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Empirical Studies of ESG Scores with Corporate Credit Spreads

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JACK WELCH COLLEGE
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Empirical Studies of ESG Scores with Corporate Credit Spreads

(Insights from popularity-based pricing)

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Abstract

This study examines various factors or characteristics (risk and non-risk) that determine a firm's credit risk premium, as measured by its credit default swap (CDS) spread, with a particular focus on the impact of environment, social, and governance (ESG) scores.

The framework employed is a general equilibrium asset pricing model which integrates classical and behavioral finance elements, known as popularity-based asset pricing. It treats all attributes or characteristics of an asset as "factors" to which investors assign a degree of popularity, which changes over time. Non-risk characteristics are classified as "tastes" or "disagreements", Fama French (2007). Firms' degree of adherence to ESG practices is treated as one of these factors, looking at data over a decade period (2010-2021) of US corporate credits. In the popularity-based framework, investors have divergent beliefs about expected returns, and a variety of risk and non-risk preferences, such as liquidity or ESG. The popularity of ESG awareness among investors is treated as a preference rather than an economic risk factor exposure.

The main results from this analysis are that, for the entire universe of US corporate credit market, both investment-grade and high-yield (sub-investment grade), the conclusion is that ESG, as a preference, is not significant in terms of the long-term credit risk protection spread levels for the entire universe, as well as investment-grade credit, but for sub-investment grade credits, that is not the case. These results indicate that a well-established and mature firm with a strong ESG consciousness and policy orientation may attract ESG-conscious investors, and these investors may be willing to pay a premium for the ESG benefits due to their popularity, leading to tighter CDS spreads or in other words ESG disclosure is negatively related to the credit default swap spread, which suggests that firms with a higher ESG disclosure have lower default risk. These results are essential for all firms' stakeholders, and bondholders, to consider the firm's ESG disclosure in conjunction with the life cycle stage before making their investment decisions.

Dedication

To Mr. Harry Okyere-Yeboah, Esq., my younger brother, who was my psychological twin. He passed away at a young age without the opportunity to make a tremendous impact in this world, given his compassionate disposition and intellectual prowess. To my mother, Mrs. Comfort Okyere-Yeboah, a true woman of substance, and a pillar of strength, and my father, Mr. Joseph Okyere-Yeboah, the definition of a gentleman and my benchmark in all walks of life; I am sure you're looking from the heavens with tremendous pride and joy. I thank you for making me who I am.

And more importantly, to my wife, Muriel, and our children, Alistair and Eleanor: my shining lights whenever the going gets tough.

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Finally, but not least, I wish to extend my most profound appreciation to my friend and mentor, Dr. Con Keating, for taking the time to peruse the drafts. Over the years, he has helped shape my ideas about the capital market and its linkage to global society. And I enormously appreciate the helpful comments and suggestions from Dr. Khawaja Mamun of Sacred Heart University, Welch College of Business & Technology

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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
ESG	Environmental, Social and Governance
E	Environmental
S	Social
G	Governance
CGM	Collin-Dufresne, Goldstein Martin
EJO	Ericsson, Jacobs and Ovied
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**
sIG	**sub-Investment Grade**
t-stat	**t-statistic**
UN	**United Nations**
USD	**U.S. Dollar**
U.S.	**United States of America**
VIX	**Volatility index**
Vol.	**Volatility**

Chapter 1

Introduction

Perhaps one of the most significant controversies among financial economists is that between classical and behavioral finance. This thesis applies a framework that integrates the two schools of thought. On the classical side, the key determinant of return is the risk factor exposure; Fama and French (1992)[12] are probably most well-known among practitioners, where risk factors are used as explanatory variable to help explain investment returns that are not well-explained by the market factor of the Capital Asset Pricing Model or CAPM (Sharpe, 1964, Lintner, 1965, Treynor, 1962, and Mossin, 1966). While the CAPM is literally the textbook equilibrium approach of the last 50 years and a key element of every finance curriculum; numerous papers have been written on the CAPM's shortcomings (e.g., Basu, 1977; Banz, 1981; Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). Despite these shortcomings, the usage of Fama-French 3-factor model and its various extensions is prevalent among practitioners; yet importantly, these multi-factor models are not asset pricing models, rather, they are models for analyzing realized returns. On the behavioral side, where asset pricing focuses on the way investor psychology can create gaps between the market prices of securities and their corresponding fundamental values and incorporates the fact that heterogeneity is a fact of life, and people are different in the way they form judgments. Whichever story you subscribe to, classical or behavioral—and both could apply—the market is very complex. It contains far more securities than can be practical to analyze individually. To reduce the units of analysis to a manageable number, researchers and investment managers have compressed securities and their attributes or characteristics into factors. The framework being introduced here is the popularity-based pricing, which allows us to integrate the two schools of thought by helping investors to interpret that characteristics or factors associated with assets through expressing their popularity.

Popularity is a phrase first coined by Roger Ibbotson and Thomas Idzorek in 2014 in their article "Dimensions of Popularity." They describe it as another word for demand, and that different securities contain more favorable characteristics toward investors. This is a relatively new financial theory, and many have come before it. However, the idea that the popularity of an asset affects its pricing, and ultimately its return is not new but is often overlooked in the mathematics of asset pricing models. It is important not to think of popularity as a factor in itself, but as a framework for understanding and predicting factors. Investors regard these factors or characteristics as positive or negative costs, and evaluate expected returns net of these costs. The popularity-based pricing framework applies to all assets—including stocks and bonds, real estate, venture capital, durables, and intangibles such as human capital—and incorporates all asset characteristics.

In this thesis, the corporate bond is the asset of interest here. According to the Securities Industry and Financial Markets Association, the bond market is large, with more than $15 trillion outstanding in the USA alone at the end of the last quarter of 2021. As such, what drives corporate bond prices and returns is an essential question. Many factors drive corporate bond prices, but its credit risk dominates it. However, this risk can be isolated and traded separately as a credit default swap. The popularity-based framework is used to examine whether the popularity of ESG impacts the prices of the credit risk in the form of CDS spreads.

1.1 Introducing popularity-based pricing - PAPM

The Capital Asset Pricing Model (CAPM) was developed over half century ago. Despite the distinction of the theory, subsequent empirical research has mostly failed to confirm it. Perhaps its biggest strength, expressing investor preferences solely in terms of risk, is its limitation. Because in practice, investors care about many characteristics that have little to do with risk. These include liquidity, taxability, scalability, divisibility, controllability, transparency, and the components of sustainability, namely environmental, social, and governance factors. Including these characteristics may even be the way to resurrect the CAPM.

This section of the thesis addresses non-risk characteristics in a CAPM like framework based on the concept of popularity introduced by Ibbotson and Idzorek (2014)[**?**] with an equilibrium model is referred to as the Popularity Asset Pricing Model, or PAPM for short.

Motivated in part by the shortcomings of the CAPM, in an academic article that is not well-known amongst practitioners called "Disagreement, Tastes, and Asset Prices," Fama and Fench (2007)[11] identifies 'disagreement' and 'tastes' as two key ingredients missing from the CAPM that should impact asset prices. Disagreement refers to heterogeneous expectations. Tastes refer to investor preferences beyond risk-tolerance. Even though Fama and French (2007) (hence force "FF") identifies two important ways to make the CAPM more realistic, FF stopped short of developing an equilibrium asset pricing model that incorporates these improvements. The Popularity Asset Pricing Model or PAPM adds to the literature by incorporating both disagreement and tastes into a intuitive, equilibrium asset pricing model that is a generalized less restrictive version of the practitioner friendly CAPM. Disagreement and especially tastes are directly related to environmental, social, and governance (ESG) investing, which has spawned a variety of recent papers that put forth specialty asset pricing models that incorporate ESG, such as Baker et al. (2020), Pástor, Stambaugh, and Taylor (2020), Pedersen, Fitzgibbon, and Pomorski (2020), and Zerbib (2020). Of course investors care about a variety of characteristics beyond ESG, such as liquidity, income returns, taxes, faith-based values, etc. The PAPM is the generalized asset pricing model that encompasses the CAPM and these new ESG-specific models, allowing for any number of asset characteristics and a wide range of investors with different expectations and tastes. The CAPM and the FF-inspired PAPM are equilibrium asset pricing models in which prices are determined partly by investor preferences or demand for various security characteristics. In contrast, Ross's Arbitrage Pricing Theory (APT) (1976) posits that the economy supplies returns in a multi-factor linear structure. Since these risk factors are systematic, arbitrage does not eliminate them, and each factor is priced in an isolated long/short portfolio. The APT provides no theory of the factors, leaving it to empiricists to identify the factor structure that the economy provides. The PAPM and the APT result in a linear structure of expected returns. However, the PAPM helps identify the linear structure since we start with some idea as to what characteristics investors in aggregate like (liquidity, ESG, brands, etc.) or dislike (market risk, negative asymmetry, etc.). Importantly, unlike the APT factors, the PAPM characteristics do not have to be risk related, just liked or disliked by enough investors. Furthermore, in the PAPM equilibrium, preferences are aggregated across all investors, and mispricing can and likely does occur as investor expectations (who disagree) are also aggregated.

Popularity builds on classical finance and the NET, stating that investors prefer lower risk and frictional costs for their assets. It also includes aspects of behavioral finance, such as different characteristics and anomalies that investors prefer and are therefore Popular. For example, while risk is Unpopular, liquidity is Popular (Ibbotson and Idzorek 2014). Popularity can also help explain temporary market mispricings. The general thesis of this model is that the less Popular a security is (based on these characteristics/anomalies), the lower the expected price, resulting in a higher expected return

While PAPM is theoretical in nature just like the CAPM, there are number of practical takeaways that practitioners will find helpful and intuitive when thinking about both asset prices and portfolio construction. First, all practitioners intuitively know that the market is not perfectly efficient (even if the market is hard to beat). With the PAPM, both disagreement and tastes individually and collectively lead to asset prices that differ from those of the CAPM; thus, the market is not efficient. If the market is not perfectly efficient, portfolio construction is more complicated than simply levering / delivering the market portfolio. In fact, portfolio construction under the CAPM and PAPM are very different. With the CAPM everyone should hold a portion of their wealth in the same market portfolio and portfolio optimization is unnecessary, while with the PAPM, portfolio optimization is necessary with investors arriving at personalized portfolios. In terms of thinking about asset prices, if enough investors simultaneously like or dislike a given characteristics, it will impact asset prices. More specifically, investments with liked characteristics are in high demand (popular) and thus more expensive, with lower expected returns. Conversely, investment with disliked characteristic are in low demand (unpopular) and thus less expensive, with higher expected returns. Finally, if aggregate tastes are changing, such as more investors are seeking investments with good ESG characteristics, changes in aggregate tastes can cause investments with liked characteristics to temporarily have better returns during periods of changing tastes.

Table 1.1: Potential Explanations of Premiums and Anomalies

Characteristic	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
Duration	Depends. (LDI investors love duration).	Mixed predictions.	Pecuniary
Liquidity	Higher is liked.	High liquidity; higher price.	Either
Marketability/ Divisibility	Higher divisibility is liked.	Higher divisibility; higher price.	Pecuniary
Nominal vs. Real Inflation Protection)	Investors like inflation protection.	High inflation protection; higher price.	Pecuniary
Callable	Investors dislike callability	Callable; lower price	Pecuniary
Issuer Brand / Reputation	Investors like issues with a good brand/ reputation	Better Brand / Reputation; higher price.	Pecuniary
Issuer ESG Score	**Investor like stronger ESG issuers.**	**Better ESGness; higher price.**	**Either**
Currency	Home Country.		

source: EOY

Table 1.1 lists various premiums, anomalies, and characteristics that have been empirically related to security returns and attempts to associate them primarily with disagreement are likely to be temporary, given that misinformed investors should eventually learn. Although the PAPM offers an explanation for the anomalies listed in Table 1 (while the CAPM does not), the CAPM and PAPM are not at odds with one another. Rather, the PAPM expands and generalizes the CAPM as well as recent ESG asset pricing models. More specifically, the CAPM assumes that only risk is unpopular, and ignores all other security characteristics, while many of the ESG models allow for just a single ESG characteristic. In the PAPM, multiple characteristics can have a price premium (or discount), as long as the characteristics are generally popular (or unpopular).

