Essays on Empirical Asset Pricing

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KRISTOFFER HALSKOV

ESSAYS ON EMPIRICAL ASSET PRICING

CBS

Essays on Empirical Asset Pricing

Kristoffer Halskov

A thesis presented for the degree of
Doctor of Philosophy

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Finally, I cannot thank my friends and family enough for their support. You have always shown nothing but patience and understanding, even during the most stressful periods of my PhD. You are truly what makes life so special.

Kristoffer Halskov

Copenhagen, June 2024

Summaries

Summaries in English

A Deep Structural Model for Empirical Asset Pricing

Over the past decade, the integration of machine learning (ML) models into financial research has led to significant advances. Despite these advances, ML models suffer from a lack of interpretability and theoretical foundation, limiting financial insight. Structural models, in contrast to ML models, are inherently theory-driven. Despite the broad range of methodologies that "structural models" encompasses, they share a core characteristic: they are born from theory and are designed to offer explicit predictions and insights into the phenomena they represent. This paper proposes a flexible framework, a *Deep Structural Model* (DSM), for combining the two methodologies, in an attempt to get the best of both worlds: the high predictability of machine learning and the economic intuition and interpretation of structural models.

The specific structural model examined in this paper is a modified version of the classic Merton (1974) model wherein the assets of the firm follow a geometric brownian motion. The asset drift is the sum of the risk-free rate, a term representing mispricing, and systematic risk compensation, while asset volatility contains a systematic and idiosyncratic component. This model jointly estimates the conditional expected equity returns and (co)variances and enables the analysis of the importance of mispricing relative to systematic risk compensation, as well as the effect of firm leverage on expected equity returns.

The DSM of this paper suggest that systematic risk compensation is the largest contributor to the average expected asset return of firms: systematic risk compensation constitutes 64%, with mispricing contributing the remaining 36%. However, mispricing is responsible for most of the dispersion in expected asset returns with an annual standard deviation of 13% compared to 7% for the systematic risk compensation component. The model also suggest that it is changes in the aggregate leverage of the economy that is responsible for an increased equity premium during economic recession, rather than changes to the underlying asset dynamics of firms. Both of these key results cannot be obtained through the common implementation method for the Merton model, first proposed by Vassalou and Xing (2004).

Finally, not only does the DSM provide new economic insight, it also provides expected equity return and (co)variance estimates that outperform pure machine learning models, such as the ones examined in Gu *et al.* (2020). These estimates can be used to construct both long-short and mean variance efficient portfolios, with much higher out-of-sample returns and Sharpe ratios compared to portfolios formed on the basis of the best performing model in Gu *et al.* (2020), namely a standard neural network model.

These results suggest that the Deep Structural Model framework is indeed able to provide new economic insight, while also having a higher predictive power compared to traditional methods.

Improving Merger Arbitrage Returns with Machine Learning

This paper attempts to answer two questions: How has the merger arbitrage market evolved over the last 20 years and can machine learning techniques provide additional insight into the merger arbitrage market beyond traditional statistical methods? To answer these two questions, the paper estimates the expected return of individual merger arbitrage trades using two different approaches: a direct modelling approach and a decomposed modelling approach. The direct modelling approach is similar to the way expected equity returns are modelled in Gu *et al.* (2020), wherein we rely on past realized merger arbitrage returns to fit a model that is then used for predictive purposes. The decomposed modelling approach instead tries to estimate the conditional probability of deal success, which can then in turn be used in a simplified decomposed expression for the expected return of a merger arbitrage trade. Both of these two modelling approaches make use of machine learning techniques to model their respective object of interests: the expected merger arbitrage return and the probability of deal success.

Out-of-sample trading strategies are then created based on the sets of expected returns from both the direct and decomposed modelling approach. Analyzing the performance of these trading strategies reveal that the decomposed expected return estimates lead to strategies with higher absolute and risk-adjusted returns compared to the strategies based on the direct modelling approach. Furthermore, it is found that the decision tree based machine learning models, namely a random forest and a gradient boosted trees model, provide more accurate conditional probabilities of deal success, relative to five other models explored in the paper.[1] The decomposed expected returns, based on these two models, are also shown to be more accurate than those based on the other models. Finally, analyzing the time series of the cross-sectional average expected merger arbitrage spread shows that after the financial crisis of '08-'09, the merger arbitrage spread has been significantly lower. Before the crisis it was about 4% after which it dropped to about 1.5% and has exhibited much less volatility over the last 10 years.

Pricing of Sustainability-Linked Bonds

Sustainability has become a central concern for governments, corporations, regulators and investors. A number of financial securities, particularly debt instruments, designed to align financial incentives with ESG objectives have come to existence in the past decade. For example, sustainable bonds where revenues from the bond issue are limited to funding ESG investments, have grown tremendously in recent years. Critics argue that companies have no direct financial incentive to act ESG-friendly once such bonds are issued. As a potential solution to this incentive problem, firms have recently begun to issue sustainability-linked bonds (SLBs). In contrast to sustainable bonds there are no limitations on how the proceeds are used, but bond cash flows are tied to the company achieving future ESG goals. In a typical SLB structure, the firm commits to a future carbon reduction target, and if the target is not met, the bond's coupon increases.

In this paper, we extensively examine the pricing of SLBs. We calculate the SLB price premium as the price difference between an SLB and a synthetic identical ordinary bond with no ESG label. First, we investigate if investors are willing to pay a markup for the ESG label itself. We find a positive but modest SLB yield premium of 1.9bps, which we call the "sustainium". Second, we examine the relationship between the SLB price premium and the

[1] The five other models are: logistic regression, logistic regression with an elastic net penalty, and three neural network models with on, two, and three hidden layers, respectively.

potential extra cash flows that investors receive if the firm fails to meet its ESG targets. We find that the SLB price premium is strongly positively related to the penalty size associated with not meeting the ESG targets. This indicates that, as basic financial theory predicts, the market accounts for the size of optional cash flows. Third, Kölbel and Lambillon (2023) report that the SLB premium is larger than the sum of penalties, which, if true, would allow firms to engage in greenwashing by issuing overpriced SLBs with no intention of reaching the ESG target(s). We find that the average SLB premium is significantly less than the sum of penalties and, thus, our results suggest no evidence of such greenwashing potential in the market. Fourth, we calculate the probability of missing the ESG target(s), for each SLB in our sample, under different scenarios, and find that the average probability of missing the target is only 14%-39%, depending on assumptions. These results support critics who argue that the ESG targets set by firms "lack ambition and are too easy to meet". Finally, we estimate the risk premium associated with ESG risk for the SLBs, and find that the average risk premium is negative, providing evidence that SLBs serve as financial hedges against ESG risk.

Resuméer på dansk

A Deep Structural Model for Empirical Asset Pricing

I løbet af det seneste årti har integrationen af maskinlæringsmodeller (ML) i finansiel forskning ført til betydelige fremskridt. På trods af disse fremskridt lider ML-modeller under en mangel på fortolkelighed og teoretisk fundament, hvilket begrænser finansiel indsigt. Strukturelle modeller, i modsætning til ML-modeller, er iboende teoridrevne. På trods af den brede vifte af metodologier, som "strukturelle modeller" omfatter, deler de en kernekarakteristik: de er baseret på teori og er designet til at tilbyde eksplicitte forudsigelser og indsigt i de fænomener, de repræsenterer. Denne artikel foreslår en fleksibel metode, en *Deep Structural Model* (DSM), som kombinerer de to metodologier i et forsøg på at få det bedste fra begge verdener: den høje forudsigelighed fra maskinlæring og den økonomiske intuition og fortolkning fra strukturelle modeller.

Den specifikke strukturelle model, der undersøges i denne artikel, er en modificeret version af den klassiske Merton (1974) model, hvor virksomhedens aktiver følger en geometrisk browniansk bevægelse. Aktivernes drift er summen af den risikofrie rente, et udtryk for fejl prisfastsætning og systematisk risikokompensation, mens aktivernes volatilitet indeholder en systematisk og en idiosynkratisk komponent. Denne model estimerer samtidig de betingede forventede aktieafkast og (ko)varianser og muliggør analysen af vigtigheden af fejl prisfastsætningen i forhold til den systematisk risikokompensation, samt effekten af virksomhedens finansielle gearing på det forventede aktieafkast.

DSM-modellen i denne artikel antyder, at systematisk risikokompensation er den største bidragsyder til det gennemsnitlige forventede aktivafkast for virksomheder: systematisk risikokompensation udgør 64%, mens fejl prisfastsætningen bidrager med de resterende 36%. Dog er fejl prisfastsætningen ansvarlig for størstedelen af spredningen i forventede aktivafkast med en årlig standardafvigelse på 13% sammenlignet med 7% for den systematiske risikokompensationskomponent. Modellen antyder også, at det er ændringer i økonomiens samlede finansielle gearing, der er ansvarlige for en øget aktiepræmie under økonomiske recessioner, snarere end ændringer i virksomhedernes underliggende aktivdynamik. Begge disse nøglekonklusioner kan ikke opnås gennem den almindelige implementeringsmetode for Merton-modellen, først foreslået af Vassalou and Xing (2004).

Endelig giver DSM-modellen ikke kun ny økonomisk indsigt, den leverer også forventede aktieafkast og (ko)variansestimater, der overgår rene maskinlæringsmodeller, såsom dem undersøgt i Gu *et al.* (2020). Disse estimater kan bruges til at konstruere både lang-kort og middel-varians effektive porteføljer, med meget højere "out-of-sample" afkast og Sharpe-ratioer sammenlignet med porteføljer dannet på basis af den bedst præsterende model i Gu *et al.* (2020), nemlig en standard neural netværksmodel.

Disse resultater tyder på, at Deep Structural Model-metoden faktisk er i stand til at levere ny økonomisk indsigt, samtidig med at den har en højere forudsigelseskraft sammenlignet med traditionelle metoder.

Improving Merger Arbitrage Returns with Machine Learning

Denne artikel forsøger at besvare to spørgsmål: Hvordan har markedet for merger arbitrage udviklet sig over de sidste 20 år, og kan maskinlæringsmetoder give yderligere indsigt i markedet for merger arbitrage i forhold til traditionelle statistiske metoder? For at besvare disse to spørgsmål bliver der i artiklen estimeret det forventede afkast for individuelle merger arbitrage handler ved hjælp af to forskellige tilgange: en direkte modelleringsmetode og en dekomponeret modelleringsmetode. Den direkte modelleringsmetode ligner den måde, forventede aktieafkast modelleres på i Gu *et al.* (2020), hvor vi bruger tidligere realiserede merger arbitrage afkast for at træne en model, der derefter bruges til at forudsige fremtidige afkast. Den dekomponerede modelleringsmetode forsøger derimod at estimere den betingede sandsynlighed for, at en handel lykkes, hvilket derefter kan bruges i et forenklet dekomponeret udtryk for det forventede afkast af en merger arbitrage handel. Begge disse modelleringsmetoder anvender maskinlæringsmetoder til at modellere deres respektive interesseobjekter: det forventede merger arbitrage afkast og sandsynligheden for, at en handel lykkes.

Der bliver lavet "out-of-sample" handelsstrategier der er baseret på de to sæt af forventede afkast fra både den direkte og dekomponerede modelleringsmetode. En analyse af handelsstrategiernes præstationerne afslører, at de dekomponerede forventede afkastestimater fører til strategier med højere absolutte og risikojusterede afkast sammenlignet med strategierne baseret på den direkte modelleringsmetode. Desuden viser det sig, at beslutningstræbaserede maskinlæringsmodeller, nemlig en random forest og en gradient boosted trees-model, giver mere præcise betingede sandsynligheder for, at en handel lykkes, i forhold til fem andre modeller undersøgt i artiklen.[2] De dekomponerede forventede afkast, baseret på disse to modeller, viser sig også at være mere præcise end dem baseret på de andre modeller. Endelig viser en analyse af tidsserien for det tværsnitsmæssige gennemsnit af forventede merger arbitrage spreads, at efter finanskrisen i '08-'09 har merger arbitrage spreadet været markant lavere. Før krisen var det omkring 4%, hvorefter det faldt til omkring 1,5% og har udvist meget mindre volatilitet over de sidste 10 år.

Pricing of Sustainability-Linked Bonds

Bæredygtighed er blevet en central bekymring for regeringer, virksomheder, regulatorer og investorer. I løbet af det sidste årti er der blevet lavet en række af nye finansielle værdipapirer, især gældsinstrumenter, designet til at tilpasse finansielle incitamenter med ESG-mål. For eksempel er bæredygtige obligationer, hvor indtægterne fra obligationsudstedelsen er begrænset til at finansiere ESG-investeringer, vokset enormt i de seneste år. Kritikere hævder,

[2] De fem andre modeller er: logistisk regression, logistisk regression med en elastic net-penalty og tre neurale netværksmodeller med henholdsvis én, to og tre skjulte lag.

at virksomheder ikke har noget direkte finansielt incitament til at handle ESG-venligt, efter sådanne obligationer er udstedt. Som en potentiel løsning på dette incitamentsproblem er virksomheder for nylig begyndt at udstede “sustainability-linked bonds” (SLBs). I modsætning til bæredygtige obligationer er der ingen begrænsninger på, hvordan provenuet anvendes, men obligations kuponer er knyttet til, at virksomheden opnår fremtidige ESG-mål. I en typisk SLB-struktur forpligter virksomheden sig til et fremtidigt mål om reduktion af kulstof, og hvis målet ikke nås, øges obligationens kupon.

I denne artikel undersøger vi prisfastsætningen af SLBs. Vi beregner SLB-præmien som prisforskellen mellem en SLB og en identisk syntetisk obligation uden ESG-mål. Først undersøger vi, om investorer er villige til at betale en præmie for ESG-stemplet i sig selv. Vi finder en positiv, men beskeden SLB-præmie på 1,9 basispoint, som vi kalder “sustainium”. For det andet undersøger vi forholdet mellem SLB-præmien og de potentielle ekstra kuponbetalinger, som investorer modtager, hvis virksomheden ikke opfylder sine ESG-mål. Vi finder, at SLB-præmien er stærkt positivt relateret til størrelsen af disse ekstra kuponbetalinger. Dette indikerer, at markedet, som grundlæggende finansiel teori forudsiger, tager højde for størrelsen af de her potentielle ekstra kuponer. For det tredje rapporterer Kölbel and Lambillon (2023), at SLB-præmien er større end summen af de ekstra kuponer, hvilket, hvis det er sandt, ville give virksomheder mulighed for at engagere sig i greenwashing ved at udstede overprisede SLBs uden intention om at nå ESG-målet/målene. Vi finder, at den gennemsnitlige SLB-præmie er betydeligt mindre end summen af de ekstra kuponbetalinger, og dermed antyder vores resultater, at der ikke er noget bevis for potentiel greenwashing på markedet. For det fjerde beregner vi sandsynligheden for at misse ESG-målet/målene for hver SLB i vores data under forskellige scenarier og finder, at den gennemsnitlige sandsynlighed for at misse målet kun er 14%-39%, afhængig af hvilke antagelser vi gør os. Disse resultater understøtter kritikere, der hævder, at de ESG-mål, virksomhederne sætter, “mangler ambition og er for lette at opfylde”. Endelig estimerer vi den risikopræmie, der er forbundet med ESG-risiko for SLBs, og finder, at den gennemsnitlige risikopræmie er negativ, hvilket tyder på at SLBs fungerer som finansielle afdækninger mod ESG-risiko.

Introduction

This thesis examines the relationship between risk and return in various areas of the financial markets. The thesis contains three chapters, which can be read independently. They represent the culmination of my Ph.D. studies at the Department of Finance, the Center for Financial Frictions (FRIC), and the Center for Big Data in Finance (BIGFI) at Copenhagen Business School.

In the first chapter, A Deep Structural Model for Empirical Asset Pricing, I introduce a novel framework that explores the potential synergy of combining structural models and machine learning. The aim is to achieve the best of both worlds: high predictability and economic interpretability. Using the simple structural model of Merton (1974), I demonstrate that the framework provides better equity return and (co)variance predictions compared to leading benchmark models. Furthermore, the model suggests that systematic risk compensation is the main contributor to the average expected equity return, while mispricing is the largest driver of the dispersion of expected equity returns. Finally, the model provides evidence that firm leverage is the main driver of an increased equity premium during economic recessions.

The second chapter, Improving Merger Arbitrage Returns with Machine Learning, examines whether machine learning models can improve the estimation of expected returns for individual merger arbitrage trades over traditional statistical models. The analysis shows that using expected return estimates from machine learning models leads to improved merger arbitrage strategies in terms of both absolute and risk-adjusted returns. Additionally, the more precise expected return estimates allow for new insights into the aggregate merger arbitrage market over time.

The third and final chapter, Pricing of Sustainability-Linked Bonds, examines the market for sustainability-linked bonds, where the bond's cash flows depend on the issuing firm meeting certain pre-specified ESG targets. The analysis suggests that investors pay a premium for these bonds, corresponding to a lower yield to maturity of 1-2 basis points. Furthermore, the results indicate that the sustainability-linked bond market is efficient, with the prices of these bonds being strongly related to the size of the potential penalty for missing the ESG targets.

Contents

Chapter 1

A Deep Structural Model for Empirical Asset Pricing

Abstract

This paper proposes a new type of modelling framework that use machine learning techniques to estimate the parameters of structural models: Deep Structural Models (DSMs). I implement a DSM with a simple Merton (1974) model as a foundation, and show that the DSM *jointly* estimates expected equity returns and (co)variances with higher predictive power than leading benchmark models. The model is used to form long-short and mean variance efficient portfolios with significantly higher average excess returns, alphas, and Sharpe ratios, compared to those formed on the basis of a state-of-the-art machine learning model. Economically, the DSM suggests that systematic risk compensation is the largest contributor to the average expected asset return of firms, while mispricing is the primary driver of the dispersion of expected returns. Finally, the DSM provides evidence that firm leverage is the main reason for an increased equity premium during economic recessions.

I am grateful for the helpful comments and feedback from Alejandro Lopez-Lira (discussant), Amit Goyal, David Lando, Grace Xing Hu, Lasse Heje Pedersen, Peter Feldhütter, Stephen Schaefer, Tarun Ramadorai, Giovanni Venturato, members of the BIGFI center at Copenhagen Business School, and seminar and conference participants at the European FMA Doctoral Student Consortium 2023, the HEC Workshop on Incentives in Finance 2023, and the FMA Annual Meeting 2023. I gratefully acknowledge support from the Center for Big Data in Finance (grant no. DNRF167).

1 Introduction

Over the past decade, the integration of machine learning (ML) models into financial research has led to significant advances. Despite these advances, ML models suffer from a lack of interpretability and theoretical foundation, limiting financial insight.[1] Structural models, in contrast to ML models, are inherently theory-driven. Despite the broad range of methodologies that "structural models" encompasses, they share a core characteristic: they are born from theory and are designed to offer explicit predictions and insights into the phenomena they represent. This does not come without a cost though: while structural models provide clear economic insights, it is not clear how to best estimate their parameters, let alone how to incorporate the vast amount of conditioning information available to econometricians. This apparent dichotomy between ML models and structural models naturally begs the question: can we combine the two and keep the flexibility and predictive power of ML, and the economic intuition and interpretability of structural models? As Giglio *et al.* (2022) write: *"...our view is that the most promising direction for future empirical asset pricing research is developing a genuine fusion of economic theory and machine learning. It is a natural marriage..."*. This paper is an attempt to officiate such a wedding. I propose a new model framework, Deep Structural Models (DSMs), that combine ML techniques with structural models.

Figure 1 illustrates how the DSM framework works by showcasing three different approaches for modelling an object of interest, $\mathbf{y}$: a deep learning model, a structural model, and a DSM.[2] When fitting the deep learning model to the data, we start from a point of observing a set of variables, denoted by $\mathbf{X}_{obs}$ in the figure, that we assume have some functional relationship with $\mathbf{y}$. We then rely on the deep learning model, represented by the black-box, to find this functional relationship. In contrast, the structural approach relies on a set of estimated parameters, denoted by $\hat{\boldsymbol{\theta}}$, that feeds through an economic model to arrive at an estimate of $\mathbf{y}$.[3] The estimation of $\hat{\boldsymbol{\theta}}$ depends on the specific choice of structural model, but usually relies on some sort of GMM, maximum likelihood, or simulation estima-

[1] Machine learning has been successful in various predictive tasks within finance, yet it faces unique challenges in this domain. Israel *et al.* (2020) provide an insightful discussion on these issues.

[2] Deep learning models are a specific type of ML models that are ideally suited for the purposes of this paper due to their flexibility in terms of customization and optimization. ML and deep learning will be used interchangeably even though one is a subset of the other.

[3] Usually, a structural model has several implications associated with it, which is illustrated by the "Other Implications" box in Figure 1.

tion. The DSM framework combines the two approaches and models the parameters of a structural model as functions of the observable data, i.e. $\mathbf{y}$ is now only indirectly a function of $\mathbf{X}_{obs}$ through $\hat{\boldsymbol{\theta}}$. This allows us to keep the ability of ML models to flexibly incorporate all observable information in the estimation of $\mathbf{y}$, while keeping the transparency of structural models. The DSM framework can therefore be viewed as a flexible methodology for estimating the parameters of structural models or, alternatively, as an economically motivated regularization of an ML model.

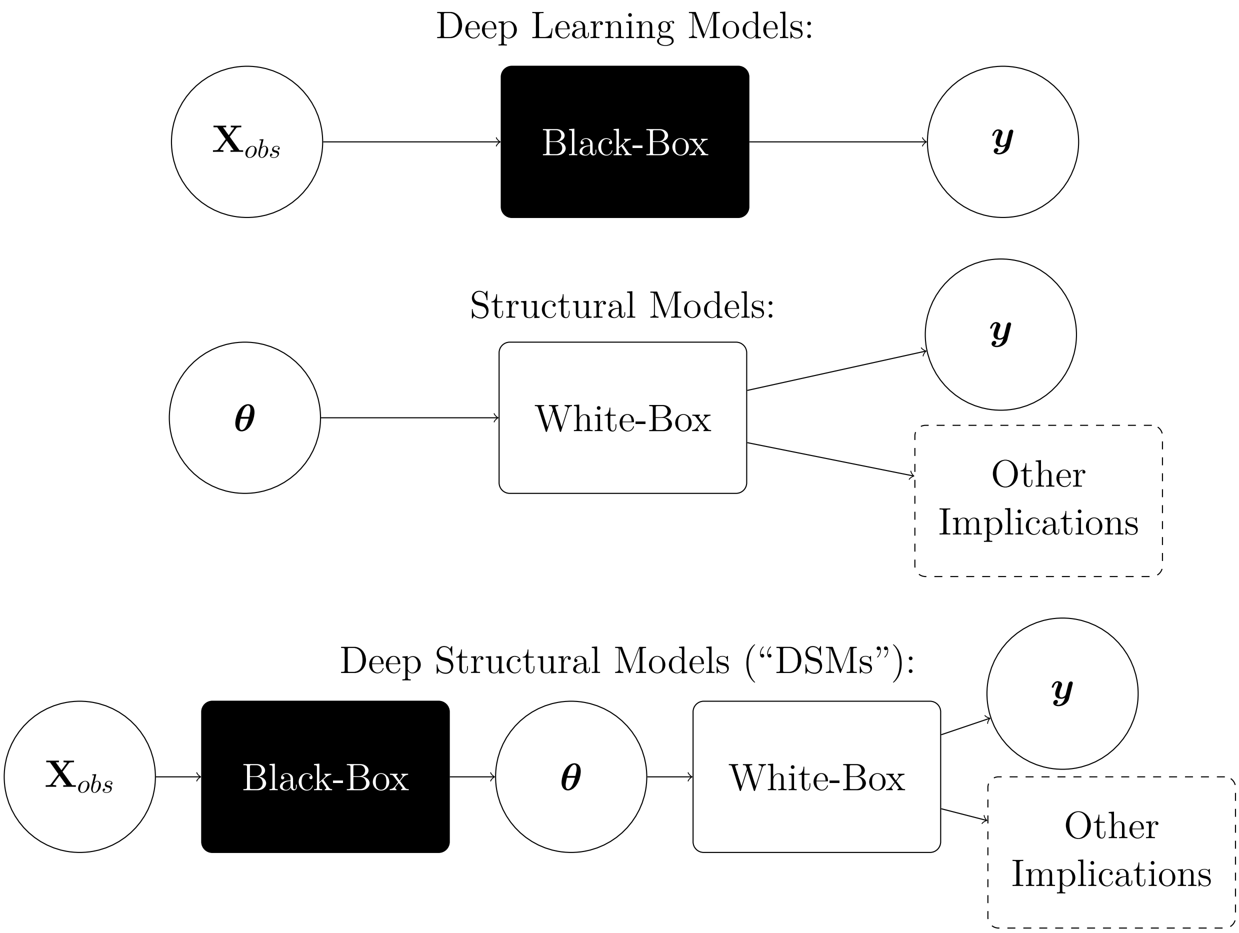


Figure 1: *Three Different Modelling Approaches.* This figures illustrates the modelling approach for three different types of models: deep learning models, structural models, and deep structural models (DSMs). For all three types of models, the object or phenomenon of interest is represented by $\boldsymbol{y}$. $\mathbf{X}_{obs}$ refers to a set of observable variables, while $\hat{\boldsymbol{\theta}}$ refers to a set of estimated parameters for some structural model. The "Black-Box" represents a deep learning model that transforms $\mathbf{X}_{obs}$ into an output, while the "White-Box" refers to the structurally determined transformation of $\hat{\boldsymbol{\theta}}$ to an estimate of $\boldsymbol{y}$, as well as any other implications associated with the structural model.

The specific structural model examined in this paper is a modified version of the classic Merton (1974) model wherein the assets of the firm follow a geometric brownian motion

(GBM). The asset drift is the sum of the risk-free rate, a term representing mispricing, and systematic risk compensation, while asset volatility contains a systematic and idiosyncratic component. This model jointly estimates the conditional expected equity returns and (co)variances and enables the analysis of the importance of mispricing relative to systematic risk compensation, as well as the effect of firm leverage on expected equity returns. The GBM parameters are modelled as functions of 238 firm-specific characteristics and 45 macroeconomic variables, and the model is estimated on a comprehensive dataset of equity returns spanning 1950-2021 with around 3.2 million firm-month observations containing 23,422 unique firms. After fitting the model, I use analytically derived expressions for the expected equity returns and (co)variances and find the following key results:

1. **The Role of Mispricing.** Systematic risk compensation is the largest contributor to the average expected excess asset return, while mispricing is responsible for most of the dispersion. Systematic risk compensation contributes 63.73% to the average expected excess asset return, while mispricing only contributes 36.27%. The standard deviations of the systematic risk compensation and mispricing parameters are 6.85% and 12.51%, respectively.

2. **The Role of Leverage.** Firm leverage, rather than the underlying asset dynamics, is responsible for an increased equity premium during recessions. The estimated asset parameters are stable through recessions, yet the time series dynamics of leverage cause the equity premium to increase. I find that the equity premium peaked at 15% during the financial crisis of 2008-09.

3. **Equity Return Prediction.** The DSM provides more accurate firm-level estimates of the expected equity return than existing state-of-the-art ML models. Different specifications of the DSM provide out-of-sample R^2 values in the range of 0.74-0.80, compared to 0.56 for a neural network (NN) benchmark.

4. **Long-Short Portfolio Performance.** The more accurate equity return predictions from the DSM lead to better performing long-short portfolios. Portfolios based on the DSM predictions outperform the NN benchmark in terms of both excess returns and annualized Sharpe ratios: the DSM portfolios have average monthly excess returns (annualized Sharpe ratios) in the range of 2.63-3.10% (1.43-1.67) compared to the NN benchmark portfolio of 1.91% (1.08).

5. **Variance Forecasting.** The DSM estimates future firm-level equity return variances better than a GARCH(1,1) model. The DSM variance forecasts has an out-of-sample mean squared error that is 23.89%-24.65% lower than the GARCH benchmark. Regression results confirm that the DSM predictions explain a higher proportion of the variance with an R^2 value of 0.42 compared to 0.39 for the GARCH benchmark.

6. **Mean Variance Efficient Portfolios.** Mean variance efficient (MVE) portfolios, formed on the basis of the expected equity returns and covariance matrix, perform even better than the long-short portfolios. I form both a leverage constrained and a short constrained MVE portfolio that are re-balanced on a monthly basis. The best performing leverage constrained MVE portfolio achieves a monthly average excess return of 4.89% with an annualized Sharpe ratio of 3.96, while the best performing short constrained MVE portfolio has a monthly average excess return and Sharpe ratio of 4.58% and 1.93, respectively. For comparison, the S&P500 index delivered an average monthly excess return of 0.60% and a Sharpe ratio of 0.48 over the same time period.[4]

This paper touches upon several strands of the literature. While I implement a modified version of the Merton (1974) model, that was not the only possible choice. The literature on structural credit risk models has since the publication of Merton (1974) added additional economic mechanisms: Black and Cox (1976) introduce a default boundary and Leland (1994) accounts for bankruptcy costs and the tax benefits of debt. More recent advancements include Du *et al.* (2019), who models the firm's asset volatility as stochastic, and Feldhütter and Schaefer (2023), who incorporate stochastic debt dynamics. Vassalou and Xing (2004) also implements the Merton (1974) model on a firm-level basis using an iterative estimation technique and uncover the so-called distress risk puzzle. Bharath and Shumway (2008) use a much simpler firm-level estimation technique to show that it is the functional form of the Merton (1974) model, rather than the specific implementation of it, that matters when using it for default prediction. ML has, in part, gained popularity within finance for its ability to overcome the curse of dimensionality: a large number of factors and characteristics has been put forth in the literature for explaining the cross-section of equity returns, leading to the so-called "factor zoo" as Cochrane (2011) put it (see Harvey *et al.* (2016), Hou *et al.* (2020), and Jensen *et al.* (2022) for an overview of the many factors proposed in the literature).

[4] These numbers are gross of transaction fees and should not be viewed as achievable by an investor. The MVE portfolios serve as a testament to the DSM's ability to accurately model not only expected equity returns but also covariances.

Freyberger *et al.* (2020), Feng *et al.* (2020), and Kozak *et al.* (2020) use various shrinkage methods on a large set of factors and characteristics to construct stochastic discount factors, while Bryzgalova *et al.* (2020) and Chen *et al.* (2023) extend this idea to non-linear ML techniques. The idea of modelling structural parameters as functions of contemporary observable variables is heavily inspired by Kelly *et al.* (2019) and Gu *et al.* (2021) who use a multitude of characteristics to determine conditional betas for equity returns in a latent factor model. Bali *et al.* (2020) use the structural model of Du *et al.* (2019) to motivate the use of hedge ratios for predicting corporate bond returns. They use different statistical methods, including ML models, to estimate expected equity returns and hedge ratios, which they then use to predict bond returns. Their paper is a great example of how to use financial theory and ML techniques in conjunction with each other. While their methodology achieves significantly better bond return predictions than traditional models, they do not estimate the underlying parameters of their structural model, and so their predictions are still of a "black-box" nature. This paper differs since I directly estimate the underlying firm-level asset dynamics, which not only allows us to analyze these estimated parameters, but also enables us to use analytically derived predictions for firm-level expected equity returns and (co)variances.

The paper proceeds as follows: Section 2 introduces the structural model, its implications, and the empirical implementation using ML. Section 3 gives an overview of the data and analyzes the out-of-sample performance of the DSM, and finally, Section 4 concludes.

2 Model

2.1 A General Model

It is assumed that all systematic risk in the economy can be characterized by K independent Brownian motions B_{kt}, for $k = 1, ..., K$. The price of risk associated with each Brownian motion is time-varying and is denoted by λ_{kt}. In addition to the systematic risks, each firm, denoted by i, is also exposed towards an idiosyncratic risk represented by another independent Brownian motion, $\mathcal{E}_{it}$. The asset value for firm i at time t, V_{it}, is then assumed to follow a $(K+1)$-dimensional geometric Brownian motion:

$$dV_{it} = \left(r_{ft} - \delta_{it} + \alpha_{it} + \sum_{k=1}^{K} \beta_{kit}\lambda_{kt}\right) V_{it}dt + \sum_{k=1}^{K} \beta_{kit} V_{it} dB_{kt} + \epsilon_{it} V_{it} d\mathcal{E}_{it} \tag{1}$$

Where r_{ft} denotes the risk-free rate, δ_{it} is the firm-wide payout, α_{it} is compensation unassociated with any risk exposure and can be viewed as a mispricing or arbitrage term, β_{kit} is the risk exposure of firm i at time t towards the systematic Brownian motion B_{kt}, while ϵ_{it} is the risk exposure towards the idiosyncratic Brownian motion $\mathcal{E}_{it}$. For convenience, equation (1) can also be written in matrix form:

$$dV_{it} = \left(r_{ft} - \delta_{it} + \alpha_{it} + \boldsymbol{\beta}_{it}^T \boldsymbol{\lambda}_t\right) V_{it}dt + \boldsymbol{\beta}_{it}^T V_{it} d\boldsymbol{B}_t + \epsilon_{it} V_{it} d\mathcal{E}_{it} \tag{2}$$

Where $\boldsymbol{\beta}_{it}$, $\boldsymbol{\lambda}_t$, and $\boldsymbol{B}_t$ are now all $K \times 1$ vectors containing the systematic risk exposures, prices of risk, and systematic shocks, respectively. The stochastic process presented in (2) is standard in the asset pricing literature, although it is commonly expressed more succinctly as:

$$dV_{it} = \mu_{it} V_{it} dt + \sigma_{it} V_{it} dW_{it} \tag{3}$$

Which, given the representation in (2), means that:

$$\mu_{it} = r_{ft} - \delta_{it} + \alpha_{it} + \boldsymbol{\beta}_{it}^T \boldsymbol{\lambda}_t \tag{4}$$

$$\sigma_{it} = \sqrt{\boldsymbol{\beta}_{it}^T \boldsymbol{\beta}_{it} + \epsilon_{it}^2} \tag{5}$$

$$dW_{it} = \frac{1}{\sqrt{\boldsymbol{\beta}_{it}^T \boldsymbol{\beta}_{it} + \epsilon_{it}^2}} \left(\boldsymbol{\beta}_{it}^T d\boldsymbol{B}_t + \epsilon_{it} d\mathcal{E}_{it}\right) \tag{6}$$

Despite the subscript on the single Brownian motion, W_{it}, it is important to note that firm i is still exposed towards the K systematic risk factors.

2.2 Simplifying Assumptions

Now, assume that the contingent claims to the firm's assets are defined as in Merton (1974). That is, at time t, each firm has two contingent claims to its assets: A single class of debt with a market value of D_{it} that promises a single cash flow at time $t+1$ equal to

F_{it+1}, and equity, E_{it}, which is the residual claim to the firm's assets. If, at time $t+1$, we have that $V_{it+1} \geq F_{it+1}$, then bondholders collectively receive F_{it+1} and equity holders receive $V_{it+1} - F_{it+1}$. On the other hand, if $V_{it+1} < F_{it+1}$, then bondholders receive V_{it+1} and equity holders receive nothing. Thus, the terminal values of debt and equity can be written as $D_{it+1} = \min[F_{it+1}, V_{it+1}]$ and $E_{it+1} = \max[V_{it+1} - F_{it+1}, 0]$. Additionally, the firm is restricted from issuing new debt, paying dividends, or buying back shares before time $t+1$. This means that in the context of the general model in Section 2.1 we have that $\delta_{it} = 0 \quad , \quad \forall t < t+1$.

Let $\boldsymbol{X}_{it}$ be a $N \times 1$ vector containing a set of observable firm characteristics for firm i at time t. Then, let $\boldsymbol{Z}_t$ be a $M \times 1$ vector of observable macroeconomic variables shared among all firms at time t. Both $\boldsymbol{X}_{it}$ and $\boldsymbol{Z}_t$ are assumed constant between t and $t+1$. For each systematic shock, k, it is assumed that there exists two sets of functions that map the observable variables into firm risk exposures and market prices of risks, respectively. Each risk exposure function, denoted β_k, transforms the firm characteristics into a single value, $\beta_k : \mathbb{R}^N \to \mathbb{R}$, while each market price of risk function, denoted λ_k, depend on the macroeconomic variables, $\lambda_k : \mathbb{R}^M \to \mathbb{R}$. Like the β_k-functions, both the mispricing term, α_{it}, and the idiosyncratic risk exposure, ϵ_{it}, are functions that solely depend on the firm characteristics, $\alpha : \mathbb{R}^N \to \mathbb{R}$ and $\epsilon : \mathbb{R}^N \to \mathbb{R}$. Finally, the risk-free rate r_{ft} is assumed to be constant between between t and $t+1$.

With these simplifying assumptions, we can rewrite the asset process of firm i from equation (3):

$$dV_{it} = \mu(\boldsymbol{X}_{it}, \boldsymbol{Z}_t)V_{it}dt + \sigma(\boldsymbol{X}_{it})V_{it}dW_{it}, \quad \forall t < t+1 \tag{7}$$

Where the "transformation" equations (4)-(6) become:

$$\mu(\boldsymbol{X}_{it}, \boldsymbol{Z}_t) = r_{ft} + \alpha(\boldsymbol{X}_{it}) + \boldsymbol{\beta}(\boldsymbol{X}_{it})^T \boldsymbol{\lambda}(\boldsymbol{Z}_t) \tag{8}$$

$$\sigma(\boldsymbol{X}_{it}) = \sqrt{\boldsymbol{\beta}(\boldsymbol{X}_{it})^T \boldsymbol{\beta}(\boldsymbol{X}_{it}) + \epsilon(\boldsymbol{X}_{it})^2} \tag{9}$$

$$dW_{it} = \frac{1}{\sqrt{\boldsymbol{\beta}(\boldsymbol{X}_{it})^T \boldsymbol{\beta}(\boldsymbol{X}_{it}) + \epsilon(\boldsymbol{X}_{it})^2}} \Big(\boldsymbol{\beta}(\boldsymbol{X}_{it})^T d\boldsymbol{B}_t + \epsilon(\boldsymbol{X}_{it}) d\mathcal{E}_{it} \Big) \tag{10}$$

Since it is clear from equations (7)-(10) which functions depend on $\boldsymbol{X}_{it}$, $\boldsymbol{Z}_t$, or both, the observable variables are omitted in the notation for the sake of simplicity, and a subscript of i is added to functions that depend on $\boldsymbol{X}_{it}$. Similarly, a subscript of t is added to the parameter functions, but it is important to note that this indicates the parameters are time-varying because of time-varying function inputs and not because the parameter functions themselves are time-varying, i.e. $\boldsymbol{\beta}(\cdot)$ does not change but its input variables, $\boldsymbol{X}_{it}$, varies across firms and time.

2.3 Model Implications

This section describes the analytical properties of the model presented in Section 2.2. Some of these properties, such as the implied default probability, are well-known in the literature, while others, such as the expected equity return and (co)variance, are not.

Default Implications

Let $\mathbb{1}_{V_{it+1}<F_{it+1}}$ be an indicator variable equal to one if firm i defaults at time $t+1$. The probability of this event is the implied default probability of Merton (1974):

$$\begin{aligned} \pi_{it} &= \mathrm{E}[\mathbb{1}_{V_{it+1}<F_{it+1}}] \\ &= \Phi(-DD_{it}) \end{aligned} \tag{11}$$

Where $\Phi(\cdot)$ is the cumulative standard normal distribution and DD_{it} is the distance to default:

$$DD_{it} = \frac{\ln\left(\frac{V_{it}}{F_{it+1}}\right) + \mu_{it} - \frac{\sigma_{it}^2}{2}}{\sigma_{it}} \tag{12}$$

Equity Implications

In a setting such as this, we know that the equity of the firm can be viewed as a European call option on the underlying firm assets, i.e. the current equity value can be expressed as:

$$E_{it} = V_{it}\Phi(d_{1it}) - F_{it+1}\exp\{-r_{ft}\}\Phi(d_{2it}) \tag{13}$$

Where:

$$d_{1it} = \frac{\ln\left(\frac{V_{it}}{F_{it+1}}\right) + r_{ft} + \frac{\sigma_{it}^2}{2}}{\sigma_{it}} \tag{14}$$

$$d_{2it} = d_{1it} - \sigma_{it} \tag{15}$$

At time $t+1$, the equity value of a firm is equal to the asset value of the firm minus the face value of debt bounded below at 0. When the asset value of a firm follows a Geometric Brownian motion we know that the terminal (or in this case, the time $t+1$) asset value is log-normally distributed, which means that we can view the time $t+1$ equity value as a mixture distribution of a constant 0 and a shifted log-normal distribution truncated at 0:

$$\mathcal{L}^E_{it+1} = \pi_{it}\delta(E_{it+1}) + \frac{1}{(E_{it+1}+F_{it+1})\sqrt{2\pi\sigma^2_{it}}} \exp\left\{-\frac{\left(\ln\left(\frac{E_{it+1}+F_{it+1}}{V_{it}}\right)-\left(\mu_{it}-\frac{\sigma^2_{it}}{2}\right)\right)^2}{2\sigma^2_{it}}\right\} U(E_{it+1}) \tag{16}$$

Where $\delta(\cdot)$ and $U(\cdot)$ are the Dirac delta and the Heaviside step functions, respectively.[5] From an empirical standpoint, it is more convenient to work with the density function for the equity return:

$$\mathcal{L}^r_{it+1} = \pi_{it}\delta(1+r_{it+1}) + \frac{1}{\left(1+r_{it+1}+\frac{F_{it+1}}{E_{it}}\right)\sqrt{2\pi\sigma^2_{it}}} \exp\left\{-\frac{\left(\ln\left(\frac{(1+r_{it+1})E_{it}+F_{it+1}}{V_{it}}\right)-\left(\mu_{it}-\frac{\sigma^2_{it}}{2}\right)\right)^2}{2\sigma^2_{it}}\right\} U(1+r_{it+1}) \tag{17}$$

Equation (17) is employed to fit the model to the data, however, to conduct an out-of-sample analysis of equity return predictions, variance predictions, and portfolio optimization, we need expressions for the expected equity returns and (co)variances. These are shown in Appendix 5.1 to be:

$$\mathrm{E}[r_{it+1}] = \frac{V_{it}}{E_{it}} \exp\{\mu_{it}\}\Phi\left(DD_{it}+\sigma_{it}\right) - (1-\pi_{it})\frac{F_{it+1}}{E_{it}} - 1 \tag{18}$$

And:

$$\begin{aligned}\mathrm{Cov}[r_{it+1}, r_{jt+1}] = {} & (1-\pi_{it}-\pi_{jt}+\mathrm{Cov}[\mathbb{1}_{V_{it+1}<F_{it+1}}, \mathbb{1}_{V_{jt+1}<F_{jt+1}}] + \pi_{it}\pi_{jt}) \\ & \times \frac{1}{E_{it}E_{jt}}\mathrm{E}\Big[E_{it+1}E_{jt+1} | \min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{jt+1}>F_{jt+1}}] = 1\Big] \\ & - (1+\mathrm{E}[r_{it+1}])(1+\mathrm{E}[r_{jt+1}])\end{aligned} \tag{19}$$

[5] Be aware of the slightly confusing notation in equations (16) and (17): π_{it} is the default probability of firm i at time t, whereas π without a subscript refers to the mathematical constant.

