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Three Essays in Empirical Asset Pricing

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Résumé

Cette thèse est composée de trois articles sur l'évaluation empirique des actifs. Elle explore une variété de sujets financiers à travers des analyses approfondies et des données empiriques. Chaque article éclaire différents aspects des marchés financiers, offrant de nouvelles perspectives et remettant en question les paradigmes existants.

Le premier article, "Le Prix du Levier des Intermédiaires Financiers", est co-écrit avec Valeri Sokolovski. Dans cette étude, nous utilisons un ensemble de données complet sur la structure du capital de dette de Capital IQ pour explorer la structure des passifs des principaux négociants agissant en tant que contreparties de la Réserve Fédérale de New York. Notre analyse révèle des aperçus significatifs de leurs arrangements de dette, et nous utilisons ces découvertes avec des estimations du coût de la dette de divers composants pour développer un facteur de dette intermédiaire. Ces principaux négociants jouent un rôle crucial dans les marchés de capitaux plus larges. Notre facteur de dette construit démontre une capacité prédictive à travers sept classes d'actifs distinctes, à la fois séparément et collectivement au sein d'un portefeuille unifié.

Le deuxième article, "Primes Sociales", est co-écrit avec Iwan Meier, Valeri Sokolovski et Hoa Briscoe-Tran. En analysant les scores sociaux MSCI, nous avons découvert que les éléments principaux du score social d'une entreprise—le capital humain et la sécurité des produits—présentent des effets statistiquement significatifs mais opposés sur les rendements parmi les actions américaines. En détail, les entreprises avec des scores élevés en capital humain voient des rendements plus élevés, tandis que celles avec des scores élevés en sécurité des produits connaissent des rendements plus

faibles. En conséquence, le score social global n'offre pas de prime de rendement car les impacts contradictoires de ses composants s'annulent mutuellement. Cette constatation pose un défi à la stratégie d'investissement ESG typique, qui fusionne souvent des facteurs sans aborder leurs implications individuelles et parfois opposées pour le risque et le rendement.

Le troisième article, "Écarts de Crédit des Obligations Souveraines et Activité Économique", examine si les écarts de crédit sur les obligations souveraines des marchés émergents peuvent prévoir la performance économique et les rendements du marché boursier dans ces nations. Il conclut que les écarts de crédit souverains sont des prédicteurs efficaces de l'activité économique et de la performance du marché boursier pour le trimestre suivant. Je décompose les écarts de crédit des obligations en composants de risque de défaut et de prime de risque, et découvre que chaque composant contribue à la prévision de l'activité économique. Notamment, l'aspect de la prime de risque est particulièrement crucial pour prédire les rendements du marché boursier.

Mots-clés

Évaluation des actifs intermédiaires, intermédiation financière, levier, contraintes financières, ESG, MSCI, prévisibilité des rendements, primes de risque, scores sociaux, écarts de crédit, activité économique, prévision, marchés émergents.

Méthodes de recherche

Évaluation des actifs empirique, modèles de facteurs, économétrie.

Abstract

This thesis is composed of three articles in empirical asset pricing. It explores a variety of financial topics through in-depth analyses and empirical data. Each article sheds light on different aspects of financial markets, offering new perspectives and challenging existing paradigms.

The first article "The Price of Financial Intermediary Leverage" is co-authored with Valeri Sokolovski. In this study, we utilize comprehensive debt capital structure dataset from Capital IQ to explore the liability structure of the primary dealers acting as counterparts to the New York Federal Reserve. Our analysis reveals significant insights into their debt arrangements, and we employ these findings along with estimates for the debt cost of various components to develop an intermediary debt factor. These primary dealers play a crucial role in the broader capital markets. Our constructed debt factor demonstrates predictive ability across seven distinct asset classes, both separately and collectively within a unified portfolio.

The second article "Social Premiums" is co-authored with Iwan Meier, Valeri Sokolovski, and Hoa Briscoe-Tran. By analyzing the MSCI social scores, we discover that the principal elements of a company's social score—human capital and product safety—exhibit statistically significant but opposite effects on returns among U.S. stocks. In detail, companies with high human capital scores see higher returns, whereas those with high product safety scores experience lower returns. As a result, the overall social score does not offer a return premium because the conflicting impacts of its components cancel each other out. This finding poses a challenge to the typical ESG

investing strategy, which often merges factors without addressing their individual and sometimes opposing implications for risk and return.

The third article “Sovereign Bond Spreads and Economic Activity” investigates whether the credit spreads on sovereign bonds from emerging markets can forecast economic performance and stock market returns in those nations. It concludes that sovereign credit spreads are effective predictors of both economic activity and stock market performance over the next quarter. I break down the credit spreads of bonds into components of default risk and risk premium, and discover that each component aids in forecasting economic activity. Notably, the risk premium aspect is especially crucial in predicting stock market returns.

Keywords

Intermediary asset pricing, financial intermediation, leverage, financial constraints, ESG, MSCI, return predictability, risk premiums, social scores, credit spreads, economic activity, forecasting, emerging markets.

Research Methods

Empirical asset pricing, factor models, econometrics.

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"مُنًى، إِن تكنْ حقًّاْ تكنْ أحسنَ المُنى وإلّا فقد عِشنا بها زمنًا رَغْدَا "

Having dreams and aspirations adds richness to life, regardless of their outcomes. If they come true, that's wonderful—the realization of our hopes is all we could ask for. But even if they don't materialize, the very act of holding onto these dreams and imagining their fulfillment provides a deep sense of satisfaction and purpose to our lives.

To my parents.

I owe it all to you, only you.

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General Introduction

Across the three articles within this thesis, a common investigative thread is woven, focusing on the predictive powers of financial indicators and their nuanced impacts on markets and investment strategies.

In "The Price of Financial Intermediary Leverage," co-authored with Valeri Sokolovski, we delve into the intricacies of the New York Federal Reserve primary dealers' liability structure. By dissecting the debt capital structure data from Capital IQ, we uncover the details of debt arrangements, allowing us to construct an intermediary debt factor that adeptly forecasts across various asset classes, tying into the larger fabric of the capital markets.

This thread continues in "Social Premiums," where alongside Iwan Meier, Valeri Sokolovski, and Hoa Briscoe-Tran, we tackle the ESG investing sphere by scrutinizing MSCI social scores. We expose the contrasting financial repercussions of human capital and product safety scores, revealing a complex interplay that refutes the oversimplification prevalent in ESG investment strategies, thereby connecting the social score's impact to broader market returns.

Finally, "Sovereign Bond Spreads and Economic Activity" furthers this exploration by testing the predictive capacity of credit spreads from sovereign bonds in emerging markets. The decomposition of credit spreads into default risk and risk premium segments enhances our understanding of their forecasting capabilities, with the risk premium playing a pivotal role, echoing the themes of intricate market dependencies and the forecasting potential introduced in the previous articles.

Collectively, these articles highlight a comprehensive approach to analyzing financial metrics and their interconnected roles in shaping economic and stock market outcomes.

Chapter 1

The Price of Financial Intermediary Leverage

Abstract

Primary dealers who serve as counterparties of the New York Federal Reserve are found to be key players in the entire universe of capital markets. In this paper[1], we use detailed debt capital structure data from Capital IQ to shed light on the liability structure of these big banks. We then use the key insights from our analysis of their debt composition alongside proxies for the cost of debt of the different debt components to construct an intermediary debt factor. We find that our debt factor exhibits explanatory power, beyond existing intermediary factors, for the seven asset classes studied both individually and jointly.

1.1 Introduction

Intermediary asset pricing offers a new perspective for understanding risk premiums. Recent research finds that factors that capture shocks to the aggregate risk-bearing

[1]This paper is joint work with Valeri Sokolovski.

capacity of financial intermediaries are important determinants of expected returns across multiple asset classes (see He & Krishnamurthy, 2018, for a survey). Moreover, intermediary health seems to matter relatively more for exotic assets that households rarely hold directly (Haddad & Muir, 2021). This view stands in contrast to standard consumption-based asset pricing models, which typically focus on households' consumption preferences. Households' comparative lack of expertise in trading assets, especially sophisticated ones like derivatives or commodities, casts doubt on the viability of household marginal utility for jointly pricing the wide array of traded assets in the economy.

In the realm of intermediary asset pricing, a significant challenge is the identification of an appropriate measure for the marginal utility of wealth of intermediaries. Two influential papers, Adrian et al. (2014) and He et al. (2017), offer proxies for this measure, advocating for the use of security broker-dealer leverage and the primary dealers' capital ratio, respectively. While both contributions enhance our understanding of asset prices, they are not without limitations. One primary concern is that both proxies rely on the book value of debt, which is less timely and less reflective of current market conditions than the market value of debt, and is only updated on a quarterly basis due to its derivation from balance sheets. Additionally, the leverage ratio proposed by Adrian et al. (2014) lacks transparency, as it is based on aggregated flow of funds data that encompasses the total financial assets and liabilities of security brokers and dealers, making it difficult to discern the specific entities and debt composition within the sample.

Our paper addresses existing gaps in the literature by making two significant contributions. Firstly, we shed light on debt financing trends among the banks in our sample by utilizing the Capital IQ debt structure dataset. This dataset offers detailed information on debt composition, allowing for a more nuanced analysis of financial strategies. Secondly, we develop an intermediary debt factor that leverages this granular data on debt composition along with corresponding market rates. Unlike previous research, our debt factor is updated on a monthly basis and is grounded in market values, thereby providing a more timely and accurate reflection of the financial landscape. This approach not only enhances the robustness of our analysis but also offers a more precise tool for understanding the dynamics of intermediary asset pricing.

We focus on New York Fed primary dealers given that they are large and sophisticated financial institutions like Goldman Sachs and JP Morgan that operate in virtually all the capital markets. It is natural to focus on these intermediaries as they are active (and hence are likely the marginal investors) in most asset markets. These banks' importance is well-documented in the literature (see, e.g., He et al. (2017), Boyarchenko et al. (2020) and Dahlquist et al. (2023)). All primary dealers in our sample are subsidiaries of large bank holding companies. We follow He et al. (2017) and conduct our analysis on a holding company level rather than on a primary dealer level due to the crucial role of internal capital markets within these conglomerates[2]. For a list of the primary dealers in our sample and their respective holding companies, see Table A1.

We establish key stylized facts about the liability composition of those systemically important banks. Despite the importance of these banks, which has been documented in numerous papers, there has not been any previous attempt to shed light on their debt side. How are these banks financed? What are the differences in debt composition between banks and among regions? We use Capital IQ database to source detailed data on the debt outstanding, such as the amount of principal outstanding, maturity date, interest rate, and different bond characteristics. We report key trends in liability composition, maturity statistics and currency denomination.

Afterwards, we construct an intermediary debt factor using our knowledge of the

[2]Holding companies often use internal capital markets to diversify and allocate financial resources across subsidiaries, meaning that financial shocks or capital needs in one part of the holding company can impact others, regardless of their individual capital positions. The capital ratio of the holding company is considered the economically relevant measure of financial distress because it raises outside equity and distributes it internally, influencing the subsidiaries' operations and stability. Both holding companies and their subsidiaries are subject to regulatory capital requirements, but the holding company's role in raising and allocating equity makes its financial health more critical. Historical evidence from the bankruptcies of Lehman Brothers and Drexel Burnham Lambert illustrates how holding companies manage and redistribute funds among subsidiaries, impacting their financial conditions. The fungibility of capital within holding companies, evident in their liquidity management practices and obligations guarantees, further supports this approach. Empirical evidence suggests that internal capital markets are key to understanding the impact of financial intermediary distress on asset prices, making the holding company level the appropriate focus for analysis.

proportion of the different debt components in the capital structure of our sample of banks and using market-based proxies for the cost of funding of the different debt constituents. We examine the asset pricing ability of our debt factor in a three-factor model alongside HKM intermediary equity returns and the excess returns on the market portfolio from February 2001 to February 2021. We use portfolios from seven asset classes in our tests: US equity, US bonds, sovereign bonds, CDS, options, commodities and FX, both individually and jointly. The price of risk of our intermediary debt factor is significant for all the asset portfolios considered. When all asset classes are examined simultaneously, the price of risk is 4.97% per month. Our debt factor survives the battery of robustness tests that we perform to validate our results. Interestingly, a two-factor model with HKM capital factor and the market factor fails to explain the variation of asset excess returns in our sample.

Related literature The significance of financial institutions in determining equilibrium asset prices has been overlooked by the finance literature until recently. Our paper contributes to a growing body of research on intermediary asset pricing, which focuses on the pricing kernel of financial intermediaries rather than that of households when understanding the pricing behaviour of sophisticated financial assets.

Adrian et al. (2014), AEM thereafter, is the first paper to include financial intermediary balance sheet components in the pricing kernel to conduct cross-sectional asset pricing tests, establishing an explicit relationship between intermediary balance sheets and asset prices. AEM designs an intermediary SDF using shocks to securities broker-dealer leverage. Their results are most closely inline with models in which deteriorating funding conditions are linked to deleveraging and high marginal value of wealth. This is similar to the models proposed by Shleifer and Vishny (1997a), Gromb and Vayanos (2002), and Geanakoplos (2010), and especially to Brunnermeier and Pedersen (2009), who demonstrate how funding liquidity influences the pricing kernel under conditions where investors are risk-neutral and subject to funding constraints. AEM's single-factor model evaluates assets such as size, book-to-market, momentum, and bond portfolios, similar to conventional multi-factor benchmark models that aim to price these assets.

He et al. (2017), HKM thereafter, builds on AEM and expand the approach to include many asset classes. HKM is related to models where the net worth of the intermediary sector (or their equity capital ratio) determines their marginal value of wealth (B. Bernanke & Gertler, 1989a; Brunnermeier & Sannikov, 2014; He & Krishnamurthy, 2012; He & Krishnamurthy, 2013; Holmstrom & Tirole, 1997). When an intermediary's equity capital is negatively impacted, its risk-bearing capacity is diminished, causing a rise in its utility from an additional dollar of equity capital. HKM calculates the intermediary capital ratio as the aggregate value of market equity divided by the sum of the aggregate market equity and the aggregate book debt of primary dealers at the bank-holding-company level. HKM empirically shows that the intermediary capital factor has significant explanatory power for the cross-sectional variation in expected returns in the seven asset classes studied: equities, US bonds, sovereign bonds, equity options, credit default swaps, commodities, and foreign exchange, using a two-factor model consisting of the intermediary capital factor and the stock market return.

What is surprising is that AEM and HKM have conflicting findings. In contrast to HKM, that finds evidence for counter-cyclical leverage and a positive price of intermediary capital risk, AEM finds evidence for pro-cyclical leverage and a positive price of intermediary leverage risk. These results are inconsistent because leverage should simply be the inverse of the capital ratio, and as a result, risk prices should also be inverted. On the other hand, macro-finance models can provide either outcome depending on whether the intermediary has a debt or equity constraint.

Adding to this debate, Ma (2018) and Kargar (2021) explore the role of heterogeneous intermediaries in asset pricing. Ma introduces a model that accounts for differences in intermediaries' risk appetites and their impact on asset prices, suggesting that the conflicting results between AEM and HKM could be due to the oversimplification of treating intermediaries as a homogeneous group. Kargar extends this line of research by providing empirical evidence that the diversity among intermediaries leads to a wide range of asset pricing behaviors, helping to explain the seemingly contradictory findings of AEM and HKM. Both studies underscore the importance of considering the diversity among financial intermediaries and how it influences equilibrium asset prices, offering new insights that complement and challenge the existing literature.