1.2 Theoretical Determinants of Credit Spreads

The spread of a CDS is the annual amount which the protection buyer must pay the protection seller over the length of the contract, expressed as a percentage of the notional amount. CDS spreads and the probability of default of the reference entity are connected by a relation of direct proportion. Greater is the probability of default of the issuer and therefore, the probability of a credit event agreed in contractual session, higher is the premium the protection seller will request to accept the credit risk. Therefore, on first approximation, CDS prices reflect the expectations of the default probability of the reference entity; in other words, it can be assumed that CDS prices are equal to the implied risk-neutral probability of default(PD) with a given recovery rate (RR), and S is the flat CDS spread. A common way to model the default probability is by the hazard rate (default intensity).From Hull[1], section 23.4 which the author defines λ, the default intensity as,

$$\lambda(t) = \frac{S(t)}{1 - RR} \tag{1.1}$$

This associated with the default probability by

$$PD(t, t + h) = \lambda(t)h + o(h) \tag{1.2}$$

with PD(t, t+h) the probability of a default occurring between t and t+h. Therefore:

$$PD(0,T) = \int_0^T (1 - PD(0,T))P(t, t + dt) = \int_0^T \lambda(t)(1 - PD(0,T))dt \tag{1.3}$$

where the first term of the integral is "default has not occurred so far" and the second is "default occurs on the next time step". This means that P satisfies:

$$\frac{dPD(0,t)}{dt} = \lambda(t)(1 - PD(0,t)) \tag{1.4}$$

If the CDS spread is assumed to be constant, then λ is constant and a solution would be:

$$PD(0,t) = 1 - \exp\left(\frac{-St}{1 - RR}\right) \tag{1.5}$$

Equivalently solution for the CDS is:

$$S = \frac{RR - 1}{t}\log(1 - PD(0,t)) \tag{1.6}$$

CDS prices also include an element connected to the credit risk premium, namely the compensation paid to investors for enduring exposure to default risk. Spread is therefore technically the compensation for the expected loss, adjusted to reflect a proportion of

[1] Option Futures and Other Derivatives

the price of the default risk. This price may be interpreted as compensation per unit of expected loss, and it is an indicator of default risk aversion for investors. It is worthwhile noting that this compensation is a premium for the default risk aversion without any mention of non-risk premium. This premium is a subjective factor related to the level of risk aversion among the investors and factors related to the volatility level of variables in the market, which may affect the probability of default. The risk premium may vary over time, since it can change the risk aversion of the participants, who will request, for the same risk loss, a higher risk premium. In theory, there are two distinct types of default risk which may require a premium. The CDS spread of prices reflect many factors, including the expected probability of default, the recovery rate in case of default, and the risk premium for the volatility of the factors describing the probability of default.

Furthermore, CDS spreads reflect the market participants' view of both probability of default and an assumption about the recovery - what the defaulted debt would be worth after the default. The recovery assumption grows more important as the CDS spread widens, and the perceived probability of default increases. CDS spread is not the same as probability of default because one also needs a recovery assumption to convert between CDS spread and probability of default.

There are two different approaches on risk credit have been identified in the literature: the reduced-form models[2] and the structural approach models[3]. The reduced-form models or intensity-based models are a relatively recent approach to credit risk. The paper focuses on the structural approach models, specifically Merton(1974)[16]. The regression variables of the proposed model use the major inputs of the Merton(1974)[16] model framework and focus on the following firm-specific variables for the regression; Stock return, Volatility (stock volatility), Leverage, and Liquidity (or a proxy). The eventual regression model would then introduce market factors such as Spot rate, Term-structure slope, Market condition, Market volatility (VIX). See Chapter 3 for more details.

1.3 Theoretical Model Proposed

There are numerous studies aimed at analyzing credit spreads determinants, including ESG as a factor. Barth et al. (2019)[3] examine the determinants of CDS spreads and the

[2] The reduced-form models or intensity-based model are originally introduced by Jarrow and Turnbull(1992)[15]

[3] Structural models originated with Black and Scholes (1973)[4], Merton(1974)[16]

impact of incorporating ESG scores. Zhang et al. (2005)[17] examine the determinants of CDS spreads. They are concentrated on the effects of the volatility in firms value and of the jump-to-default risk using variables such as ROE, leverage, dividend payout ratio or macro-financial variables, such as the inclination of the yield curve, etc. Avramov et al. (2007) analyzes the ability of the structural models to explain the variations in the credit risk using a set of common factors and company-level fundamentals. In particular, the variables used are interest rate, inclination of the rate curve, stock market yield, leverage and the related volatilities. In this paper, the objective is to adopt a similar model to account for the risk factors that mostly impact the CDS spreads; the residuals would then be treated as the non-risk factor(s), or the behavioral components (preference or taste) as the premium, either positively or negatively.

In this framework, CDS spread is the major contributor of CDS returns. And there are many factors other than default probabilities, in addition to this this major risk factor, and among others, this paper treats ESG as a non risk factor which investor can express *like* or *dislike* . This expression is not systematic in nature.

I use a linear regression version of the PAPM in this paper. The characteristics that get priced must have a rationale, i.e., they are either systematically liked or disliked. The PAPM is an equilibrium model reflecting the underlying preferences of the market. The derivation of the PAPM framework can be found in Popularity: A Bridge Between Classical and Behavioral Research. CFA Institute Research Foundation.[[14]] . Since we already have a good idea of what investors like or dislike in the bond market, I can use the PAPM to test the various drivers of spreads and returns. The PAPM is a multifactor linear asset pricing formula in which an asset's expected return is related to various exposures to various dimensions of popularity. A regression formulation for the PAPM is shown

$$\textit{Expected Return}_{\,jt} = \textit{RiskFreeRate}_{\,t} + \sum_{k}^{n} \beta_{jk}\ \textit{Premium}_{\,jt} \tag{1.7}$$

where *RiskFreeRate* is the term structure of interest rate over time (Treasure Yield Curve), and j is each of the securities in a pool (in this paper, I have 209 CDS contracts), and k is each n characteristic of the securities of interest by which the investor can express a preference.

As long as the factor set is complete, this equation holds true for all assets.Since the excess returns on securities can be expected to be proportional to the excess returns on the factors, the risk on securities is also linked to the risk on the factors.

Chapter 2

Literature Review and Contribution

2.1 Introduction

In the classical finance paradigm, the tenet is how much an investor is willing to pay for an asset with the knowledge of the asset's perceived risk. The relationship between risk and the expected return has always been the crux of finance. Historically, many academics have endeavored to find the exact and comprehensive relationship. However, recent literature, Mehra and Prescott (2008), have demonstrated that an asset has many attributes that go into its pricing, including non-risk attributes (e.g., taste, preferences, disagreement). Here we, advance this work by integrating the classical and behavioral finance when it comes to pricing an asset; using the popularity framework which subsumes the idea of only considering risks as the key elements of pricing, and including preferences, taste, disagreement (whether they are rational or irrational). In "Disagreement, Tastes, and Asset Prices" FF (2007)[11],argue that the assumptions of standard asset pricing models, such as CAPM, are unrealistic and that both 'disagreement' and 'tastes' affect asset pricing. FF did not present a formal model of how disagreement and tastes impact asset prices; that paper discusses certain elements that would go into such a model and why those elements would move prices away from what the CAPM suggested. The other shortcoming of the CAPM identified by FF is "tastes," referring to the notion that investors have preferences beyond risk tolerance. The major contribution of this paper is to apply the concepts adopted for equities to that of corporate credit, given their capital structure; thought the element of preferences are entirely different.My paper contributes to the literature fundamentally in these areas. First, as I addressed earlier; I implemented the Ibbotson and Idzorek framework on a universe of 201 corporate credit using their CDS spreads. To the best of my knowledge, this is novel. Second, we find empirical results that indicate investors preferences do impact the excess return for corporate bonds via their CDS spreads.

As explained and demonstrated with the PAPM put forth by Idzorek, Kaplan, and Ibbotson (2020)[?], both disagreement and tastes can be incorporated into a general equilibrium asset pricing model. In the PAPM, investors have heterogeneous expectations (disagreements) about expected security returns and various risk and non-risk preferences (tastes), such as tastes for ESG; thus, the PAPM takes two significant steps toward asset pricing in the real world. The PAPM is a generalization of the CAPM, framed around the two key ingredients that FF identifies as impacting asset prices – disagreement and preferences/tastes. The PAPM builds on the New Equilibrium Theory of Ibbotson, Diermeier, and Siegel (1984), the popularity framework of Ibbotson and Idzorek (2014) and Idzorek and Ibbotson (2017), 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). The CAPM is the textbook approach and a vital element of every finance curriculum; yet, in addition to FF, numerous papers have been written on the CAPM's shortcomings (e.g., Basu 1977; Banz, 1981; FF, 1992; Lakonishok, Shleifer, and Vishny, 1994). In addition to being an asset pricing model, the CAPM also provides specific guidance on portfolio construction – each investor should hold a levered or delevered position in the market portfolio, depending on their risk tolerance. The PAPM also provides a specific method of portfolio construction based upon Markowitz's (1952, 1958) mean-variance optimization, enabling personalized-preference-based portfolio construction. The majority of the body of work that has been produced to decipher the effect of ESG factors (scores) on asset premium has been done with factor construction, as did FF. Lioui and Tarelli (2021) found no evidence of factor premium associated with ESG factors. The authors proposed a factor construction methodology controlling for both ESG ratings and other firm characteristics. The methodology makes it possible to build pure ESG factors that are directly comparable across data vendors and different pillars of ESG ratings (ESG, E, S, and G). The alpha they filtered from realized returns is negatively related to an ESG sentiment variable based on media attention, while it is positively related to unexpected sentiment variations. Their findings confirmed many of the empirical literature that the evidence of premium is at best mixed. The Sharpe-Lintner-Treynor-Mossin Capital Asset Pricing Model (CAPM) was developed over 50 years ago. The prevailing assumption of the CAPM is that markets act rationally so that only undiversifiable risk is compensated with a risk premium. Efficient Capital Market Theory extends the use of the rationality assumption, leading to prices being "fair." Therefore, market participants are not expected to "beat the market" after adjusting for market risk. The CAPM application can be reduced to a simple formula that predicts an asset's expected return as equal to the risk-free rate of return plus the beta of the asset relative to the market multiplied by a single market premium for market risk. Other risk premiums have been identified (e.g., a size premium, a credit risk premium, etc.), which led researchers to posit various multi-dimensional risk-based asset pricing models, most notably the Ross (1976) Arbitrage Pricing Theory (APT). Not long after the development of the CAPM and Efficient Market Theory, psychologists Kahneman and Tversky (1979) began to question the basic assumption of rationality. Behavioral finance has offered up a plethora of behavioral biases that lead to irrational behavior, many of which seem to provide explanations for some of the documented systematic departures in observed security prices relative to those expected from the CAPM. While rich, thus far, behavioral finance has not provided a complete framework or theory for understanding asset prices. The CAPM and its multifactor extensions remain the baseline asset pricing models compared to all other asset pricing models. All of this leaves us with a need for a simple, coherent, and intuitive asset pricing theory for understanding and forecasting asset prices. I believe this starts with the concept of popularity. The popularity as an attribute of an asset would influence the asset price; in the case of this study, the credit spread of a corporate debt via CDS spreads. After accounting for liquidity, measured as bid/offer spread, and default probability, this study explores the relationship between a firm's ESG score and residual credit spread by treating ESG scores as a non-risk attribute of the asset. There have been many recent studies of this relationship, but the focus has been on the risk component, looking for the risk premium associate with ESG factors. Given the recent attention of regulators, policymakers, and asset managers to ESG factors, a plethora body of work has been conducted in this space[1], varying in consensus, especially in the ratings or scorings. The divergence in the ESG rankings or scores can have far-reaching implications on investment allocations, policy to ESG research. Many ESG researchers use these ESG data sets, and their conclusions can vary quite starkly depending on which data provider they use, as illustrated by Berg, Kölbel, and Rigobon(2020), in their research "Aggregate Confusion", the authors were able to show that there is tremendous divergence in the ESG rankings by looking at the correlation among these providers of ESG scores; on average, 0.61; by comparison, credit ratings from Moody's and Standard & Poor's are correlated at 0.99 on average. That means "the information the decision-makers receive from [ESG] providers are relatively noisy," the paper states. In terms of whether the ESG factor has a premium associated with it, Lioui and Tarelli (2021), in their research "Chasing the ESG Factor," concluded that there is no ESG factor premium associated with it. I add to the literature by answering whether ESG scores affect market price (i.e. ESG scores have become more popular and now therefore have a greater effect credit risk).

