Priced Factors

Common Investor Preferences	**Expected Priced Factor/ Expected Return Premium (Discount)**
Dislike risk (prefer safety)	Equity; Credit, and Inflation Risk Premiums
Dislike severe downside risk (prefer low downside risk)	Severe Downside Risk Premium
Dislike interest rate risk	Duration Yield Premium
Dislike illiquidity (prefer liquidity)	Illiquidity Premium
Active managers prefer to outperform in up markets	Low Beta Premium
Dislike bad ESG (prefer good ESG)	Bad ESG Premiums
Investors like recognizable names / good reputations	Glamour/Brand/Reputation Discount

Source: Domesticating the Factor Zoo with Economic Theory, Idzorek,Kaplan, and Ibbotson, (2024)

ket observers to identify the prevailing investor tastes, as these tastes can significantly impact demand and, consequently, asset prices. Our analysis suggests that these predictions align with several well-documented realized premiums and priced factors. For instance, empirical evidence strongly supports the equity premium (Ibbotson and Sinquefield, (1976)[91]; Dimson, Marsh, and Staunton, 2002), the severe downside risk premium (Harvey and Siddique, 2000; Ibbotson et al., (2018)[90]), the illiquidity premium (Amihud and Mendelson, 1986; Chordia, Subrahmanyam, and Anshuman, 2001; Feng, Kang, and Zhang, (2023)), the duration yield premium (Ibbotson and Sinquefield, 1976; Dimson, Marsh, and Staunton, 2002), the low beta premium (Jensen, Black, and Scholes, 1972; Frazzini and Pedersen, 2014), the bad ESG premiums (Shafron, 2019; Zerbib, 2020; Baker et al., 2021), and the glamour/brand/reputation discount (Anginer and Statman, 2010; Ibbotson et al., 2018). Notably, the Duration Yield Premium, as shown in Exhibit 1, aligns with the Preferred Habitat Theory of Modigliani and Sutch (1966, 1967) and serves as an early example of how investor tastes can influence asset prices.

One premium we deliberately omit is the small stock or size premium. While small-cap stocks are generally riskier, less liquid, and have less available information than large-cap stocks, we do not dispute the existence of a small stock premium. However, we believe the root causes of this premium are already captured by other factors listed in the exhibit. Moreover, with increasing demand from quantitative managers to overweight characteristics of small-cap stocks, the small stock premium may not be as significant in the future as it was historically.

Overall, when analyzing realized premiums from a backward-looking perspective, many of the most prominent premiums can be linked to investor tastes. An explanation rooted in economic theory, such as the PAPM, to be more convincing than the traditional narrative advanced by Fama and French, which attributes these premiums to unidentified systematic risk factors. Furthermore, having a solid economic rationale for a premium is more compelling than relying solely on historical realized premiums. Ultimately, when refining the factor zoo, it is essential to base evaluations on both strong theoretical foundations and empirical evidence.

When a large number of investors favor certain characteristics, assets possessing these liked traits become highly sought after ***(popular)***, leading to higher prices and lower expected returns. Conversely, assets with characteristics that investors generally dislike experience lower demand (***unpopular***), resulting in lower prices and higher expected returns. As aggregate tastes shift, such as an increased collective preference for investments with specific environmental, social, and governance (ESG) characteristics, these changes in preferences can cause temporary fluctuations in the returns of assets with liked or disliked characteristics. This is investigated in the second paper of this thesis (chapter three).

During the last 50 years, the number of reported statistically significant factors has exploded into an unmanageable and growing "factor zoo." Statistical methods for identifying the most significant factors are essential, but a theoretical construct is needed to provide an economics-based explanation. The PAPM is a theoretical construct in which the collective wealth-weighted preferences/tastes are the root cause of factor premiums.

While the Capital Asset Pricing Model (CAPM) has been the cornerstone of asset pricing for the past 50 years and a fundamental component of finance education, numerous studies have highlighted its limitations (e.g., Basu, 1977[16]; Banz, 1981[13]; Fama and French, 1992[66]; Lakonishok, Shleifer, and Vishny, 1994[103]). One significant shortcoming of the CAPM is its focus on overall market risk as the sole factor in pricing, despite widespread recognition that asset pricing is multi-dimensional. For instance, Ibbotson and Sinquefield (1976, 1979)[92] identified additional factors such as a bond horizon premium, a default risk premium, and, in subsequent work, a size premium.

As early as the 1970s, it was recognized that multiple factors likely contributed to asset prices. The most prominent of these multi-factor asset pricing models is the Arbitrage Pricing Theory (APT) proposed by Ross (1976). The APT posits that a multi-factor linear structure generates economic returns. Since these risk factors are systematic, arbitrage cannot eliminate them, and each factor is priced within an isolated long/short portfolio. However, the APT's approach to identifying supply-side systematic factors provided by the economy has yet to prove particularly useful, necessitating empirical identification of the factor structure within the economy. The assumption is that pure attribution factors would be eliminated by arbitrage.

In contrast to arbitrage-based approaches, Eugene Fama and Ken French are renowned for identifying the so-called "Fama-French factors"—high-minus-low (HML) or value/growth factor, and small-minus-big (SMB) or size factor (Fama and French, 1992). These factors help explain investment returns the single market factor does not adequately capture. Although Fama and French originally proposed these as potential pricing factors, practitioners use them as attribution factors to describe realized returns. Based on their empirical observations, Fama and French suggest that more than just overall market risk impacts asset prices, highlighting the need for a multi-factor model.

This thesis contributes to the study of pricing models by employing a simple equilibrium model, the Popularity Asset Pricing Model or PAPM. The PAPM not only generalizes the Capital Asset Pricing Model (CAPM), which is popular as the basis for multiple priced characteristics but also offers practical implications for the field of finance, making it a significant addition to the study of pricing models.

Unlike the Arbitrage Pricing Theory (APT), which is an arbitrage model, both CAPM and PAPM are equilibrium models. The PAPM can price both the risk and non-risk dimensions of securities, leading to asset prices that differ from those of the CAPM. Most recently asserted by Idzorek, Kaplan, and Ibbotson (2023[94], where the authors propose the PAPM with less restrictive assumptions than the CAPM and more realistic assumptions than the APT, thereby explaining asset prices through both risk and non-risk dimensions.

An area of asset pricing that addresses investors' preferences or tastes, which in itself is a special case of PAPM, is Amihud and Mendelson (1986a, 1986b)[5], which develops a liquidity-based equilibrium asset pricing model that incorporates heterogeneous investor horizon preferences by classifying into different clienteles. The shorter-horizon investors hold the more liquid and more expensive stocks with lower expected returns, while the longer horizon investors hold the less liquid and less expensive stocks with higher expected returns.

I adopt PAPM to pricing corporate credit research to explore the influence of investors' preferences for macroeconomic variables, the concept of popularity, and ESG preferences on corporate bonds and equity returns. Specifically, it investigates the following research questions:

1. **Influence of Macroeconomic Variables on Corporate Credit Risk Premiums:** How do preferences for macroeconomic variables, including equity market levels, liquidity conditions, and U.S. Treasury returns, influence corporate credit risk premiums measured by Credit Default Swap (CDS) spreads within the PAPM framework? Do these variables explain the variations in CDS spreads (and returns) across different firms and market conditions?

2. **Popularity Concept and its Impact on Corporate Bonds and Equity Returns:** To what extent does the concept of popularity, defined by investor preferences towards various characteristics such as ESG scores, explain the relationship between corporate bonds' returns and equity returns across different firms and market conditions?

3. **Impact of ESG Preferences on Credit Portfolio Tail Risk:** How does the preference for ESG scores, within the theoretical framework of PAPM, impact the tail risk of credit portfolios?

A significant contribution of this thesis is its application to corporate bonds. Due to the heterogeneity and illiquidity of individual bonds, this study uses CDS spreads instead of actual bond yields. CDS liquidity is significantly better than trading over-the-counter (OTC) corporate bonds, making it a more practical choice for this research. The preferences or factors considered, including default probabilities and the SBBI data set, reflect various investor preferences within the PAPM framework.

This thesis aims to adopt and use the popularity framework to explain anomalies in the premiums for expected losses in the credit market. By examining the impact of macroeconomic drivers and preferences on CDS spreads, it seeks to provide a comprehensive understanding of the factors influencing corporate credit risk premiums. Furthermore, it investigates how ESG preferences within the PAPM framework impact credit portfolio tail risk, highlighting the significance of non-risk factors in asset pricing and portfolio management.

Moreover, the best way to explain how the market works in a cause-and-effect relationship is to show how investors' preferences change when using factors affecting more than one security at a time, depending on which regime the economy is undertaking. It is well understood that these preferences could be structural, meaning that there is an underlying cause. Most traders or asset managers refrain from trading or re-balancing their portfolios when risk changes occur. They, however, trade or re-balance their portfolios based on changes in beliefs about preferences regarding the characteristics associated with particular assets. So, it's all about beliefs, preferences, and changes in these that drive valuation. This is very different from classical finance.I am mindful that the PAPM (Popularity Asset Pricing Model) has yet to be accepted in mainstream or academic circles. Still, given its generalized form and intuitiveness, it's time to be in textbooks. It's at the nascent stage of being popularized in academic journals. This thesis and its eventual publication should increase awareness of and application for PAPM. While most finance and investment professionals know about the capital asset pricing model (CAPM), PAPM knowledge is much more limited.

1.2 Popularity as a Concept

Popularity is how much anything is liked, preferred, or desired. The concept is applied to assets and securities. In this context, one can explain all the premiums in the markets, especially the capital market. Most assets and securities are in relatively fixed supply over the short or intermediate term. Popularity represents the *demand* or perhaps the excess demand for security and is thus an important determinant of prices for a set of expected cash flows. The risk factor premiums in the market are payoffs for the riskiness of securities. In classical finance, investors are risk averse, and market frictions are usually assumed away. Risk is unpopular; since it introduces an element of uncertainty, market participants are risk averse by nature, and introducing it as an asset requires a premium by investors, hence the term *"risk premium"*. The degree of uncertainty and potential financial loss associated with an investment choice is considered a risk in finance. Investors typically look for more significant returns to offset the increased risk associated with their investments. For this fundamental reason, investors dislike risk. The most significant risk premium is the equity risk premium—the extra expected return for investing in equities rather than bonds or risk-free assets. Other risk premiums include the interest rate and default risk in bond markets. In classical finance, investors are risk averse, and market frictions are usually assumed away. The PAPM asserts from Ibbotson (2018)[89], that "Investors have differing risk aversions and popularity preferences. The characteristics are priced according to the aggregate demand for each. Its risk and popularity characteristics determine the expected return of each security." This assertion is cemented by Warren Buffett's well-known comment that *"in the short term, the market is a voting machine, and in the long term, the market is a weighing machine."*

In the broadest context, the risk is unpopular. The most significant risk premium is the equity risk premium (i.e., the extra expected return for investing in equities rather than bonds or risk-free assets). Other risk premiums include, for example, the interest rate term premium (because of the greater risk of longer-term bonds) and the default risk premium in bond markets. The bond market encompasses many premiums that may or may not be related to risk, but all are related to investing in something unpopular. The idea that non-pecuniary preferences should influence asset prices and portfolio construction is not new. Cooper, Evnine, Finkelman, Huntington, and Lynch (2016)[51] present a multi-characteristic portfolio construction model similar to what the PAPM assumes, in which the characteristics are various social impact metrics.

The fundamental idea behind popularity as a concept in the capital market is that it serves as a bridge between classical and behavioral finance. Both approaches to finance rest on investor preferences, which are recast as popularity (Ibbotson, Idzorek, (2018)[90]—preferences, which can be rational or irrational.

Behavioral finance has provided examples of irrational investor preferences creating anomalies in asset pricing. For example, investors prefer assets whose distribution of returns resembles that of a lottery ticket (positive skewness and excess kurtosis resulting in a large tail on the right side of the distribution). The idea that popularity preferences or tastes impact prices is familiar, but one which was formalized in an equilibrium asset pricing model. Long ago, in his book The Intelligent Investor, Benjamin Graham (1949) noted:

Buying a neglected and, therefore, undervalued issue for profit generally proves to be a protracted and patience-trying experience. Selling short is too popular, and an overvalued issue is apt to test not only one's courage and stamina but also the depth of one's pocketbook.

One needs to be mindful not to confuse investors' sentiments with popularity; the critical difference between them is that sentiment reflects short-term demand and possible mispricing. Popularity in the PAPM is more general, reflecting long-term preferences (e.g., risk aversion, liquidity demand, well-known brand preference), and is thus priced in a pricing model. Popularity (with heterogeneous expectations) can also include short-term sentiment and mispricing.

In summary, *popularity* focuses on the overall long-term preference or liking of something, often quantified by the number of supporters or followers. On the other hand, sentiment concerns the emotional tone or attitude expressed towards some form of communication, helping to understand whether the sentiments are positive, negative, or neutral. While *popularity* is more about the extent of long-term acceptance, sentiment is more about the nature of the opinions expressed in the short term.

1.3 Popularity as a Theory

Asset pricing theories have long recognized that expected returns should differ for the various market instruments, supported by Sharpe (1964)[129] and Ross (1976)[126]. The primary explanation for these differences has been differences in risk, which is unpopular - investors do not like risk and want compensation. But there is more to asset pricing than risk premia. The traditional risk-return paradigm continues to dominate how the world thinks about modeling and forecasting asset prices. However, in reality, not all market participants act rationally, and subsequently, the market moves based on perception and changes in perception until, occasionally, reality sets in.

The CAPM is an elegant and easy-to-use theory describing investors' expected returns in an equilibrium setting concerning only one thing the investors have a preference for or not is the market risk. This framework generalizes the CAPM to include all preferences in the "popularity asset pricing model" (PAPM).In classical finance, investors exhibit risk aversion, and market frictions are often assumed to be negligible. Interestingly, risk itself is less popular. The most significant premium is the risk premium (above the risk-free), representing the additional expected return for investing in security. Risk or risk aversion is the only characteristic considered unpopular in the CAPM. In classical finance, risk is any characteristic that could contribute to the uncertainty associated with potential loss. Risk aversion is the preference for an inevitable outcome of a risky one. Thus making risk unpopular.

1.4 New Equilibrium Theory (NET)

In their 1984 paper, "The Demand for Capital Market Returns; A New Equilibrium Theory." Roger Ibbotson, Roger G., Jeffrey, J. Diermeier, and Laurence B. Siegel (1984)[87] proposed a new asset pricing theory that accounted for all the additions and subtractions for desired and undesired characteristics. The fundamental idea of the framework is that the more investors demand an asset, the more desirable the asset's characteristics. This is the initial blueprint of the PAPM, which combines elements of classical and behavioral finance. The PAPM is based on the following pillars of economic theory.

- Subjectivism—The values of assets are not determined solely by their inherent properties. Investor preferences play a significant role in determining value.
- Marginalism—Each investor constructs their portfolio so that the marginal contribution to the utility of each asset is equal to the marginal cost of holding the asset—its price.
- Equilibrium— Asset prices are determined in markets so that all assets are willingly held.

The authors note that some aspects of popularity are systematic and quasi-permanent. Other aspects of popularity may be transitory or exist only as fads. "For example, liquidity is permanently popular, but it is especially sought after on a relative basis during market distress. Society places a greater relative value (monetary or otherwise) on the more popular items." The popularity framework includes generalizing various classical and behavioral finance characteristics influencing how investors value securities. They classify these characteristics into two broad categories with two subcategories each:

Classical:

1. Risks: In classical finance, the risk usually refers to fluctuations in asset values. However, the risk can be interpreted more broadly as any risks to which a rational investor would be averse.
2. Frictional: Examples include taxes, trading costs, and asset divisibility.

Behavioral:

1. Psychological: Investors consider these characteristics because of their psychological impact. For example, buying a company with a small carbon footprint might make an investor feel good.

2. Cognitive: Investors consider these factors or fail to interpret such factors because of systematic cognitive errors accurately. For example, investors may overvalue the importance of a company's brand when evaluating its stock because they do not realize that the brand's value is already embedded in the stock's market price.

This thesis applies this concept to corporate credit bonds to explain the characteristics which investors have *likeness* or *dis-likeness*, and therefore, what impact these preferences have on the bond expected to return via CDS) credit default swap) spreads. In this thesis, I assert that relative to equities, illiquidity combined with the enormous complexities of the corporate bond market could make PAPM even more effective for corporate bonds and bank loans.

1.5 The Popularity Asset Pricing Model

The Popularity Asset Pricing Model (PAPM) is linked to a substantial body of prior research. Developed by Ibbotson, Idzorek, Kaplan, and Xiong (2018), referred to here as IIKX, the PAPM initially assumes homogeneous expectations. This thesis extends the PAPM to incorporate heterogeneous expectations. The PAPM is an evolution of the New Equilibrium Theory (NET) by Ibbotson, Diermeier, and Siegel (1984), broadening its classical focus on risk, liquidity, and tax-efficiency to include behavioral preferences such as value, ESG factors, reputation, and brand preference. Further expansions by Ibbotson and Idzorek (2014) and Idzorek and Ibbotson (2017) incorporate investor tastes into the NET framework. The PAPM formalizes this into an asset pricing model that accommodates any systematic investor preference, whether it is risk-based or not, rational or irrational, classical or behavioral .

1.5.1 Formal Presentation of the PAPM with Heterogeneous Expectations

The fundamental principle of popularity in asset pricing posits that investor preferences and tastes significantly influence asset prices. Specifically, assets possessing characteristics that are favored by a substantial number of investors experience higher demand, rendering them more expensive and yield lower expected returns. Conversely, assets with characteristics that are not favored face lower demand, making them less expensive and offering higher expected returns. Changes in collective investor preferences, such as the growing demand for assets with particular environmental, social, and governance (ESG) characteristics, liquidity, or varying interest rates, can lead to temporary fluctuations in the returns of assets possessing these characteristics during periods of shifting tastes.

The key understanding of PAPM is shown below (adapted from Ibbotson et al (2018)[90] , we aggregate across all investors to arrive at the demand for each security. We then equate demand and supply and simultaneously solve for the equilibrium prices of all securities. In equilibrium, if a given characteristic is broadly liked or disliked by enough investors, it impacts asset prices and is thus a priced characteristic.
The equation for PAPM looks like a multifactor asset pricing model but with popularity premiums rather than risk premiums. For an individual security j, such that,

$$\mu_{Mj} = \beta_j \mu_{Mj} + \sum_{k=1}^{p} \delta_{jk} \pi_j \tag{1.1}$$

where:

μ_{Mj} = average PAPM equilibrium expected excess return (above risk-free rate) on security j (market-weighted average of investors)

β_j = beta of security j relative to the market portfolio

μ_M = expected market risk premium (above the risk-free rate)

δ_{jk} = exposure of security j to characteristic k

π_j = popularity premium of characteristic k

Given the equation 1.1 the linear formulation of PAPM, in practice it may be challenging to arrive at the various popularity premiums in the equation, adapted it into a regression formulation in equation 1.2. For this the CDS return is in absolute terms, which means it has already factored in the risk-free return.

$$\mathrm{R}_{jt} - \mathrm{R}_{Ft} = \beta_j (\mathrm{R}_{Mt} - \mathrm{R}_{Ft}) + \sum_{k=1}^{p} \gamma_{jk} (\mathrm{R}_{kt}) + \varepsilon_t \tag{1.2}$$

where:

R_{jt} = security j's return for month t

R_{Ft} = risk-free return for month t

β_j = security j market beta

R_{Mt} = market return for month t

γ_{jk} = security j's regression coefficient for characteristic k

R_{kt} = return on a securities exposure to characteristic k

In this framework δ_{jk} is positive if security j 's exposure to characteristic k is less than that of the beta-adjusted market portfolio and negative if the reverse is true. In this way, a popularity loading of security is ***positive*** for a given characteristic if the security is unpopular with respect to the characteristic and ***negative*** if it is popular. π_k is the popularity premium of characteristics k.

Importantly, the PAPM, incorporates to the two missing ingredients identified in Fama-French – *tastes and disagreement* – and in the spirit of APT and the Fama-French factors, can have a *multiple linear factor structure.*

As mentioned, the PAPM can look similar to APT, in which returns are a linear function of factor/characteristic exposures. For the APT, the linear relationship between expected return and premiums follows directly from the assumption that security returns only have a linear relationship to the risk factors. Still, the PAPM extends the factor universe to include nonrisk factors or characteristics. Given that the central theme of PAPM is the heterogeneity of preferences and tastes, and also the potential that these may change over time, *in this thesis panel data analysis, I employed a fixed effects firm and time methodology to control for unobserved heterogeneity and time-specific factors. This approach is valuable because it improves parameter estimates' efficiency, helps address endogeneity issues, and handles serial correlation in panel data analysis.* Furthermore, in the regression analysis of asset price to the popularity of its characteristics, the R-squared tells how consistent the popularity premium is but does not tell its magnitude or determine whether it exists.

1.5.2 The PAPM and Other Asset Pricing Models

Fundamentally, there are two frameworks for security pricing models: equilibrium and arbitrage. Arbitrage models describe the relationships between security prices in a law-of-one-price but do not explain how root prices are formed. Arbitrage Pricing Theory (APT) relies on this framework and assumes the expected return on a security is a linear function of exposures to risk factors with corresponding premiums. In contrast, the PAPM, like CAPM, uses the equilibrium framework where the prices are derived from both the securities' characteristics and the investors' preferences. In the case of the CAPM, the preferences of investors are limited to the risk of the market (or some benchmark). The PAPM extends this idea and considers investors' preferences beyond that of the market risk, and the preferences may or may not even be risk-related. Investor preferences are aggregated to create endogenous popularity premiums, while APT factors are exogenous, and APT risk premiums are not derived from investor preferences. The PAPM is inspired solely by the New Equilibrium Theory (NET) of Ibbotson, Diermeier, and Siegel (IDS)(1984)[87]. It formalizes the NET framework into an asset pricing model that allows for any systematic investor preference to be priced, whether risk or nonrisk, rational or irrational, classical or behavioral.

Table 1.2 summarizes key aspects of the CAPM, APT, and PAPM in which the cells are color-coded with green highlighting when the PAPM is similar to the other models and orange indicated differences. The key assumptions of the PAPM are far more realistic than those of the CAPM and APT and, thus, are more practical. The APT assumes a linear structure, while the linear structure of the PAPM is not an assumption, rather it flows from the underlying utility functions of the investors linking portfolio formation to asset prices. Furthermore, the PAPM arrives at a multi-factor linear structure without APT's assumption of perfect arbitrage (no arbitrage opportunities) since it is an equilibrium model.

An area of the asset pricing literature that is a particular case of the PAPM relates to what one might think of as real-world market friction. Amihud and Mendelson (1986a,1986b)[6] develop a liquidity-based equilibrium asset pricing model incorporating heterogeneous investor horizon preferences. In that model, the investors can be classified into different clientele. Shorter-horizon investors hold more liquid and expensive stocks with lower expected returns. In comparison, the longer-horizon investors hold the less liquid and less expensive stocks with higher expected returns. Other market frictions include borrowing rates significantly higher than lending rates and restrictions on borrowing or leverage (e.g., Black, (1972)[27]; Gârleanu and Pedersen,

Table 1.2: Key Theoretical Differences between the CAPM, APT, and PAPM

	CAPM	APT	PAPM
Model Type	Equilibrium	Arbitrage	Equilibrium
Key Assumptions	Perfect Capital Markets; Homogenous Expectations; Risk Aversion	Multi-Factor Structure; Complete Markets(No Arbitrage Opportunities)	Tastes & Diverse Opinions
Multi-Factor Structure	No	Yes	Yes
Source of Linearity	Pecuniary-Only Utility Function	Linearity is Assumed	Pecuniary and Nonpecuniary Utility Function
Tastes	Single Risk	Multi-Risks	Multi-Risks & Non-Risks
Driver of Asset Prices	Investor Demand	Economy Supply	Investor Demand
Mispricing Allowed	No	No	Yes
Portfolio Construction	Levered/Unlevered Market Portfolio	Personalized	Personalized
Reasons for Personalization	N/A	External to Model	Diverse Opinions & Tastes
Non-risk Factors	No	No	Yes

Source: The CAPM, APT, and PAPM by Idzorek,Kaplan, and Ibbotson

(2011)[73]. For example, in Frazzini and Pedersen (2014)[69], contrary to the CAPM, many active managers prefer high-beta stocks due to restrictions or limitations on borrowing. Many investor preferences/tastes are inherently behavioral. In the behavioral finance literature, popularity is most closely linked to affect (Zajonc, 1980). Shefrin and Statman (2000)[132] introduce what they call "behavioral portfolio theory" as a variation to Markowitz's mean-variance optimization (Markowitz, (1952, 1959, 1987)) to address the Friedman and Savage (1948) puzzle in which people who buy insurance policies often also buy lottery tickets. Shefrin and Statman (2000) hope their behavioral portfolio theory of portfolio construction method will lead to a behavioral-based equilibrium model extension of the asset pricing model from the earlier Shefrin and Statman (1994[131]). Much of the recent literature on preferences/tastes focuses on ESG as a consumption good. As mentioned earlier, the model from Pedersen, Fitzbibbon, and Pomorski (2020)[123] is a particular case of the PAPM. Using a single-characteristic version of the PAPM (the characteristic here being ESG score), Baker et al. (2020) find that green municipal bonds are issued at a premium. Pástor, Stambaugh, and Taylor (2020)[122] determined that green firm stocks had negative alphas and brown firm stocks (which had negative externalities) had positive alphas. Similarly, Geczy, Stambaugh, and Levin (2005)[74] find that socially responsible mutual funds tend to underperform slightly. Shafron(2019) studies the impact of investors' tastes for Shariah-compliant bonds, finding that, on average, they pay between 51 basis points and 75 basis points less than conventional bonds. Barber, Morse, and Yasuda (2020) demonstrate that investors derive non-pecuniary utility from investing in impact-oriented venture capital funds and are willing to sacrifice substantial returns. Friedman and Heinle (2016) proposed a model showing how investor tastes for corporate social responsibility impact share demand.

The PAPM that is present here also allows for heterogeneous returns expectations. Lintner (1969)[107] provides the framework for aggregating investors' divergent opinions to form prices. Grossman and Stiglitz (1980)[77] extend the concept of a noisy rational expectations equilibrium introduced by Lucas (1972)[111], in which prices inform endogenous beliefs. The Grossman and Stiglitz (1980)[77] model includes both informed and uninformed participants with different expectations and concludes that if information comes at a cost, market prices do not reflect all information because if they did, no one would pay for the information in question–the so-called Grossman-Stiglitz Paradox. As such, an informationally efficient market is impossible, even in a rational world. Diamond and Verrecchia (1981)[57] show disagreement can lead to distortions, even in a rational world. Carlin, Longstaff, and Matoba(2012)[41] specifically study disagreement's impact on asset prices.

1.6 Credit Default Swap Spread and Popularity

The Credit Default Swap (CDS) spread is a metric utilized to estimate the likelihood of a company failing to meet its commitments. They are traded just like any other derivative instrument and are an excellent approximation to replicate the return of the underlying bond of the corporation. Understanding what drives CDS spreads is vital and beneficial for investors, analysts, and policymakers. The CDS market's central role in assessing a corporation's creditworthiness and ability to lead other markets represents an important research question. The growing importance of the CDS market has resulted in the extant literature analyzing CDS spreads; there have been anomalies. In this paper, I adopt a popularity framework to explain the anomalies. The drivers of the spread can be attributed to investors' preference for the characteristics of the instrument itself and the reference entity. The capital market is interconnected around the globe; supply and demand still dominate the price discovery of most liquid instruments. And CDS spread is not exempted. Here, the objective is to understand the return drivers via

CDS spreads. Therefore, I examine the drivers of the CDS spreads by regressing a set of market and idiosyncratic drivers. This study is developed in two parts. First, I conduct a panel data analysis to study the relationship between firm-specific default probability- and market-based variables on corporate CDS spreads while controlling for non-default spread drivers. Secondly, I introduced the macroeconomic variables (SBBI data set), which investors may have a preference for. This approach fundamentally extends the NET (1984) to credit risk aversion. The thesis aims to integrate classical and behavioral finance by formalizing investor preferences through PAPM, particularly in corporate bonds using CDS spreads. This approach enhances understanding of bond pricing and contributes to broader discussions on asset pricing anomalies and investor behavior in financial markets.

1.7 SBBI Dataset and Popularity

The Stocks, Bonds, Bills, and Inflation (SBBI) dataset is a set of key macroeconomic risk drivers, which in this context is regarded as a set of *unpopular* risk premiums. The dataset is a well-regarded historical financial dataset that provides extensive data on various asset classes, inflation, and economic indicators over a long period. It primarily tracks and analyzes the long-term performance of key financial instruments and inflation. The key components are:

- **Stocks:** Large-cap stocks, typically represented by indices like the SP 500, reflect the performance of large, established companies. Small-Cap Stocks: This category includes data on smaller companies, providing insights into the performance and volatility of less established firms.

- **Bonds:** Long-Term Government Bonds: This index tracks the performance of long-term U.S. government debt, highlighting interest rate trends and bond market behavior. Corporate Bonds: This section includes data on bonds issued by corporations, offering a perspective on credit risk and corporate borrowing costs.

- **Bills:** Treasury Bills (T-Bills): Short-term government securities are used as a risk-free rate proxy. They provide insight into short-term interest rates and liquidity.

- **Inflation:** Consumer Price Index (CPI): This index tracks changes in the price level of a basket of consumer goods and services, providing a measure of inflation over time.

The Popularity Asset Pricing Model (PAPM), an equilibrium model in which priced factors primarily emanate from the collective tastes of investors, provides a framework for identifying and understanding priced factors; in this thesis, I employ some of them since they offer several advantages due to its comprehensive and long-term historical data on securities and economic indicators. The advantage of using the SBBI dataset is its long-term historical perspective, including long-term interest rates, inflation, and other economic indicators that support macroeconomic research and the development of economic models. This makes it ideal for PAPM, given that its objective is long-term returns.

Ultimately, it enables a deep understanding of security performance, economic conditions, and market behavior over an extended period. Its comprehensive coverage and long-term perspective make it invaluable for developing, validating, and refining financial models, ultimately leading to more informed investment decisions and effective risk management.

1.7.1 The Popularity Asset Pricing Model Variables

The Popularity Asset Pricing Model (PAPM) extends traditional asset pricing models by incorporating investor preferences and tastes into determining asset prices. Unlike the Capital Asset Pricing Model (CAPM), which primarily focuses on risk and return, the PAPM acknowledges that non-financial characteristics (such as popularity) can influence asset prices.

Table 1.3: Potential Explanations of Premiums and Anomalies

Characteristics	**Investor Preference**	**Popularity Prediction**	**Pecuniary/Non-Pecuniary**
Yield	Higher is liked	High yield; higher price.	Pecuniary
Credit Quality	Higher is liked	High credit quality; higher price	Pecuniary
Equity Market Volatility	**Higher is disliked**	**lower price**	**Pecuniary**
Large Stocks	**High is liked**	**High liquidity; higher price.**	**Pecuniary**
Long-term Corporate Bonds	**High Yield is liked**	**High yield; higher price.**	**Pecuniary**
Long-term Govenment Bonds	**High Yield is liked**	**High yield; higher price.**	**Pecuniary**
Duration	Depends (LDI)	Mixed predictions.	Pecuniary
Liquidity	Higher is Liked	High liquidity; higher price.	Pecuniary
Marketability/ Divisibility	Higher divisibility is liked	Higher divisibility; higher price.	Non-Pecuniary
Norminal vs Real (inflation Protection)	Investor like inflation protection	High inflation protection; higher price.	Pecuniary
Callability	Investors dislike callability	Callable; lower price	Pecuniary
Issuer Brand/Reputation	Investors like issues with a good brand / reputation	Better Brand / Reputation; higher price.	Non-Pecuniary
Issuer ESG Score	Investor like stronger ESG issuers.	Better ESGness; higher price.	Non-Pecuniary
Currency denomination	Home Country is liked.	higher prices due to exchange rate	Pecuniary

Table 1.4 lists possible acceptable variables in CAPM, APT, and PAPM

Table 1.4: Possible PAPM Variables

Variable	CAPM	APT	PAPM
Default Probability(Credit Quality)	✓	✓	✓
Equity Market Volatility(VIX)	✓	✓	✓
US Large Stocks (Equity Market)	✗	✓	✓
Long-term Corporate Bonds	✗	✓	✓
Long-term Government Bonds	✗	✓	✓
US Treasury 5-Year Yield	✗	✓	✓
Duration	✗	✓	✓
Liquidity	✗	✗	✓
Marketability/ Divisibility	✗	✗	✓
Nominal vs Real (inflation Protection)	✗	✗	✓
Callability	✗	✗	✓
Issuer Brand/Reputation	✗	✗	✓
Issuer ESG Score	✗	✗	✓
Currency denomination	✗.	✗	✓

1.7.2 Unpopularity of Risk in PAPM

In the context of the Popularity Asset Pricing Model (PAPM), risk is considered unpopular because it is a characteristic most investors generally seek to avoid. The PAPM extends traditional asset pricing models by incorporating the idea that investor preferences, or "tastes," influence asset prices. In this framework, "unpopular" traits—those that investors typically find undesirable—lead to higher expected returns as compensation for holding assets with these characteristics. Being inherently undesirable for the average investor, risk is one of these "unpopular" traits. Investors require additional compensation for bearing higher risk, which manifests as a risk premium. The more investors dislike risk, the higher the premium they will demand to take it on. This leads to an inverse relationship between the popularity of risk and the return on risky assets. This contrasts with traditional models like the Capital Asset Pricing Model (CAPM), where risk is purely a function of the asset's contribution to portfolio volatility and is not directly tied to investor tastes or preferences.

Thus, in the PAPM, the risk is unpopular because it is a source of discomfort for investors, and to hold a risky asset, investors require a reward in the form of a higher expected return. This concept underscores the PAPM's broader perspective that asset prices are influenced not only by risk factors but also by the varying degrees of popularity or unpopularity of different asset characteristics among investors.

Table 1.5: Expected PAPM Variables Signs

PAPM Variables	Description	Data Source	PAPM Predicted Sign
Default Probability(Credit Quality)	**Credit quality of the issuer**	**Kamakura**	+
Equity Market Volatility(VIX)	**Equity market volatility**	**CBOE**	+
US Large Stocks (Equity Market)	**Normalized S&P500 levels**	**SBBI**	+
Long-term Corporate Bonds	**Avg. Yield on 30Yr Coperates**	**SBBI**	+
Long-term Government Bonds	**Yield on 30Yr Treasuries**	**SBBI**	+
US Treasury 5-Year Yield	**Yield on 5YrTreasuries**	**SBBI**	+
ESG Score	ESG Scores of Issuers	Refinitiv	-
CDS Spreads	Spreads over 5Yr Treasuries	TRACE	+

Table 1.3 shows various premiums, anomalies, and characteristics empirically related to security returns and attempts to associate them primarily with disagreement, tastes, or both. FF concludes that the price effects of disagreement are likely temporary, given the pricing effects of tastes for assets as consumption goods are likely to persist.

- **Risk Factors:**

  Market Risk (Beta): The traditional risk associated with the overall market, as in the CAPM.

  Other Systematic Risk Factors: Factors identified in multi-factor models (eg. Fama-French or APT), such as size (small vs. large-cap), value (book-to-market ratio), and momentum.

- **Non-Risk Factors:**

  Investor Sentiment: Measures of the overall optimism or pessimism among investors, which can influence demand for particular assets.

  Liquidity Preferences: Investors' preference for liquid versus illiquid assets.

  Brand/Company Reputation: The appeal of a company's brand or reputation, which can drive investor demand irrespective of fundamental value. ESG (Environmental, Social, and Governance) Factors: Preferences related to the social and ethical considerations of investing, such as sustainability and corporate governance practices.

  Dividend Preferences: The attractiveness of dividend-paying stocks versus those that reinvest profits into growth.

  Growth vs. Value Preferences: Preferences for growth stocks (with high expected earnings growth) versus value stocks (trading at lower price-to-earnings ratios).

1.8 Contribution of the Thesis

The thesis presented herein; consists of three main chapters, with each subsequent chapter building on and drawing from the previous chapter and focusing on a specific research aim and objectives within the overall thesis. Overall, the structure of the thesis can be seen as a collection of parts making up an overall coherent piece of work, albeit each chapter could stand independently.

- **Chapter One; as outlined and expanded on above, provides a brief introduction to existing pricing models in a historical context;** including the Capital Asset Pricing Model (CAPM), Fama and French Factor Models (FF), Arbitrage Pricing Theory (APT), and the Popularity Asset Pricing Model(PAPM). The emphasis is on the evolution of the PAPM framework from the New Equilibrium Theory (NET) to the mathematical formulation of PAPM with heterogeneous expectations. Chapter One also highlights the relationship between CDS spreads and the popularity of the SBBI dataset, which can be ascribed as risk characteristics (or factors - *unpopular*).

Ross's ubiquitous Arbitrage Pricing Theory (APT) (1976), which resembles the PAPM framework, initially had tremendous potential to create a unified pricing model by introducing linear pricing securities across multiple factors. In derivative pricing, the APT has been useful in establishing underlying prices of securities, but it has yet to be useful in forecasting non-derivative prices. This thesis contributes by adopting the theoretical asset pricing framework to corporate credit.

The PAPM offers a more comprehensive and realistic approach to asset pricing by incorporating investor tastes and expectations into a generalized equilibrium model. It addresses the limitations of CAPM and APT, providing a valuable framework for understanding and predicting asset prices in a complex and diverse market environment by accommodating behavioral finance.

This thesis contributes by adopting the theoretical framework of asset pricing to corporate credit as follows.

- **Chapter Two; contributes to the asset pricing literature by attempting to generalize the asset pricing model through its application to the CDS market through the employment of macroeconomic determinants**

of CDS spreads: Integration of Popularity Asset Pricing: The thesis enriches the understanding of corporate credit risk premiums by integrating the popularity asset pricing model. This model considers how investor preferences for macroeconomic variables influence CDS spreads, thus return, such as equity market levels, liquidity conditions, and U.S. Treasury returns. These variables are viewed as both risk and non-risk factors. Empirical Evidence on CDS Spread Variations: It provides empirical evidence on how these macroeconomic variables explain variations in CDS spreads across firms and market conditions, offering a nuanced view of credit risk assessment. Credit Default Swap (CDS) returns (rather than just CDS spreads) are less common, as CDS returns are less widely studied than CDS spreads. The closest examination of CDS determinants using an APT type of framework similar to the one being adopted in this thesis is Galil, Shapir, Amiram, Zion (2014)[71], the author's contribution was to integrate firm-specific and macroeconomic variables, the study provides a nuanced understanding of credit risk and the pricing of credit default swaps. This work is instrumental for researchers, investors, and policymakers interested in the dynamics of credit risk and the behavior of CDS markets. Their study suggests areas for future research, such as the impact of regulatory changes on CDS spreads and the role of liquidity factors, which is not a risk factor but a preference by investors, thus allowing a framework such as PAPM to introduce the liquidity preferences into the equation from an equilibrium perspective.

- **Chapter Three; provides a contribution to the literature on the popularity and the interplay of ESG Scores in the credit and the equity markets:**

  By examining the extent to which the concept of popularity, particularly investor preferences towards ESG scores, explains the relationship between corporate bond returns and equity returns, the thesis contributes to the growing body of literature on the intersection of ESG investing and traditional financial performance. Firm-Specific and Market Conditions: The thesis further explores how these dynamics vary across different firms and market conditions, adding depth to analyzing ESG preferences in investment decisions. PAPM subsumes many existing models, including ESG-specific models, by allowing for multiple tastes and heterogeneous expectations. It provides a unified rationale for various asset pricing anomalies traditionally unexplained by CAPM. The PAPM, as applicable to ESG, demonstrates how changing aggregate tastes (e.g., increasing demand for ESG investments) can affect CDS spread and their return.

- **Chapter Four; provides a contribution to the literature on the impact of ESG preferences on credit portfolio risk:**

  Tail Risk Analysis within PAPM Framework: Adopting the theoretical framework of the popularity asset pricing model (PAPM), the thesis investigates how preferences for high ESG scores impact the tail risk of credit portfolios. This analysis is crucial for understanding the risk management implications of incorporating ESG criteria into credit investment strategies.

Overall, the thesis makes significant contributions by blending macroeconomic analysis (primarily, risk characteristics – ***unpopular***) and ESG considerations (nonrisk – ***popular or unpopular***) depending on investors' preferences and tastes within the framework of popularity asset pricing, thereby offering a comprehensive approach to understanding corporate credit risk and investment performance in contemporary financial markets.