In the case where $i = j$, i.e. the variance, equation (19) has the closed-form solution:

$$\begin{aligned}\text{Var}[r_{it+1}] = \frac{1}{E_{it}^2}\Big(&\text{E}[V_{it+1}^2]\Phi\left(DD_{it} + 2\sigma_{it}\right) - V_{it}^2 \exp\{2\mu_{it}\}\Phi\left(DD_{it} + \sigma_{it}\right)^2 \\ &- 2V_{it}\exp\{\mu_{it}\}\Phi\left(DD_{it} + \sigma_{it}\right)\pi_{it}F_{it+1} + (1-\pi_{it})\pi_{it}F_{it+1}^2\Big)\end{aligned} \tag{20}$$

Where:

$$\text{E}[V_{it+1}^2] = V_{it}^2 \exp\left\{2\mu_{it} + \sigma_{it}^2\right\} \tag{21}$$

To avoid using the computationally expensive procedure of numerically estimating the covariance matrix with equation (19), I use asset return correlations as a proxy for equity return correlations. Specifically, the asset return correlation between firm i and j, at time t, can be analytically calculated as:

$$\rho_{ijt}^V = \frac{\boldsymbol{\beta}_{it}^T \boldsymbol{\beta}_{jt} + \mathbb{1}_{i=j}\epsilon_{it}\epsilon_{jt}}{\sigma_{it}\sigma_{jt}} \tag{22}$$

Then, using ρ_{ijt}^V as a proxy for the equity return correlation, the equity return covariance between firm i and j is estimated as:

$$\text{Cov}[r_{it+1}, r_{jt+1}] = \rho_{ijt}^V \sqrt{\text{Var}[r_{it+1}]\text{Var}[r_{jt+1}]} \tag{23}$$

2.4 Empirical Implementation

While the theoretical framework assumes knowledge of the model parameters, this is not the case in practice. In fact, the only value we can reasonably assume to be observable is E_{it}, which is calculated as the total number of shares outstanding, S_{it}, times the price of each share, P_{it}^S:

$$E_{it} = S_{it}P_{it}^S \tag{24}$$

Since each firm has a lot of different debt instruments in practice, it is not clear how we should measure the debt value of the theoretical framework, D_{it}, or the face value F_{it+1}. I follow the convention of previous literature, such as Vassalou and Xing (2004) and Bharath and Shumway (2008), and estimate the face value of the debt as short-term debt, F_{it+1}^{SD}, plus half of long-term debt, F_{it+1}^{LD}:[6]

$$F_{it+1} = F_{it+1}^{SD} + 0.5F_{it+1}^{LD} \tag{25}$$

The market value of debt is then estimated by discounting the face value with the risk-free rate:[7]

$$D_{it} = F_{it+1} \exp\{-r_{ft}\} \tag{26}$$

To find the total firm value add the values of equity and debt:

$$V_{it} = E_{it} + D_{it} \tag{27}$$

There are no theoretical constraints on the mispricing function, α, the risk-exposure functions, β_k, the prices of risk functions, λ_k, or the idiosyncratic asset volatility function, ϵ. This is where the "Deep" part of the "Deep Structural Model" comes into play: in order to keep the overall model as flexible as possible, the α, β_k, λ_k, and ϵ functions are all modelled as neural networks. Specifically, they will be structured as standard feed-forward neural networks with 1 hidden layer.[8] An illustrative example of the parameter functions, can be seen in Figure 2. From the figure, we see that each function takes its input variables (either $\boldsymbol{X}_{it}$ or $\boldsymbol{Z}_t$) and passes it to a set of hidden nodes. At each hidden node, some linear combination of the input variables is passed through an activation function. The machine learning literature proposes a wide range of activation functions, but a particular common one is the rectified linear unit (ReLU) function, which will be utilized by all hidden nodes across the parameter functions:

$$ReLU(x) = \max[x, 0] \tag{28}$$

The hidden nodes in Figure 2 will therefore have the following functional forms:

$$h_{git}^{\alpha/\beta/\epsilon} = \max\left[a_g^{\alpha/\beta/\epsilon} + \sum_{n=1}^{N} b_{gn}^{\alpha/\beta/\epsilon} x_{nit}, 0\right] \tag{29}$$

[6] Short-term debt and long-term debt is defined as "Debt in Current Liabilities - Total" and "Long-Term Debt - Total", respectively, from the Compustat database.

[7] This is obviously a major simplification as there should be some yield spread added to the discounting. However, due to the lack of good firm-level yield spread proxies that covers the entire data set described in Section 3.1, I follow a similar simplified debt value estimation as Bharath and Shumway (2008).

[8] It is possible to add more hidden layers to the functions, however, the results shown in Section 3 generally deteriorate when more hidden layers are added.

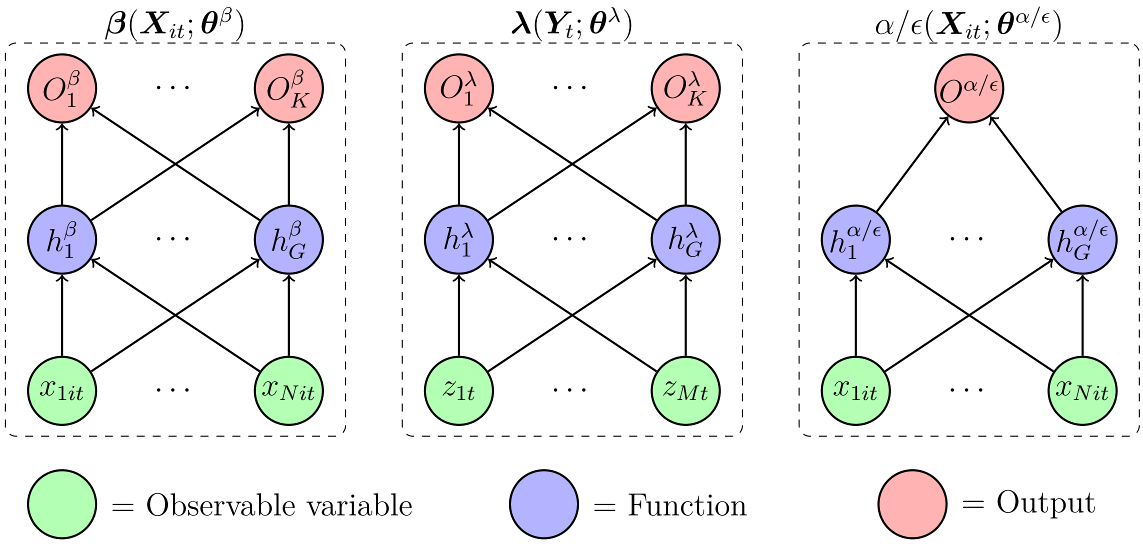


Figure 2: *The Parameter Functions.* This figure shows the general structure of the parameter functions of the asset value process, where α/ϵ indicates that α and ϵ has the same function structure. Each function takes a vector of inputs ($\boldsymbol{X}_{it}$ for α, $\boldsymbol{\beta}$ and ϵ, and $\boldsymbol{Z}_t$ for $\boldsymbol{\lambda}$) and passes them along to G hidden nodes. Each of the hidden nodes transform a linear combination of its inputs to a single positive real number through the ReLU function ($ReLU(x) = \max[x, 0]$). Finally, the outputs from each hidden node are passed to a number of output nodes (K output nodes for $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ and 1 for α and ϵ) each of which outputs some linear combination of its inputs, i.e. the activation function of all the output nodes is the identity function, $I(x) = x$.

$$h_{gt}^{\lambda} = \max\left[a_g^{\lambda} + \sum_{m=1}^{M} b_{gm}^{\lambda} y_{mt}, 0\right] \tag{30}$$

Where $\alpha/\beta/\epsilon$ indicates that the function structure is the same for α, β, and ϵ, while $g \in 1, ..., G$ with G being the number of hidden nodes.[9] All outputs from each of these hidden nodes then feed into a set of output nodes, that, similarly to the hidden nodes, transforms the linear combination of its inputs into a single real number. All output nodes utilize the identity function, $I(x) = x$, which means their functional forms are:

$$O_{it}^{\alpha/\epsilon} = a^{\alpha/\epsilon} + \sum_{g=1}^{G} b_g^{\alpha/\epsilon} h_{git}^{\alpha/\epsilon} \tag{31}$$

$$O_{kit}^{\beta} = a_k^{\beta} + \sum_{g=1}^{G} b_{gk}^{\beta} h_{git}^{\beta} \tag{32}$$

$$O_{kt}^{\lambda} = a_k^{\lambda} + \sum_{g=1}^{G} b_{gk}^{\lambda} h_{gt}^{\lambda} \tag{33}$$

[9] The choice of G is arbitrary and could be treated as a hyperparameter, however, for simplicity this paper use $G = 32$.

All parameters associated with the α, β_k, λ_k, and ϵ functions in equations (29)-(33) are denoted $\boldsymbol{\theta}^{\alpha}$, $\boldsymbol{\theta}^{\beta}$, $\boldsymbol{\theta}^{\lambda}$, and $\boldsymbol{\theta}^{\epsilon}$, respectively.

Putting it all together, the complete Deep Structural Model of this paper can be viewed as a neural network, with an architecture imposed by the structural model of Section 2. A full general model illustration can be seen in Figure 3. The specific loss function used to train the model, along with the training procedure itself, can be found in Appendix 5.2.

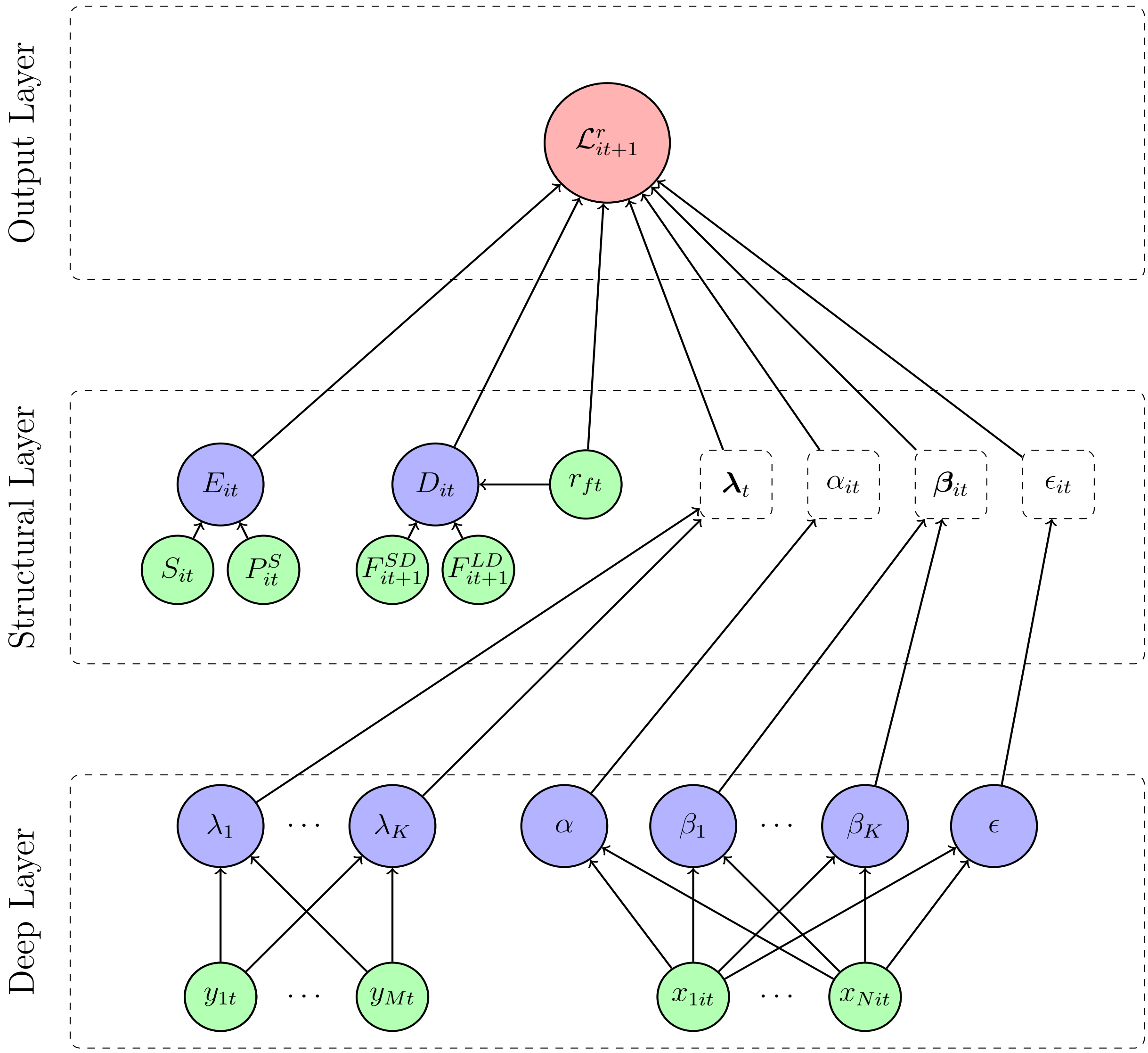


Figure 3: *Deep Structural Model Architecture.* This figure shows the full architecture of the DSM of this paper. At the bottom we have the "Deep Layer" where all observable inputs, $\boldsymbol{X}_{it}$ and $\boldsymbol{Z}_t$, feed into the α function, the risk exposure functions, $\beta_1, ..., \beta_K$, market price of risk functions, $\lambda_1, ..., \lambda_K$, and the idiosyncratic asset volatility function, ϵ. In the middle we have the "Structural Layer" containing all the structural parameters. Finally, at the top, we have the "Output Layer". This layer is essentially all the implications associated with the structural model, however, the output shown in this figure is limited to the equity return likelihood function as that is the only object used for training the model.

3 Empirical Results

3.1 Data

The primary data source for the empirical analysis is the combined US Compustat and CRSP data from Jensen *et al.* (2022), which has been provided by the authors. The data set includes 4,135,225 firm-month observations from 1925-2021. I exclude firm-month observations where one or more of the following variables is missing: (company wide) market equity value, short-term debt, long-term debt, or one-month ahead equity return. This removes all firm-months in the early part of the sample, leaving a total of 3,197,609 firm-month observations from 1950-2021 for the actual empirical analysis. For the firm specific characteristics, I use the 153 variables used as the basis for the 153 factors explored in Jensen *et al.* (2022). Additionally, a set of industry dummies based on the first two digits of a firm's SIC code (including a missing SIC dummy) are added as firm characteristics. This means that $\boldsymbol{X}_{it} \in \mathbb{R}^{238}$. For the macroeconomic variables I use the 14 variables in Welch and Goyal (2008) that covers the full time-period 1950-2021, alongside with the monthly S&P500 return.[10] I augment these 15 macroeconomic variables by taking the quarterly and yearly changes,[11] so that $\boldsymbol{Z}_t \in \mathbb{R}^{45}$. The macroeconomic variables are all extracted from Amit Goyal's personal website, from which an estimate of the monthly risk-free interest rate, r_{ft}, is also extracted. The data is then split into a training set, $\mathcal{T}_1$ (1950-1974), a validation set, $\mathcal{T}_2$ (1975-1984), and a test set, $\mathcal{T}_3$ (1985-2021). Additional information regarding data preprocessing can be found in Appendix 5.3.

3.2 The Estimated Model Parameters

Panel A of Table 1 reports the out-of-sample distribution of the annualized parameters, for the DSM with $K = 5$.[12] The expected excess asset return $\mu_{it} - r_{ft}$ parameter has an average of 6.01%, a standard deviation of 12.87%, and the empirical distribution has heavy tails as indicated by a p10 and p90 value of -7.24% and 19.58%, respectively. Breaking down $\mu_{it} - r_{ft}$ into its constituent parts: α_{it} and $\beta_{it}\lambda_t$, we see that they contribute 36.27% ($\frac{2.18}{6.01}$) and

[10] Specifically, b/m, d/e, d/p, d/y, dfr, dfy, e/p, infl, ltr, lty, ntis, sp500ret, svar, tbl, tms.

[11] For sp500ret and dfr, the quarterly and yearly returns are used instead.

[12] As will become clear in the coming sections, the DSM specification with $K = 5$ is the best performing model, however, similar distributional results are obtained for Table 1 when using $K \in 1, 2, 3, 4, 6$.

63.73% ($\frac{3.83}{6.01}$), respectively, to the average value of $\mu_{it} - r_{ft}$. Thus, the DSM suggests that, on average, the biggest contributor to the average expected excess asset return is systematic risk compensation, rather than mispricing. The contribution of α_{it} ranges from 29.95% to 39.11% across the 6 different DSM specifications with $K \in 1, ..., 6$. It is worth noting that while α_{it} is the smallest contributor to the average expected excess asset return, it is highly dispersed as indicated by a standard deviation of 12.51%, which is significantly larger than the standard deviations of 6.85% for $\beta_{it}\lambda_t$. This means that while the location of the expected asset return distribution is primarily determined by systematic risk compensation, the scale and tails are driven by the mispricing term. This effect seem to be largest at the left tail of the distribution, meaning that a negative expected asset return is more likely to be caused by overpricing (negative α_{it}), rather than because the firm's assets act as a hedge against systematic risk exposure (negative $\beta_{it}\lambda_t$).

	Mean	Std.	p10	p25	p50	p75	p90
Panel A: Annualized DSM Parameters							
$\mu_{it} - r_{ft}$	6.01	12.87	-7.24	0.98	5.26	10.90	19.58
- α_{it}	2.18	12.51	-12.01	-3.25	2.69	8.24	15.29
- $\boldsymbol{\beta}_{it}^T \boldsymbol{\lambda}_t$	3.83	6.85	-3.22	-0.50	2.80	6.19	12.30
σ_{it}	34.69	16.40	17.26	23.08	30.78	43.40	57.61
- $\sqrt{\boldsymbol{\beta}_{it}^T \boldsymbol{\beta}_{it}}$	33.78	15.88	16.54	22.01	29.44	41.70	55.43
- $\sqrt{\epsilon_{it}^2}$	7.90	6.97	0.59	2.84	6.04	11.19	17.44
$L_{it} = \frac{D_{it}}{V_{it}}$	18.94	21.16	0.00	1.49	11.09	29.68	52.65
Panel B: Annualized Expected Equity Returns							
$\mathrm{E}[r_{it+1}] - r_{ft}$	8.24	19.33	-8.99	1.06	7.15	14.04	24.81

Table 1: *DSM Parameter and Expected Equity Return Distributions.* This table shows the out-of-sample distributions of the annualized parameters for the DSM with $K = 5$ (Panel A), along with the distribution of the annualized expected equity return (Panel B). The two first columns indicate the mean and standard deviation, while the rest denote specific percentiles of the distributions. All values are reported in percentages.

Looking at σ_{it}, the DSM estimates an annualized average asset volatility of 34.69%. This is somewhat higher than previous literature such as Schaefer and Strebulaev (2008) and Feldhütter and Schaefer (2018) who estimate an average annualized asset volatility of 22% and 25%, respectively. These estimates, however, are based on samples of corporate bonds which are likely skewed towards larger firms. Limiting the sample of this paper to the 1,000 largest firms of each cross-section, as measured by market equity, reduces the average annualized asset volatility to 25.96%. Looking at the constituents of σ_{it}: $\sqrt{\beta_{it}^T \beta_{it}}$ and $\sqrt{\epsilon_{it}^2}$, it is clear that the vast majority of asset volatility is coming from systematic, rather than idiosyncratic, volatility. Both the mean and standard deviation of $\sqrt{\beta_{it}^T\beta_{it}}$ is almost identical to that of σ_{it} itself. The actual proportion of the average asset volatility coming form systematic risk exposure is 94.82% ($\frac{33.78^2}{34.69^2}$) and this proportion ranges from 88.05%-98.19% across the six different DSM specifications with $K \in 1, ..., 6$.

Leverage, as defined by the ratio of the estimated market value of debt, D_{it}, to the overall market value of the assets, V_{it}, has an average value of 18.94%, but is heavily right-skewed with a substantial minority of firms having little to no debt. Leverage has a profound effect when moving from the distribution of $\mu_{it} - r_{ft}$ in Panel A to the expected excess equity return distribution of Panel B: the average expected excess equity return is 8.24% which represents an increase of 37.10% over the average value of $\mu_{it} - r_{ft}$. Even more striking is the increase in the dispersion when moving from expected asset returns to expected equity returns: the standard deviation jumps to 19.33%, which represents a 50.19% increase. This is consistent with the empirical findings of Doshi *et al.* (2019) that leverage has a large impact on the dispersion of equity returns.

A central part of the empirical analysis in this paper is to compare the results of the DSM with those from implementing a firm-level Merton model, using the methodology in Vassalou and Xing (2004), which will be referred to as the "KMV method". Table 2 reports the mean and standard deviation of the annualized parameters from both the DSM (reposted from Table 1 for convenience), the KMV method, as well as their correlations across all observations in the test set, $\mathcal{T}_3$.[13] From the table, we see that the KMW methodology provides a much more dispersed estimate (55.84% vs 12.87%) of the expected excess asset return, with a lower mean (2.50% vs 6.01%), compared to the DSM. The correlation of the expected excess asset return between the two methodologies is also close to 0 indicating that they provide fundamentally different estimates of μ_{it}. In terms of the asset volatility, σ_{it}, the two methodologies provide more correlated estimates, with a correlation coefficient of 0.60, although the KMV estimate is once again more dispersed (30.85% vs 16.40%), while this time having a larger mean (44.12% vs 34.69%). For the estimated leverage, L_{it}, the two methodologies provide practically identical estimates, which is unsurprising given that leverage is calculated almost the same way in the DSM framework as in Vassalou and Xing (2004).

[13] Note that the KMV method does not allow for a decomposition of the drift or volatility of the firm's assets, which is why only $\mu_{it} - r_{ft}$, σ_{it}, and L_{it} are reported.

	DSM		KMV		
	Mean	Std.	Mean	Std.	Correlation
$\mu_{it} - r_{ft}$	6.01	12.87	2.50	55.84	-0.01
σ_{it}	34.69	16.40	44.12	30.85	0.60
$L_{it} = \frac{D_{it}}{V_{it}}$	18.94	21.16	18.56	21.05	1.00

Table 2: *DSM and KMV Parameter Comparison.* This table compares the out-of-sample annualized parameters for the DSM with $K = 5$ and the KMV methodology presented in Vassalou and Xing (2004). The two first columns report the mean and standard deviation of the parameters, respectively, for the two methodologies, while the last column reports their correlations.

Figure 4 plots the time series average of the expected excess asset return for the DSM (Panel A and B) and the KMV method (Panel B). From panel A, we see that the time series of $\bar{\mu}_t - r_{ft}$, as estimated by the DSM, shows a high degree of short-term time series variation, but has no clear time trend or interaction with recessions (as indicated by the shaded red areas). This is in contrast to the KMV time series. The large panel dispersion of the KMV estimates of μ_{it} from Table 2, translates into a large time-series variation as well. The average expected excess asset return of the KMV method is within the range of -60% to 60%, compared to -10% to 10% for the DSM. Furthermore, the KMV time series exhibits a clear pro-cyclical behaviour. This is unsurprising given that μ_{it} relies on historical equity returns during the estimation procedure (see Vassalou and Xing (2004) for details), i.e. during economic downturns when the market experiences large negative equity returns, μ_{it} is also estimated to be very negative.

Figure 5 shows the estimated cross-sectional average asset volatility, $\bar{\sigma}_t$ (Panel A), and leverage, $\bar{L}_t$ (Panel B), for both the DSM and the KMV method. For the DSM, the average asset volatility is quite stable over short time periods, but there is a slight upwards trend over the sample period from around 30% to 40%. Again, this is in contrast to the time-series of the KMV method, which is highly volatile over the sample period with a range of 30% to 70%. For the average asset volatility of the DSM, there is yet again no interactions with the underlying business cycle, while for the KMV method we now see a counter-cyclical behaviour, in which the estimated asset volatility is low during normal times and large during recessions. This, taken in conjunction with Figure 4, shows that the DSM suggests that the underlying asset parameters of firms are quite stable over time with no cyclical behaviour, which is in sharp contrast to the parameters provided by the traditional estimation method of Vassalou and Xing (2004). In terms of the time series of leverage, we see that the two

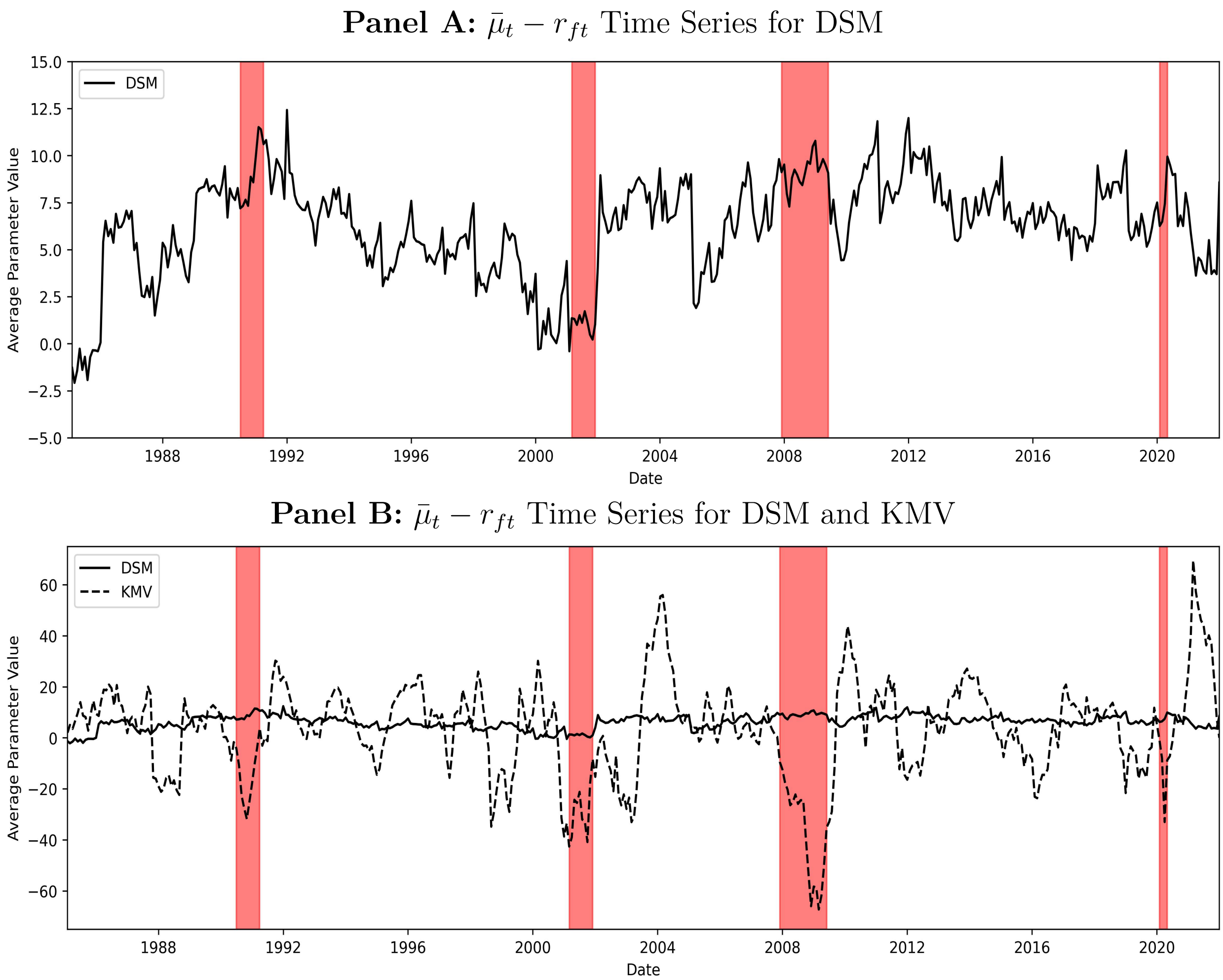


Figure 4: *Expected Excess Asset Return Time Series.* This figure plots the out-of-sample time series of the cross-sectional average annualized expected excess asset return, $\bar{\mu}_t - r_{ft}$. Panel A only shows the time series from the DSM specification with $K = 5$, while panel B shows both the DSM and the KMV time series. The time periods shaded in red indicate (NBER) recessions.

time series are (unsurprisingly) practically identical. However, it is very important to note the counter-cyclical nature of leverage: as equity prices fall during economic recessions, the leverage of firms go up.

Figure 6 plots the time series of the estimated equity premium for the DSM (Panel A and B) and the KMV method (Panel B). It is calculated as the cross-sectional value-weighted average of the expected equity return of all firms minus the risk-free rate. For comparison, the SVIX time series of Martin (2017) is also shown in the figure.[14] The equity premium of the DSM is generally above the SVIX, which is theoretically justified as it represents

[14] The SVIX time-series is extracted directly from Ian Martin's personal website and covers the time period from 1996-2011.

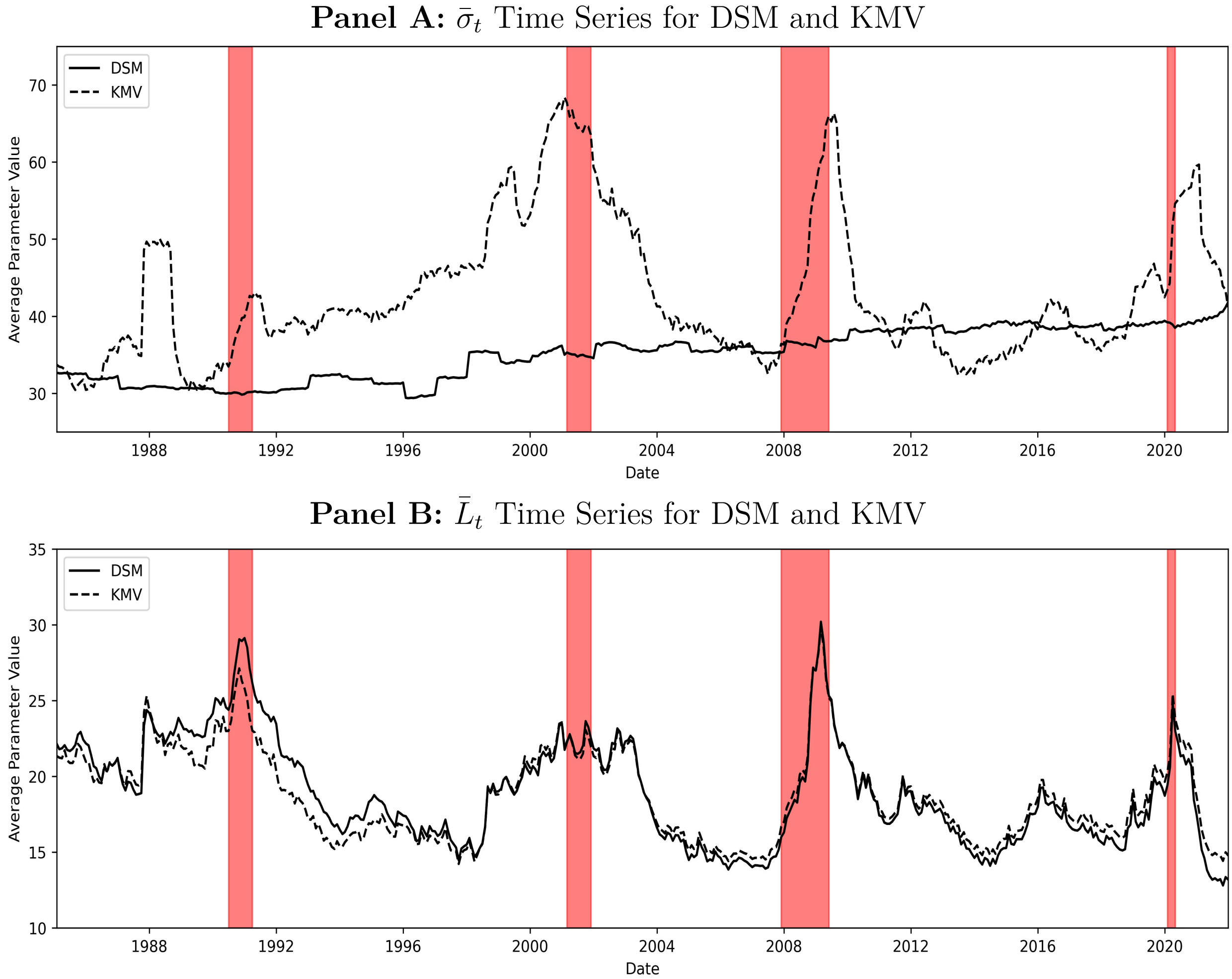
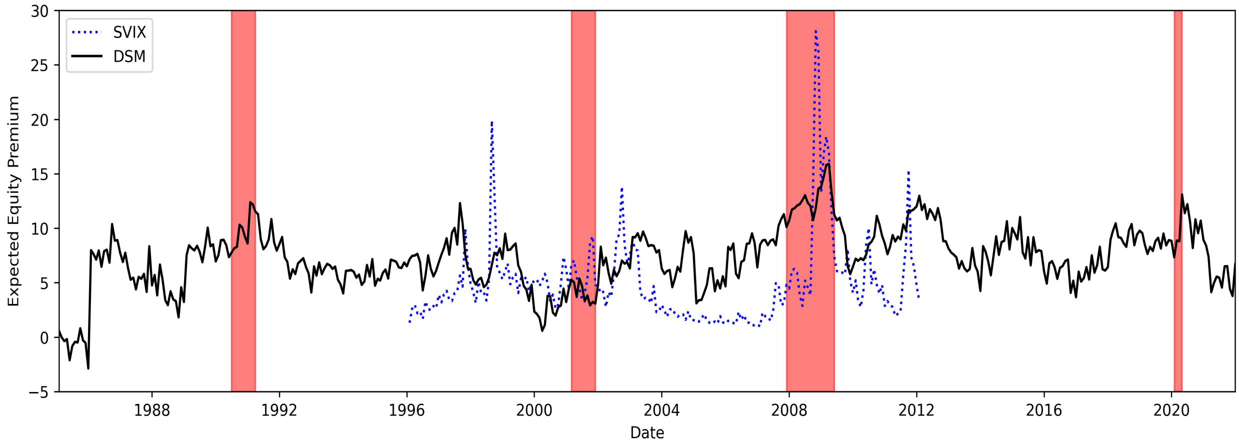


Figure 5: *Estimated Asset Volatility and Leverage Time Series.* This figure plots the out-of-sample time series of the cross-sectional average annualized asset volatility (Panel A) and leverage (Panel B). The DSM estimates are from the specification with $K = 5$. The time periods shaded in red indicate (NBER) recessions.

a lower bound, and their correlation is 0.41. Both time series peak during the financial crisis of 2008-09, although SVIX peaks at 25% whereas the DSM's estimate peaks at 15%. The fact that the equity premium of the DSM exhibits this counter-cyclicality might seem puzzling, given that the time series of $\bar{\mu}_t - r_{ft}$ in Figure 4 shows no such tendency. However, as mentioned, we saw in Panel B of Figure 5, that leverage had this exact same counter-cyclical behaviour. This suggests that the underlying asset dynamics of firms might be more stable than suggested by the literature: the time series dynamics of leverage is enough to create time series dynamics of the equity premium that are consistent with other empirical research, such as Martin (2017). Looking at Panel B, we see that the equity premium of the KMV method is on a completely different scale than the equity premium of the DSM and the SVIX. It ranges from -150% to 200% over the sample period and exhibits the same pro-cyclicality that we see in the KMV time-series of $\bar{\mu}_t - r_{ft}$ in Figure 4. The fact that the KMV method provides an estimated equity premium that is so inconsistent with both theory and other empirical observations, suggests that the structural parameters of the DSM are more accurately estimated than those from the KMV method.

Panel A: Equity Premium of the DSM



Panel B: Equity Premium of the DSM and KMV

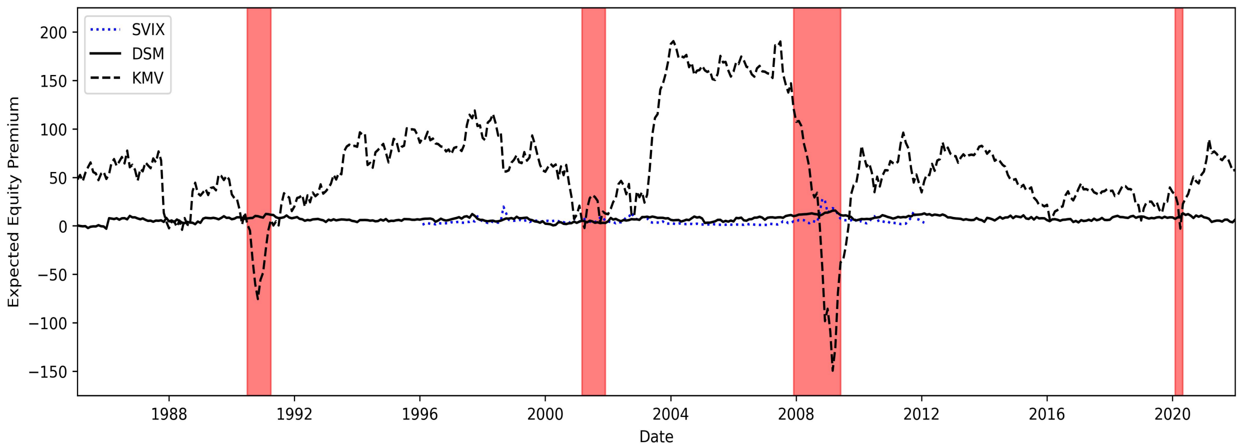


Figure 6: *Estimated Equity Premium Time Series.* This figure plots the out-of-sample time series of the estimated annualized equity premium. The equity premium is calculated using the value-weighted average expected equity return of all firms in the cross-section (see equation (18)) minus the risk-free interest rate. The DSM estimates are from the specification with $K = 5$. Additionally, the figure also plots the SVIX time series of Martin (2017). The time periods shaded in red indicate (NBER) recessions.

3.3 Equity Return Prediction

The DSM predicts firm-level equity returns by inserting the estimated model parameters into equation (18). The performance measure used to evaluate these predictions, is the zero-mean out-of-sample R^2_{oos}, also used in Gu *et al.* (2020):

$$R^2_{oos} = 1 - \frac{\sum_{(i,t)\in\mathcal{T}_3}\left(r_{it+1} - \mathrm{E}_t[r^{Model}_{it+1}]\right)^2}{\sum_{(i,t)\in\mathcal{T}_3} r^2_{it+1}} \tag{34}$$

Where $\mathrm{E}_t[r^{Model}_{it+1}]$ is the predicted equity return. The performance of the DSM is compared to two benchmark models: A machine learning benchmark (NN Benchmark), which is chosen to be a standard feed-forward neural network, as it is the best performing model in Gu *et al.* (2020), and the KMV method (which also predicts equity returns by inserting estimated parameters into equation (18)). The neural network is trained on the same data as the DSM with a similar training procedure (see Appendix 5.2 for details). Table 3 reports the performance of the DSM, along with the two benchmarks. The first six columns of the table report the performance of the DSM with an increasing number of systematic risk factors, indicated by $K \in 1, ..., 6$, while the two last columns report the performance of the benchmark models.[15] Each row of Table 3 indicate which subset of the data is used for calculating R^2_{oos}, with "All" referring to the entire test dataset, while "Top 1,000" ("Bottom 1,000") refers to the subset containing only the 1,000 largest (smallest) firms of each cross-section, as measured by market equity. From the table it is clear that the DSMs outperform both of the benchmark models in terms of R^2_{oos}: all DSM specifications have values between 0.74 and 0.80, when estimated across all out-of-sample observations, compared to 0.56 for the NN benchmark and values far below 0 for the KMV method.[16] This outperformance is not due to the presence of small-caps as the majority of the DSMs actually have higher R^2_{oos}-values for the data subset containing the largest firms.[17] To check if this difference in predictive power is statistically significant, a pooled Diebold-Mariano test is performed (see Diebold and Mariano (2002) for details):

$$DM_{Pooled} = \frac{1}{N_{\mathcal{T}_3}} \sum_{(i,t)\in\mathcal{T}_3} \left(e^{Benchmark}_{it} - e^{DSM}_{it}\right) * 100 \tag{35}$$

Where:

$$e^{Model}_{it} = \left(r_{it+1} - \mathrm{E}_t[r^{Model}_{it+1}]\right)^2 \tag{36}$$

[15] Five different versions of the NN benchmark model have been trained, with a varying number of hidden layers, $H \in 1, ..., 5$, but only the best performing one in terms of R^2_{oos} ($H = 2$) is used as a benchmark model throughout this paper.

[16] The R^2_{oos} value for the NN benchmark is similar to the one reported in Gu *et al.* (2020).

[17] Interestingly, the DSMs and the NN benchmark generally have higher R^2_{oos} for both of the data subsets examined here, indicating that these models perform worse, in terms of R^2_{oos}, for mid-sized firms compared to the firms at the ends of the size spectrum.