Further contributing to the intermediary asset pricing discourse, Haddad and Muir (2021) investigates the significance of intermediaries in aggregate asset prices. The study takes an innovative approach by averaging the factors used in AEM and HKM, providing a unified measure that captures the essence of intermediary-based asset pricing. Their analysis reveals that intermediary factors, when combined, hold substantial explanatory power for aggregate asset prices. This finding underscores the critical role intermediaries play in shaping the pricing dynamics of financial markets and offers a reconciliatory perspective between the divergent results of AEM and HKM. Haddad and Muir's work highlights the importance of considering the aggregated impact of intermediary factors in understanding the complex interplay between financial intermediaries and asset prices.

Building on the growing body of research on intermediary asset pricing, Baron and Muir (2022) provides a historical perspective by examining the role of financial intermediaries in asset pricing from an international standpoint since 1870. Their study highlights the persistent influence of intermediaries on asset prices over a long time frame and across different countries. By analyzing data spanning over a century, they offer compelling evidence that the pricing behavior of financial assets is closely tied to the health and dynamics of the intermediary sector, reinforcing the significance of intermediaries in determining equilibrium asset prices. This historical analysis further supports the notion that the intermediary-based asset pricing framework is robust and applicable across various market conditions and periods.

In addition to papers that study the link between intermediary balance sheet and asset prices, other papers take a more focused approach by providing evidence that financial intermediaries matter for specific asset prices at specific points in time. Du et al. (2018) provides evidence linking changes in Covered Interest Rate Parity (CIP) deviations to intermediation capital frictions. It points out that some banks' capital requirements are based on a snapshot of their balance sheets at the end of each quarter. As a result, capital requirements are tighter at the end of each quarter compared to the days before and after. According to the authors, the CIP deviation widens towards the end of each quarter, indicating capital tightness. The evidence for intermediary asset pricing is fairly strong, as these patterns are difficult to reconcile with other theories incorporating household risk preferences. Du et al. (2019) propose the size of the CIP violations as a priced factor across various asset classes.

Fontaine et al. (2020) explore the interaction between shocks in funding conditions and leverage constraints in financial intermediaries. They identify two types of leverage shocks: supply shocks, which relax funding constraints and improve market liquidity, and demand shocks, which tighten funding constraints and worsen liquidity. These shocks have opposite effects on financial markets, with supply shocks carrying a positive price of risk and demand shocks carrying a negative price of risk. The study highlights that disentangling these shocks strengthens the evidence for intermediation frictions in asset pricing and resolves some existing puzzles. This nuanced understanding underscores the importance of considering both supply and demand shocks in models of intermediary asset pricing, as they have distinct implications for market liquidity and asset returns.

Building on this comprehensive overview of intermediary asset pricing, our paper makes unique contributions that address specific gaps in the current literature. While previous studies have primarily focused on balance sheet components and intermediary capital ratios to understand asset pricing dynamics, our work introduces an innovative approach by analyzing debt financing trends using the detailed Capital IQ debt structure dataset. This allows for a deeper and more nuanced understanding of financial strategies employed by banks in our sample. Additionally, by developing an intermediary debt factor that is updated monthly and grounded in market values, our study offers a more precise and timely reflection of the financial landscape. Our approach not only enhances the robustness of asset pricing analyses but also provides insights that are more aligned with the rapidly changing financial markets. Importantly, while Brunnermeier and

Pedersen (2009) employed leverage constraints in their model, existing empirical factors overlook the market price of leverage which is crucial in this context, a gap our monthly-updated debt factor addresses. By integrating these detailed debt composition metrics into our pricing models, we not only fill a gap in the literature but also introduce a tool that significantly improves the predictive accuracy of financial intermediary behaviors in asset pricing. This contribution is particularly valuable given the conflicting findings of previous studies, such as those by AEM and HKM, which highlight the need for more refined and dynamic modeling approaches to better capture the complexities of intermediary finance and its impact on market valuations.

This paper is organized as follows: Section 1.2 describes the data, Section 1.3 presents the intermediaries debt stylized facts, Section 1.4 elaborates on the methodology and asset pricing results, Section 1.5 performs some robustness checks and finally Section 1.6 concludes.

1.2 Data

In this section we describe the data used in this paper. We first describe the data we source from Capital IQ database, then we talk about repo rates, LOIS spreads and bond discount rates. Finally, we describe the factors used in our model as well as our sample of test asset portfolios.

1.2.1 Capital IQ

We source our data from Standard & Poor's Capital IQ capital structure debt database, which we access via WRDS. We use this data set for the debt stylized facts in Section 1.3 and to guide the construction of our intermediary debt factor in Section 1.4.1. The database provides information on debt structure on both an annual and interim basis (semi-annual or quarterly) for thousands of public and private U.S. and non-U.S. companies. Financial reports filed with the SEC are Capital IQ's major source of data. Other sources, such as press releases and corporate websites, are also used by Capital IQ. We focus on data for the primary dealers listed in Table A1 from the beginning of 2000 to the end of 2020, even if some banks were not primary dealers during the whole period. We exclude banks that were primary dealers for only a short period, such as MF Global, Countrywide, and SG Cowen. On the one hand, we do not want to lose a lot of data and on the other hand, we wish to avoid causing unwarranted noisiness to our stylized facts by including banks that were primary dealers for short periods of time. In addition, we add banks that no longer exist such as Bear Stearns, Lehman Brothers and Merrill Lynch because they were the key primary dealers in the period before the crisis. Capital IQ aggregates all components of debt in the capital structure of firms and provides many helpful variables such as: the end date of the financial reporting period, detailed description of the debt issue, debt issue type, principal due, the currency of issuance, maturity date, interest rate, interest rate type (fixed, variable or zero-coupon), seniority level, secured type and convertible type. There are duplicated observations in some circumstances; a debt issue can occur numerous times on the same filing date with distinct issue identifiers. To address duplicate observations, we clean the data. First, when there are several filings for a given filing date, we use the latest available filings for a debt issue. Next, we identify duplicate debt items using several criteria: the end date of the financial reporting period, unique ID of the debt issue, detailed description of the debt issue, principal due, maturity, and interest rate. We then delete redundant items. Furthermore, only observations with a positive implied remaining maturity of the debt issue (Maturity Date less End Date of the Financial Reporting Period > 0) are kept. Using the variables Issue Type and Issue Sub-Type, we classify individual debt issues into 8 debt categories: commercial paper, revolving credit, term loans, bonds and notes, capital leases, trust preferred, repos and other borrowings.

1. Commercial paper: Contains commercial paper.

2. Revolving credit: Contains bank overdraft, bills payable, federal funds purchased, federal reserve bank borrowings, federal reserve facility, letter of credit outstanding,

revolving credit and revolving credit facility.

3. Term loans: Contains bank loans, term loans, FHLB borrowings and mortgage loans.

4. Bonds and notes: Contains bonds and notes, debentures, mortgage bonds, mortgage notes and notes payable.

5. Capital leases: Contains capital leases.

6. Trust preferred: Contains trust preferred securities.

7. Repos: Contains securities sold under agreement to repurchase and securities loaned.

8. Other borrowings: Contains other borrowings, general borrowings and securitization facility.

A debt instrument is defined as an obligation that Capital IQ reports separately for a company on a specific date. For example, a bond issued in 2000 that is still outstanding in 2005 is recognized as 5 different debt instruments. Using this counting procedure, the 27 primary dealers in the sample have a total of 30,874 debt instruments outstanding during the sample period. Capital IQ often groups debt of identical sub-types issued by the same firm and due on the same date as one entry, leading to understating the actual number of debt instruments. When that's the case, the maturity date and interest rate are specified as ranges.

In addition, Capital IQ has a debt category labeled "other borrowings" which often aggregates a large collection of individual debt items. We use "detailed description of debt issue" variable to comprehend what "other borrowings" category constitutes. We find that it constitutes preferred securities, short-term borrowings, current portion of long-term debt, non-recourse debt issued by consolidated VIEs, balances arising from off-balance sheet financial instruments, OTC debt instruments, structured debt, payables, call money and subsidiaries debt. So other borrowing is mainly short-term borrowings with a median remaining time to maturity of 1.5 years.

1.2.2 Repo Rates

Banks and other financial institutions rely on repurchase agreement "repo" markets as one of the vital sources of secured financing. A repo is the sale of a security with an agreement to repurchase it at a pre-specified, usually higher, price in the future. The percentage difference between the buying and selling prices is known as the repo rate. From the standpoint of the cash lender, this transaction is a called a reverse repo. In essence, a repo is a form of collateralized loan in which the cash borrower posts a security as a loan collateral. Hence, the repo can be viewed as an outflow of securities and an inflow of cash, and the reverse repo can be viewed as an inflow of securities and an outflow of cash.

Copeland and Martin (2021) mention that securities dealers are key players in the repo market and that they use repos for two main reasons: as a source of short-term funding and for market-making activities. To achieve their goals, securities dealers are active in both segments of the repo market: the bilateral repo market and the tri-party/general-collateral repo market. In a bilateral repo, the cash-borrower and the cash-lender negotiate the terms of the agreement (repo rate, agreement duration, types of collateral, etc). In contrast, a tri-party repo involves a custodian bank that acts as an intermediary, providing settlement and collateral management services. Hence, Copeland and Martin (2021) assert that the tri-party repo market enables securities dealers to manage counterparty risk which is a major concern for funding activities. Conversely, the bi-party repo market is more suitable for market making activities as well as for funding.

In our analysis, we obtain repo rates for the various countries under study from multiple sources to ensure data quality. We use the repo rate on the general collateral funding in local currency using government bonds and bills as collateral for the repurchase transactions.

Ideally, we would use the one-year repo rate, as the median remaining time to maturity of the repo holdings of the banks in our sample is approximately one year. We use the one-year repo rate whenever it is available, otherwise we use the overnight repo rate. For the US, the UK and Euro area, we use the one-year repo rates from Datastream. For Japan, we use the overnight repo rate from Bloomberg. For Canada, we use the overnight repo rate from the Bank of Canada. Figure 1.3 plots repo rates per country: Canada, the United States, Japan and Europe (which is an average of the repo rates of the Euro area and the UK). Table A2 Panel A shows the repo rates correlation matrix.

1.2.3 LOIS Spread

The Libor-OIS spread is the difference between the London Interbank Offered Rate (Libor) and the Overnight Index Swap (OIS) rate. Libor measures the marginal funding costs of banks, while the OIS rate is a proxy for the risk-free rate. LOIS directly gauges the aggregate funding costs for the banking sector. LOIS is an excellent proxy for market-wide funding conditions, as banks, acting as primary dealers, pass on unfavorable funding circumstances to their clients. As noted in Andersen et al. (2019), this is particularly concerning for over-the-counter instruments. These instruments rely heavily on dealer intermediation and, as a result, require substantial dealer funding.

We source 3-months LOIS data from Bloomberg for the following currencies: USD, CAD, JPY, EUR and GBP.[3] Figure 1.4 plots LOIS spreads per country: Canada, the United States, Japan and Europe (which is an average of the Euro and the GBP LOIS spread). Table A2 Panel B shows the LOIS spread correlation matrix.

1.2.4 Bond Discount Rate

We compute bond discount rates for our sample of banks as the yield of the long-term government bond plus the bank's CDS spread. We obtain bond yield data from

[3] Here are the Bloomberg codes: .EOLIBOIS G Index, .USLIBOIS G Index, .JPLIBOIS G Index, .UKLIBOIS G Index, .CALIBOIS G Index

Bloomberg. We use the 5-year generic bond yield of the governments where the parent company of each bank in our sample is located.[4]

We obtain CDS data from Markit, which sources daily price information of thousands of credit instruments from leading market participants. Markit then constructs daily composite quotes that reflect the average CDS spreads provided by major market participants after applying filtering criteria that remove outliers, stale prices and flat curves. This dataset provides various information about the CDS contracts, such as; restructuring clauses, currency, maturity, liquidity, rating and recovery rates.

We use a sample of daily CDS for our primary dealers covering the period from January 2001 to February 2021. We use five-year maturity CDS contracts because they are the most liquid. We only include contracts written on senior unsecured debt obligations to avoid biases resulting from differences in the seniority of the underlying issues. In addition, to maintain uniformity in the contracts, we only use CDS contracts that are denominated in USD.

CDS contracts also differ by the type of restructuring clause. Four types of restructuring clauses (doc clauses) were defined under the International Swap and Derivative Association "ISDA" 2003 credit definitions: Cumulative Restructuring (CR), Modified Restructuring (MR), Modified-Modified Restructuring (MM), and No Restructuring (XR). These definitions serve to guide the pricing of these contracts. In 2014, credit definitions were modified and as a result four additional doc clauses emerged: CR14, MR14, MM14 and XR14.

A regional breakdown of the CDS contracts of our sample of primary dealers shows that certain types of restructuring clauses prevail in different countries: Cumulative Restructuring in Japan, Modified-Modified Restructuring in Europe and the U.K. and Modified Restructuring in North America. As a result, we use this observation to guide our choice of which restructuring clause to use for every region in our sample.

Figure 1.5 plots the average bond discount rates per country: Canada, USA, Japan

[4] Here are the Bloomberg codes: GECU5YR Index, USGG5YR Index, GTCAD5YR Corp, GTGBP5YR Corp, GTJPY5YR Corp, GTDEM5YR Corp, GTCHF5YR Corp, GTFRF5YR Corp.

and Europe (which includes France, Germany, Switzerland and the UK). Table A2 Panel C shows the bond discount rates correlation matrix by country. Figure A8 plots the correlation matrix of bond discount rates of all banks in our sample.

1.2.5 Factors and Test Assets

In this section we describe the factors and test assets that we use in our empirical tests. The factors used are HKM intermediary wealth returns and the excess returns on the market portfolio. Following HKM, our test asset portfolios comprise seven asset classes.

The Market Factor To construct the market factor, we use data of the returns on the market portfolio and the risk-free rate that are available through Ken French's website. The Market factor is originally from CRSP, and the risk-free rate is the 1-month t-bill and is due to Ibbotson and Associates, Inc. The market factor we use differs slightly from the one used in HKM, even though both rely on Ken French data. This difference is due to a change in the calculation of market return in October 2012.

The HKM Intermediary Wealth Returns In our asset pricing tests, we incorporate the intermediaries equity return factor. This factor, known as 'intermediary value-weighted investment return,' is sourced from HKM and downloaded from Asaf Manela's website. We believe that detangling the equity and debt components of the capital ratio helps gain more insight on what drives the explanatory power of HKM capital risk factor of the variation in the excess returns of the different asset classes studied.

Test Assets In our asset pricing tests, we follow HKM and make use of test portfolios spanning multiple asset classes. This is essential given that in some markets, frictions can be more pronounced than in others. It is reasonable to assume that intermediaries have a larger effect in asset markets that are more intermediated. The asset portfolios that we use in our tests are equity, US government and corporate bonds, sovereign bonds, options, foreign exchange, commodities, and CDS. To avoid data-mining concerns in our choice of asset portfolios, we rely on established sources. We use asset portfolios provided by authors of pre-existing studies and Bloomberg return indexes whenever possible.