1.9 Identifying PAPM Factors

The PAPM framework aims to select the factors that connect these characteristics primarily to investor tastes, disagreement, or a combination of both. It is essential to recognize that many characteristics can be interpreted from a pecuniary perspective, which stems from disagreement, and a non-pecuniary perspective, which arises from tastes. According to Fama-French(2007), the influence of tastes on asset pricing, where assets are seen as consumption goods, will likely persist over time. In contrast, the effects of disagreement on pricing are expected to be temporary, as investors who are initially misinformed will eventually acquire better information. Consequently, premiums associated with tastes are anticipated to remain influential even after the market fully understands them. While most pricing models focus solely on priced premiums, the PAPM incorporates disagreement, which can result in mispricing or deviations from true valuation.

Table 1.6: Pricing Models and Factors vs. Attribution Regressions and Factors

Pricing Models and Priced Factors	Attribution Regressions and Attribution Factors
The PAPM, CAPM, and APT are models of single-period expected returns	Time-series and cross-section models are methods of analyzing realized returns.
Pricing factors explain expected returns and results from risk and non-risk tastes	*Attribution factors explain realized returns*
All pricing factors usually are also attribution factors.	Few of the numerous attribution factors are also pricing factors
Pricing models lead to expected premiums/discounts with non-zero means that are relatively permanent in nature.	Attribution factors may have permanent exposures/loadings, but are not expected to impact long run returns (zero means).
In aggregate, priced factors are liked / disliked and lead to premiums/discounts.	In aggregate, attribution factor net / cancel out over time
There may only be a few systematic pricing factors.	There are many diversifiable attribution factors.
Often used in forms of passive management and associated with long-term exposure to non-skill-based priced factors (betas).	Often used in forms of active management and are associated with skill-based residual exposures in the pursuit of alpha.

Source: The CAPM, APT, and PAPM Idzorek,Kaplan, and Ibbotson, (2023)

Following the approach of Ibbotson, Diermeier, and Siegel (1984) and Daniel and Titman (1997), we argue that investments should be viewed as collections of characteristics. While not all characteristics are priced, some are. We find it useful to differentiate between priced characteristics, which are related to ex ante asset pricing models, and non-priced characteristics, which are relevant to ex post regression-based attribution models. Priced characteristics, which reflect investor preferences, should be incorporated into asset pricing models. Although any priced characteristic can serve as an explanatory attribution factor, not all attribution factors are necessarily priced characteristics. Priced characteristics are valuable for forecasting returns. Table 1.6 provides a summary of the differences between pricing factors and attribution factors.

1.10 Methodology Adopted in Research

I chose a fixed-effect panel model because it best suits the nature of the data and the research question. The research aims to examine how the popularity of individual macroeconomic variables affects credit returns. The fixed-effect model is ideal for this as it controls for individual-specific effects that might correlate with the independent variables. It focuses on changes within each firm over time, providing more accurate and reliable estimates. Unlike an OLS pooled regression model, which assumes constant coefficients across all firms and ignores unique firm characteristics, the fixed-effect model captures the richness of the panel data. It accounts for correlations within firms over time while assuming independence across firms, offering clear insights into how changes in independent variables affect each firm. This detailed firm-level analysis can be aggregated to assess portfolio-level impacts, aiding in more informed portfolio management decisions.

1.11 Limited Body of Work In Factors Models for Corporate Credit Pricing

There is a limited body of work in credit asset modeling. The closet to this thesis is Beckit (2018)[19]. Beckit's thesis, titled "Factor-based Portfolio Management with Corporate Bonds," does address the limited body of work on factor models in corporate credit pricing. Specifically, it highlights that, despite the success and extensive research on factor-based investing in equity markets, similar research for fixed-income securities, including corporate bonds, is less mature. The thesis discusses the complexities of applying equity factors like size, value, momentum, and beta to credit markets and explores how these factors perform in corporate bond markets, particularly in U.S. high-yield and investment-grade segments. In addition, Van Loon (2017), "Empirical Studies in Corporate Credit Modelling: Liquidity Premia, Factor Portfolios Model Uncertainty", This thesis reviews various factor modeling efforts in corporate credit markets, highlighting the limited application and the challenges of isolating factors specific to these markets.

1.12 Overview of Data Availability

The dataset utilized in this study began in 2010, marking the point at which comprehensive and reliable ESG (Environmental, Social, and Governance) data became available in the Refinitiv database. Prior to this period, ESG data coverage was relatively sparse and inconsistent, limiting its applicability for rigorous analysis. The selection of 2010 as the starting point ensures both the robustness of the ESG metrics and consistency across the broader dataset employed in other chapters of this thesis. Using the same time horizon allows for the comparability of results across different analyses and models explored within the thesis. The initial sample includes data from over 500 firms operating in the U.S., each with consistent monthly credit spread data. These firms span both the investment-grade and sub-investment-grade credit ratings, offering a comprehensive view of corporate bond market dynamics across different credit qualities. The inclusion of both high-quality investment-grade firms and more speculative sub-investment-grade companies is critical for understanding the broader impact of ESG factors on credit spreads, as the effect of these factors may vary significantly across firms with different credit risk profiles. This dataset, therefore, provides a solid foundation for examining how ESG factors influence credit spreads over time, while also ensuring that the findings can be effectively integrated with the broader analyses conducted throughout this research. By maintaining this level of consistency and breadth, the study aims to deliver comprehensive insights into the evolving relationship between corporate ESG performance and credit market outcomes. I mapped the availability of CDS data and the corresponding ESG scores from Refinitiv[1], to create a merged database. The resulting sample comprised of 209. To this end, I took the last non-missing CDS spread for a month. Using the criteria of the availability of CDS spreads and ESG scores without missing values. The resulting sample is composed of monthly data from 209 CDS contracts that are investment grade (70%) and sub-investment grade (30%) across six different rating groups (from AA. to CCC.) and ten sectors (Basic Materials, Consumer Goods, Consumer Services, Financial, Health Care, Industrial, Oil& Gas, Technology, Telecommunications, and Utilities). The period spans from January 2010 to April 2022 and comprises more than 30,305 monthly observations. The chosen date range is because, in the other chapters where we are considering ESG scores, data availability (non-missing) starts from 2010; earlier data are very sparse.

[1]the ESG scores are used for another study in the thesis, for the sake of consistency

Chapter 2

The Drivers of CDS Spreads (and Returns)

Abstract

This paper uses a theoretical framework, popularity asset pricing, an extension of the New Equilibrium Theory, Ibbotson et al. (1984)[87] to examine the impact of macroeconomic variables along with default probability impact on bond spreads using the CDS spread as a premium for the credit risk. The framework treats every asset as a set of characteristics or preferences, either popular or unpopular among investors. The term "popularity" refers to a broad concept that can assist in explaining valuation and the permanent market premiums (for instance, the equity market risk, treasury yield, and so on). Popularity can also help explain the value. It can also assist in explaining why certain things are valued higher than others. The popularity of liquidity contrasts with the unpopularity of risk. Sometimes, liquidity could be popular, while the risk could be unpopular. Popularity can also help explain temporary mispricing (e.g., stocks the market gets overly excited about). This study uses a framework that includes a cross-section between classical and behavioral finance to examine various preferences influencing a company's credit risk premium via the Credit Default Swap (CDS) spread. These preferences define a firm's credit risk premium. The framework considers all of an asset's features to be preferences, and investors give each preference a degree of popularity that could be time-dependent. This research endeavors to explain how the bond market from a *popularity* perspective. Therefore, I have constructed the excess return of firms (with duration near the tenor of the CDS spreads) and performed a panel data analysis to capture the effect of risk factors, such as default probabilities, and SBBI macroeconomic data set, which include equity market levels, liquidity, and US Treasuries returns. The fundamental premise is that high CDS spreads are unpopular among investors, leading to higher expected returns. The initial theory and testing of the Popularity-based model have thus far been focused on equity-oriented anomalies. Nevertheless, the popularity framework is compatible with both the horizon premium (which accounts for longevity) and the credit premium (which accounts for default). In this thesis, I argue that relative to equities, illiquidity combined with the enormous complexities of the corporate bond market could make the popularity-based model even more effective for corporate bonds and bank loans.

2.1 Introduction

Global credit default swaps (CDS) have been well established as a market for financial institutions, asset managers, and corporations to manage credit risk exposure. Corporate credit risk is a growing concern among academics and practitioners since the number of corporate defaults is on the rise due to COVID-19 and the global recession that is currently reverberating. Over the last decade, the size and structure of the market have changed markedly, but the instrument is the key indicator of corporate credit risk or default risk. CDS spreads are important barometers quantifying default risk; CDS is an essential market instrument to mitigate or take speculative positions on credit risk exposure primarily because a market participant can easily take directional positions. However, the empirical asset pricing literature does not typically study CDS as another investment asset, so less is known about the quantification of risks in this market. This thesis extends the PAPM framework to corporate credit return via CDS spreads.

Previous research has explored various measures for estimating corporate credit returns, including credit ratings, bond yield spreads, and Credit Default Swap (CDS) spreads. Among these, CDS spreads are considered a more precise measure of credit risk than bond yields. This is primarily because:

- CDS spreads are directly observable for a given underlying bond and hence do not require any adjustment or assumption on a risk-free benchmark rate. In contrast, bond spreads have to be computed using a risk-free benchmark, which is often difficult to ascertain (Longstaff, Mithal, Neis, (2005)[108]; Blanco, Brenan, Marsh, (2005)[28]).
- CDS contracts are directly written on the credit event of the underlying bond. Unlike bond yields, they are not distorted by embedded options or features like call options and covenants (Duffie, (1998)[60]).
- Unlike other credit risk instruments like bonds and swaps, CDS are not interest rate-based instruments, ensuring minimal interest rate movements' effect on spread estimation.
- Studies have shown that CDS spreads react more rapidly to changes in the credit quality of the underlying reference entity compared to the bond market (Hull et

al., (2004); Blanco et al., (2005); Zhu, (2006)). During periods of financial distress, the CDS market dominates the information transmission process between the CDS and bond markets (Delatte, Gex, Lopez-Villavicencio, 2012).

Furthermore, as noted by Annaert, Ceuster, Roy, and Vespro (2012)[8], the credit premium in bond spreads is driven by liquidity factors (Sarig and Warg, (1989); Chen, Lesmond, and Wei, (2007)[?]), tax effects, and market microstructure effects such as maturity and coupon effects. These factors make bond spreads an inferior measure of credit risk compared to CDS spreads. Additionally, CDS have more pronounced liquidity relative to bonds, ensuring that credit-sensitive information is quickly processed, thus providing an excellent laboratory for studying the mechanisms of the credit market (Breitenfellner and Wagner, (2012)[32]).

The CDS market is also considered superior to the bond market due to the relative illiquidity and high barriers to shorting bonds, which impedes the price discovery process in the bond market (Blanco et al., (2005)[28]). Consequently, CDS provides an alternative, more reliable, cross-sectional, and time-series indicator of corporate credit returns. The growing popularity of Credit Default Swaps (CDS) highlights their potential as a more reliable indicator of corporate credit risk cross-sectionally and over time. Existing literature on credit risk modeling supports using CDS spreads as a superior proxy for credit risk compared to traditional measures such as bond yield spreads. Studies include Hull, J., Predescu, M., White, A. (2004). This study examines the relationship between CDS spreads and bond yield spreads, finding that CDS spreads are more responsive to changes in credit quality. However, as such, changes in CDS spreads do not represent the return dynamics for the insuring party in a CDS contract. Recently, Berndt and Obreja (2010)[24] provide a unique way of converting CDS spreads into implied returns, which gives the flexibility to estimate daily CDS returns based on changes in daily CDS spreads. These returns are driven by the underlying firm's credit risk dynamics and present a pristine source of firm credit risk evolution over time. In this study, I employed the same approach in estimating the returns and then applied the PAPM framework to identify the existence of the risk characteristics. Furthermore, applying the Popularity Asset Pricing Model (PAPM) to credit returns offers a novel approach to understanding credit risk dynamics; this is the main contribution of the literature.

This chapter investigates how preferences for macroeconomic variables, including equity market levels, leverage conditions, and U.S. Treasury returns, impact corporate credit risk premiums as measured by Credit Default Swap (CDS) spreads within the Popularity Asset Pricing Model (PAPM) framework. The central research question is whether these variables can explain the variations in CDS spreads (and returns) across different firms and market conditions.

Using a popularity-based pricing framework, this study aims to identify the drivers of credit spreads and their corresponding returns. It explores the bond market from a popularity perspective by constructing the excess return of firms (with a duration similar to the tenor of the CDS spreads) and conducting a panel data analysis to capture the effect of risk factors, such as default probabilities, alongside the SBBI macroeconomic dataset, which includes equity market levels, liquidity, and U.S. Treasury returns. The hypothesis is that high CDS spreads are unpopular among investors, resulting in higher expected returns. This chapter's main contribution to the existing literature is the novel examination of credit return drivers through the lens of popularity, a perspective not previously explored. Although SBBI data is used in this study, the PAPM model is versatile and applicable to any reasonable dataset.

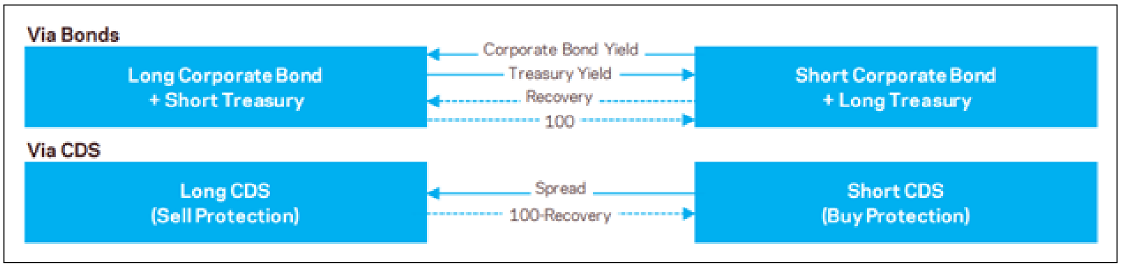
In a nutshell, the hypothesis is that high default probability, equity market volatility, along with the SBBI dataset, which are risk factors, are unpopular among investors, resulting in higher expected returns.:

- H_0 **: the signs of the aggregated coefficients of the risk factors, which are unpopular, is positive, and thus increases long-term expected return**

Corporate bond returns are primarily influenced by rates, liquidity, and spreads. This paper analyzes the drivers of CDS spreads and returns using a popularity framework to evaluate the significance of each factor. For CDS spreads, the analysis focuses on the elasticity of default probability, the U.S. large-cap index level, and U.S. Treasury yields, which reflect market participants' preferences. Linear regression is employed to measure these preferences. The same methodology is applied to CDS returns, examining CDS spreads, the total return of the large-cap stock index, and the total return on intermediate-term U.S. Treasuries. This chapter seeks to understand how the popularity of these macroeconomic variables influences credit returns via changes in corporate bond credit spreads, utilizing the PAPM framework. Given the linear nature of PAPM, linear regression is used to determine the popularity loading of each macroeconomic variable treated as preferences.

2.1.1 Pure Credit Exposure

Corporate bonds, by definition, are exposed to both interest rate and credit risk. When investors want pure exposure to credit, there are a couple of ways to achieve that objective. Firstly, holding a corporate bond and selling short a Treasury bond with the same maturity profile eliminates the interest rate component of the cash flow. The investor then only receives the credit spread component of the yield, and secondly, the credit default swap contract is used. The market for these instruments has become sufficiently developed to make CDS a meaningful asset class in its own right. A key benefit of a CDS contract is its pure exposure to credit risk — no interest-rate risk must be hedged out. The "spread" on a CDS contract is analogous to the spread on the corporate bond.



Source: AQR. For illustrative purposes only

Figure 2.1: Getting Pure Credit Exposure: the CDS covers the same period as the bond.

Conceptually, it is not noticeable compared to the cash market of taking a long position in credit exposure (direct lending or buying the bond). Figure 2.1 shows the mechanics of gaining pure credit exposure via corporate and Treasury bonds versus CDS: the boxes on the left represent credit investors; the solid arrows represent regular cash flows when there is no default; the dashed arrows represent cash flows when there is a default. CDS can be particularly useful for relative-value and tactical strategies, as these explicitly look to take views on only the credit component. The terminology in CDS markets can be confusing. In equity and fixed-income markets, one considers buyers long and sellers short. However, that is not always true in the CDS market. In single-name CDS, the buyer of credit protection has short credit exposure, and the seller of credit protection has long credit exposure. This is consistent with the fact that in the financial world, "shorts" are said to benefit when things go badly. When credit quality deteriorates, the credit protection buyer benefits, and when it improves, the credit protection seller benefits.

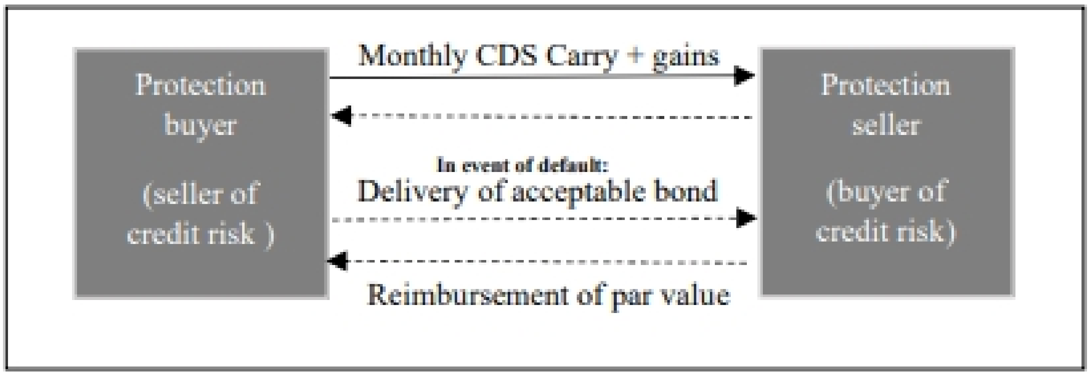
2.1.2 CDS Definition

CDS is a bilateral agreement that transfers the credit risk of one or more referenced entities (usually a corporate bond or loan) from one party, the buyer of protection (credit risk owner) to another, the seller of protection (credit risk buyer). They have the same sensitivity to default as a corporate bond of similar maturity but no interest exposure, i.e., they provide pure credit exposure. Furthermore, while a typical corporation has only a few bond issues outstanding at a time that may differ in terms besides maturity, CDS contracts are homogeneous. They are available in a grid of standard maturities, typically 1,3,5 and 10 years. However, 5 years maturity contracts are the most liquid and frequently traded. The buyer of a CDS contract (protection seeker or hedger) pays a periodic premium to the seller, who assumes the credit risk exposure, referred to as the CDS spread, which is a return over a market reference rate required to protect against credit risk. This spread payment would be determined such that the present value of the contract would be zero at the initiation of the trade; hence, the spread is referred to as a break-even CDS spread. In many ways, the economic effect of the CDS is similar to an insurance contract. However, a CDS contract has specific characteristics that significantly differ from an insurance contract; the protection buyer does not have to own the reference entity, as with the insurance contract.

2.1.3 CDS Cash Flow Mechanics

The payment flow for the CDS contract can be very confusing. This section illustrates the periodic payment between the protection buyer (credit seller) and the protection seller (credit buyer), as shown in Figure 2.2. In the context of this analysis, to create the analogy to the cash bond market, the bond owner would have the same credit exposure as the protection seller since they would be exposed to the same credit risk.

As with any traded financial instrument, a CDS has a value that fluctuates during its lifetime. That value is determined in the competitive marketplace. Market participants constantly assess the current credit quality of the reference entity (the credit risk exposure) to determine its current value and (implied) credit spread. Many factors can change over the life of the CDS. By definition, the duration shortens through time. Likewise, the probability of default, the expected loss given default, and the shape of



Source: EOY. For illustrative purposes only

Figure 2.2: Cash Flow Mechanics of Credit Default Swap(CDS)

the credit curve will all change as new information is received. The valuation procedure of the CDS is precisely the same as when the CDS is first issued and incorporates the new inputs. The new market value of the CDS reflects gains and losses for the two parties.

Consider the following example of a five-year CDS with a fixed 1% coupon. The credit spread on the reference entity is 2.5%. In promising to pay 1% coupons to receive coverage on a company whose risk justifies 2.5% coupons, the protection leg's present value exceeds the payment leg's present value. The difference is the upfront premium the credit protection buyer will pay. Assuming the reference entity's credit quality improves during the CDS life, the credit spread is now 2.1%. Consider a newly created CDS with the same maturity and a 1% coupon. The present value of the payment leg would still be less than the present value of the protection leg, but the difference would be less than when the original CDS was created because the risk is now less. Logically, it should be apparent that the seller has gained and the buyer has lost the original transaction. The difference between the original upfront premium and the new value is the seller's gain and the buyer's loss. An approximate change in the value of the CDS for a given change in the spread is as follows:

Profit for the Protection Leg = [Change in spread(bps)] * [Duration]

Alternatively, one might be interested in the CDS percentage price change, obtained as % Change in CDS price = Change in a spread in bps $\times$ Duration. The percentage change in the price of a bond is approximately the change in its yield multiplied by its modified Duration. For the CDS, the change in yield is analogous to the change in a spread measured in basis points. The Duration of the CDS is analogous to the

Duration of the bond on which the CDS is written. The changes in the price of a CDS give rise to an opportunity to unwind the position and either capture a gain or realize a loss. Returning to the example in the previous section where the reference entity's credit quality improved—the reference entity's credit spread declined from 2.5% to 2.1%. The implied upfront premium on a new CDS that matches the terms of the original CDS with adjusted maturity is now the market value of the original CDS. The new CDS premium is smaller than the original CDS's. Suppose the protection buyer in the original transaction wants to unwind her position. She would then enter a new CDS as a protection seller and receive the newly calculated upfront premium. As we noted, this value is less than what he paid initially. Likewise, the protection seller in the original transaction could offset his position by entering a new CDS as a protection buyer. He would pay an upfront premium that is less than he initially received. The original protection buyer monetizes a loss, and the seller monetizes a gain. The transaction to unwind the CDS does not need to be done with the same original party, although doing so offers some advantages. Central clearing of CDS transactions facilitates the unwind transaction. Therefore, the risk/return dynamics of CDS and a bond are very similar. CDS is the cheapest, fastest, and most efficient way of gaining credit risk in a fund. A CDS contract provides a liquid alternative to dealing with physical bonds. Because bond data can be cumbersome and challenging to standardize, using the CDS contract in this paper's analysis is very convenient.

2.1.4 Credit Spreads

Theoretically, the CDS premium (or spread) is roughly equal to the bond spread for the same borrower and maturity. Both spreads are meant to compensate for the investor's loss in the event of the borrower's default. Thus, they depend on the same main determinants: the probability of the borrower's default, expected recovery rate, and risk aversion in equilibrium. In reality, bonds and CDS spreads are never equal for several reasons, such as the underlying covenants and the primary source of their cash flows. One of the primary determinants of the credit spread, in addition to credit, is liquidity. The most liquid or traded CDS contract is the 5-year, so in this paper, I mimic corporate bonds with CDS contracts with close to a 5-year duration. There is no standard definition of a financial return in estimating the CDS returns since contracts have significant divergence in empirical applications. In this paper, I adopt one of the approaches suggested by Augustin et al. (2020)[10] because there are many ways of approximating the cash flow-based CDS returns. Given the complexities involved in computing CDS correctly, the author's work emphasizes the importance of distinguishing between changes in credit spreads and CDS returns, which incorporate the spread duration for the changes in the CDS spreads approach. The reason for using this approach is that it highlights the need to rely on actual CDS return metrics for predictive return regressions that involve the selling or buying of CDS contracts. Their approach approximation correlates with no less than 99% true CDS returns. The approach is the standard used in the CDS market to estimate returns. Other approaches include the convexity effect, but this is a minor adjustment and should not have any significant consequence on the outcome of this analysis. By definition, a CDS contract has zero value at initiation, which means the CDS spread is chosen such that the present value of the expected payments made by the protection buyer equals the present value of the expected payments made by the protection seller (see Figure 2.2).

2.1.5 CDS spread vs. Bond yield spread

CDS spreads are directly observable for a given underlying bond. Hence, they do not require any adjustment or assumption on a risk-free benchmark rate, whereas bond spread has to be computed using a riskless benchmark, which is often difficult to ascertain. The CDS spread data consists of the bid and ask quotes, which the dealer commits once they are made. On the contrary, bond yield spread data requires no commitment from the dealer (typically the protection seller) to trade on the prices. CDS contracts are directly written on the credit event of the underlying bond and so are not distorted by embedded options, features like calls, and covenants, unlike bond yields (Duffee, 1998). Unlike other credit risk instruments like bonds and swaps, CDS are not interest-rate-based instruments that ensure minimal interest rate movement effect on spread estimation.

2.1.6 Popularity and the Credit market

The popularity of anything increases its demand, which also applies to securities or assets traded in the capital market. Risk is not necessarily the only thing that gets priced. The idea of popularity is simple. Investors are willing to pay more for securities with popular characteristics and less for unpopular ones. This causes popular securities to have a lower return and unpopular ones to have higher returns —which sometimes conflicts with a traditional economic theory where risk and expected return should be positively related. The idea that popularity impacts prices is not a new one. Long ago, in his book The Intelligent Investor, Benjamin Graham (1949) noted:

Buying a neglected and, therefore, an undervalued issue for profit generally proves to be a protracted and patience-trying experience. Selling short is too popular and, therefore, overvalued, is apt to be a test not only of one's courage and stamina but also of the depth of one's pocketbook.

Consistent with traditional economic theory, investors dislike risk. Thus, riskier assets generally have higher returns. For example, riskier high-yield bonds have higher returns than safer investment-grade or sovereign bonds; riskier long-term bonds have higher returns than safer short-term bonds. Traditionally, in factor investing, we have been endeavoring to use factors to explain the performance of different asset classes, and anomalies still seem to exist to explain the source of returns. The beauty of popularity is that it applies to all security characteristics, whether concern for them is rational or irrational. These observations, which form the basis for this paper, are the essence of Ibbotson, Diermeier, and Siegel (1984). entitled "The Demand for Capital Market Returns: A New Equilibrium Theory." Investors' preferences are aggregated into an equilibrium framework, conforming to classical economics and finance. In this framework, one identifies a set of characteristics or attributes that investors either like or dislike and then tests for their significance. These characteristics were later expanded by Ibbotson and Idzorek (2014) to include classical and behavioral finance preferences. A complete treatment of the popularity with an introduction to the Popularity Asset Pricing Model (PAPM) can be found in Ibbotson, Idzorek. Kasplan, and Xiong (2018)[97].

2.1.7 Popularity Asset Pricing Model (PAPM)

The PAPM framework is a linear model that requires logically priced preferences or traits. This means that they are either systematically liked or disliked by consumers as a whole. The PAPM is a market equilibrium model that reflects the preferences that lie behind the surface of the market. The PAPM framework may be traced back to

Popularity: A Bridge Between Classical and Behavioral Research, which details how the framework was developed—the research foundation of the CFA Institute. The idea behind PAPM is that investors express preferences for a certain attributes or characteristics of an asset. Their preferences are quantified by their degree of likeness or dislikeness. So let's say an investor i has a expected excess return (above the risk-free rate), plus the nonpecuniary benefit, minus a personalized penalty for risk. Regardless of how a particular investor thinks about a given characteristics – pecuniary, nonpecuniary, or both, the PAPM aggregates across all investors to arrive at the demand for each security. We then equate demand and supply and simultaneously solve for the equilibrium prices of all securities. Then in equilibrium, if a given characteristic is broadly liked or disliked by enough investors, it impacts asset prices, and is thus a priced characteristic. s. The linear equation of PAPM that led to the regression formulation is shown in equation (2.1).

$$\underbrace{(R_{j,t} - \mathrm{RF}_t)}_{CDS\ return/spread} = \sum_{k}^{n} \beta_{j,k} \mathrm{P}_{j,t} + \epsilon_{j,t} \tag{2.1}$$

where:

$R_{j,t}$ is the Expected Return at time t and for, j securities in a pool (209 CDS contracts), and k is each n characteristic of the securities; RF_t is the risk-free rate at time t, plus a linear series of "popularity" premiums / discounts and $P_{j,t}$ are the loadings, and the error term, $\epsilon_{j,t}$.

Table 2.1: Investor Tastes and Corresponding Priced Factors

	CAPM	APT	PAPM
Model Type	Equilibrium	Arbitrage	Equilibrium
Key Assumptions	Perfect Capital Markets; Homogenous Expectations; Risk Aversion	Multi-Factor Structure; Complete Markets(No Arbitrage Opportunities)	Tastes & Diverse Opinions
Multi-Factor Structure	No	Yes	Yes
Source of Linearity	Pecuniary-Only Utility Function	Linearity is Assumed	Pecuniary and Nonpecuniary Utility Function
Tastes	Single Risk	Multi-Risks	Multi-Risks & Non-Risks
Driver of Asset Prices	Investor Demand	Economy Supply	Investor Demand
Mispricing Allowed	No	No	Yes
Portfolio Construction	Levered/Unlevered Market Portfolio	Personalized	Personalized
Reasons for Personalization	N/A	External to Model	Diverse Opinions & Tastes
Non-risk Factors	No	No	Yes

2.2 Literature Review

Various empirical studies have identified key factors that influence the difference between corporate bond yields and risk-free government bond yields in the literature on the determinants of credit spreads and returns. These determinants can be broadly categorized into macroeconomic factors, firm-specific characteristics, market conditions, and industry-specific elements. Since the development of MPT and CAPM by Markowitz (1952)[113] and Sharpe (1964)[129], researchers suspect that the one-factor model is sufficient to explain the complexity of the global stock market. Introduced by Ross (1976)[126], APT provides a multifactor approach to account for asset returns and is based on the lack of arbitrage and the law of one price. Explaining the market based on the factors that capture the common characteristics and risks of a particular class of investment vehicle is an intuitive approach to understanding the dynamics of the underlying asset class and if chosen correctly. Ultimately, you can determine the alternative risk premium.

2.3 Popularity Asset Pricing Model (PAPM) and New Equilibrium Theory

The foundation of the Popularity Asset Pricing Model (PAPM) rests on the extension of the New Equilibrium Theory first introduced by Ibbotson et al. (1984)[87]. This theory posits that market equilibrium is shaped by investor preferences beyond simple risk-return trade-offs, providing a robust alternative to the Capital Asset Pricing Model (CAPM). The PAPM builds on this foundation by considering that investors view every asset through characteristics or preferences that can be popular or unpopular. These characteristics could range from liquidity and volatility to risk and even environmental, social, and governance (ESG) factors, depending on investor sentiment at any given time. The further development of the PAPM by Ibbotson, Idzorek, Kaplan, and Xiong (2018)[90] underscores its ability to bridge classical and behavioral finance. They argue that traditional asset pricing models inadequately account for investor preferences and that "popularity" provides a missing explanatory mechanism. In their seminal work, Ibbotson et al. (2018)[89] apply the PAPM to equity markets. Still, it has yet to be comprehensively explored in fixed-income markets such as corporate bonds and credit default swaps (CDS).

Blitz (2023)[29] contributed to the factor investing space by developing the Quantitative Popularity framework, which explores how investor preferences can influence risk premiums through factor investing. While this framework shares some conceptual similarities with the Popularity Asset Pricing Model (PAPM), it is not a direct extension. Their work highlights the potential for applying preference-based investing frameworks to more complex markets, such as the corporate bond market, where factors like illiquidity and credit risk could be better explained by investor preferences rather than purely rational models.

Given the intricacies of corporate bonds and the CDS market, the PAPM offers a compelling framework to explore credit spreads, especially in a market where liquidity is often scarce and credit risk is unpopular. Investors facing these characteristics may demand higher premiums, aligning with the PAPM's notion of preference-based pricing.

2.3.1 Macroeconomic Variables and Bond Spreads

Macroeconomic factors play a significant role in determining bond yields and credit spreads. Adrian, Crump, and Moench (2015)[2] developed a model to assess how the term structure of interest rates is affected by macroeconomic variables, particularly the interaction between market expectations and broader economic conditions. Their findings indicate that term structure models incorporating macroeconomic variables provide superior predictions of treasury bond yields, shedding light on the intricate relationship between macroeconomic factors and interest rates. While not the model's primary focus, these dynamics can also inform our understanding of corporate bond spreads, which are indirectly influenced by treasury yields and broader economic conditions.

Interest rates are a significant macroeconomic determinant of credit spreads. Empirical evidence suggests that higher risk-free interest rates typically lead to wider credit spreads as corporate bond yields rise more than government bond yields in response to monetary policy changes. For instance, Longstaff and Schwartz (1995)[109] found an inverse relationship between interest rate levels and credit spreads, with lower interest rates generally resulting in tighter spreads. Another critical factor is GDP growth, which tends to have an inverse relationship with credit spreads. During periods of strong economic growth, the perceived risk of default decreases, leading to narrower spreads. Collin-Dufresne, Goldstein, and Martin (2001)[49] provide key evidence on how credit spreads respond to changes in default probability. Their research delves into the drivers of credit spread changes, highlighting the importance of macroeconomic variables, liquidity constraints, and firm-specific risk. They suggest that fluctuations in credit spreads often reflect broader market sentiment around default risk and liquidity, offering a more nuanced view of corporate credit risk pricing.

Similarly, inflationary pressures have been shown to widen credit spreads as they erode the real value of fixed-income payments, prompting investors to demand higher yields. Gertler and Lown (1999) identified inflation as a contributor to widening spreads, particularly for lower-rated bonds.

2.3.2 Firm-Specific and Market Factors

Firm-specific characteristics, such as leverage and profitability, are crucial in determining credit spreads. Companies with higher leverage ratios face wider credit spreads due to the increased risk of default associated with a higher debt burden. Elton, Gruber, Agrawal, and Mann (2001)[63] highlighted leverage as a critical determinant of credit spreads, with higher leverage leading to broader spreads. Conversely, more profitable firms tend to have narrower credit spreads, as their ability to generate sufficient earnings reduces the perceived risk of default. Huang and Huang (2003)[85] provided evidence that higher profitability, as measured by metrics like return on assets (ROA), is associated with tighter credit spreads.

Market conditions also significantly influence credit spreads. Liquidity, or the ease with which a bond can be traded, is a particularly important factor. Bonds with lower liquidity, often characterized by lower trading volumes, tend to have wider credit spreads as investors require compensation for the additional liquidity risk. Chen, Lesmond, and Wei (2007)[44] found that liquidity risk is a substantial determinant of credit spreads, particularly for corporate bonds that are less frequently traded.

Market volatility is another critical market factor, with periods of high volatility generally leading to wider credit spreads. During such times, investors demand higher compensation for bearing credit risk, resulting in broader spreads. Campbell and Taksler (2003)[39] demonstrated a positive correlation between credit spreads and market volatility, showing that spreads tend to increase during periods of heightened uncertainty. Investor sentiment also plays a role, with negative sentiment often leading to wider credit spreads as investors become more risk-averse. Previous studies have found that credit risk is not the only factor affecting corporate yield spread, churm, Panigirtzoglou (2005)[47]. Their paper examines the evolution of the different components of spreads across time and the effect of particular events. It also analyses the relationship between the derived components and other financial variables, such as swap spreads and the equity risk premium.

2.3.3 Empirical Determinants of Credit Spreads and Returns

This paper studies the drivers of CDS spreads and returns; there are few works of literature on the spreads, very little that addresses the drivers of CDS returns, and virtually none that interprets the drivers using the popularity-based and PAPM framework. Popularity Asset Pricing Model (PAPM): Some studies suggest that investor tastes and preferences, as outlined in the PAPM, play a role in determining credit spreads. For

instance, demand for green bonds or socially responsible investments can influence the credit spreads of such instruments. The gap in the literature is the role of behavioral finance in credit markets. This is where PAPM fills the gap.
The closest model framework that looks at pricing credit instruments using explanatory variables is Bektic et al.(2019)[21]. In their paper, the authors investigate the impact of the four Fama–French factors in the U.S. and European credit space. However, they focus on risk premiums and neglected other preferences that could explain anomalies.

2.3.4 Behavioral Finance and Market Preferences

The PAPM's integration of behavioral finance, which treats investor preferences as dynamic and time-sensitive, allows for a broader understanding of how CDS spreads and bond yields reflect not only default risk but also shifts in market sentiment. This approach moves beyond classical models by accounting for the popularity and unpopularity of different asset characteristics, offering a more comprehensive explanation for the observed credit risk premiums in bond markets.

Behavioral finance has provided an alternative lens for understanding how market preferences and investor behavior shape asset prices. Kahneman and Tversky's (2013)[100] Prospect Theory laid the groundwork for understanding how investors' risk preferences, shaped by loss aversion and other biases, diverge from purely rational decision-making. This has significant implications for asset pricing, particularly in explaining anomalies such as market overreaction and underreaction to risk factors.

2.3.5 Popularity, PAPM, and Asset Pricing Models

The knowledge that characteristics of an asset and investors' behavior toward them impact prices and expected returns are consistent with empirical evidence presented by Daniel and Titman (1997)[53], which empirically finds that it is an asset's characteristics, rather than the covariance structure of returns across different sources that better explain the variation in equity returns with other asset classes.

The PAPM is related to a wide variety of prior research worth noting. The PAPM of IIKX assumes homogeneous expectations. Its underlying concept and notion is inspired by the New Equilibrium Theory (NET) of Ibbotson, Diermeier, and Siegel (1984)[87]. Furthermore, the PAPM expands beyond the classical preferences of NET (e.g., various dimensions of risk, liquidity, tax efficiency) to include behavioral preferences (e.g., value, ESG, reputation, brand preference). Ibbotson and Idzorek (2014)[88] and Idzorek and Ibbotson (2017)[93] build upon and provide additional rationale for the New Equilibrium Theory by including behavioral nonpecuniary preferences in the set of things that matter to investors. IIKX continues to develop that framework, offering a popularity-based explanation for many well-known premiums/anomalies and presenting new empirical evidence with a standard version of the PAPM (limited to homogeneous expectations) as a direct extension of the CAPM. An area of the asset pricing literature that seems to be a particular case of the PAPM relates to what one might think of as real-world market frictions. Amihud and Mendelson (1986a, 1986b)[6] develop a liquidity-based equilibrium asset pricing model incorporating heterogeneous investor horizon preferences. In that model, the investors can be classified into different clientele. Shorter-horizon investors hold more liquid and expensive stocks with lower expected returns. In comparison, the longer-horizon investors hold the less liquid and less expensive stocks with higher expected returns. Other examples of market frictions include borrowing rates significantly higher than lending rates restrictions on borrowing or leverage (e.g., Black, 1972[27]and Gârleanu and Pedersen, 2011). For example, in Frazzini and Pedersen (2014) contrary to the CAPM, many active managers prefer high-beta stocks due to restrictions or limitations on borrowing. Many investor preferences/tastes are inherently behavioral. In the behavioral finance literature, popularity is most closely linked to affect (Zajonc, 1980). Shefrin and Statman (2000)[132] introduce what they call "behavioral portfolio theory" as a variation to Markowitz's mean-variance optimization (Markowitz, 1952, 1959, 1987) to address the Friedman and Savage (1948) puzzle in which people who buy insurance policies often also buy lottery tickets. Shefrin and Statman (2000) conclude with the hope that their behavioral portfolio theory portfolio construction method will lead to a behavioral-based equilibrium model extension of the asset pricing model from Shefrin and Statman (1994)[131].

2.3.6 CDS spreads as a proxy for corporate credit risk

CDS spreads serve as a valuable tool for assessing bond market anomalies, providing insight into firms' perceived credit risk. Collin-Dufresne, Goldstein, and Martin (2001)[50] explore the factors driving CDS spread changes and their relationship with bond pricing. Their research highlights that CDS spreads often deviate from expected pricing models, leading to anomalies not fully explained by traditional credit risk metrics.

Oehmke and Zawadowski (2017)[118] investigate the anatomy of the CDS market, focusing on the relationship between CDS spreads and the underlying bond markets. Their research highlights how CDS spreads are shaped by liquidity and market structure, reflecting interactions between credit risk and bond markets. While they do not explicitly focus on market inefficiencies or investor sentiment, their findings contribute to an understanding of how CDS spreads may diverge due to market mechanics. This can be linked to the Popularity Asset Pricing Model (PAPM), which suggests that investor preferences and sentiment affect market pricing, especially in bond markets where liquidity and credit risk are key factors.