2.2 ESG and Fixed income Corporate Credit Markets

A wide range of academic research and practitioner literature exists on the relationship between ESG indicators and risk and performance analysis for equity markets, providing limited scope for the fixed-income markets. At the asset level, the majority of the existing literature on ESG factors and fixed income markets focuses on corporate bonds(Klock,Mansi,Maxwell (2005); Bauer Hann (2010); Schneider (2011); Chava (2014); Bektic (2017); Menz (2010); Attig, El Ghoul, Guedhami, Suh (2013); Oikonomou Pavelin (2014); Polbennikov,Descl´ Uzun (2015); Huang, Hu, Zhu (2018); Dynkin, Descl´ (2018); Barth, Hübel, Scholz (2019)). Most of these studies report that a high ESG rating reduces the credit risk of corporate bonds; evidently indicates that the markets are rewarding higher ESG scores with a lower cost of debt (credit spreads) and higher credit ratings. More specifically, the authors document that environmental concerns are associated with a higher cost of debt financing and lower credit ratings, and proactive environmental practices are associated with a lower cost of debt. Polbennikov, Desclée, Dynkin, Maitra (2016) analyzes spread and performance for a corporate bond portfolio associated with MSCI ESG rating. They find that high ESG ratings are accompanied by an incremental

[1] there are two sets of work - one that compares ratings and another that considers whether ratings affect market prices

increase in return and lower-than-average spreads. Making these mutually inconsistent at first, but the authors concluded that the higher returns are from bonds issued before ESG was a factor and from improving ESG scores. Oikonomou Pavelin (2014) study the impact of various dimensions of sustainability performance on the Pricing of corporate debt and credit quality of specific bond issues. Their analysis suggests that each CSR factor substantially lessens the risk premia, reducing corporate debt costs. Cooper Uzun (2015) find that firms with a strong performance on corporate social responsibility (CSR) criteria have a lower debt cost. Moreover, Hoepner Nilsson (2017) show that bonds issued by companies that are indifferent significantly outperform the market benchmark. Similarly, Chava (2014) shows that firms with multiple environmental concerns must pay higher costs on their bank loans. They concluded that socially responsible lending can impact the firm's environmental policies through the cost of capital channels. Schneider (2011) supports the hypothesis that a firm's Environmental performance is reflected in bond prices. Martellini, and Vallée (2021), demonstrate that implementation choices regarding how ESG constraints are incorporated in the context of sovereign bond portfolio construction have a material impact on this opportunity cost. In particular, the authors find that higher environmental scores for developed countries and higher social scores for emerging countries are associated with lower borrowing costs for issuers and, consequently, lower yields for investors. They also confirmed that negative screening with respect to ESG screening leads to more diversified portfolios and lower tracking error levels relative their respective benchmarks.

2.3 ESG and Credit Default Swaps Spread

Barth, Hübel, and Scholz (2020) investigated the implications of firms' ESG practices for credit default swap pricing (CDS). The authors provided evidence that higher ESG score mitigate credit risks of both U.S. and European firms via cost of funding. They further investigate the link between ESG scores and country credit risks, conducting a global study that explores the impact of ESG performance on sovereign CDS spreads and the time dimension of ESG through the term structures of sovereign credit curves. Analyzing 60 countries from 2007 to 2017, They found that ESG impacts both the level and slope of the term structure of sovereign credit spreads: higher ESG performance is associated with lower CDS spread and flatter CDS implied credit curves. This research is evidence of a long-term risk-mitigating effect of country sustainability. Another strand of the literature focuses on linking sovereign bond spreads and credit ratings and one dimension of the ESG criteria (E, S, or G). Kjerstensson, and Nygren (2019), looked at the relationship between the ESG score of companies and its effect on the performance of their bonds using bond yield spreads. The authors studied listed companies on the Nordic countries' stock exchanges and established a relationship between ESG score and corporate bond yield spread. They found no such relationship can be established. Therefore, it concluded that a high ESG score does not imply a decreased level of required risk premium by bond investors and a decreased or stabilized cost of debt for companies in the Nordic countries. One would have expected to expect a similar finding for companies in the United States.

2.4 ESG and Popularity-based Pricing

Given the rise in Popularity of environmental, social, and governance (ESG) investing, citing FF, various recent papers have put forth asset pricing models that incorporate ESG (e.g., Pedersen, Fitzgibbon, and Pomorski, 2020). As a key example and demonstration of the innovation of such models, Pedersen, Fitzgibbon, and Pomorski (2020) states; "The only other models of this form with many assets that we are aware of are provided by FF (2007), who consider a model of investor "taste," Baker, Bergstresser, Serafeim, and Wurgler (2018), who consider a model in which some investors prefer green bonds, and Pastor, Stambaugh, and Taylor (2019) and Zerbib (2020), who consider ESG scores." The PAPM put forth in this paper belongs on this list, but the generalized asset pricing model encompasses these models. While the various papers related to disagreement and tastes are important, the PAPM put forth by IKI is the generalized asset pricing model. It encompasses these new ESG-specific models allowing for any number of asset characteristics (including ESG, liquidity, brands, etc.) as well as a wide range of investors and investor-specific expectations that could in part be related to asset characteristics. This paper will use the PAPM framework to answer whether CDS spreads on corporate credit are impacted by its ESG ratings. Given the growing and recent evidence that tastes for investments with various ESG characteristics (e.g., avoiding tobacco, guns, carbon emissions, animal testing, child labor, etc.) impacts asset prices (Baker et al., 2020, Barber, Morse, and Yasuda, 2020, Geczy, Stambaugh, and Levin, 2005, Pástor, Stambaugh, and Taylor, 2020, Pedersen, Fitzgibbon, and Pomorski, 2020, and Shafron, 2019), a generalized equilibrium asset pricing model that considers such tastes is needed. Consistent with these ESG-focused papers, IIKX shows that popularity is a broad umbrella under which nearly all market premiums and anomalies result from tastes. If a given characteristic is broadly liked or disliked by enough investors, it impacts asset prices. The most popular characteristics are expensive, decreasing expected returns, while the least popular characteristics are inexpensive, increasing expected returns. The notion that characteristics impact prices and expected returns is consistent with Daniel and Titman's empirical evidence (1997). They have found that security characteristics, rather than the covariance structure of returns, explain the cross-sectional variation in stock returns, thus credit risk premium for its bonds.

2.5 Liquidity

The liquidity of an asset attribute, which is desirable and popular among investors, is defined as either in funding or in trading: our primary focus is on trading liquidity as reflected by the CDS spread. Bunnermeirer and Perdersen (2009) argue that when traders (speculators, hedge funds, investment banks, all marked-to-market) buy security, they are required to use some of their capital (difference between security's price and its collateral value) to finance the trade. Similarly, short selling requires a margin on all positions. Traders are less willing to put on trades if funding is sparse, especially in capital-intensive securities, which has direct consequences for liquidity across the entire market. Market liquidity is difficult to define, especially since different market participants (for example, day traders and pension funds) and different sides (buy or sell) might have different requirements of a liquid market. Recent literature offers various definitions, and this section aims to extract all aspects of the liquidity that might need to be considered when evaluating the liquidity of a market or individual security. The resulting bid-ask spreads are of particular interest, as they are central to the understanding and modeling of liquidity premia in this research. A different branch of the microstructure literature, concerned with the decomposition of the bid-ask spread, considers the components above, such as exogenous transaction costs, private information, inventory risk, and search friction. In this study, I focus on the simple method of the bid-ask spread, and the early work on decomposing the bid-ask spread focused on explaining quoted spreads cross-sectionally using market variables such as trading volume and security risk (Benston and Hagerman, 1974 and Demsetz, 1968). Other work decomposes the spread into adverse information dealer profit components (Glosten and Harris, 1988 and Stoll, 1989), where the dealer profit represents compensation for inventory holding and order processing costs. Estimates by Stoll (1989) and Madhavan and Smidt (1991) indicate that inventory costs are relatively small for liquid asset classes but increase substantially for illiquid assets. Hence, the remainder of the spread is mainly determined by order processing costs and adverse information costs. Copeland and Galai (1983) observe that order costs, the clerical costs of carrying out the transaction, including the cost of the market makers' time, are fixed irrespective of trade size. Therefore, the average cost of order processing per unit decreases with trade size. The effect of informed counterparties has been studied at length (see, for example, Glosten and Milgrom, 1985), and models describe how dealers/market makers demand compensation for losses incurred from counterparties with superior knowledge. Specifically, Lin et al. (1995) empirically verifies a model developed by Easley and O'Hara (1987) in which well-informed traders prefer to trade more significant amounts. With the above in mind, especially considering the 'search friction' identified by Amihud et al. (2006), another aspect of liquidity can be defined as 'immediacy'; the ability to execute a trade contemporaneously. . Of course, immediacy is highly dependent on the trade size; at any given point in time, the ability to execute a trade with immediacy will differ substantially across small and large quantities. This implies that liquidity does not only operate at the level of (international) financial markets, varying by asset class or individual asset, but operates at a much more granular level: individual trades. The most intuitive liquidity proxy I employed in this chapter is the bid-ask spread, regarded as an 'aggregate' measure of liquidity (Hasbrouck and Seppi, 2001). The availability of bid-ask spread data is highly dependent on the choice of asset class understudy, period, and granularity. An indirect, implicit approximation of the effective bid-ask spread introduced by Roll (1984), continues to be a widely used proxy in recent empirical work (Dick-Nielsen et al., 2012 and Bao et al., 2011). The Roll measure constructs implicit bid-ask spreads based on prices alone.

Chapter 3

Data Description

3.1 Introduction

The research focuses on North American companies since there is data and a relatively high level of liquidity among investment grade (IG) and sub-investment grade credits. The sample comprises of Investment Grade (north of credit rating BBB-) and sub–investment Grade or High Yield Bonds (south of credit ratings BBB-) that are exchange-listed in the United States. The universe of companies is listed on the exchanges and possesses an ESG score provided by Refinitiv. Unlisted companies possess very different company characteristics and responsibilities that do not represent the sample population.

The dataset used in this Chapter comes from two primary sources, Refinitiv for the ESG scores and ICE for the CDS spreads. The critical elements of the inputs that go into estimating the default probabilities, the critical theoretical determinants of CDS spreads, came from trade data provided by ICE Data Services Inc (Interactive Data Corporation provides financial data and analysis services) via KRIS [1].
In terms of how the data was sources, I collaborated with analyst at both Eikon Refinitiv and Kamakura Corprateion (now part of SAS).I personally downloaded the data from Eikon Refinitiv databasing using their Excel Addin, and since they were non-overlapping data files I had to merge them by the following IDs in order to match the respective CDS spreads and the ESG scores. This took place over a three months period.

The assigned ESG score is done on the equity level, not on a debt level; therefore, I mapped the score to the company with its corresponding CDS spreads. Furthermore, the primary target equity market investors (and due to data availability) mainly cover pub-

[1] Kamakura Risk Integrated System from Kamakura Corporation

licly traded companies, and their ratings correspond to equity security identifiers. Thus, to obtain an ESG score for each credit in their database, one must first map it to equity security for which an ESG rating is available (for each provider and each month). The process was repeated for the sub-investment grade universe. However, the sub-investment grade universe contrasts the I.G. universe, with much lower coverage. This is partly explained by the prevalence of private issuers of sub-investment grade or high yield debt. Usually, the smaller size of high yield bond issuers relative to I.G. ones mean that covering them could often be a less immediate priority for investors and ESG providers alike than covering larger I.G. issuers. ESG scoring, by its very nature, is a complex and somewhat subjective undertaking. ESG issues span many business practices; the three principal pillar scores are calculated based on many component inputs. For example, within the environmental score, different ESG providers focus on criteria such as a company's energy usage, its contribution to air and water pollution, or the extent of its recycling efforts. These criteria are based on non-financial information assumed to be material to the company's long-term sustainability. Despite standardization efforts by industry bodies, there is no industry-wide consensus on which detailed environmental- and social-related criteria should be used to evaluate a corporation and how the criteria should be weighted. The universe looked at are all corporate bonds available in the DataStream tool provided by Refinitiv, which have then been filtered to produce a representative sample including information on all variables I aim to take into our regression model. The time I have looked at over ten years of monthly data, 2010-2021:q2. The overview of the ESG indicators by Refinitiv is described below. All data was gathered with the Refinitiv Eikon add-in from Microsoft Excel, then compiled to one excel master file containing all our data. I also matched all variables to produce our observations. This data was later imported to Stata 17.0, where I ran my regression models and did all our statistical tests, which will be described in the following sub-chapters.