	DSM						NN	KMV
	$K=1$	$K=2$	$K=3$	$K=4$	$K=5$	$K=6$	Benchmark	Benchmark
All	0.75	0.74	0.76	0.77	0.80	0.75	0.56	$\ll 0$
Top $1,000$	1.03	1.02	1.03	1.04	1.11	1.04	0.85	$\ll 0$
Bottom $1,000$	0.89	0.85	0.90	0.91	0.93	0.88	0.67	$\ll 0$

Table 3: *Equity Return Prediction Performance.* This table reports the out-of-sample equity return predictive performance for the DSM and two benchmark models: a neural network model and the KMV method. The performance measure is the zero-mean R^2_{oos} measure, $R^2_{oos} = 1 - \frac{\sum_{(i,t)\in\mathcal{T}_3}(r_{it+1}-\hat{r}_{it+1})^2}{\sum_{(i,t)\in\mathcal{T}_3} r^2_{it+1}}$, reported in percentages. The table reports the performance for six different specifications of the DSM, with a varying number of systematic shocks $K \in 1, ..., 6$, indicated by the first six columns. Each row of the table denotes the specific subset of the data used for calculating R^2_{oos}. "All" refers to the entire test dataset, $\mathcal{T}_3$, while "Top 1,000" ("Bottom 1,000") refers to the subsample consisting of only the 1,000 largest (smallest) firms of each cross-section.

The results of this test can be seen in Table 4. A positive number in the table indicates the column model (which are the six different DSM specifications) has a lower mean squared error compared to the row model (which are the two benchmark models). From the table, we see that all of the DSM specifications provide firm-level equity returns that are more accurate, and statistically different, compared to the two benchmark models.

	DSM					
	$K=1$	$K=2$	$K=3$	$K=4$	$K=5$	$K=6$
NN	0.01*	0.01*	0.01*	0.01*	0.01**	0.01*
KMV	7.46***	7.46***	7.46****	7.46***	7.47***	7.46***

Table 4: *Pooled Diebold-Mariano Test.* This table reports the pooled Diebold-Mariano test-statistic: $DM_{Pooled} = \frac{1}{N_{\mathcal{T}_3}} \sum_{(i,t)\in\mathcal{T}_3} \left(e^{Benchmark}_{it} - e^{DSM}_{it}\right) * 100$, where e^{Model}_{it} is the squared prediction error of a given model. A positive number indicates that the DSM with $K \in 1, ..., 6$ provides a better firm-level equity return prediction compared to the model indicated by the row of the table. *, **, and ** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively, with standard errors clustered at the time level.

Next, to examine if the higher R^2_{oos} values of the DSMs translate into portfolios with higher returns and Sharpe ratios, I form decile portfolios each month based on the expected equity returns from each model. In addition to the decile portfolios, I also create a long-short portfolio that is long the 10^{th} decile and short the 1^{st}. Table 5 reports the out-of-sample performance of these portfolios in terms of the average monthly excess return (Panel A), the standard deviation of the monthly excess returns (Panel B), and the annualized Sharpe ratios (Panel C). Looking at Panel A, we see that all DSMs have a strictly monotone

Decile	DSM $K=1$	$K=2$	$K=3$	$K=4$	$K=5$	$K=6$	NN Benchmark	KMV Benchmark
Panel A: Average Monthly Excess Return								
1	-0.78	-0.87	-0.84	-0.90	-1.01	-0.90	-0.16	0.38
2	-0.15	-0.15	-0.12	-0.12	-0.03	-0.11	0.30	0.66
3	0.33	0.29	0.32	0.36	0.24	0.26	0.63	0.91
4	0.53	0.58	0.57	0.58	0.51	0.48	0.78	0.82
5	0.73	0.72	0.72	0.78	0.73	0.74	0.73	0.73
6	0.85	0.87	0.89	0.95	0.99	0.94	0.98	0.72
7	1.09	0.99	1.11	1.08	1.03	1.03	1.11	0.73
8	1.20	1.26	1.20	1.23	1.25	1.23	1.20	0.72
9	1.50	1.44	1.46	1.43	1.33	1.36	1.39	1.00
10	1.85	1.88	1.99	1.86	2.09	1.89	1.75	0.86
10-1	2.63	2.75	2.83	2.76	3.10	2.79	1.91	0.48
Panel B: Std. of Monthly Excess Returns								
1	8.40	8.50	8.65	8.33	8.50	8.78	6.40	9.40
2	6.57	6.54	6.49	6.56	6.77	6.91	5.44	7.62
3	5.04	5.16	4.95	5.03	5.12	5.48	5.22	6.06
4	4.59	4.45	4.43	4.38	4.48	4.35	4.97	5.26
5	4.30	4.31	4.29	4.37	4.35	4.33	5.05	4.52
6	4.31	4.38	4.44	4.45	4.47	4.40	5.06	4.38
7	4.61	4.63	4.67	4.67	4.73	4.70	5.13	4.29
8	5.12	5.26	5.21	5.29	5.12	5.24	5.50	4.53
9	5.93	6.15	6.16	6.64	6.28	6.09	5.97	5.41
10	7.34	7.63	7.56	7.58	7.70	7.69	6.90	6.62
10-1	6.38	6.53	6.44	6.26	6.44	6.40	6.10	7.56
Panel C: Annualized Sharpe Ratio								
1	-0.32	-0.36	-0.34	-0.38	-0.41	-0.36	-0.16	0.14
2	-0.08	-0.08	-0.07	-0.06	-0.02	-0.05	0.19	0.30
3	0.23	0.20	0.22	0.25	0.16	0.16	0.42	0.52
4	0.40	0.45	0.45	0.46	0.40	0.39	0.54	0.54
5	0.59	0.58	0.58	0.61	0.58	0.59	0.50	0.56
6	0.69	0.69	0.70	0.74	0.80	0.74	0.67	0.57
7	0.82	0.74	0.82	0.80	0.73	0.76	0.75	0.59
8	0.81	0.83	0.80	0.81	0.85	0.81	0.76	0.55
9	0.88	0.81	0.82	0.75	0.74	0.75	0.81	0.64
10	0.87	0.85	0.91	0.85	0.94	0.85	0.88	0.45
10-1	1.43	1.46	1.52	1.53	1.67	1.51	1.08	0.22

Table 5: *Decile Portfolio Performance.* This table reports the out-of-sample performance of decile portfolios based on monthly sorts on the expected equity returns, $\mathrm{E}_t[r_{it+1}^{Model}]$, from one of eight different models as indicated by the columns. In addition to the decile portfolios, the performance of a long-short portfolio, which is long the 10^{th} decile portfolio and short the 1^{st}, is also reported. Panel A of the table reports the average monthly excess return (in percentages) for each portfolio, Panel B reports the standard deviation of monthly excess returns, while Panel C reports the annualized Sharpe ratios. All portfolios are value-weighted.

increase in the realized average excess returns, as we move down the panel, which is not the case for the benchmark models (although it is close in the case of the NN benchmark). Furthermore, the realized excess returns of the long-short portfolios are much higher for the DSM portfolios compared to the benchmark models: the lowest average excess return of the DSM based long-short portfolios is 2.63% ($K = 1$), which is still 0.72 percentage points higher than the NN benchmark, while the best performing DSM portfolio has an average monthly excess return of 3.10% ($K = 5$). Looking at Panel B, a curious pattern emerges: the DSMs indicate a pronounced convex relationship between the expected equity return and the standard deviation of the decile portfolios, i.e. the most volatile portfolios are those with the lowest and highest expected equity returns. One might suspect that this convex relationship between excess returns and volatility would cause the Sharpe ratios of the highest decile portfolios to be lower than the middle ones, but this is generally not the case, as is evident from Panel C: the Sharpe ratios of the DSM portfolios are generally increasing. Looking at the DSM based long-short portfolios, we see that they handily outperform the benchmark portfolios with Sharpe ratios between 1.43 ($K = 1$) and 1.67 ($K = 5$), compared to 1.08 and 0.22 for the NN benchmark and KMV benchmark, respectively. Investors can therefore achieve significant benefits in terms of both absolute returns and Sharpe ratios by adopting the DSM framework of this paper, when forming long-short portfolios, compared to an off-the-shelf machine learning approach.

3.4 Equity Return Variance Prediction

One of the advantages of the DSM presented in this paper is its versatility: it is not confined to being an equity return model but offers insights into all the model implications presented in Section 2.3. To explore this further, I use the analytical expression in (20) to produce out-of-sample equity return variance predictions. Unlike equity returns, variances are not observed over a single period and so the "realized" variance is based on the daily variance of equity returns between t and $t + 1$:

$$\mathrm{Var}[r_{it+1}] = \sum_{d=1}^{D} (r_{id} - \bar{r}_{it+1})^2 \tag{37}$$

Where D is the number of days between time t and $t + 1$, r_{id} is the daily return on day d, and $\bar{r}_{it+1}$ is the average daily return across all D days. The variance predictions of the

DSM are compared to two benchmarks: a GARCH(1,1) model that is recursively fit to each individual firm, as well as the predictions of the KMV method (which are produced the same way as the DSM, but with the structural parameters of the KMV method).[18]

	DSM						GARCH(1,1)	KMV
	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$	$K = 6$	Benchmark	Benchmark
Panel A: Regression Results								
Constant	-0.22***	-0.07***	0.02*	0.15***	0.27***	0.25***	-0.97***	-2.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\log(\text{Var}_t[r_{it+1}^{Model}])$	0.95***	0.97***	0.99***	1.02***	1.04***	1.04***	0.79***	0.56***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.42	0.41	0.41	0.42	0.42	0.42	0.39	0.32
N	1,436,705	1,436,705	1,436,705	1,436,705	1,436,705	1,436,705	1,436,705	1,436,705
Panel B: MSE								
All	2.467	2.482	2.483	2.481	2.484	2.492	3.274	90.54
Top 1,000	0.097	0.097	0.096	0.096	0.097	0.097	0.170	244.89
Bottom 1,000	14.768	14.840	14.840	14.827	14.851	14.892	17.402	125.627

Table 6: *Equity Return Variance Prediction.* This table reports the out-of-sample performance of eight different models for predicting the equity return variance over the next month. The first six columns are DSMs with an increasing number of systematic shocks, as indicated by K. The "GARCH Benchmark" refers to the performance of a GARCH(1,1) model recursively fit to each individual firm, while the "KMV Benchmark" refers to the predictions by using the KMV method's structural parameters rather than the DSMs. Panel A reports the results of the regression $\log(\text{Var}[r_{it+1}]) = \gamma_0 + \gamma_1 \log(\text{Var}[r_{it+1}^{Model}])$, where $\text{Var}[r_{it+1}]$ is the daily equity return variance between time t and $t + 1$, multiplied by the number of days in that time period, and $\text{Var}[r_{it+1}^{Model}]$ is the predicted variance of a given model. The parentheses report the estimated standard errors, while ***, **, *, indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. Panel B reports the mean squared error, $MSE_{oos} = (\text{Var}[r_{it+1}] - \text{Var}[r_{it+1}^{Model}])^2$, scaled by 100, across all out-of-sample observations, as well as the data subsets consisting of the 1,000 largest and smallest firms of each cross-section.

Panel A of Table 6 reports the out-of-sample results of regressing the log of the realized return variance onto the log of the variance prediction, for each of the six DSM specifications, the GARCH benchmark, and the KMV estimate:

$$\log(\text{Var}[r_{it+1}]) = \gamma_0 + \gamma_1 \log(\text{Var}[r_{it+1}^{Model}]) \tag{38}$$

Where $\text{Var}[r_{it+1}^{Model}]$ is the predicted equity return variance for the next period. A perfect

[18] Because of the estimation procedure of the GARCH(1,1) model, the predictions are restricted to firm-month observations without any data gaps and with at least 12 prior observations, e.g. if a firm enters the dataset in July, 1995, and exits after July, 1997, then it is required that there are a total of 24 firm-month observations for this particular firm and the first 12 observations will not be used for the variance prediction analysis. With this restriction, the test dataset shrinks from 2,334,603 to 1,436,705 observations for this particular section of the paper. The fact that we need this restriction also highlights a strength of the DSM framework: once trained, all that is needed for predicting the next-period variance is a single contemporary firm observation, i.e. no historical information is needed.

variance prediction would result in $\gamma_0 = 0$ and $\gamma_1 = 1$, and we see that the DSM predictions are much close to this ideal, compared to the two benchmarks: The γ_0 coefficients range from -0.22 to 0.27 for the DSMs, while they are -0.97 and -2.03 for the GARCH and KMV benchmarks, respectively. Likewise, the γ_1 coefficients are clustered around 1 for the DSMs, while they are lower for two benchmarks. The DSMs also explain a higher proportion of the return variance, as measured by R^2, compared to the two benchmarks. Panel B of Table 6 report the out-of-sample (scaled) mean squared error, MSE_{oos}, for each of the eight models:

$$MSE_{oos} = \frac{100}{N_{\mathcal{T}_3}} \sum_{(i,t)\in\mathcal{T}_3} (\text{Var}[r_{it+1}] - \text{Var}[r_{it+1}^{Model}])^2 \tag{39}$$

From Panel B, we see that the DSMs have MSEs that are between 23.89%-24.65% lower than that of GARCH benchmark, while the KMV predictions have much higher MSEs. This outperformance is consistent across the size spectrum of firms, as indicated by the second and third row of the panel.

These results suggest that, even though the DSMs have only been trained on equity return data, the conditional structural parameter estimates, used in conjunction with the model implications of Section 2.3, are able to accurately describe and predict, not only the first, but the second moment of equity returns, on a firm-level basis.

3.5 Mean-Variance Efficient Portfolios

To examine how well the DSM estimate the conditional covariance matrix of equity returns, I construct a classic mean-variance efficient (MVE) portfolio in the spirit of Markowitz (1952), at each point in time, by solving the following portfolio choice problem:

$$\max_{\boldsymbol{w}_t} \quad \frac{\boldsymbol{w}_t^T(\hat{\boldsymbol{r}}_{t+1} - \mathbf{1}r_{ft})}{\boldsymbol{w}_t^T\hat{\Sigma}_{t+1}\boldsymbol{w}_t} \tag{40}$$

$$\text{s.t.} \quad \boldsymbol{w}_t^T\mathbf{1} = 1 \tag{41}$$

$$||\boldsymbol{w}_t||_1 \leq 3 \tag{42}$$

Where $\boldsymbol{w}_t$ is the vector containing the MVE portfolio weights at time t, $\hat{\boldsymbol{r}}_{t+1}$ is the vector of expected returns, and $\hat{\Sigma}_{t+1}$ is the estimated conditional covariance matrix with elements calculated according to equation (23). The first constraint in equation (41) ensures the weights sum to one. The second in equation (42) states that the ℓ_1-norm of the weights cannot exceed 3, which has the practical effect of limiting the leverage of the MVE portfolio such that the sum of the negative weights do not exceed -1. In addition to the MVE portfolios created by solving equations (40)-(42), a long-only version is also constructed by replacing the constraint in equation (42) with $w_{it} \geq 0 \quad \forall i \in 1, ..., I_t$, where I_t is the number of firms in cross-section t. These two types of MVE portfolios are referred to as "leverage constrained MVEs" (LC MVEs) and "short constrained MVEs" (SC MVEs), respectively. At each point in time, both the LC and SC MVE portfolios are constructed using three different investment universes: all firms, the largest 3,000 firms, and the largest 1,000 firms.

Table 7 and 8 reports the monthly average excess returns (Panel A), the monthly standard deviation of excess returns (Panel B), and the annualized Sharpe ratios (Panel C), for the LC and SC MVE portfolios, respectively, for each of the six DSM specifications. The rows of each panel indicate which investment universe has been used for constructing the MVE portfolios. Even when only considering the 1,000 largest firms of each cross-section, the LC MVE portfolios have average monthly excess returns of over 2% and Sharpe ratios in the range of 1.07-1.54, which is comparable to the DSM based long-short portfolios of Section 3.3. Increasing the investment universe to all firms has the effect of increasing the average excess return and lowering the portfolio volatility, resulting in extremely high Sharpe ratios: the LC MVE portfolios, based on the entire investment universe, have average monthly excess returns in the range of 4.74%-5.19% and Sharpe ratios between 2.92 and 3.96. The SC MVE portfolios constructed from the entire investment universe generally have slightly lower average excess returns than their LC counterparts, while exhibiting more volatility, resulting in Sharpe ratios in the range of 1.34-1.93. Even though these Sharpe ratios seem small compared to the Sharpe ratios of the LC MVE portfolios, it is worth noting that the S&P 500 index had a Sharpe ratio of 0.48 over the same time period. The best performing SC MVE portfolio, constructed from only the 1,000 largest firms of each cross-section, had a Sharpe ratio of almost double that (0.90 for the DSM with $K = 6$).

Figure 7 plots the cumulative log returns, over the out-of-sample period, of all MVE portfolios for the DSM specification with $K = 5$. Additionally, the figure also plots the cumulative log returns of the DSM long-short portfolio (also based on the specification with $K = 5$), the long-short portfolio based on the NN benchmark model, the S&P 500 index, and the CRSP value-weighted index. All portfolios have been scaled to have an overall

	DSM					
	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$	$K = 6$
Panel A: Average Monthly Excess Return						
All	4.79	5.19	4.74	4.78	4.89	4.96
Top 3,000	3.52	3.91	3.52	3.58	3.61	3.61
Top 1,000	2.21	2.34	2.17	2.17	2.25	2.32
Panel B: Std. of Monthly Excess Return						
All	5.69	4.72	4.22	4.22	4.28	4.72
Top 3,000	5.41	4.59	4.28	4.35	4.21	4.69
Top 1,000	7.14	5.79	4.95	4.89	5.18	5.65
Panel C: Annualized Sharpe Ratio						
All	2.92	3.81	3.89	3.92	3.96	3.64
Top 3,000	2.25	2.95	2.85	2.85	2.97	2.66
Top 1,000	1.07	1.40	1.52	1.54	1.51	1.42

Table 7: *Leverage Constrained MVE Portfolio Performance.* This table reports the out-of-sample performance of the MVE portfolios formed on the basis of the six DSM specifications with $K \in 1, ..., 6$. Panel A reports the average monthly excess return (in percentages), Panel B reports the standard deviation of excess returns, while Panel C reports the annualized Sharpe ratios. The rows of each panel indicate which subset of the data has been used to construct the MVE portfolios.

	DSM					
	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$	$K = 6$
Panel A: Average Monthly Excess Return						
All	4.08	4.56	4.56	4.85	4.55	4.58
Top 3,000	2.34	2.49	2.40	2.53	2.44	2.31
Top 1,000	1.23	1.44	1.49	1.60	1.46	1.57
Panel B: Std. of Monthly Excess Return						
All	10.53	10.20	8.84	8.85	8.52	8.24
Top 3,000	8.23	8.51	7.15	7.29	7.02	6.57
Top 1,000	7.84	7.10	6.35	6.24	6.00	6.01
Panel C: Annualized Sharpe Ratio						
All	1.34	1.55	1.79	1.90	1.85	1.93
Top 3,000	0.99	1.01	1.16	1.20	1.20	1.22
Top 1,000	0.55	0.70	0.81	0.89	0.84	0.90

Table 8: *Short Constrained MVE Portfolio Performance.* This table reports the same statistics as Table 7, but for MVE portfolios that prohibits short-selling.

annualized volatility of 10%. From the figure, we see that all of the model based portfolios have outperformed the market portfolios during this period. It is also clear from the figure that the leverage constrained MVE portfolio, based on the entire investment universe, has performed several orders of magnitude better than the other portfolios and its performance seem completely uncorrelated with recessions.

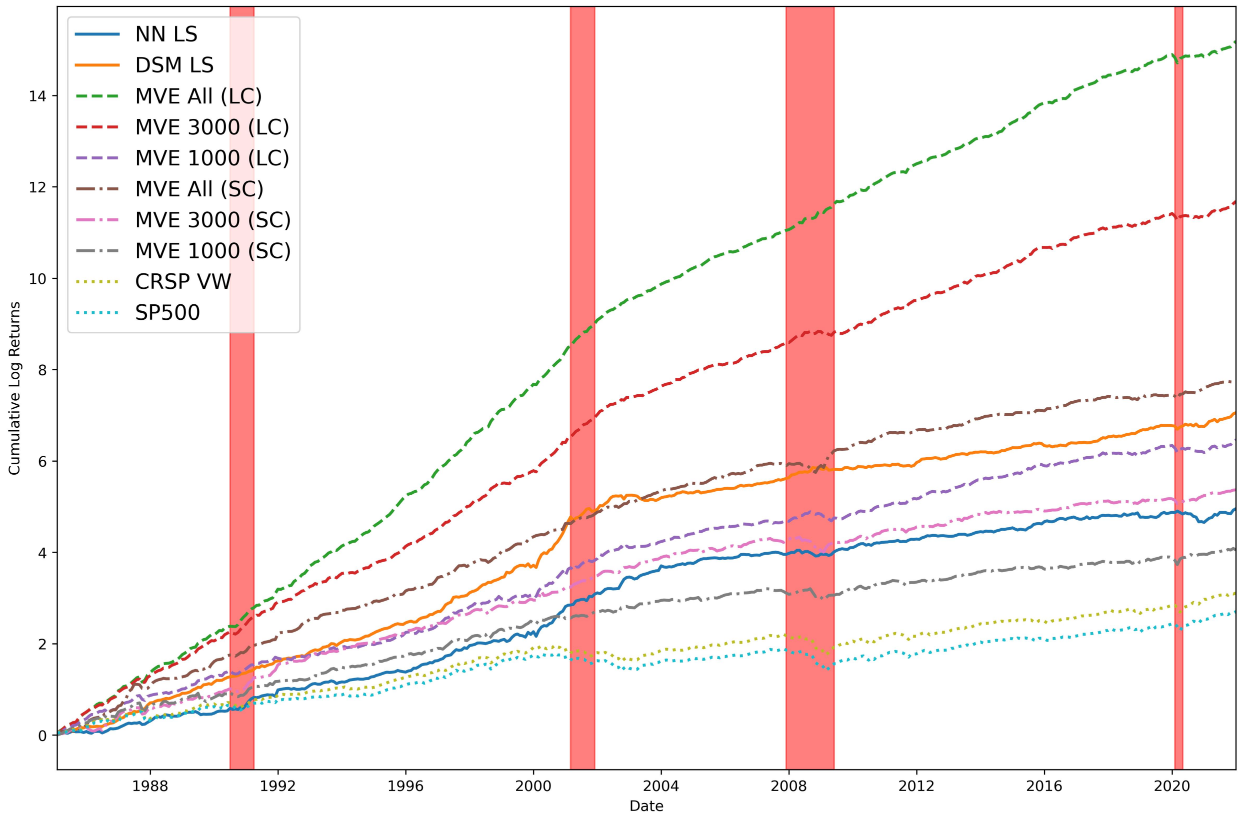


Figure 7: *MVE Portfolio Performances.* This figure shows the out-of-sample cumulative log returns for the MVE portfolios based on the DSM with $K = 5$. The figure includes three versions of a leverage constrained and short constrained MVE portfolio: one that includes all firms in the investment universe, one that only considers the largest 3,000 firms when forming the portfolio, and one which only considers the largest 1,000 firms when forming the portfolio. Additionally, the "NN LS" and "DSM LS" are the long-short portfolios formed on the basis of the expected returns of the NN benchmark model and the DSM model with $K = 5$, respectively, from Section 3.3. Finally, the figure also includes the cumulative log return of the S&P500 index and the CRSP value-weighted index. All portfolios are rebalanced monthly and scaled to have an annualized volatility of 10%.

Table 9 explores this further by reporting various other performance measures for the scaled portfolios of Figure 7. The first two rows report the average excess monthly returns and the annualized Sharpe ratios. The third row reports the estimated intercept (or α) of regressing the portfolio return onto the five factors of Fama and French (2015) and the momentum factor of Carhart (1997) (the "FF6 model"). The fourth and fifth row report the maximum portfolio drawdown and the highest 1 month loss, respectively. The key takeaway from the table is the fact that the returns of all the different MVE portfolios are considered to be α in the FF6 model, and they do not experience drawdowns of the same magnitude as those of the market portfolios.

	Long-Short		Leverage Constrained MVE			Short Constrained MVE			Market Portfolios	
	NN	DSM	All	Top 3,000	Top 1,000	All	Top 3,000	Top 1,000	CRSP VW	SP500
ER (%)	0.91	1.39	3.26	2.45	1.25	1.54	1.00	0.70	0.49	0.40
SR	1.08	1.67	3.96	2.97	1.51	1.85	1.20	0.84	0.59	0.48
FF6 α (%)	0.83	1.31	3.29	2.52	1.49	0.93	1.02	0.83	-0.01	-0.14
Max DD. (%)	-21.95	-11.10	-16.51	-13.95	-18.25	-11.02	-27.84	-21.43	-36.32	-38.02
Max 1M Loss (%)	-10.04	-6.98	-11.18	-9.05	-7.66	-11.02	-12.94	-15.03	-14.44	-14.28

Table 9: *MVE Portfolio Performance Measures.* This table reports various out-of-sample portfolio measures for the portfolios depicted in Figure 7. The first and second row report the average excess returns and annualized Sharpe ratios, respectively. The third row reports the intercept from regressing the monthly portfolio returns onto the five factors of Fama and French (2015) and the momentum factor of Carhart (1997). The fourth row shows the maximum drawdown of the portfolio, while the fifth row reports the largest 1 month loss experienced during the out-of-sample period.

The performance of the MVE portfolios is impressive, especially considering no form of covariance shrinkage is needed (see Ledoit and Wolf (2022) for a literature review on shrinking the covariance matrix). Still, it is important to note that this paper does *not* claim that these returns and Sharpe ratios can be achieved by an investor. While the leverage and shorting restrictions, along with the investment universe limits, seek to make the portfolios more realistic than a completely unrestricted MVE portfolio, there are still no considerations given to trading costs or limits to short-selling. With that being said, this section shows that not only does the DSM provide accurate return and variance predictions, it also provides useful information about the covariance of equity returns.

3.6 Enforcing No-Arbitrage

The distribution of the estimated model parameters shown in Table 1 seem to suggest that α plays an important role for the dispersion of expected asset returns, μ, and by extension, the dispersion of expected equity returns. Removing the α term from the model would force the DSM to find parameter solutions in which all excess asset returns are compensation for systematic risk exposure. It might be the case that this solution produce equity return predictions that are just as accurate as the full model. To test whether this is the case, the six different DSM specifications are re-trained with the α parameter set to zero. The equity return prediction exercise of Section 3.3 is then repeated.

Table 10 report R^2_{oos} for the no-arbitrage DSMs. The first row contains the absolute values while the the parentheses report the ratio of the no-arbitrage version to the full model counterpart. The table shows that, for low values of K, the no-arbitrage versions of the

DSM are much worse than the full model for predicting equity returns. For $K \geq 4$, the performance is better than the NN benchmark, but still not as good as their full model counterparts.

	DSM					
	$K=1$	$K=2$	$K=3$	$K=4$	$K=5$	$K=6$
R^2_{oos}	0.19	0.26	0.47	0.63	0.67	0.61
	(25%)	(35%)	(62%)	(82%)	(84%)	(81%)

Table 10: *No-Arbitrage Equity Return Prediction Performance.* This table reports the same R^2_{oos} measure as Table 3, but for the equity return predictions from the six DSM versions with α_{it} set to zero. The first row is the absolute R^2_{oos} value across all out-of-sample observations, while the second is the relative value compared to the full model performance (as found in the first row of Table 3), reported in percentages.

	DSM					
	$K=1$	$K=2$	$K=3$	$K=4$	$K=5$	$K=6$
Panel A: Monthly Excess Return						
Long-Short	-0.77	0.70	1.62	1.92	2.27	2.16
	(-29%)	(25%)	(57%)	(70%)	(73%)	(77%)
LC MVE	1.21	3.53	3.80	3.98	3.55	3.30
	(25%)	(68%)	(80%)	(83%)	(73%)	(67%)
SC MVE	-0.98	2.09	4.28	4.29	4.16	4.30
	(-24%)	(46%)	(94%)	(89%)	(91%)	(94%)
Panel B: Annualized Sharpe Ratio						
Long-Short	-0.28	0.34	0.83	0.98	1.06	1.05
	(-20%)	(23%)	(55%)	(64%)	(63%)	(70%)
LC MVE	0.91	2.58	2.99	3.15	3.03	3.09
	(31%)	(68%)	(77%)	(80%)	(77%)	(85%)
SC MVE	-0.12	0.64	1.65	1.79	1.76	1.77
	(-9%)	(42%)	(92%)	(94%)	(95%)	(92%)

Table 11: *No Arbitrage Portfolio Performance.* This table reports the monthly excess returns (Panel A) and annualized Sharpe ratios (Panel B) of three portfolios formed each month, based on the predictions from the no-arbitrage versions of the DSM: a long-short portfolio, a leverage constrained MVE, and a short constrained MVE. The parentheses report the relative performance of a given portfolio compared to the same one formed on the basis of the full DSM, which can be found in Table 5, 7, and 8.

In addition to examining the performance of the firm-level equity return predictions, Table 11 reports the performance of three portfolios formed on the basis of the no-arbitrage DSMs: a long-short portfolio, an LC portfolio, and an SC portfolio. Panel A reports the monthly excess realized returns, while Panel B reports the annualized Sharpe ratios. Again, the table reports the absolute values along with the relative performance in parentheses. Once again it becomes clear that the performance of the no-arbitrage DSMs increase as

K increases, peaking at around $K = 5$. However, none of the portfolios reach the same performance as their full model counterparts, although the SC portfolios do come quite close for large values of K.

The results of this section confirm the results of Section 3.2, namely that α is an important piece of the puzzle. It not only helps the DSM provide more accurate equity return predictions, but is also crucial when constructing portfolios based on the estimated model parameters.

4 Conclusion

Using a novel modelling framework, coined Deep Structural Models (DSMs), I estimate conditional monthly firm-level parameters of a Merton type model that allows for mispricing and decomposes the total risk of the firm's assets into a systematic and idiosyncratic component. The framework suggests that systematic risk compensation is the largest contributor to the average expected excess asset return, while the mispricing component is the primary driver of the dispersion of expected excess asset returns. Furthermore, the effect of leverage on the expected asset returns of firms is the main mechanism responsible for an increased equity premium during recessions. In fact, the DSM indicate that both the asset drift and volatility remain unaffected by recessions. The estimated parameters of the DSM jointly model the expected equity returns and (co)variances through analytically derived expressions. The estimated expected equity returns have higher predictive power than an "off-the-shelf" neural network model and the DSM predictions enable investors to form long-short portfolios with higher out-of-sample absolute returns and Sharpe ratios. Additionally, the variance predictions of the DSM have higher predictive power than a GARCH(1,1) model. Finally, I use the estimated expected returns and covariance matrix to construct leverage constrained and short constrained mean variance efficient portfolios, re-balanced on a monthly basis. These portfolios have much higher returns and Sharpe ratios than the long-short portfolios, indicating that the estimated conditional covariance matrix does indeed carry relevant information about the covariances of equity returns.

5 Appendix

5.1 Proofs

Expected Equity Return

The expected equity value at time $t+1$ can be written as:

$$\mathrm{E}[E_{it+1}] = \mathrm{E}[(V_{it+1} - F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}}]$$

By the law of iterated expectation, this can be rewritten to:

$$\begin{aligned}
\mathrm{E}[E_{it+1}] &= \mathrm{E}\Big[\mathrm{E}[(V_{it+1} - F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}}|\mathbb{1}_{V_{it+1}>F_{it+1}} = 1] \\
&\quad + \mathrm{E}[(V_{it+1} - F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}}|\mathbb{1}_{V_{it+1}>F_{it+1}} = 0]\Big] \\
&= (1-\pi_{it})\mathrm{E}[(V_{it+1} - F_{it+1})|\mathbb{1}_{V_{it+1}>F_{it+1}} = 1] + \pi_{it}0 \\
&= (1-\pi_{it})(\mathrm{E}[V_{it+1}|\mathbb{1}_{V_{it+1}>F_{it+1}} = 1] - F_{it+1})
\end{aligned}$$

Where the second equality comes from the fact that if $\mathbb{1}_{V_{it+1}>F_{it+1}} = 0$ then obviously $(V_{it+1} - F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}} = 0$. The third equality is from realizing that F_{it+1} is a constant. Now use the general result that if a random variable X is log-normally distributed, such that $\ln(X) \sim \mathcal{N}(\mu, \sigma^2)$, then the expectation of X conditional on $X \geq K$ is:

$$\mathrm{E}[X|X \geq K] = \exp\left\{\mu + \frac{\sigma^2}{2}\right\} \frac{\Phi\left(\frac{\mu - \ln(K) + \sigma^2}{\sigma}\right)}{1 - \Phi\left(\frac{\ln(K) - \mu}{\sigma}\right)}$$

Using this expression with $\mu = \ln(V_{it}) + \mu_{it}$, $\sigma = \sigma_{it}$, and $K = F_{it+1}$ we can write the expectation of V_{it+1} conditional on $V_{it+1} \geq F_{it+1}$ as:

$$\begin{aligned}
\mathrm{E}[V_{it+1}|\mathbb{1}_{V_{it+1}>F_{it+1}} = 1] &= V_{it}\exp\{\mu_{it}\} \frac{\Phi\left(\frac{\ln\left(\frac{V_{it}}{F_{it+1}}\right) + \left(\mu_{it} - \frac{\sigma_{it}^2}{2}\right) + \sigma_{it}^2}{\sigma_{it}}\right)}{1 - \Phi\left(\frac{\ln\left(\frac{F_{it+1}}{V_{it}}\right) - \left(\mu_{it} - \frac{\sigma_{it}^2}{2}\right)}{\sigma_{it}}\right)} \\
&= V_{it}\exp\{\mu_{it}\} \frac{\Phi\left(DD_{it} + \sigma_{it}\right)}{1 - \pi_{it}}
\end{aligned}$$

Inserting this in the equation for the expected terminal equity value, we get:

$$
\begin{aligned}
\mathrm{E}[E_{it+1}] &= (1-\pi_{it})\left(V_{it}\exp\{\mu_{it}\}\frac{\Phi\left(DD_{it}+\sigma_{it}\right)}{1-\pi_{it}} - F_{it+1}\right) \\
&= V_{it}\exp\{\mu_{it}\}\Phi\left(DD_{it}+\sigma_{it}\right) - (1-\pi_{it})F_{it+1}
\end{aligned}
$$

Finally, divide by E_{it} and subtract 1 to get the expected equity return:

$$
\mathrm{E}[r_{it+1}] = \frac{V_{it}}{E_{it}}\exp\{\mu_{it}\}\Phi\left(DD_{it}+\sigma_{it}\right) - (1-\pi_{it})\frac{F_{it+1}}{E_{it+1}} - 1
$$

Equity Return Covariance

The covariance between the terminal equity of firm i and j is:

$$
\mathrm{Cov}[E_{it+1}, E_{jt+1}] = \mathrm{E}[E_{it+1}E_{jt+1}] - \mathrm{E}[E_{it+1}]\mathrm{E}[E_{jt+1}]
$$

Since we know the value of $\mathrm{E}[E_{it+1}]$ and $\mathrm{E}[E_{jt+1}]$ from Appendix 5.1, we only need to focus on the first term, $\mathrm{E}[E_{it+1}E_{jt+1}]$. From the law of iterated expectation, and the fact that $E_{it+1} = (V_{it+1} - F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}}$ and $E_{jt+1} = (V_{jt+1} - F_{jt+1})\mathbb{1}_{V_{jt+1}>F_{jt+1}}$, we can write it as:

$$
\begin{aligned}
\mathrm{E}[E_{it+1}E_{jt+1}] &= \mathrm{E}\Big[\mathrm{E}[(V_{it+1}-F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}}(V_{jt+1}-F_{jt+1})\mathbb{1}_{V_{jt+1}>F_{jt+1}}|\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{it+1}>F_{it+1}}]=1] \\
&\quad + \mathrm{E}[(V_{it+1}-F_{it+1})\mathbb{1}_{V_{it+1}>F_{it+1}}(V_{jt+1}-F_{jt+1})\mathbb{1}_{V_{jt+1}>F_{jt+1}}|\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{it+1}>F_{it+1}}]=0]\Big] \\
&= \Pr[\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{it+1}>F_{it+1}}]=1]\mathrm{E}[(V_{it+1}-F_{it+1})(V_{jt+1}-F_{jt+1})|\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{it+1}>F_{it+1}}]=1] \\
&\quad + \Pr[\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{it+1}>F_{it+1}}]=0]0 \\
&= (1-\pi_{it}-\pi_{jt}+\mathrm{Cov}[\mathbb{1}_{V_{it+1}<F_{it+1}}, \mathbb{1}_{V_{jt+1}<F_{jt+1}}]+\pi_{it}\pi_{jt}) \\
&\quad \times \mathrm{E}[E_{it+1}E_{jt+1}|\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{it+1}>F_{it+1}}]=1]
\end{aligned}
$$

Where the second equality is due to the fact that $(V_{iT}-F_i)\mathbb{1}_{V_{it+1}>F_{it+1}}(V_{jt+1}-F_{jt+1})\mathbb{1}_{V_{jt+1}>F_{jt+1}} = 0$ if either $\mathbb{1}_{V_{it+1}>F_{it+1}} = 0$ or $\mathbb{1}_{V_{jt+1}>F_{jt+1}} = 0$. For the third equality we utilize the fact that the probability of at least one firm defaulting is $\mathrm{E}[\mathbb{1}_{V_{it+1}<F_{it+1}\cup V_{jt+1}<F_{jt+1}}] = \pi_{it} + \pi_{jt} - \mathrm{Cov}[\mathbb{1}_{V_{it+1}<F_{it+1}}, \mathbb{1}_{V_{jt+1}<F_{jt+1}}] - \pi_{it}\pi_{jt}$. Inserting this into the equation for the covariance, we get:

$$
\begin{aligned}
\mathrm{Cov}[E_{it+1}, E_{jt+1}] &= (1-\pi_{it}-\pi_{jt}+\mathrm{Cov}[\mathbb{1}_{V_{it+1}<F_{it+1}}, \mathbb{1}_{V_{jt+1}<F_{jt+1}}]+\pi_{it}\pi_{jt}) \\
&\quad \times \mathrm{E}\Big[E_{it+1}E_{jt+1}|\min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{jt+1}>F_{jt+1}}]=1\Big] - \mathrm{E}[E_{it+1}]\mathrm{E}[E_{jt+1}]
\end{aligned}
$$

Finally, we divide by $E_{it}E_{jt}$ to obtain the return covariance:

$$\begin{aligned}
\text{Cov}[r_{it+1}, r_{jt+1}] = &(1 - \pi_{it} - \pi_{jt} + \text{Cov}[\mathbb{1}_{V_{it+1}<F_{it+1}}, \mathbb{1}_{V_{jt+1}<F_{jt+1}}] + \pi_{it}\pi_{jt}) \\
&\times \frac{1}{E_{it}E_{jt}} \text{E}\Big[E_{it+1}E_{jt+1} | \min[\mathbb{1}_{V_{it+1}>F_{it+1}}, \mathbb{1}_{V_{jt+1}>F_{jt+1}}] = 1\Big] \\
&- (1 + \text{E}[r_{it+1}])(1 + \text{E}[r_{jt+1}])
\end{aligned}$$

5.2 DSM Implementation Details

The DSM Loss Function

Let the total set of parameters for the DSM be denoted $\boldsymbol{\theta}^{DSM} = [\boldsymbol{\theta}^{\alpha}, \boldsymbol{\theta}^{\beta}, \boldsymbol{\theta}^{\lambda}, \boldsymbol{\theta}^{\epsilon}]$. Then, the optimal set of parameters, $\hat{\boldsymbol{\theta}}^{DSM}$, are found by minimizing some loss function, $L(\cdot, \boldsymbol{\theta}^{DSM})$, over some sample, $\mathcal{S}$:

$$\hat{\boldsymbol{\theta}}^{DSM} = \underset{\boldsymbol{\theta}^{DSM}}{\text{argmin}}\, L(\mathcal{S}; \boldsymbol{\theta}^{DSM})$$

The basis for our loss function will be the negative log likelihood of observing the realized equity returns of the $\mathcal{S}$ sample:

$$L^{LL}(\mathcal{S}; \boldsymbol{\theta}^{DSM}) = -\sum_{(i,t)\in\mathcal{S}} \ln\Big(\mathcal{L}^{r}_{it+1}(r_{it+1}; \boldsymbol{\theta}^{DSM})\Big)$$

However, as is common in the machine learning literature, a parameter penalty term, $L^{P}(\boldsymbol{\theta}^{DSM})$, is added to avoid overfitting. Here, the parameter penalty is chosen to be the ℓ_1-norm of the parameter vector:

$$L^{P}(\boldsymbol{\theta}^{DSM}) = ||\boldsymbol{\theta}^{DSM}||_1$$

Additionally, since we are estimating the parameters of a structural model, it is possible to implement what can best be described as economically motivated parameter penalties. This could either be outright restrictions or a set of penalties on the size or sign of the parameters. Here, the only economically motivated parameter penalty is a penalty on the variance of the

ℓ_2-norm of $\boldsymbol{\lambda}_t$:[19]

$$L^E(\boldsymbol{\lambda}_t|\mathcal{S}) = \text{Var}_{\mathcal{S}}\Big[||\boldsymbol{\lambda}_t||_2\Big]$$

Where the $\mathcal{S}$ subscript indicates that the variance is calculated over the sample, $\mathcal{S}$. The complete DSM loss function can thereby be expressed as:

$$L(\mathcal{S};\boldsymbol{\theta}^{DSM}) = \sum_{t=1}^{T_{\mathcal{S}}}\sum_{i=1}^{I_t} L^{LL}(\mathcal{S};\boldsymbol{\theta}^{DSM}) + w^P L^P(\boldsymbol{\theta}^{DSM}) + w^E L^E(\boldsymbol{\lambda}_t|\mathcal{S})$$

Where $t \in 1, ..., T_{\mathcal{S}}$, with $T_{\mathcal{S}}$ being the number of cross-sections in $\mathcal{S}$, I_t is the number of firms in cross-section t, and w^P and w^E is the weight given to the parameter penalty term and the economically motivated penalty, respectively.