Previous studies have focused on competing measures for estimating corporate credit risk dynamics, including credit rating, bond yield spreads, and CDS spreads. CDS spreads are considered a better proxy for credit risk than bond yields for various reasons (Ericsson et al., 2009)[64]. In addition, CDSs also have more pronounced liquidity relative to bonds and provide an excellent laboratory for studying the mechanism of the credit market (Breitenfellner and Wagner, 2012)[32]. Thus, the increasingly popular CDS is considered to provide an alternative, more reliable, cross-sectional, and time-series indicator of corporate credit risk; this, coupled with the existence of a large amount of CDS data, has yielded a wide range of studies that have employed CDS spreads as a pure measure of corporate credit risk

2.3.7 Corporate Bond Market Complexity and Illiquidity

The complexity of corporate bond markets, where liquidity is often limited, and credit risk varies significantly, creates challenges for traditional asset pricing models. De Jong et al.(2006)[55] provides a key empirical foundation for understanding how liquidity risk influences corporate bond markets. The PAPM posits that assets with characteristics popular among investors, such as liquidity, tend to be priced higher. In contrast, assets with unpopular characteristics, such as illiquidity and default risk, demand a higher return to compensate investors for taking on these less desirable risks. Their research demonstrates that investors demand higher returns for holding illiquid bonds, which aligns with the PAPM's framework. In this model, liquidity is considered a popular characteristic, meaning that investors prefer liquid assets, which are easier to trade without incurring significant transaction costs. As liquidity becomes scarcer, especially during market stress, the liquidity premium widens, causing bond spreads to increase. This is because investors become more sensitive to liquidity risk during turbulent periods, driving up the demand for compensation through higher yields on illiquid bonds.

2.3.8 CDS Liquidity

Liquidity is one of the major concerns in the CDS market primarily due to the non-continuous nature of trades, which relies heavily on confidence between counterparties. Liquidity in the CDS market could dry up quickly, especially during a crisis, and could take a long time to recover. All CDS trades have certain costs, including search costs, broker commissions, and asymmetric information costs, and the higher the costs, the greater the illiquidity associated with the corresponding CDS contract (Acharya and Johnson, 2007)[1]. The CDS market liquidity has been sparsely studied including, Bongaerts et al. (2011)[30]; Arakelyan and Serrano, (2012)[9]; Lesplingart et al., (2012)[106] have focused on CDS market liquidity and found it to be a crucial factor driving CDS spreads. Overall, the literature on modeling spreads using accounting, market-based, and non-default measures provides conflicting evidence on the usefulness of these variables in explaining CDS spread. On the one hand, some studies (e.g., Das et al., (2009[54]; Batta, (2011)[17]; Hasan et al., (2016) find accounting measures to be more informative, whereas other studies such as Galil et al., (2014)[71]) find market-based variables substantially add to the model's power of explaining CDS spreads. Moreover, the growing field of research on non-default drivers of CDS spreads (e.g., Tang and Yan, (2007)[133]; Bongaerts et al., (2011)[30]) has compelled further investigation of CDS spread modeling.

2.3.9 CDS Returns

The primary challenge in constructing CDS returns is the need for more time series data on actual transaction prices for specific default swap contracts. Instead, the available data consists of at-market spreads for newly issued default swap contracts, all with a constant maturity. This thesis aims to use the CDS returns as a proxy to its reference entity. Previous studies have focused on corporate credit risk dynamics, including spreads of bond yields and CDS spreads. CDS spreads are considered a better proxy for credit risk than bond yields for various reasons (Ericsson et al., 2009[64]). In addition, 5-year CDSs also have more pronounced liquidity relative to bonds and provide an excellent laboratory for studying the mechanism of the credit market (Breitenfellner and Wagner, 2012[32]). Thus, the increasingly popular CDS provides an alternative, more reliable, cross-sectional, and time-series indicator of corporate credit risk. This, coupled with a large amount of CDS data, has yielded a wide range of studies that have employed CDS spreads as a pure measure of corporate credit risk.

Bernt and Obreja (2010)[24], research identifies a key factor driving European CDS returns and demonstrates its increased relevance during the financial crisis. This factor provides a new perspective on the systemic risk in European credit markets, distinguishing it from the factors influencing equity returns. Ericsson, Jacobs, and Oviedo (2009)[64] investigate the relationship between theoretical determinants of default risk and the actual market premia for Credit Default Swaps (CDS). It examines how firm leverage, volatility, and the riskless interest rate impact CDS spreads. The study finds that these determinants have substantial explanatory power, both statistically and economically.

2.4 Data and Methodology

For this analysis, I relied on default swap spreads instead of corporate bond yield spreads as the primary source for prices of default risk because the former are less confounded by illiquidity, taxes, and various market microstructure effects are known to have a marked effect on corporate bond yield spreads. In particular, I use North American 5-Year CDS[1] names to reference investment grade and sub-investment grade credits. I eliminated the subordinate class of CDS contracts because fewer CDS are written on subordinate obligations. The CDS-5-year spreads were retrieved from TRACE Market Data via Kamakura Corporation (now part of SAS), expressed in basis points, and converted into percentages. The CDS data focused solely on CDS spreads with a five-year maturity due to their widespread popularity and liquidity in the market (Ericsson et al., 2009; Zhang et al., 2009). The CDS data is with No Restructuring (XR): This option excludes restructuring altogether from the CDS contract, eliminating the possibility that the Protection Seller suffers a "soft" Credit Event that does not necessarily result in losses to the Protection Buyer. No-R protection typically trades cheaper than Mod-R protection. The dataset, which started in 2010[2], comprises over 500 firms with continual monthly spreads in the US across investment-grade and sub-investment-grade companies. I mapped the availability of CDS data and the corresponding ESG scores from Refinitiv[3], to create a merged database. The resulting sample comprised of 209. To this end, I took the last non-missing CDS spread for a month. Using the criteria of the availability of CDS spreads and ESG scores without missing values. The resulting sample is composed of monthly data from 209 CDS contracts that are investment grade (70%) and sub-investment grade (30%) across six different rating groups (from AA. to CCC.) and ten sectors (Basic Materials, Consumer Goods, Consumer Services, Financial, Health Care, Industrial, Oil& Gas, Technology, Telecommunications, and Utilities). The period spans from January 2010 to April 2022 and comprises more than 30,305 monthly observations. The chosen date range is because, in the other chapters where we are considering ESG scores, data availability (non-missing) starts from 2010; earlier data are very sparse. The statistics of the CDS quotes are summarized in Table 3.2.

[1] CDS and 5-Year CDS is used interchangeably

[2] data was selected from 2010, because ESG data availability, used for other chapters in the thesis

[3] the ESG scores are used for another study in the thesis, for the sake of consistency

It shows that the CDS spreads are positively skewed. Categorizing the sample by rating (using the first observation of the rating without considering the rating changes over time) shows that the mean, median, 10th percentile, 90th percentile, and standard deviation all increase as the rating decreases. I also show how the data is distributed across industries. The company's universe is listed on the exchanges and possesses CDS spreads and corporate bond returns statistics.

2.4.1 CDS Spreads

All the signs in the correlation regarding the explanatory variables are what I expected, especially between spreads and default probability, which is positively correlated. The relationship between the overall stock market level and spread is as expected; if the market performs well, the leverage effect is reduced, and the spread level decreases.

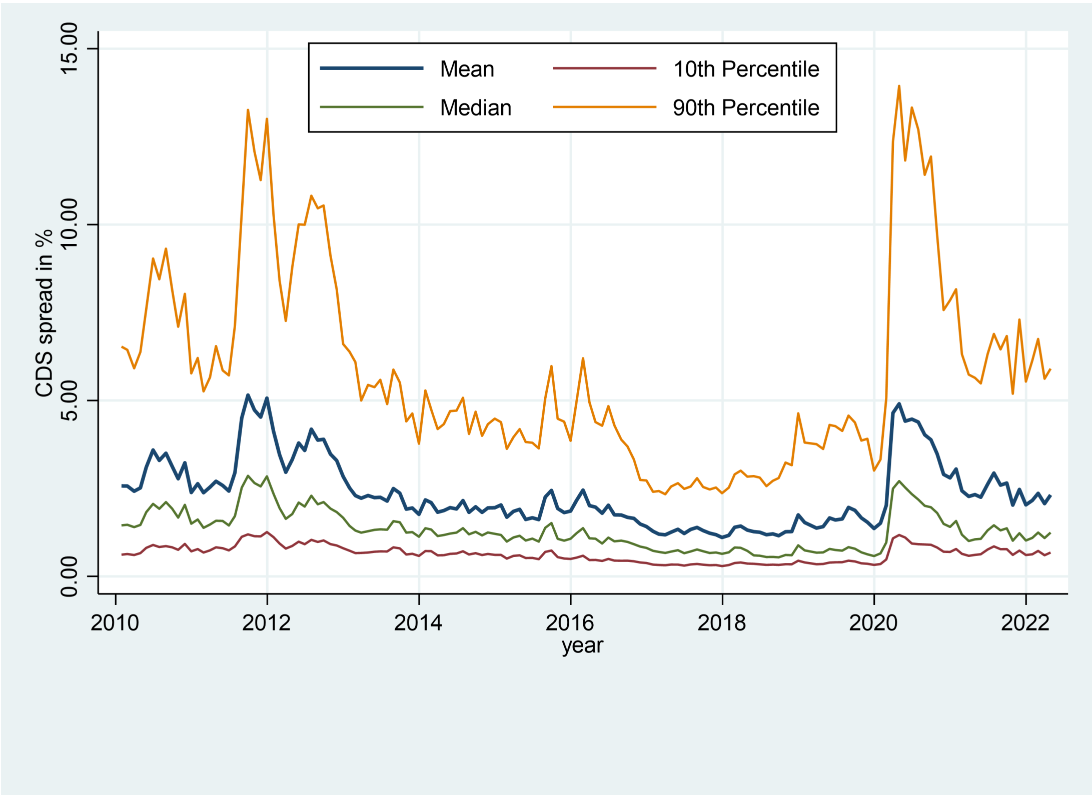


Figure 2.3: Time-variation in Weighted Average CDS Spreads: Jan2010 to April 2022: shows skewness of the CDS spread over all percentiles

Figure 2.3. shows the average CDS spread and highlights how skewed the data is by observing the 10th, median, and 90th percentile. A significant increase in average corporate CDS spreads was observed around the year 2020, which was induced by growing COVID-19 infection rates. This increase indicates that global corporate CDS markets are priced in higher levels of uncertainty, disruptions to businesses, and increased credit

risk due to the pandemic. As a result, the likelihood of default grew due to the stock market level but the high volatility.

2.4.2 5-year Default Probabilities

In this paper, I use the hybrid model of default probability, which combines elements from both the Merton structural model (KDP-ms) and the reduced-form Jarrow-Chava model (KDP-jc). The Merton model (KDP-ms) is effective in capturing rapid adjustments to declining credit quality by focusing on the structural aspects of risky debt. On the other hand, the Jarrow-Chava model (KDP-jc) uses a reduced-form approach that predicts bankruptcy based on accounting ratios, equity prices, their volatility, and company size. The hybrid model integrates the strengths of both approaches by incorporating the Merton default probabilities as an input into the Jarrow-Chava framework.

The use of hybrid measure allows to leverage the complementary strengths of both the structural and reduced-form models in a single specification. By combining these approaches, the hybrid model provides a more comprehensive and robust estimate of default probability, capturing both the rapid market-based adjustments from the Merton model and the broader, fundamental predictors of bankruptcy from the Jarrow-Chava model. Testing multiple versions separately would have been possible, but it would not have provided the same level of insight into how these different risk factors interact. The hybrid model offers a balanced approach that maximizes predictive accuracy, which is particularly valuable in the context of analyzing default risk across a diverse set of firms.

2.4.3 Market Volatility

Different volatility measures influence CDS spreads (Benkert, 2004)[22]. An alternative measure of volatility is the implied volatility. The implied volatility is based on the current values of stock options (Carol et al., 2007[4]) and might be a better proxy for looking into future volatility. Since Benkert (2004) found implied volatility to have a closer connection with CDS spreads than historical volatility, I expect the explanatory power to be more significant. Moreover, the implied volatility is based on the trader's expectations, while the historical volatility is based on past equity returns. This measure also gives investors a sense of the degree of the "fear index" in the marketplace. Given that the asset value doesn't change with volatility, a high VIX increases the overall equity value and, therefore, impacts the default probability as it changes the characteristics of the risk distribution by exhibiting a fat-tail characteristic.

2.4.4 CDS Liquidity

In terms of classical finance, rational investors prefer a more liquid asset. Amihud and Mendelson have documented in their 1986 article that less-liquid assets outperform more-liquid securities. I adopted Lesplingart et al. (2012)[106] and used the absolute difference between the Bid and the Ask spread as a proportion of the quoted spread as proxies for CDS market liquidity. I estimated liquidity using the Bid. Ask as a percentage of the spread; this proved to have high collinearity with the spread levels, so I dropped it from the analysis. But invariably, 5-year CDS contracts become more popular during the economic downturn or demand increases, leading to spread widening, so popularity increases. Bid-ask spread represents a trader's cost to unwind a position. A higher bid-ask spread indicates a more significant divergence of opinion or information asymmetry and, hence, lower liquidity (Tan and Van. 2006). This aligns with popularity, showing that liquidity is popular but yields lower returns.

2.4.5 Stocks, Bonds, Bills, and Inflation Capital Market Data

In addition to 5-year CDS spreads and default probability, I employ monthly data from SBBI and Morningstar Inc[4], which includes the following:

Table 2.2: Stocks, Bonds, Bills, and Inflation: A Capital Market Data Set

Variable	Data Source	PAPM Predicted Sign
US Large-Cap Stocks (Total Return)	**SBBI**	+
US Large-Cap Stocks Index (Level)	**SBBI**	+
US Intermediate-term (5-Years) Government Bonds (Total Return)	**SBBI**	+
US Intermediate-term 5-Years) Government Bonds (Yields)	**SBBI**	+

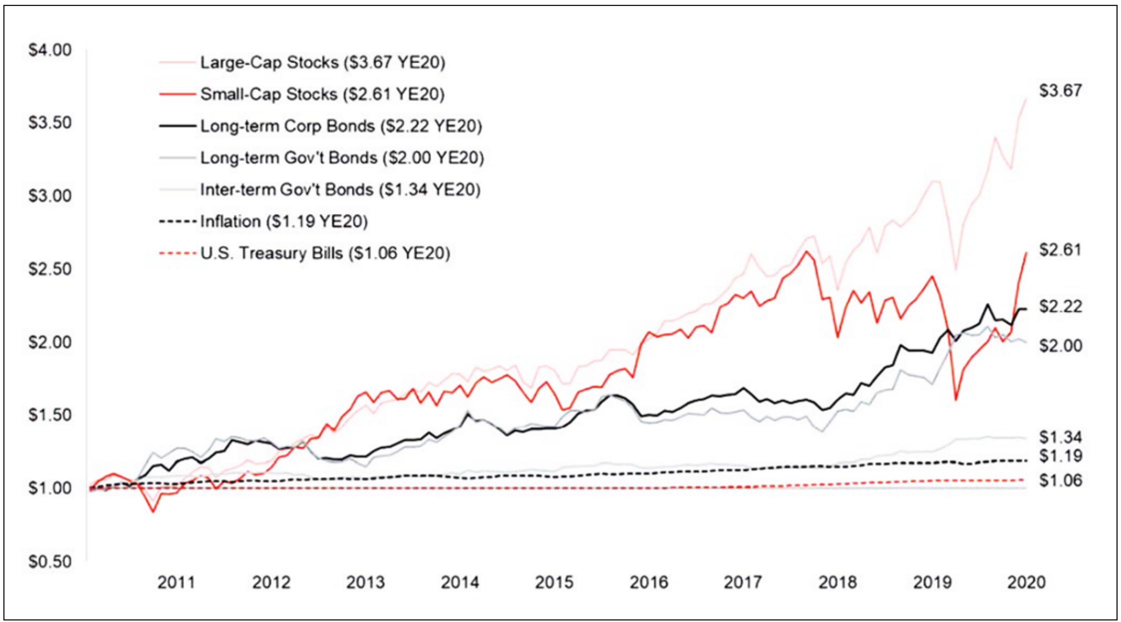
- USLargeStockTR (US Large-Cap Stocks(Total Return)) — an index that tracks the performance of US large-cap stocks. The index is based on the capital appreciation, income, and total returns of the major asset classes of the US economy, including large-cap stocks, small-cap stocks, corporate bonds, government bonds of various maturities, and inflation.

[4]Morningstar Direct. All values are in decimal format. "SBBI" stands for "Stocks, Bonds. Bills, and Inflation". "Stocks, Bonds, Bills, and Inflation," "SBBI," and "Ibbotson" (when used in conjunction with a series or publication name) are registered trademarks of Morningstar, Inc. ©2022 Morningstar.

- USLargeStockLevel (US Large-cap Stock Index[Level]) — this is essentially the Standard & Poor 500

- USTreasury5YrYield (US Intermediate-term (5-Year) Government Bonds(Total return)) - represents yield on U.S. Treasury securities with a 5-year maturity. The yield on a Treasury security is the annual interest rate paid on the bond or note, expressed as a percentage of its face value. The 5-year yield specifically represents the interest rate on U.S. Treasury securities with a 5-year term to maturity.

- USTreasury5YrTR (US Intermediate-term (5-Year) Government Bonds (Yield)) - refers to the total return (TR) associated with U.S. Treasury securities with a 5-year maturity. In the context of investments, total return typically includes capital appreciation (or depreciation) and any income generated by the investment, such as interest or dividends.



Source: Morningstar, Inc. Used with permission.

Figure 2.4: Performance Index of 1 Investment in Each of the Six Basic U.S. Asset Classes Plus Inflation, as Represented by SBBI Series Over the Most Recent Decade (2011 - 2020)(Year-end 2010 = $1.00)

2.4.6 CDS Returns

The academic literature has used different metrics of CDS returns. Ericsson et al. (2009)[64], for example, use break-even CDS spread changes to test the explanatory power of variables suggested by structural credit risk models refers to define CDS Return as:

$$\text{CreditReturns}_{it,t} = (\text{CDSSpread}_t - CDSSpread_{t-1}) \tag{2.2}$$

Another metric, used by Hilscher et al. (2015)[82] is based on percentage changes of CDS spreads[5]. Defines CDS Return as:

$$\text{CreditReturns}_{it,t} = \frac{\text{CDSSpread}_{it} - CDSSpread_{it-1}}{CDSSpread_{it}} \tag{2.3}$$

For this analysis, I calculate the returns to a sell protection position on a 5-year CDS contract over a unit of time, which is monthly throughout the analysis. I adopted one of the approaches used to approximate returns using simple changes in CDS spreads multiplied by the value of a default-able annuity of appropriate maturity, approximate returns using simple changes in CDS spreads multiplied by the value of a default-able annuity of appropriate maturity (Berndt and Obreja, (2010)[24]; Bongaerts et al., (2011)[30]; Duarte et al., (2007)[59];Hilscher et al., (2015)[82]. Palhares (2014)[121], He et al. (2017)[79], and Kelly et al. (2019)[101] add the carry component of the return from the CDS insurance payments and adopted the implementation of He et al. (2017) and define $\text{CDSReturn}_{it,t+1}$.

Equation(2.4) approximates the gain or loss from buying a 5-year CDS contract if the break-even CDS spread is paid over four quarters. It is essential to know the payment mechanics, and the seller receives the periodic payments. I can write the first order approximation of monthly credit excess returns[6] as the change in the value of the CDS contract to the investor is equal to minus the change in the CDSSpread_{it}, given that the change in the spread[7] is:

$$\text{CreditReturns}_{it,t} = \frac{\text{CDSSpread}_{it}}{12} - [(\text{CDSSpread}_t - CDSSpread_{t-1}) * \text{PV01}_t] \tag{2.4}$$

The latter term consists of the change in the par spread multiplied by the PV01_t[8].

It is the change in CDS value in reaction to a one basis point increase in the CDS spread. It measures the dollar present value changes for each basis point shift in the

[5] In their appendix, Hilscher et al. (2015) also compute returns using the change in CDS spreads multiplied by an annuity factor, similar to Bongaerts et al. (2011), and Berndt and Obreja (2010).

[6] This is an approximation, and ignores potential convexity effects.

[7] Losses from defaults are included in the change in credit spread the component in our analysis

[8] PV01 is sometimes referred to as DV01 (dollar value of 1 bps, or BPV (basis point value), the risky duration and approximates the sensitivity of the CDS contract value to changes in the break-even CDS spread. It measures the derivative in price terms: the dollar price change per change in spread

credit curve. It is similar to the standard Modified Duration in bonds, which measures in percentages instead of dollar terms. It tells the investor how much the bond price will change, given the change in its yield. In other words, the $PV01_t$ term computes the present valuation of all future premium payments - per unit of premium payment. And since the default event time is unknown, the $PV01_t$ term embeds credit risk in the discount factor. On the other hand, I propose that this simple approximation of CDS returns has a time series correlation of no less than 99% with the actual return series.

2.4.7 Data Summary

In Table 2.1, I outlined the descriptive statistics of independent and dependent variables from January 2010 to April 2022. The CDS spread mean is 234.67 basis points (bps), with a standard deviation of 318.30 bps. The default probability ranges from 0.005 to 0.30, with a mean of 0.01; the high default range is due to the inclusion of sub-investment grade credits. The monthly mean of the total return of U.S. Large-Cap Stocks is 1.5%; this means the average increment of the equity market level, a standard deviation of 0.044%, and ranges from 0.9% to 4.35%. The table also shows the sample's mean, standard deviation, minimum, 10th percentile, median, 90th percentile, maximum, and skewness values for all the explanatory variables. The maximum values of CDS spreads are unrealistically high, suggesting the presence of outliers in CDS spreads; this is not unusual in credit spreads because default probabilities can spike due to unexpected events. The median, 10th, and 90th percentile values across the whole data set indicate that they are highly skewed, which means the median value could be a representation in the analysis that is different from the mean values. Given that when it comes to credit instruments, the focus is on tail events, it is prudent to include extreme values and not exclude any outliers.

Table 2.3: Summary of Universe Statistics:
Monthly CDS Spread, Return, and the SBBI data set Jan 2010 to April 2022

Variable	**Mean**	**Std.Dev**	**Min**	**10th Pctile**	**Median**	**90th Pctile**	**Max**	**Skewness**
CDS_Spread	0.0235	0.0318	0.0009	0.0047	0.0121	0.0574	0.3519	3.4525
CDS_Return	0.0024	0.0245	-0.2714	-0.0132	0.0012	0.0203	0.3484	0.1714
DefaultProb5YR	0.0107	0.0148	0.0005	0.0043	0.0062	0.0192	0.3021	5.7003
MarketVol(VIX)	0.2108	0.05025	0.1199	0.1428	0.2107	0.2605	0.3454	0.6348
USLargeStockLevel	1.4235	0.5890	0.9407	0.9801	1.1478	2.2880	4.3501	1.9491
USTreasury5YrYield	0.0153	0.0057	0.0044	0.0074	0.0155	0.0242	0.0254	-0.0190
USLargeStockTR	0.0155	0.0433	-0.0903	-0.0523	0.0193	0.0701	0.0892	-0.5027
USTreasury5YrTR	-0.0004	0.0115	-0.0241	-0.0171	-0.0006	0.0151	0.0180	-0.4017

The Stocks, Bonds, Bills, and Inflation (SBBI) Data is a monthly dataset that includes total returns and yields of most major U.S. asset classes, such as large-cap stocks, small-cap stocks, corporate bonds, government bonds of several maturities, and inflation. The dataset was initially produced by Roger G. Ibbotson and Rex A. Sinquefield(1976)[91] and Research Foundation monographs in (1977), (1979), and (1982). The CFA Institute Research Foundation provides CFA Institute members complimentary access to the SBBI *monthly* dataset.

Table 2.4: Correlation Summary of Universe:
Monthly CDS Spread, Return, and the SBBI data set Jan 2010 to April 2022.

	CDS_Spread	**DefaultProb5YR**	**MarketVol (VIX)**	**USLargeStockLevel**	**USTreasury5YrYield**	**CDS_Return**	**USLargeStockTR**	**USTreasury5YrTR**
CDS_Spread	1.0000							
DefaultProb5YR	0.6603	1.0000						
MarketVol (VIX)	0.0422	-0.0714	1.0000					
USLargeStockLevel	-0.0372	0.0736	-0.2894	1.0000				
USTreasury5YrYield	0.0114	-0.0470	0.1959	0.0491	1.0000			
CDS_Return	0.0270	0.0210	-0.0177	0.0823	0.0669	1.0000		
USLargeStockTR	-0.0038	-0.0029	-0.1207	-0.0899	-0.2074	0.0564	1.0000	
USTreasury5YrTR	0.0281	-0.0388	0.2356	-0.1171	-0.1705	-0.0432	-0.3949	1.0000

All the correlation signs meet expectations for market-based variables, except the correlation between the US Large Stocks Index and the default probability. A reasonable explanation could be due to the reduced leveraged effect during a bear market. The underlying asset's volatility may reflect the uncertainty of the firm's security value; thus, higher equity volatility indicates higher default risk, leading one to expect a positive relationship between equity volatility and CDS premiums.

2.5 Methodology

For both models, the analysis of CDS spreads and returns assumes correlation (clustering) over time within a firm while maintaining independence across different firms. To address this, I used a fixed-effect panel data regression, which suits the nature of the data and research questions. The main goal is to examine the impact of individual macroeconomic variable popularity on credit returns. The fixed-effect model was chosen because it controls for unobserved, firm-specific effects that might correlate with the independent variables, leading to more precise estimates. These unobserved effects could include factors such as management practices or industry-specific risks that remain constant over time but influence the dependent variables. The fixed-effect approach isolates the effect of macroeconomic variables on credit returns by removing bias from these firm-specific characteristics.

In contrast, an OLS pooled regression model would be too restrictive as it assumes constant coefficients across all firms, ignoring individual heterogeneity in the panel data. This assumption overlooks each firm's unique characteristics, causing a loss of valuable information and potentially biased estimates. Additionally, since the fixed-effect model better represents the data structure, relying on an OLS pooled regression would likely result in inconsistent and unreliable estimates. Therefore, the fixed-effect model aligns with the research's theoretical framework and enhances the robustness and validity of the findings by properly addressing the data's distinctions.

2.5.1 CDS Spread Drivers

This section describes the variables and their theoretical relation to CDS spread levels from Table 3 as the data confirms that the default probability increases, which is equivalent to high credit risk; one would expect a positive correlation. In the Merton model, Merton (1974)[116] suggests the connectivity between a firm's market value of equity and its probability of default; I expect that a higher U.S. Large-Cap Stocks performance increases across-the-board firms' value, which theoretically should decrease CDS spreads. Thus, a negative relationship is expected between U.S. large-cap stocks' performance and CDS spreads, which proves to be the case. To be consistent with the five-year maturity of the CDS contracts, I measure the spot rate using the monthly

US Intermediate-term (5-Year) Government Bonds (Yield) Rate obtained from SBBI. Longstaff and Schwartz (1995)[109] argue that a higher reinvestment rate (higher spot rate) increases future value. Collin-Dufresne et al. (2001)[49] note that a higher spot rate reduces the probability of default. Both arguments support a negative connection between the spot rate and credit spreads. Longstaff and Schwartz (1995)[109] empirically confirm.

2.5.2 Models for CDS spreads

This section describes a parsimonious CDS spread model incorporating the linear version of the PAPM formulation shown in the equation (2.1).

Panel Regressions

To assess the elasticity between CDS spreads and their determinants, I estimate the following panel data linear regression model adopted from the PAPM linear model:

$$\begin{aligned} CDSSpread_{i,t} &= Constant_{i,t} + \beta_i DefProb_{i,t} \\ CDSSpread_{i,t} &= Constant_{i,t} + \beta_i MarketVol_{i,t} \\ CDSSpread_{i,t} &= Constant_{i,t} + \beta_i MarketIndex_{i,t} \end{aligned} \tag{2.5}$$

Equations in (2.5) are the elasticity of the main drivers of the CDS spreads. The full panel regression is represented in equation (2.6).

$$\begin{aligned} CDSSpread_{i,t} = Constant_{i,t} + \beta_i DefProb_{i,t} + \beta_i MarketVol_{i,t} \\ + \beta_i MarketIndex_{i,t} + \beta_i TreasuryYld_{i,t} \end{aligned} \tag{2.6}$$

where $\text{DefProb}_{i,t}$is the default probability month_t, theMarketVol_t represent the implied market volatility index.The MarketIndex_trepresent the U.S. Large-Cap Stocks, and,TreasuryYld_t, is US Intermediate-term (5-Year) Government Bonds (Yield).

In the context of PAPM, where the drivers of credit spread (return) as illustrated in equation 2.1. Table (2.5) shows the elasticity of each characteristic under study and their correlations. Investor preference for high quality (low default probability) may impact expected returns. There could be endogeneity issues where credit spreads and default probabilities influence each other, potentially biasing results and lowering

Table 2.5: The table shows the elasticity of CDS Spreads: January 2010 to April 2022. All the coefficients are statistically significant in reference to equation (2.4). This indicates all the coefficients have a positive impact on the credit spread with the exception of USLargeStockLevel, which has an adverse relationship.

VARIABLES	(M1) CDS_Spread	(M2) CDS_Spread	(M3) CDS_Spread	(M4) CDS_Spread	(M5) CDS_Spread
DefaultProb5YR	0.812***				0.849***
	(0.115)				(0.119)
MarketVol(VIX)		2.899***			3.342***
		(0.667)			(0.404)
USLargeStockLevel			-0.216***		-0.285***
			(0.0740)		(0.0545)
USTreasury5YrYield				5.704**	11.40***
				(2.376)	(2.093)
Constant	1.478***	1.734***	2.652***	2.258***	0.965***
	(0.123)	(0.141)	(0.105)	(0.0365)	(0.142)
R-squared	43.43%	18.30%	14.10%	1.03%	44.91%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: The table shows the Variance Inflation Factor (VIF). Since all the independent variables have VIF less than 4, this indicates no multicollinearity in the model

Variation	**VIF**	**1/VIF**
MarketVol(VIX)	1.15	0.870442
USLargeStockLevel	1.11	0.901411
USTreasury5YrYield	1.06	0.947865
DefaultProb5YR	1.01	0.990229
Mean VIF	1.08	

the R-squared values, as I discuss in the next section. All coefficients are statistically significant, demonstrating empirical evidence of the loadings, premiums, and discounts of the "popularity" characteristics used in the regression model.

The low R-squared values ranging from 14.10% to 43.43% - indicate that the models account for only a moderate portion of the variance in the dependent variables. This relatively low explanatory power suggests that other factors beyond those included in the models significantly influence the outcomes. It is important to recognize that credit risk and default probabilities are complex phenomena influenced by numerous factors, including macroeconomic conditions, firm-specific events, and market sentiment, which may not be fully captured by the variables used in this analysis. Additionally, the inherent noise in financial markets and the limitations of the models in representing all dimensions of credit risk contribute to the low R-squared values.

For model (5), the control variables that I analyzed and included in my study are essential components to consider when trying to explain CDS spreads. As expected, increasing company-specific variables such as default probability (DefaultProb5YR) and U.S. Treasury Yield leads to high CDS spreads. An increase in the overall stock market levels leads to low CDS spreads since the stock market is a leading indicator of the economy's overall health; its high performance causes investors to prefer high-quality credits (low CDS spreads). The low stock market environment is likely to increase spike in the VIX (implied market volatility or the fear index); this invariably causes credit spreads to widen. This is because the credit spread is proportional to the default probability-weighted expected loss given the default. The relation is expressed as follows:

$$CreditSpread \propto PD * LGD \tag{2.7}$$

where PD is the expected probability of default and LGD is the expected loss given default. Given this relationship, it follows that there are three components of the CDS spread:

1. Default Risk Component – in the popularity framework, taking this risk is unpopular; an investor would demand a higher premium, which means taking a position with a wider CDS spread.

2. Loss-given default, a function of the recovery rate, would be unpopular and demand a higher premium. The expected loss would be heavily dependent on the recovery rate.

3. Recovery rate – CDS contracts need a recovery rate to estimate the expected loss, the theoretical compensation for assuming the credit risk. In this analysis, I will examine the impact of the recovery rate from 0% to the average of 40% and see how the expected varies across different tendencies of the CDS spread, looking at the mean, 10th Percentile, Median, and 90th Percentile.

The regression analysis provides consistent evidence that increased default probability leads to widening corporate CDS spreads. Here, the coefficient of 0.812 means for a 1% change in a 5-year default probability, there will be either 81 basis points widening or tightening in CDS spread in the same direction. The constant in the regression tells us that out of the average spread of 235 basis points, 148 basis points are not explained by the default probability. This relatively strong relation, especially from the correlation point, is due to the relationship between credit spreads and default probability, given by the equation albeit not strictly true (see 2.7), an approximate:

$$CDSSpread = DefaultProbability * (1 - RecoveryRate) \tag{2.8}$$

According to the structural approach to credit spread modeling, only two factors drive credit spread: the default probability and the recovery rate. However, CDS spreads, which are expected to be good proxies, suggest that more factors are at play. Figure 2.5. shows significant variation in credit spreads via CDS spreads to default probability ratios. The ratio of spread to default probability declines as default risk increases because when a near-term default is likely, bonds trade near their anticipated recovery value, diminishing the relevance of the credit spread. This raises questions about the relationship between credit spread (via CDS spreads) and default probability. The simple and popular formula—credit spreads equal one minus the recovery rate times the default probability—appears questionable, implying that no credit spread should exceed the firm's default probability.

The tested characteristics indicate a negative correlation with the stock market, which is expected since the stock market, as a leading economic indicator, causes CDS spreads to tighten when it rises and widen when it falls. However, this relationship might be stronger due to behavioral market aspects unrelated to the fundamental drivers of a company's health. My analysis reveals that CDS prices for the entire sample are influenced by other segments of the financial markets, with market uncertainty and confidence playing a significant role.

This finding is interesting but not unexpected, as uncertainty creates illiquidity, likely driving up CDS spreads. Data limitations made it challenging to quantify liquidity in the CDS markets. Using proxies to explain the Bid-Ask spread of CDS quotes was nearly impossible, so I could not include a liquidity test. Although I attempted to use the Bid-Ask spread as a percentage of the spread, it exhibited too much collinearity and was disregarded. Nonetheless, the overall results indicate that most drivers are not primarily due to default probability, despite its significance. My study supports the financial theory that the stock market efficiently reflects firms' default probabilities in stock prices.

The relationship between CDS spreads and U.S. Treasury 5-year yields is unclear. Theoretically, there should be a high correlation between CDS spreads and credit spreads in various bond market segments. If yields increase, CDS spreads would be expected to fall. Although this inverse relationship usually holds, it doesn't always, seemingly contradicting the theory.

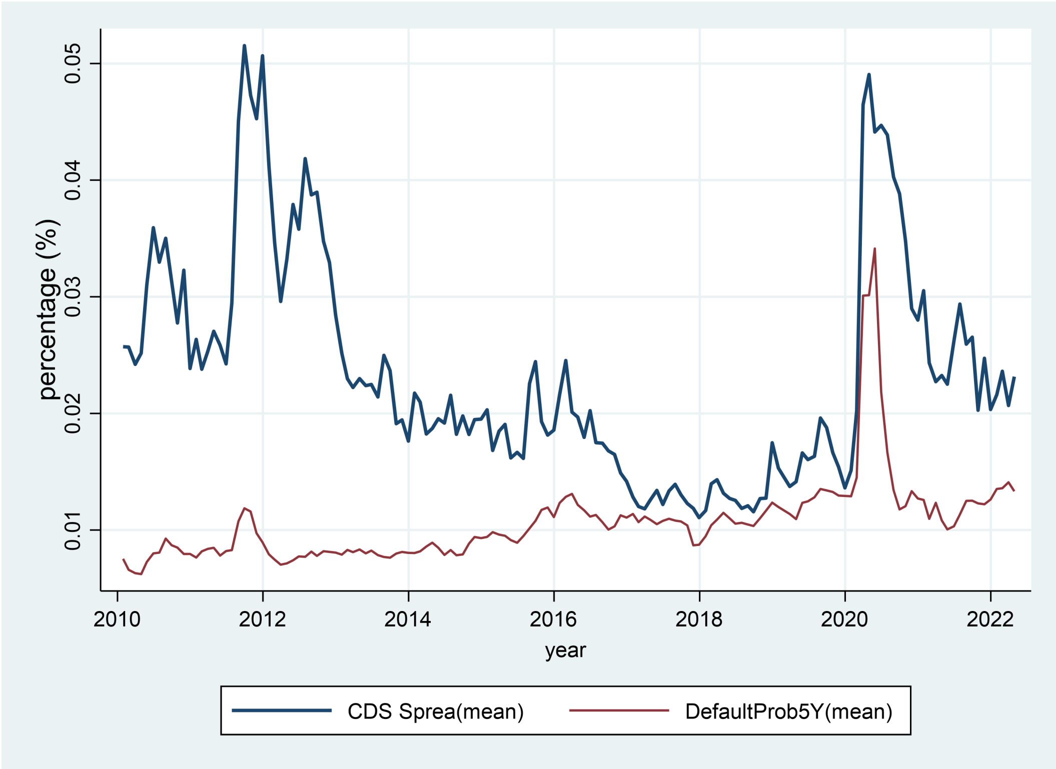


Figure 2.5: CDS spreads with 5-year Default Probabilities: January 2010 to April 2022 - this graph shows that the relation between CDS spreads and Default Probability is positive, but the level changes with time. It shows the relationship between spreads and default probabilities; they have a strong positive relationship, as expected, because they both measure the credit riskiness of the reference entity.

2.5.3 Empirical Evidence of PAPM

The PAPM extends traditional asset pricing frameworks, such as the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT), by incorporating non-risk-related factors that reflect investor preferences and popularity. Unlike CAPM and APT, which primarily focus on risk factors, PAPM integrates characteristics influencing asset popularity, such as investor sentiment, market perceptions, and other non-risk attributes. This model underscores the idea that asset returns are not solely driven by risk but also by demand driven by heterogeneous investor preferences.

My research aligns with PAPM's core principle by specifically incorporating variables that capture non-traditional risk-related characteristics for credit investors, such as equity market volatility, interest rate levels, and equity market indices. These factors or characteristics are used to capture investor preferences and perceptions of asset popularity, indicative of investor sentiment and behavior. By selecting these variables, I aim to account for the influence of popularity, consistent with the theoretical underpinnings of PAPM. The empirical models are structured to reflect PAPM's emphasis on popularity loadings by employing panel data regression with fixed effects, which controls for unobserved heterogeneity and time-specific factors, allowing for a more accurate estimation of the impact of popularity-related characteristics on asset returns. This methodological choice deliberately captures the dynamic nature of investor preferences over time, a key aspect of PAPM, enhancing the precision of parameter estimates, addressing endogeneity issues, and providing a robust framework for analyzing popularity-based asset pricing. The regression analysis results, as presented in Table (2.5), indicate that the coefficients for unpopular characteristics are positive and statistically significant, consistent with PAPM's assertion that unpopular traits lead to positive popularity loadings, thus at 1% level the high default, equity market volatility, equity market level, high US Treasury yield are unpopular. These loadings represent the influence of non-traditional, desirability-based factors on the credit returns, reflecting the impact of investor preferences and behavior on pricing. By identifying and measuring popularity loadings, they can make more informed investment decisions, potentially identifying mispriced assets based on their popularity characteristics.

This empirical evidence supports the model's predictions and demonstrates the relevance of popularity in asset pricing. Although the R-squared values are relatively low, within the PAPM context, they reflect the model's ability to capture the consistency of the popularity premium rather than its magnitude. This is a known aspect of PAPM, where the focus is on demonstrating the existence of popularity effects rather than quantifying them fully. My research aligns with and builds upon existing studies that explore the role of popularity in asset pricing, such as Pereira (2018)[125], which examines the applicability of factor models in explaining CDS returns. Additionally, their results show a substantial portion of CDS spreads in the post-crisis period that the comprehensive model points towards the growing influence of non-default drivers of CDS spreads could not explain. By integrating findings from similar empirical analyses, my research contextualizes its contributions within the broader literature, reinforcing the validity of PAPM in explaining asset pricing dynamics. In addition, the empirical results are consistent with Angelini and Febo (2014)[7], which examined the factors that define the changes of CDS premiums, therefore, to analyze the indicator ability of CDS spreads on the credit market.

2.5.4 Expected Loss and Risk Adjustment Factor

The above result offers insight into how information flows in the credit market, which may not be fully integrated into market perceptions of credit risk. A high credit spread indicates a higher perceived risk in the reference entity's credit, suggesting a lower return or a higher possibility of default by the issuer. The higher the premium, the more protection the seller will require to absorb the credit risk. Thus, CDS prices (spreads) should theoretically reflect the expected default probability of the reference entity's credit. In other words, CDS prices are directly proportional to the probability of default (PD) with a given recovery, as shown in equation (2.8).