For equities, we use the monthly return series of the "25 Portfolios Formed on Size and Book-to-Market (5x5)" building on Fama and French (1993). The series begins in February 2001 to February 2021. For US bonds, government and corporate bond portfolios are included in the same asset class. The government bonds are the ten maturity-sorted "Fama Maturity Portfolios" from CRSP with maturities in six month intervals up to five years. Our US corporate bond portfolios consist of five Bloomberg corporate bond indices. These indices represent US corporate bonds rated AAA, AA, A, B, and high yield[5], as in Du et al. (2019). Both US government and corporate bonds data are available for our entire time period from February 2001 to February 2021. The sovereign bonds portfolios are the six portfolios from Borri and Verdelhan (2011). These portfolios are constructed using a two-way sort of the bond's beta to the US equity market return and the bond's S&P credit rating. Sovereign bonds data goes from February 2001 to April 2011. For equity options, we follow HKM and we form eighteen portfolios of puts and calls sorted by moneyness and maturity using data provided by the authors of Constantinides et al. (2013). While the original methodology yields 54 portfolios, we construct equal-weighted averages of portfolios that have the same moneyness but different maturities to keep the number of portfolios roughly similar across asset classes. Equity options returns data goes from February 2001 to January 2012. For CDS, we rely on data from HKM that is composed of portfolios of single name CDS returns constructed using data from Markit and goes from February 2001 to December 2012. For commodities, we build on the commodity choice of HKM that expands on Yang (2013). We employ the same 23 commodities from Yang (2013) and we get the total return index for each commodity from Bloomberg, following Du et al. (2019). For each commodity, these indices aggregate the returns of many futures with short maturities. Data is available for our entire sample period from February 2001 to

[5]The tickers are LU3ATRUU Index, LU2ATRUU Index, LU1ATRUU Index, LUBATRUU Index, and LF98TRUU Index.

February 2021. For FX, we use 5 carry portfolios and 5 momentum portfolios from Orłowski et al. (2021). These portfolios are composed of 44 currencies of developed and emerging countries. For carry portfolios, currencies are allocated to portfolios based on their forward discounts (which is equivalent to sorting portfolios based on interest rates). Momentum portfolios are constructed based on past returns with formation period and holding period equal to one month. This dataset is available for our entire sample period from February 2001 to February 2021. Box plots for each of the asset classes described above are presented in the appendix, from Figure A1 to Figure A7. Box plots, presented in the appendix, offer a good visual representation of the descriptive statistics of the test asset portfolios used in this paper. They help demonstrate the rich cross-section of excess returns that we study in our empirical tests.

1.3 Stylized Facts

In this section, we present the key trends in the liability composition of the primary dealers of New York Federal Reserve from the beginning of 2000 until the end of 2020.

We first investigate the proportion of principal due per debt type relative to total principal outstanding for the entire sample. We rely on Capital IQ data to produce this section since it provides detailed information about the debt issuance of the banks in our sample as described in Section 1.2.1, and we add to it deposits data that we get from Bloomberg. Capital IQ reports numerous variables which enrich our analysis and help shed light on how these big banks are financed. Deposits are obviously an important source of funding for our sample of banks making up 56.78% of total funding. Coming next, in terms of importance, are bonds & notes, repos and other borrowings, which constitute 16.35%, 14.46% and 8.11% respectively. The remaining categories: term loans, commercial paper, trust preferred, revolving credit, and capital leases, each constitutes less than 2% of total funding.

Figure 1.1 [about here]

Next, we zoom in to examine whether funding composition varies across countries. Figure 1.1 shows the funding composition across countries where the parent companies of the primary dealers sample are located: Canada, the United States, Japan, and Europe (which includes France, Germany, Switzerland, and the United Kingdom). The first thing that strikes our attention is the importance of deposits in financing the bank holding companies located in Canada, which far exceeds their counterparts in other countries. Deposits constitute 83% of the funding of Canadian bank holding companies, followed by repos, 9.49%, bonds and notes, 4.67%, and other borrowings, 2%. Another interesting feature is the resemblance of the funding composition of US banks to that of banks in Europe. For banks located in the United States and in Europe, deposits represent 55% of total funding. Bonds and notes and repos have an equal importance in financing banks in these two areas with each accounting for 15% of total funding, followed by other borrowings which constitutes 10% of funding. Even though less important, term loans and commercial paper also appear to be notable sources of funding for US and European banks representing 3% and 2% of funding, respectively. Japanese banks, on the other hand, rely equally on bonds and notes and deposits with each representing 40% of total liabilities. A sizeable proportion of the funding of Japanese banks also come from repos, 15%, and other borrowings, 5%.

Table 1.1 [about here]

Table 1.1 zooms in further on the liability composition of our sample of banks and reports the average proportion of deposits, bonds and notes, repos, other borrowings and the remaining categories in their capital structure.

Royal Bank Holding has the highest mean proportion of deposits, 87.15%, followed by Toronto Dominion Bank, 86.07%. On the other end of the spectrum, Nomura Holdings and Daiwa Securities Group have the lowest mean proportion of deposits, 3.19% and 9.25% respectively. For bonds and notes, the banks with the highest mean proportions are Jefferies and Company and Daiwa Securities Group, 55.44% and 43.72% respectively, and banks with the lowest median proportions are Royal Bank Holding and

Bank of Nova Scotia, 1.54% and 2.94% respectively. Nomura Holding has the highest average proportion of repos in its capital structure, 60.12%, followed by Lehman Brothers Holdings, 53.32%, while Credit Suisse Group has the lowest median proportion of repos in its capital structure, 1.72%. Also, Credit Suisse has the highest average proportion of other borrowings in its capital structure, 32.94%, while Royal Bank Holding has the lowest proportion of other borrowings in its capital structure, 1.26%.

For Canadian banks, on average, deposits represent 80% of their funding and repos represent 10%. Royal Bank Holding appears to rely exclusively on deposits and repos, while bonds and notes and other borrowings appear to be important in the financing of Canadian Imperial Bank of Commerce. While Figure 1.1 shows that the funding of European and US banks looks similar, we cannot say the same when examining the funding composition of the individual banks. For European banks, deposits range from 50.88% (UBS Group) to 78.57% (HSBC Holdings). In addition, HSBC Holdings has the highest proportion of bonds and notes in its liability structure, 30.52%, followed by Société Générale, 28.50%. Credit Suisse diverges from other European banks in that it has the highest proportion of other borrowings, 32.94%, and the lowest proportion of bonds and notes and repos, 4.84% and 1.72%, respectively. The US banks and the Japanese banks show higher within group heterogeneity compared with Canadian and European banks. For US banks, the three banks that were key primary dealers before the crisis: Bear Stearns, Merrill Lynch and Lehman Brothers Holdings, had the lowest proportion of deposits and the highest proportion of repos in their capital structure. Zions Bancorporation and Wells Fargo don't have deposits in their capital structure while Wells Fargo and JP Morgan appear to be significant deposit-taking institutions compared with other US banks. About half of Zions Bancorporation's funding comes from the remaining categories, which is the highest proportion of remaining categories across all banks in our sample not just in the US. Goldman Sachs is financed with one third deposits, one third other borrowings, and the rest is split between repos and bonds and notes. JP Morgan, Citigroup and Bank of America are financed similarly with Bank of America having a slightly higher proportion of other borrowings in its capital structure compared with the other two banks. For Japanese banks, there is not a clear pattern in their liability structure. As we noted previously when describing Figure 1.1, deposits are not key to the financing of Japanese banks the same way they are for banks in other regions. Only Mizuho Financial Group has 55.55% of its financing coming from deposits. On the other hand, Nomura Holdings are on average 60.12% financed using repos and Daiwa Securities Group gets almost half of its financing from issuing bonds and notes.

Figure 1.2 [about here]

Figure 1.2 shows the trends in the capital structure of primary dealers across countries where the parent companies of the primary dealers sample are located: Canada, the United States, Japan, and Europe (which includes France, Germany, Switzerland, and the United Kingdom). For banks in Europe and Japan, the proportion of deposits in the capital structure doubled over the sample period and notably after the onset of the financial crisis. The proportion of deposits in the capital structure of US banks also increased since the beginning of the sample, but not at the same rate as their European and Japanese counterparts. The liability composition of Japanese banks appears to be less stable than that of the other banks in our sample. US and European banks held more bonds, notes, and other borrowings at the beginning of the sample compared with the end.

Table 1.2 [about here]

Table 1.2 presents maturity statistics for the different debt types in our sample. When the maturity date is given as a range, we use the midpoint of the range as the maturity date. The following statistics are shown in the table: the proportion of observations with non-missing maturity information (% Non-Missing) as well as several statistics related to the remaining time to maturity: the principal-weighted average, arithmetic average, minimum, first quartile, median, third quartile, and maximum. We report as many statistics as possible for the remaining time to maturity, as shown in the % Non-Missing column, maturity date information has a lot of missing observations. We believe that the weighted-average remaining time to maturity variable provides a close enough approximation of the maturity information for the different debt types in our sample, since this rules against the results being dominated by a few big banks. Thus, we will summarize them briefly here. Repos have a weighted-average maturity of 1.31 years.[6] The weighted-average maturity of bonds and notes is 15.09 years and of other borrowings is 3.24 years. For the remaining categories, revolving credit and commercial paper are at the low end of the maturity spectrum with weighted-average maturities of 2.11 years and 3.27 years, respectively, and the rest of the categories are at the high end of the maturity spectrum with weighted-average times to maturity of 10.48 years, 30.69 years, and 36.15 years for term loans, trust preferred, and capital leases, respectively. Our analysis shows that over the sample period, almost two-thirds of the funding of the banks in our sample come from debt with a time to maturity of 12 years or less. This observation was also confirmed when we inspected the current debt holdings of our sample of primary dealers that is provided by Bloomberg.

Looking at the currency arrangements, most banks raise funds in their domestic currencies, hence exchange rate risk is not a major concern. Some notable exceptions are Daiwa Securities Group and Mizuho Financial Group which are Japanese banks but are active in borrowing in other currencies. More than 50% of Mizuho's principal outstanding is in US Dollars, 45% is in Japanese Yen, and the remaining amount in Euros. Daiwa raises half of its debt in the local currency, with the other half being denominated in US Dollars, Euros, Australian Dollars, and, New Zealand Dollars. HSBC Holdings is another exception with only 3.7% of its principal outstanding being denominated in British Pounds, and the rest is mostly in US dollars. UBS Group displays an interesting pattern; before 2012, it was entirely financed in the local currency but since 2012 it started borrowing more and more in US Dollars. By 2020, all of UBS's principal outstanding is denominated in US Dollars.[7]

[6] We drop Morgan Stanley and Nomura Holding from the repos maturity statistics because they were outliers each with an average maturity close to 7 years.

[7] Currency plots are available upon request.

It is worth mentioning that Capital IQ data have been criticized for being incomplete and containing errors. (See Liu (2020) and Mathers and Giacomini (2016)). An extension of the work done here could incorporate the use of web scraping techniques to scrape banks' annual reports and 10-K forms for the same information collected from Capital IQ, to validate the results obtained in this section. (See Engelberg and Sankaraguruswamy (2007), Kizilaslan and Manakyan Mathers (2014), and Sufi (2009)).

1.4 Methodology and Asset Pricing Results

In this section we describe how we construct the intermediaries debt factor and our cross-sectional asset pricing tests. Later, we present our main results.

1.4.1 Factor Construction

We construct our intermediary debt factor using the primary dealers' repo rates, bond discount rates and LOIS spreads, guided by Capital IQ funding composition data. We first aggregate Capital IQ debt components for the sample of primary dealers in to short-term components, long-term components and other borrowings. The short-term components include deposits, repos, commercial paper and revolving credit and the long-term components include bonds and notes, capital leases, term loans and trust preferred. For each bank, we get the median proportions of these three components in each bank's capital structure, then we use this information to weight the percentage change in repo rates, bond discount rates and LOIS spreads respectively. We rely on the median proportions instead of the actual ones to eliminate the noise due to abrupt changes in capital structure. Finally, we aggregate the data for all banks on each date by taking a liability-weighted average across all banks.

For each time $t = 1, ..., T$ and bank $i = 1, ..., I$ the weighted average market price of leverage for a given bank holding company is

$$DF_{it} = w_{\overline{ST_i}} * RepoRate_t + w_{\overline{LT_i}} * BondDiscountRate_{i,t} + w_{\overline{OB_i}} * LOIS_t \tag{1.1}$$

$$DF_t = \sum_{i=1}^{I} w_{it,MVL} * DF_{it} \tag{1.2}$$

Such that $w_{\overline{ST}}$, $w_{\overline{LT}}$ and $w_{\overline{OB}}$ are the median weights of short-term debt types, long-term debt types and other borrowings in each bank's capital structure, $RepoRate$ is the percentage change of the repo rate of the country where the bank is located, $BondDiscountRate$ is the percentage change of the bond discount rate of each bank where bond discount rate is computed as the yield on the government bond where the bank is located plus the bank's CDS spread, and $LOIS$ is the percentage change of the LOIS spread of the country where the bank is located. Then to construct the intermediary debt factor DF_t we compute a liability-weighted average of DF_{it} across all banks on each month t.

Figure 1.6 [about here]

Figure 1.6, plots the intermediary debt factor from February 2001 to February 2021. The pink shading corresponds to NBER recessions. The intermediary debt factor is an indicator of the health and stability of the financial sector. The lower the debt factor, the more favorable the borrowing conditions for intermediaries, reflecting a healthy economy. Conversely, a higher or positive debt factor suggests tighter credit conditions, often aligning with economic downturns or increased market stress. Figure 1.6 highlights the impact of economic cycles on the cost of debt for intermediaries. During recessions, the cost of borrowing increases, which is likely due to higher risk premiums and decreased liquidity in the markets. Before 2005, the intermediaries debt factor was less volatile compared to the period after 2005. Moreover, the volatility of the debt factor increases even more after 2015. The long-term decrease in levels suggests that over the past two decades, there has been a shift in the debt markets, potentially due to changes in regulation, market structure, or overall economic conditions.

Table 1.3 [about here]

Table 1.3 presents the debt factor summary statistics as well as its correlation with key variables: macro-economic variables, financial conditions, liquidity and funding variables, as well as key variables from the academic literature. Panel A of Table 1.3 reports the debt factor summary statistics. The mean of the debt factor is -0.18% and the standard deviation is 7.41. The debt factor ranges from -32.20%, during the period leading to the financial crisis, to 20.74%, close to the end of the financial crisis, with a median value of -0.26%. The slight negative skewness of -0.65 and kurtosis of 5.36 show that there are some outliers on the left side of the distribution. Panel B of Table 1.3 reports the correlation of the debt factor with an array of macro variables, specifically the growth (log change) of GDP, unemployment rate, industrial production, CPI, real disposable income, S&P500 Price to Earnings ratio from Shiller and real M2 money stock. We also include the correlation of the debt factor with Lettau and Ludvigson (2001) cay factor which captures the trend deviations of consumption-wealth. A counter-cyclical variable should be negatively correlated with GDP growth, industrial production growth, real disposable income growth, CPI growth and the cay factor and positively correlated with the remaining macro variables examined. The intermediaries debt factor is not correlated with any of the macro variables considered.

Panel C of Table 1.3 reports the correlation of the intermediaries' debt factor with financial conditions variables, liquidity variables and funding variables: the Financial Conditions Index (which is an index from the Chicago Fed for which a high level indicates weak financial conditions), Pastor Stambaugh liquidity innovation factor (a measure of market liquidity), Baa-Aaa spread (an indicator of funding liquidity), Fontaine and Garcia (2012) funding liquidity variable, the term spread, the ted rate and the VIX. Like in Panel B of Table 1.3, the correlation between the intermediaries debt factor and the myriad of market condition variables examined is close to zero.