The DSM Training Procedure

The algorithm used to train the DSM, i.e. minimize the loss function, is the Adam algorithm of Kingma and Ba (2014), with batch sizes of 10,000. The learning rate of the algorithm follows a decaying schedule, in which it is reduced by 5% after each epoch. The initial learning rate is set to 10^{-2}, and the learning rate decay stops when/if it reaches 10^{-4}. In addition to the penalties described in Appendix 5.2, the training procedure also involves other regularization techniques. Specifically, the parameter functions, shown in Figure 2, also employ batch normalization (Ioffe and Szegedy (2015)) and dropout (Srivastava *et al.* (2014)).[20] When training the DSM, the total dataset is split into a training, validation and test dataset. The actual training procedure, outlined above, is done on the training data, while the validation data is used for early stopping and choosing the optimal set of hyper-parameters. The early stopping procedure terminates training when the loss function has not improved across the validation data for 10 epochs. The choice of the optimal hyper-parameters are determined through a grid search. That is, for the two hyperparameters of the model, w^P and w^E, the DSM is trained for all combinations of $w^P \in 10^{-3}, 10^{-4}, 10^{-5}$ and $w^E \in 10^{-5}, 10^{-6}, 0$, and the set of hyperparameters with the lowest loss function value,

[19] This particular penalty seem to be important to avoid overfitting on the training data. Other economically motivated parameter penalties have been tested, such as a penalizing high values of the mispricing term, α_{it}, encouraging a positive risk compensation, $\boldsymbol{\beta}_{it}^T\boldsymbol{\lambda}_t$, etc. Yet, they all lead to a worse performance score on the validation and test data.

[20] The dropout rate could be treated as a hyperparameter but is fixed in this paper to 0.5 for the sake of simplicity and computational costs.

across the validation data, is chosen. Finally, the optimal solution is sensitive to the choice of starting parameters and so 10 DSMs are trained and the final model output is the average across the 10 models. For the neural network benchmark model in Section 3.3, the training procedure is identical to that of the DSM, with two changes: The loss function is the mean squared error, $MSE = (r_{it+1} - \hat{r}_{it+1})^2$, and the hyperparameter grid search only involves searching across $w^P \in 10^{-3}, 10^{-4}, 10^{-5}$.

All models are trained on a rolling one year basis. After training the models on the initial training and validation set, predictions are made for all months in the first year of the test set. Then, the validation set is rolled forward one year, such that the training data grows by one year, the validation data has the same length in years, and the test data shrinks by one year. The models are then re-estimated using this new training and validation split and predictions are made on the first 12 months of the new test data. This process continues until all observations of the *initial* test data has a set of model predictions.

5.3 Data Preprocessing

As is standard in the financial machine learning literature, the 153 firm characteristics are ranked at each cross-section and then transformed to lie in the $[-1, 1]$ range. The 45 macroeconomic variables are discretized based on the combined training and validation data and then, similarly to the firm characteristics, transformed to lie in the $[-1, 1]$ range. That is, for each macroeconomic variable, all observations are assigned a value between one and ten, based on a decile sort of the combined training and validation data, meaning that no information in the test data is used for the discretization process. Then, each macroeconomic variables is squeezed into the $[-1, 1]$ range. Both the equity returns and the monthly "realized" variances in Section 3.4 have been winsorized at the 99.99$^{\text{th}}$ percentile, using information from the entire data set, to exclude the most extreme outliers. Finally, the Compustat values for short-term debt, F^{SD}_{it+1}, and long-term debt, F^{LD}_{it+1}, have been modified to minimize the effect of extremely levered firms:

1. All negative values of F^{SD}_{it+1} and F^{LD}_{it+1} are set to zero.
2. A simple short-term and long-term leverage value is calculated as $L^{SD}_{it+1} = \frac{F^{SD}_{it+1}}{E_{it}}$ and $L^{LD}_{it+1} = \frac{F^{LD}_{it+1}}{E_{it}}$, respectively.

3. Both L_{it+1}^{SD} and L_{it+1}^{LD} are cross-sectionally winsorized at the 98$^{\text{th}}$ percentile.

4. The final values for F_{it+1}^{SD} and F_{it+1}^{LD} are then calculated based on the winsorized leverages, i.e. $F_{it+1}^{SD} = E_{it}L_{it+1}^{SD}$ and $F_{it+1}^{LD} = E_{it}L_{it+1}^{LD}$.

Chapter 2

Improving Merger Arbitrage Returns with Machine Learning

Abstract

This paper present a novel decomposition of expected returns for merger arbitrage trades, utilizing modern machine learning techniques to model individual components. This decomposition lead to better proxies for expected returns than relying on realized merger arbitrage returns. Additionally, they yield large economic gains for merger arbitrage investors in terms of both absolute and risk-adjusted returns. Finally, the decomposed expected return estimates provide new insight into the aggregate market, by showing a persistent decrease for the cross-sectional average expected merger arbitrage return, over the last decade.

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1 Introduction

Since the seminal paper by Mitchell and Pulvino (2001) on the risk and return characteristics of merger arbitrage (alternatively, risk arbitrage), the literature has been relatively quiet on the topic. There are of course notable exceptions such as Jetley and Ji (2010) who show a declining merger arbitrage spread post 2002, Giglio and Shue (2014) who examine the market information contained in the passage of time, and Jiang *et al.* (2018) who examine the role of activist merger arbitrageurs. This relative absence of papers on the topic is despite the fact that a lot of the early work, such as Dukes *et al.* (1992), Baker and Savaşoglu (2002), and Jindra and Walkling (2004), document large excess returns in the merger arbitrage market, which one could have thought would encourage a deeper understanding of this market. In this context, it is therefore interesting in and of itself to examine the merger arbitrage market over the last 20 years, especially during the financial crisis of '08-'09.

During this same time, in which the literature has been quiet on merger arbitrage, there has been an increasing interest, among both academics and practitioners, in the use of machine learning techniques in finance. This increasing interest spans many areas of finance such as consumer credit risk (e.g. Khandani *et al.* (2010) and Butaru *et al.* (2016)), equity risk premiums (e.g. Freyberger *et al.* (2020), Gu *et al.* (2020), and Kozak *et al.* (2020)), bond risk premiums (e.g. Bianchi *et al.* (2021)), among others. Many of these papers find that machine learning techniques can indeed provide financial insight beyond what "traditional" statistical techniques are capable of. It is therefore natural to examine whether this extends to the merger arbitrage market.

This paper attempts to answer the two questions posed above, namely: How has the merger arbitrage market evolved over the last 20 years and can machine learning techniques provide additional insight into the merger arbitrage market beyond traditional statistical methods? To answer these two questions, the paper estimates the expected return of each individual merger arbitrage trade using two different approaches: a direct modelling approach and a decomposed modelling approach. The direct modelling approach is similar to the way expected equity returns are modelled in Gu *et al.* (2020), wherein we rely on past realized merger arbitrage returns to fit a model that is then used for predictive purposes. The decomposed modelling approach instead tries to estimate the conditional probability of deal success, which can then in turn be used in a simplified decomposed expression for the expected return of a merger arbitrage trade. Both of these two modelling approaches make use of machine learning techniques to model their respective object of interests: the expected merger arbitrage return and the probability of deal success.

M&A deal data is extracted from the Thomson ONE database, and this data is augmented by both equity price and firm fundamental data from CRSP and Compustat. After applying some necessary filters to the data, the total data set contains 4,828 M&A deals from 1984-2020 and includes 111 explanatory variables to be used as model inputs. This data set is then initially split into a training and test set, each containing roughly 50% of all M&A deals, although the training window will expand to incorporate as many past deals as possible for out-of-sample predictions.

Seven different classification models[1] are then trained on the training data to predict the probability of deal success and out-of-sample predictions are made on the test set. The models based on decision trees (random forest and gradient boosted trees) statistically outperform the remaining five, who all show similar capabilities in estimating the conditional probability of deal success. The most important variables, in determining the outcome of an M&A deal, are deal specific variables, with the indicator variable 'Friendly' (indicating whether the M&A deal is backed by the board of directors of the target firm) being, by far, the most important variable.

In addition to the predicted probabilities about M&A deal outcomes, two sets of estimated expected returns are also estimated using the two modelling approaches described above. For the direct modelling approach the same seven models are used for predictions, although modified to a regression setting.[2] Thus, in total, there are fourteen sets of out-of-sample expected merger arbitrage return predictions: seven using the decomposed approach and seven using the direct modelling approach. Each of these sets are used to construct four out-of-sample trading strategies: a normal strategy, in which a merger arbitrageur engages in all trades with an expected return above 0%, and a selective strategy, in which the threshold is instead 2.5%. Both of these then have a value-weighted and equal-weighted version. Analyzing the performance of these strategies reveal that the group of strategies based on the decomposed expected return estimates outperform the group based on the directly modelled

[1] The seven classification models are: logistic regression, logistic regression with elastic net penalty, random forest, gradient boosted trees, and three versions of a neural network with 1, 2 and 3 hidden layers, respectively.

[2] The seven regression models are: linear regression, linear regression with elastic net penalty, random forest, gradient boosted trees and three versions of a neural network with 1, 2 and 3 hidden layers, respectively.

expected return estimates, across several evaluation metrics. However, within the group of trading strategies based on the decomposed expected returns, the performance is similar. This suggests that for merger arbitrageurs, the decomposition of the expected return, rather than the complexity of the underlying model, is what matters most for improving both absolute and risk-adjusted merger arbitrage returns.

Even though the trading strategies based on the decomposed expected return estimates perform similar, it does not necessarily mean that the quality of the predictions are the same. To determine what set of expected returns align best with realized returns, the realized out-of-sample merger arbitrage returns are regressed onto each of the estimated sets of expected returns. If a set of expected return estimates is a perfect proxy for the actual expected returns, then we would expect a regression coefficient close to 1 and an intercept of 0. The results once again indicate, that as a group, the decomposed expected return estimates outperform the directly modelled expected return estimates, both in terms of regression coefficients and R^2 values.[3] Within the group of decomposed expected return estimates, the sets based on the random forest and gradient boosted trees models outperform the rest, indicating that these models' superior ability to model the conditional probability of deal success, does indeed translate into more accurate expected return estimates.

Finally, the paper examine the evolution of the aggregate merger arbitrage market from 2001-2020. Both the cross-sectional average expected and realized merger arbitrage returns are calculated and examined over this time period. While both of the cross-sectional average time series have about the same mean at around 3%, they exhibit very different time series variation over this period of time. Specifically, the time series of the average expected return indicate a significant decline post the financial crisis, to a level of around 1.53%, that has been persistent since then. On the other hand, no such phenomenon can be found through the time series of the average realized return. This highlights that using the decomposed expected return estimates provide new insight into the aggregate merger arbitrage market, that cannot be uncovered when relying on a small (noisy) sample of realized returns.

The paper will proceed as follows: Section 2 will go through a couple of examples in the data and give a brief overview of merger arbitrage. Section 3 will discuss the machine learning techniques and general methodology of this paper. Section 4 will go through the

[3] The coefficients (R^2 values) are in the range of 0.32-0.52 and 0.02-0.18 (0.020-0.038 and 0.000-0.007) for the decomposed and directly modelled expected returns, respectively.

data gathering and filtering process, as well as review the full data sample. Section 5 will present, analyze and discuss the empirical results and Section 6 concludes.

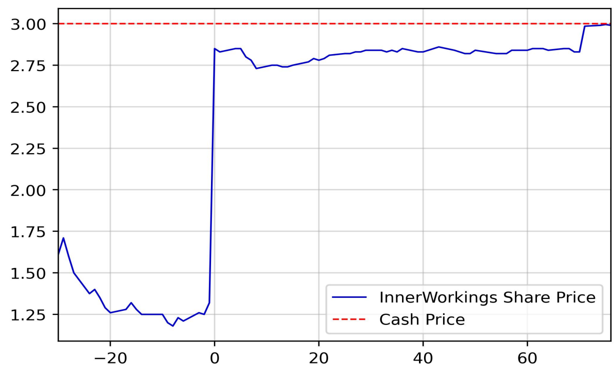
2 Risk Arbitrage Review

M&A deals can vary across several dimensions: the acquiring entity can be anything from private investors to public companies, the target company can be private or public, the payment can be in the form of cash, equity or a hybrid of the two, and deals can include various clauses such as collar agreements, termination fees and more. A detailed breakdown of the data can be found in Section 4, but for now it is sufficient to point out that this paper only examines deals in which the payment is either all-cash or all-equity. Now, in order to better understand why it makes sense to decompose the expected return of merger arbitrage trades, it is useful to go through a couple of examples of how typical M&A deals progress and how merger arbitrage works. The following four examples are taken directly from the data and each example represent one of the four general deal scenarios present in the sample (a deal is either successful or unsuccessful and, as mentioned, either all-cash or all-equity).

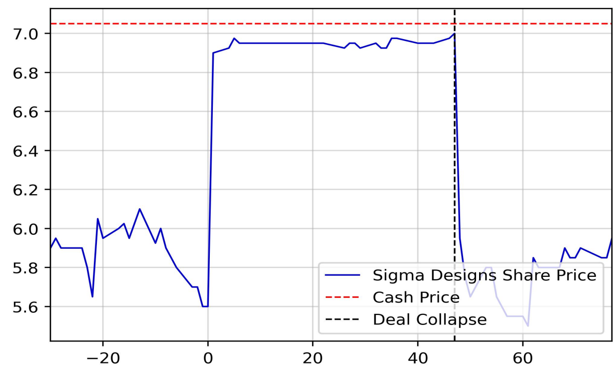
Let us start by considering the case of a simple all-cash deal: On July 16$^{\text{th}}$, 2020 HH Global Group Limited announced a definitive agreement between themselves and InnerWorkings, Inc. to combine operations.[4] HH Global would acquire 100% of InnerWorking's shares at a price of \$3 per share, which represented a premium of 127% compared to the closing price the day before the announcement (\$1.32). At the day of the announcement, the share price of InnerWorkings closed at \$2.85, which meant that a merger arbitrageur could bet on the deal being successful, by buying shares of InnerWorkings at \$2.85 and get \$3 per share from HH Global, some time in the future, thus netting a profit of \$0.15 (5.26%) per share (not considering transaction costs or any potential dividend payments by InnerWorkings). As it happens, this particular deal was completed on October 1$^{\text{st}}$ that same year. The share price of InnerWorkings 1 month prior to the announcement date, up until deal closure on October 1$^{\text{st}}$, is shown in Figure 1(a).

The second example is also an all-cash deal, but one that ultimately ended up unsuccessful. On December 7$^{\text{th}}$, 2017 Silicon Labs announced a definitive agreement to acquire Sigma

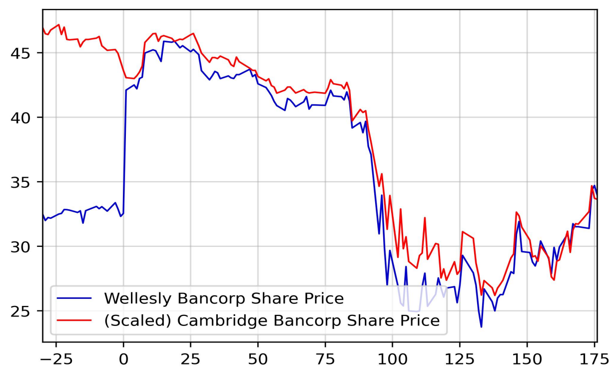
[4] https://hhglobal.com/news/hh-global-and-innerworkings-to-create-combined-global-marketing-services-company/



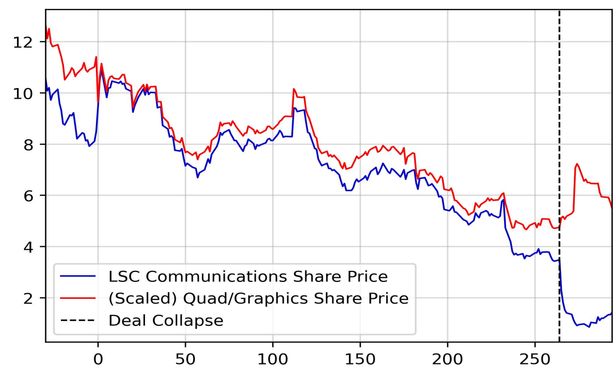
(a) InnerWorkings Deal



(b) Sigma Designs Deal



(c) Wellesly Bancorp Deal



(d) LSC Communications Deal

Figure 1: *M&A Examples.* This figure illustrates the progression of four different risk arbitrage trades from the data. Graph (a) is an example of a successful all-cash deal, and shows the target share price (full blue line) and the offer price (red dashed line). Graph (b) is an unsuccessful all-cash deal, with the black vertical dotted line representing the time of deal failure. Graph (c) is a successful all-equity deal where the red dashed line represents the evolution of the acquirer's share price scaled by the exchange ratio of the deal. Graph (d) is an unsuccessful all-equity deal with the dotted black vertical line once again representing the time of deal failure. All y-axes represent US dollar amounts and all x-axes are days from deal announcement, so that 0 represents the day of the deal announcement.

Designs Inc.[5] for $7.05 per share, which represented a premium of 25.89% compared to the previous closing price ($5.60). The following day, the stock price of Sigma Designs closed at $6.90 and a merger arbitrageur would therefore stand to make $0.15 (2.17%) per share if the deal succeeded. However, a little over a month later on January 23rd, 2018 the deal fell through, and the share price of Sigma Designs dropped to $5.95, which meant that a merger arbitrageur would have lost $0.95 (13.77%) per share. The share price of Sigma Designs is illustrated in Figure 1(b) from one month prior to the deal announcement and up to one month after the deal collapsed.

[5] `https://news.silabs.com/2017-12-07-Silicon-Labs-Announces-Definitive-Agreement-to-Acquire-Sigma-Designs-Inc`

The third example is a case of a successful all-equity deal. On December 5$^{\text{th}}$, 2019 Cambridge Bancorp announced a definitive agreement to merge with Wellesly Bancorp, Inc. in a stock for stock merger.[6] The exchange ratio was set to 0.58, meaning that every Wellesly Bancorp share would be exchanged for 0.58 of Cambridge Bancorp shares. The previous closing share prices of Cambridge Bancorp and Wellesley Bancorp was \$75.22 and \$32.55, respectively. The following day, the closing prices of the two companies were \$74.25 and \$42.10, respectively. A merger arbitrageur could have made an unhedged bet by simply buying shares of Wellesly Bancorp and expect to make \$0.97 ($\$74.25*0.58-\$42.1$)(2.3%) per share, on the condition that the share price of Cambridge Bancorp did not move until after the deal was completed, which is quite an unrealistic assumption. Therefore, the much more common strategy is to make a hedged bet that includes a short position of the acquirer's shares. Specifically, for every share you buy of the target company, you also sell short an amount equal to the exchange ratio of the acquirer's shares. This way, the merger arbitrageur is hedged against general market movements, and the spread between the target share price and the acquirer's share price (scaled by the exchange ratio) is secured, given that the deal is completed under the initial terms proposed. In our example, a hedged bet would still stand to make \$0.97 per share of Wellesly Bancorp purchased, but it would not require the share price of Cambridge Bancorp to remain stable. As mentioned, this particular deal ended up successful and was finalized on June 1$^{\text{st}}$, 2020. The share prices of both companies are illustrated in Figure 1(c), with the share price of Cambridge Bancorp being scaled by the exchange ratio of 0.58 to better illustrate the evolving merger arbitrage spread.

The fourth and final example is an all-equity deal that ended up unsuccessful. On October 31$^{\text{st}}$, 2018 Quad/Graphics, Inc. announced a definitive agreement to acquire LSC Communications, Inc. in an all-equity merger, with an exchange ratio of 0.625.[7] Prior to the announcement, the share prices of the two companies were \$18.25 and \$8.49, respectively. The day of the announcement their respective shares closed at \$15.43 and \$9.43. Thus, a merger arbitrageur could go long 1 share of LSC Communications and short 0.625 shares of Quad/Graphics for a potential net gain of \$0.21 per share ($\$15.43*0.625-\$9.43$)(2.23%) if the deal succeeded. However, this deal was terminated roughly 9 months later on July 22$^{\text{nd}}$, 2019 with the share prices of Quad/Graphics and LSC Communications closing at \$8.19 and

[6] `https://ir.cambridgetrust.com/news-market-information/press-releases/news-details/2019/Cambridge-Bancorp-and-Wellesley-Bancorp-Inc.-to-Merge/default.aspx`

[7] `https://www.quad.com/newsroom/quad-graphics-to-acquire-lsc-communications-in-all-stock-transaction`

\$2.29, respectively, on the next day. Assuming a merger arbitrageur unwinds their positions at those closing prices, they would have made \$4.53 ((\$15.43 − \$8.19) ∗ 0.625) on the short leg of the trade, and −\$7.14 (\$2.29 − \$9.43) on the long leg of the trade, for a total loss of \$7.14 − \$4.53 = \$2.61 (27.68%) per share traded of LSC Communications. The share prices of the two companies are illustrated in Figure 1(d), and like the previous example, the share price of Quad/Graphics have been scaled by the exchange ratio of 0.625 to show the merger arbitrage spread.

The four examples help us understand the typical situation a merger arbitrageur faces: a possibility of a low positive return if a deal is successful and a possibility of a large negative return if the deal is unsuccessful. A lot of the literature, such as Mitchell and Pulvino (2001), examine the return series of a typical merger arbitrageur who trade all M&A deals. However, in this paper, the primary concern is the equilibrium prices determined by merger arbitrageurs and other market participants after a given M&A deal has been announced. In other words, is it possible to get accurate estimates of the expected return for each deal? In the general empirical asset pricing literature, a standard procedure for estimating the expected equity return of a firm is to take a vector of characteristics and/or risk factors $\boldsymbol{X}_{it} \in \mathbb{R}^n$ associated with firm i at time t and transform it via some function, $f : \boldsymbol{X}_{it} \to \mathbb{R}$, into an expected return estimate. The parameters of f, denoted by θ_f, are then found through various optimization techniques (depending on the functional form of f) on a subset of the complete data set (training set) and the estimated expected return for stock i at time t then takes the form $E_t[r_{it+1}] = f(\boldsymbol{X}_{it}; \hat{\theta}_f)$. This is a very simple and direct approach that is easily transferred to the problem of estimating expected merger arbitrage returns of individual deals. Instead of training the model to predict the equity return of firm i at time t, we instead train the model to predict the expected return of M&A deal i at announcement, also denoted by t. This approach will be referenced throughout the paper as the "direct modelling approach". However, it is very natural to view the outcome of an M&A deal as being one of two mutually exclusive events: the deal is either successful or unsuccessful. Therefore, in addition to the direct modelling approach, this paper also explores the following decomposition of the expected return of each M&A deal:

$$E_t[r_i] = \hat{p}_{it} E_t[r_i | D_i = 1] + (1 - \hat{p}_{it}) E_t[r_i | D_i = 0] \tag{1}$$

Where $\hat{p}_{it}$ is the estimated probability that the M&A deal i is successful, D_i is an indicator variable that takes on the value of 1 if a M&A deal i is successful and 0 otherwise, while $E_t[r_i|D_i]$ is the expected return of M&A deal i conditional on the outcome of the deal. The probability that deal i is successful, p_{it}, is modelled as a function of some the same variables as in the direct modelling approach, $\boldsymbol{X}_{it}$. The other two terms, $E_t[r_i|D_i = 1]$ and $E_t[r_i|D_i = 0]$, are estimated by making some simplifying assumptions: for cash deals, it is assumed that the target company pays no dividends, if the deal is successful, the target will be acquired at the price per share of the initial announcement, while if the deal is unsuccessful, the share price of the target company will revert back to its pre-announcement level. Similarly, for equity deals, it is assumed that neither the target or the acquirer pays dividends, investors do not receive interest on their short-sale proceeds, if the deal is successful, the exchange ratio at deal closure is the same as in the initial terms of the merger, while both the target's and acquirer's share prices revert back to their pre-announcement levels if the deal is unsuccessful. With these assumptions we get the following simple expressions:

$$E_t[r_i|Cash, D_i = 1] = \frac{Cash_i - P^{(T)}_{i,post}}{P^{(T)}_{i,post}} \tag{2}$$

$$E_t[r_i|Cash, D_i = 0] = \frac{P^{(T)}_{i,pre} - P^{(T)}_{i,post}}{P^{(T)}_{i,post}} \tag{3}$$

$$E_t[r_i|Equity, D_i = 1] = \frac{P^{(A)}_{i,post} xr_i - P^{(T)}_{i,post}}{P^{(T)}_{i,post}} \tag{4}$$

$$E_t[r_i|Equity, D_i = 0] = \frac{\left(P^{(A)}_{i,post} - P^{(A)}_{i,pre}\right) xr_i + \left(P^{(T)}_{i,pre} - P^{(T)}_{i,post}\right)}{P^{(T)}_{i,post}} \tag{5}$$

Where P is some price identified by the super- and subscript: the superscripts T and A refer to target and acquirer, respectively, while the $pre/post$ subscript refers to whether the price is before or after the deal announcement. $Cash$ is the offer price in a cash deal, and xr is the exchange ratio in an equity deal. The assumptions that lead to the expressions above will be discussed and analyzed further in Section 3, but for now, this "decomposed modelling approach" allow us to view the expected return of a merger arbitrage trade purely as a function of the probability of deal success, since all inputs to equations (2)-(5) are known at time t, which is defined to be at close of the first trading day after deal announcement.

3 Methodology

This section will briefly discuss the various machine learning techniques, meta procedures, performance evaluation, and return calculations employed in the analysis. It serves as an overview of the general methodology with the technical details and optimization choices reserved for the appendix.

Since this paper focus on the decomposition of expected merger arbitrage returns, the primary variable of interest is the conditional (physical) probability of deal success p_{it}. This variable is never observed and will thus be modelled using the classification models described in this section. Each classification model takes in a vector $\boldsymbol{X}_{it} \in \mathbb{R}^N$ and returns a single scalar value $\hat{p}_{it} \in [0, 1]$. M&A deals are indexed by $i = 1, 2, ..., I$ and even though vector $\boldsymbol{X}_{it}$ refers to variables measured at a given time t, it will be suppressed for notational simplicity, since t is always defined as the first trading day after deal announcement. This means that equation (1) takes the form:

$$E_t[r_i] = f_C(\boldsymbol{X}_i; \theta) E_t[r_i | D_i = 1] + \Big(1 - f_C(\boldsymbol{X}_i; \theta)\Big) E_t[r_i | D_i = 0] \tag{6}$$

Where f_C is some classification model.

As mentioned in the previous section, this paper also examines the expected return estimates from a direct modelling approach, that takes the following form:

$$E_t[r_i] = f_R(\boldsymbol{X}_i; \theta) \tag{7}$$

Where f_R is some regression model. Specifically, each classification model f_C will have an analogous regression version f_R trained on the same data, with the same variables, in order to make a fair comparison between the decomposed and direct modelling approaches.

3.1 Classification and Regression Models

The models used in this paper can be categorized as belonging to one of three broader family of models: Generalized linear models, decision tree models, and deep learning models. Using a diverse set of model families increases the chance of capturing a potentially very complex underlying data structure. The seven classification models, f_C, and their regression analogues, f_R, are as follows:

1. Logistic/linear regression (f_C: Logit, f_R: OLS)
2. Penalized logistic/linear regression (f_C: ENLogit, f_R: ENLinear)
3. Random forest (f_C: RF, f_R: RFR)
4. Gradient boosted trees (f_C: GBTrees, f_R: GBR)
5. Neural network with 1 hidden layer (f_C: NN1, f_R: NNR1)
6. Neural network with 2 hidden layers(f_C: NN2, f_R: NNR2)
7. Neural network with 3 hidden layers (f_C: NN3, f_R: NNR3)

Logistic/linear regressions are some of the most applied statistical models when dealing with classification and regression tasks, and in this paper serves as benchmarks for which the more complex models can be compared against. The penalized regressions are similar, but penalizes large coefficients and encourage sparsity. The random forest and the gradient boosted trees are both ensemble models, that use decision trees as their base learners, and the primary difference between them lies in how these base learners are trained and optimized. The final three models of this paper are all standard feed-forward neural networks, with a varying number of hidden layers to allow for complex variable interactions. The details of how the models are structured and optimized can be found in Appendix 7.1.

To find the optimal set of hyperparameters associated with the models listed in 2-7, the data is split into three: a training set, $\mathcal{T}_1$, a validation set, $\mathcal{T}_2$, and a test set, $\mathcal{T}_3$. The training set is for finding the optimal model parameters, the validation set is for finding the optimal hyperparameters, while the test set is for a true out-of-sample analysis of model performance. The details of this procedure can be found in Appendix 7.2.

Finally, all of the classification models make use of probability calibration (see Niculescu-Mizil and Caruana (2005)). The details of this procedure can be found in Appendix 7.3.

3.2 Performance Evaluation

There are two primary concerns when it comes to evaluating the performance of our machine learning models. The first is how well a model performs individually, and the second is how well a model performs compared to other models, and whether or not any difference in performance is statistically significant by some measure. The out-of-sample brier score is the primary performance measure of the classification models:

$$BS_{oos} = \frac{1}{N_{oos}} \sum_{i=1}^{N_{oos}} (f_C(\boldsymbol{X}_i) - D_i)^2 \tag{8}$$

With N_{oos} being the total number of out-of-sample M&A deals indexed by i. Additionally, the paper will also report the out-of-sample accuracy, precision, and recall scores:

$$accuracy_{oos} = \frac{1}{N_{oos}} \sum_{i=1}^{N_{oos}} \mathbb{1}(\hat{D}_i = D_i) \tag{9}$$

$$precision_{oos} = \frac{\sum_{i=1}^{N_{oos}} \mathbb{1}(\hat{D}_i = D_i = 1)}{\sum_{i=1}^{N_{oos}} \mathbb{1}(\hat{D}_i = 1)} \tag{10}$$

$$recall_{oos} = \frac{\sum_{i=1}^{N_{oos}} \mathbb{1}(\hat{D}_i = D_i = 1)}{\sum_{i=1}^{N_{oos}} \mathbb{1}(D_i = 1)} \tag{11}$$

Where $\hat{D}_i$ is the predicted deal outcome from a classification model.[8]

In order to compare model outputs in a pairwise fashion, the Diebold and Mariano (2002) test statistic is calculated:

$$d_{i12} = (f_{C1}(\boldsymbol{X}_i) - D_i)^2 - (f_{C2}(\boldsymbol{X}_i) - D_i)^2 \tag{12}$$

$$DM_{12,oos} = \frac{\bar{d}_{12,oos}}{\frac{\hat{\sigma}_{12,oos}}{\sqrt{N}}} \tag{13}$$

Where $\bar{d}_{12,oos}$ and $\hat{\sigma}_{12,oos}$ denote the mean and Newey-West standard error of d_{12}, respectively, across all out-of-sample observations.

3.3 Variable Importance

A key question in an analysis such as the one in this paper, is how important specific variables are for the models' predictions. While some of the models explored in this paper have their own measures,[9] it is more helpful in a comparative analysis to have a universal methodology

[8] The predicted deal outcome of a classification mode, f_C, is simply 1 if $f_C(\boldsymbol{X}_i) \geq 0.5$ and 0 otherwise.

[9] Logistic regression have p-values as well as the absolute size of coefficients, and decision tree methods have impurity based measures.

to judge variable importance. Therefore, to measure variable importance across the different models of this paper, a permutation based approach is used. Specifically, for each variable, j, the out-of-sample data will be randomly permuted five different times, and the average increase in brier score is measured.[10] The exact details can be found in Appendix 7.4.

3.4 Calculating Merger Arbitrage Return Series

To get an idea of the economic benefits for merger arbitrageurs, a set of return series will be calculated in Section 4 and 5. For an all-cash deal, the return for M&A deal i on day t is calculated as follows:

$$r_{it} = \frac{P_{it}^{(T)} + D_{it}^{(T)} - P_{it-1}^{(T)}}{P_{it-1}^{(T)}} \tag{14}$$

$P_{it}^{(T)}$ is the closing share price of the target company on day t, $D_{it}^{(T)}$ is the dividend payment made by the target company on day t and $P_{it-1}^{(T)}$ is the closing share price of the target company on day $t-1$. Similarly, the return for an all-equity deal is calculated as follows:

$$r_{it} = \frac{P_{it}^{(T)} + D_{it}^{(T)} - P_{it-1}^{(T)} - xr_i \left(P_{it}^{(A)} + D_{it}^{(A)} - P_{it-1}^{(A)} - r_{ft} P_{it-1}^{(A)} \right)}{P_{it-1}^{(T)}} \tag{15}$$

Where xr_i is the exchange ratio of the deal, and $r_{f,t}$ is the daily risk-free rate on day t. The weight, for deal i at time t, for a value-weighted (VWMA) and equal-weighted (EWMA) portfolio, respectively, is then given by:

$$w_{it}^{VWMA} = \frac{P_{i1}^{(T)} CSHO_{i1}^{(T)} \prod_{j=2}^{t}(1 + r_{ij})}{\sum_{n=1}^{N_t} P_{n1}^{(T)} shrout_{n1}^{(T)} \prod_{j=2}^{t}(1 + r_{nj})} \tag{16}$$

$$w_{it}^{EWMA} = \frac{\frac{1}{N_t} \prod_{j=2}^{t}(1 + r_{ij})}{\sum_{n=1}^{N_t} \frac{1}{N_t} \prod_{j=2}^{t}(1 + r_{nj})} \tag{17}$$

Where $CSHO_{i1}^{(T)}$ is the number of shares outstanding for the target company one day after the deal announcement and N_t is the total number of M&A deals in the cross-section of the return series at time t.

[10] The average increase in the brier score will be normalized so that the sum across all j variables is equal to 1.

4 Data

4.1 Data Gathering and Filtering

Data is gathered from three different sources: Thomson ONE for M&A deal specific information, Compustat for company financial data, and CRSP for firm equity prices. After a filtering process, described in Appendix 7.5, we are left with a sample of 4,828 M&A deals for publicly traded US companies, spanning from 1984-2020. The explanatory variables used to predict either the probability of deal success, $\hat{p}_{it}$, or the expected return of an M&A deal directly, $E_t[r_i]$, can be split into three categories: deal specific variables, (target) firm specific variables, and macroeconomic variables. There are 15 deal specific variables, 87 firm specific variables, and 9 macroeconomic variables, for a total of 111 explanatory variables, the details of which can be found in Appendix 7.6.

4.2 Full Sample Overview

Table 1 shows the number of transactions, average success rate, percentage of deals that are all-cash, average deal value, and average deal return for the merger arbitrage trades in the final sample. As can be seen from the table, all the shown statistics vary quite substantially from year to year. Both the number of M&A deals announced and the average deal value seem to have significant run-ups in the years prior to recessions (as defined by NBER), with a subsequent fall during and after these recessions. Furthermore, the average deal value has had a substantially higher average level from 2014 and onward. This could possibly be related to the bull market during this period, increasing company valuations (and by extension the offer values needed to buy them), high availability of corporate credit, lack of other investment opportunities or some combination of the three. The last column of Table 1 is perhaps the most interesting one, since the return profile of merger arbitrage has been extensively studied (see for example Mitchell and Pulvino (2001), Baker and Savaşoglu (2002), and Jetley and Ji (2010)). From the table it seems that the results of Mitchell and Pulvino (2001) hold: merger arbitrage returns decrease during market downturns.

To further explore this, I start by computing the full sample VWMA and EWMA return series, which can be seen in Figure 2. Over the sample period, both the VWMA and EWMA investment strategies have outperformed the market (S&P 500 index), however, since the

Year	Transactions (Count)	Success (%)	Cash (%)	Deal Value ($Millions)	Return (%)
1984	31	61.3	100	373	7.3
1985	96	64.6	100	541	7.6
1986	136	72.8	99.3	444	7.4
1987	109	74.3	100	412	6.7
1988	188	68.6	99.5	467	10.4
1989	127	69.3	96.9	431	3.7
1990	67	73.1	95.5	307	3.1
1991	20	75	100	149	3.4
1992	39	80	50	199	7.4
1993	67	76.1	67.2	303	3.2
1994	121	73.8	71.3	440	6.7
1995	185	80.7	57.2	769	5.5
1996	174	84	57.1	687	5.6
1997	210	88.5	47.8	823	6.9
1998	271	83.6	51.5	2,108	5.1
1999	310	83.7	68.9	1,321	4.1
2000	295	80.8	67	1,343	4.1
2001	194	87.4	64.1	707	3.4
2002	134	82.5	80.3	564	4.6
2003	138	83.5	80.6	578	7.3
2004	118	83.9	74.6	1,781	5.2
2005	165	83.6	86.7	1,300	5.3
2006	177	85.9	91	1,192	3.7
2007	204	86.3	88.7	1,961	0
2008	151	69.1	88.8	1,320	-1.9
2009	79	85.2	80.2	603	8.2
2010	135	89.6	91.1	994	2.8
2011	106	87.9	90.7	1,325	3.1
2012	121	86.8	90.9	815	4.4
2013	87	83.9	88.5	962	2.3
2014	82	89.2	75.9	3,046	2.5
2015	104	85.6	87.5	4,282	2.2
2016	122	93.4	86.9	2,025	3.6
2017	83	89.2	86.7	1,370	2.9
2018	87	94.3	77	2,708	1.6
2019	63	93.7	69.8	3,338	2.5
2020	30	83.9	77.4	2,803	0
Recession Years	745	81.3	82.7	1,196	1.7
Non-Recession Years	4,083	82.1	77.4	1,180	5
Training Set (1984-2000)	2,446	78.4	72.7	954	5.7
Test Set (2001-2020)	2,382	85.7	83.8	1,519	3.2
All	4,828	82	77.8	1,182	4.5

Table 1: *Sample Summary Statistics.* This table shows the number of transactions, the percentage of successful deals, the percentage of all-cash deals, the average deal value, and the average return across all deals, for each year in the full data sample. Additionally, the last five rows of the table reports the same summary statistics for recession years (as defined by NBER), non-recession years, the initial training data, the initial test data, and the full sample.

financial crisis of '08-'09, the cumulative return series of the two merger arbitrage strategies and the market have converged, indicating a decrease in relative performance of the merger arbitrage. This is confirmed if we look at the monthly risk and return characteristics of these three return series, shown in Table 2. There is a sharp drop in the average excess return of both the VWMA and EWMA return series in the latter half of the sample (test set), compared to the first half (training set). Even though the standard deviation also decreases, it is comparatively not enough to offset the decrease in average excess return, and so the Sharpe ratio is also smaller in the test set compared to training set. If we instead look at the performance of the two MA strategies in recessions compared to non-recessions, we see that both the VWMA and EWMA return series perform much worse during recessions, with both lower average excess return and higher standard deviations, resulting in drastically lower Sharpe ratios. Despite all of this, the two MA strategies have outperformed the market, in terms of both returns and Sharpe ratios, across all subsamples.[11]

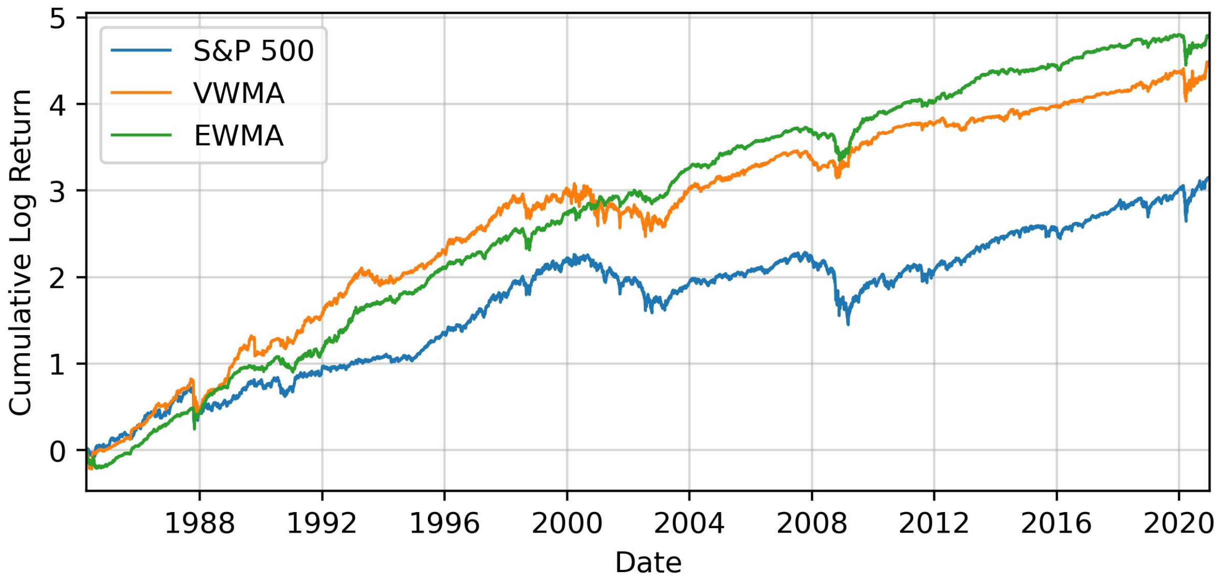


Figure 2: *Cumulative Merger Arbitrage Returns.* This figure shows the cumulative log return of the value-weighted (yellow line) and equal-weighted (green line) merger arbitrage return series (using all M&A deals in the sample), as well as the overall equity market (blue line) as proxied by the S&P 500 index, from 1984 to 2020.

[11] This is of course without accounting for transaction costs, which have been shown to significantly impact the performance of merger arbitrage strategies.

	ER (%)	SD (%)	Sharpe
	Panel A: Full Sample		
S&P 500	0.54	4.37	0.42
VWMA	0.86	4.23	0.69
EWMA	0.89	3.05	1.00
	Panel B: Training Set (1984-2000)		
S&P 500	0.69	4.37	0.55
VWMA	1.03	4.69	0.76
EWMA	1.08	3.34	1.11
	Panel C: Test Set (2001-2020)		
S&P 500	0.41	4.37	0.31
VWMA	0.67	3.31	0.69
EWMA	0.70	2.81	0.87
	Panel D: Recession Months		
S&P 500	-1.55	6.61	-0.80
VWMA	-0.03	5.14	-0.03
EWMA	-0.40	4.78	-0.28
	Panel E: Non-Recession Months		
S&P 500	0.62	4.37	0.48
VWMA	0.92	4.04	0.80
EWMA	1.00	2.87	1.21

Table 2: *Merger Arbitrage Summary Statistics.* This table shows the average monthly excess return (ER), the monthly standard deviation of excess returns (SD), and the annualized Sharpe ratios (Sharpe), for three return portfolios: the S&P 500 index, a value-weighted merger arbitrage portfolio, and an equal-weighted merger arbitrage portfolio. Each panel reports the summary statistics for a specific subsample. Excess returns are calculated by subtracting the risk-free interest rate, extracted from Kenneth French's data library.