One way to view CDS prices is as an insurance policy, with the premium representing the credit risk premium. This premium compensates investors for the risk of default they are exposed to. The spread is calculated by adding the risk premium to the expected loss.

$$CDSSpread = ExpectedLoss + RiskPremium$$

The above equation then leads to:

$$CDSSpread = ExpectedLoss * RiskAdjustmentFactor$$

where

$$RiskAdjustmentFactor = \frac{CDSSpread}{ExpectedLoss}$$

The CDS price (spread) could be interpreted as compensation for each unit of expected loss, which reflects the investors' aversion to the possibility of their investments being lost due to default. It is essential to emphasize that this payment is a premium to eliminate the possibility of defaulting on the agreement. However, other premiums, such as liquidity, will not be covered here. Both of these factors can potentially influence the likelihood of defaulting on a financial commitment. Because the participants' degree of comfort with risk can fluctuate throughout the experiment, they can negotiate a higher risk premium in exchange for the same amount of risk loss. Because of this, the risk premium could shift over time. The default risk can be broken down into two distinct parts, and a premium is usually required for them.

The components of the CDS spread typically include:

- Probability of Default (PD): The CDS spread incorporates the market's assessment of the probability of default by the reference entity. Higher default probabilities result in wider spreads, indicating higher credit risk.
- Recovery Rate: The expected recovery rate in the event of default is another component of the CDS spread. A higher expected recovery rate leads to tighter spreads since the potential loss in case of default is lower.
- Time Value of Money: The CDS spread considers the time value of money. The longer the maturity of the CDS contract, the higher the spread is likely to be, as there is more uncertainty and potential risk over a longer period.
- Liquidity Premium: Less liquid CDS contracts may carry an additional premium due to the increased difficulty in trading and hedging the positions.
- Market Risk Premium: The CDS spread may also reflect the prevailing market conditions and general risk appetite. During periods of heightened market volatility or economic uncertainty, the spread may widen due to increased perceived credit risk.

These factors are incorporated in the simple relation is shown in equation (2.8).

In Table (2.7)., if one compares the Expected Loss across the mean, min, 10th percentile, median, 90th percentile, and the max of the default probability, one can see how the RiskAdjustmentFactor changes with a given RecoveryRate.

2.6 Hausman Test

The Hausman test was implemented in this paper by comparing the results of both fixed and random effects models, and to decide between the effect and random effect regression; first, the panel data model was estimated using fixed and random effects approaches. This involved running a regression analysis with the dependent and independent variables, using either fixed or random effects specifications. Stata allows one

Table 2.7: Expected Loss and Risk Adjustment Factor: Shows discrepancies in the expected loss to the actual CDS spreads and varies across various recovery rates. Given the skewed CDS data, using the median as a central tendency measure and low recovery rate, the ratio of actual CDS spreads to expected loss is 2:1, and the RiskAdustmentFactor is $2x^9$.

Recovery Rate 0%							
	Mean	**Minimum**	**10th Pctile**	**25thPctile**	**Median**	**90thPctile**	**Maximum**
DefaultProb5Yr	0.0107	0.0005	0.0043	0.0049	0.0062	0.0192	0.3021
CDS Spread	0.0235	0.0009	0.0047	0.0072	0.0121	0.0574	0.3519
Expected Loss	0.0107	0.0005	0.0043	0.0049	0.0062	.0.0192	0.3021
Risk Adjusted Factor	2.2019	2.0334	1.0881	1.4581	1.9523	2.9822	1.1647

Recovery Rate 20%							
	Mean	**Minimum**	**10thPctile**	**25Pctile**	**Median**	**90thPctile**	**Maximum**
DefaultProb5Yr	0.0107	0.0005	.0.0043	0.0049	0.0062	0.0192	0.3021
CDS Spread	0.0235	0.0009	0.0047	0.0072	0.0121	0.0574	0.3519
Expected Loss	0.0085	0.0004	0.0034	0.0040	0.0050	0.0154	0.2417
Risk Adjusted Factor	2.7523	2.5418	1.3602	1.8226	2.4403	3.7278	1.4558

Recovery Rate 40%							
	Mean	**Minimum**	**10thPctile**	**25Pctile**	**Median**	**90thPctile**	**Maximum**
DefaultProb5Yr	0.0107	0.0005	.0.0043	0.0049	0.0062	0.0192	0.3021
CDS Spread	0.0235	0.0009	0.0047	0.0072	0.0121	0.0574	0.3519
Expected Loss	0.0064	0.0003	0.0026	0.0030	0.0037	0.0115	0.1813
Risk Adjusted Factor	3.6698	3.3890	1.8136	2.4301	3.2538	4.9704	1.9411

Table 2.8: Hausman test for the Proposed Model Jan2010 to Apr2022 - since p value is < 0.05, fixed effects model was chosen

Coefficients

		Model		
	Fixed (f)	**Random(r)**	**Difference**	**Stand.Err**
DefaultProb5YR	0.8482	0.8700	-0.0220	0.0012
Market Vol (VIX)	0.0330	0.0332	-0.0002	0.0000
USLargeStocklndex	-0.0028	-0.0029	-0.0001	0.0000
USTreasury5YrYield	0.1260	0.1230	0.0030	0.0000
F=307.79	**p-value=**	**0.0000**		

to keep all the coefficient estimates and the respective standard error for both models. Then, it computes the respective t-statistics. The p-value being zero is why the Random effect model is rejected, according to the results of executing or running the Hausman test for the model; see Table 2.8. The Hausman statistics tests if the unique errors are correlated with the regressors, the null hypothesis being they are not correlated with the regressors. If the value for Prob is less than the critical value of 0.05, the fixed effect is the preferred model for evaluating the panel data regression function. The Hausman test is significant for the whole period.

2.7 Bias of Endogeneity and Reverse Causality

Endogeneity and reverse causality are critical issues in empirical finance that can significantly bias the results of regression analyses. Endogeneity arises when an explanatory variable is correlated with the error term, often due to omitted variables, measurement error, or simultaneity. Reverse causality occurs when the direction of causation between variables is unclear, such that changes in the dependent variable might influence the independent variable rather than the other way around. To address these concerns in the analysis of SBBI data and credit returns, lagged variables are employed. By including lagged values of the independent variables, the model can account for past influences on current outcomes, thus mitigating the risk of endogeneity and reverse causality. Lagged variables help ensure that the causation direction is correctly specified, as they capture the effect of past values of the predictors on current credit returns, rather than contemporaneous feedback loops. This approach improves the reliability of the results by isolating the impact of macroeconomic variables on credit returns while controlling for potential reverse causality and endogenous relationships.

Credit Spread

$$\begin{aligned}\text{CDSSpread}_{i,t} = {} & Const_{i,t} + \beta_1 \text{DefProb}_{i,t-1} + \beta_2 \text{MarketVol}_{i,t-1} + \beta_3 \text{USLargeStockIndex}_{i,t-1} \\ & + \beta_4 \text{USTreasuryYield}_{i,t-1}\end{aligned} \tag{2.9}$$

and then lagged by 2.

$$\begin{aligned}\text{CDSSpread}_{i,t} = {} & Const_{i,t} + \beta_1 \text{DefProb}_{i,t-2} + \beta_2 \text{MarketVol}_{i,t-2} + \beta_3 \text{USLargeStockIndex}_{i,t-2} \\ & + \beta_4 \text{USTreasuryYield}_{i,t-2}\end{aligned} \tag{2.10}$$

To mitigate these reverse causality issues, I estimated alternative Equation specifications (2.9). Specifically, I test the influence of the SBBI data in the *t-1* year on the CDS spread in the t year. I report the results in Column 2 (Lag 1) and Column 3 (Lag 2) of Table (2.9). As can be seen from these results, SBBI data are negatively related to CDS, suggesting that the prior-year SBBI data inversely affects the current year's credit risk. These results suggest that the direction of causation runs from the SBBI data to credit risk but not vice versa.

An alternative specifications of Equation (2.10) was estimated to mitigate the reverse causality. Specifically, the influence of the SBBI data was tested with the *t-1* year on the CDS spread in the t year. See Column 2 (Lag 1) and Column 3 (Lag 2) of Table (3.8). These results suggest that the direction of causation runs from the SBBI dataset to credit risk but not vice versa.

Table 2.9: SBBI data set and CDS Spread—endogeneity bias (lagged independent variables)

VARIABLES	Lag(1) CDS_Spread	Lag(2) CDS_Spread
DefaultProb5YR	82.45***	76.40***
	(1.063)	(1.059)
VIX	4.246***	4.439***
	(0.233)	(0.235)
USLargeStockLevel	-0.282***	-0.315***
	(0.0195)	(0.0197)
USTreasury5YrYield	7.803***	19.50***
	(1.946)	(1.964)
Constant	0.877***	0.768***
	(0.106)	(0.106)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.8 Conclusion

This paper analyzes the credit spreads of corporate bonds in the U.S. using an approximately 11-year history. When researching individual company credit spreads, individual company historical data is more likely to be difficult to find. My universe of CDS spreads consisted of 70% investment grade and 30% sub-investment grade corporate. I employed the popularity of corporate credit risk drivers' characteristics to test investor preferences. I extended the analysis to CDS returns (as a proxy to bond returns). Universally liked characteristics are in high demand (popular) and thus expensive, leading to lower expected returns. Credit spreads also give investors an idea of where the economy is heading. Improved economic conditions are signaled by improvements in company profitability and lower corporate default rates; this causes investors to view investment-grade and high-yield corporate bonds more favorably, which causes the credit spread to contract. Moreover, economic improvement prompts the Fed to hike interest rates to ward off inflationary pressure. This increase in interest rates causes Treasury yields to spike, tightening credit spreads. Therefore, the popularity of credit instruments in a good economic environment leads to tightening credit spreads, making them expensive, thus lowering the expected return. The reverse happens in the case of an economic slowdown. And given that credit investors worry about mitigating losses while equity investors care more about the potential upside. Impending bad times for the economy are priced into corporate bonds before equity markets catch on. Conversely, characteristics nearly universally disliked are low demand (unpopular) and thus inexpensive, leading to higher expected returns. In this paper, I have shown that the popularity-based pricing framework drives CDS spreads and returns. In calm times, if the stock market is underperforming, there are overall increases in credit spread because the risk level is elevated; investors dislike spread widening, so the cost of buying protection goes up. The seller of protection, the credit risk buyer, gets periodic payment increases; therefore, the correlation between CDS spreads and returns and the market is negative. In addition, I also conclude that the risk adjustment factor (for risk aversion) is approximately 2-times for the low recovery rates and 3-times for the average recovery rate of 40%, which means the protection seller (credit risk buyer) has a preference spread widening at higher recovery rate. Again, I see how investors' preference for the quality characteristic has impacted valuations, with quality credit at higher valuations than the market. Since valuations are the best predictor of future returns, investors should at least consider them when making investment decisions. Therefore, contrarian investing, buying the unpopular, has tended to produce superior results. Keep this in mind as you consider your asset allocation. Valuations do matter.

Chapter 3

Interplay Between ESG, Credit and Equity Returns

Abstract

The relationship between equity returns and credit returns is complex and often not immediately apparent, as equity holders are the residual claimants on a firm's cash flows and do not receive a promised nominal return, unlike bondholders. Previous studies have examined the role of default risk in explaining equity returns, primarily focusing on the ability of the default spread to predict returns. This thesis revisits this relationship by exploring the link between equity returns and credit returns using structural models, such as Merton (1974), and the Popularity Asset Pricing Model (PAPM). These models suggest that both equity and credit claims must compensate investors for bearing risk, creating a fundamental connection between these instruments.

The Merton model conceptualizes corporate debt as a combination of a risk-free asset and a short put option on the firm's assets, with equity represented as a long call option. While extensions by Black and Cox (1976)[26] and Leland (1994)[104] have refined this framework, the key features of corporate bond pricing and its co-movement with equity prices remain consistent with Merton's original model. In theory, equity prices and credit spreads should be negatively correlated, a relationship that is typically stronger for firms with higher default risk. Equities tend to be more sensitive to firm-specific difficulties than bonds, as equity holders bear the residual risk.

This thesis extends the existing literature by analyzing this relationship through the lens of investor preferences as captured by the PAPM. The PAPM posits that investor preferences for certain risk characteristics, such as default risk or ESG factors, influence the pricing of both equity and credit instruments. Specifically, stocks that are sensitive to default risk may be less attractive to investors, leading to higher required returns. To explore this, I bifurcate the analysis into investment-grade and high-yield (sub-investment grade) credit markets, acknowledging that these two segments represent different risk profiles and investor behavior.

Empirical results suggest a positive relationship between equity and credit returns in the high-yield segment, particularly for firms with high default risk or low ESG scores, where investor preferences play a more significant role. However, this relationship is weaker for investment-grade credits, where the sensitivity of equity returns to default

risk is less pronounced. This bifurcation underscores the importance of recognizing distinct market segments when analyzing the co-movement of equity and credit returns.

By combining insights from structural models, default risk, and the PAPM, this thesis contributes to a deeper understanding of the dynamics between equity and credit markets. It highlights how investor preferences, especially in relation to default risk and ESG factors, influence the relationship between equity and credit returns, with important implications for both investment-grade and high-yield markets.

3.1 Introduction

In the financial market, assets (or securities) can be conceptually viewed as having a set of characteristics associated with them. These characteristics can be systematic and idiosyncratic. Investors' behavior toward these characteristics affects valuation. A substantial body of research examines the relationship between the equities and corporate bond markets. The majority of the research conducted looks at correlations by using models of capital structure. Merton (1974)[116] and Leland (1994)[104] are two of the most well-known models in this field. They introduced a model that explicitly linked the valuation of debt and equity (represented by a corporate bond and a joint stock) to a standard variable: the firm's total assets. In this thesis, I examine this relationship using investors' preference for environmental, social, and governance(ESG), Default risk, and SBBI dataset[1] in credit returns (through CDS) and equity returns. The modeling process uses common preferences of characteristics that impact both equity returns and the credit default swap spread of the same firm. Equity and debt (credit) are risk hierarchies of risk classes' potential expected return. Still, they are contingent claims on the same underlying assets of the firm, and therefore, the risk-return trade-off of each security should be systematically and intrinsically related. According to the well-established work by Merton[117], the structural model investigates the unconditional relationship between the credit spread (or the bond yield); this study estimates the correlation between equity and CDS returns and then examines the determinants of this correlation. This approach enables a more thorough analysis that extends the existing empirical evidence on determinants of the correlation between equity and CDS returns using their common preference characteristics of which ESG scores are among. The main contribution of this thesis is to examine the correlation between the impact of ESG on credit and equity return using the SBBI macroeconomic dataset. Any reasonable dataset could be used instead of the SBBI data set to illustrate the application of PAPM. The examination of the impact of ESG as a preference in the capital market, especially the credit market, has not been well studied with exceptions by Okyere-Yeboah, E. (2022)[120].

There has been a lot of debate about whether or not ESG factors in corporate bond and equity markets have boosted returns ever since the introduction of sustainable and

[1] Stock Bonds Bills and Inflation

ethical investment. This discussion is ongoing. Unfortunately, the empirical evidence on ESG issues in corporate bond markets is contradictory and does not provide a definitive answer. There is evidence that implies a negative association, there is evidence that suggests a positive relation, and there is literature that concludes that the relationship is unstable. Some evidence supports positive returns, while other research suggests a negative relation. However, the research that has been done on this subject has produced results that appear to conflict with one another. In this article, I address this discrepancy in empirical research and with factors in general by considering ESG as a preference. Finally, investigating the link between a company's ESG aspects and the excess return on the bond issued by that company holds promise for corporate bond investors for at least the two reasons detailed below. Looking at the most recent numbers makes it impossible to deny that environmental, social, and governance considerations are becoming increasingly important in the financial markets. On the other hand, a strategy with a strong ESG factor tends to have a lower risk profile and displays relatively high risk-adjusted returns, particularly during bear markets. Because of these characteristics, the strategy is an essential component.

The unprecedented level of fund flows into ESG-related investments has focused attention on the risk and return from such investments. As an example of the fund flows, despite Covid-19 volatility, UK and US investors poured £37.1bn and $100bn, respectively, into sustainable strategies last year, according to Morningstar data. On February 8, 2020, Bloomberg reported that Europe alone has "some $15 trillion committed to sustainable investing." Fish, Kim, and Venkatraman (2019) state that sustainable assets under management worldwide will be approximately $40 trillion by 2021. By 2025, ESG assets are projected to exceed $53 trillion, constituting more than a third of the anticipated $140.5 trillion in total assets under management (AUM) worldwide, according to Deloitte[2]. Finance theory teaches that premiums over the risk-free rate arise from three general sources: 1) rewards for bearing risk, 2) behavior biases, and 3) market impediments, such as limited liquidity. Because this paper focuses on the relation between risk, return, and ESG characteristics, it is assumed that the securities in question are traded in actively developed markets, so impediments are of secondary importance. Furthermore, the only behavioral biases considered here are investor preferences related to ESG characteristics. For this reason, the term bias should not be thought of as pejo-

[2] https://www2.deloitte.com/us/en/insights/industry/financial-services/esg-investing-and-sustainability.html

rative. For example, investors may prefer common stock issued by companies with high ESG scores because they value ESG characteristics, such as reduced carbon emissions, in addition to the pecuniary return offered by a corporation. The thesis looks at the preference of ESG score on both parts of the capital structure, the equity, and the credit, in terms of investment returns. According to structural credit risk models, equity and corporate debt are driven by the fundamentals of the same underlying corporations, implying that equity prices and credit spread changes must be related to ensure the absence of arbitrage. Consequently, risk premia in equity and corporate bond markets should be related. Additionally, with the increasing size of the Credit Default Swap (CDS) market, capital structure arbitrage grew in popularity and aims to profit from temporal mispricing between a firm's equity and corporate bonds or CDS (Duarte et al.,(2007)[59]. Finally, the relationship between a firm's default risk and equity risk premia has been analyzed in numerous studies (see Vassalou and Yuhang, (2004)[135]

Despite the difficulties, there is growing literature on the performance of ESG-based investment strategies. Recent papers include Berg, Koelbel, and Rigobon (2019)[23], Chatterji, Durand, Levine, and Touboul (2015)[46], Dorfleitner, Halbritter, and Nguyen (2015)[58], Gibson, Krueger, and Schmidt (2020)[75], Semenova and Hassel, (2015)[127], and Li and Polychronopoulos (2020)[40] and the list is growing rapidly. The point of this paper is not to add to the list but to address the conceptual issues that arise when attempting to assess the relationship between risk, return, and ESG on the same firm's credit and equity. With that objective in mind, the next section analyses the impact of investor preferences for ESG corporate credit on expected CDS return. The following section turns to the issue of the relationship between ESG and investment risk (both equity and credit). A key question is whether ESG can be considered a risk factor and, if so, what implications that has for expected returns. In this paper, our frame of reference is to treat ESG as a characteristic of an asset for which investors may have a preference, therefore attributed to behavior. For instance, while the banking system is aware of the strategic importance of ESG issues, their practical introduction into lending processes (and in the monitoring tools that guide management actions) is still extremely heterogeneous and fragmented.

Data uniformity, standardization, and availability have constrained research, especially in fixed-income credit. Still, the prospect looks good as the ESG data coverage and the span of the data have improved by definition, and ESG scoring companies have expanded their coverage. This means that today, meaningful studies can be undertaken. And therefore be able to analyze their impact on equity returns.

3.1.1 Return Dynamics Between Credit and Equity Returns

A firm's capital structure may consist of different securities that are broadly classified into two categories: debt and equity. Despite the difference in the way they are structured, all these securities represent claims to the same cash flow stream and therefore are impacted by the same set of fundamental drivers that influence the firm's activities. Therefore the relationship between the equity market and the corporate bond market has existed and been studied by many researchers, notably Merton (1974), and most relatively recently by Crosbie and Bohn (2019)[52] who shows intuitively that there is a formal relation between the values of equity and debt and the relationship is formalized as changes in equity and credit returns of a firm are related as they contingent claims against the assets of the same company. Figure 3.1 visually depicts the dynamic relationship between equity and credit returns; both Crosbie and Merton used the option theory, so several insights help provide estimates of default risk or the risk of non-payment, providing deep insight into the bond market. The fundamental idea is that considering the firm's equity and the payoff to the owner or shareholders' position is an option. If the asset value is above the face value of their debt, then the payoff goes to the equity holders. This can be conceptually and mathematically demonstrated as follows:

Let's assume the value of the firm asset is A_t, and the changes in its value are assumed to follow a geometric Brownian motion, W_t,where μ and σ are the drift and volatility, respectively.

The stochastic process is defined as:

$$dA_t = \mu A_t dt + \sigma A_t dW_t \tag{3.1}$$

It is assumed that the company issues only a single zero-coupon bond with face value F payable at T where the payoff to the creditors D_T at date T is:

$$D_T = \min\{A_T, F\} = F + \min\{A_T - F, 0\} = F - \max\{F - A_T, 0\} \tag{3.2}$$

The creditors' (the debt component) payoff is thus the sum of a safe claim payoff, and a short position is in a put option written on the firm's asset value; here, the put option represents the Loss-Given Default (LGD). Otherwise, equity holders receive the following:

$$E_t = \max\{A_T - F, 0\} \tag{3.3}$$

To link the equity and debt components in the Merton model, the equity portion of the capital structure is valued as a call option on the firm's asset value. By applying the put-call parity concept, the value of debt, D_t, and equity, E_t, as $E_t + D_t = A_t$ where:

$$E_t = \text{Call}\left(A_t, F, \mu, T - t, \sigma\right) \tag{3.4}$$

$$D_t = P_t - Put\left(A_t, F, \mu, T - t, \sigma\right) \tag{3.5}$$

P_t in equation 3.5 represents the value of debt (borrowed funds). According to the Merton model, the spread between risky credit debt and risk-free debt is the value of the put option. Therefore, determinants of credit spreads or returns are the company's business risk of the assets σ, time to maturity T, and the face value F.

An important insight from the formalized Merton model is the relationship between a company's equities and corporate bonds, which are linked through their exposure to the underlying company's asset value. Therefore, equity market preferences are relevant for pricing corporate debt only if they capture changes in firm asset value (A_t) or changes in risk-neutral probabilities (W_t). $\text{Call}\left(A_t,\ \text{F}, \mu, \text{T} - \text{t}, \sigma\right)$ denotes the value of a call option and $Put\left(A_t,\ \text{F}, \mu, \text{T} - \text{t}, \sigma\right)$ is the value of a put option according to Black and Scholes (1973[27]. In other words, the same characteristics used in the PAPM for the equity return should impact the credit return similarly. The evolution of mathematics could present challenges (an area for further research); mapping the impact of a preference on equity prices to that on CDS spreads is outside the scope of this thesis, particularly when using the structural modeling approach.

3.2 Literature Review

3.2.1 Introduction

This literature review extensively explores the core areas relevant to understanding the relationship between equity returns and credit returns, specifically through the lenses of default risk, structural models, the Popularity Asset Pricing Model (PAPM), and the role of ESG factors in asset pricing. These areas are vital to analyzing the co-movement of equity and credit instruments and understanding how different investor preferences shape the dynamics of investment-grade and high-yield markets. The core concept underpinning all asset pricing models is the relationship between risk and return—specifically, the expected risk and the expected return of an asset. Traditionally, these models were built on the premise that risk is the primary driver of returns, assuming that higher risk demands higher compensation through expected returns. However, practitioners and academics have long recognized that factors or characteristics beyond risk also play a significant role in influencing the expected return of an asset. These factors include liquidity, momentum, and investor preferences, which may not directly correlate with traditional risk measures. Introduction to how popularity might influence market dynamics, particularly in the equity and credit markets, is an essential aspect of the dynamism of the capital market. With ESG fast becoming part of the financial decision-making process, its impact on credit and equity return is worth an examination. The bifurcation between investment-grade and high-yield credits and the growing role of investor preferences for ESG factors provide a comprehensive framework for understanding how default risk and investor tastes influence both equity and credit markets. This review establishes the theoretical and empirical foundation necessary to support the thesis' contribution to the literature on corporate bond pricing and the relationship between credit and equity instruments.

In the context of this thesis, the PAPM helps explain the observed positive relationship between equity and credit returns in high-yield (sub-investment grade) markets. These firms often exhibit higher default risk, making their equity and credit instruments less attractive to risk-averse investors. As a result, both credit and equity returns are driven by the same set of unpopular characteristics, leading to a positive co-movement between these two asset classes. By contrast, this relationship is weaker in the investment-grade market where default risk is less salient.

3.2.2 Structural Models of Credit and Equity Returns

A detailed review of Merton's structural model posits that corporate debt can be modeled as a risk-free bond combined with a short put option and equity as a call option on the firm's assets. The model remains one of the foundational frameworks for analyzing the relationship between corporate debt and equity pricing. This model was extended by Black and Cox (1976)[26], who introduced bond covenants and focused on the implications of a firm's capital structure for debt pricing. Later, Leland (1994)[104] extended Merton's model to account for bond covenants, optimal capital structures, and strategic default decisions, enhancing the model's applicability to corporate bond pricing. The model notably incorporated the firm's leverage and bankruptcy costs into the analysis, providing a richer view of the interplay between a firm's capital structure and its risk premiums. These models suggest a natural negative correlation between equity prices and credit spreads, as equity holders are the residual claimants in the event of distress. At the same time, bondholders are senior in the capital structure. This correlation tends to be more pronounced for riskier companies, as explored in studies by Ericsson, Reneby, and Wang (2015)[65]. Their model tested the ability of structural models like Merton's to explain bond and credit default swap (CDS) pricing. While these models offer a strong theoretical basis for pricing default risk, they require significant modifications to account for market imperfections such as liquidity risk and investor behavior. Their findings support that equity and credit markets are linked through a firm's asset risk but highlight the need to incorporate real-world complexities such as market frictions and liquidity constraints.

These models assume that the firm's asset value and volatility drive both debt and equity pricing, establishing a theoretical link between the two markets. However, these models do not fully capture the impact of investor behavior, which is where newer frameworks like the PAPM come into play.

3.2.3 Theoretical and Empirical Link Between CDS and Equity Prices

The empirical literature shows that credit spreads (the yield difference between corporate bonds and risk-free assets) and equity returns are correlated due to their mutual dependence on a firm's asset value and default risk. However, this relationship is not always straightforward. A core aspect of this thesis is the empirical and theoretical link between credit spreads and equity prices, particularly in the context of default risk. Previous research shows that credit spreads and equity prices are inversely related, driven by the firm's likelihood of default. Chen, Roll, and Ross (1986)[45] provided critical insights into how macroeconomic factors influence stock market performance, particularly through their development of the Arbitrage Pricing Theory (APT). While they did not focus specifically on default risk, subsequent research in structural models (e.g., Merton (1974)) has shown that equity prices tend to incorporate information about a firm's likelihood of default, as equity holders are more sensitive to financial distress than bondholders. This sensitivity is particularly pronounced in the high-yield (sub-investment grade) bond market, where default risk is higher and both equity and credit markets react strongly to changes in the firm's financial health.

Further evidence of this relationship is provided by Campbell, Hilscher, and Szilagyi (2008)[37], who investigated how distress risk is priced in equity markets. They found that firms with high distress risk often experience lower equity returns, contradicting the intuitive assumption that higher risk should be compensated with higher returns. Their research highlights that default risk can depress equity values as investors become increasingly concerned about the firm's financial stability. This empirical finding supports the Merton model's prediction of a negative correlation between equity prices and default risk but challenges some assumptions about how this risk is priced.

3.2.4 Impact of Popularity on the Equity Market

Over time, it has become increasingly evident that "risk" is just one of many factors or characteristics that impact expected returns. As a result, researchers (eg. Sharpe, W.(1964), Fama and French (1993), (2015), Carhart, 1997), Hou,Xue, and Zhang,(2021) etc.) have sought to identify and quantify these additional factors to develop a more comprehensive understanding of asset pricing. The ongoing challenge has been to discover the exact and complete relationship between these various factors and expected returns. However, Mehra and Prescott (2003)[114] and more recently, Hou,Xue, and Zhang,(2020)[84] extended the idea that there is more to the perceived risk in their research, "The Equity Premium: Why Is Ita Puzzle?", and "Replicating Anomalies." respectively. They established that an asset has numerous aspects that influence its value, including non-risk features (such as taste, preferences, and conflicts), which influence an asset's valuation. These findings suggest that non-risk factors have a role in the pricing of an asset. This thesis introduces a paradigm that integrates the idea that the price of an asset is determined by the two parties transacting in a marketplace. Each party has a set of preferences, tastes, and disagreements regarding the "characteristics" associated with the asset being transacted. The aggregation of these characteristics collapses into their popularity among market participants. Specifically, this paper integrates classical and behavioral finance regarding asset pricing. The fact that market participants are asked to declare whether they like or dislike particular features or characteristics of an asset sets this framework apart from others (the characteristics in question could be related to or unrelated to risk).

Eugene Fama and Keneth French (2007)[67] (Fama-French hereafter), wherein their paper "Disagreement, Tastes, and Asset Prices” asserted that the assumptions of standard asset pricing models such as the CAPM, Sharp, (1964)[130], are unrealistic at best and that both 'taste' and 'disagreement' do affect asset valuation which most model disregard. In the case of CAPM, the only characteristic or attribute of security the market participant should be concerned about is systematic market risk. Although this claim seems logical, the authors did not provide a formal model of how disagreement and preferences affect asset prices. Instead, they discussed certain factors that would be included in such a model and why they would cause prices to diverge from what the CAPM predicted. In the CAPM, the only characteristic or attribute of an asset that the market participant ought to be concerned about is market risk. Their findings are especially pertinent to high-yield (sub-investment grade) markets, where ESG risks are often more significant. High-yield bonds are already characterized by higher default risk, and firms in this category are more vulnerable to financial shocks, including those related to ESG issues. Investors in the high-yield market, already sensitive to default risks, are likely to demand higher returns (i.e., wider credit spreads) when ESG performance is poor, further increasing the cost of borrowing for these firms.

3.2.5 Impact of ESG Factors on Credit and Equity Markets

The rise of ESG factors as key determinants of asset pricing has gained significant attention in recent years. Giese et al. (2019)[76] provide comprehensive evidence that ESG factors affect both equity valuation and credit risk. They demonstrate that companies with higher ESG scores exhibit lower risk premia and credit spreads, as investors are increasingly willing to pay a premium for sustainability and corporate responsibility. Further, Hoepner et al. (2021)[83] examine how ESG factors influence corporate credit spreads. They found that firms with poor ESG performance tend to have higher borrowing costs. This reflects the growing recognition among investors that ESG-related risks (such as environmental violations, poor governance, or negative social impacts) can affect a firm's financial stability and its ability to repay debt. As a result, these firms face wider credit spreads to compensate investors for taking on the additional ESG-related risk.

3.2.6 Popularity and Credit Markets

Much of the recent literature on tastes focuses on ESG as a consumption good. Zerbib (2020)[137] develops an asset pricing model incorporating tastes for green stocks and an exclusionary preference regarding sin stocks. Barber, Morse, and Yasuda (2021)[14] demonstrate that investors derive nonpecuniary utility from investing in impact-oriented venture capital funds and are willing to sacrifice substantial returns. Friedman and Heinle (2016)[70] put forth a model that shows how investor tastes for corporate social responsibility impact demand for shares.

The main contribution of this article is to adopt the popularity-based pricing framework to equities and credit and then compare the degree of preferences on their returns. A Plethora of researchers have examined the relationship between equity returns and bond returns by extending the seminal work of Merton (1974)[116] from the classical approach of risk/return paradigm of Fama and Schwert (1977)[68], Campbell and Ammer (1993)[36], Fama and French (1992)[66], and Boudoukh, Richardson, and Whitelaw (1994)[31], for theoretical and empirical investigations of common factors driving equity and bond returns. In particular, several papers have tried to explain the periods in which equity returns and bond returns have been negatively correlated (under different macroeconomic regimes). These were mostly done with the underlying engine being a consumption-based asset pricing paradigm, especially in Cambell (2000)[35], Campbell, Sunderam, and Viceira (2009)[38] and Koijen, Lustig, and Van Nieuwerburgh (2017)[102]. This paper takes a different approach. This paper takes a different approach to why equity and bond markets can move in opposite directions using a popularity-based asset pricing model. Although many other researchers have looked at this relationship using non-risk determinants(Baker, and Wurgler,(2007)[12]; Baele, Bekaert, and Inghelbrecht(2010))[11], the approach adopted in this thesis is relatively simple, where the same set of preferences used to explain equity return is also applied to CDS returns, and a comparison is made by examining their unconditional correlation.

3.2.7 Credit and Equity Markets

Explanation of why the relationship between equity and credit markets is significant for investors, policymakers, and researchers. Modigliani, F., Miller, M. H. (1958) proposed that in a frictionless market (i.e., without taxes, bankruptcy costs, or asymmetric information), the value of a firm is unaffected by its capital structure and established the groundwork for modern financial theory, particularly in understanding the impact of capital structure on firm value. It stimulated extensive research on capital structure and corporate finance, leading to the development of theories that account for market imperfections.

In their influential paper, Chen, Collin-Dufresne, and Goldstein (2009)[43] investigate the relationship between credit risk and equity returns, contributing significantly to our understanding of how credit risk factors influence stock prices. Their research provides insights into the interplay between credit and equity markets, shedding light on how changes in credit risk, as reflected in credit spreads and default probabilities, affect equity returns. They argue that credit risk factors, including changes in the likelihood of default and the perceived credit quality of firms, have a substantial impact on stock returns. This seminar work, combined with the concept of the PAPM framework, provides a valuable contribution to the literature by elucidating the relationship between credit risk and equity returns. Their research enhances our understanding of how credit risk factors impact stock prices and offers important implications for financial modeling, investment strategies, and market analysis.

The PAPM is a general equilibrium asset pricing model that accommodates 'taste' and 'disagreement,' as Idzorek, Kaplan, and Ibbotson [95]. The PAPM reflects market participants' diverse expectations for expected asset returns and a range of preferences (liking), such as tastes for ESG, Low Treasury Yield, and High Market Indices. As a result, the PAPM makes two substantial advancements toward the actual asset pricing process. The fundamental original idea behind the PAPM framework is the New Equilibrium Theory by Ibbotson, Diermeier, and Siegel (1984)[87], the popularity framework of Ibbotson and Idzorek (2014)[88] and Idzorek and Ibbotson (2017)[96], and the empirical evidence and formal PAPM, with homogeneous expectations developed in the CFA Institute Research Foundation publication, ***Popularity: A Bridge Between Classical and Behavioral Finance***, by Ibbotson, Idzorek, Kaplan, and Xiong (2018)[97]. In this thesis, as mentioned earlier, the credit risk, EGS score, large US stock indices, and treasury levels are introduced as characteristics that market participants prefer or taste. The analysis looks at how the popularity of these characteristics impacts credit and equity returns.

3.2.8 Popularity Asset Pricing Model and ESG

Environmental, Social, and Governance (ESG) criteria are fundamental standards that socially conscious investors use to assess an investment's sustainability and ethical impact on a company or business. There are many schools of thought about its place in developing asset pricing models. ESG has gained popularity and support in recent years, but there are also controversies, such as lack of standardization, greenwashing, and subjectivity (or heterogeneity). However, many papers and articles develop ESG-specific asset pricing models (e.g., Baker, Bergstresser, Serafeim, and Wurgler 2020; Pástor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2021; and Zerbib 2020); many others examine the impact of ESG on realized returns (e.g., Barber, Morse, and Yasuda 2021; Geczy, Stambaugh, and Levin 2005; Shafron 2019; and Xiong 2021). In addition to the CAPM, the more recent ESG-centric asset pricing models are included in the PAPM, which combines disagreement (pecuniary views) and tastes (non-pecuniary preferences). A fundamental tenet of these models is that investors maximize their utility by building customized portfolios that represent their non-pecuniary preferences and pecuniary views.

3.2.9 Equity Returns and ESG

The story of equity investing with ESG preceded all asset classes, but the consensus on its impact on equity returns is still mixed. This is primarily because most researchers have treated ESG as a risk factor, but there is no evidence of an associated risk premium in the classical finance paradigm. In their paper, Foundation of ESG Investing", Giese, Lee, et al.[76], the authors provide a link between ESG information and the valuation and performance of companies by examining three transmission channels within a standard discounted cash flow model—which they call the cash-flow channel, the idiosyncratic risk channel, and the valuation channel—and concluded that ESG does affect the valuation and performance of companies, both through their systematic risk profile (lower costs of capital and higher valuations) and their idiosyncratic risk profile (higher profitability and lower exposures to tail risk). In addition, the authors concluded that ESG scores were lower in intensity than traditional factors such as momentum or low volatility (i.e., the financial impact per unit of time for ESG ratings is relatively low) but typically last for several years. Classical factors such as momentum typically exhibit persistence over only a few months, which makes them suitable for factor investing strategies but not necessarily ideal as long-term policy benchmarks. These factors are often treated in an idiosyncratic manner, focusing more on their statistical properties rather than as expressions of investor preferences or tastes. In contrast, the growing interest in Environmental, Social, and Governance (ESG) factors has prompted many researchers to investigate the widely held belief that a portfolio constructed using ESG scores, or one that is skewed toward equities with better ESG ratings, can generate higher risk-adjusted returns. This interest reflects a shift toward incorporating non-traditional factors that align with investor preferences and societal values into the asset pricing framework.

Capelle-Blancard and Petit,(2019). The study suggests that ESG factors significantly shape investor sentiment and stock market reactions, with implications for both equity and credit markets. The study finds that positive ESG news generally leads to an increase in equity returns, while negative ESG news has a stronger negative impact, reflecting an asymmetric reaction from investors. This asymmetry indicates that markets penalize negative ESG events more harshly than they reward positive ones, highlighting the significant downside risk associated with poor ESG performance. The authors' findings align with the broader literature that suggests ESG factors impact financial performance through risk mitigation and enhanced investor perception. Their results on equity returns can be extended to the understanding of credit markets, where similar dynamics influence CDS spreads and returns. The asymmetric response to ESG news highlights a critical area for further exploration in both equity and credit markets, where negative ESG events may disproportionately affect CDS spreads, raising the perceived credit risk. Their study provides empirical evidence of how ESG factors affect market behavior, directly supporting the notion that ESG performance is priced into financial instruments. Additionally, the study's findings on investor sentiment and behavior could underscore the PAPM's approach to incorporating rational and irrational investor preferences, especially in the context of ESG.

Giese, Lee, Melas, Nagy, and Nishikawa (2019). provide a robust empirical foundation for understanding the impact of ESG factors on equity valuation, risk, and performance, directly supporting your thesis on ESG's role in financial markets, including CDS spreads and returns. Their foundational study explores how ESG factors influence equity markets, specifically examining the effects of ESG integration on equity valuation, risk, and performance. The study finds that companies with higher ESG scores tend to have lower levels of systematic risk, lower idiosyncratic risk, and reduced drawdowns during periods of market stress. This risk mitigation effect leads to more stable equity returns and improved valuation.

3.2.10 Equity Returns and Default Risk

The modeling of default risk to value corporate debt and derivative instruments written on it has received significant study effort. On the other hand, the impact of default risk on equity returns has received very little attention. The potential of the default spread to explain or predict returns has been the primary subject of many earlier studies investigating the impact of default risk on equity markets. The impact of default risk on equity return was investigated by Vassalou and Xing (2004)[135], where Fama-French factors SMB and HML, which contained the necessary default information was applied to explain the cross-section of equity returns. Equities may have a payoff from being sensitive to bond default risk, as Chen, Roll, and Ross (1986) suggest. In an empirical investigation looking at the relationship between equity and bond returns, Demirovic et al. (2017)[56] where the authors examined the conditional correlation between these two securities, found the relationship to be positively conditioned on the credit risk. Still, the reverse was truly conditioned on the volatility of equities, confirming a relation between these securities depending on the potential wealth transfer from equities to credit. In the PAPM (demand) framework, this would be because investors do stocks sensitive to default risk. In the APT (supply) framework, default risk is systematic in the economy, not arbitraged away, and thus gets priced.