3.2 ESG Dataset

The data used for this study came from one source, Refinitiv, which captures and calculates over 500+ company-level ESG data measures. A subset of 186 of the most comparable and material per industry is used to arrive at the ESG scores. These 186 data measures are divided into ten categories – Resource Use, Emissions, Innovation, Workforce, Human

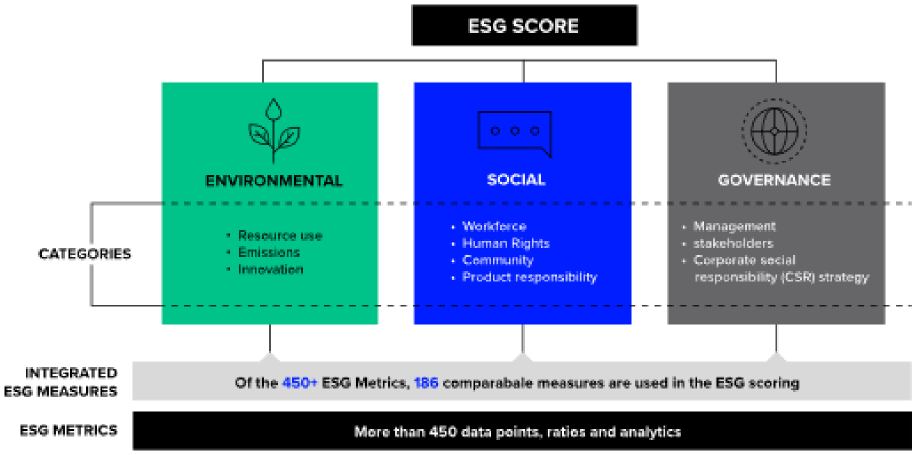
Rights, Community, Product Responsibility, Management, Shareholders, CSR Strategy. These ten categories then are grouped under the following three pillars – Environment, Social Governance (E, S, G). Category scores indicate the company performance in the respective categories. The scores are calculated based on the below category benchmarks:

- To calculate the Environmental and Social category scores and the Controversies score, TRBC Industry Group is used as the benchmark as these topics are more relevant and like companies within the same industries.

- Country of Headquarters is used as the benchmark to calculate the Governance category scores as best governance practices are more consistent within countries.

The ESG Scores are based on the percentile formula and are a relative performance score of a company compared to its peers. Environmental and Social data measures and Controversies are benchmarked against Industry Group and Governance measures against the country of incorporation. Therefore, a comparison of scores between industry Groups would not be of any value. One can compare the Environment and Social Pillar Score of Companies belonging to the same Industry Group and Governance Pillar Score of companies with the same incorporation country. They have different KPIs for different industries based on relevance and transparency. Refer to the attached file to know about KPI's that are part of scoring for each industry. For ESG scores, Refinitiv captures and calculates over 500 company-level ESG measures. The underlying measures are based on considerations around comparability, impact, data availability, and industry relevance that vary across each industry group. The Refinitiv ESG scores are data-driven, accounting for the most material industry metrics, with minimal company size and transparency biases. All the 186 data measures are divided into ten categories – Resource Use, Emissions, Innovation, Workforce, Human Rights, Community, Product Responsibility, Management, Shareholders, CSR Strategy. These ten categories then are grouped under the following three pillars – Environment, Social Governance (E, S, G). Category scores indicate the company performance in the respective categories.

Category weights will be calculated based on data to determine the relative importance of each theme to each industry group. Based on the themes covered in each category, suitable data points are identified which are used as a proxy for industry magnitude. The Themes to data points (KPIs) have a one-to-one relationship, in other words, there is one data point identified per the theme. For some themes, there are no KPIs that can be



Source: Refinitiv

Figure 3.1: ESG Score Metrics
The detail was provided by Refinitiv methodology guidelines

used as good proxies of relative importance due to primarily insufficient disclosure. Across categories of more than one theme and respective data points, the scoring methodology takes the average of each data point per industry group to calculate the weight at a category level. The category scores are rolled up into three-pillar scores – environmental, social, and corporate governance. ESG pillar score is a relative sum of the category weights, which vary per industry for the 'Environmental' and 'Social' categories. For 'Governance,' the weights remain the same across all industries.

The three categories of ESG are increasingly integrated into investment analysis, processes, and decision-making. The "E" captures energy efficiencies, carbon footprints, greenhouse gas emissions, deforestation, biodiversity, climate change and pollution mitigation, waste management and water usage. The "S" covers 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 issues. The "G" covers the governing of the "E" and the "S" categories—corporate board composition and structure, strategic sustainability oversight and compliance, executive compensation, political contributions and lobbying, and bribery and corruption.

The universe our dataset is focused US Dollar-denominated markets, both investment grade(I.G.) and high yield (or sub-Investment grade, sIG). Eligibility for inclusion in both categories is that at least two years of monthly ESG score is available, and at least corre-

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

sponding CDS spread data is available.

3.2.1 Population sample

This study focuses on the United States of America credit market for the practicality of data availability. The population universe across both Investment grade and sub-investment grade are companies listed on the New York Stock Exchange, and the availability of CDS Spread data, mainly the 5-year. In addition, I trust that listed companies are likely to have an ESG score by Refinitiv and that unlisted companies are most likely to have different characteristics and responsibilities that are not representative of our purposes.

3.2.2 Investment grade universe

Our ESG Population of issuers is such that there are 565 companies for the I.G.s with the following profile. As the materiality of the ESG scores are highly related to the industry in which the firm operates, I grouped issuers into 11 industries using the GIC category. The minimum and maximum values indicate that our variables do not seem to contain erroneous data entries that could distort our empirical results. On the industry sector level, Environmental and social ratings range between 1.59 and 95.19, averaging around 50.74. In comparison, our sample firms exhibit, on average, lower governance performances indicated by an average governance rating of 55. In each Sector, for the individual component scores, if the data retrieved from the Eikon database is zero, it's replaced as blank. Since the lowest assigned score by Refinitiv is 1, this is very important because it significantly affects the average and variability score across industries.

All corporate bonds issuers in the sample are available in the Eikon database tool provided by Refinitiv, which have then been filtered to produce a representative sample including information on all variables I aimed to take into our regression model. The time

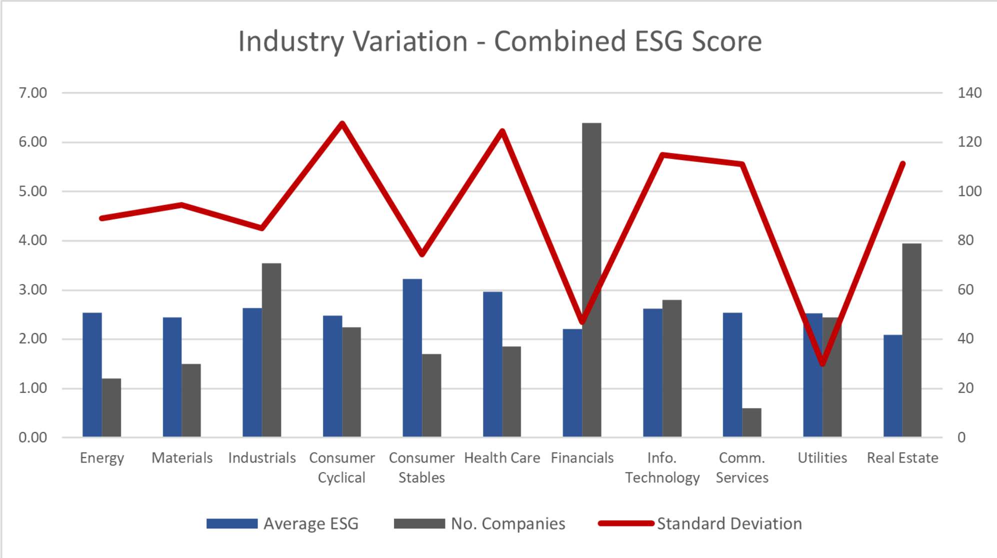


Figure 3.2: Industry Variation Among Investment Grades.

I have looked at ranges from 10 years 2010-2021 (up to the second quarter, June); this is to ensure I have sufficient CDS spreads and ESG scores available but excluded companies with less than two years ESG scores available. I decided upon this time frame to produce a sample with enough observations to perform our statistical tests upon and with which I could see the long-term effects of ESG score on corporate bonds issuers. I have not taken older observations as I believe that might entail the risk of not finding proper ESG scores for the bond issuers as it is a relatively new concept to the financial market. Refinitiv has an ESG rating from 2002, mainly U.S. and European, but it was first from 2008 that the rating started to become more widespread (Refintiv, 2019, p. 5-6). A more prolonged period might also introduce differences in the CDS market's characteristics and the financial landscape, which might be challenging to know and incorporate into our model.

Table 3.2: Correlation Matrix of Determinants

This table shows the connection between CDS spread and the determinant factors. The data contain 692 firms during the period from January 2010 to April 2021. It describes the correlation between the variables.

	CDS_Spread	**MktRFree**	**SMB**	**HML**	**StockReturn**	**StockVol**	**VIX**	**1yrExReturn**	**Mkt_Leverage**	**ESG_CScore**	**E_Score**	**S_Score**	**G_Score**
CDS_Spread	1.0000												
MktRFree	0.0798	1.0000											
SMB	0.1723	0.1573	1.0000										
HML	0.0939	0.1363	0.0003	1.0000									
StockReturn	-0.0012	0.4845	-0.0031	-0.2651	1.0000								
StockVol	0.0804	0.1817	0.0793	0.0903	0.0855	1.0000							
VIX	0.0579	-0.3136	0.0533	-0.2561	-0.2277	0.4304	1.0000						
1yrExReturn	-0.1180	0.1270	0.1234	-0.2267	0.2100	0.3363	0.3725	1.0000					
Mkt_Leverage	-0.2057	-0.1790	-0.0581	0.0694	-0.2475	-0.5133	-0.2603	-0.4184	1.0000				
ESG_CScore	-0.3224	0.1044	-0.0646	-0.0462	0.0648	0.6750	0.2708	0.3785	-0.2407	1.0000			
E_Score	-0.4744	0.0561	-0.0465	-0.1396	0.0446	0.5784	0.3636	0.3876	0.0083	0.8193	1.0000		
S_Score	-0.1950	0.1213	-0.0449	-0.0092	0.0744	0.7134	0.2816	0.2565	-0.3710	0.9529	0.7194	1.0000	
G_Score	-0.3924	-0.0138	-0.0826	-0.0831	-0.0106	0.0363	-0.0323	0.4512	0.2613	0.4049	0.3750	0.1191	1.0000

3.2.3 Correlation analysis

This section explores the ability of firm-specific variables to vary cross-sectionally. Correlation coefficients between the variables are presented in Table 3.2. It shows that CDS is relatively correlated with *MarketLeverage* and *ESG_score*. This provides information on how satisfactorily single factors are associated with CDS spread changes.All correlation coefficients between the independent variables and changes in CDS spreads have the expected sign.

3.2.4 sub-Investment grade universe

As in the Investment grade sample universe, I have used data spanning over ten years with 55 companies across the industry sectors. I eliminated companies with less than two years' worth of ESG scores.

3.3 Credit Default Swap

A company's credit risk can be defined as the probability of a financial loss if borrowers and counter-parties default on repaying their debt. Banks have traditionally traded this risk via Credit Default Swap, and the associated premium is the spread; this is referred to as CDS spread. A CDS is like an insurance contract in its most basic terms, providing the buyer with protection against specific risks. Investors often buy credit default swaps for protection against default, but these flexible instruments can be used in many ways to customize exposure to the credit market. CDS contracts can mitigate risks in bond investing by transferring a given risk from one party to another without transferring the underlying bond or other credit assets. Before credit default swaps, there was no vehicle to transfer the risk of a default or other credit event from one investor to another. A single-name CDS contract structure is relatively straightforward; two parties are involved in the contract, the protection buyer looking to insure against the possibility of default on a particular bond and the protection seller, who is willing to bear the risk. The company that issued the bond is referred to as the reference entity; the bond itself is the reference issue. In case of a credit event (default, failure to pay, or other 'trigger'), the protection seller agrees to buy the reference issue at face value and, in return, receives a default swap premium, a periodic (quarterly) fee. The contract expires at the maturity date in case no credit event happens during its lifetime. If there is a credit event, the protection seller buys the reference issue at face value and discontinues the periodic payments. It is then reasonable to assume that credit risk can be measured using credit spread. Credit spread is defined as follows:

$$Creditspread = BondYield–RiskfreeRate \tag{3.1}$$

Moreover, studies by Hull (2000)[13] show that the credit spread is equivalent to the CDS spread. The relationship between credit spreads and CDS spreads must hold under a no-arbitrage argument, otherwise, an investor can make a risk-free profit. Blanco (2005)[6] test this theoretical equivalence and find that the parity holds as a long-run equilibrium condition. This analysis hypothesizes that a company's ESG score would impact the credit spreads via its popularity. Previous studies, as mentioned in the Literature review, previous empirical studies have used CDS spreads to measure credit risk. Collin-Dufresne, Goldstein Martin (2001)[8] investigates credit risk using bonds credit spreads. Ericsson, Jacobs, and Oviedo (2004)[10] use CDS spreads in their investigations of the credit risk, albeit not treating ESG as investors' preference. For this analysis, I chose to use CDS as a proxy for credit spread performance given its following advantages:

1. isolation of credit risk given the instrument's insensitivity to interest rate risk
2. constant maturity, removing the need for potential rolldown adjustments during the simulation,
3. standardized structure, given a senior unsecured ranking and bullet maturity (lack of optionality), allowing for more accurate performance comparisons.