Panel D of Table 1.3 presents the correlation of the intermediaries' debt factor with key factors from the academic literature: the market factor (see Section 1.2.5), HKM capital and equity factors from He et al. (2017), the intermediary leverage factor from Adrian et al. (2014), the forward CIP (covered interest rate parity) return from Du et al. (2019), the noise factor from Hu et al. (2013), the financial intermediaries constraints measure from H. Chen et al. (2019), the risk aversion index from Bekaert et al. (2022) and the variance risk premium from Bollerslev et al. (2009). The intermediaries' debt factor is not correlated with most variables examined in Panel D of Table 1.3. It is noteworthy that while our debt factor is not correlated with BTZ VRP, which is a proxy for household risk aversion, there is a weak negative correlation -0.32 between the intermediary debt factor and BEX RA factor which is a measure of economy-wide risk aversion. The intermediary debt factor shows moderate positive correlation with AEM intermediary leverage factor, 0.41, that can be interpreted as the cost of debt increasing when intermediaries' leverage is high. The fact that the intermediary debt factor is not correlated with most of the variables tested in Table 1.3 suggests that it carries unique information that is not captured by most of the widely used variables and factors.

1.4.2 Asset Pricing Tests

In this section, we describe our empirical tests, which examine whether the variation in expected returns across asset classes can be explained by their differential exposure to intermediary funding shocks. We study each asset class individually, then perform joint tests using the aggregated asset classes.

We begin by performing cross-sectional asset pricing tests separately for each asset class. We estimate betas from time-series regressions of portfolio excess returns for each portfolio m in asset class k, $R^{m_k}_{t+1} - r^f_t$, on our intermediary debt factor, DF_{t+1},HKM equity factor, ME_{t+1}, and the excess returns of the market portfolio, $R^W_{t+1} - r^f_t$:

$$R^{m_k}_{t+1} - r^f_t = a^{m_k} + \beta^{m_k}_{DF} DF_{t+1} + \beta^{m_k}_{ME} ME_{t+1} + \beta^{m_k}_{W}(R^W_{t+1} - r^f_t) + \varepsilon^{m_k}_{t+1} \tag{1.3}$$

We then estimate the asset class-specific risk prices λ^k_{DF}, λ^k_{ME}, and λ^k_W by running a cross sectional regression of average excess portfolio returns on the estimated betas for each asset class k:

$$\hat{E}[R^{m_k}_{t+1} - r^f_t] = \mu_{\mathbf{R,m}} = \gamma_k + \lambda^k_{DF}\hat{\beta}^{m_k}_{DF} + \lambda^k_{ME}\hat{\beta}^{m_k}_{ME} + \lambda^k_W\hat{\beta}^{m_k}_W + \nu^{m_k} \tag{1.4}$$

A good pricing model is characterized by an intercept γ that is economically small and statistically insignificant, prices of risk λ that are statistically significant and stable across different asset classes, and pricing errors ν that are close to zero. To quantify the size of the pricing errors, we rely on two measures that are easy to interpret from an economic standpoint: the adjusted R^2, which focuses on the size of the sum of squared errors
$(1-\sigma^2_\nu/\sigma^2_{\mu_\mathbf{R}})$, and the mean absolute pricing error (MAPE) $(\frac{1}{N}\Sigma|\nu|)$, which is less influenced by outliers compared to the adjusted R^2. When including all portfolios of all asset classes simultaneously in the cross-sectional asset pricing tests, we use an unbalanced panel of portfolio returns because some asset classes are not available over our entire sample, such as sovereign bonds, CDS and options.

1.4.3 Asset Pricing Results

A summary of the results of the first-step time series regression is shown in Table 1.4. We report the average excess return and the average standard deviation of excess returns across the portfolios of each asset class. We also report the mean, standard deviation, minimum, and maximum of the time-series beta of each risk factor across all portfolios of each asset class. The table also presents the average R^2 of the time-series regression, the number of portfolios of each asset class, and the number of months. We observe significant risk dispersion within and across asset classes, which is crucial for our tests. For instance, the standard deviation of the 25 Fama-French portfolios' time-series intermediary debt factor beta (β_{DF}) is 0.02, while its mean is 0.00. The dispersion is much higher for commodities, with a standard deviation that is eight times its mean. For the portfolio that aggregates all asset classes, the standard deviation of the time-series intermediary debt factor beta is approximately twice its mean.

Table 1.4 [about here]

Our main specification includes the intermediary debt factor, HKM equity factor, and the market factor. Table 1.5 reports estimates for the February 2001 to February 2021 period using monthly data. The results from independent estimation within each asset class are shown in the first seven columns of the table. We present GMM t-statistics that account for cross-correlation and first-stage estimation error in betas between parenthesis. The cross-sectional R^2 for average portfolio returns and the corresponding mean absolute pricing error (MAPE) in percentage terms are the model fit measures that we provide.

The mean price of risk of intermediary debt is negative in all asset classes, which is expected, as the cost of funding typically rises leading up to and during economic downturns. The price of risk estimates of the debt factor ranges from -8.62% for CDS to -3.07% for US equity and is statistically significant at the 1% level for US bonds, CDS, and all portfolios; significant at the 5% level for US equity and commodities; and significant at the 10% level for sovereign bonds and options. The model has the best fit for options with R^2 of 98% and the worst fit for US equity with R^2 of 17%.

The high R-squared value for options in the table, despite only the debt factor being significant at the 10% level, can be influenced by the low number of observations and the resulting low degrees of freedom. In this context, the options have only 123 observations, which is relatively low compared to other asset classes. This reduction in degrees of freedom can inflate the explanatory power of the model, making the R-squared value appear higher than it might be with a larger sample. Therefore, while the model seems to explain a large portion of the variance in options returns, the high R-squared should be interpreted with caution.

Table 1.5 [about here]

We report the results when the 117 portfolios from all asset classes are included simultaneously in the regression in the last column of Table 1.5. The price of risk estimate of the debt factor is -4.97% per month with a t-statistic of -3.63 and an R^2 of

55%. Economically, this risk price estimate is substantial. For instance, the cross-sectional standard deviation of the debt factor betas of all portfolios is 0.05 (see Table 1.4). As a result, a one standard deviation difference in the debt risk beta of two assets equates to a difference in their annual risk premia of $0.05 \times 4.97 \times 12$, or 2.98 percentage points. The price of risk estimate of HKM equity factor has a negative sign in the case of US equity and a positive sign for the rest of the asset portfolios examined. It is significant in the case of sovereign bonds, CDS, FX and all portfolios. The price of risk estimate of market factor is negative for US bonds, CDS, commodities and FX, and is significant at the 5% significance level for all portfolios only. To benefit from the time series variation in the liability composition shown in Figure 1.2, we construct the debt factor using five-year moving average proportions of the different debt components instead of median proportions, then we re-estimate the model specification presented here. We report the results in Table A3. To sum up, even after controlling for HKM equity and market risk factors, our debt factor continues to be a significant driver of asset pricing behaviour.

Table 1.6 [about here]

Table 1.6 presents the results of estimating a two-factor model using HKM capital and market factors (see Panel A) and HKM equity and market factors (see Panel B). Panel A shows that HKM capital has a positive sign for all asset portfolios examined except for US bonds. The price of risk of HKM capital factor is significant at the 1% level for CDS; significant at the 5% level for sovereign bonds; and significant at the 10% level for all portfolios. Panel B shows that HKM equity has a positive sign for all asset portfolios examined except for US bonds. The price of risk of HKM equity factor is only significant at the 1% level for CDS; and at the 5% level for FX. From this table it is clear that both HKM factors have very weak statistical significance in explaining the variation of excess returns of the test asset portfolios during the period February 2001 until February 2021. Hence, the three-factor model that adds the intermediary debt factor to HKM equity and market factors provides added value, as evidenced by the negative and statistically significant coefficients of the debt factor.

In their main specification shown in Table 5 of the paper, He et al. (2017) use quarterly data because it corresponds to the frequency of the balance sheet data used in their capital factor construction. However, they point out that there could be within-quarter variation in the debt component that drives the pricing power of the capital factor and as a result, would distort the performance of the model at a monthly frequency. Their claim is indeed supported by the results in Table 9 of their paper, which show that book debt growth possesses some pricing power which explains the weaker monthly results presented in Table 14 of their paper. The results discussed in this section support HKM's suggestion.

1.5 Robustness Checks

In this section, we conduct several robustness checks to validate the findings of our main model, which estimates the price of risk associated with the intermediary debt factor across various asset classes. These tests are crucial for ensuring the reliability and generalizability of our results. We examine the model's performance under different conditions, including using quarterly data, alternative methodologies for constructing the debt factor, replacing HKM equity factor with HKM capital factor, experimenting with different test asset portfolios, and estimating the model with a zero intercept.

1.5.1 Quarterly Frequency

To assess the temporal stability of our model, we estimate it using quarterly data. While daily data is available for repo rates, LOIS spreads, and bond yields, we construct the intermediary debt factor on a monthly basis to leverage the long-term predictive power of asset pricing models. AEM leverage factor has a quarterly frequency as it uses flow of funds data that is also quarterly. HKM capital ratio has a quarterly frequency that matches the frequency of the balance sheet data used in its construction. In this section we estimate the model at a quarterly frequency, and display the results in Table 1.7. The estimate of the price of risk of the intermediary debt factor is negative across all asset classes, and is significant at the 1% level for CDS; at the 5% level for US bonds, sovereign bonds, commodities and all portfolios; and significant at the 10% level for US equity. However, the economic magnitude of the coefficient of the debt factor is higher in the quarterly tests, which suggests a stronger adverse effect on asset prices over the longer-term quarterly periods.

Table 1.7 [about here]

1.5.2 Different Construction Method of the Debt Factor

We examine a different way to construct the intermediary debt factor to rule out the possibility that our results are influenced by the way the factor is constructed. Instead of constructing the debt factor by aggregating the data using a liability-weighted average across all banks as described in Section 1.4.1, we construct it by aggregating the data using a trimmed mean[8]. To further test the robustness of our results, Table 1.8 presents the outcomes when the debt factor is constructed using an arithmetic mean, another alternative aggregation method. The estimate of the price of risk of the debt factor is negative for all asset classes and is significant at the 1% level for US equity, CDS, commodities and all portfolios; significant at the 5% level for US bonds and options; and significant at the 10% level for FX. Thus, the intermediary debt factor is robust to using a different factor construction method.

Table 1.8 [about here]

1.5.3 Intermediary Capital Risk Factor

Throughout our main model and different robustness tests, we examined the explanatory power of the intermediary debt factor after controlling for HKM equity factor and market

[8]The data below the first percentile and above the ninety-ninth percentile are replaced with data at the first and ninety-ninth percentiles, respectively.

factor. In Table 1.9 we control for HKM capital factor instead of controlling for HKM equity factor. The estimated price of risk of the intermediary debt factor is significant at the 1% level for CDS and all portfolios, and significant at the 5% level for US equity, US bonds, and commodities. Thus, intermediary debt factor is statistically significant even after controlling for other intermediary risk factors.

Table 1.9 [about here]

1.5.4 Different Test Assets Sample

To rule out the possibility that our results might be driven by our choice of test asset portfolios, we estimate the model using the same test assets data used in He et al. (2017) and made available through Asaf Manela's website. Compared with our set of test assets, the sample of HKM test assets ends in April 2012 instead of February 2021. Also, we differ in our choice of test asset portfolios in the case of US bonds, commodities, and FX[9]. Table 1.10 presents the results of the main specification when HKM test assets are used to estimate the model. The estimate of the intermediaries debt factor is significant at the 1% level for CDS and for all portfolios; significant at the 5% level for FX; and significant at the 10% level for US equity, sovereign bonds, options, and commodities. Notice that the estimated coefficients in case of sovereign bonds, options and CDS differ from those in Table 1.5, even though the same test assets are used for both tables. The reason for that is that in this section we use the market factor provided with HKM data which is different from the market factor currently available from Ken French website as explained previously in Section 1.2.5.

Table 1.10 [about here]

[9]Please refer to the original paper for more details about these asset portfolios.

1.5.5 Restricted Intercept

The intercept γ_k, as allowed by the empirical specification in Equation 1.4, can differ between asset classes. However, as mentioned previously in Section 1.4.2, a good asset pricing model is characterized by having an economically small and statistically insignificant intercept. In Table 1.11 we rerun our main specification but without an intercept. We find that the estimate of the price of risk of the intermediary debt factor is significant at the 1% level for US bonds, CDS, and all portfolios; significant at the 5% level for commodities; and significant at the 10% level for US equity and sovereign bonds. In general, our debt factor is robust to estimating the model with or without a constant.

Table 1.11 [about here]

In summary, our robustness checks reinforce the validity of our main model, demonstrating its reliability across different frequencies, construction methodologies, risk factors, test asset samples, and intercept treatments. These findings underscore the robust adverse effect of the intermediary debt factor on asset prices, lending credence to its relevance in asset pricing models.

1.6 Conclusions

Since the financial crisis, there has been increased interest in intermediary asset pricing. Our paper belongs to this stream of literature. Our aim is not to introduce a novel intermediary risk factor but to improve our understanding of the primary dealers' liability composition and the market price of their leverage, which further helps in anticipating the shocks that most affect these dealers and the market frictions to which they are most susceptible.

In this paper, we analyze the liability composition of the primary dealers, which numerous research works have shown to be key players in many sophisticated asset markets. We present debt stylized facts for this sample of banks over the 2000 to 2020 period, including debt composition trends, average maturity, currency of debt issuance, and interest rate. Then we construct a debt factor using intermediary cost of funding proxies and Capital IQ debt composition. We find that when including our debt factor in a three-factor model with the HKM equity and market factors, it explains the variability in asset returns for all asset classes studied, whether estimated individually or jointly.

1.7 Figures and Tables

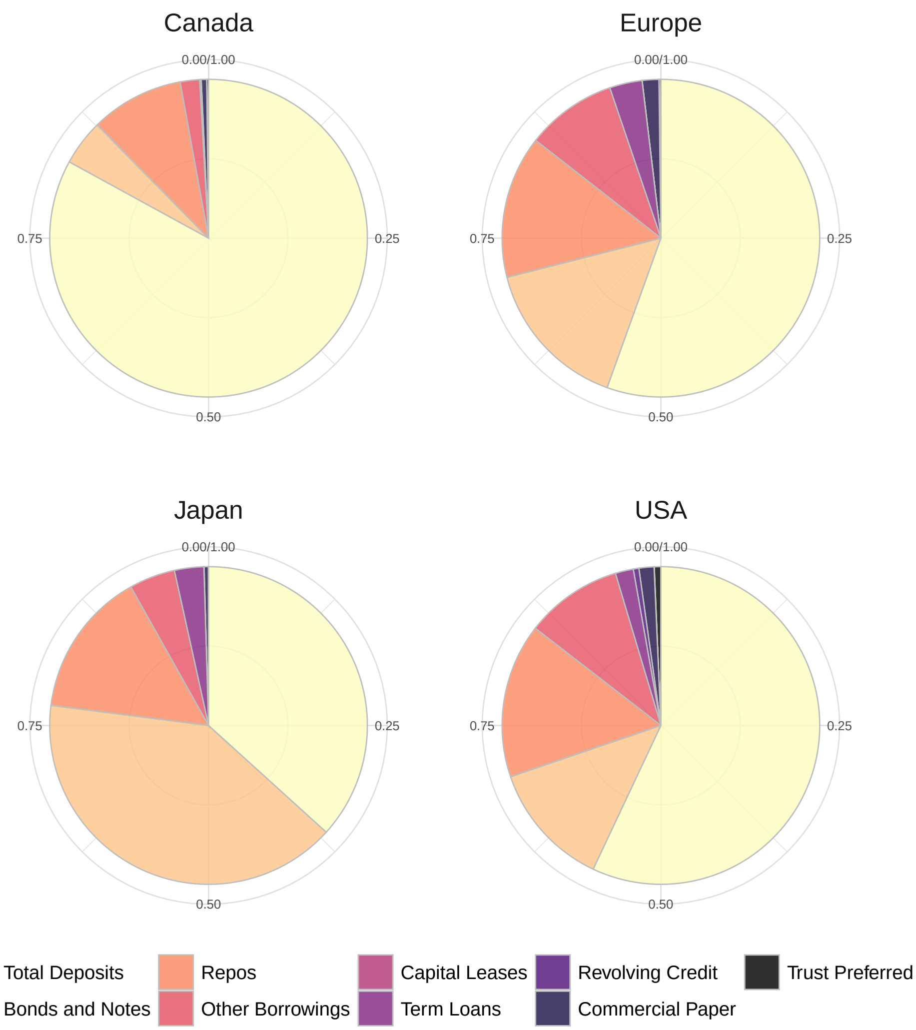

Figure 1.1: **Debt Breakdown by Region**
This figure shows the composition of debt types in the primary dealers capital structure over the period January 2000 to December 2020. The analysis is done at the bank holding company level. Results are aggregated by region: Canada, Europe, Japan and the USA, with Europe including France, Germany, Switzerland and the UK.