Li and Polychronopoulos, A. (2020). provides valuable insights regarding the variability and implications of ESG ratings on financial markets, including CDS and equity returns. Their study examines how discrepancies in ESG ratings across different rating providers can affect financial outcomes, particularly for equity and credit markets. It highlights the lack of standardization in ESG ratings and how these differences can influence investor perceptions and asset pricing. The paper finds significant variations in ESG ratings between providers, leading to different interpretations of a firm's ESG performance. This inconsistency can create noise in the market, affecting equity and CDS returns in unpredictable ways. The study highlights that these discrepancies can result in mispricing, where the same firm might be viewed favorably by one ESG provider and poorly by another, causing disparate impacts on stock prices and CDS spreads. The authors' work complements other studies that explore the impact of ESG factors on financial performance by highlighting the critical role of ESG rating quality and consistency. It provides a nuanced understanding of why ESG impacts on returns might vary across studies and market contexts. The study aligns with findings that emphasize the materiality of ESG factors in both equity and credit markets but also draws attention to the challenges posed by inconsistent ESG ratings, which can complicate the assessment of ESG's true impact on financial performance. This paper supports a critical view of ESG data, suggesting that while ESG factors are important, the effectiveness of their integration into asset pricing models (like the PAPM) depends significantly on the reliability and comparability of the underlying data.

3.2.11 Credit Default Swap Return and ESG Scores

In recent years, there has been an increased interest in environmental, social, and governance (ESG) concerns; nevertheless, until recently, the main emphasis has been on investing in these topics to generate higher returns, increase investment diversification, or create a higher risk-adjusted return portfolio. This applies to equities and debt (credit), but for equities, a plethora of research, albeit inconclusive, has surfaced, but not so much on the credit side. Understanding how these ESG elements might be incorporated into the credit decision process to discover better quality credit opportunities in terms of reduced risk or permit more sustainable future business prospects has just begun to develop. The impact of ESG in credit investing is conveniently undertaken via the CDS market.

Barth, Hübel, and Scholz (2020)[15] used Credit Default Swap (CDS) pricing as the subject of an investigation. In their paper, the authors concluded that better ESG scores result in greater costs for firms in the Western economies. They examined the connection between ESG scores and country credit risks by conducting a global study that looked into the impact of ESG performance on sovereign CDS spreads and the time dimension of ESG through the term structures of sovereign credit curves. Both of these aspects were investigated using term structures of sovereign credit curves. The authors examined 60 countries over a decade (between 2007 and 2017), and concluded that ESG scores impact the level and slope of sovereign credit spreads and, thus, their cost of funding or their sovereign debt. They found that a higher ESG performance is associated with lower CDS spreads and flatter CDS-implied credit curves. In the final analysis, they concluded that ESG impacted not only the level of the term structure of sovereign credit spreads but also on the slope of the structure. Therefore, a greater performance regarding ESG factors is connected with smaller CDS spreads and flatter CDS-implied credit curves. The findings of this study provide proof of the long-term influence of a country's sustainability that mitigates risk. Another school of thought in the academic community proposes establishing a connection between sovereign bond spreads, credit ratings, and a certain component of the ESG criteria (E, S, or G).

Kjerstensson and Nygren (2019) investigated the connection between a company's ESG score and its influences on the performance of the company's bonds by analyzing bond yield spreads. Their research was conducted on companies that were traded on the stock exchanges of Nordic nations, and a correlation was discovered between a company's environmental, social, and governance score and the yield spread on its corporate bonds. They concluded that such a connection could not be made. Consequently, the researchers concluded that a high ESG score does not necessarily reflect a lower level of necessary risk premium by bond investors or a lower or more stable cost of debt for enterprises based in Nordic nations. This conclusion was reached due to the findings presented in the previous section. One would have been led to think that companies based in the United States would have achieved results equivalent to those seen elsewhere.

Okyere-Yeboah (2022)[119] extends the literature by investigating the influence of Environmental, Social, and Governance (ESG) factors on corporate credit risk premiums through the lens of the Popularity Asset Pricing Model (PAPM). While traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM) and Fama-French multi-factor models, predominantly focus on risk-based variables, they often neglect the role of non-risk factors like investor preferences. In contrast, this thesis builds on Fama and French (2007), which recognized investor "disagreement" and "tastes" as crucial elements shaping asset prices, to explore how non-risk preferences manifest in credit markets. By applying the PAPM to corporate credit markets, the thesis demonstrates that ESG scores, as a proxy for investor preferences, significantly impact credit spreads, particularly within investment-grade firms. Specifically, firms with higher ESG scores exhibit narrower Credit Default Swap (CDS) spreads, reflecting reduced perceived credit risk.

In addition to ESG factors, the study underscores liquidity as a critical determinant of credit spreads, in alignment with existing research on the liquidity premium in bond pricing. By utilizing the PAPM framework, this research provides a unique perspective on how non-risk factors—ESG and liquidity—play a role in asset pricing. Although the thesis identifies a clear connection between ESG scores and credit risk for investment-grade firms, the results for sub-investment-grade firms are less conclusive, highlighting potential deficiencies in traditional credit rating systems. The thesis contributes to the ongoing discourse on ESG investing and behavioral finance, emphasizing the importance of investor preferences in shaping credit risk. The findings call for further research into the relationship between ESG performance and credit risk in sub-investment grade firms.

The thesis model incorporates three main categories of drivers: firm-specific variables such as equity returns, market leverage, and one-year excess returns (over the risk-free rate), alongside market factors like volatility and the slope of the yield curve, reflecting market expectations of future interest rates. ESG scores are integrated into the model to examine their triangulating effect on the interaction between credit and equity returns. In this chapter, I extended the methodology to equity returns, credit returns, and ESG interplay, using SBBI macroeconomic drivers, namely USLargeStock Levels, and USTreasury5YearYield.

3.2.12 Popularity-based Asset Pricing and ESG

One of the most salient advantages of the Popularity Asset Pricing Model (PAPM) is its simplicity and intuitiveness; the framework aims to unify the general theory of asset pricing by allowing both rational and irrational investors, individual risk and return expectations, and many pecuniary and non-pecuniary "characteristics" preferences that impact asset valuation and returns. There are many schools of thought as to whether the consideration of ESG has pecuniary and non-pecuniary characteristics in its utility derivation, notably Ibbotson, Idzorek, Kaplan, and Zhang (2018)[90], Pedersen (2021)[124], and Hartzmark and Sussman, (2019)[78]. Regarding investors' perception of ESG (rational or irrational), the PAPM is an ideal framework for formulating its impact on asset valuation. The PAPM offers a new generalized equilibrium pricing framework for rational and irrational investors, multiple individual risks and return expectations, and any non-financial preferences. Earlier work that led to the PAPM includes the New Equilibrium Theory of Ibbotson, Diermeier, and Siegel (1984), Popularity: A Bridge Between Classical and Behavioral Finance (Ibbotson, Idzorek, Kaplan, and Xiong 2018), "Dimensions of Popularity" from The Journal of Portfolio Management (Ibbotson and Idzorek 2014), and "Popularity and Asset Prices". Of the very disagreement and preferences of ESG, the PAPM framework is ideal for analyzing utility maximization among investors' pecuniary views and non-pecuniary preferences regarding ESG characteristics. Previous research papers on the impact of ESG on returns have recently surfaced, investigating the impact of ESG on realized returns (e.g., Baker, Bergstresser, Serafeim, and Wurgler 2020; Pástor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2021[123]; and Zerbib 2020). However, the popularity-based framework, on the other hand, integrates preferences, tastes, disagreements, and risks, so it subsumes all the factor-based models. In a way, it was accomplished by combining traditional finance with behavioral economics in the study. This methodology is unique in soliciting feedback from market players regarding specific aspects or qualities of an asset, inquiring as to whether they favor or dislike certain features or characteristics. There may or may not be a connection between these traits and risk. The current asset pricing framework will be improved with the help of this research by merging traditional finance with behavioral finance.

3.3 Data and Methodology

Due to the availability of data and the relatively high level of liquidity among investment grade (IG) and sub-investment grade (sIG) credits, the research primarily focuses on North American businesses. The sample consists of American exchange-listed Investment Grade and sub-investment grade or High-Yield Bonds[3] with credit ratings north of BBB- and south of BBB-, respectively. The universe of businesses has an ESG score issued by Refinitiv and is listed on exchanges. Unlisted corporations have obligations and corporate features that differ considerably from those of the sample group. The sources of the data set are;

- SBBI and Morningstar Inc[4],
- Refinitiv (now part of the London Stock Exchange) for the ESG scores, and ICE for the CDS spreads.
- Default probabilities were sourced from ICE Data Services Inc via KRIS [5]

ESG concerns encompass many aspects of a company's activities and can be difficult to measure. Several providers use a range of criteria to score environmental and social performance. Still, there is no consensus on the factors that should be considered and how they should be weighted. After being retrieved from Refinitiv EIKON, all of the corporate bonds available in the Data Stream tool were used to create the analyzed universe. Since they were non-overlapping data, the files were merged using their common identifiers across their respective CDS spreads and ESG scores. This universe was then filtered to construct a representative sample that included information on all of the variables that were intended to be included in the regression model.

Evaluating company sustainability concerns is an inherently convoluted process, with many individual factors considered. The three primary pillars of ESG ratings are derived from the inputs of many different parts. For environmental impact, for example, providers focus on things like a business's use of energy, its contribution to air and water pollution, or its level of recycling efforts. These factors aren't based on financial data but are considered important indicators of an organization's long-term

[3] high-yield and sub-investment grade interchangeably to mean the same group of data.

[4] Morningstar Direct. All values are in decimal format. "SBBI" stands for "Stocks, Bonds. Bills, and Inflation". "Stocks, Bonds, Bills, and Inflation," "SBBI," and "Ibbotson" (when used in conjunction with a series or publication name) are registered trademarks of Morningstar, Inc. ©2022 Morningstar.

[5] Kamakura Risk Integrated System from Kamakura Corporation *(now part of SAS)*

viability. Despite the best efforts of several industry organizations, there is no broad agreement about the specific environmental and social factors that should be used when evaluating a company and how they should be weighted. The analysis was conducted using monthly data which spanned over ten years, 2010-2022[6]

3.3.1 ESG data set

The ESG data set was sourced from Refinitiv (now part of LSE). This source records and computes more than 500 company-level ESG data metrics. The ESG scores were estimated from a selection of 186 of the most comparable and material factors across all industries. According to Refinitiv, these 186 data measures are organized into ten distinct categories: resource use, emissions, innovation, workforce, human rights, community, product responsibility, management, shareholders, and corporate social responsibility strategy. The following three pillars—Environment, Social, and Governance, abbreviated as E, S, and G—are used to organize these ten categories. The scores are based on a percentile formula, and the final scores serve as a comparative indicator of how well a company performed in relation to its rivals. The industry group is used as a comparison for the environmental, social, and controversial data metrics, and the nation where the company was founded is used for the governance data metrics; comparing the results of the different industry groups would, therefore, not be productive in any manner. It is possible to compare the Governance Pillar Scores of businesses incorporated in the same country and the Environment and Social Pillar Scores of businesses in the same Industry Group. They consider elements like relevance and transparency as they customize their key performance indicators (KPIs) to the unique requirements of each industry. Over five hundred different company-level ESG indicators are gathered by Refinitiv and used to calculate ESG ratings. The fundamental measurements are derived from considerations of comparability, impact, data availability, and industry relevance, all of which differ from one industry group to the next. The Refinitiv ESG ratings or scores are data-driven; they consider the indicators that matter the most to the industry and account for firm size and transparency to a minimal degree. The comprehensive outline of the methodology can be found at Open PDF File[7]

The 186 different data measurements are all organized into 10 distinct categories:

[6] data span from January 2010 to April 2022

[7] https://www.refinitiv.cn/content/dam/marketing/en$_us/documents/methodology/refinitiv - esg - scores - methodology.pdf$

resource use, emissions, innovation, workforce, human rights, community, product responsibility, management, shareholders, and corporate social responsibility strategy. The following three pillars—Environment, Social, and Governance, abbreviated as E, S, and G—are used to organize these ten categories. The category scores indicate how well the company performed in each category. Below highlights what constitutes each of the categories or pillars:

- "E" measures energy efficiency, carbon footprints, greenhouse gas emissions, deforestation, biodiversity, climate change and pollution mitigation, waste management, and water usage. It also takes into account the management of waste and water usage.
- "S" addresses issues of labor standards, wages, and benefits, workplace and board diversity, racial justice, pay equity, human rights, talent management, community relations, privacy and data protection, health and safety, supply-chain management, and other human capital and social justice concerns.
- "G" encompasses the governance of the "E" and the "S" categories, which include the makeup and structure of corporate boards, the oversight and compliance with strategic sustainability, executive compensation, political contributions and lobbying, and bribery and corruption.

Table 3.1: ESG Score Indicator

Score Range	Description	
0 to 25	First Quartile	Score within this range indicate poor relative ESG performance and an insufficient degree of transparency in reporting material ESG data publicly.
>25 to 50	Second Quartile	This range indicates satisfactory relative ESG performance and a moderate degree of transparency in reporting material ESG data publicly.
>50 to 75	Third Quartile	Scores within this range indicate good relative ESG performance and an above-average degree of transparency in reporting material ESG data publicly.
>75 to 100	Fourth Quartile	A score within this range indicates excellent relative ESG performance and a high degree of transparency in reporting material ESG data publicly.

source: Refinitiv

My data set focuses on the universe denominated in US dollars, including investment grade (I.G.) and high yield or sub-investment grade (sIG) markets. To qualify for inclusion in either or both of these categories, comparable CDS spread data and at least two years' worth of monthly ESG scores must be available.

3.3.2 Limitation of ESG Scores

ESG scores are widely used to assess corporate sustainability, but there is significant variability among different rating systems due to diverse methodologies, data sources,

Table 3.2: Monthly CDS Returns, Equity Returns, and ESG score Summary Statistics for All Issuers: **January 2010 to April 2022**: summarizes the CDS and equity returns statistics and the primary elements that determine them. Due to the high level of collinearity with the real CDS spread levels and the fact that the Bid/Ask Spread was derived by simply subtracting the Ask from the Bid, it was decided to eliminate it as a potential proxy for liquidity.

Investment and sub-Investment Grade Issuers

Variable	Mean	Std. dev.	Min	10th Pctile	Median	90th	Max	Skewness
CDS_Return	0.0024	0.0245	-0.2714	-0.0132	0.0012	0.0203	0.3484	0.1714
Equity_Return	0.0120	0.0944	-0.6748	-0.0882	0.0111	0.1084	0.9347	0.4932
DefaultProb5YR	0.0107	0.0148	0.0005	0.0043	0.0062	0.0192	0.3021	5.7003
MarketVol(VIX)	0.2108	0.0503	0.1199	0.1428	0.2107	0.2605	0.3454	0.6348
USLargeStockLevel	1.4235	0.5890	0.9407	0.9801	1.1478	2.2880	4.3501	1.9491
USTreasury5YrYield	0.0153	0.0057	0.0044	0.0074	0.0155	0.0242	0.0254	-0.0190
USLargeStockTR	0.0155	0.0433	-0.0903	-0.0523	0.0193	0.0701	0.0892	-0.5027
USTreasury5YrTR	-0.0004	0.0115	-0.0241	-0.0171	-0.0006	0.0151	0.0180	-0.4017
ESG_CScore	55.8453	21.2029	0.0000	27.5089	59.6842	80.0649	95.1947	-0.7831
E_Score	51.2737	28.3243	0.0000	4.0356	56.5821	84.9042	98.5458	-0.4012
S_Score	56.3626	23.6248	0.0000	24.3774	59.6737	84.9615	98.0091	-0.5268
G_Score	58.2546	23.4361	0.0000	26.0542	63.0026	84.6825	98.5279	-0.7505

Investment Grade Issuers

Variable	Mean	Std.Dev	Min	10th Pctile	Median	90th Pctile	Max	Skewness
CDS_Return	0.0010	0.00949	0.0079	0.0342	0.0771	0.1881	1.7556	4.8344
Equity_Return	0.0119	0.081434	-67.3112	-7.6767	1.2032	9.7519	86.9338	0.2932
DefaultProb	0.6638	0.3564	0.3500	0.4316	0.5687	0.9494	7.1669	5.4511
MarketVol(VIX)	0.2108	0.0501	0.1199	0.1428	0.2097	0.2605	0.3454	0.6345
USLargeStockLevel	2.1137	0.8617	0.9700	1.1458	1.9126	3.4726	4.3655	0.8090
USTreasury5YrYield	0.0149	0.0066	0.0022	0.0058	0.0149	0.0248	0.0303	0.2980
ESG_CScore	60.0040	18.2299	0.0000	35.6046	63.2797	80.7326	95.1947	-0.7989
E_Score	56.7682	25.9719	0.0000	17.7135	61.6085	86.1540	98.5458	-0.6329
S_Score	60.8819	20.5663	0.0000	32.4536	63.5010	86.1027	98.0091	-0.5743
G_Score	60.7679	21.2892	0.0000	31.0426	64.7008	85.2628	98.5279	-0.6894

sub-Investment Grade Issuers

Variable	Mean	Std.Dev	Min	10th Pctile	Median	90th Pctile	Max	Skewness
CDS_Return	0.0047	0.0020	0.0017	0.0021	0.0043	0.0077	0.01026	0.4774
Equity_Return	1.1637	9.8642	-67.4801	-9.3089	1.0184	11.2088	93.4747	0.5095
DefaultProb	2.1491	2.4702	0.0467	0.4022	1.3689	5.0428	30.2122	3.0915
MarketVol(VIX)	0.2105	0.0501	0.1199	0.1428	0.2097	0.2605	0.3454	0.6357
USLargeStockLevel	-0.4626	1.7375	-5.4970	-2.3534	-0.6603	1.8682	5.9536	0.6874
USTreasury5YrYield	0.0020	0.0033	-0.0067	-0.0021	0.0017	0.0058	0.0134	0.2529
ESG_CScore	41.8567	24.2923	0.0000	0.0000	43.7150	71.6365	92.0016	-0.2081
E_Score	32.7922	28.0871	0.0000	0.0000	30.5939	76.2138	95.6685	0.4336
S_Score	41.1614	26.7036	0.0000	0.0000	36.7713	80.7684	96.0831	0.1535
G_Score	49.8008	27.9219	0.0000	0.0000	55.3703	82.9035	96.0931	-0.5035

factor weightings, and subjective interpretations. Each ESG score provider applies distinct criteria and emphasizes different aspects of ESG performance, leading to inconsistent scores for the same company across various systems. Differences in data quality further compound this inconsistency, the weighting of ESG factors, and the inherent subjectivity in how data is interpreted. However, the differences among ESG scoring systems do not necessarily indicate flaws but rather reflect the complexity and multidimensionality of measuring corporate sustainability. Therefore, while one ESG score provides insight, it should be contextualized within the broader landscape of available ratings. By acknowledging the methodological nuances, stakeholders can better interpret ESG scores and make more informed assessments of corporate sustainability performance. Consequently, in this thesis, relying on a single ESG score can present a limited view of a company's sustainability performance, resulting in a different conclu-

Table 3.3: Correlation Matrix: Jan2010 to April 2022

Investment and sub-Investment Grade Issuers

	CDS_Return	Equity_Return	DefaultProb	MarketVol(VIX)	USLargeStockTR	USLargeStockLevel	USTreasury5YrYield	USTreasury5YrTR	ESG_CScore	E_Score	S_Score	G_Score
CDS_Return	1											
Equity_Return	0.2684	1										
DefaultProb	-0.0004	-0.0264	1									
MarketVol(VIX)	-0.0126	0.079	-0.0699	1								
USLargeStockTR	0.0522	0.0206	0.0018	-0.16	1							
USLargeStockLevel	0.0746	0.0262	0.0714	-0.4457	-0.1265	1						
USTreasury5YrYield	0.0524	0.0505	-0.0478	0.2407	-0.2015	0.1066	1					
USTreasury5YrTR	-0.0424	-0.0392	-0.0383	0.2651	-0.3765	-0.1281	-0.1982	1				
ESG_CScore	-0.0485	-0.0182	-0.213	-0.1063	-0.0071	0.1428	-0.0167	-0.0517	1			
E_Score	-0.0463	-0.0195	-0.2319	-0.09	-0.0064	0.1226	-0.0197	-0.0449	0.8613	1		
S_Score	-0.0497	-0.0196	-0.212	-0.0987	-0.0067	0.1378	-0.013	-0.0487	0.9177	0.7706	1	
G_Score	-0.0231	-0.0055	-0.1117	-0.0601	-0.0038	0.0786	-0.0051	-0.028	0.6855	0.4278	0.4664	1

Investment Grade Issuers

	CDS_Return	Equity_Return	DefaultProb	MarketVol(VIX)	USLargeStockTR	USLargeStockLevel	USTreasury5YrYield	USTreasury5YrTR	ESG_CScore	E_Score	S_Score	G_Score
CDS_Return	1											
Equity_Return	0.0051	1										
DefaultProb	0.5483	-0.029	1									
MarketVol(VIX)	0.1067	0.135	-0.0438	1								
USLargeStockTR	-0.0165	-0.0058	0.0352	-0.0619	1							
USLargeStockLevel	-0.2077	-0.0341	0.0474	-0.4508	0.1284	1						
USTreasury5YrYield	-0.3138	0.0276	-0.2476	-0.0353	-0.1049	-0.0242	1					
USTreasury5YrTR	0.0725	0.0062	0.1022	0.0765	-0.3779	-0.1285	-0.0171	1				
ESG_CScore	-0.2388	-0.0218	-0.0481	-0.117	0.0163	0.2379	0.0099	-0.0131	1			
E_Score	-0.2292	-0.0218	-0.0803	-0.1015	0.0162	0.2137	-0.0171	-0.0152	0.8381	1		
S_Score	-0.2197	-0.0225	-0.04	-0.1103	0.0168	0.2335	0.0072	-0.0119	0.8965	0.7325	1	
G_Score	-0.1186	-0.0073	-0.0084	-0.0651	0.0053	0.1125	0.0358	-0.0053	0.6855	0.3607	0.3911	1

sub-Investment Grade Issuers

	CDS_Return	Equity_Return	DefaultProb	MarketVol(VIX)	USLargeStockTR	USLargeStockLevel	USTreasury5YrYield	USTreasury5YrTR	ESG_CScore	E_Score	S_Score	G_Score
CDS_Return	1											
Equity_Return	-0.1470	1										
DefaultProb	-0.2424	-0.0846	1									
MarketVol(VIX)	0.2211	-0.0521	-0.2197	1								
USLargeStockTR	0.1352	0.0638	0.0884	0.0033	1							
USLargeStockLevel	0.0623	-0.4512	0.0661	0.0644	0.1088	1						
USTreasury5YrYield	-0.2102	0.0094	-0.1915	0.3210	-0.1624	-0.0272	1					
USTreasury5YrTR	-0.5133	-0.1922	0.2438	-0.0251	-0.0889	0.2130	0.0321	1				
ESG_CScore	-0.6227	0.0616	0.3115	-0.4308	-0.1458	-0.0314	0.1316	0.1271	1			
E_Score	-0.4910	0.0751	0.0962	-0.4201	-0.2101	-0.0557	0.1803	-0.0233	0.9249	1		
S_Score	-0.6205	0.0567	0.3036	-0.4339	-0.1486	-0.0299	0.1289	0.1377	0.9990	0.9315	1	
G_Score	-0.6448	0.0650	0.4062	-0.3984	-0.1004	-0.0229	0.1090	0.1552	0.9691	0.8126	0.9591	1

sion. This could be an area of future research to make a comparison.

3.3.3 Population sample

Given the maturity of the credit market in the US, the research data sample universe, and data availability, this study focuses on the credit market there. Both investment-grade and sub-investment-grade bonds have a population universe made up of companies that are listed on the New York Stock Exchange. Additionally, it's vital to have CDS Spread data available, mainly for the past five years. Furthermore, there is a high degree of confidence that publicly traded organizations are more likely to receive an ESG score from Refinitiv, whereas privately held companies are more likely to have unique characteristics and requirements that are inconsistent with our goals. The accessibility of ESG and CDS spread data limits the choice of the equities universe.

3.3.4 Correlation analysis

This section examines whether or not firm-specific factors (characteristics) can fluctuate throughout different sections of the study. Table 3.3 displays the correlation coefficients calculated between all the different variables. The results indicate that CDS prices positively correlate with *ESGScore*. This gives information on the degree to which individual factors are connected with variations in CDS spread. Each correlation coefficient between the independent variables, changes in CDS returns, and changes in equity returns all have the expected sign. However, the relationship between equity returns and credit returns seems negative, possibly due to regime change; it would need further investigation.

3.3.5 Equity returns

The historical universe of equity data is driven by the availability of ESG and CDS spreads, especially for the high-yield universe. According to the Merton model, there is an inverse relationship between the amount of equity a company has and the likelihood that it will default on its obligations. To demonstrate how a company's equity has changed over time, the monthly equity returns were acquired from Eikon[8]. A company's worth increases due to higher stock returns, which should, theoretically, reduce CDS spreads. As a result, one might anticipate that there is a negative link between equity

[8] does Refinitiv provide Excel Addin

returns ($R_{i,t}$)and CDS returns. The equity monthly returns were calculated using the usual formula of log of the percentage change of total cash received:

$$R_{i,t} = \ln \frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} \tag{3.6}$$

where $P_{i,t}$ is defined as the stock price of the firm i at time t. This monthly return is regressed a set of preferences again to obtain their popularity loading using the PAPM framework

3.3.6 Investment and sub-Investment grade universe

TRACE (Trade Reporting and Compliance Engine) provides CDS (Credit Default Swap) spreads for over 1,200 companies. TRACE is operated by FINRA (Financial Industry Regulatory Authority) and offers data on various fixed-income securities, including CDS spreads, which are crucial for tracking credit risk and market conditions. The number of companies that met the requirement was 565 for investment-grade credits, indicating that the ESG population of issuers is relatively significant. The requirement criteria were such that a corresponding CDS spread was available in the Refinitiv database. The GIC category was used to separate the issuers into 11 different industries because the importance of the environmental, social, and governance (ESG) scores is strongly related to the company's sector. The minimum and maximum values have been considered because our variables do not appear to include any inaccurate data inputs that could bias our empirical findings. Environmental and social scores can range from 0.00 to 95.19 at the industry sector level, with an average score of roughly 50.74. In comparison, the corporations in our sample exhibit poorer governance performance on average. This is reflected in a governance rating of 55 on average. If the data returned from the Eikon database for a certain Sector's component scores is missing, that information is replaced with a blank value. This is critical because, according to Refinitiv, a score of 0 is the lowest conceivable, significantly impacting the average and variability of scores across industries; see Table 3.1. I matched the CDS and ESG scores using a combination of the company's TICKERS and CUSIPS.

The Eikon database tool that Refinitiv offers contains information on all of the corporate bond issuers that are included in the sample. This information was then filtered to construct a representative sample that included information on all the variables I intended to include in our regression model. The time that I have analyzed spans from 2010 to 2022 (up to the end of the second quarter, in June). I have done this to guarantee that I have adequate CDS spreads and ESG scores at my disposal; however, I have omitted businesses with fewer than two years of ESG scores at their disposal. I selected this time range because it would allow me to build a sample with a sufficient number of observations upon which to conduct our statistical tests and through which I would be able to observe the long-term effects of ESG scores on corporate bond issuers. Time series before 2010 were excluded from the data set because the notion of ESG ratings is very new to the financial sector. Since 2002, Refinitiv has maintained an ESG rating, mostly for companies based in the United States and Europe; nonetheless, it wasn't until 2008 that the rating became more widely used (Refintiv, 2019, pages 5-6). So, our selected date range of 2010 to 2022 safeguards a robust sample. A longer period to incorporate earlier times may also change the characteristics of the CDS market and the financial industry's landscape, which may be difficult to ascertain and incorporate into our model. The sub-investment-grade or high-yield sample universe consisted of 55 firms and spans ten years; the sample data was collected from various industries. Issuers with fewer than two years' worth of ESG scores and CDS spreads were removed from consideration.

3.3.7 Credit Default Swap Market

There is a natural interlink between credit risk, equity risk, and the general economy as a whole. Credit risk is measured in this thesis as the degree of the CDS spread.

A company's credit risk can be described as the chance of a financial loss if borrowers and counter-parties fail to repay the debt they owe to the company. Banks have historically transacted this risk through the use of Credit Default Swaps, and the premium associated with these trades is known as the spread; more specifically, the CDS spread. A contract for difference (CDS) functions, in its most fundamental sense, similarly to an insurance policy in that it offers the customer protection against certain risks. Credit default swaps are flexible products that can be utilized in various ways to customize an investor's exposure to the credit market. Investors frequently purchase credit default swaps to protect themselves against default. By moving a certain risk from one party to another without actually transferring the underlying bond or any other credit assets, credit default swap (CDS) contracts can help investors reduce the risks associated with bond investing. Before the advent of credit default swaps, there was no mechanism for transferring the risk of a default or any other type of credit event from one investor to another.

The contract structure for a single-name credit default swap is not overly complicated. Two parties are engaged in the transaction: the protection buyer, who is trying to purchase insurance against the risk of default on a specific bond, and the protection seller, who is willing to take on the risk. The name given to the corporation that was responsible for creating the bond and selling it to investors is called the reference entity, while the bond itself is known as the reference issue. The protection seller commits to buying the reference issue at face value if there is a credit event, such as a default, failure to pay, or other 'trigger.' In exchange for this purchase, the protection seller will get a default swap premium, which is a periodic (quarterly) cost. If there is no credit event during the contract's lifetime, it will terminate on the maturity date. If a credit event does occur, the protection seller will acquire the reference issue at its face value and will no longer make the quarterly payments. If this is the case, it is a valid assumption to make that credit risk can be quantified using credit spread. In addition, CDS can potentially improve risk allocation both inside an economy and at the global level and increase the stability of the banking and financial markets. This is because of its capacity to price risks more accurately. CDS enables financial institutions to increase or reduce credit risks independently of the transactions that underpin those risks, to spread those risks across industries and nations, and as a result, to optimize their overall risk profiles. Banks are now in a stronger position to prevent financial troubles and alleviate credit problems in certain industries or areas thanks to the development of CDS, which puts them in a better position to do so. The banking industry could ultimately benefit from this as it should become more stable. It is easily calculated as the difference between the redemption yield of the corporate bond and the redemption yield of the benchmark governmental bond. This difference is referred to as the spread S:

$$S_t = Y_{t,c} - Y_{t,b} \tag{3.7}$$

where

$Y_{t,c}$ is the redemption yield of a corporate bond, and

$Y_{t,b}$ is the redemption yield of a benchmark government bond

Hull (2000)[86] shows that the credit spread is equivalent to the CDS spread similar to the above equation. If the relationship between credit spreads and CDS spreads does not hold true in the face of a no-arbitrage argument, then an investor has the opportunity to make a profit without incurring any risk. This theoretical equivalency is tested by Blanco (2005)[28], who finds that parity holds as a long-run equilibrium condition. The results of this investigation lead the authors to the conclusion that the ESG score of a company will impact the credit spreads due to the company's popularity. In earlier research, CDS spreads have been used as a measurement instrument for credit risk, including studies listed in the literature review and studies conducted empirically in the past. The authors Collin-Dufresne, Goldstein, and Martin (2001)[49] explore credit risk utilizing bond credit spreads in their study. Ericsson, Jacobs, and Oviedo (2004)[110] use CDS spreads in their research of credit risk, despite the fact that they do not treat default risk and ESG Score as the preference of investors.

The extra yield is called the "credit spread," and it's the reason why the yield on a corporate bond is higher than the yield on a "risk-free" gilt or swap. This credit spread makes up for the extra risk that investors take by holding the bond. For instance, the bond's issuer could fail on the bond, the bond's issuer could be downgraded, and the bond could be difficult to convert into cash, which is another way of expressing that it is illiquid. These are all examples of what is meant by the term "illiquid." If you want to avoid the complications of converting a bond into cash, a straightforward solution is to keep the bond in your possession until it matures. This is not the same as the risk of failing, which is always present and cannot be eliminated entirely through diversification. When determining the value of their bonds, investors should ideally be able to factor in the amount that is associated with the liquidity risk premium. This is according to one school of thought.

3.3.8 Default Probabilities

There are two main schools of thought when it comes to estimating the default probabilities: The structural model by Merton (1972) and the reduced-form model, mainly by the classic works by Jarrow, Lando, and Turnbull (1997)[98], and Duffie and Singleton (1999)[61]. Reduced-form models are tractable and empirically fit. However, choosing a functional model form introduces subjectivity. Empirical results may have high in-sample fitting properties but are unsuitable for population properties. Finally, reduced-form models do not directly relate business debt and equity values. They do not give a comprehensive and conceptually acceptable framework for equity-credit risk analysis. The model employed in this thesis is the first Kamakura Default Probability series, KDP-ms, which is a variation of the Merton structural model of risky debt fitted to adjust rapidly to declining credit quality. The second default probability series, KDP-jc, was developed by Kamakura Research Director Robert Jarrow. This reduced-form model predicts bankruptcy based on accounting ratios, equity prices and their volatility, and company size. The third reduced-form hybrid model includes the Jarrow-Chava KDP-jc inputs and the Merton default probabilities from KDP-ms as another input. This creates a "hybrid" reduced form model, which is the one employed in this paper.

3.3.9 Market Volatility (VIX)

Variations in equity returns can be broken down into two separate components. The first type of volatility is market or systematic volatility, which is caused by events that affect the entire market. The second type of volatility is idiosyncratic volatility, which refers to differences in returns caused by risks unique to a particular company. According to Campbell et al. (2001) findings, these two components of total volatility respond differently over time. While there was no discernible pattern in the systematic volatility over the same time period, an increased tendency could be seen in the idiosyncratic volatility. The market's volatility drives the volatility of idiosyncratic events and increases when recessions occur. Brandt et al. (2008) point to a sudden decline in the idiosyncratic volatility during the previous few years and claim that the time-series behavior of idiosyncratic volatility observed by Campbell et al. (2001) is attributable to sporadic, extremely volatile periods rather than the temporal trend. This is because Brandt et al. (2008) point to the sudden drop in idiosyncratic volatility over the last few years.

It should be noted, however, that the volatility that affects CDS spreads is assumed (Benkert, 2004). It has been suggested that looking at the implied volatility, which is calculated using the present values of stock options (Carol et al., 2007), is a more accurate proxy for predicting future volatility. Because Benkert (2004)[22] discovered that implied volatility is more connected with CDS spreads than historical volatility, I anticipate the explanatory power will be greater. In addition, the historical volatility is determined by prior equity returns, but the implied volatility is based on the traders' expectations. This metric also gives investors an understanding of the "fear index" currently in the market. A high VIX leads to an increase in the overall asset value and, as a consequence, an impact on the probability of default since it alters the characteristics of the risk distribution by displaying a fat-tail characteristic.

Stocks, Bonds, Bills, and Inflation Capital Market Data

The SBBI data set includes monthly, quarterly, and yearly returns and yields of most of the significant U.S. asset classes: large-cap stocks, small-cap stocks, corporate bonds, government bonds of several maturities, and inflation (See List 1). The data set includes capital appreciation, income, and total returns of major asset classes of the U.S. economy: large-cap stocks, corporate bonds, government bonds of various maturities, and inflation (January 1926 to present, monthly).

3.4 Methodology

The fixed-effect model was chosen for this analysis because it allows for a detailed examination of the relationship between independent and dependent variables within each entity, in this case, individual firms. The panel dataset includes multiple companies, each possessing unique characteristics that may influence the dependent variable, such as credit or equity returns, and possibly the independent variables as well. The focus of this thesis is on understanding how factors like ESG scores (and their individual pillars), default risk, performance, market volatility, and the returns on large U.S. stocks and government bonds affect credit returns, as measured by CDS spreads, and equity returns under controlled conditions.

The fixed-effect approach is particularly appropriate because it accounts for the potential bias arising from unobserved, time-invariant characteristics specific to each firm that could correlate with the independent variables. These characteristics might include factors such as a firm's management quality, industry sector, or regulatory environment, which do not change over time but could still impact the relationship between the variables of interest. By controlling for these unobservable factors, the fixed-effect model provides more accurate and reliable estimates, ensuring that the observed effects are truly due to the independent variables under study and not confounded by firm-specific characteristics.

Moreover, the fixed-effect model is well-suited for capturing the impact of time-invariant individual-specific traits that could influence the results. This is crucial in a study where the diversity of firms and their inherent characteristics might otherwise introduce bias into the analysis. By eliminating the effect of these time-invariant features, the fixed-effect model enhances the validity of the findings, offering a clearer understanding of how the specified factors influence credit and equity returns across different firms. This methodological choice aligns with the objective of providing a robust analysis that accurately reflects the complexities of the data.

In this analysis, Gail, Shapir, and Ben-Zion's (2012)[72] models were similarly adopted, which explore the factors that impact CDS spreads and spread changes. The models particularly emphasized the classical framework that uses a standard factor model, similar to the one endorsed by Fama-French (2007).

The variant in this model is slight; the critical determinants are credit returns and equity returns. Collin-Dufresne, Goldstein Martin (2001)[50] (henceforth CGM), where the authors investigated the credit risk by using bonds credit spreads, and that used by Angelini et al.(2014)[7]. Ericsson, Jacobs, and Oviedo (2004)[64] (henceforth EJO) use CDS spreads in their investigations of credit risk. Zhang et al. (2005)[138] examine the determinants of CDS and equity returns.

In this model (3.8), the core determinants are those employed in Chapter 2, the SBBI, equation 2.6 in the panel regression combined with ESG scores. The panel methodology allows us to consider cross-sectional and temporal variation simultaneously. The beta the combined ESG score is the main coefficient used in our analysis. It captures the marginal effect of the preferences levels of the determinants, along with the ESG on CDS returns. The regressions are conducted over a period. Firstly, the universe of data used covered the mixture of Investment Grade names) and sub-investment Grade (55 names) over the period 2010 to 2022. The objective is the effect of firm-specific variables (default probability and ESG scores), common characteristics (USMarket Index, USTreasuryYield Yield, and MarketVol), and panel regressions. Table 3.5 presents the results of the following multivariate regressions:

$$\begin{aligned}\text{CDSReturn}_{i,t} = {} & Constant_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} \\ & + \beta_3\text{USMarketIndex}_{i,t} + \beta_4\text{TreasuryYield}_{i,t} + \beta^{ESG}\text{ESGScore}_{i,t}\end{aligned} \tag{3.8}$$

In this model (3.9), the core determinants for PAPM were with the individual pillar E.

$$\begin{aligned}\text{CDSReturn}_{i,t} = {} & Constant_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} \\ & + \beta_3\text{USMarketIndex}_{i,t} + \beta_4\text{TreasuryYield}_{i,t} + \beta^{E}\text{EScore}_{i,t}\end{aligned} \tag{3.9}$$

In the model (3.10), the core determinants for PAPM were with the individual pillar S.

$$\begin{aligned}\text{CDSReturn}_{i,t} = {} & Constant_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} \\ & + \beta_3\text{USMarketIndex}_{i,t} + \beta_4\text{TreasuryYield}_{i,t} + \beta^{S}\text{GScore}_{i,t}\end{aligned} \tag{3.10}$$

In this model (3.11), the core determinants for PAPM were with the individual pillar G.

$$\begin{aligned} \text{CDSReturn}_{i,t} &= Constant_{i,t} + \beta_1 \text{DefProb}_{i,t} + \beta_2 \text{MarketVol}_{i,t} \\ &+ \beta_3 \text{USMarketIndex}_{i,t} + \beta_4 \text{TreasuryYield}_{i,t} + \beta^G \text{GScore}_{i,t} \end{aligned} \tag{3.11}$$

where i comprises the number of firm's fixed effects characteristics, and t includes time fixed effects. The panel regression methodology allows the simultaneous consideration of cross-sectional and temporal variation. Standard errors are double-clustered at firm month levels to account for correlation in the error terms(Petersen 2009; Cameron and Miller 2015). β^{ESG} is the main coefficient for our analysis. It captures the marginal effect of the preferences on equity returns. And β^{ESG} is the coefficient for the analysis. It captures the marginal effect of ESG score on CDS returns. The regression is repeated for the equity returns, and the core determinants are those employed in Chapter 2, equation 2.6 in the regression with the combined ESG scores.