Table 3 reports the results of regressing the VWMA and EWMA returns series on the five factors of Fama and French (2015) for the same five subsamples as in Table 2:

$$ER_{MA} = \alpha + \beta_{mkt}(ER_{mkt}) + \beta_{smb}R_{smb} + \beta_{hml}R_{hml} + \beta_{rmw}R_{rmw} + \beta_{cma}R_{cma} \tag{18}$$

As can be seen from the table, both MA return series have positive and statistically significant alphas over all sub samples except for recession months (where they are positive but not statistically significant). Additionally, the two MA strategies have positive, and statistically significant market risk exposure across all subsamples. Exposure towards the other risk factors does not seem to be consistent across time or market conditions, with the exception of the EWMA strategy being consistently exposed to the size factor, which is perhaps unsurprising given its higher portfolio weights on small stocks. Comparing the first half of the data to the second, it can be seen that the two MA strategies generate more

	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}	R^2	N
				Panel A: Full Sample				
VWMA	0.57**	0.50***	0.08	0.08	-0.1	-0.35**	0.40	440
	(0.20)	(0.07)	(0.09)	(0.11)	(0.14)	(0.23)		
EWMA	0.62***	0.41***	0.25***	0.15**	-0.09	-0.13	0.55	440
	(0.13)	(0.04)	(0.05)	(0.05)	(0.05)	(-0.13)		
				Panel B: Training Set (1984-2000)				
VWMA	0.58*	0.61***	0.20	0.38**	-0.05	-0.45	0.40	200
	(0.28)	(0.11)	(0.18)	(0.12)	(0.19)	(0.28)		
EWMA	0.69***	0.51***	0.35***	0.30***	-0.06	-0.14	0.54	200
	(0.21)	(0.06)	(0.07)	(0.07)	(0.07)	(0.13)		
				Panel C: Test Set (2001-2020)				
VWMA	0.50*	0.44***	0.09	-0.03	-0.23	-0.31	0.44	240
	(0.21)	(0.08)	(0.14)	(0.12)	(0.13)	(0.23)		
EWMA	0.53***	0.34***	0.23***	0.12	-0.17*	-0.13	0.60	240
	(0.17)	(0.04)	(0.07)	(0.07)	(0.08)	(0.08)		
				Panel D: Recession Months				
VWMA	0.50	0.54***	0.16	-0.15	0.07	-0.10	0.61	40
	(0.60)	(0.10)	(0.14)	(0.24)	(0.29)	(0.32)		
EWMA	0.26	0.43***	0.40**	0.02	-0.26	0.10	0.70	40
	(0.41)	(0.09)	(0.13)	(0.16)	(0.18)	(0.22)		
				Panel E: Non-Recession Months				
VWMA	0.55**	0.52***	0.07	0.17	-0.14	-0.43*	0.37	400
	(0.21)	(0.07)	(0.08)	(0.10)	(0.12)	(0.18)		
EWMA	0.67***	0.40***	0.25***	0.15**	-0.08	-0.14	0.50	400
	(0.12)	(0.04)	(0.04)	(0.06)	(0.06)	(0.08)		

Table 3: *Merger Arbitrage Factor Exposures.* This table shows the results of regressing the excess monthly returns of a value-weighted (VWMA) and equal-weighted (EWMA) merger arbitrage portfolio onto the five risk factors of Fama and French (2015). Each panel reports the regression results for a specific subsample. The parentheses report Newey-West standard errors for panel A, B, and C, and White standard errors for panel D and E. *, **, and *** indicate statistical significance at the 0.05, 0.01, and the 0.001 level, respectively.

alpha, while also having higher risk exposures, in the first half of the sample. This possibly explains the results of Jetley and Ji (2010) that show a decreasing merger arbitrage spread over time: both the α and risk exposures are lower in the latter half of the sample leading to a lower average merger arbitrage spread. The regression results indicate that the market exposures of the two MA strategies are constant over the business cycle, i.e. the β_{mkt} coefficients are more or less the same for the recession months and the non-recession months. This is puzzling since Mitchell and Pulvino (2001) find that the aggregate merger arbitrage return series exhibits a highly non-linear market exposure: high β_{mkt} during market downturns and low β_{mkt} during normal times. This discrepancy seem to arise from the difference in how a market downturn is defined: in this paper it is defined as NBER recessions, whereas in Mitchell and Pulvino (2001) they use a market return cutoff to identify market downturns. It is also worth noting, that if we sum all months in which the economy is classified as being in a recession, only 22.5% of those months fall in the first half of the dataset. This could be part of the explanation as to why merger arbitrage has performed worse in the latter half: the economy has spend comparatively more time in recessions during that half.

5 Empirical Results

5.1 Conditional Probabilities

In this subsection, the seven classification models, outlined in Section 3, are used to estimate the conditional probability that a given M&A deal will be successful. Table 4 reports the out-of-sample brier score, accuracy, precision and recall for all seven models. The table shows that the RF and GBTrees models outperform the other five models across all four performance measures.[12] The ENLogit model have slightly worse performance measures than the tree based methods, but it actually performs better than the more advanced neural networks. This is quite surprising since neural networks are shown in Gu *et al.* (2020) to outperform other models, including tree based ones, for predicting equity returns. The exact cause of the poor performance of the neural networks is unclear, but it might be due to the relatively small sample of this paper, since neural networks generally require large amounts of data to accurately determine the underlying functional relationships. Table 5 reports the pairwise Diebold-Mariano test statistic, described in Section 3. The test-statistic confirms the results of Table 4: the RF and GBTrees models outperform all other models, and this outperformance is found to be statistically significant.

Finally, Figure 3 shows the 10 most important variables, for each of the seven classification models, measured across all out-of-sample observations. Looking at the charts, a few things become clear: first, all models tend to agree on the five or six most important variables with the 'Friendly' indicator being, by far, the most important determinant of deal success, with 'ttf/dv' being the second most important. This provides insight for potential acquirers when considering a merger/acquisition: the graphs in Figure 3 suggest that it is important

[12] Note that a low brier score indicates a better performance than a large brier score.

	Brier Score	Accuracy	Precision	Recall
Logit	0.073	0.909	0.925	0.973
ENLogit	0.069	0.916	0.927	0.980
RF	0.065	0.921	0.928	0.988
GBTrees	0.064	0.920	0.928	0.983
NN1	0.073	0.913	0.927	0.975
NN2	0.072	0.912	0.926	0.975
NN3	0.074	0.909	0.921	0.978

Table 4: *Performance of Classification Models.* This table reports the performance of seven different classification models for predicting the probability of success across all out-of-sample M&A deals. The reported performance measures are: brier score, accuracy, precision, and recall. These measures are described more in detail in Section 3.

	ENLogit	RF	GBTrees	NN1	NN2	NN3
Logit	1.79	4.97*	5.91*	-0.04	0.85	-0.31
ENLogit		4.67*	6.07*	-2.85*	-1.46	-2.35*
RF			1.48	-5.71*	-5.02*	-5.66*
GBTrees				-6.9*	-6.02*	-6.78*
NN1					1.1	-0.32
NN2						-1.11

Table 5: *Pairwise Diebold-Nariano Test-Statistic.* This table shows the pairwise out-of-sample Diebold-Mariano test-statistic. Both the rows and columns refer to a given classification model. A positive number indicates that the column model provides more accurate conditional probability estimates, compared to the row model, and vice versa. A * indicate that the test-statistic is statistically significant at the 0.05 level.

to have the board of directors of the target company backing the deal, and that including a target termination fee, will significantly affect the chance of deal success. Second, even though the 'Friendly' indicator is the most important variable, the best performing models, namely the RF and GBTrees models, place a relatively higher importance on other variables as well, suggesting that these variables do indeed contain information, but extracting it is difficult. Third, at least half of the 10 most important variables for each classification model are deal specific variables, despite this group of variables only constituting 13.5% of the total explanatory variables. This is perhaps not surprising, but nevertheless, it suggests that any improvement in conditional probability estimates, is likely to come from adding relevant deal specific information and not variables that are otherwise traditionally associated with the risk premium of individual firms.

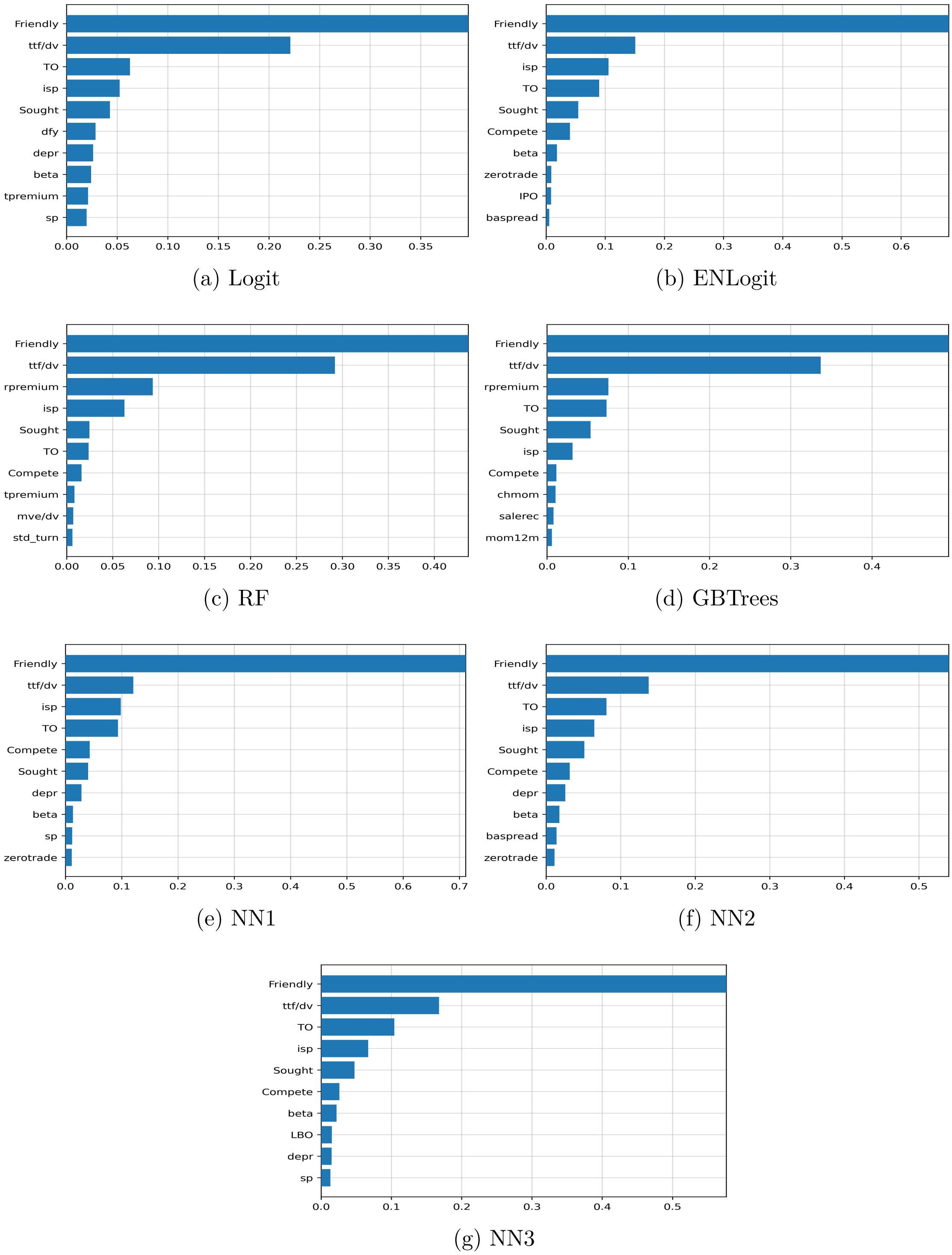


Figure 3: *Variable Importance of Classification Models.* In this figure, each horizontal bar chart (a)-(g) shows the 10 most important variables for one of seven classification models. The variable importance measure, for a given variable, is calculated as the increase in out-of-sample brier score after randomly permuting the variable across all out-of-sample observations. The variable importance measures are then normalized so that they sum to one.

5.2 Expected Return Estimates

Decomposed Expected Return Estimates

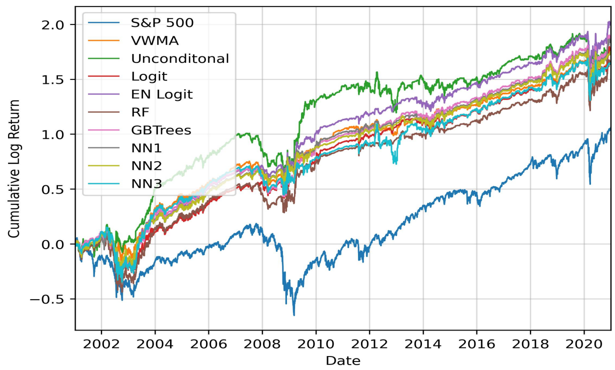
Now that we have a conditional probability estimate for each deal in the test set, we can use equation (1) from Section 2 to find the decomposed expected return estimates. After calculating the decomposed expected return for each out-of-sample M&A deal, two trading strategies are analyzed:

1. Normal Strategy (NS) in which merger arbitrageurs trade all deals for which $E_t[r_i] > 0\%$.

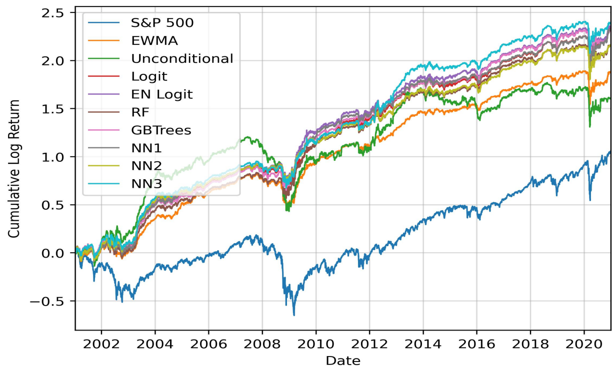
2. Selective Strategy (SS) in which merger arbitrageurs trade all deals for which $E_t[r_i] > 2.5\%$.

The performance of these two trading strategies (each of which have a value-weighted and equal-weighted version) can be seen in Figure 4, alongside the market return, the VW-MA/EWMA return series, and a strategy using the unconditional probability of deal success (82%), for calculating the decomposed expected return. It is difficult to visually tell the difference between the seven model return series for each of the four graphs. This is due to the fact the models generally agree on the subset of M&A deals that make the cutoffs of 0% and 2.5%, respectively. While this is true for both the normal and the selective strategies, it is clear that increasing the selectiveness also increases the cumulative return of the strategies, as expected.

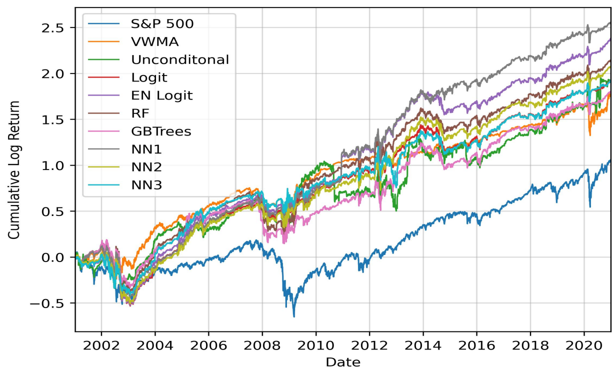
To further explore the return properties of the two strategies, Table 6 reports the average monthly excess return, standard deviation, annualized Sharpe ratio, average number of active deals in the cross-section, and the percentage of all deals above the expected return threshold. Looking at the table, there are a couple of things to take note of. First of all, in terms of both excess return and Sharpe ratios, all models (excluding the unconditional probability "model") perform relatively similar to each other within each category, although the performance across models is slightly more dispersed for the value-weighted strategies. This also means that the apparent superior conditional probability estimates coming from the decision tree based methods, do not appear to translate into better trading strategies. Thus, for investors, it is the decomposition itself rather than the specific decomposition model



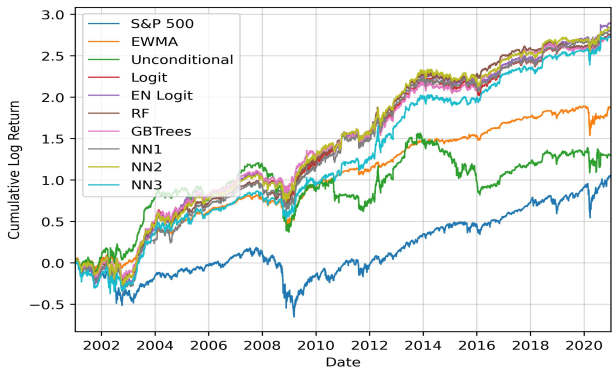
(a) VWNS



(b) EWNS



(c) VWSS



(d) EWSS

Figure 4: *Decomposed Strategies Return Series.* This figure illustrates four graphs (a)-(d), each of which shows the out-of-sample cumulative log return for various merger arbitrage strategies. All strategies illustrated in the four graphs (except for 'S&P 500', 'VWMA', and 'EWMA') are based on the expected return decomposition in equation (1). Graph (a) and (b) show the cumulative log return of strategies engaging in all merger arbitrage trades with a decomposed expected return above 0%, with a value-weighted and equal-weighted weighting scheme, respectively. Graph (c) and (d) show the cumulative log return of strategies engaging in all merger arbitrage trades with a decomposed expected return above 2.5%, also with both a value-weighted and equal-weighted weighting scheme, respectively. For comparison, each graph also contain the market return series as well as the VWMA (graphs (a) and (c)) and the EWMA (graphs (b) and (d)) return series.

that matters most. Second, by looking at the relatively poor performance of the strategies based on the unconditional probability, it is clear that the decomposition performs better when conditioned on deal/target specific information. Third, increasing the strategy selectiveness increases the average excess return of all strategies (again, except the unconditional model), suggesting that the decomposed expected return estimates are indeed able to rank merger arbitrage trades fairly well. Finally, strategies based on the decomposed expected returns, generally outperform the VWMA and EWMA return series in terms of excess returns (especially the selective strategies), but the Sharpe ratios remain somewhat similar. It is therefore not entirely clear from Table 6 that the decomposed expected return strategies actually provide higher risk-adjusted returns than the VWMA and EWMA strategies.

	ER (%)	SD (%)	Sharpe	Active	Fraction
		Panel A: Benchmark Strategies			
VWMA	0.67	3.31	0.69	38.27	1.00
EWMA	0.70	2.81	0.87	38.27	1.00
		Panel B: Normal Strategies			
Unconditional (VW)	0.72	4.23	0.59	14.59	0.30
Logit (VW)	0.68	3.43	0.69	25.94	0.65
ENLogit (VW)	0.78	3.52	0.76	25.35	0.63
RF (VW)	0.64	3.73	0.59	27.20	0.65
GBTrees (VW)	0.73	3.45	0.73	27.48	0.68
NN1 (VW)	0.72	3.56	0.69	24.74	0.62
NN2 (VW)	0.67	3.35	0.69	24.89	0.61
NN3 (VW)	0.66	3.96	0.59	24.26	0.56
Unconditional (EW)	0.66	4.57	0.48	14.59	0.30
Logit (EW)	0.90	3.15	1.00	25.94	0.65
ENLogit (EW)	0.91	3.20	0.97	25.35	0.63
RF (EW)	0.82	3.06	0.94	27.20	0.65
GBTrees (EW)	0.88	2.92	1.04	27.48	0.68
NN1 (EW)	0.89	3.12	1.00	24.74	0.62
NN2 (EW)	0.82	3.11	0.90	24.89	0.61
NN3 (EW)	0.93	3.30	0.97	24.26	0.56
		Panel C: Selective Strategies			
Unconditional (VW)	0.86	6.06	0.48	7.91	0.16
Logit (VW)	0.70	4.19	0.62	10.45	0.20
ENLogit (VW)	1.00	4.56	0.76	10.24	0.20
RF (VW)	0.89	4.60	0.66	10.69	0.20
GBTrees (VW)	0.74	4.22	0.59	10.86	0.22
NN1 (VW)	1.07	4.75	0.80	10.05	0.20
NN2 (VW)	0.84	4.17	0.69	9.93	0.19
NN3 (VW)	0.80	4.57	0.62	10.15	0.20
Unconditional (EW)	0.60	6.02	0.35	7.91	0.16
Logit (EW)	1.14	4.65	0.83	10.45	0.20
ENLogit (EW)	1.22	4.87	0.87	10.24	0.20
RF (EW)	1.14	4.6	0.87	10.69	0.20
GBTrees (EW)	1.11	4.19	0.94	10.86	0.22
NN1 (EW)	1.18	4.82	0.83	10.05	0.20
NN2 (EW)	1.18	4.78	0.87	9.93	0.19
NN3 (EW)	1.15	4.90	0.83	10.15	0.20

Table 6: *Decomposed Strategies Return Characteristics.* This table shows the monthly average return (ER), the standard deviation of monthly returns (SD), the annualized Sharpe ratios (Sharpe), the average number of active positions across all months (Active), and the fraction of active positions relative to all M&A deals (Fraction). These statistics are reported for three different types of strategies. The VWMA and EWMA strategies that serve as benchmarks (Panel A), the normal strategies that engage in all M&A deals with an expected return above 0% (Panel B), and the selective strategies that engage in all M&A deals with an expected return above 2.5%.

To examine this further, I run regressions of the same type as in equation (18), but replace the left hand side with the monthly excess return of the normal and selective decomposed return strategies. The result of these regressions can be seen in Table 7. The first thing to note is that, overall, the risk exposures of the decomposed expected return strategies are generally not far off (in terms of magnitude/direction and significance) from their respective benchmark strategy (VWMA/EWMA). The only exception to this is that the equal-weighted selective strategies have lower and insignificant SMB exposures and significantly negative RMW exposures. The second thing to note is that the normal strategies have similar or higher alphas, with the selective strategies having much higher alphas, compared to their respective benchmark strategies. These two facts combined suggest that the increased excess returns of the decomposed expected return strategies, as reported in Table 6, are not simply a result of increased risk exposures to the five factors explored here, i.e. they seem to produce higher alpha than simply trading all M&A deals.

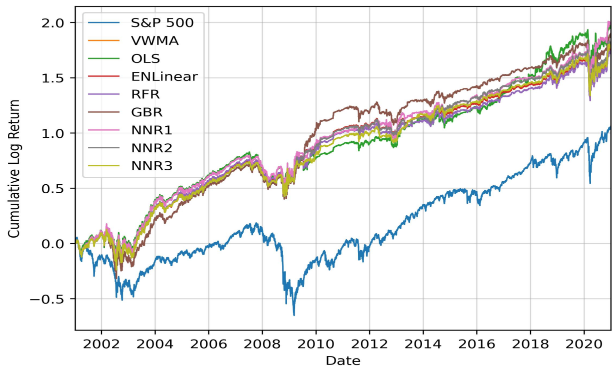
Directly Modelled Expected Return Estimates

As mentioned, the direct modelling approach is an alternative to the decomposition explored so far. To examine the quality of the predictions of the direct modelling approach, the same normal and selective trading strategies are produced, but based on the return expectations from the regression models described in Section 3. The cumulative log return of these *direct strategies* can be seen in Figure 5. Additionally, their return and risk characteristics are reported in Table 8. From the figure and the table a few things become clear. First of all, the set of normal strategies are extremely homogeneous. They almost mirror the benchmark strategies, seen by the fact that most of these strategies trade almost all M&A deals, as indicated by the 'Fraction' column of Table 8. This means that the direct modelling approach almost always predicts a positive expected return for the M&A deals in the test set. Second, the selective strategies generally do not have higher average excess returns than the normal strategies. So while the direct normal strategies are somewhat comparable to their decomposed counterparts, the selective direct strategies have lower average excess returns compared to their decomposed strategy counterparts, especially the equal-weighted selective strategies. Because the decomposed strategies generally contain less active positions at any given time, it could be the case that increasing the selectiveness of the direct strategies even more, so that they, on average, have about as many active positions as the decomposed

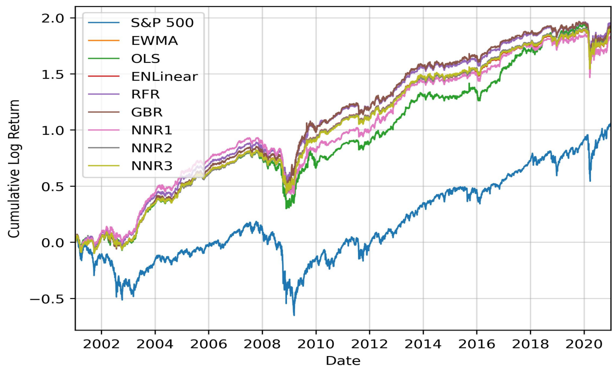
	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}	R^2	N
Panel A: Benchmark Strategies								
VWRA	0.50*	0.44***	0.09	-0.03	-0.23	-0.31	0.44	240
EWRA	0.53***	0.34***	0.23***	0.12	-0.17*	-0.13	0.60	240
Panel B: Normal Strategies								
Unconditional (VW)	0.43	0.46***	-0.02	0.04	0.04	-0.06	0.23	240
Logit (VW)	0.38*	0.43***	0.12	-0.15	-0.10	0.13	0.38	240
ENLogit (VW)	0.51**	0.43***	0.12	-0.11	-0.19*	0.18	0.41	240
RF (VW)	0.38	0.46***	0.08	0.00	-0.18	0.09	0.40	240
GBTrees (VW)	0.42*	0.45***	0.10	-0.07	-0.09	0.17	0.40	240
NN1 (VW)	0.42*	0.43***	0.12	-0.15	-0.15	0.21	0.38	240
NN2 (VW)	0.39*	0.40***	0.10	-0.12	-0.04	0.06	0.32	240
NN3 (VW)	0.39	0.47***	0.00	-0.06	-0.15	0.16	0.32	240
Unconditional (EW)	0.33	0.50***	0.19	0.07	-0.10	0.00	0.32	240
Logit (EW)	0.63***	0.40***	0.20**	0.00	-0.12	0.03	0.49	240
ENLogit (EW)	0.66***	0.39***	0.23***	0.05	-0.17*	-0.01	0.50	240
RF (EW)	0.57***	0.39***	0.18**	0.00	-0.13	0.02	0.47	240
GBTrees (EW)	0.62***	0.37***	0.22***	0.03	-0.10	0.05	0.51	240
NN1 (EW)	0.62***	0.40***	0.23***	0.01	-0.13	0.02	0.52	240
NN2 (EW)	0.56***	0.39***	0.20***	0.03	-0.11	0.00	0.48	240
NN3 (EW)	0.69***	0.38***	0.18*	0.08	-0.15	0.04	0.42	240
Panel C: Selective Strategies								
Unconditional (VW)	0.53	0.50***	-0.05	-0.15	0.06	-0.05	0.13	240
Logit (VW)	0.64*	0.35***	-0.13	-0.07	-0.19	0.02	0.17	240
ENLogit (VW)	0.84**	0.38***	-0.13	-0.07	-0.25	0.19	0.17	240
RF (VW)	0.72*	0.39***	-0.13	-0.08	-0.17	0.06	0.16	240
GBTrees (VW)	0.55*	0.39***	-0.07	-0.05	-0.14	0.01	0.19	240
NN1 (VW)	0.94**	0.41***	-0.23	-0.04	-0.29	0.17	0.18	240
NN2 (VW)	0.68**	0.35***	-0.11	-0.12	-0.18	0.10	0.17	240
NN3 (VW)	0.62*	0.40***	-0.15	-0.05	-0.11	0.03	0.16	240
Unconditional (EW)	0.29	0.49***	0.19	-0.10	-0.19	0.10	0.18	240
Logit (EW)	0.92***	0.45***	0.03	-0.12	-0.39**	0.32	0.29	240
ENLogit (EW)	0.95***	0.46***	0.10	-0.17	-0.32*	0.36	0.27	240
RF (EW)	0.96***	0.37***	0.02	-0.19	-0.36*	0.32	0.21	240
GBTrees (EW)	0.93***	0.38***	0.08	-0.09	-0.36**	0.28	0.28	240
NN1 (EW)	0.95***	0.47***	0.05	-0.16	-0.43**	0.34	0.30	240
NN2 (EW)	0.95***	0.43***	0.09	-0.18	-0.40**	0.40*	0.27	240
NN3 (EW)	0.92***	0.49***	-0.01	-0.12	-0.33*	0.25	0.27	240

Table 7: *Decomposed Strategies Factor Exposures.* This table shows the results of regressing the excess monthly returns of various merger arbitrage strategies onto the five risk factors of Fama and French (2015). The table reports the results for the benchmark strategies that trades all M&A deals (Panel A), the normal decomposed M&A strategies (Panel B), and the selective decomposed M&A strategies (Panel C). *, ** and *** indicate significance at the 0.05, 0.01 and 0.001, respectively, calculated with Newey-West standard errors.

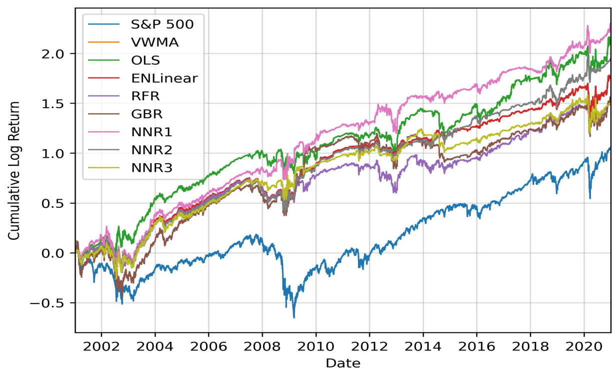
strategies, would lead to more similar results. However, while not reported in this paper, increasing the selectiveness of the direct strategies, does not increase their average excess return.



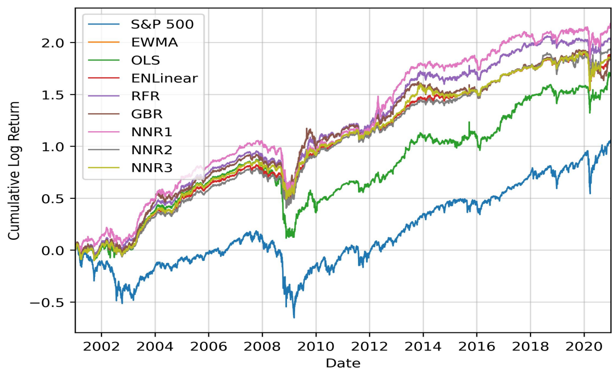
(a) VWNS



(b) EWNS



(c) VWSS



(d) EWSS

Figure 5: *Direct Strategies Return Series.* This figure illustrates four graphs (a)-(d), each of which shows the out-of-sample cumulative log return for various merger arbitrage strategies. All strategies illustrated in the four graphs (except for 'S&P 500', 'VWMA', and 'EWMA') are based on the direct modelling approach described in Section 2. Graph (a) and (b) show the cumulative log return of strategies engaging in all merger arbitrage trades with an expected return above 0%, with a value-weighted and equal-weighted weighting scheme, respectively. Graph (c) and (d) show the cumulative log return of strategies engaging in all merger arbitrage trades with an expected return above 2.5%, also with both a value-weighted and equal-weighted weighting scheme, respectively. For comparison, each graph also contain the market return series as well as the VWMA (graphs (a) and (c)) and the EWMA (graphs (b) and (d)) return series.

Like with the decomposed strategies, I also examine the direct strategies' ability to generate alpha, as well as their factor risk exposures. These results can be seen in Table 9. The primary thing to take note of is that these new direct strategies generally have similar factor exposures, but lower and less significant alphas.

	ER (%)	SD (%)	Sharpe	Active	Fraction
		Panel A: Benchmark Strategies			
VWRA	0.67	3.31	0.69	38.27	1.00
EWRA	0.70	2.81	0.87	38.27	1.00
		Panel B: Normal Strategies			
OLS (VW)	0.77	3.72	0.73	28.47	0.74
ENLinear (VW)	0.67	3.31	0.69	38.27	1.00
RFR (VW)	0.66	3.39	0.69	36.31	0.94
GBR (VW)	0.73	3.45	0.73	31.99	0.81
NNR1 (VW)	0.78	3.58	0.76	29.73	0.77
NNR2 (VW)	0.69	3.32	0.73	37.59	0.99
NNR3 (VW)	0.68	3.33	0.69	37.67	0.98
OLS (EW)	0.73	3.40	0.73	28.47	0.74
ENLinear (EW)	0.67	3.31	0.69	38.27	1.00
RFR (EW)	0.73	2.86	0.87	36.31	0.94
GBR (EW)	0.72	3.04	0.83	31.99	0.81
NNR1 (EW)	0.69	3.11	0.76	29.73	0.77
NNR2 (EW)	0.70	2.83	0.73	37.59	0.99
NNR3 (EW)	0.70	2.84	0.83	37.67	0.98
		Panel C: Selective Strategies			
OLS (VW)	0.86	4.36	0.69	21.42	0.56
ENLinear (VW)	0.67	3.31	0.69	38.27	1.00
RFR (VW)	0.56	3.46	0.55	25.56	0.60
GBR (VW)	0.59	4.35	0.45	23.28	0.55
NNR1 (VW)	0.91	3.66	0.87	20.08	0.51
NNR2 (VW)	0.75	3.31	0.80	33.15	0.88
NNR3 (VW)	0.56	3.27	0.59	31.77	0.84
OLS (EW)	0.66	3.92	0.59	21.42	0.56
ENLinear (EW)	0.67	3.31	0.69	38.27	1.00
RFR (EW)	0.76	3.12	0.87	25.56	0.60
GBR (EW)	0.71	3.69	0.66	23.28	0.55
NNR1 (EW)	0.85	3.56	0.83	20.08	0.51
NNR2 (EW)	0.73	3.14	0.80	33.15	0.88
NNR3 (EW)	0.69	3.03	0.80	31.77	0.84

Table 8: *Direct Strategies Return Characteristics.* This table shows the monthly average return (ER), the standard deviation of monthly returns (SD), the annualized Sharpe ratios (Sharpe), the average number of active positions across all months (Active), and the fraction of active positions relative to all M&A deals (Fraction). These statistics are reported for three different types of strategies. The VWMA and EWMA strategies that serve as benchmarks (Panel A), the normal strategies that engage in all M&A deals with an expected return above 0% (Panel B), and the selective strategies that engage in all M&A deals with an expected return above 2.5%. Unlike Table 6, the expected return estimates, used as the basis for the strategies of this table, are from the direct modelling approach.

	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}	R^2	N
				Panel A: Benchmark Strategies				
VWRA	0.50*	0.44***	0.09	-0.03	-0.23	-0.31	0.44	240
EWRA	0.53***	0.34***	0.23***	0.12	-0.17*	-0.13	0.60	240
				Panel B: Normal Strategies				
OLS (VW)	0.40	0.51***	0.03	-0.07	0.12	0.04	0.34	240
ENLinear (VW)	0.39*	0.46***	0.02	0.00	-0.05	-0.03	0.43	240
RFR (VW)	0.39*	0.45***	0.00	-0.03	-0.01	-0.08	0.38	240
GBR (VW)	0.48*	0.47***	-0.03	0.06	-0.05	-0.12	0.41	240
NNR1 (VW)	0.44*	0.48***	0.04	-0.11	0.03	0.03	0.36	240
NNR2 (VW)	0.41*	0.47***	0.02	-0.01	-0.04	-0.03	0.40	240
NNR3 (VW)	0.40*	0.47***	0.02	-0.01	-0.05	-0.02	0.43	240
OLS (EW)	0.48**	0.40***	0.22**	0.11	-0.13	-0.12	0.47	240
ENLinear (EW)	0.50***	0.36***	0.21***	0.10*	-0.18**	-0.13	0.60	240
RFR (EW)	0.55***	0.34***	0.22***	0.11*	-0.22**	-0.15	0.58	240
GBR (EW)	0.56***	0.33***	0.22***	0.10	-0.22**	-0.17	0.49	240
NNR1 (EW)	0.47***	0.38***	0.21***	0.13*	-0.19**	-0.08	0.55	240
NNR2 (EW)	0.51***	0.36***	0.21***	0.10	-0.19**	-0.14	0.60	240
NNR3 (EW)	0.51***	0.36***	0.21***	0.11*	-0.19**	-0.13	0.60	240
				Panel C: Selective Strategies				
OLS (VW)	0.59*	0.43***	-0.01	0.00	0.03	-0.10	0.20	240
ENLinear (VW)	0.39*	0.46***	0.02	0.00	-0.05	-0.03	0.43	240
RFR (VW)	0.35	0.39***	0.01	-0.01	-0.09	-0.04	0.29	240
GBR (VW)	0.37	0.50***	0.00	-0.06	-0.33**	0.02	0.38	240
NNR1 (VW)	0.75**	0.32***	0.00	-0.06	-0.13	0.00	0.19	240
NNR2 (VW)	0.61**	0.35***	-0.01	-0.06	-0.21*	-0.08	0.31	240
NNR3 (VW)	0.36	0.39***	-0.02	0.02	-0.07	-0.12	0.32	240
OLS (EW)	0.46*	0.41***	0.18*	0.14	-0.23*	-0.22	0.40	240
ENLinear (EW)	0.50***	0.36***	0.21***	0.10*	-0.18**	-0.13	0.60	240
RFR (EW)	0.62***	0.33***	0.16*	0.11	-0.26**	-0.11	0.45	240
GBR (EW)	0.58**	0.32***	0.23**	0.09	-0.35***	-0.05	0.37	240
NNR1 (EW)	0.63***	0.38***	0.18*	0.09	-0.19	-0.01	0.39	240
NNR2 (EW)	0.49**	0.38***	0.21***	0.02	-0.10	-0.09	0.46	240
NNR3 (EW)	0.49***	0.37***	0.17**	0.13*	-0.14	-0.15	0.49	240

Table 9: *Direct Strategies Factor Exposures.* This table shows the results of regressing the excess monthly returns of various merger arbitrage strategies onto the five risk factors of Fama and French (2015). The table reports the results for the benchmark strategies that trades all M&A deals (Panel A), the normal direct M&A strategies (Panel B), and the selective direct M&A strategies (Panel C). *, ** and *** indicate significance at the 0.05, 0.01 and 0.001, respectively, calculated with Newey-West standard errors. Unlike Table 9, the expected return estimates, used as the basis for the strategies of this table, are from the direct modelling approach.

All in all, the comparison between the two sets of strategies shows that, from a purely practical standpoint, the decomposed expected return estimates are superior in terms of identifying merger arbitrage trades with high expected returns. Strategies based on the decomposed expected return estimates have higher excess returns and alpha, with comparable Sharpe ratios and factor risk exposures, compared to the strategies based on the direct modelling approach.

Which Estimates to Use?

While the trading strategies explored above do give some indication about the quality of a set of expected return estimates, they are more indicative of a model's ability to rank merger arbitrage trades. To see this, imagine a model that is "only" able to correctly classify the expected return of a merger arbitrage trade as being higher or lower than 2.5%, but is otherwise unable to provide an expected return estimate. If you were to construct the selective strategy, using this model, then you would produce the same return series as an "oracle" model that knows the true expected return. Therefore, to better asses the various model's ability to estimated expected returns, the actual merger arbitrage return is regressed onto the model prediction:

$$r_i = \gamma_0 + \gamma_1 \hat{r}_i \tag{19}$$

Where $\hat{r}_i$ is the predicted merger arbitrage return for M&A deal i. Asymptotically, you would expect γ_0 and γ_1 to approach 0 and 1, respectively, as the number of M&A deals in our sample approach infinity. The results of this regression, for both the decomposed (Panel A) and direct (Panel B) expected return estimates, are reported in Table 10. Looking at the table, we see that the decomposed expected return estimates have higher γ_1 coefficients and R^2 values, compared to the direct estimates. Based on this, as well as the results of the trading strategies explored previously, it seems fair to conclude that the decomposed return methodology provide more accurate estimates of the expected returns of M&A deals, relative to the direct modelling approach. Within the group of decomposed expected returns there is quite a bit of variation in terms of γ_0, γ_1, and R^2. However, the best performing models are the decision tree based models (RF and GBTrees).[13] Thus, it seems like the superior conditional probability estimates of these models, observed in Section 5.1, do lead to better

[13] Best performing in the sense that they are closer to the "oracle" benchmark of $\gamma_0 = 0$ and $\gamma_1 = 1$, while also having the largest R^2 values.

expected return estimates.

			Panel A: Decomposed Expected Returns				
	Logit	ENLogit	RF	GBTrees	NN1	NN2	NN3
Int.	3.20***	3.16***	3.02***	3.02***	3.26***	3.23***	3.26***
	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)
Coef.	0.37***	0.41***	0.52***	0.48***	0.34***	0.42***	0.40***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
R^2	0.022	0.029	0.035	0.038	0.020	0.029	0.027
N	2,382	2,382	2,382	2,382	2,382	2,382	2,382
			Panel B: Direct Expected Returns				
	OLS	ENLinear	RFR	GBR	NNR1	NNR2	NNR3
Int.	3.08***	2.82***	3.33***	3.18***	3.13***	3.17***	2.67***
	(0.38)	(0.37)	(0.42)	(0.38)	(0.40)	(0.54)	(0.43)
Coef.	0.09*	0.17*	0.02	0.07	0.09	0.05	0.18*
	(0.04)	(0.07)	(0.06)	(0.05)	(0.06)	(0.09)	(0.08)
R^2	0.003	0.007	0.000	0.001	0.001	0.000	0.004
N	2,382	2,382	2,382	2,382	2,382	2,382	2,382

Table 10: *Expected Return Regressions.* This table shows the results of regressing the realized return of all out-of-sample M&A deals onto the model predictions. Panel A shows the results for the decomposed expected return estimates, while Panel B reports the results for the predictions of the direct modelling approach. Standard errors are reported in parentheses, while *, **, *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively.