The yield on a corporate bond is higher than on a 'risk-free' gilt or swap, with the additional yield referred to as the credit spread. This credit spread compensates investors for the excess risk the holder bears; for example, the bond's issuer may default, the bond's issuer may get downgraded, and the bond may be difficult to convert to cash, i.e., it is illiquid. Whereas the default-related risk is always present and cannot be fully diversified away, the difficulty to turn a bond into cash is easily avoided by holding the bond until maturity. The argument goes that the bondholder can capture the value of that liquidity risk premium in their valuation.

3.3.1 Stock return

The Merton model suggests a negative connection between a firm's Equity and its probability of default. I used monthly stock returns obtained from CRSP to indicate changes in a firm's Equity. Higher stock returns increase a firm's value, which should decrease CDS spreads theoretically. Hence, a negative relationship is expected between equity returns and CDS spreads.

3.3.2 Stock volatility

The second theoretical determinant central to the Merton model is the volatility of the firm value (Ibid). The difficulty with this measurement is that a firm's volatility is unobservable. For that reason, proxies of the volatility are done by measuring historical volatility. Historical volatility is based on historical stock data. Substantiated by option theory, the price of an option should increase with the volatility of the underlying. This is because the increasing volatility of the underlying makes it more probable that the put option will be exercised. The value of the put option therefore increases with volatility, which follows that an increase in volatility increases the probability of default. And since the probability of default increases, the cost for insuring against default – reflected by the CDS spread – should increase.

3.3.3 Market leverage

In Merton's model, the firm's leverage ratio is a key variable in determining the credit spread. Leverage is defined as the firm's debt (D) ratio to the firm value (V). Merton's model assumes that default occurs when the firm's value falls below its debt value. Hence, the higher the leverage (D/V), the higher the risk of default. With respect to the put option expressed in the previous section, if D increases relatively more than V, and other variables stay unchanged, then the price of the put option – and the credit spread – will increase. Put in another way, the higher the leverage, the more likely it is that the firm will default and hence the more costly the insurance against default should be. The cost of this insurance is thus reflected by a higher CDS spread. Therefore, the CDS spread should increase as leverage increases. In Merton's approach, higher leverage indicates a shorter distance to the default barrier and a higher probability of default. Therefore, the effect of this control variable in the regression should be a positive correlation; thus, an increase in leverage should result in higher CDS spreads.

3.3.4 Liquidity

Like CGM , I included a proxy for the liquidity risk in the CDS market for our robustness regressions. I chose the bid-ask spread which has become a commonly used measure of market liquidity. The motivation for this proxy of liquidity risk is that according to Fleming (2003), the bid-ask spread outperforms other proxies when measuring liquidity in the U.S. treasury market. As investors demand an additional premium for liquidity risk, higher bid-ask spreads are associated with higher CDS spreads. Liquidity does not require a behavioral explanation. Rational investors want more liquidity so that those with longer horizons earn a liquidity premium. There are several potential measures of liquidity, which are likely to measure somewhat different characteristics. Longstaff et. al. (2005) discovered illiquidity to be characteristic for a bond's default risk. The bid-ask spread is simply the difference between the bid and ask CDS spread. Evidently, investors demand an additional premium for liquidity risk, since the higher the bid-ask spreads are, the higher the CDS spreads are. This bid-ask spread would provide us with valuable information, in addition to raise the intensity of the explanatory factor. Amihud and Mendelson (1986) document that fewer liquid stocks outperform more liquid stocks. Haugen and Baker (1996) and Datar, Naik, and Radcliffe (1998) show that low-turnover stocks earn higher future returns than high-turnover stocks. Ibbotson et al. (2013) demonstrate that liquidity premiums could be a missing style since liquidity premiums appear to be at least comparable to size and value premiums. Building on stock level liquidity premiums, Idzorek, Xiong, and Ibbotson (2012) found that after controlling for other characteristics, mutual funds that held illiquid stocks outperformed, the same argument holds for bonds (via CDS) net of fees. From a popularity perspective, all else equal, investors

Term Structure Slope

Although only the risk-free rate appears in Merton's model the future movement of a risk-free rate could be influenced by the slope of the yield curve. According to Carol et al. (2007)[1], the steeper the yield curve, the higher expected future interest rates are. Therefore, I expect a negative relationship between the slope of the yield and the CDS spread.

TBI Return

Transaction-based indices refer to a mode of monitoring the performance of the commercial real estate market, and an overall liquidity in the financial system. Such indices are rare since the acquisition of property is a personal endeavor. Appraisal-based indices are the most common form of indices since, to some extent, investors are obliged to revalue the assets they hold. Consequently, the appraisal-based index gives lagged and smoothed price estimates in the market.

It is a forward indicator for cost living adjustment and business climate.Business climate could be seen as a macroeconomic variable. Including this variable, default probability could depend on the stages of the business climate. Both CGM and EJO proxy the business climate of their U.S. datasets with the SP500, and they predict that an increase in the SP500 will decrease the credit spread. This is quite logical, since when the economy is booming firms are doing well, but when the economy is in a recession, the credit risk is higher. Therefore, there is a negative relationship between the business climate and CDS spreads.

Chapter 4

Regression Methodology

4.1 Introduction

In this section, the Fixed-effect was adopted, since it explores the relationship between the independent and dependent variables within an entity (in this case within individual companies). Each firm in the panel dataset has certain characteristics that may or may not influence the independent variable. In this thesis, I am analyzing the effect that ESG will have in CDS under ceteris paribus conditions. In addition, given that the Fixed-effects techniques assume that individual heterogeneity in a specific entity may bias the independent or dependent variables, it will be most suitable to control for the bias as mentioned earlier. And in this respect,the model removes the effect of time-invariant characteristics.

The model used here is like that adopted by Gail, Shapir, and Ben-Zion (2012). They examined the determinants of CDS spreads and spread changes, focusing on the classical framework using the standard factor model, like the one adopted by Fama-French (2007). In this model, I have adopted similar critical elements of determinants of CDS spreads. Collin-Dufresne, Goldstein Martin (2001)[8] (henceforth CGM), where the authors investigated the credit risk by using bonds credit spreads, and that used by Angelini et al.(2014)[2]. Ericsson, Jacobs and Oviedo (2004)[10] (henceforth EJO), use CDS spreads in their investigations of the credit risk. Zhang et al. (2005)[17] examine the determinants of CDS spreads.

This subsection presents our regression models and discusses the panel method by which the regressions are estimated. The method is very similar to Eberhardt (2012)[9] which uses Mean Group (MG) estimators, and we also adopted the Pooled Mean Group (PMG) estimator for the non-stationary aspect of the data-set as in Blackburn III (2007)[5]. Panel data regressions are suitable for our analysis since our data contain both a cross-sectional and a time-series dimension. Some benefits of panel data are that it permits more degrees of freedom, reduces collinearity among variables, and accounts for the heterogeneity of individual cross-sections or the characteristics of each firm. At the end MG and PMG are compared using Hausman test.

This analysis has been carried out through two models at fixed effects to exploit both the information within and that between, which is included in the dataset through a GLS analysis. The model is also assessed with a dynamic fixed-effect (DFE) and random effect panel regression to check its stability. As described in the previous sections, Merton's model states that credit spread is a function of the value of the asset volatility, risk-free rate and leverage. The first empirical model denotes the following structure:

In this model the core determinants from the Merton's model were employed plus additional common factor such as *[one year return On the MIT TBI Commercial Real Estate Index]* and *the slope of the terms structure between the 2-year and the 10-year rates* with the combined ESG scores. The regressions are done conducted over a number of periods. Firstly, the universe of data use covered the mixture of Investment Grade (156 names) and sub-Investment Grade (55 names),over the periods 2010 to 2021, 2010 to 2015, and then 2015 to 2021.

$$\begin{aligned}\text{CDS}_{t,i} = \alpha_{0,i} &+ \beta_1\text{EquityReturn}_{t,i} + \beta_2\text{MarketLeverage}_{t,i} + \beta_3\text{MarketVolatility}_{t,i} \\ &+ \beta_4\text{ExcessReturn1yr}_{t,i} + \beta_5\text{ReturnTBI}_{t,i} \\ &+ \beta_6\text{TermStructSlope}_{t,i} + \beta^{ESG}\text{ESG\_Score}_{t,i} + \varepsilon_{t,i}\end{aligned} \tag{4.1}$$

Equation (4.1) shows the ability of structural variables consistent with Merton (1974) model (equity return, volatility and leverage), of which is referred to in this section as Merton's model, to explain CDS spreads. It should be noted that the risk-free interest rate, which is also used in the Merton (1974) model, has to be omitted in a cross-section analysis. In this model the core determinants from the Merton's model were employed with the individual pillars E,S, and G scores.

$$
\begin{aligned}
\mathrm{CDS}_{t,i} = \alpha_{0,i} &+ \beta_1 \mathrm{EquitykReturn}_{t,i} + \beta_2 \mathrm{MarketLeverage}_{t,i} + \beta_3 \mathrm{MarketVol}_{t,i} \\
&+ \beta_4 \mathrm{ExcessReturn1yr}_{t,i} + \beta_5 \mathrm{ReturnTBI}_{t,i} + \beta_6 \mathrm{TermStructSlope}_{t,i} \\
&+ \beta^E \mathrm{E\_Score}_{t,i} + \beta^S \mathrm{S\_Score}_{t,i} + \beta^G \mathrm{G\_Score}_{t,i} + \varepsilon_{t,i}
\end{aligned}
\tag{4.2}
$$

In this model the core determinants from the Merton's model were employed with the individual pillar E.

$$
\begin{aligned}
\mathrm{CDS}_{t,i} = \alpha_{0,i} + \beta_1 \mathrm{EquitykReturn}_{t,i} \quad & + \beta_2 \mathrm{MarketLeverage}_{t,i} + \beta_3 \mathrm{MarketVol}_{t,i} \\
+ \beta_4 \mathrm{ExcessReturn1yr}_{t,i} \quad & + \beta_5 \mathrm{ReturnTBI}_{t,i} + \beta_6 \mathrm{TermStructSlope}_{t,i} \\
+ \beta^E \mathrm{E\_Score}_{t,i} \quad & + \varepsilon_{t,i}
\end{aligned}
\tag{4.3}
$$

In this model the core determinants from the Merton's model were employed with the individual pillar S.

$$
\begin{aligned}
\mathrm{CDS}_{t,i} = \alpha_{0,i} + \beta_1 \mathrm{EquityReturn}_{t,i} \quad & + \beta_2 \mathrm{MarketLeverage}_{t,i} + \beta_3 \mathrm{MarketVol}_{t,i} \\
+ \beta_4 \mathrm{ExcessReturn1yr}_{t,i} \quad & + \beta_5 \mathrm{ReturnTBI}_{t,i} + \beta_6 \mathrm{TermStructSlope}_{t,i} \\
+ \beta^S \mathrm{S\_Score}_{t,i} \quad & + \varepsilon_{t,i}
\end{aligned}
\tag{4.4}
$$

In this model the core determinants from the Merton's were employed with the individual pillar G.

$$
\begin{aligned}
\mathrm{CDS}_{t,i} = \alpha_{0,i} + \beta_1 \mathrm{EquityReturn}_{t,i} \quad & + \beta_2 \mathrm{MarketLeverage}_{t,i} + \beta_3 \mathrm{MarketVol}_{t,i} \\
+ \beta_4 \mathrm{ExcessReturn1yr}_{t,i} \quad & + \beta_5 \mathrm{ReturnTBI}_{t,i} + \beta_6 \mathrm{TermStructSlope}_{t,i} \\
+ \beta^G \mathrm{G\_Score}_{t,i} \quad & + \varepsilon_{t,i}
\end{aligned}
\tag{4.5}
$$

In the above model the CDS spread is of firm i at the end of month t. The $ESG\_Score_{t,i}$ is the respective combined ESG score. The $EquityReturn_{t,i}$, $MarketVol_{t,i}$, $ExcessReturn1yr_{t,i}$, $ReturnTBI_{t,i}$, and $TermStrucSlope_{t,i}$ are the other determinants. η_i comprises firm fixed effects that absorb any unobserved time-constant firm characteristics and v_t includes time fixed effects. $\varepsilon_{i,t}$ is the i.i.d. standard normal error term. The panel methodology allows us to consider cross-sectional and temporal variation simultaneously. All standard errors are double-clustered at firm month levels to account for cross-sectional and serial correlation in the error terms. And β^{ESG} is the main coefficient for this analysis. It captures the marginal effect of ESG score on CDS spreads.