For the regression, the data used covered a mixture of Investment Grade (156 names) and sub-investment Grade (55 names) from 2010 to 2022.

$$\begin{aligned} \text{EquityReturn}_{i,t} &= Constant_{i,t} + \beta_1 \text{DefProb}_{i,t} + \beta_2 \text{MarketVol}_{i,t} \\ &+ \beta_3 \text{USMarketIndex}_{i,t} + \beta_4 \text{TreasuryYield}_{i,t} + \beta^{ESG} \text{ESGScore}_{i,t} \end{aligned} \tag{3.12}$$

Equations (3.12, 3.13,3.14, ad 3.15) show the ability of structural variables consistent with PAPM to explain equity returns. In this model, the core determinants from SBBI were employed with the combined ESG scores. The betas would then be the popularity loadings. In this model, the determinants for PAPM were employed with the individual pillars E, S, and G scores being added in the equations (3.9,3.10, ad 3.11).

$$\begin{aligned} \text{EquityReturn}_{i,t} &= Constant_{i,t} + \beta_1 \text{DefProb}_{i,t} + \beta_2 \text{MarketVol}_{i,t} \\ &+ \beta_3 \text{USMarketIndex}_{i,t} + \beta_4 \text{TreasuryYield}_{i,t} + \beta^E \text{EScore}_{i,t} \end{aligned} \tag{3.13}$$

$$\begin{aligned} \text{EquityReturn}_{i,t} &= Constant_{i,t} + \beta_1 \text{DefProb}_{i,t} + \beta_2 \text{MarketVol}_{i,t} \\ &+ \beta_3 \text{USMarketIndex}_{i,t} + \beta_4 \text{TreasuryYield}_{i,t} + \beta^S \text{SScore}_{i,t} \end{aligned} \tag{3.14}$$

$$
\begin{aligned}
\text{EquityReturn}_{i,t} = {} & Constant_{i,t} + \beta_1 \text{DefProb}_{i,t} + \beta_2 \text{MarketVol}_{i,t} \\
& + \beta_3 \text{USMarketIndex}_{i,t} + \beta_4 \text{TreasuryYield}_{i,t} + \beta^G \text{GScore}_{i,t}
\end{aligned}
\tag{3.15}
$$

3.5 Empirical Results Analysis

The model uses panel regression to estimate the effect of a set of investors' preferences, such as default risk, a data set from SBBI, and ESG scores, on a corporation's credit risk (measured by CDS spreads) and equity return. This is done by regressing all the important independent factors that impact the credit and equity returns and the ESG scores.

This section provides an illustration of the findings that were obtained from the empirical research that was conducted. The model has been estimated using a panel regression, which employs three-panel time-series estimators adopted by Markus Eberhardt[62] to accommodate for varied slope coefficients across group members.

In the first model, credit return is considered the dependent variable, while Merton's model treats all the theoretical determinants as independent variables. Table 3.2 provides a comprehensive list of possible determinants for corporate credits (investment and sub-investment grades). The significance of the inputs used to calculate the default probability or distance to default is meticulously analyzed in Merton's model to determine the appropriate set of determinants. The loading of these inputs is considered when determining the popularity level.

As indicated in Table 3.4 of the impact of preferences (independent variables) on credit and equity return for the entire universe comprising of both investment and sub-investment grade. The model appears to have strong explanatory power with significant t-statistics for all variables. However, the key question is on the parsimony of the model. Many characteristics that were not considered could easily be included here; this makes the PAPM flexible within the data set and can enhance the model.

The 5-year Default Probability, US Large Stock Index, and 5-year US Treasury Yield are all significant at the 1% level. The combined score for the ESG, along with the individual pillars, is also statistically significant. Across all the models (M1 to M4), check the ability of structural model-induced firm-specific variables, such as Default probability and the combined ESG score, to explain changes in CDS return. The MarketVol(VIX) is not statistically significant, reflecting the impact of their popularity loadings.

In addition, we find that this model can explain between 15.23% and 20.47% of CDS return changes, compared to between 10.39% 16.23% explained the equity return

Table 3.4: Shows the results of the regressions for CDS return change and the various preferences. The data refer to both investment and sub-investment credit firms during the period from January 2010 to April 2022. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10%.

Credit Returns				
	(M1)	(M2)	(M3)	(M4)
VARIABLES	CDS_Return	CDS_Return	CDS_Return	CDS_Return
DefaultProb5YR	-0.0353***	-0.0356***	-0.0355***	-0.0132
	(0.0129)	(0.0129)	(0.0129)	(0.0126)
MarketVol(VIX)	0.00344	0.00382	0.00359	0.00458
	(0.00344)	(0.00344)	(0.00344)	(0.00345)
USLargeStockLevel	0.402***	0.395***	0.401***	0.370***
	(0.0341)	(0.0340)	(0.0340)	(0.0339)
USTreasury5YrYield	16.86***	16.79***	16.92***	17.51***
	(2.748)	(2.749)	(2.748)	(2.751)
ESG_CScore	-0.00705***			
	(0.000714)			
E_Score		-0.00496***		
		(0.000535)		
S_Score			-0.00643***	
			(0.000640)	
G_Score				-0.00296***
				(0.000629)
Constant	-0.251**	-0.388***	-0.286***	-0.484***
	(0.108)	(0.104)	(0.106)	(0.106)
R-squared	20.47%	18.53%	20.39%	15.23%
Equity Returns				
	(M1)	(M2)	(M3)	(M4)
VARIABLES	Equity_Return	Equity_Return	Equity_Return	Equity_Return
DefaultProb5YR	-0.234***	-0.241***	-0.237***	-0.197***
	(0.0509)	(0.0511)	(0.0509)	(0.0499)
MarketVol(VIX)	0.198***	0.198***	0.198***	0.200***
	(0.0136)	(0.0136)	(0.0136)	(0.0136)
USLargeStockLevel	1.458***	1.456***	1.461***	1.405***
	(0.135)	(0.135)	(0.135)	(0.134)
USTreasury5YrYield	25.58**	25.26**	25.60**	26.62**
	(10.88)	(10.88)	(10.88)	(10.88)
ESG_CScore	-0.0107***			
	(0.00283)			
E_Score		-0.00871***		
		(0.00212)		
S_Score			-0.0103***	
			(0.00253)	
G_Score				-0.00308
				(0.00249)
Constant	-4.548***	-4.689***	-4.566***	-4.985***
	(0.427)	(0.410)	(0.420)	(0.421)
R-squared	16.23%	16.03%	16.98%	10.39%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

changes. These differences in the range of explanatory power may be attributed to market signals or information flow.

On the credit side, the effect of the popularity of ESG scores (including the individual pillars) is negative. This unpopular characteristic could be due to an increase in risk associated with low ESG scores or the preference for companies with strong ESG scores leading to lower credit spread (low default probability), which improves performance. This seems to be the case across all the individual pillars. This result indicates that for a

decrease of 100bps, one should expect a 3.53bps increase in credit return. These results intuitively make a lot of sense. The result is very similar to equity returns. This result is not surprising since investment-grade corporate credits dominate the sample universe. These results are for the combined investment and sub-investment grade credit sample. In reference to the equity returns, the Market Volatility, 5-year Default Probability, US Large Stock Index, and the combined score for the ESG are all significant at the 1% level. Regarding the equity returns, the results seem to align with Cerqueti et al. (2019)[42]. Only the 5-year US Treasury Yield is significant at the 5% level. This result is not surprising since investment-grade corporate credits dominate the sample universe. These results are for the combined sample of investment and sub-investment grade issuers for the equity returns. So, from this observation, one can conclude that a correlation between credit returns and equity returns is indeed positive. The Market Volatility is not significant for credit returns, but for the equity returns, it's significant, confirming the relationship expected from the Merton model.
This result for the investment-grade credit universe, Table 3.5, is similar to that of Table 3.4, except here the coefficient of the default is positive, which is counter to what is expected. Re-sampling to focus on just the sub-investment grade, as in Table 3.6, the combined ESG score proved not to be significant at the 1% level; the fundamental or plausible reason behind this could be that the determinants of default probability dominate the credit spread as opposed to ESG concerns for such firms.

The results in Tables 3.5 and 3.6 indicate that popularity considerations are essential for the investment-grade universe as most companies are more mature. Given the negative correlation and coefficients of the aggregate ESG score and the individual pillars, their commitment and transparency to the various pillars of ESG have become part of their strategic aims. Investors favor businesses with tighter CDS spreads, making them more desirable (high in popularity). The tighter the spreads, the better the score. The results for the universe of sub-investment grade securities weren't as strong, indicating that investors disliked the combined ESG scores. Finally, there is no multicollinearity among the factors as indicated by the Variance Inflation Factor(VIF) results in Appendix A, Table 4.1. All the VIF of the independent variables of the regression are less than 4.

Table 3.5: Fixed Effect For Investment Grade Names Regression Results of all Models over **January 2010 to April 2022**

Credit Returns				
	(1)	(2)	(3)	(4)
VARIABLES	CDS_Return	CDS_Return	CDS_Return	CDS_Return
DefaultProb5YR	0.124***	0.123***	0.123***	0.123***
	(0.00126)	(0.00125)	(0.00126)	(0.00125)
MarketVol(VIX)	0.000325***	0.000327***	0.000340***	0.000322***
	(8.37e-05)	(8.36e-05)	(8.38e-05)	(8.36e-05)
USLargeStockLevel	-0.0269***	-0.0267***	-0.0297***	-0.0282***
	(0.000630)	(0.000621)	(0.000632)	(0.000570)
USTreasury5YrYield	-2.899***	-2.936***	-2.931***	-2.882***
	(0.0593)	(0.0592)	(0.0594)	(0.0593)
ESG_CScore	-0.000382***			
	(4.87e-05)			
E_Score		-0.000321***		
		(3.52e-05)		
S_Score			0.000102**	
			(4.40e-05)	
G_Score				-0.000277***
				(2.79e-05)
Constant	0.133***	0.129***	0.110***	0.130***
	(0.00550)	(0.00526)	(0.00539)	(0.00532)
R-squared	17.56%	17.03%	16.98%	16.39%

Equity Returns				
	(1)	(2)	(3)	(4)
VARIABLES	Equity_Return	Equity_Return	Equity_Return	Equity_Return
DefaultProb5YR	-0.397**	-0.413**	-0.396**	-0.378**
	(0.162)	(0.162)	(0.162)	(0.161)
MarketVol(VIX)	0.246***	0.246***	0.246***	0.246***
	(0.0127)	(0.0127)	(0.0127)	(0.0127)
USLargeStockLevel	0.430***	0.429***	0.433***	0.395***
	(0.0874)	(0.0870)	(0.0874)	(0.0858)
USTreasury5YrYield	36.72***	35.99***	36.72***	36.84***
	(8.863)	(8.869)	(8.862)	(8.869)
ESG_CScore	-0.00652**			
	(0.00319)			
E_Score		-0.00496**		
		(0.00223)		
S_Score			-0.00631**	
			(0.00282)	
G_Score				-0.00102
				(0.00267)
Constant	-4.749***	-4.837***	-4.766***	-5.029***
	(0.463)	(0.447)	(0.456)	(0.457)
R-squared	12.23%	10.03%	11.98%	8.39%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6 Hausman Test

The Hausman test was implemented by comparing the results of both fixed and random effects models; first, the panel data model was estimated using fixed and random effects approaches. This involved running a regression analysis with the dependent variable and independent variables, using either fixed effects or random effects specifications. Stata allows one to keep all the coefficient estimates and the respective standard error for both models. Then, it computes the respective t-statistics. The p-value being zero is why

Table 3.6: Fixed Effect For sub-Investment Grade Names Regression Results of all Models over **January 2010 to April 2022**

Credit Returns				
	(M1)	(M2)	(M3)	(M4)
VARIABLES	CDS_Return	CDS_Return	CDS_Return	CDS_Return
DefaultProb5YR	-0.0194	-0.0464***	-0.0207	-0.00450
	(0.0146)	(0.0150)	(0.0145)	(0.0149)
MarketVol(VIX)	-1.64e-05	0.00249	-6.27e-05	0.000774
	(0.00328)	(0.00360)	(0.00329)	(0.00313)
USLargeStockLevel	0.00547	0.00535	0.00563	0.00521
	(0.00787)	(0.00852)	(0.00787)	(0.00770)
USTreasury5YrYield	-9.860**	-12.98**	-10.03**	-9.912**
	(4.936)	(5.363)	(4.933)	(4.799)
ESG_CScore	-0.00635***			
	(0.000909)			
E_Score		-0.0132***		
		(0.00280)		
S_Score			-0.00406***	
			(0.000583)	
G_Score				-0.00724***
				(0.000963)
Constant	0.651***	0.626***	0.655***	0.606***
	(0.0828)	(0.0938)	(0.0831)	(0.0779)
R-squared	14.22%	13.03%	13.98%	9.39%

Equity Returns				
	(M1)	(M2)	(M3)	(M4)
VARIABLES	Equity_Return	Equity_Return	Equity_Return	Equity_Return
DefaultProb5YR	-0.270***	-0.281***	-0.274***	-0.257***
	(0.0724)	(0.0727)	(0.0724)	(0.0721)
MarketVol(VIX)	-0.0513	-0.0508	-0.0515	-0.0435
	(0.0319)	(0.0318)	(0.0319)	(0.0317)
USLargeStockLevel	-3.355***	-3.355***	-3.355***	-3.355***
	(0.0865)	(0.0865)	(0.0865)	(0.0865)
USTreasury5YrYield	67.95	67.13	69.00	61.99
	(50.49)	(50.42)	(50.49)	(50.45)
ESG_CScore	-0.0135**			
	(0.00617)			
E_Score		-0.0138***		
		(0.00534)		
S_Score			-0.0137**	
			(0.00561)	
G_Score				-0.00483
				(0.00532)
Constant	1.630**	1.526**	1.638**	1.123
	(0.788)	(0.749)	(0.773)	(0.769)
R-squared	20.23%	18.03%	20.98%	11.39%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the Random effect model is rejected, according to the results of executing or running the Hausman test for the model; see Table 3.7. Thus, the conclusion emphasizes that the more germane and appropriate model is the fixed effect for this analysis.

3.7 Bias of Endogeneity and Reverse Causality

Examining the relationships between ESG Score and equity return, as well as ESG score and corporate credit return, could not generate an endogenous relationship. The

Table 3.7: Hauman test for the Proposed Model Jan2010 to Apr2022

Coefficients

	Model			
	Fixed (f)	**Random(r)**	**Difference**	**Stand.Err**
DefaultProb5YR	1.11929	1.13702	-0.01772	0.00200
Market Vol (VIX)	0.00017	0.00017	0.00000	0.00000
USLargeStockIndex	-0.00073	-0.00066	-0.00007	0.00002
USTreasury5YrYield	0.05805	0.05796	0.00008	0.00000
ESG_CScore	-0.00031	-0.00029	-0.00002	0.00001
E_Score	0.00002	0.00001	0.00001	0.00000
S_Score	0.00010	0.00008	0.00002	0.00000
G_Score	0.00006	0.00005	0.00000	0.00000
Ratings	0.00060	0.00064	-0.00004	0.00002
F=84.9	**p-value=**	**0.0000**		

relationship between equity and credit return is a function of information flow since they share a common capital structure, and there is a structural relationship. Buchanan et al. (2018)[34] researched the connection between ESG and firm value and subsequently suggested there may be a relationship between ESG and firm financial performance, which could provide an endogeneity issue.

Buchanan et al. (2018)[34] researched the connection between ESG and firm value and subsequently suggested there may be a relationship between ESG and firm financial performance, which could provide an endogeneity issue. Endogeneity and reverse causality are significant challenges when examining the influence of ESG scores on CDS spreads. Endogeneity arises when ESG scores are correlated with unobserved factors affecting CDS spreads, such as firm-specific risk characteristics or broader economic conditions. Reverse causality, on the other hand, suggests that changes in CDS spreads might influence ESG scores, rather than the other way around. To address these issues, lagged ESG scores are incorporated into the regression models. By using lagged values of ESG scores, the analysis captures the effect of past ESG performance on current CDS spreads, thus reducing the risk of endogeneity and reverse causality. This approach ensures that the influence of ESG scores on CDS spreads is assessed based on historical data, minimizing contemporaneous feedback effects and providing a clearer understanding of the true relationship between ESG performance and credit risk.

Credit Return

$$\begin{aligned}\text{CDSReturn}_{i,t} = {} & Const_{i,t} + \beta_1 \text{DefProb}_{i,t-1} + \beta_2 \text{MarketVol}_{i,t-1} + \beta_3 \text{USLargeStockIndex}_{i,t-1} \\ & + \beta_4 \text{USTreasuryYield}_{i,t-1} + \beta^{ESG} \text{ESGScore}_{i,t-1}\end{aligned} \tag{3.16}$$

and then lagged by 2.

$$\text{CDSReturn}_{i,t} = Const_{i,t} + \beta_1 \text{DefProb}_{i,t-2} + \beta_2 \text{MarketVol}_{i,t-2} + \beta_3 \text{USLargeStockIndex}_{i,t-2} + \beta_4 \text{USTreasuryYield}_{i,t-2} + \beta^{ESG} \text{ESGScore}_{i,t-2} \tag{3.17}$$

To mitigate these reverse causality issues, I estimated alternative equation specifications (3.16). Specifically, I test the influence of the ESG score in the previous year on the CDS spread in the current year(6.1). I report the results in Column 2 (Lag 1) and Column 3 (Lag 2) of Table (3.8). As can be seen from these results, ESG is negatively related to CDS, suggesting that the prior-year ESG inversely affects the current year's credit risk. These results suggest that the direction of causation runs from ESG disclosure to credit risk but not vice versa.

An alternative specifications of equation (3.17) was estimated to mitigate the reverse causality. Specifically, the influence of the ESG score was tested with the previous year on the CDS spread in the current year(6.1). See Column 2 (Lag 1) and Column 3 (Lag 2) of Table (3.8). These results suggest that the direction of causation runs from ESG disclosure to credit risk but not vice versa, because ESG is negatively related to CDS, suggesting that the prior-year ESG inversely affects the current year's credit risk.

Table 3.8: Endogeneity bias (lagged independent variables

Credit Return		
	Lag(1)	Lag(2)
VARIABLES	CDS_Return	CDS_Return
DefaultProb5YR	0.212***	0.256***
	(0.0120)	(0.0121)
MarketVol(VIX)	-0.0486***	0.0108***
	(0.00322)	(0.00324)
USLargeStockLevel	-0.222***	0.321***
	(0.0318)	(0.0320)
USTreasury5YrYield	25.95***	-47.67***
	(2.570)	(2.582)
ESG_CScore	-0.00432***	-0.00404***
	(0.000668)	(0.000671)
Constant	1.181***	0.285***
	(0.101)	(0.101)
Equity Return		
VARIABLES	Equity_Return	Equity_Return
DefaultProb5YR	0.340***	0.220***
	(0.0513)	(0.0508)
MarketVol(VIX)	-0.0799***	-0.202***
	(0.0138)	(0.0137)
USLargeStockLevel	-0.181	-1.417***
	(0.137)	(0.134)
USTreasury5YrYield	65.73***	25.76**
	(11.07)	(10.83)
ESG_CScore	-0.00592**	-0.00565**
	(0.00285)	(0.00282)
Constant	2.168***	7.248***
	(0.430)	(0.423)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Equity Return

$$\begin{aligned}\text{EquityReturn}_{i,t} = Const_{i,t} &+ \beta_1 \text{DefProb}_{i,t-1} + \beta_2 \text{MarketVol}_{i,t-1} + \beta_3 \text{USLargeStockIndex}_{i,t-1} \\ &+ \beta_4 \text{USTreasuryYield}_{i,t-1} + \beta^{ESG} \text{ESGScore}_{i,t-1}\end{aligned} \tag{3.18}$$

and then lagged by 2.

$$\begin{aligned}\text{EquityReturn}_{i,t} = Const_{i,t} &+ \beta_1 \text{DefProb}_{i,t-2} + \beta_2 \text{MarketVol}_{i,t-2} + \beta_3 \text{USLargeStockIndex}_{i,t-2} \\ &+ \beta_4 \text{USTreasuryYield}_{i,t-2} + \beta^{ESG} \text{ESGScore}_{i,t-2}\end{aligned} \tag{3.19}$$

3.8 Conclusion

This thesis departs from the traditional asset pricing models by combining behavioral and classical finance to empirically investigate the relationship that may exist between equity and credit returns by examining the effect of ESG along with Default Risk and other macro characteristics from the SBBI data set on credit and equity returns. The SBBI data set was US Large Stock Levels and US Treasury 5-Year Yield. The fundamental premise is that there is connectivity between equity prices and bonds, which implies that equity price dynamics and, more broadly, information from its markets can impact credit investors; thus the preferences in the respective market impact their markets in both ways. The research has endeavored to use the PAPM framework to ascertain the magnitude and direction of the popularity loading of the set of common preferences. Here, it has been established that the common characteristics are significant, but their impact on their respective returns is not the same, there are several reasons why the information reflected in the pricing of bonds and equity prices of the same company may not be identical. First, there are significant differences in the institutional investor bases in the two markets, which could lead to divergent information sets. Furthermore, unlike equities markets, where a variety of behavioral biases have been documented, the corporate bond market is virtually exclusively institutional, making it less susceptible to market hype. Second, because there is no widely acknowledged method for pricing stocks, the valuation dispersion in the equity market is much higher than it is in the bond market. Furthermore, several input assumptions, including projected growth and payout ratios, have a significant impact on equity prices. The sensitivity is caused by the payout structure of stocks (call options on the assets of the company) as well as the requirement to extrapolate these inputs in time to infinity. In contrast, bond valuation models are built on concepts of pricing that are well-liked by investors. Due to the short duration and little potential upside of bonds, these models are relatively unaffected by the aforementioned assumptions. Third, investors will engage in secondary market trading, except for non-economically motivated trading, when the value of the gathered knowledge they possess exceeds the marginal cost of trading (Lesmond, Ogden, and Trzcinka 1999)[105]. Since trading bonds are more expensive than trading equities, fresh information might affect equity prices more quickly.

The fact that the PAPM accepts and takes into account both rational and irrational investors, unique risk and return expectations, a wide range of pecuniary and non-pecuniary characteristics that affect asset prices, and investors who benefit from non-pecuniary attributes allows it to serve as a unifying theory. In contrast to the bulk of studies that examine the link between credit and equity returns, this thesis treats the drivers as mere preferences, with the ESG score being considered a non-risk attribute. The behavioral non-risk factors take into account the reality that people acquire opinions differently and that heterogeneity is a fact of life. Similar to liquidity, not all investors prioritize ESG disclosure equally when making investment decisions. By including the two essential components mentioned by Fama and French, the popularity-based framework (PAPM) offers a much-needed upgrade over the CAPM. The PAPM has solid results and significant practical implications for practitioners. The PAPM contributes to the bridging of classical and behavioral finance by taking two important steps toward a more realistic asset pricing model: including varied viewpoints and allowing for a range of investor preferences/tastes.

The dependability of this finding is unaffected by endogeneity, tests of reverse causation, controls for known reasons for credit return, and unobservable heterogeneity at the company and temporal levels. The risk mitigation idea, which contends that higher ESG performance is linked to a reduced level of firm risk and, as a result, credit risk, is supported by this research.

For the investment grade credit sample, the ESG score preference is significant regarding the spread of long-term credit risk protection. However, it is also similar to the sample universe of the United States corporate credit market, including both investment grade and high yield (sub-investment grade). However, I could not find a statistically significant link between ESG and credit returns for credits with ratings below investment grade. One of the reasons this might be the case is because the sample consisted of 30% sub-investment-grade and 70% investment-grade credits.

The significance of ESG to below-investment-grade credit, it is reasonable to predict that the possibility of default will greatly affect or dominate the credit protection spread. This is because the likelihood of default is the most important factor. This is because the likelihood of the debt being unpaid is the single most essential consideration. It's possible that further study was conducted across the board in all of the different firms. In addition to this, it is essential to determine whether or not it is feasible to investigate the influence that ESG factors have on tail risk. In conclusion, the outcomes of this research suggest that there is a connection between environmental, social, and governance (ESG) variables, equity return and credit returns in terms of information flow through investors' preferences, in particular with investment-grade loans. This conclusion is drawn from the fact that the ESG elements were found to correlate with credit risk. As a direct result of this, the amount of environmental, social, and governance (ESG) disclosure that firms offer can be regarded as an additional element that influences the credit returns for those firms. If practitioners selected assets for their portfolios taking into account the environmental, social, and governance (ESG) exposure of the companies in which they invested, they might be able to incorporate a considerable quantity of additional information that could lead to the production of alpha. Moreover, given the nature of the contingent claim for the debt and equity of the same capital structure, one would have expected the returns to move in the same direction, the contemporaneous correlation is expected to be positive and significant. Furthermore, the relationship between equity and credit returns should be stronger for firms with higher default probabilities (i.e. sub-investment grade credits), and the direction and magnitude of the popularity loadings or the coefficients indicate as such.

Abstract

A measure of tail risk in credit markets is essential to understand the behavior of credit risk. This thesis chapter (paper) examines the possible impact of environmental, social, and governance (ESG) on the tail risk, measured using the expected shortfall of individual credit obligors via credit default swap (CDS) spreads. The analysis looks at a 5-year default probability and an assumed recovery rate of 50% to estimate the tail risk for each credit with a 99% confidence level (1% significance). In this paper, I examined the relationship of ESG ratings coupled with Credit ratings with Unexpected loss and Expected Shortfall. I assumed the loss distribution followed a Gaussian distribution. The analysis is repeated using the individual pillars of the composite ESG scores across all industries and ratings. The impact of ESG risk on US corporate credit is examined through the lens of Refinitiv ESG risk-rating measures from January 2010 to April 2022. The findings are that corporate credit with higher ESG scores negatively correlated with the second and third moments of the loss distribution, namely Unexpected loss and Expected shortfall, respectively, and those with lower ESG scores are significant and positively correlated with ES. Concluding that bonds with higher ESG scores provide better tail-risk protection.

Finally, I find that the impact of individual ESG pillars on the tail risk is consistent with the composite ESG scores. And concludes that there is a case of integrating ESG into fixed-income credit portfolios as a tail risk mitigation strategy.

3.9 Introduction

Investing is no longer just about the returns. Many investors also want their money to fund companies as committed to a better world as they are to their bottom line. Socially responsible investing is an investment approach that explicitly acknowledges the relevance to the investor of environmental, social, and governance factors and of the long-term health of the market as a whole; its subsets, impact investing, have attracted more than one-third of the assets under professional management in the U.S., according to a 2020 survey by the U.S. Forum for Sustainable and Responsible Investment. That amounted to more than $17 trillion in assets under management based on socially responsible criteria, an increase of 42% from 2018 to 2022. The growing demand has fueled a proliferation of funds and strategies integrating ethical considerations into the investment process. Environmental, social, and governance (ESG), socially responsible investing (SRI), and impact investing are industry terms often used interchangeably by clients and professionals alike, under the assumption that they all describe the same approach. Use SRI, and ESG interchangeably.

There are, however, divergences in the impact and treatment of ESG in asset valuation and risk management. This paper endeavors to show the significance of ESG ratings or scores on the ***Unexpected Loss, and the Expected Shortfall*** of corporate credits via their CDS spreads. In fixed-income credit investing, the primary risk is the tail risk, and I use the expected shortfall as the main measure of this risk. As in any portfolio construction and individual instrument, the loss distribution matters. I focus on using a parametrized loss distribution. There have been many studies on the measure of tail-risk[9], except for Bax K et al. (2021)[18], their study findings on real-world data show positive, not negligible, dependencies between clusters determined by ESG scores, especially during the 2008 crisis. The focus of this thesis is to examine if there is a relationship between ESG scores and the tail risk of basket credit credit instruments.

Most of the research on how ESG impacts the risk profile of instruments has been focused on equities, with very little on fixed-income credit; this is probably because ESG has been traditionally associated with stocks, possibly the lack of liquidity in the fixed-income space with the availability of reliable CDS spread data. The rationale behind the statement that most research on ESG impacts has focused on equities rather

[9]Tail risk is a form of portfolio risk that arises when the possibility that an investment will move more than three standard deviations from the mean is greater than what is shown by a normal distribution.

than fixed-income credit instruments, such as bonds or CDS, stems from several interconnected factors:

1. **Traditional Association of ESG with Equities:**

    - Historically, ESG investing has been more closely associated with equities because of the visibility and direct influence shareholders can exert on corporate behavior through voting rights, resolutions, and public scrutiny. Equity investors have traditionally been more vocal and active in demanding sustainable practices and responsible corporate governance, making ESG considerations more prevalent in the stock market.
    - Equity markets have a well-established history of integrating ESG factors, with many ESG-focused funds and indices being equity-based, leading to a wealth of data and research focused on equities.

2. **Data Availability and Transparency:**

    - Equity markets generally have more comprehensive and transparent ESG data, partly due to regulatory requirements for listed companies to disclose environmental, social, and governance-related information. This transparency facilitates the study of ESG impacts on equity risk and performance.
    - In contrast, the fixed-income market, including corporate bonds and CDS, often needs more data transparency and standardization, making it more challenging for researchers to access reliable data. ESG data for fixed-income securities is typically less detailed, and many bond issuers are not subject to the same stringent ESG disclosure requirements as publicly traded companies.

3. **Liquidity and Market Structure Differences:**

    - The fixed-income market, especially for corporate bonds and CDS, is generally less liquid than the equity market. This lack of liquidity can make it harder to capture real-time market reactions to ESG information and complicates the study of ESG impacts on bond prices and CDS spreads.

- Illiquidity can also lead to wider bid-ask spreads, less frequent trading, and more noise in price data, which can obscure the true impact of ESG factors on credit risk and returns.

4. **Challenges with CDS Spread Data:**

   - CDS spread data, which reflects the cost of insuring against credit default, can be more challenging to obtain, particularly reliable and consistent historical data across different issuers and time periods. The market for CDS is more opaque, with trading often conducted over the counter (OTC), leading to less readily available information compared to exchange-traded equities.
   - Additionally, the CDS market is relatively specialized and complex, involving institutional investors who may prioritize different risk considerations compared to equity investors, adding another layer of complexity to research.

5. **Focus on Risk Factors:**

   - Much of the research on ESG has traditionally focused on risk factors that are directly observable and measurable in equity markets, such as stock volatility, beta, and downside risk. The impact of ESG on credit risk, such as credit spreads or default probabilities, is less straightforward to measure and has historically been underexplored.
   - The development of robust frameworks and models for assessing ESG impacts on fixed-income instruments is still evolving, with a growing but limited body of literature compared to the extensive work on equities.

6. **Evolving Investor Interest:**

   - The investor base for fixed-income securities, such as institutional investors, pension funds, and insurers, has historically needed to integrate ESG considerations faster than equity investors. However, this rapidly changes as awareness of ESG risks and opportunities grows in the fixed-income space.

ESG research dominance in equities is mainly due to traditional associations, better data availability, market liquidity differences, and challenges related to fixed-income and CDS markets. While research on ESG impacts on fixed income is growing, it remains constrained by these factors, resulting in a relative scarcity of studies compared to equities.

The primary purpose of this study is to provide further insight into how ESG rating impacts the tail risk of corporate credit or bonds. There are few research materials on this topic, so this paper adds to the small body of research on the fixed-income credit market. I believe further research would be necessary for the future by simulating the loss distribution using macroeconomic and market factors that incorporate the dynamic correlation between them to generate the empirical loss distribution. This approach makes the capturing of the tail risk much more realistic. However, for the sake of tractability in this paper, the distribution is parameterized. The primary focus of the paper is on tail risk. Still, I have included how ESG impacts the first two moments of the distribution, namely, the expected and unexpected losses (as adapted by the Basel Committee). I finalize the analysis by making these comparisons with the expected shortfall measure. In addition to exploring the impact of the composite ESG rating, I examined the impact of the individual pillars on the tail risk.

The existing literature tends to focus on the beneficial role of ESG integration in generating excess returns or alpha generation (positive or negative). However, this literature largely overlooks how ESG scores affect the tail risk of corporate credits. The question of whether credit markets incorporate ESG is very far from settled. This is a crucial gap in the literature because the tail risk is the most critical measure of credit risk from the perspectives of both buyers (bond investors) and sellers (bond issuers). Credit risk concerns the risk of loss arising from an obligor's inability to honor obligations. Among other sources of risk, it is the most important one that a bank has to deal with due to significant exposures concentrated in the portfolios. A fund manager is concerned about the potential of losing funds invested. Because of this, financial institutions have to quantify credit risk at a portfolio level. In this paper, I examine the impact of ESG scores on the loss distribution for individual credit exposure and the portfolio level. I specifically focus on the expected shortfall, defined as the expected loss once the unexpected event (1% probability) has materialized. The analysis is extended to the individual pillars as well. To measure the unexpected losses for the credit group, one would have to introduce a level of correlation between credit losses and the overall portfolio. This paper examines the effect of ESG scores on the tail risk of corporate credit portfolios. This paper estimates the unexpected loss of a credit portfolio of CDS spreads, then tests the significance of the 99th percentile losses, approximated as three times the standard deviations of the obligor with ESG scores. Credit tail risk is estimated from extreme credit default swaps (CDS) price fluctuations. In asset management, the tail risk measure shows how much each credit exposure will likely lose beyond the expected loss.

3.9.1 Credit Risk Measures

Credit risk has to do with the risk of loss arising from the failure of a counterparty to make a promised payment, or more precisely, the risk of default or reduction in market value caused by changes in the counterparty's credit quality, which is time-dependent. Strictly speaking, credit risk is indeed part of market risk, as the volatility of credit spreads invariably impacts the default probability, that is, the tail risk. 1.2 Expected shortfall (Tail-risk) in credit The Expected Shortfall (ES) is a statistic used to quantify the risk of unlikely events. Given a certain confidence level, this measure represents the expected loss when it is greater than the value of the Value at Risk (VaR) calculated with that confidence level. This measure answers the following question: What could the expected loss be if things go bad?

3.9.2 ESG Scores

An ESG score measures a company's level of sustainability. The calculation is based on many factors, and an ESG score ranges from 0 to 100. It considers everything from environmental impact to how they treat employees and the level of adherence to governance, including ethics, to establish if they're meeting best practices in the areas. In recent years, the scores have become a central part of decision-making when building a sustainable business and economy. Firms with higher ESG scores may combine ESG strength with other corporate strategies to successfully capitalize on ESG benefits in their financial risk management (Teece et al., 1997)[134]. For instance, ESG score is associated with brand value, and its popularity amongst customers leads to higher sales and, thus, profitability (Brown Dacin, 1997; Luo Bhattacharya, 2006). S). Such a popularity level helps ensure a stream of consistent cash flows, reducing a firm's financial distress. Moreover, in adverse events, firms continue to enjoy stable future cash flows due to moral capital among customers, which leads to unpopularity. Further, disclosure of ESG information contributes to reduced information asymmetry (Cho et al., 2013)[], leading to its popularity among investors. The symmetric flow of information increases the availability of debt capital and reduces the cost of funds (Cheng et al., 2014; El Ghoul et al., 2011; Waddock Graves, 1997). I, therefore, argue that the ESG score reduces firms' tail risk by increasing their level of profitability and by decreasing their performance variability and cost of debt capital.

3.9.3 ESG and the Credit Market

Credit risk via its default probability affects a corporation's cost of funding and, therefore, its lifeblood. The company's level of vulnerability increases if firm cash flows are shaky and there is no access to the capital market. This type of peril becomes a yardstick to evaluate a firm's financial health (Rego et al., 2009). And during any unforeseen event could cause the company to default, increasing the likelihood of its bondholders, either via cash position or CDS contract, losing their investments. So it is likely to increase their tail risk and expected shortfall. In a nutshell, the ESG score represents important initiatives that create a valuable image, increase cash flow, decrease performance volatility, and garner support for the easy availability of low-cost funding, leading to a reduction in default risk and tail risk. Therefore, I hypothesize as follows:

- H1: ESG score is negatively associated with a firm's tail risk (via expected shortfall).
- H2: High ESG scores decrease the overall size of the expected shortfall

3.10 Literature Review

The interest in ESG has been driven by the sustainability requirements established by the United Nations Socially Responsible Investment Investment goal and by regulators. Much research by both industries and academia has focused on alpha generation and asset pricing. In the previous paper, see Chapter 3, where I treated ESG ratings as a preference by investors using the popularity-based framework, others have treated ESG ratings as a risk factor, and the latter have found little evidence that ESG has been a risk factor; in fact, their jury is still out there as to technically how ESG impact corporate credit portfolio. In the case of the former, I show investors' preference in the context of homogeneity impacts corporate credit pricing via CDS spreads by controlling other preferences such as market volatility, stock market levels, and US treasury rates.

One could have taken different approaches, including direct simulation and portfolio sorting approaches. The challenge faced by this approach is the treatment of the correlation between the corporate credits. I opted for the panel regression approach to circumvent the correlation issue in this paper. It is, however, more realistic to approach this analysis using a modeled portfolio with an assumed term structure of correlation matrix between corporate credit. This approach is rather challenging, so the best approach would be the simulation method, but for traceability, I adopted the parameterized approach as an approximation.

3.10.1 Body of Recent Work and Discoveries

In the past decade, interest in incorporating ESG into portfolio construction has been reverberating globally, especially in fixed-income credit. Recent academic research has suggested a limited impact on returns for portfolios tilted to high ESG scores across industries.

In their paper, Henisz and McGlinch (2019)[80], the authors examine the correlation between ESG and credit risk. They concluded that no empirical evidence has yet linked ESG performance to cost or expense variances or revenue shortfalls that might explain these correlations. The authors attempt to address this lack of mechanism-based empirical evidence by citing and then building on several well-publicized cases by analyzing two major ESG issues—indigenous land claims and biodiversity—as they affect the global project finance and agriculture sectors. Broadening these single-sector results, the authors use a novel dataset that systematically codes material events reported in the media across various empirical settings to produce the first large-sample empirical evidence of the mechanisms linking ESG performance to credit risk. A growing body of research has extended the analysis of the materiality of ESG criteria from the perspective of equity investors to creditors. Past research and analysis have demonstrated the link between better management of ESG criteria and better risk management overall. Despite this growing consensus and consistent evidence that ESG performance is correlated with credit risk, no empirical evidence has yet linked ESG performance to cost or expense variances or revenue shortfalls that could explain these correlations.

Another example, a recent paper by ScientificBeta[10], discovered that there is no evidence supporting recent claims that ESG strategies generate out-performance. They, however, caveat these findings not to discourage investors but rather to use the ESG criteria in their portfolio construction to hedge climate or litigation risk, aligning investment norms and positively impacting society. This is an example of the typical findings of recent academic and industry research. There has been very limited or perhaps never been research to test the significance or the impact of ESG scores on the tail risk of a credit portfolio. This is not the case with equities portfolios. The fundamental reason could be that equities have obvious 'ESG enabling' characteristics, mainly the opportunity for shareholders to engage firm management directly and through voting rights. By definition, bondholders do not have these ownership mechanisms. However, given the size of the debt market, I expect more research to be done in this area since the main risks in corporate credit are tail risk and default probability. It would make sense to see ESG integration and issuer engagement gaining prevalence in fixed-income investing, making this research question germane and apropos. A very recent paper, The Case for Integrating ESG into Fixed Income Portfolios, A Clare et al., 2022 [48]. In this paper, the authors confirmed the consensus that investing in companies that try to limit their impact on the environment, that operate in a way that is more beneficial to broader society, and that have robust governance structures can all help to provide more sustainable outcomes for the benefit of all. Regarding the impact of risk-return characteristics, they concluded that approaching their portfolio construction by excluding specific sectors or companies showed some evidence that building a more sustainable portfolio leads to improving risk-return characteristics. Finally, they find some limited evidence that enhancing the ESG credentials of a portfolio can lead to an improvement of the tail risk in a portfolio; that is, it helps to reduce the frequency of extreme downside outcomes. However, the authors failed to capture the relationship between the ESG score and the tail risk. In his paper, "Effectively managing risks in an ESG portfolio," Bertolotti(2020)[25], here the author reviews ESG risks from the practitioner's point of view, including risks found in ESG data itself that stem from the definition, collection, and aggregation process. The author then discusses the portfolio characteristics associated with integrating ESG data and the challenges in building tools to measure risk and report on attribution. Next, he looked at connections between screening and

[10] "Honey, I Shrunk the ESG Alpha": Risk-Adjusting ESG Portfolio Returns, April 2021

reputation risks and the beneficial role that engagement can play. Finally, he discusses tail risks and reviews physical climate risk's role in managing portfolios.

The authors, Mendiratta, Varsani, and Giese (2021)[115], examined whether ESG added value beyond credit ratings—a significant point of interest for bondholders. They discovered that ESG complemented credit ratings. ESG ratings had characteristics distinct from credit ratings, delivering additional insights into risk and performance. ESG was generally more financially relevant in high-yield (HY) bonds than in investment-grade (IG) bonds and more relevant in IG bonds with longer, rather than shorter, maturities. Higher-ESG-rated issuers tended to have more robust cash flow metrics, lower levels of ex-ante risk, and less frequent severe incidents than lower-rated-ESG issuers. The above research's brief description shows that ESG impacts the tail risk. Fundamentally, this paper differs from many by directly focusing on the impact on tail risk in terms of expected shortfall using exclusively US corporate credit via credit default swap (CDS) spreads.