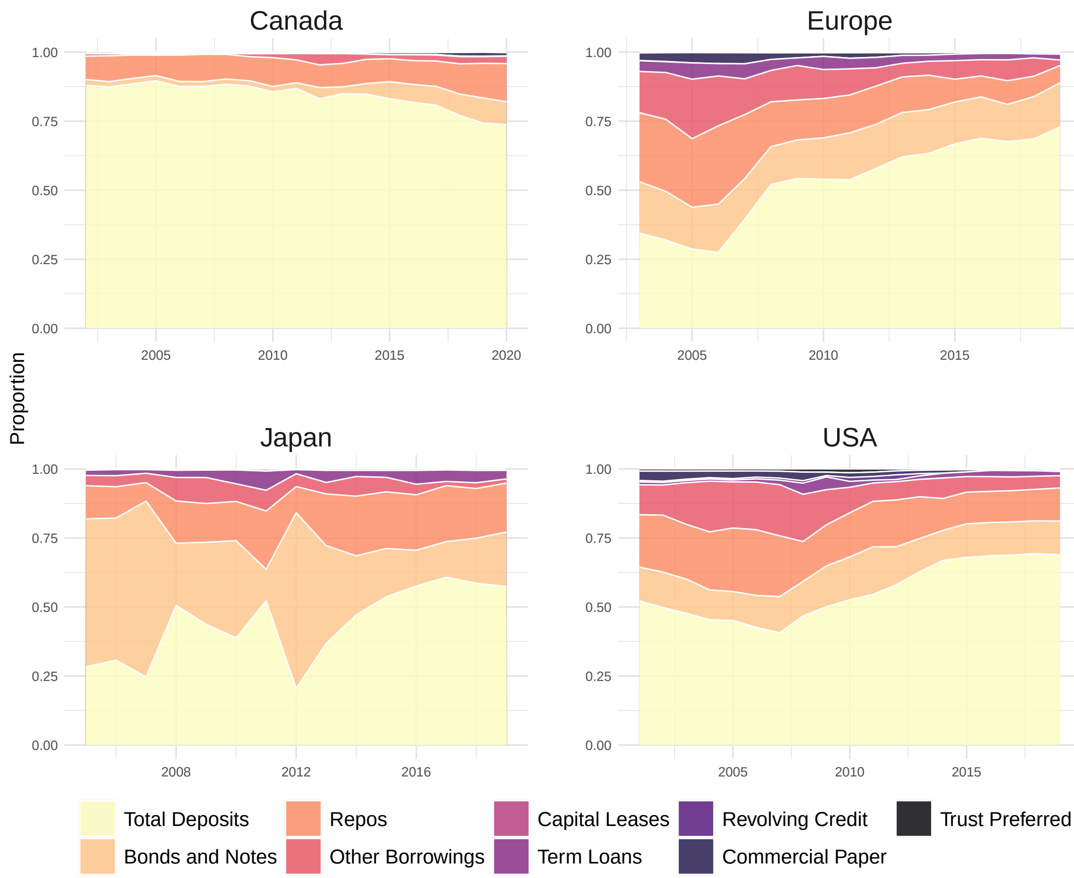

Figure 1.2: **Financing Trends by Region**
This figure shows the financing trends in the primary dealers capital structure over the period January 2000 to December 2020. The analysis is done at the bank holding company level. Results are aggregated by region: Canada, Europe, Japan and the USA, with Europe including France, Germany, Switzerland and the UK.

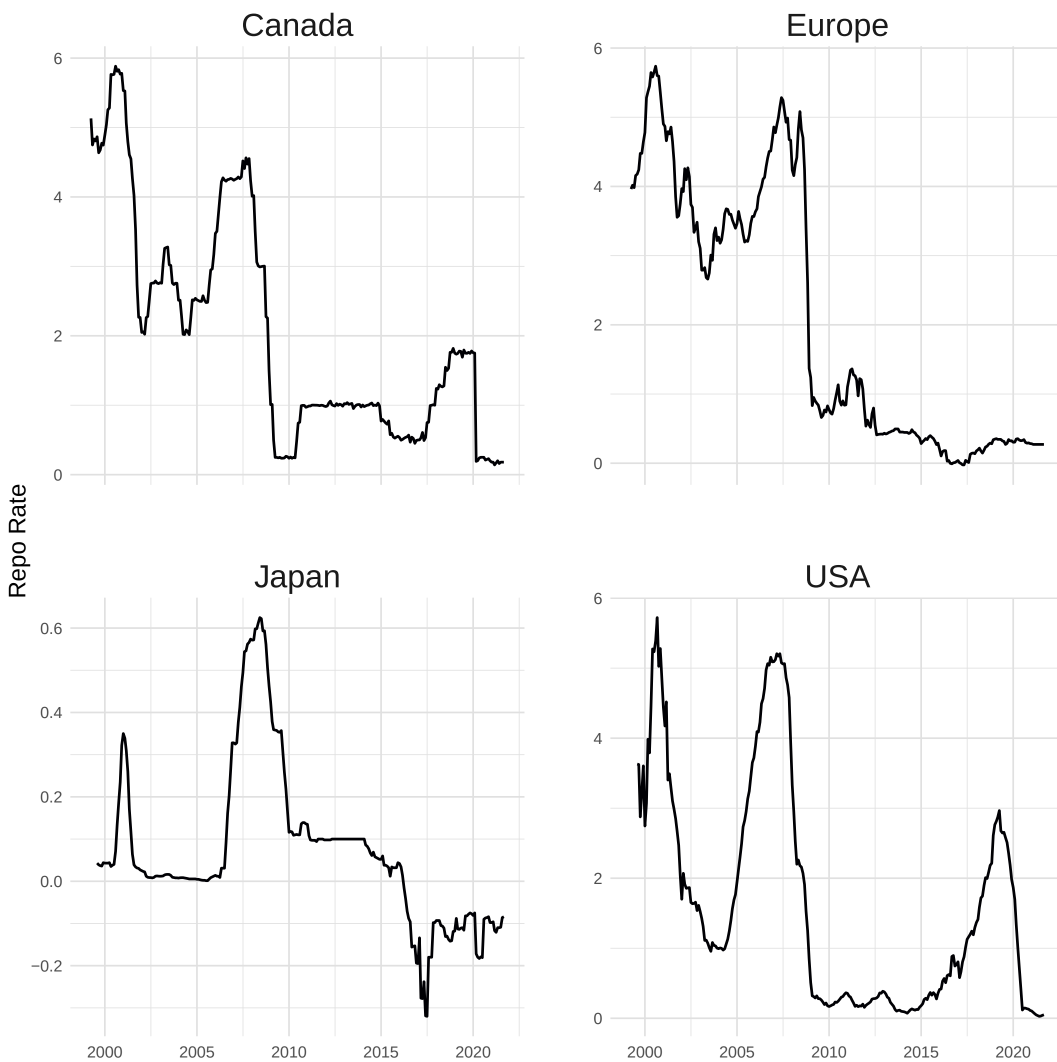

Figure 1.3: **Repo Rates**
This figure plots the repo rates (in percent) of the countries in which the holding companies of our sample of primary dealers are located: Canada, Europe, Japan and the USA from February 2001 to February 2021. The repo rate data is from Bloomberg, DataStream and the Bank of Canada website.

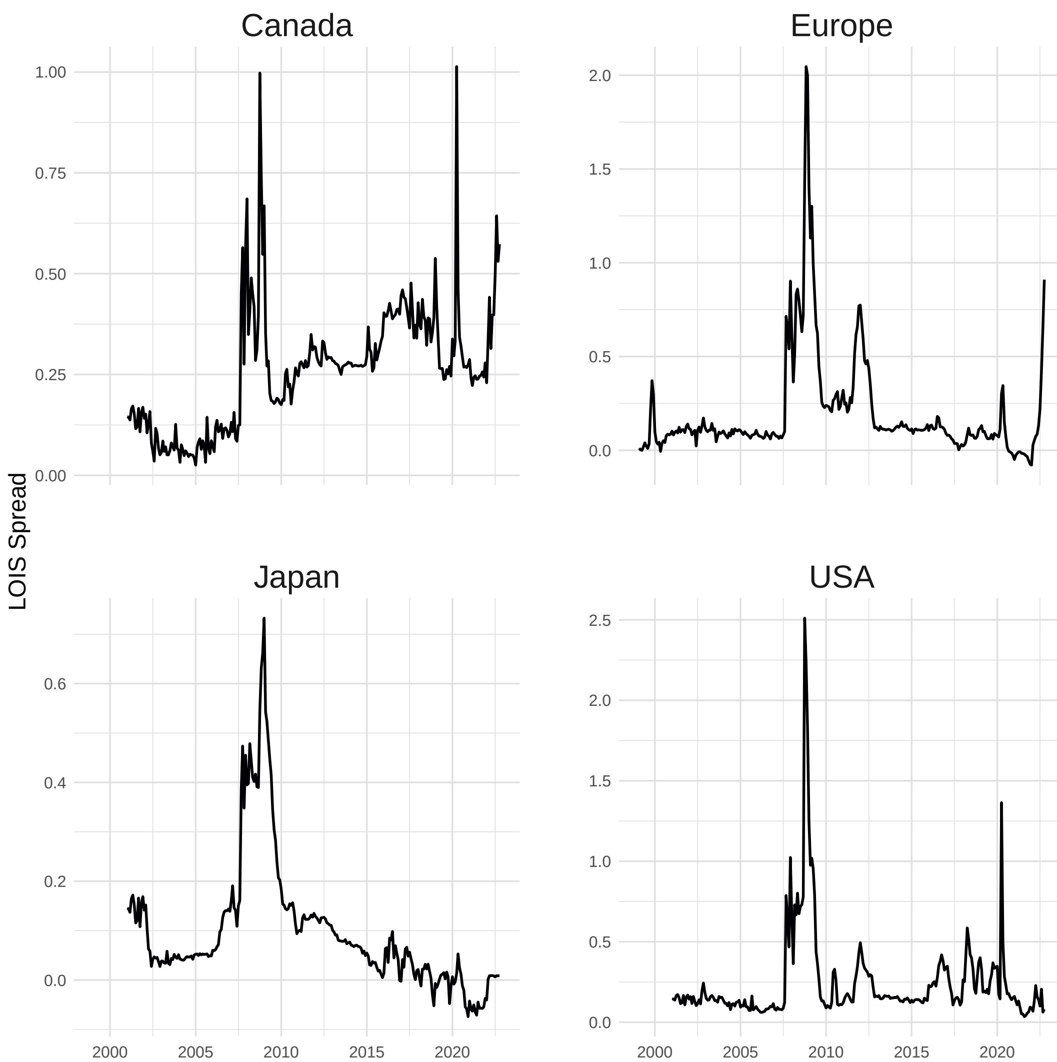

Figure 1.4: **LOIS Spreads**
This figure plots the three-month Libor OIS spread (in percent) of the countries in which the holding companies of our sample of primary dealers are located: Canada, Europe, Japan and the USA from February 2001 to February 2021. The LOIS spread data is from Bloomberg.

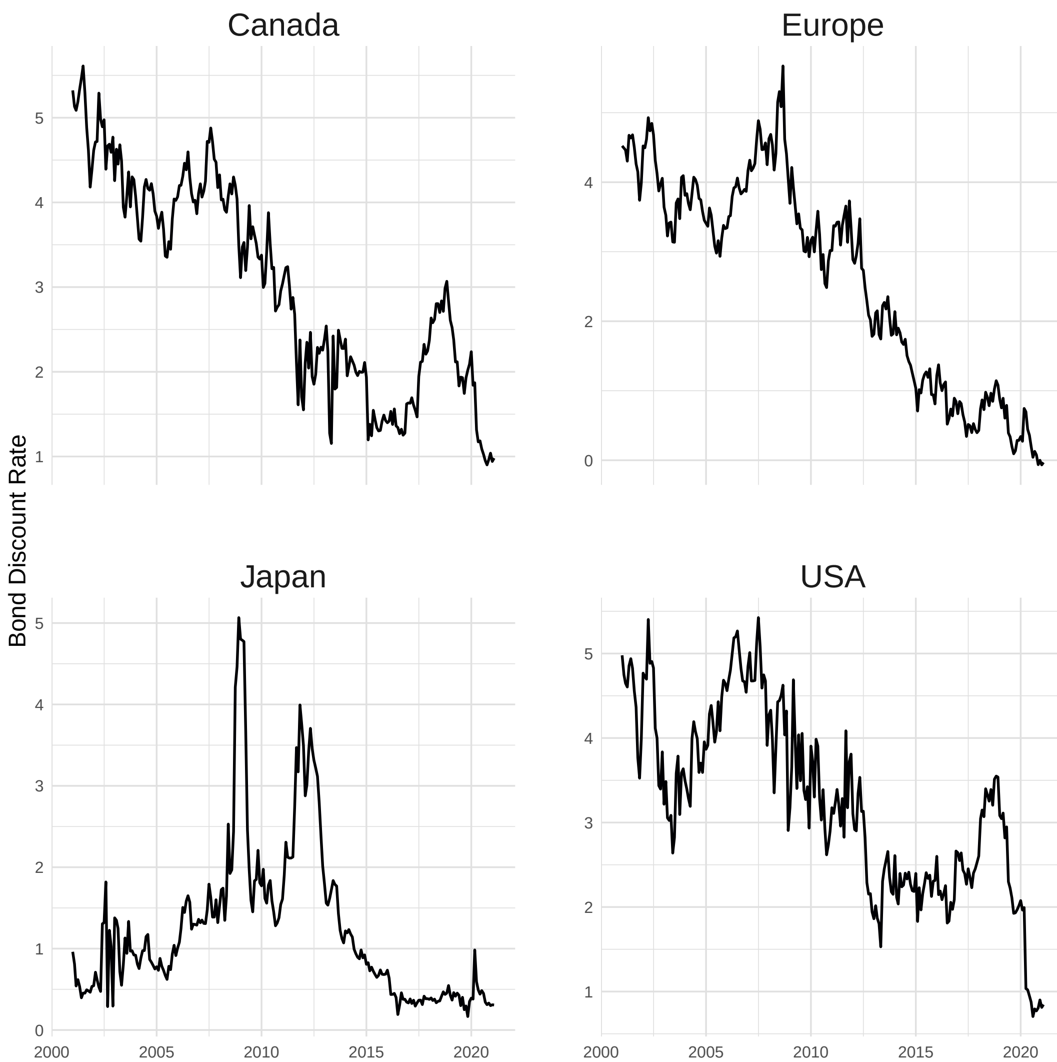

Figure 1.5: **Bond Discount Rate**
This figure plots the median bond discount rate (in percent) of the countries in which the holding companies of our sample of primary dealers are located: Canada, Europe, Japan and the USA from February 2001 to February 2021. Bond discount rates are computed as the yield of the long-term government bond plus the bank's CDS spread. Bond discount rates data are from Bloomberg and CDS data are from Markit.