5.3 The Aggregate Merger Arbitrage Market

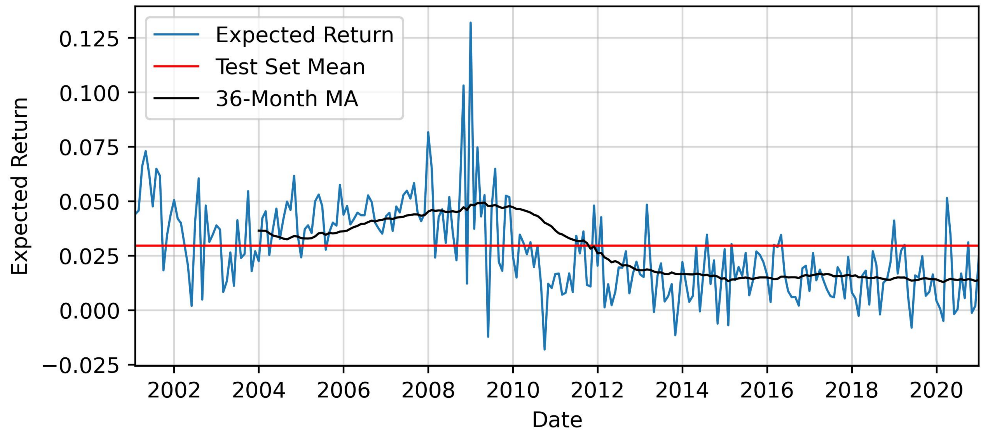
This section briefly examines the overall merger arbitrage market over the out-of-sample period. To calculate an aggregate expected return, one could use any of the estimates from the decomposed or direct modelling approach. However, based on the results of previous sections, the most accurate estimates seem to be coming from the decomposed expected return estimates, using the GBTrees or RF models for estimating conditional probabilities. As such, to create an aggregate expected merger arbitrage return for each month, the decomposed expected return estimates with the GBTrees model is used:[14]

$$E_t[\bar{r}] = \frac{1}{N_t} \sum_{i=1}^{N_t} E_t[r_i] \tag{20}$$

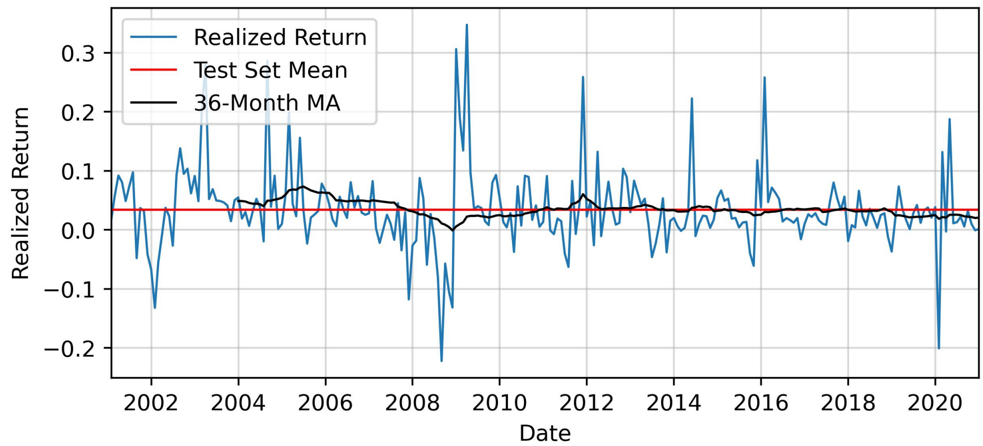
Where N_t is the total number of M&A deals in month t. This aggregate expected M&A return can be seen in Figure 6(a) alongside the overall mean, and the 36-month moving

[14] Using the RF model instead leads to practically identical results.

average. Figure 6(b) shows the same aggregate time series using the cross-sectional average realized M&A returns. As we would expect, the aggregate expected return time series, is much less volatile than the time series of average realized returns, despite their overall test set means being quite close at around 3%. It is also worth noting, that Figure 6(a) clearly shows that over the last 10 years, the average expected return has been below its test set mean. Specifically, the cross-sectional average expected return is 3.96% before 2011 and 1.53% afterwards. This phenomenon is not present in Figure 6(b) indicating that the decomposed expected return estimates provide different economic insight than realized returns.



(a) Expected Returns



(b) Realized Returns

Figure 6: *Aggregate Merger Arbitrage Returns.* This figure shows the time series of the cross-sectional average expected merger arbitrage return (top figure) and the cross-sectional average realized merger arbitrage return (bottom figure). In addition to the two cross-sectional averages, the figures also show the overall test set mean (red line), as well as the 36-month moving average (black line).

6 Conclusion

This paper proposes a decomposition of the expected return of a merger arbitrage trade into three parts: the probability of deal success, the expected return conditional on success, and the expected return conditional on failure. The paper finds that modeling the probability of deal success using machine learning techniques, while making simplifying assumptions for the two conditional expected return terms, yields more accurate estimates of the expected return of individual merger arbitrage trades compared to the traditional direct modeling approach often used in empirical asset pricing. The best performing models for predicting the probability of deal success are machine learning models related to decision trees, specifically gradient boosted trees and random forest models. The decomposed expected return estimates enable merger arbitrage investors to form trading strategies that yield higher absolute and risk-adjusted returns, measured as alpha in a Fama-French five-factor regression, compared to the benchmark strategy of engaging in all merger arbitrage trades. Furthermore, constructing an aggregate expected merger arbitrage return series, using the cross-sectional average of the decomposed expected return estimates, reveals that the aggregate merger arbitrage risk premium has been consistently low over the last decade. This phenomenon cannot be uncovered using the cross-sectional average of realized merger arbitrage returns, demonstrating that the decomposition proposed in this paper has value beyond improving the returns of merger arbitrage investors.

7 Appendix

7.1 Model Structure and Optimization

Logistic Regression

A logistic regression is a generalized linear model that uses the logit link function to relate the linear combination of explanatory variables $\boldsymbol{X}_i$ and a vector of associated coefficients θ to the conditional log-odds:

$$\ln\left(\frac{Pr[y_i|\boldsymbol{X}_i]}{1 - Pr[y_i|\boldsymbol{X}_i]}\right) = \theta^T \boldsymbol{X}_i \tag{21}$$

Which leads the functional form of the conditional probability to be:

$$f(\boldsymbol{X}_i; \theta) = \frac{1}{1 + \exp\{-\theta^T \boldsymbol{X}_i\}} \tag{22}$$

Note that the notation above assumes that a vector of ones is added to the complete data matrix of all explanatory variables so the model contains a constant. The objective function that we will look to maximize is the log-likehood:

$$\begin{aligned} \ell(\theta) &= \sum_{i=1}^{N} \Big(y_i \ln f(\boldsymbol{X}_i; \theta) + (1 - y_i) \ln \Big(1 - f(\boldsymbol{X}_i; \theta)\Big)\Big) \\ &= \sum_{i=1}^{N} \Big(y_i \theta^T \boldsymbol{X}_i - \ln\Big(1 + \exp\{\theta^T \boldsymbol{X}_i\}\Big)\Big) \end{aligned} \tag{23}$$

Which will have the following score functions:

$$\frac{\partial \ell(\theta)}{\partial \theta} = \sum_{i=1}^{N} \boldsymbol{X}_i \Big(y_i - f(\boldsymbol{X}_i; \theta)\Big) = 0 \tag{24}$$

There is no closed-form solution to these score functions and some sort of numerical optimization is therefore required. In this paper, the Newton-Rhapson algorithm is used for optimization.

Penalized Logistic Regression

The functional form of this model is exactly the same as for the standard logistic regression model, and the difference between them arises from the objective function. More precisely, the objective function we are looking to maximize is the log-likelihood function in Equation (23) with an added extra term, penalizing large values in θ:

$$\max_{\theta} \left[\sum_{i=1}^{N} \left(y_i \theta^T \boldsymbol{X}_i - \ln \left(1 + \exp\{\theta^T \boldsymbol{X}_i\} \right) \right) - \lambda \sum_{j=2}^{p+1} \left(\frac{1}{2}(1-\alpha)\theta_j^2 + \alpha |\theta_j| \right) \right] \tag{25}$$

Note the notation of the last summation sign that indicates no penalty is applied to the constant. This particular penalization scheme of the regression coefficients is the elastic net penalty of Zou and Hastie (2005) and is equal to a ridge penalty when $\alpha = 0$, a lasso penalty when $\alpha = 1$, and a compromise between the two when α is between 1 and 0. This type of penalty can considerably improve out-of-sample performance if the number of explanatory variables, p, is large. The reason is that the “ridge part” of the penalty will tend to give highly correlated variables the same level of importance, while the ”lasso part” of the penalty allows for a sparsity. This also means that, unlike the standard logistic regression, there are two hyperparameters (λ and α) to be determined with the validation set. The SAGA algorithm of Defazio *et al.* (2014) is used to find the optimal values of θ.

Linear Regression with Elastic Net Penalty

Like in the case of logistic regression with an elastic net penalty, linear regression with elastic net penalty has the same objective function as the standard version but with an added penalty term:

$$\min_{\theta} \left[\sum_{i=1}^{N} (y_i - \theta^T \boldsymbol{X}_i)^2 + \lambda \sum_{j=2}^{p+1} \left(\frac{1}{2}(1-\alpha)\theta_j^2 + \alpha |\theta_j| \right) \right] \tag{26}$$

With $\sum_{i=1}^{N} (y_i - \theta^T \boldsymbol{X}_i)^2$ being the loss function of a standard linear regression. Note that we are minimizing this objective function with respect to θ and thus add the penalty term instead of subtracting it like in the case of the logistic regression. The objective function is minimized via coordinate descent method described in Friedman *et al.* (2010), and the hyperparameters (λ and α) are found via the validation set.

Ensembles of Trees

This appendix section briefly covers the basics of how a single decision tree is structured and trained, and then introduces the two ensemble of trees classification models used in this paper, namely, a random forest and gradient boosted trees.

A single decision tree is a nonparametric function that has the potential to accommodate many different forms of interactions between explanatory variables that other methods might find difficult. A decision tree, in its simplest form, starts by making a binary split of the feature space based on a single explanatory variable, which creates two distinct feature spaces. Next, the decision tree splits one, both, or none of the two feature spaces into two new distinct feature spaces. This process continues until some stopping criteria is fulfilled. The final distinct feature spaces produced by the decision tree is referred to as end nodes. When using decision trees for classification purposes, the output of the decision tree can either be a binary indicator (0 or 1), based on the majority class of each end node, or the proportion of data points that belong to class 1. Since this paper is concerned with estimating conditional probabilities, the latter of the two is the natural choice of output, since it is more naturally interpreted as a probability. Formally, that means the output of a classification decision tree will take the form:

$$f(\boldsymbol{X}_i) = \sum_{k=1}^{K} \frac{N_{success,k}}{N_{total,k}} \mathbb{1}[\boldsymbol{X}_i \in R_k] \tag{27}$$

Where K is the total amount of end nodes, k is a particular end node, $N_{success,k}$ and $N_{total,k}$ are the number of successful and total M&A deals in end node k, respectively, while $\mathbb{1}[\boldsymbol{X}_i \in R_k]$ indicates whether or not $\boldsymbol{X}_i$ belongs to the distinct feature space R_k. An example of a decision tree with three variables (x_1, x_2 and x_3) and its associated output functions can be seen in Figure 7.

Searching through all possible splits for each internal node, whilst also taking into account what that means for all subsequent splits, is computationally infeasible even with a low amount of explanatory variables. Therefore, each split is decided through a greedy approach as in Breiman *et al.* (1984). There are multiple ways of judging a split's ability to classify the data, but a common one is the gini impurity measure, which is therefore used in this paper:

$$I_G = 2\frac{N_{success}}{N_{total}}\left(1 - \frac{N_{success}}{N_{total}}\right) = 2p(1-p) \tag{28}$$

Specifically, if for some split in an internal node we have some subsample $N_{original}$, that is being split on a variable j at point s, thus producing two distinct feature spaces with observations N_l and N_r, we look to solve:

$$\min_{j,s}\left[\frac{N_l(j,s)}{N_{original}}2p_l(j,s)\Big(1-p_l(j,s)\Big)+\frac{N_r(j,s)}{N_{original}}2p_r(j,s)\Big(1-p_r(j,s)\Big)\right] \tag{29}$$

Where p_l and p_r indicates the proportion of successful M&A deals in the left and right split, respectively. This process starts at the "root" of the tree with $N_{original}$ being the entire dataset, and proceeds until the tree has reached a certain depth, which is a hyperparameter that will be chosen through the validation data.

Now that the basic classification decision tree has been covered we can move on to the actual models used in this paper. The first of these is the random forest model described in Breiman (2001). A random forest is an ensemble of individual decision trees trained on bootstrap samples of the original dataset, with the goal of reducing the variance of the model compared to a single decision tree. In addition to training several individual decision trees on boostrap samples, each split for every individual tree only considers a random subset of the explanatory variables, m, where $m < p$, with p indicating the number of variables. This further reduce the correlation between individual decision trees. Formally, the output of a random forest model is:

$$f(\boldsymbol{X}_i;\theta_B)=\frac{1}{B}\sum_{b=1}^{B}T_b(\boldsymbol{X}_i;\theta_b) \tag{30}$$

Where B is the total amount of individual decision trees and $T_b(\boldsymbol{X}_i;\theta_b)$ is the output of decision tree b, with θ_b containing the information about the split variables and split points. The hyperparameters to be chosen with the validation set are the number of individual decision trees, B, and the max depth of the individual decision trees.

The second and final model based on decision trees is the gradient boosted trees model of Friedman (2001). Just as with the random forest model, the gradient boosted trees model trains a large number of individual trees. However, there are some significant differences compared to the random forest model. First of all, the first tree, T_1, is actually not a tree at all, but instead simply the log odds of the training data:

$$T_1=\ln\left(\frac{Pr[y]}{1-Pr[y]}\right) \tag{31}$$

Secondly, every subsequent tree is trained to minimize some loss function with respect to the training data, which in our case is the negative binomial log-likelihood:

$$\min_T \left[-\sum_{i=1}^{N} \left[y_i \ln\Big(f_{b-1}(\boldsymbol{X}_i) + T(\boldsymbol{X}_i)\Big) - (1-y_i)\Big(\ln\Big(1 - f_{b-1}(\boldsymbol{X}_i) + T(\boldsymbol{X}_i)\Big)\Big)\right]\right] \tag{32}$$

Where $f_{b-1}(\boldsymbol{X}_i) = \sum_{j=1}^{b-1} l^{j-1} T_j(\boldsymbol{X}_i;\theta_j)$ is the complete model before including tree b. Note that l is a scaling factor in the $[0,1]$ range that will be found through the hyperparameter optimization step. The final step of the gradient boosted trees model is to let the model output go through the logistic function $\sigma(x) = \frac{1}{1+\exp\{-x\}}$, thus making the final output of the model:

$$f(\boldsymbol{X}_i;\theta_B) = \frac{1}{1+\exp\left\{\sum_{b=1}^{B} l^{b-1} T_b(\boldsymbol{X}_i;\theta_b)\right\}} \tag{33}$$

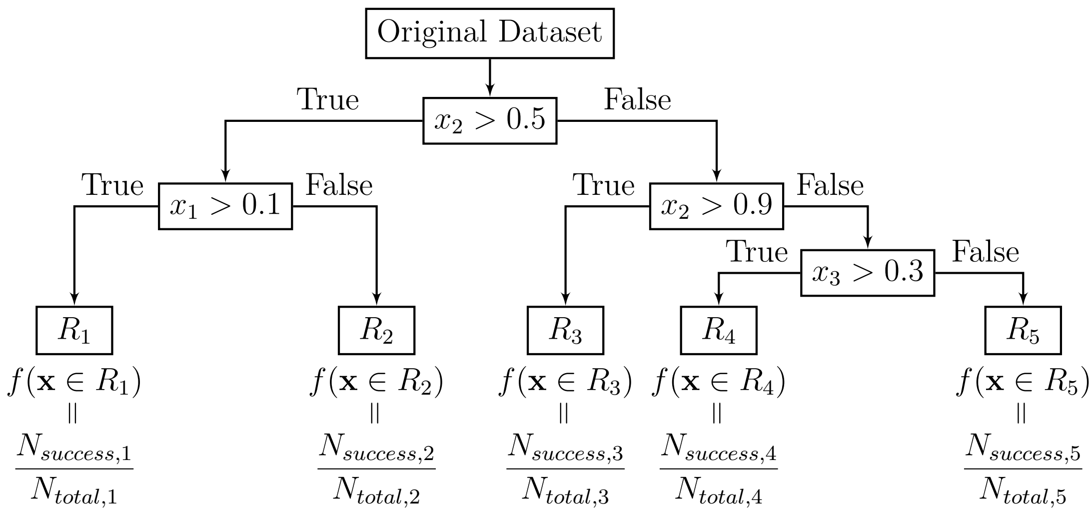


Figure 7: *Decision Tree Example.* This figure shows an example of a classification decision tree with three variables: x_1, x_2, and x_3. At each split, the decision tree sends an observation down one path or another depending on the value of a specific variable. This happens until you reach an end node, which in this tree is one of five (R_1,...R_5) distinct feature spaces. The output of the decision tree is then the proportion of successful cases to total cases across all training observations in that same end node.

Modifying Random Forests and Gradient Boosted Trees for Regression

The overall structure and training process is identical when applying the random forest and gradient boosted trees models for regression purposes. The thing that changes is the impurity measure used for assessing the quality of a split and the way the output is calculated for end nodes. Instead of the gini impurity measure in Equation 28, the model uses the mean squared error instead:

$$I_{MSE} = \sum_{i=1}^{N_{total}} \left(y_i - \frac{1}{N_{total}} \sum_{j=1}^{N_{total}} y_j \right)^2 = \sum_{i=1}^{N_{total}} (y_i - \bar{\mathbf{y}})^2 \tag{34}$$

Which changes 29 to:

$$\min_{j,s} \left[\frac{N_l(j,s)}{N_{original}} \sum_{i=1}^{N_l(j,s)} (y_i - \bar{\mathbf{y}}_l)^2 + \frac{N_r(j,s)}{N_{original}} \sum_{i=1}^{N_r(j,s)} (y_i - \bar{\mathbf{y}}_r)^2 \right] \tag{35}$$

The end node output of individual decision trees also changes from 27 to:

$$f(\boldsymbol{X}_i) = \sum_{k=1}^{K} \bar{\mathbf{y}}_k \mathbb{1}[\boldsymbol{X}_i \in R_k] \tag{36}$$

With $\bar{\mathbf{y}}_k$ being the average outcome of all observations belonging to the feature space k.

Neural Networks

Neural networks are an extremely flexible class of models that come in a lot of different variations. However, in this paper, only the straightforward "vanilla" feed-forward neural network is considered. An illustration of such a neural network (with one hidden layer) is illustrated in Figure 8. For the empirical analysis in Section 5 three different neural networks are considered with one, two, and three hidden layers, respectively.[15] As can be seen in the figure, the neural network starts of by feeding a linear combination of all p explanatory variables (plus a constant or "bias") through M different "activation" functions $g_m^{(1)} : \mathbb{R} \to \mathbb{R}$. Several different types of activation functions can be chosen (identity, sigmoid, softmax, hyperbolic, etc.), but in this paper the rectified linear unit function (ReLU) is used:

$$g^{(1)}(X) = ReLU(x) = \max(0, x) \tag{37}$$

Going from the hidden layer to the output layer we have another function $g^{(2)} : \mathbb{R} \to \mathbb{R}$ that takes as input the linear combination of the neurons in the hidden layer and transforms it to some output. Since we are interested in a probabilistic output in the $[0, 1]$ range, a natural

[15] The NN1 model will have one 12-neuron layer, the NN2 model will have one 12-neuron layer feeding into a 6-neuron hidden layer, and the NN3 model will have one 12-neuron layer feeding into a 6-neuron layer feeding into a 3-neuron layer.

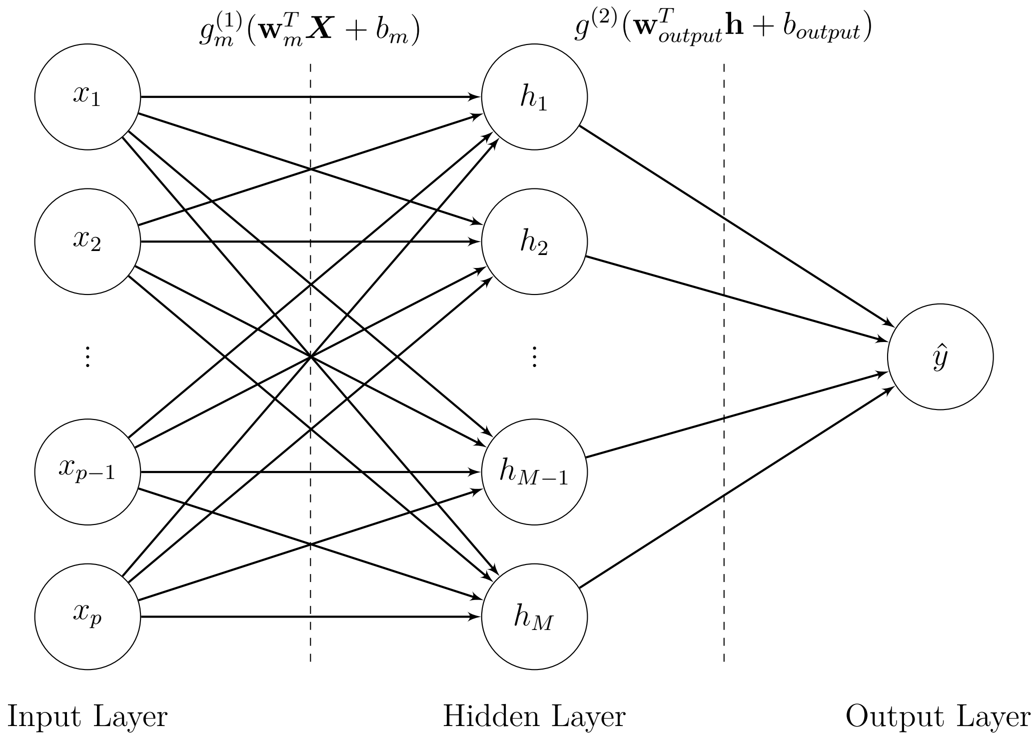


Figure 8: This figure shows an example of a feed-forward neural network with 1 hidden layer. The linear combination of the raw input variables (x_1,...x_p) are feed through M different functions ($g_1^{(1)}$,...,$g_M^{(1)}$), which results in M neurons in the hidden layer. The linear combination of these neurons are then in turn fed through a function $g^{(2)}$, which gives the final scalar output of the neural network $\hat{y}$.

choice of output function is the logistic function:

$$g^{(2)}(x) = \frac{1}{1 + \exp\{-x\}} \tag{38}$$

Which formally results in the neural network model of Figure 8 taking the form:

$$f(\boldsymbol{X}_i; \theta) = \frac{1}{1 + \exp\{-\sum_{j=1}^{M}(\max(0, \mathbf{w}_j^T \boldsymbol{X}_i + b_j) w_{output,j}) + b_{output}\}} \tag{39}$$

Where θ denotes all the parameters, namely the weights and constants associated with the activation functions as well as the output function. The objective function that we are looking to minimize is the penalized cross-entropy:

$$\min_{\theta} \left[-\sum_{i=1}^{N} \Big(y_i \ln \Big(f(\boldsymbol{X}_i; \theta) \Big) - (1 - y_i) \ln \Big(1 - f(\boldsymbol{X}_i; \theta) \Big) \Big) + \lambda ||\mathbf{W}||_2^2 \right] \tag{40}$$

Where $\lambda||\mathbf{W}||_2^2$ is a scaled L2-penalization on the entire set of weights. Multiple algorithms have been developed for solving this type of objective function for neural networks, with most of them being some variation of the stochastic gradient descent (SGD) method. One such variation of the classic SGD method is the ADAM algorithm of Kingma and Ba (2014), which is used in this paper. The only hyperparameter that needs to be tuned through the validation data is the regularization strength (λ).

Modifying Neural Networks for Regression

When using the neural network models for regression purposes, the overall structure and the activation functions are the same. The only thing that will change is the final output function and the objective function that we seek to minimize. Instead of the logistic function, the output function will simply be the identity function:

$$g^{(2)}(x) = x \tag{41}$$

So that the output of the neural network in Figure 8 instead becomes:

$$f(\boldsymbol{X}_i;\theta) = \sum_{j=1}^{M} \max(0, \mathbf{w}_j^T \boldsymbol{X}_i + b_j) w_{output,j} + b_{output} \tag{42}$$

The objective function will still be optimized with the ADAM algorithm, but will take the form:

$$\min_{\theta} \left[\sum_{i=1}^{N} \frac{1}{2} ||y_i - f(\boldsymbol{X}_i;\theta)||_2^2 + \frac{\lambda}{2} ||\mathbf{W}||_2^2 \right] \tag{43}$$

7.2 Model Training Procedure

The specifics, of the train-validation-test scheme in this paper, are as follows. Initially, the first (measured chronologically) 37.5% of the total dataset is used as training data, the next 12.5% as the validation data, and the last 50% as test data. For the particular dataset of this paper, this means that all M&A deals from 2001 and onwards are used as the test data for an out-of-sample analysis. Using the training data, both the classification and regression models are trained with different sets of hyperparemters (e.g. the number of base learners in the random forest model), and the performance of the models, based on some objective function, are then judged on the validation data. The model with the best performing hyperparameters are then re-trained on the combined training and validation data. Then, out-of-sample predictions are made for the first year of the test set, after which the above procedure is redone, with the first year of the test set now being included in the training-validation data. This is repeated until predictions have been made for all of the *original* test set observations. The measures used for hyperparameter tuning are the brier score (for classification models) and the mean squared error (for regression models):

$$BS = \frac{1}{N}\sum_{i=1}^{N}(f_C(\boldsymbol{X}_i;\theta) - D_i)^2 \tag{44}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_R(\boldsymbol{X}_i;\theta) - r_i)^2 \tag{45}$$

7.3 Probability Calibration

Probability calibration is performed, on all of the classification models, after hyperparameter tuning and therefore utilize all non-test data. Specifically, the non-test data is split into five pairs of training-validation sets with a ratio of 80%-20%, just as you would in a normal 5-fold cross-validation procedure. Then, for each training set, T_s, with $s \in [1, 2, ..., 5]$, a classification model, $f_{cs}(\boldsymbol{X}_i)$, is trained. Each classification model is then used to make predictions for all observations in its corresponding validations set V_s. For each of the five validation sets, a new model is trained to predict the outcome of each M&A deal, using the predictions of $f_{cs}(\boldsymbol{X}_i)$ as its input. These new models are denoted $g_s\Big(f_{cs}(\boldsymbol{X}_i)\Big)$ with each of them also giving an output in the $[0, 1]$ range. The final out-of-sample prediction for a given classification model is then the average prediction of the five g_s models:

$$\hat{p}_i = \frac{1}{5}\sum_{s=1}^{5} g_s\Big(f_{cs}(\boldsymbol{X}_i)\Big) \tag{46}$$

For g_s, two common choices are considered: Platt scaling (Platt *et al.* (1999)) and an isotonic regression (Robertson *et al.* (1988)). The results reported in the paper are from using the isotonic regression, but the results are qualitatively the same if Platt scaling is used.

7.4 Variable Importance Measure

Algorithm 1 shows the exact procedure for calculating the variable importance measure used for the classification models of the paper.

Algorithm 1: Calculating Variable Importance

Input: A fitted model $f_C(\boldsymbol{X};\hat{\theta})$ and associated outputs on the test data.

Initialize: Compute brier score of test data $BS_{oos}(f_C(\boldsymbol{X};\hat{\theta}), \mathcal{T}_3)$.

for *every* j **do**

  Set $k = 0$

  repeat *5* **times**

    Set $k = k + 1$

    Randomly shuffle all x_j resulting in a corrupted test dataset $\mathcal{T}_3^{jk}$

    Calculate $BS_{oos}(f_C(\boldsymbol{X};\hat{\theta}), \mathcal{T}_3^{jk})$

  end

  Set $VI_j^{raw} = \frac{1}{5}\sum_{k=1}^{5}\left[BS_{oos}(f_C(\boldsymbol{X};\hat{\theta}), \mathcal{T}_3^{jk}) - BS_{oos}(f_C(\boldsymbol{X};\hat{\theta}), \mathcal{T}_3)\right]$

end

for *every* j **do**

  Set $VI_j = \frac{VI_j^{raw}}{\sum_{i=1}^{J} VI_i^{raw}}$

end

Output: Vector of VI_j's

7.5 Data Filtering

Here, the filtering and construction of the combined data sample from Thomson ONE, Compustat, and CRSP is described. To begin with, deals from the Thomson ONE database are extracted, with the following restrictions:

- Target company is a U.S. publicly traded company.
- The deal is either an all-cash deal or an all-equity deal.
- The deal involves buying 100% (or the remaining stake) of the company and is not a bankruptcy acquisition.
- There is available information about the *initial* offer (cash price for cash deals and exchange ratio information for equity deals).

The companies that pass the filtering above is then linked to the Compustat and CRSP database through their historical CUSIPs. Finally, M&A deals, in which the target share price jumps above the offer price after announcement, are removed.[16] This final filtering deserves a more in-depth explanation. As an example, imagine if a deal is announced in which company A wants to acquire company T for \$10 per share, with a current share price of \$8 for company T. After the announcement, the share price of company T jumps to \$12. How can this jump to \$12 per share be rationally explained? There are four (five) possible explanations:

1. Investors expects at least \$2 worth of dividends to be paid out by company T between now and the time of deal closure.

2. Investors believe the terms of the deal will be adjusted upwards so the offer price equals \$12 per share or more.

3. Investors believe that a competing offer with an offer price of \$12 per share or more will be presented and accepted.

4. In a world of asymmetric information, the deal announcement might signal to investors that company T is worth \$12 per share or more and investors actually believe this deal is more likely to be unsuccessful (so they do not lose \$2 per share).

5. (Some combination of the above).

All explanations clearly violate the simplifying assumptions of investor expectations for the decomposed modelling approach in Section 2. Even with this final filtering it cannot be concluded that the assumptions hold for the remaining deals, but it is less likely that they severely violated. All results of this paper still hold qualitatively if this final filtering is omitted, but the results become quantitatively weaker. The size of the dataset, after each filtering step, can be seen in Table 11.

[16] The offer price is the cash price for cash deals and the exchange ratio times the acquiring company's share price, after announcement, for equity deals.

	Observations
Keep only public U.S. firms	67,034
Keep only deals that: Are all-cash or all-equity deals. 100% merger or acquisition. Not a bankruptcy deal. Have information on initial deal terms.	8,071
Keep only deals with a valid CRSP/Compustat link	6,899
Keep only deals with necessary price data	6,233
Keep only deals with target share price below offer price	4,828

Table 11: *Data Filtering.* This table shows the total number of deals in the entire sample after each filtering step.

7.6 Explanatory Variables

The (target) firm specific variables of this paper are the 94 variables of Green *et al.* (2017), excluding the ones using I/B/E/S data, reducing the number to 87.[17] The 87 firm specific variables include balance sheet, cash flow, income statement and share price information.[18] The primary reason for not including company variables related to the acquiring firm, is that a lot of acquirers are foreign or private entities without any firm variables. Requiring acquirer firm variables would therefore shrink the dataset substantially.

As in Gu *et al.* (2020), the firm specific variables are augmented with 9 macroeconomic variables: dividend-price ratio (dp), earnings-price ratio (ep), book-to-market ratio (bm), net equity expansion (ntis), Treasury-bill rate (tbl), term spread (tms), default spread (dfy), stock variance (svar), and the overall market return (mktr). This data is extracted from Amit Goyal's personal website. Finally, 15 M&A deal specific variables are added:

1. Cash: Indicator variable that takes the value 1 if it is an all-cash deal.
2. A Exp: Indicator variable that takes the value 1 if the acquirer has successfully acquired another company in the 2 years prior to deal announcement.
3. Friendly: Indicator variable that takes the value 1 if the board of directors of the target company is backing the merger/acquisition.
4. US: Indicator variable that takes the value 1 if the acquirer is also a U.S. entity.

[17] Excluding I/B/E/S variables is due to a lot of missing data, especially in the beginning of the data period.
[18] An adapted version of the SAS code available on Jeremiah Green's website has been used to extract the 87 variables from CRSP and Compustat.

5. Compete: Indicator variable that takes the value 1 if an offer is a competing bid.
6. LBO: Indicator variable that takes the value 1 if this is a leveraged buyout.
7. TO: Indicator variable that takes the value 1 if this is a tender offer.
8. Private: Indicator variable that takes the value 1 if the acquirer is a private entity.
9. Sought: Variable in the range of $[0, 100]$ that is equal to the stake that the acquirer is looking to acquire in the target firm.[19]
10. mve/dv: Market value to deal value. The market value is the market value (of the target company) 1 week prior to deal announcement and deal value is the offer value in cash or acquirer shares, but scaled as if 100% of the company is being acquired.
11. atf/dv: Acquirer termination fee to deal value.
12. ttf/dv: Target termination fee to deal value.
13. tpremium: Percent increase in target share price post deal announcement compared to the share price 1 week prior to deal announcement.
14. rpremium: Offer price divided by post announcement target share price minus 1. With the assumptions of Section 2 this is equal to $E_t[r_i|D_i = 1]$.
15. isp: Implied Success Probability. This measure, first explored in Samuelson and Rosenthal (1986) as well as Brown and Raymond (1986), can be viewed as a risk-neutral probability of deal success under the assumptions in Section 2.[20] It is calculated by setting the expected return of a merger arbitrage trade equal to 0 and solving for the probability of success. For cash deals it can be calculated as follows:

$$isp_{i,cash} = \frac{P^{(T)}_{i,post} - P^{(T)}_{i,pre}}{Cash_i - P^{(T)}_{i,pre}} \tag{47}$$

For equity deals the expression is a bit more complicated:

$$isp_{i,equity} = \frac{(P^{(T)}_{i,post} - P^{(T)}_{i,pre}) - xr_i(P^{(A)}_{i,post} - P^{(A)}_{i,pre})}{xr_i P^{(A)}_{i,post} - P^{(T)}_{i,pre}} \tag{48}$$

[19] Since the data only includes 100% acquisitions, this will only take a value of less than 100 if the acquiring company already has a stake in the target company.
[20] With the additional assumption of a risk-free interest rate of 0.

A final transformation of both $isp_{i,cash}$ and $isp_{i,equity}$ is performed to make sure it only takes values in the $[0,1]$ range:

$$isp_{i,cash/equity} = \min[\max[isp_{i,cash/equity}, 0], 1] \tag{49}$$

The firm specific and macro variables are all recorded on a monthly basis, whereas deal specific variables are recorded at the first trading day after announcement. Therefore, when predicting the conditional probability of success or the expected return for a deal that falls in month t, the firm specific and macro variables available at the beginning of month t are used. However, to avoid look-ahead bias, the yearly firm specific variables are lagged by 6 months, quarterly variables by 4 months, and monthly variables by 1 month. Any missing firm specific variables at month t is replaced by the median value of the cross-section of *all* firms at month t. Furthermore, every time a model is trained, and out-of-sample predictions are made, all the "raw" explanatory variables are transformed as follows:

$$x_{ji} = \frac{x_{ji}^{(raw)} - \min\left[\mathbf{x}_j^{(Training)}\right]}{\max\left[\mathbf{x}_j^{(Training)}\right] - \min\left[\mathbf{x}_j^{(Training)}\right]} \tag{50}$$

Where $x_{ji}^{(raw)}$ is the pre-transformed variable j for deal i, while $\min\left[\mathbf{x}_j^{(Training)}\right]$ and $\max[\mathbf{x}_j^{(Training)}]$ are the minimum and maximum values of variable j in the training set, respectively. This ensures that all variables in the *training set* is in the $[0,1]$ range and the rest are similarly scaled but could take on values outside the $[0,1]$ range if a variable takes on a higher (smaller) value than the maximum (minimum) of that same variable in the training set.

Chapter 3

Pricing of Sustainability-Linked Bonds

with Peter Feldhütter and Arthur Krebbers.

Abstract

We examine the pricing of sustainability-linked bonds (SLBs), where the cash flows depend on the bond issuer achieving one or more Environmental, Social and Governance (ESG) goals. Investors are willing to accept a 1-2bps lower yield due to the bond's ESG label, providing evidence of investors caring about environmental impact. Furthermore, we find the average probability of missing the target is 14%-39% so firms set ESG targets that are easy to reach. We find that the SLB market is efficient: the prices of SLBs depend strongly on the size of the potential penalty and there is no evidence of mispricing. Finally, our results suggest that SLBs serve as financial hedges against ESG risk.

Feldhütter is at Copenhagen Business School. Krebbers is at NatWest and University of Strathclyde. We are grateful for valuable comments and suggestions received from Jens Dick-Nielsen, Thomas Geelen, Lena Jaroszek, David Lando, Lasse Heje Pedersen and seminar participants at Copenhagen Business School. Peter Feldhütter gratefully acknowledges support from the Danish Finance Institute (DFI) and the Center for Big Data in Finance (Grant no. DNRF167).

1 Introduction

Sustainability has become a central concern for governments, corporations, regulators and investors. A number of financial securities, particularly debt instruments, designed to align financial incentives with ESG objectives have come to existence in the past decade. For example, sustainable bonds where revenues from the bond issue are limited to funding ESG investments, have grown tremendously in recent years. Critics argue that companies have no direct financial incentive to act ESG-friendly once such bonds are issued. As a potential solution to this incentive problem, firms have recently begun to issue sustainability-linked bonds (SLBs). In contrast to sustainable bonds there are no limitations on how the proceeds are used, but bond cash flows are tied to the company achieving future ESG goals. In a typical SLB structure, the firm commits to a future carbon reduction target, and if the target is not met, the bond's coupon increases. Compared to standard sustainable bonds, SLBs may be more effective at directing companies to contribute to a sustainable economy. However, if firms choose easy targets or SLBs are mispriced as Kölbel and Lambillon (2023) find, SLBs will not work as intended.

In this paper, we extensively examine the pricing of SLB. We calculate the SLB price premium as the price difference between an SLB and a synthetic identical ordinary bond with no ESG label and find 1) investors are willing to pay a premium for the ESG label itself, 2) there is a strong relation between the SLB price premium and the penalty size for missing the target, 3) the average SLB price premium is less than the sum of penalties, i.e. "no arbitrage", 4) the average probability of meeting the target is high at 61%–86%, and 5) evidence that SLBs serve as hedges against ESG risk.

We calculate the SLB price premium as the price difference between the SLB and an ordinary bond. To take into account differences in coupon rates between the SLB and ordinary bonds, we start by calculating an SLB yield premium and then convert it to an SLB price premium. The SLB yield premium is calculated in the secondary market as the difference in yield spread between an ordinary non-labelled bond and an SLB, both issued by the same firm. Specifically, on a daily basis, we match each SLB with two non-labelled bonds that have a longer and shorter maturity and interpolate the non-labelled bonds' yield spreads to generate a non-SLB synthetic yield spread with the same maturity as the SLB. The difference between the synthetic yield spread and the SLB yield spread is the SLB yield premium. We convert the SLB yield premium to an SLB price premium,

$$\text{SLB price premium} = \text{SLB bond price - ordinary bond price},$$

using our pricing model.

We first investigate if investors are willing to pay a markup for the ESG label itself. Evidence from the literature on green bonds has established that investors are willing to pay a markup for a green bond label (Zerbib (2019), Caramichael and Rapp (2022), Feldhütter and Pedersen (2023) and others), implying that ESG investors accrue non-pecuniary benefits through indirect ownership of green assets (Bonnefon *et al.* (2022)). Since SLBs are not tied to specific assets, a green bond markup does not imply an SLB markup. If the impact of investment decisions is important for investors (Moisson (2022)), however, they would pay a premium for SLBs because the bonds incentivize firms to take ESG-friendly actions. Testing if investors are willing to pay a markup for the ESG label of SLBs on its own is difficult since one would need to separate the value of potential additional cash flows to bondholders from the value of the ESG label itself. To circumvent this difficulty, we use a subset of SLBs that have a penalty defined in terms of donations or carbon offset. These bonds are ideal for studying the value of the ESG label, because there are no potential additional payments to bond holders and therefore the SLB premium must be due to the ESG label itself. We find a positive but modest SLB yield premium of 1.9bps – which we call the sustainium – for this subset of SLBs providing empirical support for the importance of impact investing.

Turning next to our main sample of SLBs where investors do receive additional cash flows if the firm fails to reach the ESG target(s), we investigate the size and determinants of the SLB price premium. We find that the SLB price premium is strongly positively related to the penalty size – the sum of penalty cash flows in case the firm fails to reach the ESG target(s). This result indicates that, as basic financial theory predicts, the market accounts for the size of optional cash flows. Surprisingly, Kölbel and Lambillon (2023) report that the SLB premium is larger than the sum of penalties. This may be the case if investors misprice cash flows or are willing to pay a sufficiently large sustainium. If so, firms can engage in greenwashing by issuing overpriced SLBs with no intention of reaching the ESG target(s). We find that the average SLB premium is significantly less than the sum of penalties and, thus, our results suggest no evidence of such greenwashing potential in the market.

Investors and regulators voice concerns that targets "lack ambition and are too easy to meet"[1], which is why the International Capital Market Association recommends that targets are ambitious and "beyond a Business as Usual trajectory" (ICMA (2020)). In a survey of professional investors in 2021, investors' main concern regarding SLBs was the "risk of greenwashing".[2] If correct, firms can engage in greenwashing behavior by issuing SLBs with targets that are easy to reach and then earn the sustainium. We investigate whether these concerns are warranted by estimating the probability of firms missing their ESG target(s). To do so, we exploit that many SLB issuers follow the International Capital Market Association's guidance and publish historical values of Key Performance Indicators (KPIs) on which the targets are based. We assume that the KPI follows a generalized Wiener process, calibrate the parameters to historical values and use the parameters to calculate the probability that the future target will be missed. We calculate the probability under different scenarios and we find that the average probability of missing the target is only 14%-39%, depending on assumptions. Even under the most relaxed assumption about the firm's commitment, that the future commitment is the same as the historical commitment, the probability of missing the target is only 39%. This suggests that targets are indeed too soft and business-as-usual, interpreting business-as-usual as continuing a historical trajectory in the future.

Finally, we estimate the risk premium associated with ESG risk for the SLBs with ESG-linked cash flows. To do so, we first regress the yield sustainium on firm characteristics for the subset of SLBs with no ESG-linked cash flows, and use the regression coefficients to estimate the yield sustainium for the larger sample. Then, we use the estimated yield sustanium to calculate the price of a synthetic SLB bond – sustainium-only price – with the same maturity and coupon, but without ESG-linked cash flows. We compute the price of the optional ESG cash flows as:

$$\text{ESG cash flow price} = \text{SLB bond price - sustainium-only bond price,}$$

and use the estimates of probabilities of missing the target in conjunction with our pricing model to compute the expected present value of the optional ESG cash flows, $\mathrm{E}\Big[\text{ESG cash flows}\Big]$. The ESG risk premium is then:

$$\text{ESG risk premium} = \mathrm{E}\Big[\text{ESG cash flows}\Big] \text{ - ESG cash flow price.}$$

[1] See for example Reuters, November 9, 2022, "Explainer: Decoding COP27: the many shades of green bonds" (https://www.reuters.com/business/cop/decoding-cop27-many-shades-green-bonds-2022-11-09/.