3.10.2 ESG and Corporate Credit Risk

The integration of Environmental, Social, and Governance (ESG) factors into financial risk assessments has gained prominence in recent years, particularly in equity markets. However, studies examining the role of ESG in credit markets could be more extensive. Traditionally, ESG has been more closely associated with equity investing, often linked to excess returns or alpha generation, as highlighted in studies by Friede, Busch, and Bassen (2015), which found that the majority of academic research identifies a positive relationship between ESG performance and financial performance in equities. This focus has led to an under-exploration of ESG's impact on fixed-income securities and the corresponding risk metrics associated with corporate credits (Verheyden, Eccles, and Feiner, 2016)[136].

Moreover, research into the relationship between ESG and fixed-income assets has typically emphasized portfolio-level dynamics, often highlighting the benefits of ESG in mitigating systematic risk factors like interest rate or market risk (Henke el at., 2016)[81]. The relevance of ESG in mitigating credit risk, particularly tail risk, still needs to be explored. This study aims to fill that gap by analyzing how ESG scores influence tail risk in the credit market through expected shortfall (ES) measures based on CDS spreads.

3.10.3 ESG and Tail Risk in Credit Markets

The specific focus of this thesis on tail risk—measured by expected shortfall—extends beyond the more traditional research that links ESG performance to reduced volatility or average risk levels. Studies by Albuquerque, Koskinen, and Zhang (2019)[3] found that firms with strong ESG scores tend to exhibit lower downside risk in equity markets, suggesting that ESG practices could play a role in mitigating tail risk in credit markets as well. This thesis builds on that foundation, hypothesizing that ESG scores are inversely related to tail risk, as firms with higher ESG scores are likely to have more robust risk management practices, better stakeholder relationships, and access to capital during periods of financial distress, Brown and Dacin (1997)[33]; Luo and Bhattacharya,(2006)[112].

3.10.4 Methodological Considerations

Much empirical research on ESG and credit risk has focused on average credit spread levels or downgrades, Sengupta (1998)[128]. Still, more studies need to address the relationship between ESG scores and the tail risk of credit portfolios. This thesis uses CDS spreads as a proxy for credit risk, which is particularly novel. Previous studies by Longstaff, Mithal, and Neis (2005) have used CDS spreads to capture default probabilities and credit risk premiums. Still, these analyses often omit tail-risk measures such as expected shortfall.

The assumption of a Gaussian loss distribution, used in this thesis, is a simplifying assumption, as the true distribution of credit losses may exhibit fat tails, implying that extreme events occur more frequently than a normal distribution would predict, Jorion, (2007)[99]. Nevertheless, a Gaussian distribution offers a tractable framework for modeling the loss distribution, and its use is consistent with approaches taken in prior research on credit risk (Basel Committee on Banking Supervision, 2013). Future research might extend this analysis by exploring non-parametric loss distributions, such as those driven by macroeconomic shocks or stochastic processes.

3.11 Data and Methodology

Due to the availability of data and the relatively high level of liquidity among investment grade (IG) and sub-investment grade credits, the research primarily focuses on North American businesses. The sample consists of American exchange-listed Investment Grade (north of BBB-) and Sub-Investment Grade or High Yield Bonds (south of BBB-). The universe of businesses has an ESG score issued by Refinitiv and is listed on the exchanges. Unlisted companies possess very different company characteristics and responsibilities that do not represent the sample population. And the control variables are all;

- 5year-Default Probability,
- Market Volatility (VIX),
- US Large Stock Index,
- US Treasury 5Year Yield,
- Standard Poors Credit Ratings, and
- Composite ESG score (and its pillars).

3.11.1 CDS Spread and Default Probability Data

A Credit Default Swap (CDS) is a financial agreement between the CDS seller and buyer. The CDS seller agrees to compensate the buyer in case the payment defaults. In return, the CDS buyer makes periodic payments to the CDS seller till maturity. The main reason for using CDS spread with the corresponding default probability is due to its relatively high liquidity levels. This paper focuses on using 5-year CDS spread and their corresponding 5-year implied default probabilities to provide the Kamakura Corporation[11]. Kamakura provides default probability measures for public, non-public, U.S.banks,and sovereign counterparties. These can be used to assess the creditworthiness of an entire credit portfolio or on a single-name basis. Inputs to the Kamakura models include company-specific attributes, industry-related measures, and relevant macroeconomic factors. The default probability service via the Refnitiv web-based Eikon platform.

[11] Global AI and analytic leader SAS have acquired Honolulu-based Kamakura Corporation. Privately held Kamakura provides specialized software, data, and consulting that helps financial organizations across the spectrum – banks, insurance companies, asset managers, pension funds, and more – manage various financial risks.

3.11.2 5-year Default Probabilities

The first Kamakura Default Probability series, KDP-ms, is a variation of the Merton structural model of risky debt fitted to adjust rapidly to declining credit quality. The second default probability series, KDP-jc, was developed by Kamakura Research Director Robert Jarrow. This reduced-form model predicts bankruptcy based on accounting ratios, equity prices and their volatility, and company size. The third reduced-form hybrid model includes the Jarrow-Chava KDP-jc inputs and the Merton default probabilities from KDP-ms as another input. This creates a "hybrid" reduced form model, which is the one employed in this paper.

3.11.3 Market Volatility (VIX)

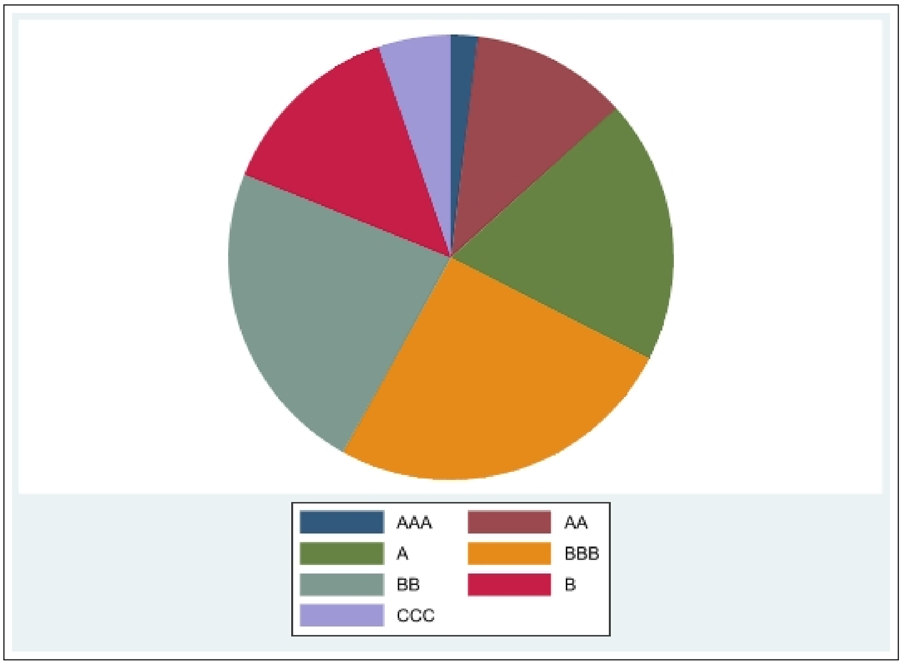
Different volatility measures are influencing the CDS spreads (Benkert, 2004). An alternative measure of volatility is implied volatility. The implied volatility is based on the current values of stock options (Carol et al., 2007) and might be a better proxy for looking into future volatility. Since Benkert (2004) found implied volatility to have a closer connection with CDS spreads than historical volatility, I hence expect the explanatory power to be greater. Moreover, the implied volatility is based on the trader's expectations, while the historical volatility is based on past equity returns. This measure also gives investors a sense of the degree of "fear index" in the marketplace. A high VIX increases the overall asset value and, therefore, impacts the default probability as it changes the characteristics of the risk distribution by exhibiting a fat-tail characteristic.

3.11.4 Credit Rating Data

A credit rating is an evaluation of the credit risk of a prospective borrower; this could be a corporation or sovereign. The focus here is on corporations. Refinitiv provides ratings via Standard Poors. I converted the string rating categories into numerical equivalents such as AAA = 1, AA=2, A= 3, BBB = 4, BB = 5, B= 6, CCC=7, CC=8, and C=9. I downloaded monthly time series ratings from Refinitiv.

3.11.5 ESG Data

To examine the impact of ESG ratings on the tail risk of US corporate credit, I needed to augment the CDS spread data with ESG ratings for the underlying corporate credits,



Source: EOY

Figure 3.1: Shows rating distribution for the sample - investment and sub-investment grade credits

which the CDS referenced. To this end, I use Refinitiv's ESG Ratings. I consider monthly CDS spreads and monthly environmental, social, and governance (ESG) data of 209 US companies from Refinitiv, which have values between 0 and 100, available from January 2010 to April 2022. The unexpected loss is measured in absolute numeric terms. The ESG scores range from 0 to 100, with 100 being the highest. The score seems relatively stable, except for pillar G, which has a standard deviation of over 15, whereas ESG, E, and S have that of 4.1995, 2.1285, and 6.4581, respectively. Like other ESG rating companies, Refinitiv calculates a composite ESG score comprising scores for E, S, and G. They also provide scores for E, S, and G, along with ten main sub-components. In total 186 metrics go into the calculation of an issuer's ESG score(s). The majority of the results presented in this paper relate to the composite and individual E, S, and G scores, but I have also analyzed the 9 main components of these scores:

- Environmental: Resource Use; Emissions; and Innovation.
- Social workforce: Human Rights; Community; and Product Responsibility.
- Governance: Management; Shareholders; and CSR Strategy.

3.11.6 Measuring ESG

To measure a firm's ESG scores following prior literature (e.g., Barthet al., 2015; Sassen et al., 2016), I use ESG scores as an umbrella measure provided by Refinitiv to examine the effect on the firm's expected shortfall (tail-risk). ESG scores range from 0 to 100; see Table 3.1. My additional analysis employed the individual environmental, social, and governance scores separately. These individual scores represent firm performance on each factor individually.

Table 3.9: ESG Definition Refinitiv

Pillar	*Themes*	*37 ESG Key Issues*	
Environment	Climate Change	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Resources	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opportunities in Renewable Energy
Social	Human Capital	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chamical Safety Financial Product Safety	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing	
	Social Opportunities	Access to Communications Access to Financ	Access to Health Care Opportunities in Nutrition & Health
Governance	Corporate Governance	Board Pay	Ownership Accounting
	Corporate Behavior	Business Ethics Anti-Competitive Practices Tax Transparency	Corruption & Instability Financial System Instability

For instance, environmental scores are based on firm performance relating to climate change policies, hazardous wastes, nuclear energy, and sustainability indicators. Social scores are based on firm performance relating to consumer protections, diversity, human rights, animal welfare, child labor, and employee health and safety indicators. Governance scores are based on firm performance of management structure, executive compensation, and conflict of interest indicators. Figure 3.2 shows the monthly distribution of the ESG score from January 2010 to April 2022. It is moderately negatively skewed but close to being normally distributed.

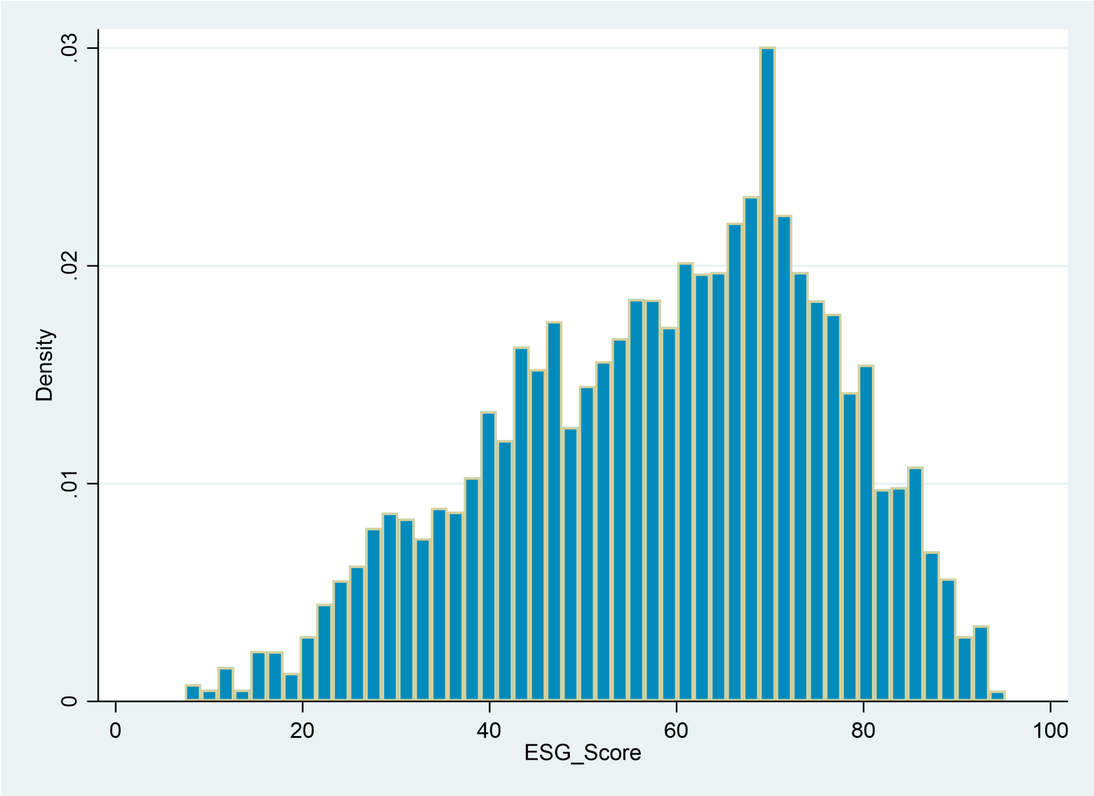


Figure 3.2: ESG monthly ESG Score January 2010 to April 2022

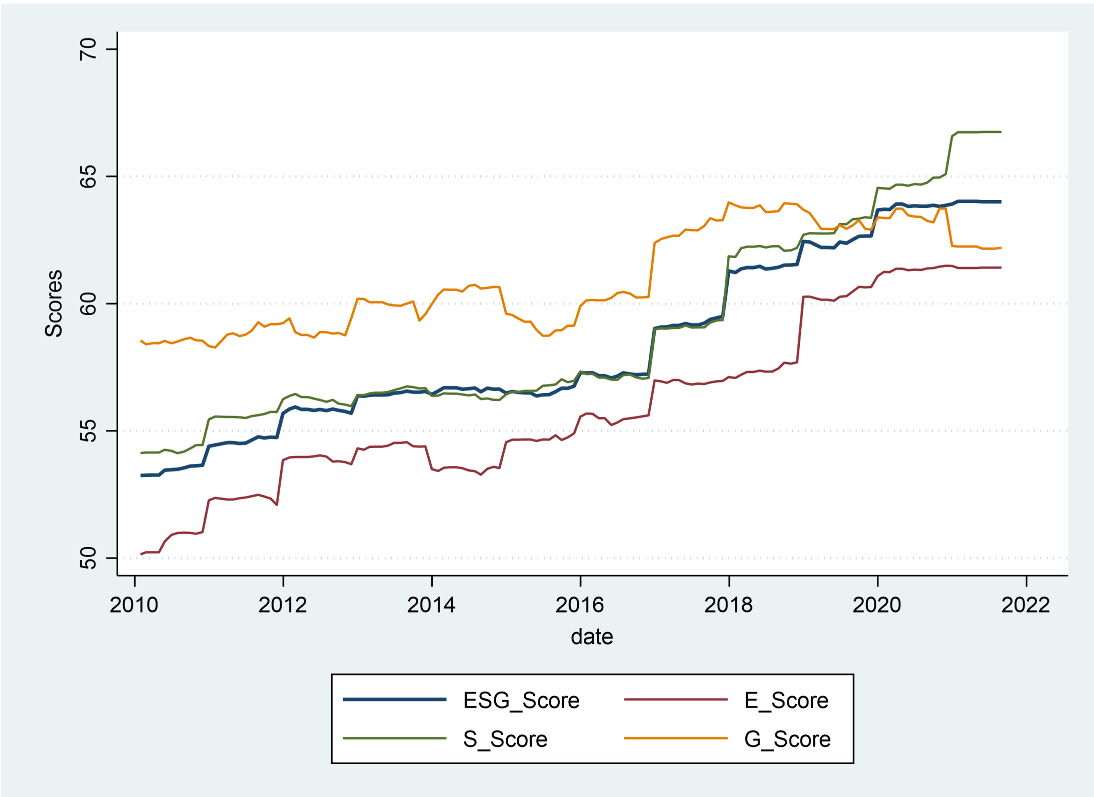


Figure 3.3: Average ESG Scores over Time 2010 to April 2022

3.11.7 Data Statistics

Table (3.10) shows the data summary where the mean unexpected loss is 463 basis points (bps), with the minimum being 108 bps and skewness of 2.89, which is very high and positive, which indicates the median may be the best central tendency figure to use, that is 392 bps. The combined ESG and individual pillars are moderately skewed or approximately symmetric, as seen in Figure 3.2.

Table 3.10: Sumary of Monthly Control Variables with Expected Shortfall and Unexpected Loss: Jan2010 to April 2022

Variable	Mean	Std.Dev	Min	10th Pctile	Median	90th Pctile	Max	Skewness
UnExpexctedLoss	0.0463	0.0208	0.0108	0.0327	0.0392	0.0687	0.2296	2.8918
ExpectedShortfall	0.0367	0.0212	0.0076	0.0243	63.0026	0.0562	0.3067	3.6742
DefaultProb5YR	0.0107	0.0148	0.0005	0.0043	0.0062	0.2845	0.3021	5.6856
Market Vol (VIX)	0.2108	0.05025	0.1199	0.1428	0.2097	0.2605	0.3454	0.6272
USLargeStocklndex	1.4235	0.5890	0.9407	0.9943	1.1478	2.2880	4.3501	1.9413
USTreasury5YrYield	0.0153	0.0057	0.0044	0.0074	0.0155	0.0242	0.0254	-0.0125
ESG_CScore	55.8946	21.1800	0.0000	27.6193	59.7458	80.0910	95.1947	-0.7854
E_Score	51.3448	28.3020	0.0000	4.1719	56.6551	84.9720	98.5458	-0.4042
S_Score	56.4098	23.6134	0.0000	24.4064	59.7504	84.9615	98.0091	-0.5280
G_Score	58.2792	23.4204	0.0000	26.0989	63.0450	84.6825	98.5279	-0.7518
Ratings	4.1859	1.4256	1.0000	2.0000	5.0000	6.0000	7.0000	0.0039

The correlation signs indicate the opposite direction of the ESG scores and Expected Shortfall. This indicates that one should expect an increase in ESG scores likely to reduce the tail risk.

3.11.8 Correlation analysis

The correlation matrix section of Table (3.11) presents the pairwise correlation among the variables used in empirical analysis. The correlation between ESG and Expected Shortfall is -0.15, which is very low, suggesting that these are the alternative proxies of tail risk, but the negative relationship is what I anticipated. In the relationship between S, the social pillar, Expected shortfall, is relatively higher than the combined ESG scores. This is an indication that perhaps the driving force behind the combined score is the company's policy toward its employees.

Stocks, Bonds, Bills, and Inflation Capital Market Data

The SBBI data set includes monthly, quarterly, and yearly returns and yields of most of the significant U.S. asset classes: large-cap stocks, small-cap stocks, corporate bonds, government bonds of several maturities,*See List 1.*

Table 3.11: Correlation Matrix: Jan2010 to April 2022

	UnExpLoss	**ExpShortfall**	**DefProb5YR**	**MarketVol**	**USLStockIndex**	**USTreas5YrYld**	**ESG_CScore**	**E_Score**	**S_Score**	**G_Score**	**Ratings**
UnExpLoss	1.0000										
ExpShortfall	0.9950	1.0000									
DefProb5YR	0.9544	0.9793	1.0000								
MarketVol	-0.0941	-0.0906	-0.0803	1.0000							
USLStockIndex	0.0978	0.0928	0.0794	-0.4386	1.0000						
USTreas5YrYield	-0.0646	-0.0611	-0.0517	0.2016	0.1466	1.0000					
ESG_CScore	-0.2522	-0.2394	-0.2056	-0.0643	0.1012	0.0152	1.0000				
E_Score	-0.2813	-0.2674	-0.2306	-0.0499	0.0831	0.0088	0.8526	1.0000			
S_Score	-0.2414	-0.2297	-0.1986	-0.0590	0.1001	0.0156	0.9041	0.7476	1.0000		
G_Score	-0.1050	-0.0972	-0.0779	-0.0331	0.0475	0.0131	0.6579	0.3779	0.4010	1.0000	
Ratings	0.1016	0.0977	0.0865	0.0421	-0.0723	-0.0099	-0.2526	-0.2401	-0.2816	-0.0596	1.0000

3.11.9 Expected Loss

The expected loss portion is the green portion of Figure(3.4). The expected loss formula calculates the average loss over a specified period. This portion of the loss distribution is the implied spread for the credit; it is not part of the tail risk. It is typically expressed as:

$$\text{ExpLoss} = \text{PD} * \text{LGD} * \text{ExposureAtDefault}] \tag{3.20}$$

3.11.10 UnExpected Loss

I use the same framework the Basel Committee uses to asses the unexpected loss (UL) and stress loss in a credit portfolio. The unexpected loss is the average total loss over and above the expected loss. It is calculated as a standard deviation from the mean at a certain confidence level at a certain confidence level. It is also referred to as Credit VaR or Economic Capital. This is the grey area of Figure(3.4).

$$\text{UnExpLoss} = \text{ExposureAtDefault} * \sqrt{[}\big(\text{PD}^2 * \sigma^2_{\text{LGD}}\big) + \big(\text{LGD}^2 * \sigma^2_{\text{PD}}\big)\Big] \tag{3.21}$$

where

σ^2_{LGD} = Variance of the loss given default

σ^2_{PD}= Variance of probability of default = $(PD)(1 - PD)$

I used STATA to estimate the Unexpected Loss for each of the 209 credits.

3.11.11 Expected Shortfall (ES)

In estimating the ES, I assumed the Gaussian distribution for tractability. We assumed a 99% confidence level, meaning at this level, once we have reached that loss threshold, the average of the remaining loss distribution, Figure(3.4) shows a typical loss distribution of a credit instrument; a comprehensive representation of the potential losses associated with credit risk. It incorporates the probabilities of default, the severity of losses given default, and the exposure at default. It provides a framework for assessing and managing credit risk in financial institutions, which is highly skewed - the green section represents the expected loss. The blue section represents the unexpected loss, with the red section being the tail or stress loss. However, in this thesis, I assumed a Gaussian. After adding Value-at-Risk(VaR) as a credit risk measure, the Expected shortfall was introduced as a more practical measure by the Basel Committee. For this thesis, the interest is to estimate the tail risk via Expected shortfall and test its significance to the level of ESG scores. By definition, the VaR is the maximum loss likely lost after an unexpected event over a predefined period. Let's assume that a random variable X with continuous distribution function F models losses on credit over a particular time horizon, in our case, over a month.VaR_{α} can be defined at the α^{th}quantile of the distribution F

Alternatively, we expect alpha % of the time the loss amount would be in the tail of the loss threshold or worse. Expected Shortfall gives the average loss within the quantile (tail). As you can see from the equation (3.22), the ES is a conditional probability for which the expected loss is conditional on exceeding the quantile, that what the integral in the in equation (3.22) represents.

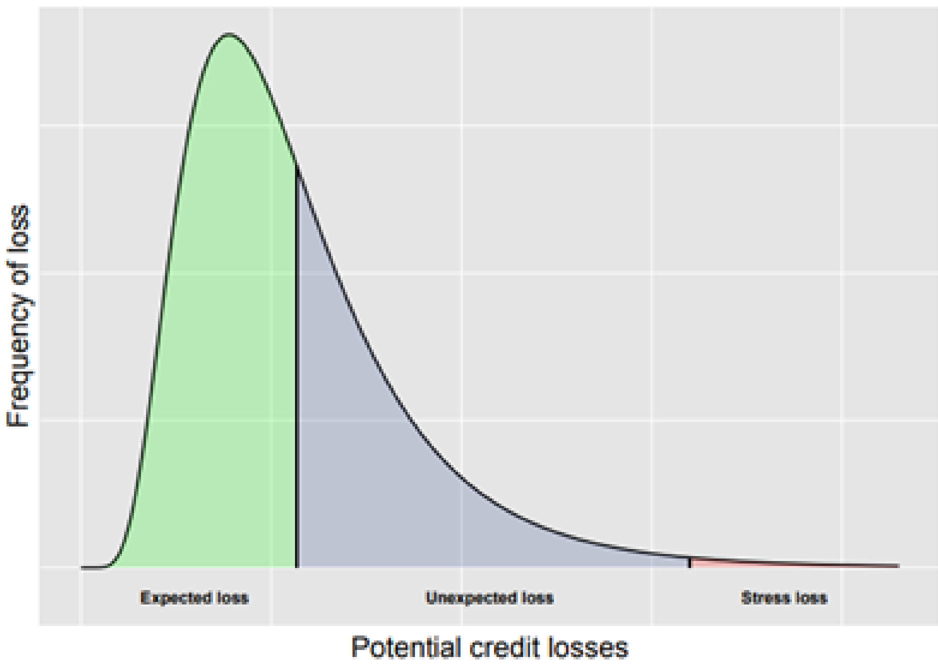


Figure 3.4: Loss distribution of a credit instrument, illustrating the three different types of losses in credit risk measures; Expected Loss, Unexpected Loss, and Expected Shortfall (or Stress Loss)

The equation 3.22 measures the Stress loss or the average tail-loss as indicated using the close form of the Expected shortfall formula for a given confidence interval and significance level, 99% and 1%, respectively.

$$ExpectedShortfall_{\alpha} = E(X|X > VaR_{\alpha}) = \int_{\alpha}^{1} \frac{1}{1-\alpha} \Phi_p dp \tag{3.22}$$

In the final analysis, the ES is a tail-risk measure developed to counter some of VaR's shortcomings. It is used both for managing the market and credit risk of investment portfolios. The expected shortfall tells you the expected loss given the

$\alpha\%$ worst return occurrences in a portfolio.

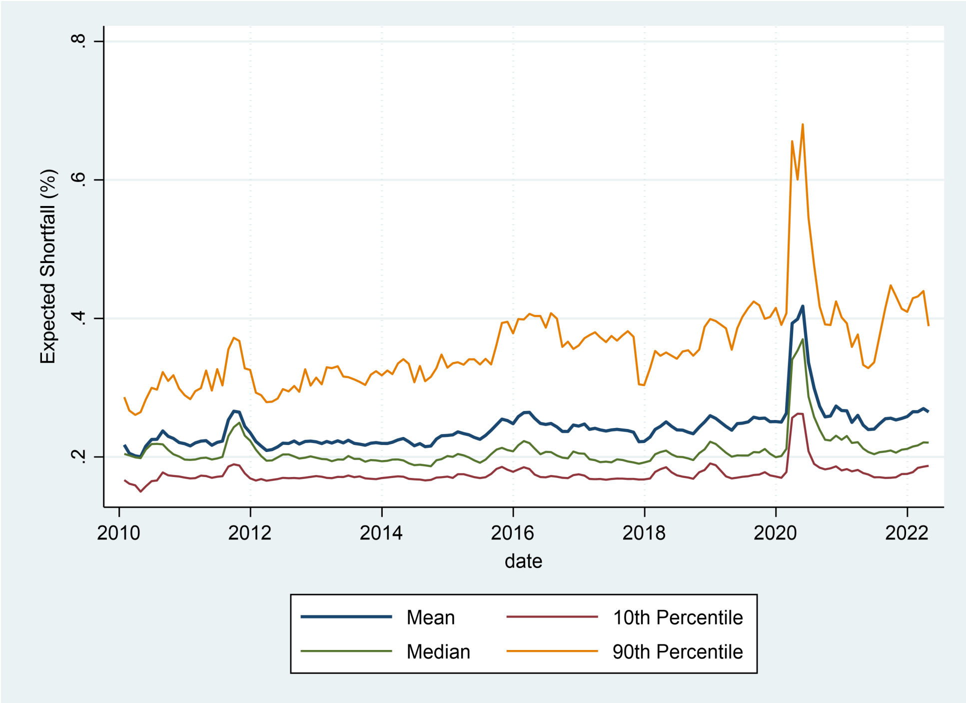


Figure 3.5: Expected Shortfall Variation over Time in Percentiles from January 2010 to April 2022

3.12 Methodology

In this model, I analyze the direct effects of individual ESG pillars—Environmental (E), Social (S), and Governance (G)—as well as the combined ESG score, using a panel regression with fixed effects at the firm level. This approach is particularly appropriate given the nature of the data, where the entities are individual firms, and observations are made over time for each firm. The dataset comprises 209 U.S. corporate credits, spanning both investment-grade and sub-investment-grade categories across all major industries. Importantly, I have included potentially biased sectors such as Tobacco, Mining, Oil and Gas, and Defense, to ensure a comprehensive analysis that does not exclude industries that might exhibit distinct ESG-related dynamics.

The fixed-effect model was chosen for this analysis because it allows for a detailed examination of the relationship between independent and dependent variables within each entity, in this case, individual firms. The panel dataset includes multiple companies, each possessing unique characteristics that may influence the dependent variable, such as credit or equity returns, and possibly the independent variables as well. The focus of this thesis is on understanding how factors like ESG scores (and their individual pillars), default risk, performance, market volatility, and the returns on large U.S. stocks and government bonds affect credit returns, as measured by CDS spreads, and equity returns under controlled conditions.

The fixed-effect approach is particularly appropriate because it accounts for the potential bias arising from unobserved, time-invariant characteristics specific to each firm that could correlate with the independent variables. These characteristics might include factors such as a firm's management quality, industry sector, or regulatory environment, which do not change over time but could still impact the relationship between the variables of interest. By controlling for these unobservable factors, the fixed-effect model provides more accurate and reliable estimates, ensuring that the observed effects are truly due to the independent variables under study and not confounded by firm-specific characteristics.

Moreover, the fixed-effect model is well-suited for capturing the impact of time-invariant individual-specific traits that could influence the results. This is crucial in a study where the diversity of firms and their inherent characteristics might otherwise introduce bias into the analysis. By eliminating the effect of these time-invariant features, the fixed-effect model enhances the validity of the findings, offering a clearer understanding of how the specified factors influence credit and equity returns across different firms. This methodological choice aligns with the objective of providing a robust analysis that accurately reflects the complexities of the data.

Furthermore, this methodological choice ensures that the analysis captures the true effects of the ESG factors, independent of other firm-specific influences that could confound the results. While investors might choose to construct their portfolios by incorporating default probability correlations tailored to their preferences, the fixed-effect model provides a robust foundation for understanding the impact of ESG factors across a diverse set of firms, making the findings relevant and applicable to a broad range of investment contexts.

3.12.1 Estimation of model

Unexpected Loss

Equations (3.23) give the elasticities of the individual pillars with the UnExpected Loss

$$\begin{aligned}\text{UnExpectedLoss}_{i,t} = &Const_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} + \beta_3\text{USLargeStockIndex}_{i,t}\\ &+ \beta_4\text{USTreasuryYield}_{i,t} + \beta_5\text{Rating}_{i,t} + \beta^{ESG}\text{ESGScore}_{i,t}\end{aligned} \tag{3.23}$$

Equations (3.24) gives the elasticity of the individual pillars with the UnExpected Loss

$$\begin{aligned}\text{UnExpectedLoss}_{i,t} = &Const_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} + \beta_3\text{USLargeStockIndex}_{i,t}\\ &+ \beta_4\text{USTreasuryYield}_{i,t} + \beta_5\text{Rating}_{i,t} + \beta^{E}\text{EScore}_{i,t} + \beta^{S}\text{SScore}_{i,t}\\ &+ \beta^{G}\text{GScore}_{i,t}\end{aligned} \tag{3.24}$$

Expected Shortfall

Equations (3.25) give the elasticities of the individual pillars with the Expected Shortfall

$$\begin{aligned}\text{ExpectedShortfall}_{i,t} = &Const_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} + \beta_3\text{USLargeStockIndex}_{i,t}\\ &+ \beta_4\text{USTreasuryYield}_{i,t} + \beta_5\text{Rating}_{i,t} + \beta^{ESG}\text{ESGScore}_{i,t}\end{aligned} \tag{3.25}$$

Equations (3.26) give the elasticities of the combined individual pillars with the Expected Shortfall

$$\begin{aligned}\text{ExpectedShortfall}_{i,t} = &Const_{i,t} + \beta_1\text{DefProb}_{i,t} + \beta_2\text{MarketVol}_{i,t} + \beta_3\text{USLargeStockIndex}_{i,t}\\ &+ \beta_4\text{USTreasuryYield}_{i,t} + \beta_5\text{Rating}_{i,t} + \beta^{E}\text{EScore}_{i,t} + \beta^{S}\text{SScore}_{i,t}\\ &+ \beta^{G}\text{GScore}_{i,t}\end{aligned} \tag{3.26}$$

3.13 Empirical Results Analysis

In this section, I examine the relationship and popularity of the ESG score across a metric of risk measures, mainly the distributions' second and third moments: unexpected loss and the expected shortfall. The analysis estimates a panel data model, and the regression performed is an ordinary least-squares linear regression. The justification comes from the argument that when the assumptions of independence of observations and residuals are violated, as in the case of varying parameter estimates, maximum likelihood estimators provide parameter estimates that are relatively consistent, asymptotically normal, and efficient.

3.13.1 Baseline results

The coefficients are in basis point (bps) terms. The empirical results are reported in Tables 3.12, and (3.13) corresponding to the Unexpected Loss, and Expected Shortfall, respectively, with models one through nine, considering the four alternative proxies for the ESG Score, i.e., total, environmental, social and governance, respectively. The results indicate that across all nine model specifications, the popularity of ESG variants negatively impacts the expected loss as one would expect on the spread or bond yields. Regarding the other controls, the estimates are per theoretical expectations. The control variables or characteristics are all; 5-year-default Probability, Market Volatility (VIX), US Large Stock Index, US Treasury 5Year Yield, Standard & Poor Credit Ratings, and lastly, the composite ESG score.

Unexpected Loss

The Unexpected Loss is the measure of the standard deviation of the losses, given the level of 5-year default probability. From Table 3.12, the level of impact is marginal, with a large component coming from the constant term, which is also significant. The main empirical results in Table 3.12 are qualitatively identical to those presented in Table 3.13, and almost quantitatively identical. This suggests that unexpected loss incorporates the exposures of low ESG firms to newly emerging ESG risks in credit spreads and confirms our baseline result that CDS markets incorporate ESG when assessing credit risks.

Table 3.12: Unexpected loss, Ratings, and the Composite ESG Scores and its pillar

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps	UnExpectedLossbps
DefaultProb5YR	1.3137***	1.2814***	1.2817***	1.3129***	1.2817***	1.3132***	1.2815***	1.3142***	1.2819***
	(0.0724)	(0.0783)	(0.0777)	(0.0729)	(0.0781)	(0.0726)	(0.0777)	(0.0723)	(0.0779)
VIX	-0.0016*	-0.0014*	-0.0015*	-0.0015*	-0.0015*	-0.0015*	-0.0014*	-0.0015**	-0.0015*
	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
USLargeStockLevel	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
USTreasury5YrYield	-0.0580***	-0.0615***	-0.0617***	-0.0581***	-0.0620***	-0.0577***	-0.0616***	-0.0574***	-0.0615***
	(0.0076)	(0.0074)	(0.0076)	(0.0077)	(0.0076)	(0.0076)	(0.0076)	(0.0074)	(0.0074)
ESG_CScore	-0.0000		-0.0000						
	(0.0000)		(0.0000)						
nRatings		-0.0001	-0.0001		-0.0001		-0.0001		-0.0001
		(0.0001)	(0.0001)		(0.0001)		(0.0001)		(0.0001)
E_Score				-0.0000	-0.0000				
				(0.0000)	(0.0000)				
S_Score						-0.0000	-0.0000		
						(0.0000)	(0.0000)		
G_Score								-0.0000	-0.0000
								(0.0000)	(0.0000)
Constant	0.0330***	0.0327***	0.0329***	0.0327***	0.0330***	0.0327***	0.0328***	0.0331***	0.0330***
	(0.0013)	(0.0010)	(0.0016)	(0.0011)	(0.0012)	(0.0012)	(0.0015)	(0.0010)	(0.0013)
R-squared	86.50%	84.99%	84.99%	86.49%	84.99%	86.49%	84.99%	86.51%	84.99%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Expected Shortfall

In this section, from a theoretical view, one would expect the expected shortfall to be mitigated concerning high composite ESG score, so if we hypothesize this to be the case, that is, making this the null hypothesis, then the negative coefficient of the composite ESG, and the respective pillars (see Table 3.13 and their p-value being almost zero provides sufficient evidence to fail to reject the null, and therefore accept that there is the negative relationship between expected shortfall and ESG scores with 99% confidence level.

Table 3.13: Expected Shortfall, Ratings, and the Composite ESG Scores and its pillar

VARIABLES	(M1) ExpShortFallbps	(M2) ExpShortFallbps	(M3) ExpShortFallbps	(M4) ExpShortFallbps	(M5) ExpShortFallbps	(M6) ExpShortFallbps	(M7) ExpShortFallbps	(M8) ExpShortFallbps	(M9) ExpShortFallbps
DefaultProb5YR	1.3903***	1.3684***	1.3686***	1.3898***	1.3687***	1.3899***	1.3685***	1.3907***	1.3687***
	(0.0491)	(0.0531)	(0.0527)	(0.0494)	(0.0529)	(0.0492)	(0.0527)	(0.0490)	(0.0528)
VIX	-0.0011*	-0.0010*	-0.0010*	-0.0011*	-0.0011*	-0.0010*	-0.0010*	-0.0011**	-0.0010**
	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
USLargeStockLevel	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
USTreasury5YrYield	-0.0395***	-0.0419***	-0.0420***	-0.0396***	-0.0423***	-0.0393***	-0.0420***	-0.0391***	-0.0419***
	(0.0052)	(0.0050)	(0.0052)	(0.0052)	(0.0052)	(0.0051)	(0.0051)	(0.0050)	(0.0050)
ESG_CScore	-0.0000		-0.0000						
	(0.0000)		(0.0000)						
nRatings		-0.0001	-0.0001		-0.0001		-0.0001		-0.0001
		(0.0001)	(0.0001)		(0.0001)		(0.0001)		(0.0001)
E_Score				-0.0000	-0.0000				
				(0.0000)	(0.0000)				
S_Score						-0.0000	-0.0000		
						(0.0000)	(0.0000)		
G_Score								-0.0000	-0.0000
								(0.0000)	(0.0000)
Constant	0.0224***	0.0222***	0.0223***	0.0222***	0.0224***	0.0222***	0.0222***	0.0224***	0.0224***
	(0.0009)	(0.0007)	(0.0011)	(0.0007)	(0.0008)	(0.0008)	(0.0010)	(0.0007)	(0.0009)
R-squared	93.97%	93.35%	93.35%	93.97%	93.35%	93.97%	93.35%	93.98%	93.35%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.14: Hauman test for the Proposed Model Jan2010 to Apr2022

Coefficients

	Model			
	Fixed (f)	**Random(r)**	**Difference**	**Stand.Err**
DefaultProb5YR	1.370	1.3750	-0.0054	0.0004
Market Vol (VIX)	-0.0011	-.0011	0.0000	0.0000
USLargeStocklndex	0.0005	.0006	-0.0000	0.0000
USTreasury5YrYield	-0.0417	-0.0418	0 .0001	0.0000
Ratings	0.0006	0.0006	-0.0000	0.0000
ESG_Score	0.0000	0.0000	0.0000	0.0000
E_Score	0.0001	0.0001	0.0000	0.0000
S_Score	0.0001	0.0001	0.0000	0.0000
G_Score	0.0001	0.0001	0.0000	0.0000
Ratings	0.0006	0.0006	-0.0000	0.0000
F=199.75	**p-value=**	**0.0000**		

3.14 Hausman Test

The Hausman test was implemented in this paper by comparing the results of both fixed and random effects models; first, the panel data model was estimated using fixed and random effects approaches. This involved running a regression analysis with the dependent variable and independent variables, using either fixed effects or random effects specifications. Stata allows one to keep all the coefficient estimates and the respective standard error for both models. Then, it computes the respective t-statistics. The p-value being zero is why the Random effect model is rejected, according to the results of executing or running the Hausman test for the model; see Table 3.7. Thus, the conclusion emphasizes that the more germane and appropriate model is the fixed effect for this analysis.

3.15 Bias of Endogeneity and Reverse Causality

Examining the relationships between ESG scores and corporate credit return could not generate an endogenous relationship. The relationship between ESG score and credit return is a function of information flow since they share a common capital structure, and there is a structural relationship.