Chapter 5

Empirical Results Analysis

5.1 Empirical Results Analysis

To understand the effect of ESG scores on corporate credit risk via CDS spreads, the model regresses all the key independent variables that determines default probability along with the ESG scores via panel regression. Results of the empirical analysis carried out are illustrated in this section. The model has been estimated through a panel regression that uses three panel time-series estimators allowing for heterogeneous slope coefficients across group members adopted by Markus Eberhardt [9]

In the first model credit spread is set as a dependent variable while the independent variables are all the theoretical determinants of the Merton's model and the universe of potential determinants for the investment grade companies are listed in Table 5.1. In deciding on the universe of the determinants we Looked at the major inputs that goes into determining the default probability or the distance to default in the Merton's model. The loadings of these inputs are considered as the degree of popularity.

In addition, to assess the effect of each ESG component, we replace the overall ESG index with E (environmental quality index), S (social quality index), and G (governance quality index). Both social and governance performance have a significantly negative correlation with sovereign funding cost. This result is unchanged based on Beyond Ratings ESG scores.

Table 5.1 shows the summary statistics of the CDS spreads and the main determinants factors. The Bid/Ask Spread as a proxy for liquidity was excluded due to high level of collinearity with the actual CDS spread levels, since it was calculated as simple the Bid minus the Ask.

Table 5.1: Investment Grade and sub Investment Grade Summary Statistics

This table presents the descriptive statistics of the dataset for the period from January 2010 to April 2021.It describes the variables divided into five groups: spread variables, firm-specific variables as determinants. The spread and firm-specific variables are calculated using data from 250 rated and unrated firms

VARIABLES	Observations	Mean	Min	Max	StdDev
Bid	28,397	2.065	0.0842	32.51	2.855
Ask	28,397	2.353	0.0968	35.64	3.212
BidAksSpread	28,397	11.86	0.0377	225.2	13.75
CDS_Spread	27,775	153.5	10.32	4,311	225.4
ESG_Score	27,105	57.76	7.390	95.19	18.33
E_Score	25,773	55.68	0.433	98.55	25.01
S_Score	27,105	58.39	0.865	98.09	21.03
G_Score	27,048	60.11	1.337	98.53	20.74
MarketLeverage	28,397	0.486	0.0263	0.996	0.223
ExcessReturn1yr	28,397	0.0235	-1.151	11.30	0.434
MarketVolatility(VIX)	28,397	18.45	9.510	53.54	7.034
ReturnTBI	28,397	0.0914	-0.225	0.299	0.0999
TermStructSlope(10y-2y)	28,397	-0.398	-2.410	1.500	0.975
EquityReturn	27,876	1.230	-70.92	147.0	9.824

From Table 5.2, The sample pool consists of both investment and sub-investment grade credits; using the fixed effect panel regression model, it is evident that all the major inputs of the Merton's model with exception of Stock Return are significant at the 1% confidence level, and with R^2 being approximate 14%. The combine ESG is particularly significant, and the sign of the coefficient is inversely related to the CDS spread as expected, the high ESG score mean imply a lower cost of funding and more stable stream of income, so implies lower credit risk, implying lower default probability and therefore lower spread.

Table 5.2: Fixed Effect for both IG and SubIG Regression Results of All Proposed Models over **2010 to 2021**

VARIABLES	(Model1) CDS	(Model2) CDS	(Model3) CDS	(Model4) CDS	(Model5) CDS
EquityReturn	0.0218	-0.0591	-0.0370	0.0128	0.0370
	(0.0821)	(0.0799)	(0.0799)	(0.0820)	(0.0806)
MarketVolatility	1.466***	1.396***	1.369***	1.487***	1.491***
	(0.140)	(0.134)	(0.134)	(0.140)	(0.137)
MarketLeverage	540.0***	467.1***	474.9***	536.3***	513.4***
	(10.36)	(10.37)	(10.35)	(10.37)	(10.31)
termStructSlope	-5.057***	-5.397***	-5.214***	-5.306***	-4.792***
	(1.000)	(0.957)	(0.957)	(0.999)	(0.981)
ReturnTBI	50.85***	31.62***	35.65***	46.97***	52.93***
	(8.665)	(8.426)	(8.411)	(8.665)	(8.413)
1yrExcReturn	-31.07***	-34.89***	-33.60***	-31.84***	-29.05***
	(2.075)	(2.021)	(2.021)	(2.076)	(2.021)
ESG_Score	-0.673***				
	(0.0976)				
E_Score		-0.128	-0.366***		
		(0.0784)	(0.0696)		
S_Score		-0.879***		-0.894***	
		(0.0971)		(0.0890)	
G_Score		0.418***			0.139**
		(0.0570)			(0.0569)
Constant	-108.1***	-78.41***	-95.84***	-93.07***	-143.4***
	(8.092)	(8.337)	(6.812)	(7.815)	(6.420)
Observations	26,220	24,817	24,907	26,220	26,146
R-squared	0.149	0.140	0.136	0.151	0.138

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

As indicated in Table 5.2, The Market Volatility, Leverage, Slope of the Yield Curve, return excess of TBI, and 1yr Excess Return are all significant at 1% level. And the combined score for the ESG is also statistically significant. This result is not surprising since investment grade corporate credits dominate the sample universe. This result is similar to that of Table 5.3, which narrows the sample universe to just investment grade credits. However, with the sample universe restricted to the sub-Investment Grade in Table 5.4, the combined score for the ESG proved to be not significant of 1% level, the fundamental reason behind this is because the credit spread is dominated by the determinants of default probability as opposed to ESG concerns.

Table 5.3: Fixed Effect Investment Grade Regression Results of All Proposed Models over **2010 to 2021**

	(M1)	(M2)	(M3)	(M4)	(M5)
VARIABLES	CDS	CDS	CDS	CDS	CDS
EquityReturn	-0.0958**	-0.104**	-0.0886*	-0.101**	-0.0662
	(0.0477)	(0.0486)	(0.0486)	(0.0477)	(0.0478)
MarketVol	0.753***	0.720***	0.708***	0.768***	0.748***
	(0.0683)	(0.0694)	(0.0695)	(0.0682)	(0.0685)
MarketLeverage	351.20***	364.3***	367.8***	349.8***	360.1***
	(6.153)	(6.36)	(6.362)	(6.143)	(6.131)
TermStructSlope	-2.115***	-2.283***	-2.226***	-2.177***	-1.776***
	(0.485)	(0.494)	(0.495)	(0.485)	(0.486)
ReturnTBI	45.46***	47.16***	51.25***	43.44***	51.02***
	(4.152)	(4.295)	(4.280)	(4.154)	(4.136)
1yrReturn	-12.43***	-12.73***	-11.55***	-12.77***	-9.829***
	(1.601)	(1.632)	(1.629)	(1.597)	(1.590)
ESG_Score	-0.599***				
	(0.0484)				
E_Score		-0.176***	-0.351***		
		(0.0413)	(0.0365)		
S_Score		-0.449***		-0.628***	
		(0.0504)		(0.0432)	
G_Score		-0.0228			-0.153***
		(0.0313)			(0.0297)
Constant	-51.11***	-54.53***	-75.42***	-48.24***	-82.51***
	(4.390)	(4.665)	(3.928)	(4.171)	(3.440)
Observations	19,920	19,287	19,287	19,920	19,920
R-squared	0.216	0.227	0.224	0.218	0.211

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

The results shown in both Tables 5.2 and 5.3 indicate that considerations of popularity are important for the investment-grade universe as most of the companies are more matured and their adherence and transparency to the individual pillars of ESG has become part their strategic goals, given their negative correlation and coefficients of the combined ESG score as well as for the individual pillars. The higher the scores, the lower the spreads, and investor prefer companies with tighter CDS spreads, making them more popular. The results for the sub-investment grade universe wasn't as strong, indicating the combined ESG scores were unpopular among investors.

Table 5.4: Fixed Effect sub-Investment Grade Regression Results of All Proposed Models over **2010 to 2021**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	qCDS_Spread	qCDS_Spread	qCDS_Spread	qCDS_Spread	qCDS_Spread
EquityReturn	0.458*	0.415	0.442	0.455*	0.459*
	(0.257)	(0.281)	(0.278)	(0.257)	(0.264)
MarketVolatility	3.681***	3.990***	3.564***	3.826***	3.805***
	(0.621)	(0.672)	(0.659)	(0.621)	(0.636)
MarketVolatility	396.4***	361.2***	387.5***	398.2***	421.9***
	(39.86)	(46.02)	(44.98)	(39.69)	(41.82)
TermStructSlope	-6.958	-5.482	-4.367	-7.311	-7.059
	(4.838)	(5.280)	(5.163)	(4.840)	(5.017)
ReturnTBI	-112.9	-151.2	-105.8	-156.2*	-102.0
	(88.71)	(97.27)	(94.93)	(88.22)	(89.25)
1yrExcessReturn	-66.58***	-72.76***	-72.18***	-65.73***	-65.13***
	(6.324)	(6.826)	(6.766)	(6.300)	(6.454)
ESG_Score	0.198				
	(0.531)				
E_Score		4.010***	2.678***		
		(0.532)	(0.452)		
S_Score		-3.174***		-0.876*	
		(0.610)		(0.468)	
G_Score		-0.252			0.180
		(0.358)			(0.335)
Constant	9.050	50.98	-80.33**	60.19*	-5.046
	(35.96)	(45.08)	(33.85)	(34.83)	(33.80)
Observations	3,920	3,508	3,598	3,920	3,780
R-squared	0.114	0.128	0.122	0.115	0.116
Number of id	55	55	55	55	55

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

Chapter 6

Robustness Test

6.1 Different Vendor Dataset

As a robustness check, again the use of CDS spreads is adopted as a dependent variable. CDS spreads are regarded as a purely market-driven measure of corporate credit risk. In most cases, they are more liquid than the underlying physical bonds, and are immune to liquidity constraints. The results remain unchanged when I used the MSCI dataset even though the correlation between the ESG score is around 60%. MSCI ESG Ratings data are a successor to the MSCI KLD data used in many academic studies. According to Eccles and Stroehle (2018), MSCI is the world's largest provider of ESG ratings. One needs to be mindful of the correlation between Refinitiv's data and that of MSCI. Table 6.1 shows the output for the regression using the ESG date from MSCI for the investment-grade credit. And the regression was done separately for the sub-investment grade credit the results is shown in Table 6.2, the results are similar with that of Refinitiv dataset, in terms of the siginificance of ESG as a determinant for the CDS spreads.

Table 6.1: Investment Grade Regression Results of All Proposed Models: Data from MSCI

VARIABLES	(Model 1) CDS_Spread	(Model 2) CDS_Spread	(Model 3) CDS_Spread	(Model 4) CDS_Spread	(Model 5) CDS_Spread
EquityReturn	-0.00465	-0.00816	0.00736	-0.00585	-0.00386
	(0.0208)	(0.0215)	(0.0202)	(0.0212)	(0.0217)
MarketVolatility	0.505***	0.465***	0.479***	0.506***	0.551***
	(0.107)	(0.0905)	(0.0975)	(0.107)	(0.106)
MarketLeverage	281.1***	297.7***	292.0***	281.4***	257.5***
	(61.94)	(62.53)	(56.12)	(65.60)	(57.76)
TermStrucSlope	-2.410***	-1.576**	-2.184***	-2.392***	-2.203***
	(0.909)	(0.777)	(0.833)	(0.853)	(0.845)
ReturnTBI	40.87***	26.10**	39.38***	37.63***	44.06***
	(12.56)	(12.19)	(12.64)	(12.67)	(12.76)
1yrExcessReturn	5.013	5.623	7.303**	4.881	4.615
	(3.663)	(3.766)	(3.526)	(4.211)	(3.292)
ESG_Score	-0.0205				
	(0.0174)				
E_Score		0.101	0.0744		
		(0.119)	(0.105)		
S_Score		0.0370		0.0467**	
		(0.0274)		(0.0227)	
G_Score		-0.0179			-0.0177
		(0.0153)			(0.0128)
Constant	-97.52*	-110.8*	-103.5**	-110.0*	-74.78
	(55.25)	(57.57)	(49.57)	(59.67)	(50.46)
Observations	16,845	16,844	16,844	16,844	16,844
Number of id	149	149	149	149	149

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

6.2 Hausman Test

According to the results from running the hausman test for the model in the Table xx, since the p-value is 0, we reject the Random effect model and accept Fixedeffect model as more germane and appropriate for this model.