[2] https://gsh.cib.natixis.com/api-website-feature/files/download/11818/SLB-Survey-Short-Results_2021-03-FinalVersion_LAST.pdf.

There is no consensus on the sign of the ESG risk premium, and for the most common targets related to greenhouse gas (GHG) emissions, there are arguments for both a positive and negative risk premium.[3] The risk premium would be positive if, when the economy experiences a positive growth shock, output and GHG emissions increase (Nordhaus (1977)). In these states of high consumption, firms are more likely to miss their ESG targets and SLBs pay out additional cash flows. The risk premium would be negative if global warming, caused by GHG emissions, results in higher risk of climate disasters leading to a negative macro-economic shock (Bansel *et al.* (2019)). In such a scenario, SLBs act as a hedge against climate risk, since firms have not reduced GHGs and SLBs pay out extra cash flows. We find that the average risk premium is negative and statistically significant in most specifications, providing evidence that SLBs serve as financial hedges against ESG risk. However, the evidence for a negative risk premium is weak for SLBs where targets are tied to GHC emissions, suggesting that the negative risk premium is not driven by a negative climate change risk premium.

The theoretical model uses the intensity-based method proposed by Lando (1998) and Duffie and Singleton (1999). There is a stochastic riskfree interest rate, the firm defaults with a stochastic default intensity and, in case of default, bondholders receive a stochastic recovery rate. Investors may have a stochastic convenience of holding an SLB, which we denote the sustainium. The firm sets one or more future ESG targets and for each target there is an incremental set of future cash flows bondholders receive if the target is not met. We derive the bond price and provide closed-form solutions in the case of a constant interest rate, default intensity, sustainium and recovery rate.

Our work is most closely related to Kölbel and Lambillon (2023) who compare the SLB yield at issuance with the issuance yield of a non-SLBs from the same issuer issued no more than five years apart. We refine their approach as we match the secondary market SLB yield spread with an interpolated yield spread from non-SLB bonds from the same issuer on the same day. Thus, while we compare SLB and non-SLB yield spreads from the same issuer on the same day, Kölbel and Lambillon (2023) compare SLB issuance yields with yields of ordinary bonds that are on average issued 1 1/2 years earlier and changes in riskfree rates, macro variables, and issuer-specific credit risk introduces noise in their results. Furthermore, in contrast to their paper, we estimate a model, estimate the sustainium, the probability of hitting the target and investigate ESG risk premiums. We focus on pricing SLBs in this paper

[3] See Giglio *et al.* (2021) for an extensive review.

and do not study the optimal design of SLBs. Our anecdotal evidence indicates that the size of penalties relative to overall interest expenses is low, making it unlikely that the value of the ESG-related penalties in itself have a material impact on firms' transition to a greener economy, and Berrada *et al.* (2022) provide a theoretical framework for understanding the relation between firm effort and size of penalties. Erlandsson and Mielnik (2022) provide a pricing model for SLBs and calibrate it to two bonds at issuance while we have an extensive sample of SLB bonds over a longer period.[4]

The structure of the paper is the following. In Section 2 we provide an overview of the market for SLBs. Section 3 describes the model and estimation approach, while Section 4 details the data. Section 5 describes the empirical results and Section 6 concludes.

2 Sustainability-Linked Bonds

A variety of new debt securities have been introduced in recent years to aid firms make the transition to a greener and more socially responsible economy. For instance, the proceeds from green bonds are restricted to green projects, the proceeds from blue bonds are used for investments in healthy oceans, while funds raised from social bonds are used for projects that have a positive impact on society. Such debt securities do not impose any limitations on the company's future behavior once the underlying projects have been funded. Sustainability-linked bonds (SLBs), a more recent innovation that was introduced in 2018, are fundamentally different from other ESG-related securities. SLBs directly link the cash flows of the bond to one or several ESG-related Key Performance Indicators (KPIs) rather than placing restrictions on how bond proceeds are used. This implies that the firm have financial incentives to act in an ESG-friendly manner after the bonds are issued.

For the purpose of illustration, consider a typical SLB: a 10-year bond issued by General Mills on October 14, 2021, with a fixed coupon rate of 2.25% and semi-annual payments. General Mills' annual coupon rate will increase by 25 basis points starting on April 14, 2026, if it is unable to reduce scope 1 and scope 2 greenhouse gas emissions by 21 percent by

[4] More broadly, there is a growing literature on green bonds including Zerbib (2019), Baker *et al.* (2022), Caramichael and Rapp (2022)), Flammer (2021), and Larcker and Watts (2020). Pedersen *et al.* (2021), Pastor *et al.* (2021) and Feldhütter and Pedersen (2023) investigate pricing in presence of ESG investors and Engle *et al.* (2020), Ilhan *et al.* (2021), Huynh and Xia (2021), Seltzer *et al.* (2022), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022), Oehmke and Opp (2022) and Avramov *et al.* (2022) look at the pricing of ESG risk.

the target date May 25, 2025, in comparison to a benchmark for 2020. The cash flows of the bond is illustrated in Figure 1. To assess how large the penalty is relative to the size

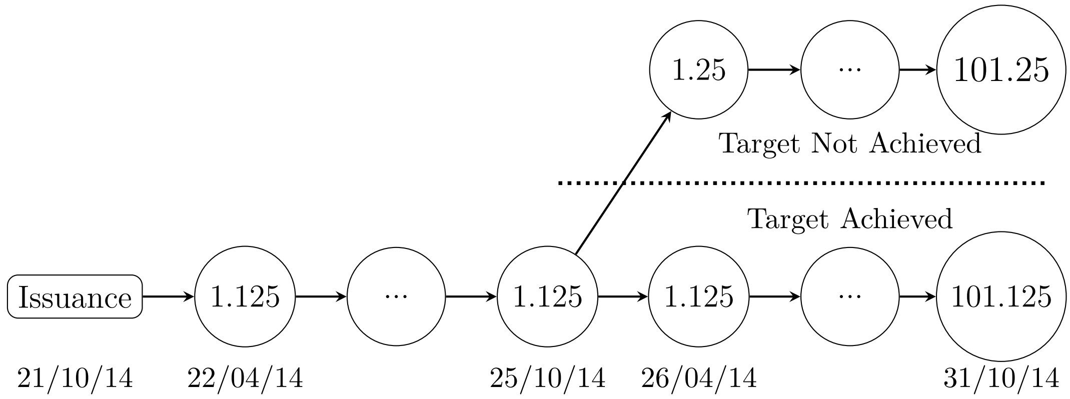


Figure 1: *SLB issued by General Mills in 2021.* This figure illustrates the possible cash flows of the SLB issued by General Mills on October 14, 2021. The bond has a fixed semi-annual coupon of 1.125% and if General Mills fails to achieve a target reduction of 21% in scope 1 and scope 2 greenhouse gas emissions by 2025, the semi-annual coupon increases by 0.125%.

of General Mills, we note that the offering amount of the SLB is \$500mio, so the annual penalty amounts to \$1.25mio. Additionally, General Mills had a sustainability-linked loan with a notional amount of \$1,000mio and a maximum penalty of 10bps. Overall, this implies a penalty of \$2.25mio if General Mills miss both targets. For comparison, the firm's interest expenses in 2021 was \$430.9mio according to their annual report, so missing sustainable-linked targets would only increase their interest rate expenses by 0.52%. The firm may issue more SLBs with higher penalties in the future as the market matures, but the current penalties are too small to affect the firm in a material way.

A recent example of triggered SLB penalties is Enel. The Italian energy company triggered a penalty of 25bps on ten SLBs on April 23, 2024 by missing its greenhouse-gas emissions targets (Fitch(2024)). The higher coupons means an additional interest expense of EUR 25mio (\$26.8mio) amounting to 0.44% of Enel's overall interest expenses (according to their 2023 annual report), suggesting that the SLB market has not yet matured to an extent that penalties have a sizeable impact on total interest expenses.

It is advised by the International Capital Market Association that firms publish at least three years of historical values of their target KPIs and the historical greenhouse gas emissions of General Mills are shown in Table 1. General Mills must reduce emissions by 32.9% in 2025 compared to 2018. A reduction of 19.3% was made in 2019 alone, but this was followed by an increase of 5.6% in 2020.

	2018	2019	2020	2025 (Target)
GHG Scope 1 and 2 Emissions (million metric tons of CO2e)	0.88	0.71	0.75	0.59
YoY Reduction (%)		-19.32	5.63	

Table 1: *General Mill's greenhouse gas emissions.* Historical data for scope 1 and scope 2 greenhouse gas emissions by General Mills, provided in the second party opinion by Institutional Shareholder Services Inc ahead of General Mill's issue of a 10-year SLB on October 2021.

The development of the SLB market is depicted in Figure 2. Both the number and notional amount issued have dramatically increased, as shown in Panel A. Between 2018 and March, 2024, 722 SLBs have been issued. The total notional amount issued for the 722 SLBs is 273 USD billions. Panel B shows that half of the bonds were issued in Europe, followed by 33 percent in Asia and 12 percent in North America.

Different KPIs, KPI targets, penalty types, and penalty sizes are used to structure SLBs as Table 2 shows. The most common KPI measures greenhouse gas emissions (GHG), intended to lower scope 1, 2, or 3 greenhouse gas emissions for the entire company or a particular segment of the firm's operations. The second-most popular group of KPIs is related to renewable energy, such as an increase in the portfolio of renewable energy assets for energy companies or a greater reliance on renewable energy for non-energy firms. A significant number of KPIs are concerned with maintaining or raising a company's ESG rating. Finally, some KPIs are related to diversity, typically the proportion of minority groups to the majority. For instance, on September 13, 2021 Suzano Austria GmbH issued an SLB with one of the KPI targets being to reach a level of at least 30% women in leadership roles by 2025. "Other" KPIs includes metrics that are company-specific, such as decreased food and water waste for food and beverage companies or the building of affordable housing for construction companies.

Table 2 Panel B lists type of penalties and we see that most SLBs are accompanied by a coupon step up, i.e. an increase in the bond's coupon. Some bonds have a coupon step-down reducing the coupon if the company achieves the target. Pure step-downs are uncommon, whereas coupon step up/down, where the coupon rate can change based on the KPI's performance at the target observation date, are more frequent (a common structure is to let the coupon depend on the firm's ESG rating). A cash/redemption penalty implies that the company pays a one-time cash premium or increases the bond's redemption price.

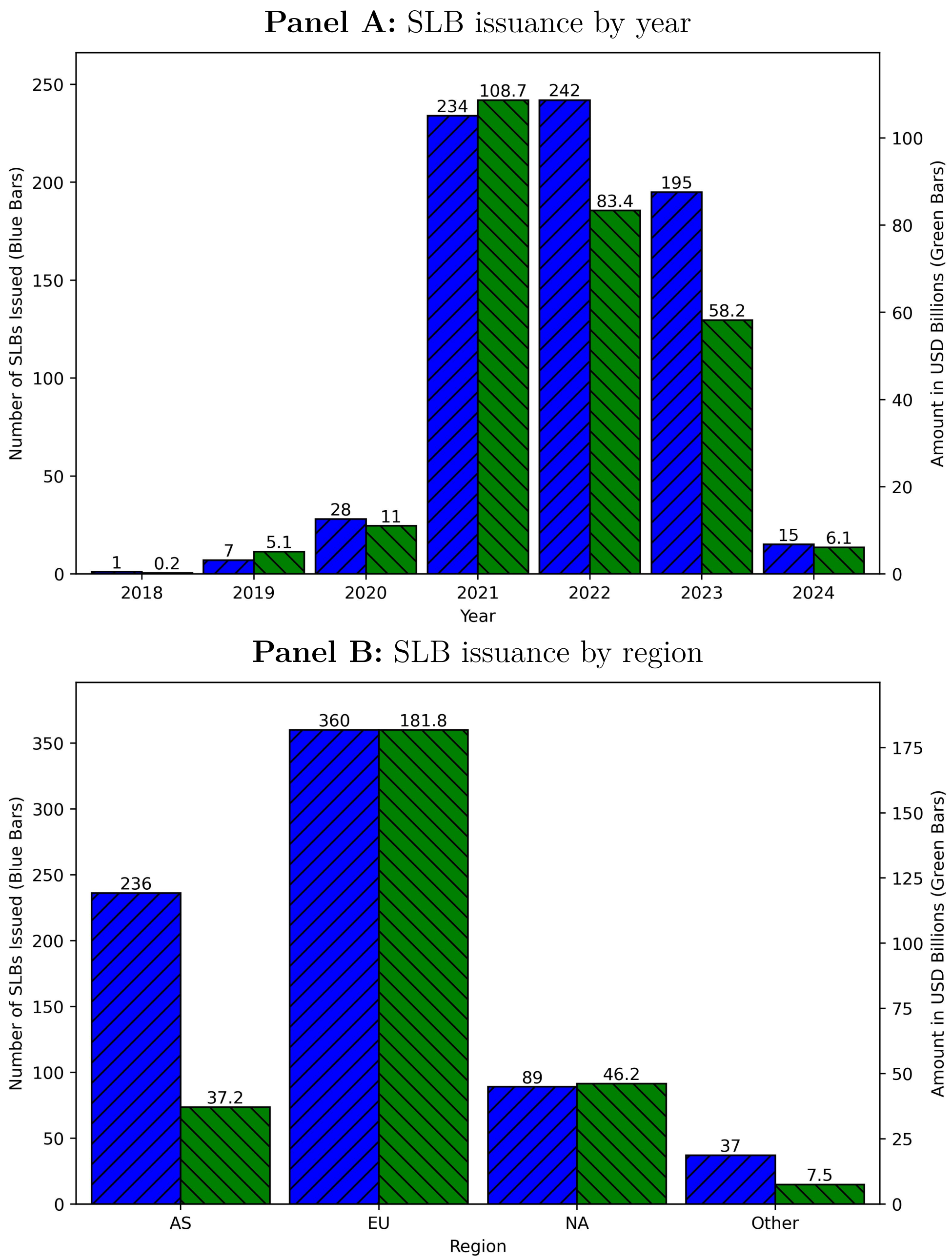


Figure 2: This figure shows the growth of the SLB market since its inception in 2018. The left (blue) bars show the number of SLBs issued each year while the right (green) bars show the notional amount of SLBs issued (in USD billions). The data is from Bloomberg and includes all bonds that have a sustainability-linked indicator equal to 1. The data for 2024 ends March 4.

There are 62 bonds where the penalty is to donate money to a charity or buy carbon offset certificates. The distribution of the size of the penalty for targets with a step-up feature is displayed in Panel C. Out of 427 SLBs with a coupon step up, 220 (52%) have a 25 bps coupon increase, 120 (28%) have less than a 25 bps increase, and 76 (18%) have more than a 25 bps increase.

Panel A: KPI Type

	# of SLBs Issued	Issuance Amount (USD Billions)
GHG (Greenhouse Gas)	410	195.4
Other	233	72.0
Renewables	125	37.6
ESG Rating	65	16.8
Diversity	38	16.5
Missing Info	36	8.2
Multiple KPIs	268	108.2

Panel B: Penalty Type

	# of SLBs Issued	Issuance Amount (USD Billions)
Coupon Step Up	427	198.3
Cash/Redemption	86	29.1
Coupon Step Up/Down	68	16.9
Carbon Offset/Donation	62	11.3
Missing Info	36	7.9
Complex	33	7.7
Coupon Step Down	8	0.5

Panel C: Coupon Step Up Penalty

	# of SLBs Issued	Issuance Amount (USD Billions)
= 25 BPS	220	131.8
< 25 BPS	120	26.0
> 25 BPS	76	39.5
Missing Info	11	1

Table 2: *Structure of SLBs.* Panel A shows types of KPIs, Panel B types of penalties and Panel C the distribution of penalty size for SLBs that have a coupon step up penalty. In Panel A 268 SLBs have multiple KPIs and can thus enter into multiple rows of the panel. The KPI information is manually collected using a combination of Bloomberg notes, bond prospectuses, company websites, and second party opinions. The data period is December, 2018 to March, 2024.

3 A model for sustainability-linked bonds

In Section 3.1 we derive a model for pricing SLBs using the default-intensity method proposed by Lando (1998) and Duffie and Singleton (1999). We derive the model with multiple ESG targets, a stochastic interest rate, default intensity, recovery rate, and a premium for sustainability. In Section 3.2 we simplify the model by assuming constant values for the interest rate, default frequency, recovery, and sustainability premium, and detail how we estimate the model.

3.1 A general model

The bond has promised cash flows $C_1, ..., C_M$ at times $t_1^C, ..., t_M^C$ and without loss of generality we assume that we are pricing the bond at time 0. The firm has K ESG factors $G_t^j, j = 1, ..., K$ and if factor j is above some target at time T_j, K_j, bond investors receive additional positive cash flows $S_1^j, ..., S_{N_j}^j$ at times $t_1^j, ..., t_{N_j}^j$, where $T_j \leq t_i^j \leq t_M^C, i = 1, ..., N_J$.

We consider a low ESG factor to be favorable in an ESG sense. For instance, if the ESG factor is carbon emissions, a firm that has not sufficiently reduced its carbon emissions will be penalized by having to pay additional coupons if the factor is above the target. A high ESG factor is positive in some cases, for instance when the goal is to reach a certain percentage of female employees. In this case we look at $-G_t$ and the condition is then $-G_t > -K$. Some bonds (although none in our empirical sample) have a step-down coupon structure, such that the coupons are reduced if the firm reaches the ESG target. In this case we think of the cash flows $C_1, ..., C_M$ as the cash flows in case the firm reaches the ESG target and additional cash flows $S_1^j, ..., S_{N_j}^j$ as the negative value of the step-down coupons.

Independent of the cash flows, investors may have a convenience of holding the bond, the sustainability premium or "sustainium", which we denote ω_t.

Let λ_t be the default intensity for the bond-issuing firm and r_t the riskfree rate. If the firm defaults at time τ bondholders receive δ_τ. We can think of the investor as selling the bond at default in which case δ_τ is the trading price of the bond. The value of bond cash flows is (see Lando (1998) and Duffie and Singleton (1999)):

$$\begin{aligned}
P_0^{SLB} &= E_0^Q\Big[\sum_{i=1}^{M} C_i e^{-\int_0^{t_i^C}(r_s+\lambda_s-\omega_s)ds}\Big] + \sum_{j=1}^{K} E_0^Q\Big[1_{\{G_{T_j}^j > K_j\}} \sum_{i=1}^{N_j} S_i^j e^{-\int_0^{t_i^j}(r_s+\lambda_s)ds}\Big] && (1)\\
&+E_0^Q\Big[\int_0^{t_M^C} \delta_u \lambda_u e^{-\int_0^u (r_s+\lambda_s-\omega_s)ds} du\Big] && (2)\\
&= \sum_{i=1}^{M} C_i D(r_0, \lambda_0, \omega_0, t_i^C) + \sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j F(r_0, \lambda_0, G_0^j, K_j, t_i^j, T_j) && (3)\\
&+R(r_0, \lambda_0, \omega_0, \delta_0, t_M^C) && (4)
\end{aligned}$$

Where:

$$\begin{aligned}
D(r_0, \lambda_0, \omega_0, t) &= E_0^Q\Big[e^{-\int_0^t (r_s+\lambda_s-\omega_s)ds}\Big] && (5)\\
F(r_0, \lambda_0, G_0, K, t, T) &= E_0^Q\Big[1_{\{G_T > K\}} e^{-\int_0^t (r_s+\lambda_s)ds}\Big] && (6)\\
R(r_0, \lambda_0, \omega_0, \delta_0, t) &= E_0^Q\Big[\int_0^t \delta_u \lambda_u e^{-\int_0^u (r_s+\lambda_s-\omega_s)ds} du\Big] && (7)
\end{aligned}$$

Note that the model takes into account that ESG-investors value penalty cash flows less than the other bond cash flows since the sustainium is not included when discounting potential penalties in the last term in equation (1). We decompose the price of the SLB into a standard bond component and an option:

$$\begin{aligned}
P_0^{SLB} &= P_0^{SUS} + O_0 && (8)\\
P_0^{SUS} &= \sum_{i=1}^{M} C_i D(r_0, \lambda_0, \omega_0, t_i^C) + R(r_0, \lambda_0, \omega_0, \delta_0, t_M^C) && (9)\\
O_0 &= \sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j F(r_0, \lambda_0, G_0, K_j, t_i^j, T_j) && (10)
\end{aligned}$$

Where P_0^{SUS} is the price of a "sustainium bond" without any option-linked cash flows and O_0 is the value of the option-linked cash flows. The price of an ordinary (non-ESG) bond with no option features is:

$$P_0^o = \sum_{i=1}^{M} C_i D'(r_0, \lambda_0, t_i^C) + R'(r_0, \lambda_0, \delta_0, t_M^C) \quad (11)$$

Where:

$$D'(r_0, \lambda_0, t) = E_0^Q\Big[e^{-\int_0^t (r_s+\lambda_s)ds}\Big] \quad (12)$$

$$R'(r_0, \lambda_0, \delta_0, t) = E_0^Q\Big[\int_0^t \delta_u \lambda_u e^{-\int_0^u (r_s+\lambda_s)ds} du\Big] \quad (13)$$

The lower bound of the option price is zero, $O_0^{LB} = 0$, while the upper bound is given by:

$$O_0^{UB} = \sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j \quad (14)$$

If the ESG factor(s) G are independent of the risk free rate r and the default intensity λ, equation (6) reduces to:

$$F(r_0, \lambda_0, G_0, K, t, T) = E_0^Q\Big[1_{\{G_T>K\}}\Big]D'(r_0, \lambda_0, t) \quad (15)$$

The required dollar compensation for ESG-related cash flow risk – the ESG premium – is:

$$\begin{aligned} ESGP_0 &= \sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j E_0^P\Big[1_{\{G_{T_j}>K\}}\Big]D'(r_0, \lambda_0, t_i^j) - O_0 && (16)\\ &= \sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j E_0^P\Big[1_{\{G_{T_j}>K\}}\Big]D'(r_0, \lambda_0, t_i^j) && (17)\\ &\quad -\sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j E_0^Q\Big[1_{\{G_{T_j}>K\}}\Big]D'(r_0, \lambda_0, t_i^j) && (18)\\ &= \sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j \Big(E_0^P\Big[1_{\{G_{T_j}>K\}}\Big] - E_0^Q\Big[1_{\{G_{T_j}>K\}}\Big]\Big)D'(r_0, \lambda_0, t_i^j) && (19)\end{aligned}$$

3.2 A tractable model: Formulas and estimation

We now assume that the recovery rate, default intensity, sustainability premium, and riskfree rate are constant and estimate the model using a three-step procedure. For a given bond-day, as Section 3.2 details, we first estimate the price of a synthetic ordinary non-ESG bond with the same fixed cash flows as the SLB bond but with no option features and no sustainium. Then, we estimate the price of a bond with a sustainability premium but no option-linked cash flows as outlined in Section 3.2 and finally we estimate the ESG risk premium as Section 3.2 explains.

Ordinary bond and estimation of λ

The price of an ordinary (non-ESG) bond with no option features, given in equations (11)-(13) simplifies to:

$$P_0^o = \sum_{i=1}^{M} C_i D'(r, \lambda, t_i^C) + R'(r, \lambda, \delta, t_M^C) \tag{20}$$

$$D'(r, \lambda, t) = e^{-(r+\lambda)t} \tag{21}$$

$$R'(r, \lambda, \delta, t) = \frac{\delta\lambda}{r+\lambda}\left(1 - e^{-(r+\lambda)t}\right) \tag{22}$$

To estimate the price of an ordinary bond, we first compute the yield spread $s_{j,t}^o$ of an ordinary synthetic bond at time t with the same time-to-maturity as that of SLB j, $T_{j,t}$, by interpolating the yield spread of two ordinary bonds, one with a shorter maturity $T_{S,t}$ and one with a longer maturity $T_{L,t}$:

$$s_{j,t}^o = \frac{T_{L,t} - T_{j,t}}{T_{L,t} - T_{S,t}} * s_{S,t} + \frac{T_{j,t} - T_{S,t}}{T_{L,t} - T_{S,t}} * s_{L,t} \tag{23}$$

Where $s_{S,t}$ ($s_{L,t}$) is the yield spread of the short (long) maturity bond. If there is not a shorter and longer maturity bond, but two bonds with either shorter or longer maturity we extrapolate the yield spread. For example, if there are two ordinary bonds with a maturity of $T_{2,t} > T_{1,t} > T_{j,t}$, the yield spread of the ordinary bond is:

$$s_{j,t}^o = \frac{T_{2,t} - T_{j,t}}{T_{2,t} - T_{1,t}} * s_{1,t} + \frac{T_{j,t} - T_{1,t}}{T_{2,t} - T_{1,t}} * s_{2,t} \tag{24}$$

The yield-to-maturity of the ordinary bond is $y_{j,t}^o = s_{j,t}^o + r_{t,T_{j,t}}$ where $r_{t,T_{j,t}}$ is the $T_{j,t} - t$-year riskfree rate at time t.[5] We convert the discretely-compounded yield-to-maturity to a continuously-compounded yield-to-maturity $y_{j,t}^{o,cc}$ using the formula $y_{j,t}^{o,cc} = f_j * \ln(1 + \frac{y_{j,t}^o}{f_j})$, where f_j is the coupon frequency for bond j. The price of the ordinary synthetic bond is then:

$$\hat{P}_{j,t}^o = \sum_{i=1}^{M} C_i e^{-y_{j,t}^{o,cc} * t_i^C} \tag{25}$$

[5] The riskfree rate is the swap rate at time t for the same currency and maturity as the SLB: $r_{t,T_{j,t}} = y_{j,t}^{observed} - s_{j,t}^{observed}$, where the superscript *observed* refers to the actual observed yield-to-maturity and yield spread for SLB j at time t.

The default intensity $\hat{\lambda}_{j,t}$ is estimated by solving equation (20) for $\lambda_{j,t}$:

$$\hat{P}^o_{j,t} = \sum_{i=1}^{M} C_i D'(r_{t,T_{j,t}}, \lambda_{j,t}, t^C_i) + R'(r_{t,T_{j,t}}, \lambda_{j,t}, \hat{\delta}, t^C_M) \tag{26}$$

Where we use the historical recovery rate between 1987-2021 of 34.8% from Moody's (2022) as our estimate of the recovery rate $\hat{\delta}$.

Sustainium bond and estimation of ω

We use the subset of SLBs with no option-linked cash flows to compute the price of a synthetic bond with a sustainability premium but no option-linked cash flows. SLBs with penalty type "Carbon Offset/Donation" have no options embedded and (absent other frictions impacting the price such as liquidity) the yield-to-maturity difference between ordinary bonds and these SLBs is solely due to a convenience of holding the SLB bond. We call these bonds for sustainium-only bonds.

Specifically, for sustainium-only bond j at time t with a yield spread of $s^{SUS}_{j,t}$, and a corresponding synthetic yield spread of an ordinary bond of $s^o_{j,t}$, we estimate the sustainium $\omega^{SUS}_{j,t}$ as:

$$\omega^{SUS}_{j,t} = s^o_{j,t} - s^{SUS}_{j,t} \tag{27}$$

Using all sustainium-only bond-day observations we estimate the regression:

$$\omega^{SUS}_{j,t} = \beta X_{j,t} + \epsilon_{j,t} \tag{28}$$

Where $X_{j,t}$ is a vector containing a constant and firm-level characteristics, and compute a firm-time level sustainium for the full sample as:

$$\hat{\omega}_{j,t} = \hat{\beta} X_{j,t} \tag{29}$$

Where $\hat{\beta}$ is the vector with regression coefficients. The price of a sustainium bond is calculated as:

$$\hat{P}^{SUS}_{j,t} = \sum_{i=1}^{M} C_i D(r_{t,T_{j,t}}, \hat{\lambda}_{j,t}, \hat{\omega}_{j,t}, t^C_i) + R(r_{t,T_{j,t}}, \hat{\lambda}_{j,t}, \hat{\omega}_{j,t}, \hat{\delta}, t^C_M) \tag{30}$$

With:

$$D(r,\lambda,\omega,t) = e^{-(r+\lambda-\omega)t} \tag{31}$$

$$R(r,\lambda,\omega,\delta,t) = \frac{\delta\lambda}{r+\lambda-\omega}\Big(1-e^{-(r+\lambda-\omega)t}\Big) \tag{32}$$

Where $\hat{\omega}_{j,t}$ is the sustainium at time t of the bond issuer, and the sustainium bond premium for SLB j at time t is $\hat{P}^{SUS}_{j,t} - \hat{P}^{o}_{j,t}$.

ESG risk premium and estimation of $E^P_t\Big[1_{\{G_T>K\}}\Big]$

The implied option price is estimated as (see equation (8))

$$\hat{O}_{j,t} = P^{SLB,observed}_{j,t} - \hat{P}^{SUS}_{j,t} \tag{33}$$

We calculate the ESG premium by estimating $E^P_t\Big[1_{\{G^j_{T_j}>K_j\}}\Big]$ and inserting the empirical estimates $\hat{O}_{j,t}$ and $\tilde{E}^P_t\Big[1_{\{G^j_{T_j}>K_j\}}\Big]$ into equation (16).

We provide several estimates of $E^P_t\Big[1_{\{G^j_{T_j}>K_j\}}\Big]$ based on different assumptions about the firm's future ESG commitments. To provide empirical grounding for our estimates, they are based on the firm's historical ESG commitment.

To estimate the firm's historical ESG commitment, we assume that G^j follows a generalized Wiener process:

$$dG^j_t = \mu_j dt + \sigma_j dW_t \tag{34}$$

At time t we observe historical observations of the factor at times $t^j_1 < t^j_2 < ... < t^j_k < t$ where $t^j_{i+1} - t^j_i$ is one year[6]. To estimate the parameters μ_j and σ_j, we note that $G^j_T - G^j_t \sim N\Big(\mu_j(T-t), \sigma^2_j(T-t)\Big)$ and estimate the linear regression:

$$G^j_{t+1} - G^j_t = \beta + \epsilon_{t+1}, t = t^j_1, ..., t^j_{k-1} \tag{35}$$

[6] We assume an informational lag of 3 months for KPI data. This means that KPI data for year $t-1$ will become available in April of year t. The informational lag differs between firms/SLBs and we choose three as this is a typical lag. The empirical results of Section 3 do not qualitatively change if we use an informational lag of zero or six months.

Where $\epsilon_{t+1} \sim N(0, \xi^2)$. The parameter estimates are then:

$$\hat{\mu}_j = \hat{\beta} \tag{36}$$

$$\hat{\sigma}_j = \hat{\xi} \tag{37}$$

Based on the historical estimates $\hat{\mu}^h_{j,t}$ and $\hat{\sigma}^h_{j,t}$ (with superscript h to indicate that these are historical estimates), we make different assumptions about the future μ^f and σ^f, and it is then straightforward to calculate $\hat{E}^P_t\Big[1_{\{G^j_{T_j} > K_j\}}\Big] = P_t\Big[G^j_{T_j} > K_j | G^j_{t^j_k}\Big]$. Specifically, we include three different assumptions about future firm commitment in our empirical estimates:

- Same commitment. In this scenario we assume that the future commitment of the firm is the same as the past, i.e. $\mu^f = \hat{\mu}_{j,t}$ and $\sigma^f = \hat{\sigma}_{j,t}$, and issuing an SLB does not change the ESG behaviour of the firm.

- Stronger commitment. In this scenario we assume that the future commitment of the firm is stronger than in the past by assuming that $\mu^f = \min(2\hat{\mu}_{j,t}, 0)$ and $\sigma^f = \hat{\sigma}_{j,t}$. If SLBs work as intended, issuing such a bond should incentivize the firm's ESG efforts and a lower ESG drift captures this increase in effort.

- Stronger and more focused commitment. In this scenario we assume that the future commitment of the firm is both stronger and more focused than in the past by assuming that $\mu^f = \min(2\hat{\mu}_{j,t}, 0)$ and $\sigma^f = \frac{1}{2}\hat{\sigma}_{j,t}$. Here, the firm is increasing ESG efforts as well as focusing more on making sure targets are met, for example through increased monitoring.

Most estimates of $\hat{E}^P_t\Big[1_{\{G^j_{T_j} > K_j\}}\Big]$ are based on relatively few observations of G^j and are therefore noisy. To reduce the noise, we calculate a shrinkage estimator as in Vasiček (1973) and Blume (1975) and calculate in all three scenarios a common time-t probability of missing the target as:

$$E^{com}_t = \sum_{j=1}^{N} \hat{E}^P_t\Big[1_{\{G^j_{T_j} > K_j\}}\Big] \tag{38}$$

Where N is the number of targets for which we can calculate a probability at time t. Our time-t estimate of the probability of missing the target under any of three scenarios,

$\tilde{E}_t^P\left[1_{\{G_{T_j}^j > K_j\}}\right]$, is then:

$$\tilde{E}_t^P\left[1_{\{G_{T_j}^j > K_j\}}\right] = 0.25\hat{E}_t^P\left[1_{\{G_{T_j}^j > K_j\}}\right] + 0.75E_t^{com} \tag{39}$$

4 Data

In this section we describe the data and Appendix 7.1 provides further details.

We restrict our sample of corporate bonds to fixed-rate bonds with a time-to-maturity of at least six months. We exclude callable bonds, except if the call option is a make-whole call or a fixed-price call restricted to the last 3 months (or less) before the bond matures. We collect price and yield information on all corporate bonds from Bloomberg that are marked as sustainability-linked until the end of our sample period, March 4, 2024. The yield-to-maturity on SLBs is calculated using the current coupon without using the information on potential step-up coupons.

For each SLB we look up comparable ordinary bonds (i.e. not green, sustainable, or sustainability-linked) on Bloomberg issued by the same company that have a maturity that is less than four years from the SLB's maturity and have the same currency and seniority. Every day, we select two ordinary bonds that have available yield data and with a maturity closest to but smaller and larger, respectively, than the maturity of the SLB. If it is not possible to find two such bonds, we look for two ordinary bonds that both have either shorter or longer maturity. In this case, we choose the bonds with a time-to-maturity closest to that of the SLB and where the difference in time-to-maturity between the two ordinary bonds is at least six months.

To calculate transactions-based liquidity measures, we extract transactions from the TRACE database for bonds issued by FINRA-regulated firms, typically United States dollar denominated bonds and use the cleaning procedure described in Dick-Nielsen (2009). We augment the TRACE data with transactions for European bonds, done through the solution provided by Propellant.digital B.V. European trading venues are through MIFID II required to disseminate all their transactions in spirit similar to the data collection for the TRACE database, but unlike U.S. transactions, different venues' data come in different formats and are not collected in one database. Propellant provides a software solution that collects the major trading venues' data and allows for one homogeneous data set. Further details are provided in Appendix 7.1. There are 17,464 transactions across 8,566 bond-days that are overlapping between the TRACE and Propellant data (transactions with identical volume and price on the same day) and to avoid double counting these transactions, we remove the one present in the Propellant data set.

Table 3 shows the coverage of our three main data sources: Bloomberg, TRACE, and Propellant. A bond-day is in the sample if there is Bloomberg data available on that day and therefore the number of bond-days with Bloomberg data in Panel A is equal to the total number of bond-days. Propellant covers more bond-days and bonds than TRACE, while bonds that TRACE covers has more transactions. Panel B shows the number of bond-days with data in different regions and we see that TRACE covers predominantly U.S. while Propellant covers Europe and the coverage of the rest of the world is low. Propellant reports the trading venue where the transaction took place and Panel C shows that the main trading platforms are Bloomberg, Marketaxess and Tradeweb and the three platforms have a fairly similar share of the trading while other platforms have modest transaction activity. Our data sample starts on September 10, 2019; the earliest issuance date of the SLBs in our final sample.

After cleaning the data, the details of which can be found in Appendix 7.1, we are left with a final sample that contains 75 SLBs with 98 associated options[7], a combined issuance amount of 52.53 billion USD, and a total of 24,349 SLB bond-day observations spanning from April 1, 2020, to March 4, 2024. The data sample contains 10.4% of the total number of SLBs in the Bloomberg database and 19.2% of the total issuance amount. We see in Table 4 that the distributions of the KPIs, penalty types, and penalty sizes of coupon step ups in our final sample are similar to those of all SLBs: KPIs related to greenhouse gases are the most common KPI type and the most commonly associated penalty is a coupon step up of 25 bps. Table 5 shows that on average the SLBs have a time-to-maturity of 6.33 years, a coupon of 2.29 and an issuance size of 862$ million.

[7] There are 6 SLBs with three KPIs, 11 SLBs with two KPIs, and 58 SLBs with one KPI.

Panel A: Data Sources Overview

	Bonds	Transactions	Bond-Days
Bloomberg	1,129	-	551,837
TRACE	81	354,645	32,552
Propellant	366	270,920	79,948

Panel B: Regions

	EU	US	AS	Other
Bloomberg	213,462	53,222	252,507	32,646
TRACE	10,144	20,287	175	1,946
Propellant	72,064	4,864	1,083	1,937

Panel C: Propellant Venues

	Bonds	Transactions	Bond-Days	Volume (Millions)
Bloomberg	354	83,021	44,257	65,111.84
Marketaxess	339	66,442	36,330	40,534.62
Tradeweb	330	110,153	46,425	76,149.16
LSE	298	7,333	6,495	3,291.23
Tradeecho	229	3,801	2,508	2,249.17
Tradition	41	158	52	201.33
Liquidnet	7	12	12	11.09

Table 3: *Data sources.* Panel A summarizes the number of bonds covered and the total number of observations (at both the bond-day level and the transaction level for TRACE and Propellant) for each of the three data sources. Panel B breaks down the regional distribution of all bond-days from each source. Panel C shows the same statistics as Panel A, but for each individual venue in the Propellant data set. The data covers the period from September 10, 2019, to March 4, 2024.

Panel A: KPI Type

	# of SLBs Issued	Issuance Amount (USD Billions)
GHG (Greenhouse Gas)	65	44.1
Other	20	20.0
Renewables	6	6.8
ESG Rating	3	0.6
Diversity	4	3.4
Missing Info	0	0.0
Multiple KPIs	17	15.9

Panel B: Penalty Type

	# of SLBs Issued	Issuance Amount (USD Billions)
Coupon Step Up	63	60.8
Cash/Redemption	11	10.4
Coupon Step Up/Down	0	0.0
Carbon Offset/Donation	24	3.7
Missing Info	0	0.0
Complex	0	0.0
Step Down	0	0.0

Panel C: Step Up Coupon Penalty

	# of SLBs Issued	Issuance Amount (USD Billions)
= 25 BPS	28	30.6
$<$ 25 BPS	21	19.4
$>$ 25 BPS	14	10.8
No Information	0	0.0

Table 4: *SLB sample.* This tables shows statistics for the sample of SLBs used in the empirical analysis. Panel A breaks down the SLBs by types of KPI. Panel B show the types of penalties most commonly used in the structuring of SLBs. Finally, Panel C show the distribution of the penalty size for those SLBs that have a coupon step up penalty.

	Mean	Std	Min	p1	p25	p50	p75	p99	Max
Age (In Years)	1.14	0.77	0.00	0.02	0.50	1.04	1.71	3.13	3.47
TTM (In Years)	6.33	2.47	1.46	2.01	4.36	5.84	8.64	11.78	12.51
Coupon	2.29	1.92	0.00	0.00	0.50	2.25	3.75	7.38	7.88
Yield-to-Maturity	3.57	2.14	-0.37	-0.13	1.19	3.95	5.31	7.12	8.39
Yield Spread	1.22	0.92	-0.57	0.05	0.48	1.03	1.70	3.87	4.58
Issuance (USD Millions)	862	514	67	70	500	856	1,190	2,161	2,300

Table 5: *Summary statistics for the SLB sample.* The distribution of the age, time-to-maturity, coupon, yield-to-maturity, yield spread, and issuance amount for the final sample. There are 24,349 bond-day observations in the period from April 1, 2020 to March 4, 2024.

5 Empirical results

In this section we discuss the pricing of SLBs. We first look at the liquidity of SLBs as well as ordinary bonds issued by the same firm. Then we investigate if SLBs require a premium unrelated to cash flows for being labelled ESG and whether SLBs are mispriced. Finally, we examine determinants of SLB prices and ESG risk premiums.

5.1 Liquidity

The ease with which a corporate bond is traded affects corporate bond prices,[8] and we therefore compare the liquidity of SLBs to that of the corresponding regular bonds. We calculate liquidity of the synthetic ordinary bond as the weighted average liquidity of the two ordinary bonds that are used to calculate the synthetic yield, where the weights for the liquidity measures are the same as those used to determine the synthetic yield.

Table 6 shows the average liquidity of SLB bonds and synthetic ordinary bonds. The transaction-based Amihud measure, trade size and Imputed Roundtrip Cost (IRC) of Feldhütter (2012) suggest that SLBs are more liquid than ordinary bonds: the Amihud measure and IRC are higher and trade size is lower for ordinary bonds. The differences are not statistically significant and the number of bond-days with computable liquidity measures are only a fraction of all bond-days, and different for different measures, so it is difficult to draw conclusions from trade-based liquidity measures that can only be computed conditional on a transaction occurring.