Buchanan et al. (2018)[34] researched the connection between ESG and firm value and subsequently suggested there may be a relationship between ESG and firm financial performance, which could provide an endogeneity issue. Endogeneity can arise if ESG scores are correlated with unobserved factors that also affect expected shortfall, such as firm-specific risk profiles or broader market conditions. Reverse causality may occur if expected shortfall fluctuations influence ESG score changes rather than the reverse.

To mitigate these issues, lagged ESG scores are incorporated into the analysis. By utilizing past values of ESG scores, the model captures the historical impact of ESG performance on the current expected shortfall, effectively disentangling the direction of causation. This approach helps to isolate the influence of ESG scores on future risk metrics, minimizing the potential biases introduced by endogeneity and reverse causality and providing a more accurate assessment of how historical ESG performance relates to changes in expected shortfall.

UnExpected Loss

$$\begin{aligned}\text{UnExpectedLoss}_{i,t} = Const_{i,t} &+ \beta_1\text{DefProb}_{i,t-1} + \beta_2\text{MarketVol}_{i,t-1} + \beta_3\text{USLargeStockIndex}_{i,t-1} \\ &+ \beta_4\text{USTreasuryYield}_{i,t-1} + \beta^{ESG}\text{ESGScore}_{i,t-1}\end{aligned} \tag{3.27}$$

and then lagged by 2.

$$\begin{aligned}\text{UnExpectedLoss}_{i,t} = Const_{i,t} &+ \beta_1\text{DefProb}_{i,t-2} + \beta_2\text{MarketVol}_{i,t-2} + \beta_3\text{USLargeStockIndex}_{i,t-2} \\ &+ \beta_4\text{USTreasuryYield}_{i,t-2} + \beta^{ESG}\text{ESGScore}_{i,t-2}\end{aligned} \tag{3.28}$$

To mitigate these reverse causality issues, I estimated alternative Equation specifications (3.27). Specifically, I test the influence of the ESG score in the *t-1* year on the UnExpected loss in the current t year. I report the results in Column 2 (Lag 1) and Column 3 (Lag 2) of Table (3.15). As can be seen from these results, ESG is negatively related to CDS, suggesting that the prior-year ESG inversely affects the current year's credit risk. These results suggest that the direction of causation runs from ESG disclosure to credit risk but not vice versa.

An alternative specifications of Equation (3.28) was estimated to mitigate the reverse causality. Specifically, the influence of the ESG score was tested with the *t-1* year on the UnExpected loss in the current t year. See Column 2 (Lag 1) and Column 3 (Lag 2) of Table (3.16). These results suggest that the direction of causation runs from ESG score to credit risk but not vice versa. ESG is negatively related to the expected shortfall, suggesting that the prior-year ESG inversely affects the t year's credit risk.

Table 3.15: Unexpected Loss and ESG — endogeneity bias (lagged independent variables

VARIABLES	Lag(1) UnExpectedLossbps	Lag(2) UnExpectedLossbps
DefaultProb5YR	1.224***	1.121***
	(0.00454)	(0.00556)
VIX	-0.00429***	-0.00481***
	(0.000871)	(0.00108)
USLargeStockLevel	0.000407***	3.82e-05
	(8.77e-05)	(0.000109)
USTreasury5YrYield	-0.0484***	0.0590***
	(0.00694)	(0.00863)
ESG_CScore	-1.49e-05***	-1.34e-05***
	(3.84e-06)	(4.57e-06)
Constant	0.0350***	0.0349***
	(0.000381)	(0.000440)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.16: ExpectedShaort Fall and ESG — endogeneity bias (lagged independent variables

VARIABLES	Lag(1) ExpShortFallbps	Lag(2) ExpShortFallbps
DefaultProb5YR	1.295***	1.198***
	(0.00403)	(0.00521)
VIX	-0.00416***	-0.00471***
	(0.000784)	(0.00104)
USLargeStockLevel	0.000176**	-0.000128
	(7.88e-05)	(0.000105)
USTreasury5YrYield	-0.0326***	0.0675***
	(0.00625)	(0.00833)
ESG_CScore	-1.40e-05***	-2.10e-05***
	(3.30e-06)	(4.01e-06)
Constant	0.0247***	0.0250***
	(0.000317)	(0.000392)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

ExpectedShort fall

$$
\begin{aligned}
\text{ExpectedShortfall}_{i,t} = Const_{i,t} &+ \beta_1 \text{DefProb}_{i,t-1} + \beta_2 \text{MarketVol}_{i,t-1} + \beta_3 \text{USLargeStockIndex}_{i,t-1} \\
&+ \beta_4 \text{USTreasuryYield}_{i,t-1} + \beta^{ESG} \text{ESGScore}_{i,t-1}
\end{aligned} \tag{3.29}
$$

and then lagged by 2.

$$
\begin{aligned}
\text{ExpectedShortfall}_{i,t} = Const_{i,t} &+ \beta_1 \text{DefProb}_{i,t-2} + \beta_2 \text{MarketVol}_{i,t-2} + \beta_3 \text{USLargeStockIndex}_{i,t-2} \\
&+ \beta_4 \text{USTreasuryYield}_{i,t-2} + \beta^{ESG} \text{ESGScore}_{i,t-2}
\end{aligned} \tag{3.30}
$$

3.16 Conclusion

A measure of tail risk in credit markets is essential to understanding overall portfolio risk. ESG disclosure has emerged as an important consideration for evaluating investment decisions, cost of funding, and access to capital markets. This paper aimed to investigate the possible impact of composite ESG and its individual pillars' score on a tail risk of corporate credit. To this end, I collated a comprehensive fixed-income data set comprising CDS spreads, assumed recovery levels, and other detailed corporate credit characteristic information. I combined this fixed income data with ESG scores of the underlying corporate issuers via its 5-year CDS spreads and corresponding default probabilities. Using this rich combined data set, I conducted a panel regression to establish whether there was an "ESG effect" on the tail risk of corporate credits across the US. To achieve this objective, I had to make the significant assumption that the underlying default distribution follows a Gaussian distribution for the sake of tractability; I assume an approximate measure of the 99th percentile loss to be the expected shortfall (or stress loss), the mean of the loss distribution of individual credit using the CDS spread implied default probability. I find a negative relationship between ESG scores and tail risk of credit exposure across investment and sub-investment grade corporate credits. My results have important implications for investors and academics. From an investor's perspective, credit risk models can be improved when incorporating ESG, resulting in more efficient risk management and potential performance benefits, especially risk-adjusted returns. On the academic, it could help us to determine stochastic discount factors in asset pricing.

Based on a sample of 33,909 firm-month data covering 209 US enterprises from January 2010 to April 2022, my findings show a strong and adverse link between ESG and tail risk. When compared to the sub-investment grade sample, the investment grade sample exhibits a bigger ESG risk mitigation effect, which is consistent with theories linking the financial benefits of ESG to industries with better ESG standards, higher investor protection standards, and higher transaction costs.

However, the lack of consistency in composite ESG scores originates from divergences in objectives, methodologies, and assessments. Scores could (and do) diverge because they relate to fundamentally different concepts, such as the measurement of the ESG impact or performance of a company versus the measurement of the financial materiality of ESG issues for a company. They also diverge on the choice and weighting of criteria (as a result of divergences of focus or disagreements concerning the proper manner to approach the same issue) and because of differences in data sources and treatment, including arising from subjectivity. This means that the ESG scoring of the same pool of corporate names with two different data sets, e.g., one using the Refinitiv versus MSCI, would lead to a very different tail-analysis.

Chapter 4

Overall Conclusion

4.1 Summary of Results

The overall thesis has shown that the popularity framework can be useful in such a way that it is generalized and consistent with existing well-known empirical results. It could also predict premiums and anomalies that have not been considered before as priced characteristics. In this thesis, I have empirically demonstrated that the macroeconomic data set from SBBI is priced or affects the credit market along with default probabilities. What is becoming increasingly clear from these empirical results is that many of the premiums are not associated with extra risk and, in some cases, are associated with a risk reduction. For this reason, popularity enables one to explain any anomalies in the credit market. In contrast to Bektic et. el (2019)[21], and Bektic (2018)[20], which tried to extend Fame-French factors to explain the anomalies in the corporate bond yields, this thesis goes beyond risk factors and include any potential impactful non-risk preference by the market participants. It can be concluded that a linear model can be applied to the pricing of corporate credit, and the PAPM can be used to explain any anomalies that may exist.

4.2 Implication of Results

As demonstrated in the first paper, preference, and credit spreads also give investors an idea of where the economy is heading. Improved economic conditions are signaled by improvements in company profitability and lower corporate default rates; this causes investors to view investment-grade and high-yield corporate bonds more favorably, which causes the credit spread to contract. Moreover, economic improvement prompts the Fed to hike interest rates to ward off inflationary pressure. This increase in interest rates causes Treasury yields to spike, tightening credit spreads. Therefore, the popularity of credit instruments in a good economic environment leads to tightening credit spreads, making them expensive, thus lowering the expected return. The reverse happens in the case of an economic slowdown. And given that credit investors worry about mitigating losses while equity investors care more about the potential upside. Impending bad times for the economy are priced into corporate bonds before equity markets catch on. Conversely, characteristics nearly universally disliked are low demand (unpopular) and thus inexpensive, leading to higher expected returns. In this paper, I have shown that the popularity-based pricing framework drives CDS spreads and returns. In calm times, if the stock market is underperforming, there are overall increases in credit spread because the risk level is elevated; investors dislike spread widening, so the cost of buying protection goes up. The seller of protection, the credit risk buyer, gets periodic payment increases; therefore, the correlation between CDS spreads and returns and the market is adverse. In addition, I also conclude that the risk adjustment factor (for risk aversion) is approximately 2-times for the low recovery rates and 3-times for the average recovery rate of 40%, which means the protection seller (credit risk buyer) has a preference spread widening at higher recovery rate. Again, investors' preference for the quality characteristic has impacted valuations, with quality credit at higher valuations than the market. Since valuations are the best predictor of future returns, investors should at least consider them when making investment decisions. Therefore, contrarian investing, buying the unpopular, has tended to produce superior results. Keep this in mind as you consider your asset allocation. Valuations do matter.

4.3 Limitation of Results

The fact that the PAPM accepts and takes into account both rational and irrational investors, unique risk and return expectations, a wide range of pecuniary and non-pecuniary characteristics that affect asset prices, and investors who benefit from non-pecuniary attributes allows it to serve as a unifying theory. In contrast to the bulk of studies that examine the link between credit and equity returns, this thesis treats the drivers as mere preferences, with the ESG score being considered a non-risk attribute. The behavioral non-risk factors consider the reality that people acquire opinions differently and that heterogeneity is a fact of life. Like liquidity, not all investors prioritize ESG disclosure equally when making investment decisions. By including the two essential components mentioned by Fama and French, the popularity-based framework (PAPM) offers a much-needed upgrade over the CAPM. The PAPM has solid results and significant practical implications for practitioners. The PAPM bridges classical and behavioral finance by taking two necessary steps toward a more realistic asset pricing model: including varied viewpoints and allowing for various investor preferences/tastes.

For the investment grade credit sample, the ESG score preference is significant regarding the spread of long-term credit risk protection. However, this is also similar to the sample universe of the United States corporate credit market, including both investment grade and high yield (sub-investment grade). However, I could not find a statistically significant link between ESG and credit returns for credits with ratings below investment grade. One of the reasons this might be the case is because the sample consisted of 25% sub-investment-grade and 75% investment-grade credits.

The significance of ESG to below-investment-grade credit is that it is reasonable to predict that the possibility of default will significantly affect or dominate the credit protection spread. This is because the likelihood of default is the most important factor. This is because the likelihood of the debt being unpaid is the most essential consideration. Further study was conducted across the board in all the different firms. In addition, it is essential to determine whether or not it is feasible to investigate the influence of ESG factors on tail risk. In conclusion, the outcomes of this research suggest a connection between environmental, social, and governance (ESG) variables, equity return, and credit returns in terms of information flow through investors' preferences, particularly with investment-grade loans. This conclusion is drawn from the fact that the ESG elements correlate with credit risk. As a direct result of this, the amount of environmental, social, and governance (ESG) disclosure that firms offer can be regarded as an additional element that influences the credit returns for those firms. Suppose practitioners selected assets for their portfolios, considering the environmental, social, and governance (ESG) exposure of the companies they invested in. In that case, they could incorporate a considerable quantity of additional information that could lead to the production of alpha. Moreover, given the nature of the contingent claim for the debt and equity of the same capital structure, one would have expected the returns to move in the same direction; the contemporaneous correlation is expected to be positive and significant. Furthermore, the relationship between equity and credit returns should be stronger for firms with higher default probabilities (i.e., sub-investment grade credits), and the direction and magnitude of the popularity loadings or the coefficients indicate such.

Therefore, as demonstrated in the final paper, a measure of tail risk in credit markets is essential to understanding overall portfolio risk. ESG disclosure has emerged as an important consideration for evaluating investment decisions, cost of funding, and access to capital markets. This paper aimed to investigate the possible impact of composite ESG and its individual pillars' score on a tail risk of corporate credit. However, the need for more consistency in composite ESG scores originates from divergences in objectives, methodologies, and assessments. Scores could (and do) diverge because they relate to fundamentally different concepts, such as the measurement of the ESG impact or performance of a company versus the measurement of the financial materiality of ESG issues for a company.

4.4 Future Direction of Research

Further research would be based on simulating future market uncertainties and estimating portfolio values on each path. This approach should incorporate a simulation of fat-tail events with the probabilities embedded in the observable market variables (equity and other asset prices, yield and credit spread curves, etc.) and overlay that with ESG scores on each random path; this is necessary because, in reality, models break down when one is dealing with the tail of a distribution. Then, to construct the outcome distribution of portfolio risks, one must first understand the nature of fat tail behavior in the underlying drivers of risk. It is empirically known that most distributions of financial risk are fat-tailed. Yet for traceability, standard risk analysis such as the approach taken here approximates risks as usually or log-normally distributed. This works quite well under stable covariance assumptions. The problem arises in crisis times, when volatilities and correlations of observable market variables are very high, causing a much higher probability of extreme events. In such situations, approximating fat tails with normal or log-normal distributions makes it impossible to predict rare or unique events, such as changes in ESG scores, and analyze their impact on the overall performance, an essential task for any risk management process.

4.5 Appendix A

Table 4.1: Variance Inflation Factor for ESG and Individual Pillars

CDS Return	**ESG Score**		**Equity Return**	**ESG Score**	
Variable	VIF	1/VIF	Variable |	VIF	1/VIF
Market Volatility(VIX)	1.40	0.715309	VMarket Volatility(VIX)	1.40	0.715309
USLargeStockLevel	1.35	0.739106	USLargeStockLevel	1.35	0.739106
USTreasury5YearYield	1.13	0.882499	USTreasury5YearYield	1.13	0.882499
ESG_CScore	1.08	0.925489	ESG_CScore |	1.08	0.925489
DefaultProbability	1.07	0.938831	DefaultProbability	1.07	0.938831
Mean VIF	**1.21**		**Mean VIF**	**1.21**	
CDS Return	**E Score**		**Equity Return**	**E Score**	
Market Volatility(VIX)	1.40	0.715841	Market Volatility(VIX)	1.40	0.715841
USLargeStockLevel	1.35	0.741264	USLargeStockLevel	1.35	0.741264
USTreasury5YearYield	1.13	0.882243	USTreasury5YearYield	1.13	0.882243
E_Score	1.08	0.923256	E_Score	1.08	0.923256
DefaultPro~R |	1.07	0.930918	DefaultProbability	1.07	0.930918
Mean VIF |	**1.21**		**Mean VIF**	**1.21**	
CDS Return	**S Score**		**Equity Return**	**S Score**	
Market Volatility(VIX)	1.40	0.715633	Market Volatility(VIX)	1.40	0.715633
USLargeStockLevel	1.35	0.739597	USLargeStockLevel	1.35	0.739597
USTreasury5YearYield	1.13	0.882629	USTreasury5YearYield	1.13	0.882629
S_Score	1.08	0.928286	S_Score	1.08	0.928286
DefaultProbability	1.06	0.939741	DefaultProbability	1.06	0.939741
Mean VIF |	**1.20**		**Mean VIF**	**1.20**	
CDS Return	**G Score**		**Equity Return**	**G Score**	
Market Volatility(VIX)	1.40	0.716313	Market Volatility(VIX)	1.40	0.716313
USLargeStockLevel	1.34	0.747491	USLargeStockLevel	1.34	0.747491
USTreasury5YearYield	1.13	0.883139	USTreasury5YearYield	1.13	0.883139
DefaultProbability	1.02	0.976928	DefaultProbability	1.02	0.976928
G_Score	1.02	0.978793	G_Score	1.02	0.978793
Mean VIF	**1.18**		**Mean VIF**	**1.18**	

Bibliography

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

[2] Tobias Adrian, Richard K Crump, and Emanuel Moench. Regression-based estimation of dynamic asset pricing models. *Journal of Financial Economics*, 118(2):211–244, 2015.

[3] Rui Albuquerque, Yrjö Koskinen, and Chendi Zhang. Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10):4451–4469, 10 2019.

[4] Carol Alexander and Leonardo M Nogueira. Stochastic local volatility. *Available at SSRN 1107685*, 2008.

[5] Yakov Amihud and Haim Mendelson. Asset pricing and the bid-ask spread. *Journal of financial Economics*, 17(2):223–249, 1986.

[6] Yakov Amihud and Haim Mendelson. Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2):223–249, 12 1986.

[7] Eliana Angelini and Elisa Di Febo. CDS Spreads: an Empirical Analysis on the Determinants. Technical Report 2, 2014.

[8] Jan Annaert, Marc De Ceuster, Patrick Van Roy, and Cristina Vespro. What determines Euro area bank CDS spreads? *Journal of International Money and Finance*, 32:444–461, 2013.

[9] Armen Arakelyan and Pedro Serrano. Liquidity in credit default swap markets. *Journal of Multinational Financial Management*, 37:139–157, 2016.

[10] Patrick Augustin, Fahad Saleh, and Haohua Xu. CDS Returns. *Journal of Economic Dynamics and Control*, 118:103977, 9 2020.

[11] Lieven Baele, Geert Bekaert, and Koen Inghelbrecht. The determinants of stock and bond return comovements. *The Review of Financial Studies*, 23(6):2374–2428, 2010.

[12] Malcolm Baker and Jeffrey Wurgler. Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2):129–151, 2007.

[13] Rolf W Banz. THE RELATIONSHIP BETWEEN RETURN AND MARKET VALUE OF COMMON STOCKS*. Technical report.

[14] Brad M Barber, Adair Morse, and Ayako Yasuda. Impact investing. *Journal of Financial Economics*, 139(1):162–185, 2021.

[15] Florian Barth, Benjamin Hübel, Hendrik Scholz, Dirk Baur, Theodor Cojoianu, Ambrogio Dalò, Lammertjan Dam, Halit Gonenc, Andreas Hoepner, Julia Kapraun, Thomas Marta, Stefan Mittnick, Loriana Pelizzon, Aurélien Philippot, Auke Plantinga, Artem Prokhorov, Michael Rockinger, Stephen Schaefer, Bert Scholtens, Nassima Selmane, Andréanne Tremblay-Simard, Paul Smeets, Arjan Trinks, Gregor Weiß, and Wim Westerman. ESG and corporate credit spreads. Technical report.

[16] S Basu. American Finance Association Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios : A Test of the Efficient Market Hypothesis Author (s): S . Basu Source : The Journal of Finance , Vol . 32 , No . 3 (Jun ., 1977), pp . 66. *The Journal of Finance*, 32(3):663–682, 1977.

[17] George Batta. The direct relevance of accounting information for credit default swap pricing. *Journal of Business Finance & Accounting*, 38(9-10):1096–1122, 2011.

[18] Karoline Bax, Özge Sahin, Claudia Czado, and Sandra Paterlini. ESG, Risk, and (tail) dependence. *arXiv preprint arXiv:2105.07248*, 2021.

[19] Demir Bektić. Extending Fama-French Factors To Corporate Bond Markets. Technical report.

[20] Demir Bektić. Factor-based Portfolio Management with Corporate Bonds. Technical report, 2018.

[21] Demir Bektic, Josef-Stefan Wenzler, and Michael Wegener. Extending Fama-French Factors to Corporate Bond Markets . *Journal of Portfolio Management,*, 45(3):141–158, 2 2019.

[22] Christoph Benkert. Explaining credit default swap premia. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 24(1):71–92, 2004.

[23] Florian Berg, Julian Kölbel, and Roberto Rigobon. Aggregate Confusion: The Divergence of ESG Ratings. *SSRN Electronic Journal*, (617):1–64, 2019.

[24] Antje Berndt and Iulian Obreja. Decomposing European CDS Returns*. *Review of Finance*, 14(2):189–233, 4 2010.

[25] Andre Bertolotti. Effectively managing risks in an ESG portfolio. *Journal of risk management in financial institutions*, 13(3):202–211, 2020.

[26] Fischer Black and John C. Cox. VALUING CORPORATE SECURITIES: SOME EFFECTS OF BOND INDENTURE PROVISIONS. *The Journal of Finance*, 31(2):351–367, 1976.

[27] Fischer Black and Myron Scholes. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, 81(3):637–654, 5 1973.

[28] ROBERTO BLANCO, SIMON BRENNAN, and I A N W MARSH. An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. *The Journal of Finance*, 60(5):2255–2281, 2005.

[29] David Blitz. Factor Investing: The Best Is Yet to Come. *The Journal of Portfolio Management*, 49(2):10–18, 2023.

[30] Dion Bongaerts, Frank De Jong, and Joost Driessen. Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. *The Journal of Finance*, 66(1):203–240, 2011.

[31] JACOB BOUDOUKH, MATTHEW RICHARDSON, and ROBERT F WHITELAW. Industry Returns and the Fisher Effect. *The Journal of Finance*, 49(5):1595–1615, 12 1994.

[32] Bastian Breitenfellner and Niklas Wagner. Explaining aggregate credit default swap spreads. *International Review of Financial Analysis*, 22:18–29, 2012.

[33] Tom J Brown and Peter A Dacin. The company and the product: Corporate associations and consumer product responses. *Journal of marketing*, 61(1):68–84, 1997.

[34] Bonnie Buchanan, Cathy Xuying Cao, and Chongyang Chen. Corporate social responsibility, firm value, and influential institutional ownership. *Journal of Corporate Finance*, 52:73–95, 2018.

[35] John Y Campbell. Asset Pricing at the Millennium. *The Journal of Finance*, 55(4):1515–1567, 8 2000.

[36] John Y Campbell and John Ammer. What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns. *The Journal of Finance*, 48(1):3–37, 1993.

[37] John Y Campbell, Jens Hilscher, and Jan Szilagyi. In search of distress risk. *The Journal of finance*, 63(6):2899–2939, 2008.

[38] John Y Campbell, Adi Sunderam, and Luis M Viceira. Inflation Bets or Deflation Hedges? The Changing Risks of Nominal Bonds. *National Bureau of Economic Research Working Paper Series*, No. 14701, 2009.

[39] John Y. Campbell and Glen B. Taksler. Equity Volatility and Corporate Bond Yields. *The Journal of Finance*, 58(6):2321–2350, 12 2003.

[40] VINCENZO CAPIZZI, ELEONORA GIOIA, GIANCARLO GIUDICI, and FRANCESCA TENCA. THE DIVERGENCE OF ESG RATINGS: AN ANALYSIS OF ITALIAN LISTED COMPANIES. *Journal of Financial Management, Markets and Institutions*, 09(02):2150006, 2021.

[41] Bruce I Carlin, Francis A Longstaff, Kyle Matoba, Karen Chaltikian, Anna Cieslak, Andrea Eisfeldt, Mark Grinblatt, Chris Hrdlicka, Terry Nercessian, Praveen Kumar, Hanno Lustig, Jeff Pontiff, Mike Rierson, Jules Van Binsbergen, Jialin Yu, Francis Longstaff, and Asset Prices. NBER WORKING PAPER SERIES DISAGREEMENT AND ASSET PRICES We would like to thank. Technical report, 2012.

[42] Roy Cerqueti, Rocco Ciciretti, Ambrogio Dalò, and Marco Nicolosi. ESG investing: A chance to reduce systemic risk. *Journal of Financial Stability*, 54:100887, 2021.

[43] Long Chen, Pierre Collin-Dufresne, and Robert S Goldstein. On the relation between the credit spread puzzle and the equity premium puzzle. *The Review of Financial Studies*, 22(9):3367–3409, 2009.

[44] Long Chen, David A Lesmond, and Jason Wei. Corporate yield spreads and bond liquidity. *The journal of finance*, 62(1):119–149, 2007.

[45] Nai-Fu Chen, Richard Roll, and Stephen Ross. Economic Forces and the Stock Market. *The Journal of Business*, 59(3):383–403, 1986.

[46] Darwin Choi, Zhenyu Gao, and Wenxi Jiang. Attention to global warming. *Review of Financial Studies*, 33(3):1112–1145, 3 2020.

[47] Rohan Churm and Nikolaos Panigirtzoglou. Decomposing credit spreads. *Available at SSRN 724043*, 2005.

[48] Andrew D. Clare, Aneel Keswani, and Nicholas E. Motson. The Case for Integrating ESG into Fixed Income Portfolios. *SSRN Electronic Journal*, pages 1–35, 2022.

[49] Pierre Collin-Dufresn, Robert S. Goldstein, and J. Spencer Martin. The Determinants of Credit Spread Changes. *The Journal of Finance*, 56(6):2177–2207, 12 2001.

[50] Pierre Collin-Dufresne, Robert S. Goldstein, and J. Spencer Martin. The determinants of credit spread changes. *Journal of Finance*, 56(6):2177–2207, 2001.

[51] Lisette Cooper, Jeremy Evnine, Jeff Finkelman, Kate Huntington, and D Lynch. Social Finance and the Postmodern Portfolio: Theory and Practice. *The Journal of Wealth Management*, 18:21 – 9, 2016.

[52] Peter J Crosbie and Jeffrey R Bohn. Modeling Default Risk. *World Scientific Reference on Contingent Claims Analysis in Corporate Finance*, 2019.

[53] Kent Daniel and Sheridan Titman. Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance*, 52(1):1–33, 1997.

[54] Sanjiv R Das, Paul Hanouna, and Atulya Sarin. Accounting-based versus market-based cross-sectional models of CDS spreads. *Journal of Banking & Finance*, 33(4):719–730, 2009.

[55] Frank De Jong and Joost Driessen. Liquidity risk premia in corporate bond markets. *Available at SSRN 686681*, 2006.

[56] Amer Demirovic, Ali Kabiri, David Tuckett, and Rickard Nyman. A common risk factor and the correlation between equity and corporate bond returns. *Journal of Asset Management*, 21(2):119–134, 3 2020.

[57] Douglas W Diamond and Robert E Verrecchia. Information aggregation in a noisy rational expectations economy. *Journal of Financial Economics*, 9(3):221–235, 1981.

[58] Gregor Dorfleitner, Gerhard Halbritter, and Mai Nguyen. Measuring the level and risk of corporate responsibility–An empirical comparison of different ESG rating approaches. *Journal of Asset Management*, 16(7):450–466, 2015.

[59] Jefferson Duarte, Francis A Longstaff, and Fan Yu. Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller? *The Review of Financial Studies*, 20(3):769–811, 5 2007.

[60] Gregory R. Duffee. The Relation Between Treasury Yields and Corporate Bond Yield Spreads. *The Journal of Finance*, 53(6):2225–2241, 12 1998.

[61] Darrell Duffie and Kenneth J Singleton. Modeling Term Structures of Defaultable Bonds. *The Review of Financial Studies*, 12(4):687–720, 1999.

[62] Markus Eberhardt. Estimating panel time-series models with heterogeneous slopes. Technical Report 1, 2012.

[63] Edwin J Elton, Martin J Gruber, Deepak Agrawal, and Christopher Mann. Explaining the Rate Spread on Corporate Bonds. *The Journal of Finance*, 56(1):247–277, 2001.

[64] Jan Ericsson, Kris Jacobs, and Rodolfo Oviedo. The Determinants of Credit Default Swap Premia. *Journal of Financial and Quantitative Analysis*, 44(1):109–132, 2 2009.

[65] Jan Ericsson, Joel Reneby, and Hao Wang. Can structural models price default risk? Evidence from bond and credit derivative markets. *Quarterly Journal of Finance*, 5(03):1550007, 2015.

[66] Eugene F Fama and Kenneth R French. The Cross-Section of Expected Stock Returns. Technical Report 2, 1992.

[67] Eugene F. Fama and Kenneth R. French. Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83(3):667–689, 3 2007.

[68] Eugene F Fama and G.William Schwert. Asset returns and inflation. *Journal of Financial Economics*, 5(2):115–146, 1977.

[69] Andrea Frazzini and Lasse Heje Pedersen. Betting against beta. *Journal of financial economics*, 111(1):1–25, 2014.

[70] Henry L. Friedman and Mirko S. Heinle. Taste, information, and asset prices: implications for the valuation of CSR. *Review of Accounting Studies*, 21(3):740–767, 9 2016.

[71] Koresh Galil, Offer Moshe Shapir, Dan Amiram, and Uri Ben-Zion. The determinants of CDS spreads. *Journal of Banking & Finance*, 41:271–282, 2014.

[72] Koresh Galil, Offer Moshe Shapir, and Uri Ben-zion. CDS spreads and spread change determinants : A firm-specific and market-factors study. pages 1–32, 2012.

[73] Nicolae Gârleanu and Lasse Heje Pedersen. Margin-based Asset Pricing and Deviations from the Law of One Price. *The Review of Financial Studies*, 24(6):1980–2022, 6 2011.

[74] Christopher Geczy, Robert F Stambaugh, and David Levin. Investing in socially responsible mutual funds. *Available at SSRN 416380*, 2005.

[75] R Gibson, P Krueger, and P Schmidt. ESG Rating Disagreement and Stock Returns (Working paper). 2020.

[76] Guido Giese, Linda-Eling Lee, Dimitris Melas, Zoltán Nagy, and Laura Nishikawa. Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance. Technical Report 5, 2019.

[77] Sanford J Grossman and Joseph E Stiglitz. On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, 70(3):393–408, 1980.

[78] Samuel M. Hartzmark and Abigail B. Sussman. Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows. *Journal of Finance*, 74(6):2789–2837, 12 2019.

[79] Feng He, Zhifeng Liu, and Sicen Chen. Industries return and volatility spillover in Chinese stock market: An early warning signal of systemic risk. *IEEE Access*, 7:9046–9056, 2018.

[80] Witold J Henisz and James McGlinch. ESG, Material Credit Events, and Credit Risk. *Journal of Applied Corporate Finance*, 31(2):105–117, 2019.

[81] Hans-Martin Henke. The effect of social screening on bond mutual fund performance. *Journal of Banking & Finance*, 67:69–84, 2016.

[82] Jens Hilscher, Robert Alan Jarrow, Donald Robert, Van Deventer, Robert A Jarrow, and Donald R Van Deventer. The Valuation of Corporate Coupon Bonds * Risk Management and Performance Measurement of Financial Institutions View project Credit Default Market Volume Studies View project The Valuation of Corporate Coupon Bonds *. Technical report.

[83] Andreas G F Hoepner and Joeri Rogelj. Emissions estimations should embed a precautionary principle. *Nature Climate Change*, 11(8):638–640, 2021.

[84] Kewei Hou, Chen Xue, and Lu Zhang. Replicating anomalies. *The Review of financial studies*, 33(5):2019–2133, 2020.

[85] Jing-Zhi Huang and Ming Huang. How Much of Corporate-Treasury Yield Spread Is Due to Credit Risk?: A New Calibration Approach. *SSRN Electronic Journal*, 5 2003.

[86] John C Hull and Alan D White. Valuing Credit Default Swaps I. *The Journal of Derivatives*, 8(1):29, 8 2000.

[87] Roger G. Ibbotson, Jeffrey J. Diermeier, and Laurence B. Siegel. The Demand for Capital Market Returns: A New Equilibrium Theory. *Financial Analysts Journal*, 40(1):22–33, 1 1984.

[88] Roger G Ibbotson and Thomas M Idzorek. Dimensions of popularity. *The Journal of Portfolio Management*, 40(5):68–74, 2014.

[89] Roger G. Ibbotson, Thomas M. Idzorek, and Paul D. Kaplan. *Popularity : bridge between classical and behavioral finance.*

[90] Roger G Ibbotson, Thomas M Idzorek, Paul D Kaplan, and James X Xiong. Popularity: A Bridge between Classical and Behavioral Finance. *Behavioral & Experimental Finance (Editor's Choice) eJournal*, 2018.

[91] Roger G Ibbotson and Rex A Sinquefield. Stocks, Bonds, Bills, and Inflation: Year-by-Year Historical Returns (1926-1974). *The Journal of Business*, 49(1):11–47, 1976.

[92] Roger G Ibbotson and Rex A Sinquefield. Stocks, Bonds, Bills and Inflation: Updates. *Financial Analysts Journal*, 35(4):40–44, 1979.

[93] Thomas M Idzorek and Roger G Ibbotson. Popularity and Asset Pricing. *The Journal of Investing*, 26(1):46–56, 2017.

[94] Thomas M.' 'Idzorek, Paul D.' 'Kaplan, and Roger G. ' 'Ibbotson. The CAPM, APT, and PAPM. 9 2023.

[95] Thomas M Idzorek, Paul D Kaplan, and Roger G Ibbotson. The popularity asset pricing model. *Available at SSRN 3451554*, 2021.

[96] Thomas M Idzorek, Paul D Kaplan, and Roger G Ibbotson. The popularity asset pricing model. *Available at SSRN 3451554*, 2021.

[97] Felix Irresberger, Gregor N.F. Weiß, Janet Gabrysch, and Sandra Gabrysch. Liquidity tail risk and credit default swap spreads. *European Journal of Operational Research*, 269(3):1137–1153, 9 2018.

[98] Robert Jarrow, David Lando, and Stuart M Turnbull. A Markov Model for the Term Structure of Credit Risk Spreads. *Review of Financial Studies*, 10(2):481–523, 1997.

[99] Philippe Jorion. *Value at risk: the new benchmark for managing financial risk.* McGraw-Hill, 2007.

[100] Daniel Kahneman and Amos Tversky. Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making: Part I*, pages 99–127. World Scientific, 2013.

[101] Bryan T Kelly, Gerardo Manzo, and Diogo Palhares. Credit-implied volatility. *Available at SSRN 2576292*, 2019.

[102] Ralph S J Koijen, Hanno Lustig, and Stijn Van Nieuwerburgh. The cross-section and time series of stock and bond returns. *Journal of Monetary Economics*, 88:50–69, 2017.

[103] Josef Lakonishok, Andrei Shleifer, and Robert W Vishny. Contrarian Investment, Extrapolation, and Risk. Technical Report 5, 1994.

[104] Hayne E Leland. Corporate Debt Value, Bond Covenants, and Optimal Capital Structure. *The Journal of Finance*, 49(4):1213–1252, 1994.

[105] David A Lesmond, Joseph P Ogden, and Charles A Trzcinka. A New Estimate of Transaction Costs. *The Review of Financial Studies*, 12(5):1113–1141, 10 1999.

[106] Clothilde Lesplingart, Christophe Majois, and Mikael Petitjean. Liquidity and CDS premiums on European companies around the Subprime crisis. *Review of Derivatives Research*, 15(3):257–281, 2012.

[107] John Lintner. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. Technical Report 1, 1965.

[108] FRANCIS A. LONGSTAFF, SANJAY MITHAL, and ERIC NEIS. Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *The Journal of Finance*, 60(5):2213–2253, 10 2005.

[109] FRANCIS A. LONGSTAFF and EDUARDO S. SCHWARTZ. A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *The Journal of Finance*, 50(3):789–819, 7 1995.

[110] Francis Longstaff Sanjay Mithal Eric Neis, Dennis Adler, Warren Bailey, Sanjiv Das, Darrell Duffie, Joseph Langsam, Jun Liu, Jun Pan, Eduardo Schwartz, Jure Skarabot, Soetojo Tanudjaja, Francis Longstaff, Sanjay Mithal, Eric Neis, Francis A Longstaff, and Sanjay Mithal Deutsche Bank Eric Neis. Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default Swap Market. Technical report, 2004.

[111] Robert E Lucas. Expectations and the neutrality of money. *Journal of Economic Theory*, 4(2):103–124, 1972.

[112] Xueming Luo and Chitra Bhanu Bhattacharya. Corporate social responsibility, customer satisfaction, and market value. *Journal of marketing*, 70(4):1–18, 2006.

[113] Harry Markowitz. PORTFOLIO SELECTION*. *The Journal of Finance*, 7(1):77–91, 3 1952.

[114] Rajnish Mehra. The Equity Premium: Why Is It a Puzzle? *Financial Analysts Journal*, 59(1):54–69, 2003.

[115] Rohit Mendiratta, Hitendra D Varsani, and Guido Giese. How ESG Affected Corporate Credit Risk and Performance. *The Journal of Impact and ESG Investing*, 2(2):101–116, 2021.

[116] R. C Merton. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance*, 29:449–470, 1974.

[117] Robert C. Merton. ON THE PRICING OF CORPORATE DEBT: THE RISK STRUCTURE OF INTEREST RATES*. *The Journal of Finance*, 29(2):449–470, 5 1974.

[118] Martin Oehmke and Adam Zawadowski. The anatomy of the CDS market. *The Review of Financial Studies*, 30(1):80–119, 2017.

[119] Eugene Okyere-yeboah. Empirical Studies of ESG Scores with Corporate Credit Spreads. 2022.

[120] Eugene' 'Okyere-Yeboah. *Empirical studies of ESG scores with corporate credit spreads (Insights from popularity-based pricing)*. PhD thesis, Jack Welch College of Business & Technology dissertation, Sacred Heart University, Fairfield CT, 10 2022.

[121] José Augusto Palhares. Centralidades e periferias nos quotidianos escolares e não-escolares de jovens distinguidos na escola pública. *Investigar em Educação*, 2(1), 2014.

[122] Lubos Pastor, Robert F. Stambaugh, and Lucian A. Taylor. Dissecting Green Returns. *SSRN Electronic Journal*, 2021.

[123] Lasse Heje Pedersen, Shaun Fitzgibbons, and Lukasz Pomorski. Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 2020.

[124] Lasse Heje Pedersen, Shaun Fitzgibbons, and Lukasz Pomorski. Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 142(2):572–597, 2021.

[125] John Pereira, Ghulam Sorwar, and Mohamed Nurullah. What drives corporate CDS spreads? A comparison across US, UK and EU firms. *Journal of International Financial Markets, Institutions and Money*, 56:188–200, 2018.

[126] Stephen A Ross. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341–360, 1976.

[127] Natalia Semenova and Lars G Hassel. On the validity of environmental performance metrics. *Journal of Business Ethics*, 132(2):249–258, 2015.

[128] Partha Sengupta. Corporate disclosure quality and the cost of debt. *Accounting review*, pages 459–474, 1998.

[129] William F. Sharpe. CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK. *The Journal of Finance*, 19(3):425–442, 1964.

[130] William F Sharpe. Journal of Finance. 1964.

[131] Hersh Shefrin and Meir Statman. Behavioral capital asset pricing theory. *Journal of financial and quantitative analysis*, 29(3):323–349, 1994.

[132] Hersh Shefrin and Meir Statman. Behavioral portfolio theory. *Journal of financial and quantitative analysis*, 35(2):127–151, 2000.

[133] Dragon Yongjun Tang and Hong Yan. Liquidity and Credit Default Swap Spreads. *SSRN Electronic Journal*, 2007.

[134] David J. Teece, Gary Pisano, and Amy Shuen. Dynamic capabilities and strategic management. *Knowledge and Strategy*, 18(March):77–116, 2009.

[135] Maria Vassalou and Yuhang Xing. Default Risk in Equity Returns. *Journal of Finance*, 59(2):831–868, 4 2004.

[136] Tim Verheyden, Robert G Eccles, and Andreas Feiner. ESG for all? The impact of ESG screening on return, risk, and diversification. *Journal of Applied Corporate Finance*, 28(2):47–55, 2016.

[137] Olivier David Zerbib. A Sustainable Capital Asset Pricing Model (S-CAPM): Evidence from Green Investing and Sin Stock Exclusion. *Econometric Modeling: Capital Markets - Asset Pricing eJournal*, 2020.

[138] Benjamin Yi-Bin Zhang, Hao Zhou, and Haibin Zhu. Explaining Credit Default Swap Spreads With the Equity Volatility and Jump Risks of Individual Firms. *SSRN Electronic Journal*, 2008.