Coefficients

	Models			
	Fixed (f)	**Random(r)**	**Difference (f-r)**	**Stand. Err**
EquityReturn	0.021786	.0241908	-.0024048	.0009399
MarketVolatility	1.465932	1.480443	-.0145106	.0032091
MarketLeverage	540.0408	532.4016	7.639212	2.192292
TermStructSlope	-5.056517	-5.209051	.152534	.0271598
ReturnTBI	50.85488	50.32458	.530297	.1834229
1yrExcess Return	-31.06976	-31.00465	-.065114	.0993697
ESG_Score	-0.72931	-0.734265	0.061334	0.015534
F = 114.67	p-value = 0.0000			

6.3 Endogeneity bias and reverse causality

A model such as this one, looking at the impact of ESG Score on Corporate Credit spread, could not generate an endogenous relationship (i.e., omitted variable bias and reverse causality) between a firm's ESG score and corporate credit spread, since potentially the adherence to ESG policies could impact the cost of funding for the firm and liquidity of its CDS spreads, but not the other way round. However, Buchanan et al (2018)[7] study the relationship between ESG and firm value in the context of influential institutional ownership and argue that there might be a recursive relation between ESG and the financial performance of firms entailing an endogeneity problem. At the same time the test for endogeneity and reverse causality for this body of research is still in a relatively early stage and it is not sufficiently clear to what extent these models can explain patterns uncovered by empirical research on how CDS spreads impact ESG scores. In addition, asset pricing models that aim to predict corporate bond spreads not only depend on transaction costs, but also on liquidity risk. The available evidence indicates that liquidity is an important factor in asset pricing. However, most studies do not explicitly examine whether ESG factors can be explained by liquidity factors, which is excluded as a deter-

Table 6.2: sub-Investment Grade Regression Results of All Proposed Models: Data from MSCI

VARIABLES	(Model 1) CDS_Spread	(Model 2) CDS_Spread	(Model 3) CDS_Spread	(Model 4) CDS_Spread	(Model 5) CDS_Spread	(Model 6) CDS_Spread	(Model 7) CDS_Spread
EquityReturn	0.460	0.204	0.274	0.246	0.272*	0.230	0.307*
	(0.313)	(0.181)	(0.183)	(0.154)	(0.161)	(0.151)	(0.161)
MarketVolatility	4.327***	7.759*	3.954***	3.759***	3.719***	3.738***	3.951***
	(1.213)	(3.966)	(1.050)	(0.990)	(0.840)	(0.967)	(0.914)
MarketLeverage	1,059**	1,392*	1,480**	1,816*	2,176**	1,998**	1,665*
	(413.1)	(743.5)	(741.6)	(985.6)	(998.3)	(991.7)	(868.4)
TermStrucSlope		-7.457	-9.432	-6.217	-4.128	0.519	-9.454
		(10.65)	(10.91)	(11.09)	(11.82)	(12.40)	(10.44)
ReturnTBI			222.9**	244.9**	132.3	212.3**	224.5**
			(102.9)	(106.5)	(108.1)	(89.72)	(100.2)
1yrExcessReturn				-9.767	18.57	-5.871	-5.710
				(13.41)	(12.70)	(15.52)	(11.61)
ESG_Score	-2.137						
	(4.344)						
E_Score					0.0872	0.860	
					(1.535)	(1.243)	
S_Score					0.0955		-0.0216
					(1.025)		(0.684)
G_Score					0.423		
					(0.536)		
ESG_Score		-4.959	-0.172	0.0904			
		(4.601)	(0.503)	(0.673)			
Constant	-632.3	-997.7	-1,086	-1,416	-1,720*	-1,625*	-1,260
	(420.9)	(702.4)	(702.4)	(946.2)	(1,002)	(962.1)	(844.6)
Observations	3,920	3,414	3,407	3,407	3,406	3,406	3,406
Number of id	55	56	55	55	55	55	55

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

minant due to its collinearity with the CDS spreads. In the framework of popularity-based pricing, ESG factors can be linked to the behavior of less rational investors, in the sense that these investors may prefer assets with specific characteristics. These developments resulted in major ESG-related risks for firms, arising from regulatory action and changes in customer behavior (Hübel and Scholz 2020). Hermalin and Weisbach (2001)[?] suggest that a firm's governance structure is endogenously determined. Bouslah et al. (2013) find a bidirectional causality between corporate social performance and firm risk. Given this, it is possible that ESG disclosure and credit risk via CDS spreads are determined simultaneously: that is, not only does ESG disclosure influence firm risk—firms also adjust ESG disclosure based on the current risk exposure. In such circumstances, current ESG disclosure is likely to be influenced by a past realization of credit risk (i.e., reverse causality). In this paper, I address this issue by lagging indepependent variable, ESG to control for reverse causality, as this help to control for reverse causality and thus tend to be less susceptible to endogeneity effects.

$$\begin{aligned}\text{CDS}_{t,i} = \beta_{0,i} + \beta_1 \text{StockReturn}_{t-1,i} \quad & + \beta_2 \text{MarketLeverage}_{t-1,i} + \beta_3 \text{VIX}_{t-1,i} \\ + \beta_4 \text{ExReturn }_1\text{yr}_{t-1,i} \quad & + \beta_5 \text{ReturnTBI}_{t-1,i} \\ + \beta_6 \text{TERM}_{t-1,i} \quad & + \beta_7 \text{ESG Score}_{t-1,i} + \epsilon_{t,i}\end{aligned} \tag{6.1}$$

To mitigate these reverse causality issues, I estimated alternative specifications of Equation 4.1 (6.1 above). 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 6.3. 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.

Table 6.3: ESG and CDS Spread—endogeneity bias (lagged independent variables)

	Lag 1	**Lag 2**
VARIABLES	qCDS	qCDS
EquityReturn	-0.105	0.117
	(0.0916)	(0.0920)
MarketVol	2.731***	2.736***
	(0.155)	(0.155)
MarketLeverage	7.911*	0.427
	(4.102)	(4.119)
TermStructSlope	-12.67***	-12.76***
	(1.102)	(1.107)
ReturnTBI	80.58***	81.87***
	(9.551)	(9.595)
1yrExcReturn	6.412***	5.267**
	(2.213)	(2.233)
ESG	-0.272***	-0.1427***
	(0.0497)	(0.0499)
Constant	103.8***	99.20***
	(13.37)	(13.26)
Observations	26,189	26,200

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

Chapter 7

Conclusion

In conclusion, this thesis deviates from the conventional asset pricing models and has combined both classical and behavioral finance to analyze the impact of ESG on credit risk pricing. The majority of literature in analyzing ESG has been treated as a risk factor. I have treated ESG as a preference or a non-risk factor. The non-risk factors (behavioral) incorporate that heterogeneity is a fact of life, and people differ in how they form judgments. As with liquidity, not every investor equally cares about ESG disclosure in their investment decision. The popularity-based framework (PAPM) provides a needed improvement over the CAPM by incorporating the two critical ingredients identified by Fama and French. The PAPM leads to robust findings and important real-world implications for practitioners. By incorporating diverse opinions and allowing for various investor preferences/tastes, the PAPM takes two significant steps towards a more realistic asset pricing model while helping to bridge classical and behavioral finance.

This analysis was conducted over a decade from January 2010 to April 2021. However, when the United Nations Principles on Responsible Investment were undertaken in 2006, companies did not have a clear cohesive guideline as to what universally constitutes sustainability. Data vendors did not have a robust database of their scores until 2010. This is really when institutional investors had just started to pay attention to ESG. In addition, companies face growing public awareness of their sustainability practices, increasing regulatory pressure, and comprehensive disclosure requirements. As credit rating agencies shift their focus toward ESG, these developments raise the question of whether credit markets reflect the sustainability practices of firms. I contribute to this question and apply credit default swap (CDS) spreads to examine whether markets price the popularity of firms'

ESG practices among investors. My findings indicate a significant and negative relationship between ESG and credit risk based on a sample of 20,551 firm-month observations representing 250 U.S firms from January 2010 to April 2021.

This result is robust to endogeneity, reverse causality tests, and controls for established credit spread determinants and firm-and time-level unobservable heterogeneity. This is supporting evidence for the risk mitigation view, which links better ESG performance to a reduction in firm risk, and, thus, credit risk. I find that for the sample universe of the U.S. corporate credit market, both investment grade and high yield (sub-investment grade) and concluded that ESG as a preference is significant in terms of the long-term credit risk protection spread levels for the entire universe as well as investment grade credit. Still, I did not find a significant relationship between ESG and CDS spreads for sub-investment grade credits. One possible reason is that the entire sample consisted of 75% investment grade credit and 25% of sub-investment grade credit.

Regarding the significance of ESG to the sub-investment grade credit, it would be reasonable to assume that the credit protection spread would be heavily influenced or dominated by its probability of default. Further analysis could have been conducted across industries. In addition, the possibility of examining the effect of ESG on the tail-risk should also be investigated. In summary, through this analysis, it is established that there is a link between ESG and credit risk via CDS spreads, especially with investment grade credits. As a result, firms' ESG disclosure can be considered an additional determinant of their CDS spreads. Practitioners could gain a tremendous insight into portfolio construction to generate alpha by factoring in ESG exposure of firms in the security selection.

Appendix A

MSCI ESG Ratings Methodology Overview

MSCI ESG Ratings aim to measure a company's resilience to long-term, financially relevant ESG risks.

- Of the negative externalities that companies in an industry generate, which issues may turn into unanticipated costs for companies in the medium to long-term?
- Conversely, which ESG issues affecting an industry may turn into opportunities for companies in the medium to long-term?

More specifically, the MSCI ESG Ratings model seeks to answer four key questions about companies:

- What are the most significant ESG risks and opportunities facing a company and its industry?
- What are the most significant ESG risks and opportunities facing a company and its industry?
- How exposed is the company to those key risks and/or opportunities?
- How well is the company managing key risks and/or opportunities?
- What is the overall picture of a company and how does it compare to its global industry peers?

MSCI ESG Ratings Process

Data Sources

To assess companies' exposure to and management of ESG risks and opportunities, The firm collects data from the following sources:

- Macro data at segment or geographic level from academic, government, NGO datasets (e.g., Transparency International, US EPA, World Bank)
- Company disclosure (10-K, sustainability report, proxy report, AGM results, etc.)
- Government databases, 3,400+ media, NGO, other stakeholder sources regarding specific companies

Issuer Communications and Feedback Process

The firm proactively reach out to companies as part of our standardized and systematic data review processes. They do not issue surveys or questionnaires or conduct general interviews with companies, nor do they accept or consider in our analysis any data provided by issuers that is not publicly available to other stakeholders. Being mindful of the "survey fatigue" faced by issuers, we make efforts not to overburden companies with data review requests. Typically, companies receive an alert, when the ESG Rating review is complete. Given the dynamic nature of our research, companies can access the data we have collected to date via the issuer portal at any time to review. They are welcome to ask questions and provide feedback at any time. They commit to updating a company profile as required promptly. This process is also in accordance with the objective of frequently updating company exports with the latest available information as provided by companies. Please note that updates to ESG data will not necessarily result in changes to a company's ESG rating or score.