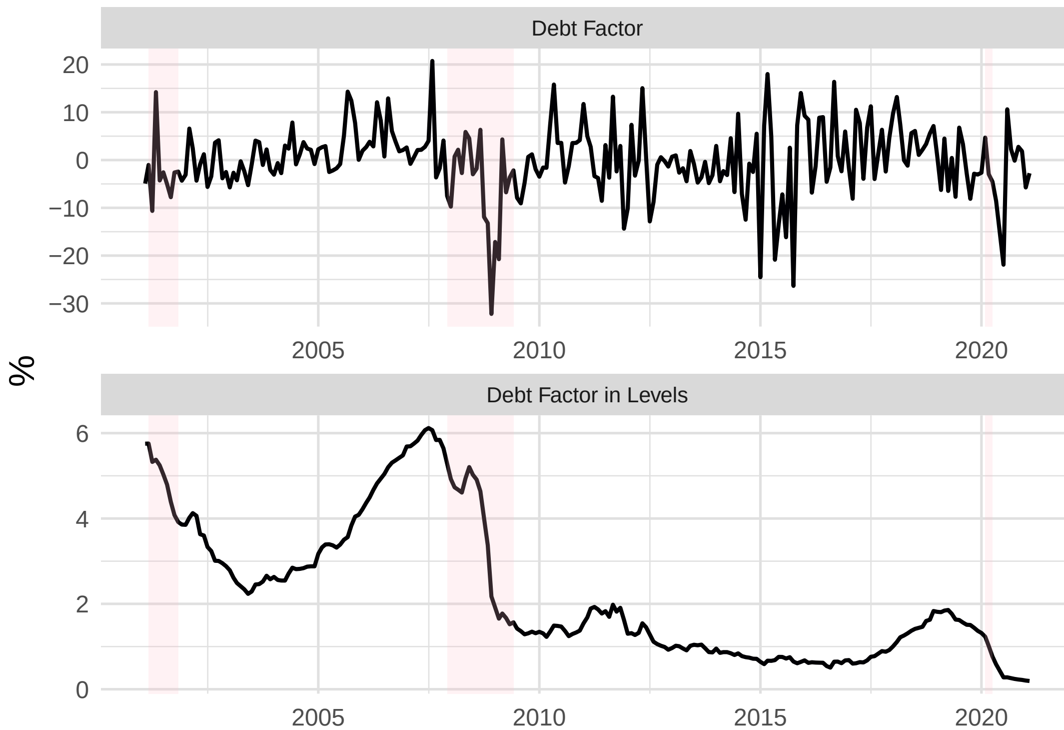

Figure 1.6: **Intermediary Debt Factor with NBER Recession Shading**
This figure shows the intermediary debt factor from February 2001 to February 2021. The top panel shows our debt factor which is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. The bottom panel plots the debt factor constructed using bond discount rates, repo rates and LOIS spreads in levels. The pink shading represents NBER recessions.

Table 1.1: **Proportion of Debt Types by Bank Holding Company**
This table reports the proportion of the different debt types in the capital structure of the holding companies of our primary dealers sample over the period January 2000 to December 2020. It presents the most important categories individually (deposits, bonds and notes, repos and other borrowings) and aggregates the remaining categories in one group (capital leases, term loans, revolving credit, commercial paper and trust preferred).

Bank	Deposits	Bonds and Notes	Repos	Other Borrowings	Remaining Categories
Bank of Montreal	79.72%	3.97%	10.92%	5.57%	1.73%
Canadian Imperial Bank of Commerce	83.74%	5.49%	7.48%	4.33%	0.45%
Royal Bank Holding, Inc.	87.15%	1.54%	10.52%	1.26%	0.16%
Bank of Nova Scotia	84.96%	2.94%	11.35%	2.98%	0.33%
Toronto-Dominion Bank	86.07%	5.37%	5.76%	2.83%	1.27%
BNP Paribas	51.14%	16.21%	35.55%	9.53%	7.40%
Credit Suisse Group AG	60.54%	4.84%	1.72%	32.94%	1.54%
Deutsche Bank AG	59.16%	17.72%	6.38%	11.78%	4.97%
Société Générale	61.24%	28.50%	16.41%	9.28%	5.97%
UBS Group AG	50.88%	15.05%	16.75%	7.49%	10.35%
Barclays PLC	56.39%	12.25%	22.24%	12.64%	2.74%
HSBC Holdings PLC	78.57%	30.52%	9.59%	8.29%	0.77%
NatWest Group PLC	68.93%	15.29%	24.34%	12.12%	3.47%
Daiwa Securities Group, Inc.	9.25%	43.72%	30.38%	18.64%	16.25%
Mizuho Financial Group, Inc.	55.55%	34.39%	9.77%	5.23%	1.60%
Nomura Holdings, Inc.	3.19%	16.19%	60.12%	5.21%	15.58%
Bank of America Corporation	59.61%	11.41%	14.23%	10.83%	3.92%
Citigroup, Inc.	59.92%	13.24%	12.64%	8.64%	5.56%
Jefferies & Company, Inc.	-	55.44%	29.88%	3.74%	14.42%
JPMorgan Chase & Co.	63.71%	11.80%	14.91%	3.35%	6.22%
Lehman Brothers Holdings, Inc.	14.77%	25.61%	53.32%	4.81%	1.49%
Merrill Lynch & Co.	23.31%	18.00%	39.35%	14.63%	7.40%
Morgan Stanley	37.92%	19.48%	27.48%	12.39%	2.73%
Bear Stearns Companies, Inc.	34.72%	20.01%	33.56%	8.20%	7.45%
Goldman Sachs Group, Inc.	40.81%	7.77%	21.54%	27.86%	2.02%
Wells Fargo & Co.	72.91%	12.55%	5.46%	8.93%	4.34%
Zions Bancorporation	-	33.68%	13.45%	10.15%	46.47%

Table 1.2: **Maturity Statistics by Debt Type.**

This table presents maturity statistics of the different debt types in the capital structure of the holding companies of our primary dealers sample over the period January 2000 to December 2020. The following statistics are shown in the table: the proportion of observations with non-missing maturity information (% Non-Missing) as well as several remaining time to maturity statistics: the principal-weighted average, arithmetic average, minimum, first quartile, median, third quartile and maximum

Debt Type	% Non-Missing	VW Average	Average	Minimum	Q1	Median	Q3	Maximum
Bonds and Notes	68.19%	15.09	12.38	0.00	4.21	7.67	14.26	99.28
Repos	7.77%	1.31	1.45	0.25	1.00	1.25	1.88	9.01
Other Borrowings	27.26%	3.24	4.87	0.00	1.25	1.50	4.25	33.19
Term Loans	44.02%	10.50	6.94	0.00	1.50	3.91	10.51	46.78
Commercial Paper	50.71%	3.65	3.39	0.25	1.25	2.25	4.29	13.76
Trust Preferred	82.64%	30.89	26.67	0.25	19.00	23.44	28.77	99.56
Revolving Credit	47.37%	2.11	3.17	0.25	1.25	2.25	3.76	14.01
Capital Leases	27.96%	36.15	11.38	0.25	5.25	7.76	12.01	50.04

Table 1.3: **Debt Factor Summary Statistics**

This table presents the debt factor summary statistics as well as its correlation with key variables. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. Panel A reports the debt factor summary statistics: mean, standard deviation, minimum, first quartile, median, third quartile, maximum, skewness and kurtosis. Panel B reports the correlation of the debt factor with a number of macroeconomic factors in log change (growth): GDP, unemployment, industrial production, CPI, real disposable income, LL cay, Shiller PE ratio and real M2 money supply. Panel C reports the correlation of the debt factor with financial conditions, liquidity and funding variables: financial conditions index, PS liquidity innovation factor, Baa-Aaa spread, FG funding liquidity, term spread, ted rate and VIX. Panel D reports the correlation of the debt factor with factors from academic literature: the market, HKM capital risk, HKM equity returns, AEM leverage, DHW covered interest rate parity returns, HPW noise factor, CJN intermediaries constraints PNBO, BEX risk aversion and BTZ variance risk premium. The sample is from February 2001 to February 2021.

				Panel A: Debt Factor Summary Statistics				
Mean	Stdev	Min	Q1	Q2	Q3	Max	Skew	Kurt
-0.18	7.41	-32.20	-3.60	-0.26	3.82	20.74	-0.65	5.36
				Panel B: Macro Variables				
GDP	Unemp	Industrial Prod.	CPI	Real Disp. Income	Cay	Shiller PE ratio	Real M2	
0.16	-0.08	0.06	0.20	-0.04	-0.15	0.06	-0.23	
				Panel C: Financial Conditions, Liquidity and Funding Variables				
NFCI	PS Liquidity	Baa_Aaa	FG Funding Liquidity	Term Spread	Ted Rate	VIX		
-0.06	-0.07	0.02	0.03	-0.06	0.17	0.11		
				Panel D: Factors from Academic Literature				
Mkt-RF	HKM Capital	HKM Equity	AEM Leverage	DHW CIP	HPW Noise Factor	CJN PNBO	BEX RA	BTZ VRP
-0.02	0.03	0.04	0.41	0.06	-0.33	-0.01	-0.32	-0.01

Table 1.4: **Expected Returns and Risk Exposure by Asset Class.**
This table shows the average percent excess returns $\mu_m - r_f$, and risk exposures (betas) to shocks to the intermediary debt factor ($\beta_{m,DF}$), HKM equity factor ($\beta_{m,ME}$), and market excess returns ($\beta_{m,W}$), across portfolios of each asset class. The monthly sample is from February 2001 to February 2021. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. Betas are estimated in a first-stage time-series regression. Mean(x), Std(x), Min(x) and Max(x) represent the mean, standard deviation, minimum and maximum of x, respectively, across portfolios in each asset class.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Mean($\mu_m - r_f$)	0.89	0.22	0.64	-0.11	0.09	0.19	0.00	0.29
Std($\mu_m - r_f$)	0.18	0.15	0.35	0.50	0.17	0.70	0.15	0.53
Mean($\beta_{m,DF}$)	0.00	-0.02	-0.07	-0.03	-0.01	-0.01	-0.02	-0.02
Std($\beta_{m,DF}$)	0.02	0.02	0.03	0.05	0.01	0.08	0.01	0.05
Min($\beta_{m,DF}$)	-0.05	-0.05	-0.11	-0.12	-0.04	-0.16	-0.03	-0.16
Max($\beta_{m,DF}$)	0.06	0.00	-0.04	0.04	0.00	0.17	-0.01	0.17
Mean($\beta_{m,ME}$)	0.12	-0.01	0.09	-0.03	0.05	0.09	0.10	0.06
Std($\beta_{m,ME}$)	0.17	0.04	0.10	0.03	0.03	0.17	0.03	0.12
Min($\beta_{m,ME}$)	-0.16	-0.04	0.01	-0.07	0.01	-0.20	0.06	-0.20
Max($\beta_{m,ME}$)	0.56	0.11	0.27	0.03	0.12	0.41	0.15	0.56
Mean($\beta_{m,W}$)	1.00	0.01	0.16	0.95	0.03	0.31	0.14	0.45
Std($\beta_{m,W}$)	0.23	0.10	0.10	0.26	0.03	0.18	0.06	0.45
Min($\beta_{m,W}$)	0.55	-0.06	0.03	0.49	0.00	-0.07	0.05	-0.07
Max($\beta_{m,W}$)	1.47	0.28	0.28	1.32	0.09	0.66	0.23	1.47
Mean(R^2)	79.25%	17.73%	21.38%	77.47%	44.57%	8.39%	25.95%	43.71%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

Table 1.5: **Three-Factor Model: Liability-Weighted Debt Factor, HKM Equity, and Market, Monthly.**
Estimates of the prices of risk for shocks to the intermediary debt factor, HKM equity factor and the market's excess return factor. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. HKM equity is the intermediary equity return factor and the market factor is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas) , expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-3.07**	-8.42***	-4.68*	-6.86*	-8.62***	-6.75**	-7.33	-4.97***
	(-2.16)	(-2.70)	(-1.68)	(-1.81)	(-3.31)	(-2.38)	(-1.34)	(-3.63)
HKM Equity	-0.08	0.38	2.93**	1.77	2.90**	1.87	3.67*	1.33**
	(-0.12)	(0.36)	(2.19)	(0.34)	(2.07)	(1.19)	(1.73)	(2.06)
Market Factor	0.08	-0.04	0.93	0.70	-0.06	-0.43	-0.70	0.63**
	(0.16)	(-0.07)	(0.82)	(0.62)	(-0.08)	(-0.38)	(-0.49)	(2.08)
Intercept	0.80*	0.08***	0.08	-0.92	-0.12***	0.10	-0.42	-0.10
	(1.91)	(3.43)	(0.32)	(-1.07)	(-3.61)	(0.30)	(-1.23)	(-1.19)
R^2	17.00%	85.00%	90.00%	98.00%	87.00%	59.00%	51.00%	55.00%
MAPE	0.12%	0.05%	0.07%	0.07%	0.04%	0.34%	0.09%	0.26%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

Table 1.6: **Two-Factor Model using HKM Factors.**
Estimates of the prices of risk for shocks to HKM factors and the market excess return. Panel A shows the results when HKM intermediary capital factor is used in the model and panel B shows the results when HKM intermediary equity return factor is used. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas), expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

Panel A: HKM Capital Factor and Market Factor								
	FF25	US Bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
HKM Capital	0.01	-1.88	2.86**	8.16	4.04***	1.55	2.91	1.27*
	(0.01)	(-1.17)	(2.17)	(0.75)	(3.09)	(1.47)	(1.60)	(1.96)
Market Factor	0.16	1.87	0.17	2.82	1.02	0.53	-0.21	0.64**
	(0.31)	(1.55)	(0.14)	(1.06)	(1.34)	(0.72)	(-0.20)	(2.14)
Intercept	0.73*	0.13***	0.63*	-2.47	-0.14***	-0.09	-0.10	-0.03
	(1.81)	(3.72)	(1.86)	(-1.36)	(-5.09)	(-0.38)	(-0.39)	(-0.34)
R^2	3.00%	83.00%	80.00%	94.00%	69.00%	16.00%	19.00%	37.00%
MAPE	0.13%	0.05%	0.13%	0.09%	0.07%	0.48%	0.13%	0.29%
Panel B: HKM Equity Factor and Market Factor								
	FF25	US Bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
HKM Equity	0.02	-1.97	2.79	8.05	4.89***	1.01	3.20**	0.88
	(0.03)	(-1.05)	(1.52)	(1.30)	(3.39)	(0.96)	(1.97)	(1.40)
Market Factor	0.15	1.69	0.81	2.92	0.55	1.22	-0.47	0.69**
	(0.30)	(1.48)	(0.67)	(1.48)	(0.60)	(1.63)	(-0.39)	(2.30)
Intercept	0.74*	0.17***	0.45*	-2.66*	-0.15***	-0.28	-0.25	-0.03
	(1.87)	(3.41)	(1.70)	(-1.71)	(-4.15)	(-1.12)	(-0.90)	(-0.32)
R^2	3.00%	76.00%	76.00%	94.00%	72.00%	13.00%	40.00%	37.00%
MAPE	0.13%	0.06%	0.14%	0.09%	0.07%	0.47%	0.11%	0.29%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