Trade count, trading volume and bond age can be calculated on all bond days and it is clear that SLBs are newer bonds that trade more. The average age of SLBs in our sample is 1.144 years while it is 5.902 years for the ordinary bonds. Given that bonds trade more frequently when they are recently issued, it is not surprising that SLBs trade more often (2.467 pr. day vs 1.498 pr. day for ordinary bonds) and that the trading volume is higher ($1.517m pr. day vs $0.900m pr. day for ordinary bonds). The differences in age and trading volume are highly significant and it is therefore important to control for the liquidity differences in our results. We do so by adding trade count, volume and age as controls in our regressions (we restrict the controls to those three liquidity measures in order not to reduce

[8] See Friewald *et al.* (2012), Bao *et al.* (2011), Dick-Nielsen *et al.* (2012), Feldhütter (2012) and others.

the sample size).[9]

	SLBs	Ordinary bonds	Difference	N
Amihud	0.058	0.077	-0.019	9,238
			(0.020)	
IRC	0.209	0.225	-0.015	5,555
			(0.048)	
Trade Size (Millions)	0.723	0.619	0.104	10,356
			(0.065)	
Trade Count	2.467	1.498	0.969**	24,349
			(0.406)	
Volume (Millions)	1.517	0.900	0.617***	24,349
			(0.223)	
Age	1.144	5.902	-4.758***	24,349
			(0.721)	

Table 6: *Bond liquidity.* At the bond-day level we calculate the Amihud measure, IRC measure, average trade size, trade count, volume, and age. The first and second columns show the average for SLBs and a weighted average of ordinary bonds (where the weights are the same as those in equations (23)-(24)), respectively. The Amihud and IRC measures are calculated on a daily basis as in Dick-Nielsen, Feldhütter, and Lando (2012) and we winsorize at the 1% and 99% level. Trade count, total volume, and age are calculated on all bond-days, while average trade size requires at least one transaction on a bond-day to be computable. Additionally, for the Amihud, IRC, and trade size measures, we use a trailing 90-day average as our final daily measure. The third column shows the difference between the two groups on days where both groups have observations, while the fourth shows the number of bond-day pairs with non-missing data. The parentheses show standard errors (clustered at the bond-level) of the difference. *, **, and *** indicate statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

5.2 Sustainium

We expect SLBs to trade at higher prices than ordinary bonds issued by the same firm, i.e. a positive SLB premium, since SLBs have potential future additional cash flows. Part of the SLB premium may also be due to ESG investors willing to pay a premium for ESG-friendly securities (Pedersen *et al.* (2021), Pastor *et al.* (2021), Feldhütter and Pedersen (2023) and others). If ESG investors' non-pecuniary benefits accrue solely through ownership as experimental evidence in Bonnefon *et al.* (2022) suggests, the sustainium may be zero, since SLBs do not finance specific green projects. In contrast, if investors are concerned with

[9] Specifically, we add $\log(1 + L^o_{j,t}) - \log(1 + L^{SLB}_{j,t})$, where $L^o_{j,t}$ is the weighted average liquidity measure of the two bonds used to determine the synthetic yield on day t for SLB j, and $L^{SLB}_{j,t}$ is the SLB's liquidity measure.

the actual impact of their portfolio decisions as in Oehmke and Opp (2022) and Moisson (2022), the sustainium might be significantly positive.

As outlined in Section 3.2 we estimate a bond-time sustainium for a subset of SLBs where the penalty is in terms of donations or carbon offset. For these bonds, there are no potential additional payments to bond holders and therefore a yield difference between the SLB and an ordinary bond, $\omega_{j,t}^{SUS} = s_{j,t}^{o} - s_{j,t}^{SUS}$, can be attributed to the ESG label itself. For these sustainium-only bonds we estimate the regression:

$$\omega_{j,t}^{SUS} = \beta X_{j,t} + \epsilon_{j,t} \tag{40}$$

Where $X_{j,t}$ is a vector containing a constant, log(size), equity volatility, leverage, profitability, Tobin's q, credit rating, ESG rating, and industry-adjusted ESG rating. Appendix 7.1 details the calculation of the variables.

Table 7 shows the regression results. There are three variables that have predictive power for the sustainium: equity volatility, credit rating, and industry-adjusted ESG rating. In the richest specification (6) the sustainium decreases by 1.62bps for every rating notch. The standard deviation of credit rating is 1.49, so a one standard deviation improvement in rating implies an increase of 2.41bps in the sustainium (a higher numeric value of credit rating implies a lower credit quality). The positive relation between the sustainium and credit quality has the same sign as the relation between the greenium and credit quality, see Caramichael and Rapp (2024). The table also shows that there is a negative relation between industry-adjusted ESG rating and sustainium. A one standard increase in industry-adjusted ESG rating implies a 2.34bps lower sustainium (the standard deviation of industry-adjusted ESG rating is 1.28). A potential explanation for the negative relation between sustainium and industry-adjusted ESG rating is that for green firms the "ESG gap" between ordinary bonds and SLBs is smaller as implied by the model in Feldhütter and Pedersen (2023). Finally, a one standard increase in equity volatility implies a 0.45bps higher sustainium (the standard deviation of equity volatility is 0.23).

We use regression specification (6) in Table 7 to compute a firm-time level sustainium for all firm-time observations as:

$$\hat{\omega}_{j,t} = \hat{\beta} X_{j,t}. \tag{41}$$

If the ranges of firm characteristics are substantially different in the full sample compared

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	17.01	8.22	7.17	20.59	9.45	10.18
	(21.61)	(21.97)	(18.87)	(16.84)	(20.28)	(16.45)
Log(size)	1.19	1.03	1.08	1.21	1.04	1.09
	(1.73)	(1.85)	(1.79)	(1.74)	(1.85)	(1.78)
Equity vol	1.97***	1.95***	2.00***	1.92***	1.93***	1.94***
	(0.29)	(0.23)	(0.29)	(0.33)	(0.29)	(0.33)
Leverage	−11.06	−8.39	−8.44	−11.92	−8.67	−9.13
	(11.53)	(10.83)	(10.02)	(10.25)	(10.27)	(9.17)
Profitability	−7.13	−4.60	−6.70	−9.41	−5.59	−9.30
	(15.81)	(14.04)	(14.92)	(13.31)	(12.46)	(12.51)
Tobin's q	−3.51	−1.13	−3.81	−3.60	−1.13	−3.95
	(3.41)	(2.72)	(3.34)	(3.39)	(2.72)	(3.29)
Credit rating	−1.54***	−1.23**	−1.41***	−1.74***	−1.31*	−1.62**
	(0.40)	(0.57)	(0.48)	(0.65)	(0.73)	(0.68)
Industry-adj ESG rating	−1.47**		−1.73***	−1.53*		−1.83***
	(0.72)		(0.62)	(0.79)		(0.66)
ESG rating		−0.63	1.92		−0.60	2.14
		(2.55)	(2.36)		(2.60)	(2.35)
Liquidity controls	No	No	No	Yes	Yes	Yes
R^2	0.168	0.130	0.173	0.172	0.131	0.178
N	4509	4509	4509	4509	4509	4509

Table 7: *Sustainium determinants.* There are 24 SLB bonds issued by 18 firms with 4,509 bond-day observations with no option-linked cash flows in the sample period 2020:04–2024:03. This table shows results of a regression of the SLB premium (in basis points) on firm characteristics for this subsample. The liquidity controls are $\frac{1}{N_t^{SUS}}\sum_{j=1}^{N_t^{SUS}}\left(\log(1+L_{i,j,t}^{o})-\log(1+L_{i,j,t}^{SUS})\right), i=1,..,3$ where $L_{i,j,t}^{SUS}$ ($L_{i,j,t}^{o}$) is the value of liquidity variable i on day t for SLB j with no cash flow effects (ordinary bond) and the three liquidity variables are trade count, trading volume and bond age. Standard errors clustered at the bond level are in parentheses and *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

to the sustainium-only sample, this approach would be problematic because the approach would lead to extrapolation outside the range of the independent variables in the regression. Therefore, Table 8 shows the distribution of the variables for the sustainium-only sample as well as for the remaining sample where the bond coupons are linked to ESG targets. The table shows that firms issuing sustainium-only bonds are smaller, have better credit rating and lower ESG rating than firms using coupon-linked SLBs. The biggest sustainium-only issuers are predominantly Japanese – SingTel, Ajinomoto, Mitsubishi, Daiwa, Shiseido, TDK, ANA, Tokyu, Obayashi, and Asics – while the biggest coupon-linked SLB issuers are international firms – Optus Finance, Novartis Finance, Sanofi, Enel, Analog Devices, Enbridge, Eaton, SK Hynix, Eni, L'Oreal, Air France-KLM and General Mills. Importantly, we see that there is significant overlap in the distribution of all firm-level variables, validating the calculation of the sustainium using the regression in equation (41).[10]

The average sustainium is 1.89bps in the sustainium-only bond sample, 1.18bps in the coupon-linked SLB sample, and 1.31bps overall. Thus, the sustainium is small but positive. The sustainium is similar in sign and magnitude as the average green bond premium of 3.37bps in Feldhütter and Pedersen (2023). Figure 3 shows the time series of the average sustainium in the complete sample including sustainium-only and coupon-linked SLBs. The sustainium is consistently small and positive and largest in the early part of the sample period.[11]

[10] In conversions with bond issuers, they often mention two reasons for issuing sustainium-only bonds, 1) rewarding investors if the firm fails ESG goals creates the wrong investor incentives, and 2) if the coupons are linked to ESG targets, their investors may be forced to treat the overall bond as a derivative and hence regularly mark to market the position from an SPPI perspective (for more on SPPI see https://www.bdo.co.uk/en-gb/insights/business-edge/business-edge-2017/ifrs-9-explained-solely-payments).

[11] At the individual bond-day level, there are a number of negative sustainium observations; 32.0% of the predicted sustainium values are negative. This is noise at the individual bond-day level that is averaged out when aggregating in the cross section as the figure shows.

	Coupon-linked SLBs						Sustainium-only bonds						
	Mean	q5	q25	q50	q75	q95	Mean	q5	q25	q50	q75	q95	Mean diff
Log(size)	10.47	8.51	9.52	10.89	11.21	12.09	9.12	6.49	8.34	9.26	9.66	12.63	1.35***
	(0.16)						(0.35)						(0.38)
Equity vol	0.12	0.01	0.01	0.02	0.14	0.47	0.12	0.01	0.01	0.02	0.02	1.65	0.01
	(0.03)						(0.09)						(0.10)
Leverage	0.47	0.11	0.41	0.50	0.59	0.68	0.39	0.00	0.23	0.33	0.57	0.77	0.08
	(0.03)						(0.06)						(0.06)
Profitability	0.14	0.05	0.07	0.10	0.22	0.32	0.20	-0.04	0.07	0.18	0.29	0.58	−0.05
	(0.01)						(0.04)						(0.04)
Tobin's q	0.02	0.01	0.01	0.01	0.01	0.02	0.10	0.01	0.01	0.01	0.01	1.10	−0.08
	(0.01)						(0.09)						(0.09)
Industry-adj ESG rating	6.92	2.30	5.60	7.90	8.80	10.00	6.69	4.60	6.00	6.90	8.10	8.40	0.23
	(0.42)						(0.28)						(0.50)
ESG rating	6.07	4.00	5.40	6.30	7.20	7.40	5.52	4.60	5.10	5.50	5.90	6.50	0.55**
	(0.20)						(0.13)						(0.24)
Credit rating	8.60	6.00	8.00	8.00	9.00	12.00	6.68	4.00	6.00	7.00	8.00	9.00	1.92***
	(0.27)						(0.35)						(0.44)

Table 8: *SLB and sustainium bond issuer characteristics.* There are 75 SLB bonds issued by 41 firms with 24,349 bond-day observations in the sample period 2020:04–2024:03. There are 24 SLB bonds issued by 18 firms with 4,509 bond-day observations with no option-linked cash flows in the sample period 2020:04–2024:03, called sustainium bonds. The remaining SLB bonds have option-linked cash flows, called coupon-linked SLBs. This table shows the distribution – across bond-days – of firm characteristics in the two samples. Standard errors clustered at the bond level are in parentheses and the last column tests for a difference in means and *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

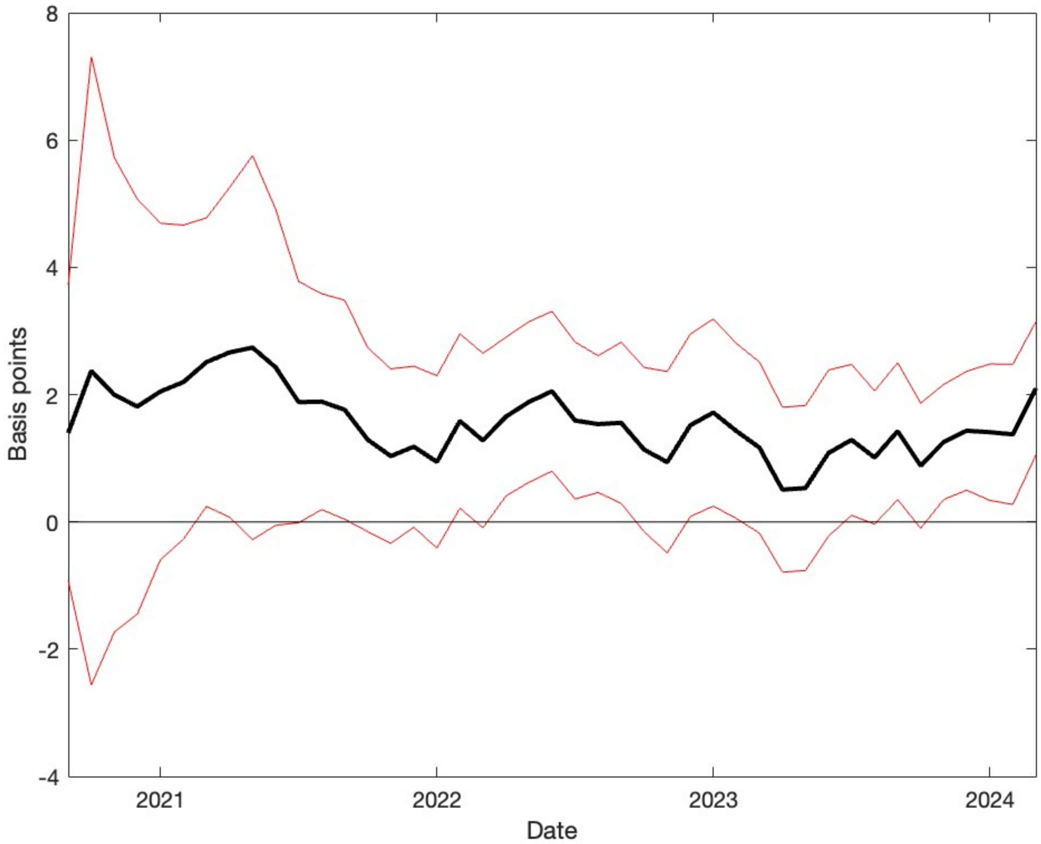


Figure 3: *Yield sustainium.* A raw sustainium is estimated by calculating the yield difference between the yield of non-SLBs and the yield on a subset of SLBs with the feature that their coupon is not tied to the issuing firm reaching a sustainability target (instead the firm donates money to sustainability-linked causes). For that sample the raw sustainium is regressed on firm-level characteristics and a predicted sustainium is computed for all firms using the regression coefficients. The graph shows the monthly average predicted sustainium for months with at least four bonds in the sample period with a 95% confidence band using standard errors clustered at the bond level.

5.3 SLB premium determinants

Absent frictions and the presence of ESG investors, the value of the embedded conditional cash flows in SLBs will be determined by the size of the cash flows, the probability of the firm missing the target and a potential ESG risk premium. Kölbel and Lambillon (2023) find surprisingly that there is no relation between the penalty size and the SLB premium. If the market does not price SLBs correctly, firm behaviour is unlikely to be aligned with investor ESG preferences.

Table 9 Panel A shows the probabilities of missing the target under the different assumptions about the future commitment of the firm issuing the SLB (outlined in Section 3.2). Here, we focus on the subset of SLBs with ESG-linked coupons. The average probability is between 14% and 39% and quite low for both reducing green house gasses (GHG), 15%-37%, and non-GHG targets, 11%-41%. According to industry reports, the historical frequency of missing targets has been low[12] and our results imply that this trend of meeting targets is due to firms setting easy targets. These results support the concern in the ESG market that targets "lack ambition and are too easy to meet" and "are too soft".[13]

Panel B shows that the relation between the SLB premium and the penalty size in our sample is positive and highly significant: the regression coefficient when regressing the SLB premium on penalty size is 1.05–1.17 depending on specification. Thus investors take into account penalty sizes when pricing SLBs and higher penalties translate into higher bond prices as basic financial theory implies. Furthermore, we see that the interaction between the penalty size and the probability of missing the target is positive in all specifications, as expected, between 1.05–1.92, and statistically significant in half of the specifications.

We also see in Panel B that equity volatility is a firm-specific characteristic that consistently has statistical significance in explaining the SLB premium: a higher equity volatility implies a higher SLB premium. A potential explanation is that different types of uncertainty are correlated and equity volatility is correlated with uncertainty about meeting the target. Indeed, we find that there is a positive correlation between equity volatility and σ_j in equation (34)[14]. Since σ_j is based on relatively few data points and updated on an annual basis (when a new historical observation of the factor is released) while equity volatility is updated on a daily basis, equity volatility will provide current information about σ_j and thus the probability of missing the target. While beyond the scope of this paper, calculating the

[12] NatWest report that "based on our tracker of selected public SLBs in the European and US market, 86% were on track to meet their target at the end of 2022" (NatWest, April 18, 2023, "SLB target misses aren't necessarily a negative: it's about the context", https://www.natwest.com/corporates/insights/sustainability/slb-target-misses-arent-necessarily-a-negative-its-about-the-context.html).

[13] Reuters, November 9, 2022, "Explainer: Decoding COP27: the many shades of green bonds" (https://www.reuters.com/business/cop/decoding-cop27-many-shades-green-bonds-2022-11-09/) and GlobalCapital, April 4, 2023, "In defense of SLBs" (https://www.globalcapital.com/article/2bhpp15s781netjeiefi8/sri/green-and-social-bonds-and-loans/in-defence-of-slbs).

[14] Since different G_j's have different scales, we calculate a scaled version as $\sigma_j^{scaled} = \log(\frac{\sigma_j}{G_t - K})$ and the correlation in the panel of σ_j^{scaled} and equity volatility is 0.07 both at the KPI-level and at the bond level (where we compute an average σ_j^{scaled} for bonds with multiple KPIs.).

Panel A: Probability of missing target								
	All	GHG	non-GHG					
Same	0.39***	0.37***	0.41***					
	(0.01)	(0.01)	(0.02)					
Stronger	0.14***	0.11***	0.11***					
	(0.02)	(0.03)	(0.02)					
Stronger & Focused	0.14***	0.15***	0.12***					
	(0.01)	(0.01)	(0.02)					
N	[19,840]	[12,354]	[7,486]					
Panel B: Determinants of SLB premium								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	3.56	5.85	6.53	5.89	0.16	2.05	2.15	1.57
	(6.01)	(5.80)	(6.18)	(6.21)	(4.95)	(4.79)	(4.96)	(4.96)
Penalty size	1.20***				1.07***			
	(0.33)				(0.28)			
Penalty x Prob (Same)		1.86**				1.55**		
		(0.74)				(0.66)		
Penalty x Prob (Stronger)			1.05				1.08	
			(0.89)				(0.80)	
Penalty x Prob (More Focused)				1.92				1.87*
				(1.23)				(1.11)
Log(size)	-0.08	-0.14	-0.13	-0.11	-0.01	-0.06	-0.04	-0.03
	(0.33)	(0.32)	(0.34)	(0.35)	(0.29)	(0.29)	(0.29)	(0.30)
Equity Vol	0.62*	0.82***	0.93***	0.89***	0.58**	0.76***	0.85***	0.81***
	(0.32)	(0.32)	(0.33)	(0.33)	(0.29)	(0.29)	(0.29)	(0.30)
Leverage	0.29	0.18	0.48	0.34	-0.86	-1.03	-0.91	-1.05
	(1.11)	(1.20)	(1.34)	(1.32)	(1.30)	(1.31)	(1.40)	(1.40)
Profitability	-3.11	-4.97	-5.91	-5.58	-1.17	-2.83	-3.39	-3.08
	(3.38)	(3.66)	(3.93)	(3.84)	(3.09)	(3.27)	(3.43)	(3.35)
Tobin's q	-0.75	-1.41	-1.71*	-1.67*	-1.25*	-1.85**	-2.21**	-2.15***
	(0.65)	(0.78)	(0.97)	(0.89)	(0.67)	(0.74)	(0.88)	(0.82)
Industry-adj ESG Rating	0.06	0.16	0.20	0.17	-0.03	0.06	0.10	0.07
	(0.14)	(0.16)	(0.18)	(0.17)	(0.11)	(0.13)	(0.14)	(0.13)
ESG rating	-0.38	-0.60	-0.66	-0.60	-0.09	-0.28	-0.32	-0.25
	(0.44)	(0.50)	(0.54)	(0.52)	(0.38)	(0.42)	(0.46)	(0.43)
Credit rating	-0.14	-0.17	-0.18	-0.17	0.03	0.01	0.03	0.05
	(0.20)	(0.19)	(0.21)	(0.21)	(0.19)	(0.19)	(0.20)	(0.20)
Liquidity controls	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.18	0.12	0.07	0.08	0.24	0.19	0.17	0.17
N	19,840	19,840	19,840	19,840	19,840	19,840	19,840	19,840

Table 9: *SLB premium determinants.* Panel A shows the average estimated probability of meeting the ESG target. 'GHG' is the subsample of targets that are related to green house gasses, while 'non-GHG' are all other targets. In Panel B the SLB premium is regressed on explanatory variables. The liquidity controls are $\log(1+TC^{o}_{j,t})-\log(1+TC^{SLB}_{j,t})$, $\log(1+V^{o}_{j,t})-\log(1+V^{SLB}_{j,t})$, and $\log(1+A^{o}_{j,t})-\log(1+A^{SLB}_{j,t})$, where $TC_{j,t}$ is the trade count, $V_{j,t}$ is the volume, and $A_{j,t}$ is the age for ordinary bond (superscript o) j and SLB (superscript SLB) j on day t. Standard error clustered at the bond level are in parentheses, the number of observations in square brackets (in Panel A), and *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

probability of missing the target using information from both historical observations of the KPI as well as current financial data is an interesting topic for future research.

5.4 Are SLBs mispriced?

The existing literature on SLBs finds that they are mispriced. Kölbel and Lambillon (2023) conclude that the yield difference between on ordinary bond and an SLB issued by the same issuer exceeds the maximum potential penalty (expressed in yield) that issuers need to pay in case the target is not reached. This implies that even if the market prices an SLB with a probability of one of missing the target, the SLB price is higher than that of an ordinary bond with same (ordinary and penalty) coupons and SLBs are overpriced. In contrast Berrada *et al.* (2022) find that SLBs trade at lower prices than ordinary bonds on average, i.e. SLBs are underpriced on average.[15]

We revisit these conflicting results by relying on a mispricing measure similar to that proposed by Berrada *et al.* (2022). For a given bond at time t the measure is given as:

$$Mispricing_t = \frac{P_t^{SLB} - P_t^o}{O_t^{UB}} \tag{42}$$

Where P_t^{SLB} is the SLB price, P_t^o is the price of an ordinary non-ESG bond given in equation (11), and O_t^{UB} is the upper bound in equation (14). If the mispricing measure is greater than one, the SLB price premium is greater than the sum of all penalties and the SLB is overpriced. If the measure is less than zero, the SLB premium is negative and the SLB is underpriced. For values between zero and one there is no mispricing.

Table 10 Panel A shows summary stats for the variables used in calculating the mispricing measure. The average ordinary bond price is 90.93 while the average sustainium-only bond price is 90.99 (i.e. an average sustainium of 1.28bps in yield space documented in Section 5.2 translates into 6bps in price space). The SLBs have a price that is on average \$0.58 higher for a face value of \$100 than an ordinary bond. We test if there is mispricing in Table 10 Panel B. The table shows that without liquidity controls the average SLB price premium is significantly higher than zero and significantly below the upper bound. The SLB price premium reduces when controlling for bond liquidity, but the conclusion that there is no statistical evidence for mispricing remains.

Figure 4 shows the mispricing measure over time. The figure shows that there are periods in 2022–2023 where the mispricing measure is less than zero, but the underpricing is short and

[15] Berrada *et al.* (2022) also finds that a subset of SLBs are overpriced.

Panel A: Average prices		
	Mean	
$P^{o}_{j,t}$	90.93	
$P^{SUS}_{j,t}$	90.99	
$P^{SLB}_{j,t}$	91.51	
Panel B: Mispricing test		
SLB price premium	0.58***	-0.01
	(0.18)	(0.15)
UB - SLB price premium	0.46***	1.04***
Liquidity controls	No	Yes
N	19,840	19,840

Table 10: *Mispricing.* Panel A shows the average estimate of the ordinary bond $P^{o}_{j,t}$ in equation (11), the "sustainium bond" $P^{SUS}_{j,t}$ in equation (9), and the observed bond price $P^{SLB}_{j,t}$. Panel B shows if the SLB premium is significantly different from the upper bound of the option value as well as zero (in which case $P^{SLB}_{j,t} = P^{o}_{j,t}$). There are 19,840 bond-day observations and standard errors are clustered at the bond-level and *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

statistically insignificant. In the last part of the sample, the mispricing measure is slighly greater than one, but again the distance to the mispricing bound of one is statistically insignificant. Overall, we find no evidence that SLBs are mispriced.

Why are our results different from the existing literature? First, Berrada *et al.* (2022) and Kölbel and Lambillon (2023) focus on pricing of SLBs in the primary market, while we focus on pricing in the secondary market. Second, and perhaps more importantly, our matching procedure is different from theirs. Kölbel and Lambillon (2023) compare the yield-at-issuance of an SLB with the yield-at-issuance with an ordinary bond issued by the same firm with the closest issue date, maturity and issue size. On average, the issuance date of the SLB is 528 days later than the ordinary bond in their sample and this difference is likely to introduce systematic noise due to changes in macro-economic variables such as interest rates and macro-economic uncertainty. For example, the average issuance date of the ordinary bonds in their matched sample is March 2020 – when Covid shocked markets – while the average issuance date of the SLBs is September 2021, a significantly more calm period. This may explain why they find a "free lunch", i.e. that the prices of SLBs are so high that on average the mispricing measure is higher than one. Berrada *et al.* (2022) discount SLB cash flows without the penalty with sector curves estimated using bonds with the same rating issued by firms in the same industry and find that on average SLB prices are lower, i.e. a mispricing measure lower than zero. Within a rating category there is a wide range

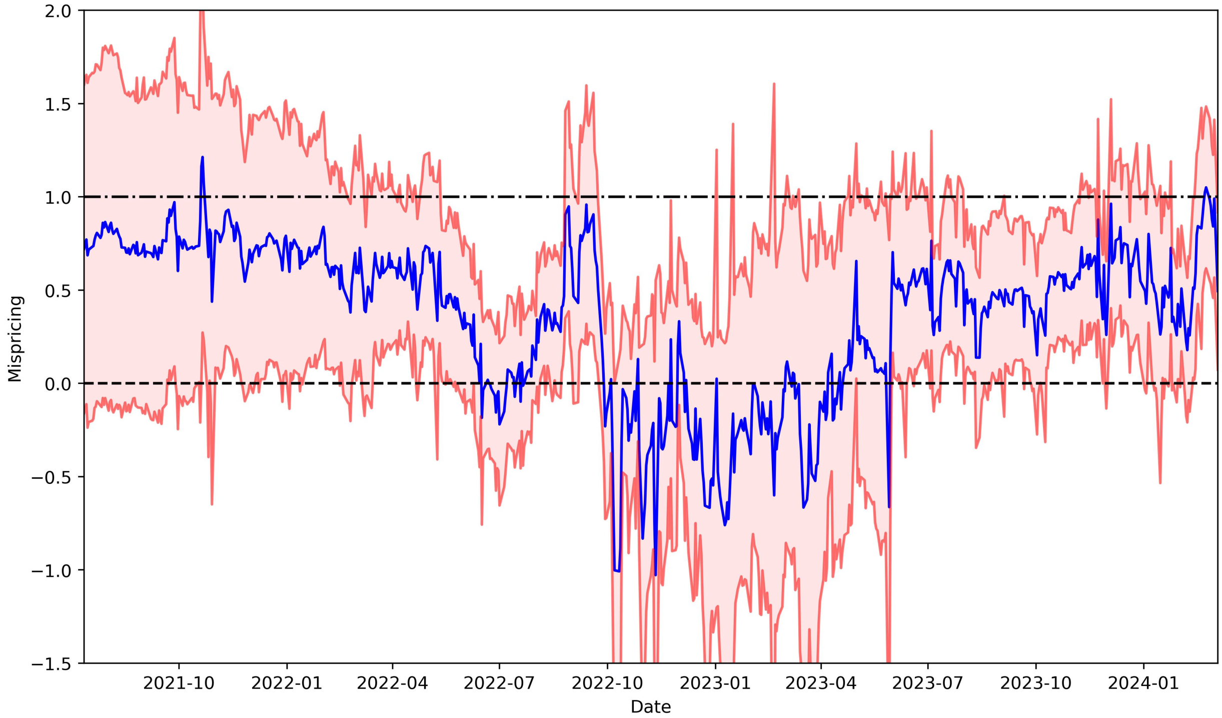


Figure 4: *Mispricing.* The figure shows the time series variation of the mispricing measure for the SLB premium. On each day in the sample where we have at least ten observations we compute the mispricing measure as the average SLB premium on that day divided by the average upper bound on the same day and the figure shows the time series variation.

of yields and the sector curve yield might therefore not reflect the yield of the SLB issuer with sufficient accuracy, leading to a noisily estimated mispricing measure. In contrast, our approach carefully matches the secondary market SLB yield with an interpolated yield from non-SLB bonds with similar maturity from the same issuer on the same day, leading to more precise estimates.

5.5 ESG risk premium

The SLBs in our sample span a range of distinct ESG targets and some may command a risk premium. Since targets related to emission of greenhouse gasses are most common we separate them into GHG and non-GHG. It is not clear if there is a GHG risk premium and if so what sign it is expected to have. On one hand emissions of GHGs contribute to global warming and if there is a global lack of coordination in reducing GHGs, emissions increase more than expected resulting in increased risk of states with low consumption due to climate disasters. In this case, the embedded options in SLBs are a hedge against climate risk because the firm is more likely to miss the target in such bad states of the world, leading to extra bond cash flows, and SLBs have a negative risk premium. On the other hand high economic activity may result in large emissions of GHGs which in turn make it more likely that the SLB option ends in the money. Here, the option pays of in a good state of the world – in terms of consumption – and investors may require a positive risk premium.[16]

Since we are interested in the risk premium related to cash flow risk, we estimate the risk premium as the expected value of the optional cash flows minus the market price of those cash flows as outlined in Section 3.2. Table 11 Panel A shows the average ESG risk premium and we see that the point estimates are mostly negative, and statistically significant in some specifications, consistent with the embedded option being a hedge against ESG risk. However, when we focus on SLBs with GHG targets, the average risk premium is statistically insignificant and the sign is not consistently negative, suggesting that the negative risk premium is not due to hedging of climate risk. For non-GHG SLBs the risk premium is significantly negative in some specifications. The non-GHG targets include a range of different ESG areas and this suggests that ESG risks unrelated to climate change are priced.[17]

Turning to determinants of the risk premium, Panel B shows that there is no significant relation between the ESG risk premium and risk premiums in general – as measured through the VIX. The only firm characteristics that have significant explanatory power for the risk premium across specifications is equity volatility and a higher equity volatility implies a more negative ESG risk premium.

[16] See Giglio *et al.* (2021) for an extensive review.

[17] Besides those mentioned in Section 2, examples include number of electric vehicle charging points installed in managed infrastructure (Abertis), reduction in the amount of packaging placed on the market (Carrefour), increasing amount of recycled plastic usage (Hera), increase patient outreach/access (Novartis), and reducing industrial water withdrawal intensity (Suzano).

Panel A: ESG risk premium						
	All	GHG	non-GHG			
Same	-0.22	0.03	-0.63			
	(0.19)	(0.17)	(0.41)			
Stronger	-0.41**	-0.14	-0.85**			
	(0.20)	(0.18)	(0.41)			
Stronger & Focused	-0.42**	-0.15	-0.86**			
	(0.20)	(0.18)	(0.41)			
N	[19,840]	[12,354]	[7,486]			
Panel B: Determinants of the ESG risk premium						
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-7.57	-7.17	-7.12	-2.99	-2.39	-2.34
	(6.52)	(6.77)	(6.77)	(5.18)	(5.40)	(5.40)
VIX	2.01	1.89	1.94	1.97	1.86	1.91
	(1.31)	(1.34)	(1.35)	(1.34)	(1.35)	(1.35)
Log(size)	0.25	0.22	0.22	0.17	0.13	0.13
	(0.36)	(0.37)	(0.37)	(0.30)	(0.31)	(0.31)
Equity Vol	-0.75**	-0.77**	-0.77**	-0.67**	-0.68**	-0.68**
	(0.35)	(0.36)	(0.36)	(0.31)	(0.31)	(0.31)
Leverage	-0.88	-0.94	-0.96	0.58	0.60	0.58
	(1.30)	(1.34)	(1.35)	(1.38)	(1.43)	(1.43)
Profitability	5.73	5.81	5.80	3.10	3.08	3.08
	(4.09)	(4.14)	(4.13)	(3.53)	(3.57)	(3.56)
Tobin's q	1.06	1.16	1.16	1.57**	1.69**	1.69**
	(0.84)	(0.87)	(0.88)	(0.79)	(0.81)	(0.81)
Industry-adj ESG Rating	-0.26	-0.25	-0.25	-0.15	-0.14	-0.15
	(0.18)	(0.18)	(0.18)	(0.14)	(0.14)	(0.14)
ESG rating	0.74	0.71	0.71	0.38	0.34	0.34
	(0.56)	(0.56)	(0.56)	(0.46)	(0.46)	(0.46)
Credit rating	0.14	0.13	0.13	-0.08	-0.10	-0.10
	(0.22)	(0.23)	(0.23)	(0.21)	(0.21)	(0.21
Liquidity controls	No	No	No	Yes	Yes	Yes
R^2	0.08	0.08	0.08	0.18	0.19	0.19
N	19,840	19,840	19,840	19,840	19,840	19,840

Table 11: *ESG risk premium.* Panel A shows the average ESG risk premium given in equation (16). 'GHG' is the subsample of targets that are related to green house gasses, while 'non-GHG' are all other targets. If an SLB has multiple targets, it is included in the GHG sample if all options are GHG related, else it is included in the non-GHG sample. Panel B shows regressions with the ESG risk premium on the lefthand side. The credit rating variables measures the bond's credit rating and takes the value 1 for AAA, 2 for AA+, 3 for AA, ..., 21 for C. The liquidity controls are $\log(1+TC^{o}_{j,t})-\log(1+TC^{SLB}_{j,t})$, $\log(1+V^{o}_{j,t})-\log(1+V^{SLB}_{j,t})$, and $\log(1+A^{o}_{j,t})-\log(1+A^{SLB}_{j,t})$, where $TC_{j,t}$ is the trade count, $V_{j,t}$ is the volume, and $A_{j,t}$ is the age for ordinary bond (superscript o) j and SLB (superscript SLB) j on day t. Standard error clustered at the bond level are in parentheses, the number of observations in square brackets (in Panel A), and *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively. Regressions (1) and (4), (2) and (5), and (3) and (6) use the ESG premium as calculated with the same, stronger, and stronger & focused commitment assumptions, respectively.

6 Conclusion

A major issue in global financial markets is how to speed up the shift to a greener and more socially inclusive economy. Aligning financial incentives of companies with ESG incentives is a critical component of the solution, and sustainability-linked bonds (SLBs) have recently emerged as a class of securities that can support such alignment. Because SLB cash flows are directly linked to achieving future ESG goals, they encourage issuing companies to take ESG-conscious actions.

Financial market practitioners, regulators, NGOs and academics are concerned that SLBs do not work as intended. Firms may chose easy targets that reflect "business-as-usual" and the ESG-related option element may be difficult to price and the bonds overpriced. If this is the case, SLBs will not work as intended and may even hinder firms' transition to a greener economy. We provide a flexible theoretical framework for pricing SLBs that include credit risk, investor preferences for sustainable securities, the likelihood that the firm will fulfil the target and the penalty size in order to analyze these important concerns.

SLB cash flows are identical to cash flows of an ordinary fixed-rate bond plus ESG-linked cash flows that only pay out if a combination of ESG targets are not reached. Absence of mispricing requires that the value of the ESG-linked cash flows is greater than zero but less than the sum of potential cash flows. Empirically, we find that SLBs on average satisfy these "no-mispricing" bounds, in contrast to existing literature. Also, we find that the value of the ESG option embedded in SLBs is strongly related to the size of the penalty. Overall, our empirical results indicate no mispricing.

We also find that firms set targets that are easy to reach: the average probability of meeting the target in our sample period is 61-86%. Furthermore, we find that investors are willing to accept a 1–2bps lower yield due to SLBs ESG label, providing new empirical evidence showing that impact investing matters for asset prices. Finally, we estimate the ESG premium as the expected value of the potential penalty minus the extracted market price. The ESG premium is negative, and statistically significant under some assumptions, providing evidence that SLBs can be used as financial hedges against ESG risk.

7 Appendix

7.1 Data

In this Appendix we discuss in more detail how we clean the data.

Bloomberg

Bloomberg has several data sources available and we prioritise the data sources in the order: 'CBBT', 'BGN', 'BMRK', and 'BVAL'. That is, for a given bond-day, we extract price and yield spread information from CBBT, and if there is none, we try BGN, and so on. We use Bloomberg's I-spread as yield spread, which uses the relevant swap rate in the same currency as the bond when calculating the spread.

Propellant

The Propellant data used in the paper covers transactions from: Bloomberg, London Stock Exchange, Marketaxess, Tradeecho, Tradeweb, Tradition, and Liquidnet. We clean the Propellant data the following way:

1. Multiple amended trades ('AMND' = True) point to the same 'ORIGINAL_TRANSACTION_IDENTIFICATION_CODE', so we only keep the last amended trade for a given 'ORIGINAL_TRANSACTION_IDENTIFICATION_CODE' and drop any amended trades without one.
2. Drop trades without any 'TRADING_DATE_AND_TIME' and 'PRICE' information.
3. Drop cancelled trades ('CANC' = True).
4. Drop all observations that are not in the percentage of par price format ('PRICE_NOTATION' $\neq$ 'PERC').
5. Drop entries with extreme prices (below 10 and above 1,000). These are mostly due to wrong price information due to a misplaced decimal point.

6. There is no volume cap in the Propellant data set, however, since there is a volume cap on TRACE data of 5,000,000, we impose the same cap on the Propellant data for comparability.

Table A1 below shows the amount of transactions that are removed at each step of the cleaning process described above.

Cleaning Step	# of Transactions Removed	# of Transactions Remaining
Uncleaned Data	-	382,766
Step 1	2,723	380,043
Step 2	65,199	314,844
Step 3	4,891	309,953
Step 4	9,479	300,474
Step 5	188	300,286
Step 6	-	300,286

Table A1: *Cleaning process of the Propellant data set.* This table shows the number of transactions that are removed at each step of the cleaning process, as well as how many transactions remain afterwards. The description of each step can be found in the text.

Final Sample

To arrive at the final sample used in our empirical analysis, we first discard all SLB bond-days after the bond's first option target date. Next, we remove SLB bonds from the sample if there are less than 20 bond-day observations for the bond. Also, we discard a bond-day if we are not able to calculate the price of an ordinary bond ($P_{j,t}$), the price of a sustainium bond ($P_{j,t}^{SUS}$), and – for the SLBs with ESG-linked coupons – the physical option value $\sum_{j=1}^{K}\sum_{i=1}^{N_j} S_i^j E_t^P\left[1_{\{G_{T_j}>K\}}\right] D(r_{t,T}, \lambda_t, \omega_t, t_i^j)$. In particular, this implies that we can compute the firm characteristics $X_{j,t}$ in equation (29) on day t for the firm issuing bond j and we have at least three historical observations of the ESG factor such that we can calculate $E_t^P\left[1_{\{G_{T_j}>K\}}\right]$. For sustainium-only bonds, we require that we can compute the firm characteristics $X_{j,t}$ in equation (29) on day t for the firm issuing bond j. Finally, we exclude the bond with Bloomberg ticker 'BS422627 Corp' because the bond prices in Bloomberg are not consistent with the reported yield-to-maturity.

Calculation of Firm Characteristics

Since we are dealing with a sample of global firms, we use Compustat to gather both price and accounting data. This requires finding the unique GVKEY of each firm in our sample, which has been done manually. All accounting data has been lagged 3 months to avoid look-ahead bias. Furthermore, all accounting data have been converted to USD by following the "*Currency Translation*" guide provided by Compustat. The following list details the calculation of the eight firm characteristics used in Section 5 of the paper:

1. **Log(Size):** $\log(E_{it}^M)$, where E_{it}^M is the market value of equity calculated as "*Common Shares Outstanding*" times "*Price - Close - Daily*" for firm i at time t.

2. **Equity Volatility:** $\sqrt{\frac{1}{21}\sum_{t=1}^{21}(r_{it}-\bar{r}_i)^2}$, where r_{it} is the equity return of firm i at time t and $\bar{r}_i$ is the average equity return over the past 21 days for firm i. Returns are calculated using the daily prices from Compustat, adjusted for dividends and stock buybacks/issuance/splits.

3. **Leverage:** $\frac{D_{it}^S+D_{it}^L}{E_{it}^M+D_{it}^S+D_{it}^L}$, where D_{it}^S and D_{it}^L is "*Debt in Current Liabilities*" and "*Long-Term Debt - Total*", respectively.

4. **Profitability:** $\frac{R_{it}-C_{it}}{A_{it}}$, where R_{it}, C_{it}, and A_{it} is "*Revenue - Total*", "*Cost of Goods Sold*", and "*Assets - Total*", respectively.

5. **Tobin's Q:** Defined as $\frac{E_{it}^M+L_{it}^M}{E_{it}^B+L_{it}^B}$, where E and L refer to the equity and liabilities values of the firm, respectively, while the superscripts M and B indicates the market and book values, respectively. Because we do not have data on the total market value of a firm's liabilities, we let $L_{it}^M = L_{it}^B$. The book value of equity, E_{it}^B, is calculated as "*Stockholder's Equity*" plus "*Deferred Taxes and Investment Tax Credit*" minus "*Preferred/Preference Stock (Capital) - Total*". Missing values of "*Stockholder's Equity*" and "*Preferred/Preference Stock (Capital) - Total*" are set to 0 and equity book values below 0 are set to 0. The book value of liabilities, L_{it}^B, is "*Liabilities - Total*". Finally, the variable is scaled by dividing with 100.

6. **Credit Rating:** Extracted manually from Bloomberg and converted to a numerical value such that a higher number corresponds to a lower credit rating, i.e. $AAA = 1$, $AA+ = 2$, ..., $C = 21$.

7. **ESG Rating:** Numerical ESG rating extracted from MSCI. Values are between 0 and 10 with a higher number corresponding to a more green and sustainable firm.

8. **Industry-Adjusted ESG Rating:** Numerical (industry demeaned) ESG rating extracted from MSCI.

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