Appendix B

The Popularity Asset Pricing Model

A presentation of the mathematical formulation is done in this section adopted from the monograth for The CFA Institute by Roger Ibbotson [**?**]. The PAPM is a generalization of the CAPM in which securities have characteristics other than risk and expected return that investors are concerned about.Its assumptions are:

1. Taxes, transaction costs, and other real-world considerations can be ignored.[1]
2. Each security has a bundle of characteristics.
3. Investors have preferences regarding these characteristics in addition to their preferences regarding risk and expected return.
4. All investors use a generalized form of Mean-Variance Optimization (MVO) that incorporates their preferences regarding security characteristics.
5. All investors have the same forecasts,; i.e., the same capital market assumptions (expected returns, standard deviations, and correlations.)
6. All investors agree on what the characteristics of the securities are.
7. All investors can borrow and lend at the same risk-free rate without limit

The conclusions of the PAPM are:

1. The market portfolio is not on the efficient frontier.
2. Each investor forms a customized portfolio of the risky assets that reflects his attitudes towards security characteristics. This portfolio is combined with the risk-free

[1] While things like taxes can be ignored, a strength of the PAPM is that they could be easily incorporated as a characteristic

asset (long or short). Portfolio optimization is required to find the overall investor-specific portfolio.

3. The expected excess return of each security is a linear function of its beta and its popularity loadings which measure the popularity of the security based on its characteristics relative to the those of the beta-adjusted market portfolio. The popularity loadings are multiplied by the popularity premiums which are aggregations of the preferences of the investors regarding the characteristics. In this way, the market aggregates investor preferences in determining the influence of security characteristics on the expected returns and prices of the securities.

Note that the conclusions of the PAPM are nearly the exact opposite of those of the CAPM. Additionally, conclusion (2) is much more consistent with observed investor portfolios.

$$\max_{\vec{\boldsymbol{x}}_i} U_i \left(\vec{\boldsymbol{x}}_i\right) = \vec{\boldsymbol{\mu}}_i' \vec{\boldsymbol{x}}_i - \frac{\lambda_i}{2} \vec{\boldsymbol{x}}_i' \Psi x_i \tag{1}$$

where

n = the number of risky securities in the market

$\vec{\boldsymbol{\mu}}_i$ = the n-element vector of expected security excess returns reflecting investor i' s views [9]

Ψ = the $n \times n$ variance-covariance matrix of returns on the risky securities

$\vec{\boldsymbol{x}}_i$ = the n-element vector of investor i's allocations (portfolio weights) to the risky securities [10]

λ_i = the risk aversion parameter of investor i

Based on investor i 's forecasts $\vec{\boldsymbol{\mu}}_i$ and risk aversion coefficient λ_i, investor i seeks to maximize utility.

From the first-order condition, leads to:

$$\vec{\boldsymbol{\mu}}_i = \lambda_i \Psi \boldsymbol{x}_i \tag{2}$$

Solving for $\vec{x}_i$, gives:

$$\vec{\boldsymbol{x}}_i = \frac{1}{\lambda_i} \Psi^1 \vec{\boldsymbol{\mu}}_i \tag{3}$$

In other words, from equations 2 and 3 , it could be started with either an investor's portfolio holdings or expected excess returns and solve for the other.

Let

m = the number of investors

w_i = the fraction of wealth held by investor $i; \sum_{i=1}^{m} w_i = 1$

Note the utility function is quadratic in portfolio weights, leading to the optimal portfolio weights being linear in expected returns.

By excess returns, we mean in excess of the return on a risk-free security.

There is a risk-free security to which investor i allocates $1-\sum_{j=1}^{n} x_{ij}$. Aggregating across investors, in equations 4,5 , and 6 , we have the market average level of risk aversion (λ_M), market-weighted average of investor expected security excess returns $(\vec{\boldsymbol{\mu}}_M)$, and the market portfolio $(\vec{x}_M)$ consisting of the weighted aggregation of the security weights of the investors:

$$
\begin{aligned}
\lambda_M &= \frac{1}{\sum_{i=1}^{m} \frac{w_i}{\lambda_i}} \\
\vec{\boldsymbol{\mu}}_M &= \lambda_M \sum_{i=1}^{m} \frac{w_i}{\lambda_i} \vec{\boldsymbol{\mu}}_i \\
\vec{\boldsymbol{x}}_M &= \sum_{i=1}^{m} w_i \vec{\boldsymbol{x}}_i
\end{aligned} \tag{4}
$$

Aggregating equation 3 across investors, in which it is solved for each investor's portfolio based on their expectations, we have the asset-weighted average holdings (the market portfolio):

$$
\vec{\boldsymbol{x}}_M = \frac{1}{\lambda_M} \Psi^{-1} \vec{\boldsymbol{\mu}}_M \tag{5}
$$

So that:

$$
\vec{\boldsymbol{\mu}}_M = \lambda_M \Psi \vec{x}_M \tag{6}
$$

Equation 9 decomposes the right side of equation 3, to show that each investor's portfolio differs from the market portfolio due to the difference between each investor i's expected security excess returns and the market-weighted average security excess returns:

$$
\vec{\boldsymbol{x}}_i = \frac{\lambda_M}{\lambda_i} \vec{\boldsymbol{x}}_M + \frac{1}{\lambda_i} \Psi^{-1} \left(\vec{\boldsymbol{\mu}}_i - \vec{\boldsymbol{\mu}}_M \right) \tag{7}
$$

Note that the first term on the right-hand side is same as in the standard CAPM, the fraction of the market average portfolio owned by investor i. The second term on the right-hand side pinpoints that the uniqueness of investor i 's portfolio is driven by the difference between the investor's expected excess returns and the market average excess returns. Note the similarity of equation 9 to the Black-Litterman (1992) model in which an investor's views about expected returns on assets are combined with market consensus views to arrive at an investor's expectations and ultimately their specific portfolio.

The expected excess return on the market portfolio remains:

$$\mu_M = \vec{\boldsymbol{x}}_M{}' \vec{\boldsymbol{\mu}}_M \tag{8}$$

Multiplying equation 8 through by $\vec{\boldsymbol{x}}'_M$, yields:

$$\mu_M = \lambda_M \sigma_M^2 \tag{9}$$

where $\sigma_M^2 = \vec{\boldsymbol{x}}'_M \Psi \vec{x}_M$, which is the variance of the market portfolio.

Rearranging equation 11 , it follows that:

$$\lambda_M = \frac{\mu_M}{\sigma_M^2} \tag{10}$$

Thus, λ_M, the average level of risk aversion, identifies the units of excess return per unit of market variance. Substituting the right-hand side of equation 12 for λ_M in equation 8 , and rearranging terms, yields the familiar CAPM equation for security expected excess returns, but at the aggregate market level:

$$\vec{\boldsymbol{\mu}}_M = \vec{\boldsymbol{\beta}}_M \mu_M \tag{11}$$

where the vector of betas is the covariance of each security with the market portfolio divided by the market variance

$$\vec{\boldsymbol{\beta}}_M = \frac{\Psi x_M}{\sigma_M^2} \tag{12}$$

The beta vector is subscript with M to make it clear that these are betas with respect to the market average portfolio and not the betas that could be defined with respect to each investor's tangency portfolio.

As discussed below, the equilibrium market values of the securities reflect the aggregation of the expected ending values across all investors. Expected excess returns, the variances and covariances of returns are all inversely proportional to market values. In the CAPM equilibrium, market values are such that equation 13 holds.

Formal Presentation of the PAPM with Heterogeneous Expectations

Moving to the PAPM, let

ρ = the number of popularity characteristics

$\boldsymbol{C}$ = the $n \times \rho$ matrix of characteristics exposure of the securities

$\overrightarrow{\boldsymbol{\Phi}}_i$ = the p-element vector of investor i's allocations (portfolio weights) to the risky securities

Investor i 's problem is:

$$\max_{\overrightarrow{\boldsymbol{x}}_i} U_i\left(\overrightarrow{\boldsymbol{x}}_i\right) = \overrightarrow{\boldsymbol{\mu}}_i' \overrightarrow{\boldsymbol{x}}_i + \overrightarrow{\boldsymbol{\phi}}_i' \boldsymbol{C}' \overrightarrow{\boldsymbol{x}}_i - \frac{\lambda_i}{2} \overrightarrow{\boldsymbol{x}}_i' \Psi \boldsymbol{x}_i \tag{13}$$

Relative to equation 1, equation 15 contains an additional term (middle term on the right-hand side) that captures popularity characteristics and investor i 's additional preferences. Investor i 's preferences for different characteristics can be driven by expectations around popularity premiums or non-return related preferences.

From the first-order condition, we have:

$$\overrightarrow{\boldsymbol{\mu}}_i = \lambda_i \Psi \boldsymbol{x}_i - \overrightarrow{\boldsymbol{\phi}}_i \tag{14}$$

The solution is:

$$\overrightarrow{\boldsymbol{x}}_i = \frac{1}{\lambda_i} \Psi^1 \left(\overrightarrow{\boldsymbol{\mu}}_i + \boldsymbol{C}\vec{\phi}_i\right) \tag{15}$$

Aggregating equation 17 across investors, we have the security weights of the market portfolio:

$$\overrightarrow{\boldsymbol{x}}_M = \frac{1}{\lambda_M} \Psi^{-1} \left(\overrightarrow{\boldsymbol{\mu}}_M + \boldsymbol{C\pi}\right) \tag{16}$$

where $\vec{\boldsymbol{\mu}}_M$ is as defined in equation 5 and

$$\vec{\boldsymbol{\pi}} = \lambda_M \sum_{i=1}^{m} \frac{w_i}{\lambda_i} \vec{\boldsymbol{\phi}}_i \tag{17}$$

$\vec{\boldsymbol{\pi}}$ is the p-element vector of aggregate, wealth and risk aversion-weighted investor preferences for different characteristics, and for reasons that will become apparent below, we call $\vec{\pi}$ the vector of popularity premiums. Combining the matrix of security characteristics with the vector of popularity premiums, $C\vec{\pi}$ leads to a n-element vector of popularity-based adjustments that augment the market expected returns and impact the market portfolio.

From equations 17 and 18, we derive an equation for the portfolio decision of each investor relative to the market portfolio:

$$\vec{\boldsymbol{x}}_i = \frac{\lambda_M}{\lambda_i} \vec{\boldsymbol{x}}_M + \frac{1}{\lambda_i} \Psi^{-1} \left[\left(\vec{\boldsymbol{\mu}}_i - \vec{\boldsymbol{\mu}}_M \right) + \boldsymbol{C} \left(\vec{\boldsymbol{\phi}}_i - \vec{\boldsymbol{\pi}} \right) \right] \tag{18}$$

Hence, both differences in expected returns and differences in popularity preferences impact individual portfolio construction.

Solving equation 18 for $\vec{\boldsymbol{\mu}}_M$ yields:

$$\vec{\boldsymbol{\mu}}_M = \lambda_M \Psi \vec{x}_M - C\vec{\pi} \tag{19}$$

Multiplying equation 21 through by $\vec{\boldsymbol{x}}'_M$ yields:

$$\mu_M = \lambda_M \sigma_M^2 - \vec{\boldsymbol{c}}_M{}' \vec{\boldsymbol{\pi}} \tag{20}$$

where $\vec{\boldsymbol{c}}_M = \boldsymbol{C}' \vec{\boldsymbol{x}}_M$, which is the vector of security characteristic exposures of the market portfolio.

From equation 22 , it follows that:

$$\lambda_M = \frac{\mu_M + \vec{c}'_M \vec{\pi}}{\sigma_M^2} \tag{21}$$

Substituting the right-hand side of equation 23 for λ_M in equation 21 , and rearranging terms, yields the generalization of the CAPM equation for market average expected excess returns:

$$\vec{\boldsymbol{\mu}}_M = \vec{\boldsymbol{\beta}}\mu_M + \left(\vec{\boldsymbol{\beta}}\,\vec{\boldsymbol{c}}'_M - \boldsymbol{C}\right)\vec{\boldsymbol{\pi}} \tag{22}$$

In equation 24 the first term on the right-hand is the same as the right-hand side of the CAPM. The second term represents the impact of popularity on security expected returns. This equation looks like a multifactor asset pricing model, but with the popularity premiums rather than risk premiums. For an individual security j, let

$$\delta_{jk} = \beta_j c_{Mj} - C_{jk} \tag{23}$$

so we can write:

$$\mu_{Mj} = \beta_j \mu_M + \sum_{k=1}^{p} \delta_{jk}\pi_j \tag{24}$$

We call δ_{jk} security j 's popularity loading on characteristic k. It 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 a security is positive for a given characteristic if the security is unpopular with respect to the characteristic and negative if it is popular.

As mentioned early, the PAPM can looks like 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 have a linear relationship to the risk factors. In contrast, in the CAPM and PAPM, the linear structure of expected returns originates from the assumption that the utility derived from the portfolio holdings is quadratic. For the PAPM, this is simplifying assumption that could be dropped.

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