Table 1.7: **Three-Factor Model: Liability-Weighted Debt Factor, HKM Equity, and Market, Quarterly.** Estimates of the prices of risk of shocks to the intermediary debt factor, HKM equity factor and the market's excess return factor. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. HKM equity is the intermediary equity return factor and the market factor is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas) , expressed in percentage terms. Betas are calculated in a first-stage time series regression. The quarterly sample is from 2001 Q1 to 2021 Q1. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-5.75*	-19.83**	-14.34**	-26.94	-22.26***	-13.73**	-7.66	-9.66**
	(-1.66)	(-2.11)	(-2.00)	(-1.62)	(-4.40)	(-2.39)	(-0.94)	(-2.15)
HKM Equity	-0.08	3.88	5.29**	5.25	6.76***	2.23	10.56***	2.62
	(-0.04)	(1.10)	(2.35)	(0.59)	(2.80)	(0.57)	(2.58)	(1.34)
Market Factor	0.38	1.83	3.04	2.91	2.53	2.45	1.82	2.06**
	(0.27)	(0.99)	(0.98)	(1.26)	(1.47)	(1.21)	(0.65)	(2.12)
Intercept	2.48**	0.18***	0.55	-3.21*	-0.21***	0.72	-1.15*	0.16
	(2.43)	(3.77)	(1.13)	(-1.75)	(-3.83)	(0.72)	(-1.66)	(0.69)
R^2	13.00%	86.00%	92.00%	99.00%	93.00%	35.00%	74.00%	54.00%
MAPE	0.39%	0.14%	0.26%	0.08%	0.09%	1.29%	0.17%	0.75%
Assets	25	15	6	18	20	23	10	117
Quarters	80	79	40	43	47	80	78	80

Table 1.8: **Three-Factor Model: Arithmetic Mean Debt Factor, HKM Equity, and Market, Monthly.**
Estimates of the prices of risk for shocks to the intermediary debt factor, HKM equity factor and the market's excess return factor. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. HKM equity is the intermediary equity return factor and the market factor is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas), expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-3.99***	-7.47**	-6.29	-6.83**	-10.08***	-5.76***	-8.67*	-4.96***
	(-2.70)	(-2.49)	(-1.61)	(-2.09)	(-3.04)	(-2.69)	(-1.73)	(-3.94)
HKM Equity	-0.10	-0.04	2.64*	1.89	2.09	1.57	3.38	1.22*
	(-0.13)	(-0.04)	(1.95)	(0.37)	(1.45)	(1.06)	(1.47)	(1.88)
Market Factor	0.08	-0.12	0.52	0.55	-0.65	-0.12	-1.04	0.63**
	(0.16)	(-0.21)	(0.40)	(0.49)	(-0.74)	(-0.12)	(-0.68)	(2.10)
Intercept	0.78*	0.09***	0.04	-0.70	-0.11***	0.05	-0.36	-0.09
	(1.82)	(3.36)	(0.16)	(-0.80)	(-3.33)	(0.16)	(-0.96)	(-1.09)
R^2	26.00%	83.00%	90.00%	98.00%	88.00%	55.00%	57.00%	57.00%
MAPE	0.12%	0.05%	0.08%	0.06%	0.04%	0.36%	0.08%	0.25%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

Table 1.9: **Three-Factor Model: Liability-Weighted Debt Factor, HKM Capital, and Market, Monthly.** Estimates of the prices of risk for shocks to the intermediary debt factor, HKM capital factor and the market's excess return factor. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. The model also includes HKM intermediary capital ratio and the market factor which is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas) , expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-3.12**	-5.77**	-4.11	-7.77	-8.89***	-5.69**	-1.73	-5.04***
	(-2.22)	(-2.13)	(-1.58)	(-1.44)	(-3.31)	(-2.53)	(-0.46)	(-3.75)
HKM Capital	-0.09	-0.60	2.76**	-3.16	2.11*	1.74	2.94	1.57**
	(-0.13)	(-0.74)	(2.36)	(-0.78)	(1.76)	(1.32)	(1.58)	(2.39)
Market Factor	0.08	0.66	0.45	0.04	0.39	-0.24	-0.23	0.59*
	(0.16)	(1.03)	(0.36)	(0.03)	(0.54)	(-0.25)	(-0.22)	(1.95)
Intercept	0.80*	0.10***	0.28	-0.50	-0.11***	0.12	-0.14	-0.09
	(1.87)	(3.28)	(0.84)	(-0.52)	(-3.92)	(0.35)	(-0.49)	(-1.04)
R^2	16.00%	85.00%	92.00%	98.00%	85.00%	63.00%	20.00%	57.00%
MAPE	0.12%	0.05%	0.07%	0.06%	0.04%	0.32%	0.12%	0.25%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

Table 1.10: **Three-Factor Model: Liability-Weighted Debt Factor, HKM Equity, and Market, Monthly, HKM Test Assets.** Estimates of the prices of risk for shocks to the intermediary debt factor, HKM equity factor and the market's excess return factor. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. HKM equity is the intermediary equity return factor and the market factor is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas) , expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. We use the sample of test assets that HKM use and make available on their website. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-3.35*	-4.48	-4.64*	-6.89*	-8.00***	-3.45*	-11.73**	-3.54***
	(-1.70)	(-1.61)	(-1.67)	(-1.88)	(-3.27)	(-1.80)	(-2.02)	(-2.79)
HKM Equity	1.17	3.55***	2.99**	2.24	3.49**	1.22	4.17	2.00**
	(0.94)	(3.15)	(2.16)	(0.36)	(2.18)	(0.85)	(1.60)	(2.30)
Market Factor	0.10	-0.12	0.99	0.76	-0.29	-0.77	0.00	0.20
	(0.15)	(-0.15)	(0.94)	(0.54)	(-0.37)	(-0.96)	(0.00)	(0.50)
Intercept	0.35	0.08*	0.07	-1.01	-0.12***	0.60*	-0.66	0.04
	(0.59)	(1.80)	(0.31)	(-0.94)	(-3.53)	(1.76)	(-1.34)	(0.44)
R^2	16.00%	90.00%	90.00%	98.00%	88.00%	36.00%	51.00%	31.00%
MAPE	0.22%	0.05%	0.07%	0.07%	0.04%	0.45%	0.21%	0.28%
Assets	25	20	6	18	20	23	12	124
Months	143	131	123	132	143	143	108	143

Table 1.11: **Three-Factor Model: Liability-Weighted Debt Factor, HKM Equity, and Market, Monthly, With Restricted Intercept.**

Estimates of the prices of risk for shocks to our debt factor, HKM equity factor and the market's excess return factor with restricted intercept. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. HKM equity is the intermediary equity return factor and the market factor is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas) , expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-2.63*	-13.34***	-5.40*	-8.44	-10.41***	-6.56**	0.06	-4.70***
	(-1.71)	(-2.85)	(-1.72)	(-1.12)	(-2.86)	(-2.39)	(0.02)	(-3.38)
HKM Equity	0.75	1.56	2.98**	-5.78	0.11	1.95	1.64	1.17*
	(1.03)	(1.07)	(2.13)	(-0.83)	(0.08)	(1.27)	(1.09)	(1.77)
Market Factor	0.77	-1.03	1.05	-0.52	0.71	-0.18	-1.09	0.53*
	(1.45)	(-1.12)	(0.89)	(-0.34)	(0.77)	(-0.16)	(-1.12)	(1.81)
R^2	51.00%	105.00%	98.00%	97.00%	57.00%	60.00%	25.00%	43.00%
MAPE	0.13%	0.05%	0.07%	0.07%	0.06%	0.35%	0.11%	0.27%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

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Chapter 2

Social Premiums

Abstract

While there is extensive research on governance (G) and a growing focus on environmental (E) issues, the social dimension (S) of ESG investing is still underscrutinized. Using the MSCI social scores, we[1] find that the two main components of a firm's social score, human capital and product safety, command statistically significant (yet opposing) return premiums in the cross-section of US stocks. Specifically, stocks with a high human capital score earn higher returns, and stocks with a high product safety score earn lower returns. Consequently, the aggregate social score commands no premium as the opposing effects of its components neutralize each other. Our findings challenge the common ESG investing approach of amalgamating factors without considering their distinct, potentially contradictory, risk and return implications.

2.1 Introduction

Global investors have invested trillions of dollars based on environmental, social, and governance (ESG) criteria, frequently citing the prospect of enhanced returns as their

[1]This paper is joint work with Iwan Meier, Valeri Sokolovski, and Hoa Briscoe-Tran.

primary motivation for ESG investing.[2] Many ESG opponents, however, argue that it is purely value-destructive, with some policymakers even attempting to criminalize the use of ESG criteria in state pension funds.[3] Therefore, research into the relation between a firm's ESG ratings and its future returns is crucial. There exists an established literature on governance (G), predominantly demonstrating that improved governance enhances firm value (e.g., Gompers et al., 2003), and an expanding and active body of research on the impact of the environmental (E) dimension on stock returns (e.g., Bolton & Kacperczyk, 2021, 2023; Pástor et al., 2021, 2022). In contrast, the social (S) dimension has received relatively little attention. In this paper, we aim to fill this gap, examining whether a firm's social ratings predict its future stock returns.

We concentrate on the social scores within the MSCI ESG ratings.[4] The MSCI social rating is comprised of two primary components: the human capital score and the product safety score. For the human capital score, MSCI assesses how well a company manages its relationships with employees, labor health and safety, human capital development, and supply chain labor standards. We validate this measure and find, consistent with its description, that the MSCI human capital score is a strong predictor of a firm's likelihood to be listed on Fortune's "100 Best Companies to Work For" (Best Companies hereafter), which is determined based on an anonymous survey of the firms' employees. For the product safety score, MSCI assesses companies on their control of potential product-related liabilities, including product recalls and quality, chemical safety, privacy and data security, and consumer financial protection, as applicable. We also validate this measure and find, consistent with its intent, that a higher product safety score strongly predicts product-related controversies, such as drug or medical equipment safety violations for a

[2]See, e.g., Schroders' "Global Investor Study" of 2020 or BNP Pariabas' "The ESG Global Survey 2019".

[3]See "Making ESG a Crime", M. Levine, 17 January 2024, Bloomberg.

[4]We focus on MSCI scores for three reasons. First, MSCI is the largest provider of ESG ratings by revenue (Berg, Koelbel, Pavlova, & Rigobon, 2022). Second, as stated by Berg, Heeb, and Kölbel, 2022 in their study of five major ESG ratings, "only the MSCI ESG ratings can explain the holdings of US funds with an ESG mandate." Similarly, Serafeim and Yoon, 2023 find that the power to predict ESG news is strongest for MSCI ratings compared to those of other major rating agencies. Third, existing research studying the returns on ESG investing often uses MSCI ratings (e.g., Pástor et al., 2022). Thus, by focusing on the MSCI social rating, we can better relate our findings to the studies on the other aspects of ESG.

pharmaceutical company, for up to three years in the future.

The expected impact of a firm's social ratings on its future stock returns varies depending on whether the ratings pertain to human capital or product safety. There is extensive literature documenting that product safety incidents adversely affect firm value (e.g., Dowdell et al., 1992; Jarrell & Peltzman, 1985). In other words, product safety incidents are detrimental to business. Consequently, in the absence of any mispricing, we would expect firms with superior product safety to have safer cash flows and command lower expected returns, in line with their lower risk. However, if mispricing exists, which is possible for an intangible like product safety, then stocks with higher product safety scores may not necessarily yield lower average returns.

The expected impact of a firm's human capital score on its stock returns is even less clear. Given that the human capital score incorporates concerns about labor health and safety, economic intuition would suggest that firms with high human capital scores (characterized by fewer accidents due to safer working conditions) could exhibit lower risk in their cash flows. Consequently, these firms could command lower expected returns. However, empirical evidence suggests that firms providing a safe workplace have lower odds and length of survival (Pagell et al., 2020). Therefore, it may be that such firms actually command higher expected returns to compensate for their lower survival odds. It is also conceivable that investors have a non-pecuniary preference for employee well-being akin to investors having a preference for environmentally-friendly firms. Thus, investors could be content with lower expected returns in equilibrium (Pástor et al., 2021). However, the prevalence of such preferences, or even their existence, remains uncertain. Notably, employee satisfaction is a key component considered in constructing MSCI human capital scores, and existing literature indicates that employee satisfaction has a positive effect on returns. Specifically, several studies find that firms with high employee satisfaction consistently outperform the market (e.g., Boustanifar & Kang, 2022; Edmans, 2011; Edmans et al., 2023), a pattern consistent with the market underpricing employee satisfaction. Therefore, the expected impact of the human capital score on average returns is ambiguous, highlighting the importance of a thorough empirical investigation.

We assess the presence of social premiums in the cross-section of US stock returns using a standard cross-sectional regression approach, following Bolton and Kacperczyk, 2021, 2023. Consistent with economic intuition and efficient pricing, we identify a negative and statistically significant premium associated with the product safety score. This means that firms with safer products generate relatively lower average returns. Specifically, a one standard deviation increase in a firm's product safety score is associated with an approximate annual average return reduction of 1.20%, controlling for a battery of other return predictors from the extant literature as well as E and G scores. Contrary to our findings on product safety, but consistent with prior research, we find a positive and statistically significant premium associated with the human capital score. Moreover, the human capital score supersedes the indicator for Best Companies when both predictors are included in the regression specification. The pattern is consistent with the notion that markets do not fully price intangible assets like human capital (see Bongaerts et al., 2023, for other examples), but price the risks associated with product safety concerns.

Notably, the magnitude of the estimated human capital premium is comparable to that of the product safety score. Consequently, in our sample, the aggregate social score has no predictive power for future stock returns, as its two key components have opposing and neutralizing effects. In sum, while the aggregate social score does not predict stock returns in the cross-section, its individual components do. Our results call into question the approach in ESG investing that combines various factors, which may display divergent risk and return characteristics, into a single score. This has implications for investors, portfolio managers, and policy makers.

Related literature This paper contributes to several strands of the literature. First, it adds to the substantial and rapidly expanding ESG investing literature (see Matos, 2020, for a survey). A large portion of this literature investigates the effects of ESG characteristics on returns, treating ESG as a unified category (e.g., Glossner, 2021; Hartzmark & Sussman, 2019; Pedersen et al., 2021). Nonetheless, many studies focus on the return impact of one of the three broad ESG categories, predominantly concentrating on the G (e.g., Aggarwal et al., 2009; Bebchuk et al., 2013; Gompers et al., 2003) and more recently, the E (e.g., Aswani et al., 2024; Bolton & Kacperczyk, 2021, 2023; Pástor et al., 2021, 2022; Zhang, 2024). Our paper contributes to the ESG investing literature by not only focusing on the relatively overlooked S category, but also by dissecting it into its components. In this manner, we directly address Edmans, 2023's call for ESG research to adopt a more granular approach, as broad ESG categories may encompass many potentially contradictory factors.

Second, our paper contributes to the literature on ESG ratings. Prior research shows that ESG ratings often disagree with each other (e.g., Berg, Koelbel, & Rigobon, 2022). Despite this disagreement, users of commercially available ESG ratings frequently accept these ratings at face value without attempting to validate them. Hence, we conduct formal tests to validate the subcomponent scores of the MSCI ESG ratings, one of the most widely used ESG ratings, focusing specifically on S. This validation is crucial because our research necessitates a deeper examination of the various components within S to fully comprehend what these components capture. By doing this, we gain greater confidence in our inferences and formally connect the widely used ESG ratings to established concepts in the literature, specifically human capital and product safety. Our findings echo Edmans, 2023's perspective that ESG is not a new concept in itself but rather a reflection of a firm's intangible capital, a key research topic in finance.[5]

Third, this paper contributes to the literature on the asset pricing impact of product safety. Product safety, as a dimension of a firm's intangible capital, receives significantly less attention in the asset pricing literature compared to human capital. Exceptions include studies examining the impact of ex-post adverse tail events related to product safety on a firm's stock prices, such as product recalls (e.g., Dowdell et al., 1992; Pozo & Schroeder, 2016; Thomsen & McKenzie, 2001), data breaches (Kamiya et al., 2021), and safety concerns (Krüger, 2015). In contrast, our paper investigates product safety in

[5] Eisfeldt et al., 2020 document that over half of the overall corporate capital stock is intangible, with the largest portion being intangible assets created by investments in employees (i.e., human capital), brand, and knowledge capital.

the cross-section, focusing on an ex-ante measure of product safety.[6] Thus, our paper aligns with research at the intersection of marketing and finance, which demonstrates that higher customer satisfaction predicts increased future stock returns (Anderson et al., 2004; Fornell et al., 2016; Huang, 2018). Since our findings indicate that improved product safety predicts lower stock returns, this suggests that the product safety score is distinct from a general sense of customer satisfaction.

Finally, our paper contributes to the literature on the asset pricing impact of human capital. Existing research in this area examines indicators of human capital, such as membership on the Best Companies list (Boustanifar & Kang, 2022; Edmans, 2011, 2012; Edmans et al., 2023), and their relationship with stock returns. However, little research has connected these existing indicators with commercially available human capital ratings within ESG frameworks. We demonstrate that commercial ESG ratings indeed capture aspects of human capital related to some of these existing indicators. However, they also encompass information beyond what these indicators provide.

2.2 Background, definitions, and hypotheses

In this section, we outline the motivation behind our main empirical investigation, offering essential background information on ESG investing. Additionally, we describe how the MSCI S scores are calculated and formulate the hypotheses that are tested in the paper.

2.2.1 Background on ESG investing

This subsection provides background information on ESG investing and motivates the main empirical questions explored in the paper.

[6]Recent anecdotal evidence of investors' concerns regarding ex ante product safety can be seen in the apprehensions expressed by Coca-Cola and Pepsi investors about potential safety issues surrounding artificial sweeteners. See "Coca-Cola and Pepsi face investors' bubbling health concerns", L. Harris and S. Mundy, 1 May 2024, Financial Times.

The practice of combining multiple issues into broad ESG categories

The assets under management committed to ESG investing have surged more than tenfold, from under \$10 trillion in 2006 to over \$120 trillion in 2021.[7] This dramatic increase occurred shortly after the introduction of the acronym"ESG", which was developed in a 2004 report by major financial institutions responding to a call from Kofi Annan, then Secretary-General of the United Nations. Since then, the term "ESG" has been widely adopted to collectively describe environmental, social, and governance practices.

However, the term "ESG" is very broad, encompassing E and S, formerly referred to as CSR (corporate social responsibility), and G (governance).[8] Hence, many have raised questions about the practice of combining G with E and S issues. As Edmans, 2023 succinctly notes: "ESG is an umbrella term, capturing many potentially contradictory factors. E and S is primarily about stakeholders, whereas G often ensures that managers act in shareholders' interest (rather than their own)." Aswath Damodaran, in a *Financial Times* article, raises a similar point regarding governance, stating that "its presence in ESG has always been puzzling, since it replaces the original notion of corporate governance, where managers are accountable to shareholders, with one where managers are accountable to all stakeholders, effectively making them accountable to none of them."[9]

Within each broad ESG category, combining many subcategories may not be logical either, as different subcategories can have varied implications for risk, return, and corporate policies. Unfortunately, research on how distinct ESG issues uniquely affect financial returns is scarce, leaving little scientific foundation for the current practice of evaluating firms on multiple ESG issues and aggregating them into a composite E, S, or G scores. Edmans, 2023 acknowledges this research gap and recommends future research "to be more granular", noting that "sweeping questions such as 'Does ESG work?' are unlikely to be fruitful."

[7] See UNPRI's Anuual Report 2021 "Enhance our global footprint".
[8] See Gillan et al., 2021 for an overview.
[9] See "ESG is beyond redemption: may it RIP", A. Damodaran, 22 October 2023, *Financial Times*.

In this paper, we directly address this call by focusing on the S category to examine how its subcomponents influence stock returns. We explain our emphasis on the S category over E and G in the following subsection.

Limited attention to the S category of ESG

In the ESG investing literature, specifically among the studies on stock returns and ESG factors, there is a notable imbalance in the distribution of attention across the E, S, and G. Corporate governance, or G, issues have been extensively studied in the literature, particularly from a theoretical perspective, since at least the nineties (see, e.g., Shleifer & Vishny, 1997b, and references therein). Empirically, Gompers et al., 2003 show that US firms with better corporate governance, characterized by stronger shareholder rights, earn significantly higher stock returns and exhibit higher values, profits, and sales growth. Their seminal study then spawned a large literature on the impact of various dimensions of corporate governance on firm outcomes (see, e.g., McCahery et al., 2016, and the extensive references therein). In sum, there exists a comprehensive body of work on G.

Similarly, and more recently, there is a rapidly expanding body of research on the E category. Notably, Pástor et al., 2021 develop a theoretical model featuring heterogeneous investors with "green" preferences, providing clear predictions that environmentally-friendly (green), and hence relatively safer, assets should yield lower expected returns than polluting assets in equilibrium. In other words, the model rationalizes the so-called "greenium", the positive premium paid by investors for green assets, which naturally implies lower expected returns as well. Bolton and Kacperczyk, 2021, 2023 offer evidence corroborating the model's predictions, finding that polluting stocks earn a risk premium in the cross-section of US and international stocks. While some disagreements about the empirical conclusions remain (e.g., Aswani et al., 2024; Atilgan et al., 2023; Pástor et al., 2022; Zhang, 2024), the E dimension, nevertheless, appears well-researched.

In contrast, the S category has received significantly less attention. Earlier studies explored various aspects of a firm that could be related to social issues, such as employee satisfaction (Edmans, 2011, 2012), and recent work shows that institutional investors tilt their portfolio holdings toward stocks with better S ratings (Pástor et al., 2024). However, there is limited research on what a higher S rating signifies for a firm's stock return, and particularly, whether an S premium exists. There are some exceptions, like Lindsey et al., 2023, who examine whether a firm's social rating correlates with stock returns within their broader investigation of ESG ratings' impact on stock returns. These studies typically just document that the aggregate S score does not significantly affect stock returns, and do not delve deeper into the individual components of the S score. Hence, it remains an open question whether investing based on a firm's social ratings is fruitless, or if the diverse components of a firm's social ratings have implications for stock returns but become obscured in the aggregation process. This paper aims to address this gap.

2.2.2 Hypotheses development

In this sub-section, we articulate our hypotheses regarding the potential effects of S on stock returns. To formulate an ex-ante theoretical prediction about the effect of S on expected returns, one could potentially reinterpret the previously-mentioned equilibrium model of Pástor et al., 2021 to accommodate investors' preferences for S in addition to or instead of E. The predictions of the model about returns would then mirror those about E: firms that are socially responsible should command lower expected returns. However, while there is little contention over what defines a polluting firm, the criteria for a socially responsible firm are less clear. In other words, without a solid understanding of what S measures, such a theoretical interpretation is not fruitful. Therefore, a precise definition of S is crucial for formulation of a valid hypothesis. As we detail below and in the next section, the MSCI aggregate social score is comprised of two main components: the human capital score and the product safety score (other rating agencies typically also consider similar themes). We, thus, turn to these components to formulate hypotheses about the relation of S to returns.

Human capital score

Definition The MSCI human capital score (Human Capital score hereafter) considers four key issues: Health & Safety, Human Capital Development, Labor Management, and Supply Chain Labor Standards, with Human Capital Development being the primary issue as in cases where data for other issues are missing, the Human Capital Development sub-score is used to compute the aggregate Human Capital score. Health & Safety score assesses companies on their management of workplace safety and adherence to safety standards. Human Capital Development score addresses talent requirements and the ability to recruit, retain, and develop a qualified workforce. Notably, the evaluation of the Human Capital Development score considers attributes such as the frequency of employee satisfaction surveys and external recognition as an employer of choice. This is similar to Fortune's Best Companies list, analysed by Edmans, 2011, that is also derived from employee satisfaction surveys. In addition, Human Capital Development score considers the extent of eligibility for employee stock purchase/ownership plans and whether non-officer and non-sales staff are eligible for variable performance-based pay. These remuneration-related attributes are likely to affect employee satisfaction indirectly. Labor Management score evaluates a company's workforce complexity, the management-labor dynamic, worker rights effectiveness, and employee engagement. Lastly, Supply Chain Labor Standards score reviews the management, transparency, and working conditions within the supply chain.[10] In summary, the core of the Human Capital score centers on employee well-being and satisfaction, as well as effective human resource management — attributes that are potentially value-enhancing.[11]

Hypothesis Economic intuition, theory, and prior empirical research offer somewhat conflicting predictions regarding the expected impact of a firm's human capital score on

[10] See, "MSCI ESG Ratings Methodology: Human Capital Development Key Issue" for additional details.

[11] For example, Hazarika et al., 2023 find that global firms adopting executive ESG-linked pay experience better employee satisfaction and also better financial performance.

its stock returns. First, since the human capital score includes considerations about labor health and safety, economic intuition would suggest that firms with high human capital scores, characterized by fewer labor incidents, might exhibit lower risk in their cash flows and, consequently, could command lower expected returns. However, empirical evidence indicates that firms that maintain a safe workplace tend to have shorter lifespans and lower survival probabilities (Pagell et al., 2020). Consequently, these firms might require higher expected returns as compensation for their reduced likelihood of long-term survival. Hence, the effect of that consideration on returns is not ex ante obvious. Second, as previously mentioned, it is plausible that investors have a non-pecuniary preference for employee well-being as in Pástor et al., 2021's model, which would suggest that firms with higher human capital scores could have lower expected returns in equilibrium. However the extent to which such "warm glow" preferences influence investment decisions, or whether they are influential at all, is still not clearly established. Third, and perhaps most crucially, employee satisfaction is a fundamental component used in calculating human capital scores, and existing literature suggests that employee satisfaction positively influences returns. Specifically, Edmans, 2011 finds that between 1984-2009, firms on Fortune's Best Companies list outperform, achieving a four-factor alpha of 3.5% per year and an industry-matched alpha of 2.1% per year. Boustanifar and Kang, 2022 corroborates the original findings over an extended sample period, noting only a slight reduction in outperformance in later years, especially when accounting for a more comprehensive set of risk factors. Hence, this outperformance appears persistent and is also documented in other contexts (e.g., Shan & Tang, 2023; Yee et al., 2008). Edmans, 2011 provides two potential reasons for these findings: 1) the market is not fully aware of the benefits of employee satisfaction, because theory predictions are not conclusive, 2) conventional valuation methods do not incorporate intangible assets properly. Therefore, the following hypothesis emerges: If we assume that firms with higher human capital scores are characterized by more productive and satisfied employees, and if we further assume that the market does not fully incorporate the value-enhancing properties of greater employee well-being, then we would expect firms with higher human capital scores to earn higher average returns.

Product safety score

Definition The MSCI product safety score (Product Safety score hereafter) considers five key issues: Product Safety & Quality, Chemical Safety, Privacy & Data Security, Consumer Financial Protection, and Responsible Investment. Notably, different issues apply only to firms in certain industries and not to others. Product Safety & Quality issue measures companies' risk of product safety incidents or recalls, supply chain and sourcing system effectiveness, quality control in manufacturing, and responsible marketing. Chemical Safety score evaluates the use of hazardous chemicals in products, exposure to evolving or strict regulations, and efforts to develop safer alternatives. Privacy & Data Security score examines the volume of personal data collected, adherence to privacy regulations, data breach susceptibility, and efficacy of data protection procedures. Consumer Financial Protection score assesses financial institutions on product stewardship, transparency, and handling potential reputation and regulatory risks, such as unethical lending, greenwashing, and misrepresentation of financial products. Responsible Investment score captures how investment companies or asset managers integrate ESG factors in managing their own or others' assets. In summary, the essence of the Product Safety score focuses on assessing the relevant risks associated with the firms' main products.

Hypothesis In contrast to the factors underpinning the Human Capital score, the issues central to the Product Safety score do not seem inherently value-enhancing, but rather measure potential future liabilities pertaining to a firm's main products (interestingly, MSCI has recently renamed Product Safety to Product Liability).

Product safety concerns form the core of the Product Safety score, and there is ample evidence that product safety issues lead to significant financial losses.[12] The financial

[12]The literature documents a negative impact on firm value from (i) recall campaigns by car manufacturers (e.g., Barber & Darrough, 1996), (ii) food recalls (Kong et al., 2019; Pozo & Schroeder, 2016; Thomsen & McKenzie, 2001), (iii) recalls or repairs of consumer goods (Davidson III & Worrell,

impact of product safety violations and recalls includes direct costs in lost revenue and indirect costs from damage to a company's brand reputation and higher future insurance premiums. Direct costs entail expenses associated with notifying customers, the logistics of retrieving products from the market, and repairing, correcting, or replacing defective items. Moreover, a company may need to bear expenses related to compensating retailers and distributors for their losses (supply chain costs). Investigating the source of a safety issue may involve expenses for laboratory testing to identify contamination and costs associated with non-compliance with regulatory standards e.g., Dranove and Olsen, 1994. Crisis management, which includes responding to media and public relations inquiries or hiring an external crisis management team, also incurs significant costs.[13] In the aftermath of a product recall, defending against lawsuits, settling disputes with consumers harmed by the recalled product, and responding to regulatory inquiries can be costly and time-consuming. Additionally, public relations campaigns aimed at restoring brand image after negative publicity also demand significant financial and time investments.

The indirect costs associated with the loss of brand reputation are often more substantial than direct costs (Jarrell & Peltzman, 1985; Karpoff & Lott Jr, 1993; Mitchell, 1989). Beyond the immediate revenue loss from the recall itself, the perception of reduced quality, erosion of trust among loyal customers, and the loss of goodwill following a product safety issue can lead to decreased sales. Consequently, this often results in a reduction in market share and lost business opportunities (Barber & Darrough, 1996). Additional knock-on costs include the negative impacts of complying with more stringent drug testing requirements (Dranove & Olsen, 1994) and the fact that companies with a history of product safety issues often face higher insurance premiums.

1992), and (iv) drug recalls (Ahmed et al., 2002; Dowdell et al., 1992; Dranove & Olsen, 1994; Jarrell & Peltzman, 1985). Relatedly, Borenstein and Zimmerman, 1988 and Mitchell and Maloney, 1989 document significant adverse effects on firm value resulting from airline crashes. Notably, Krüger, 2015 examines adverse CSR events within an event study framework, finding that approximately half of the adverse CSR events in his sample pertained to product safety issues. These events resulted in significant negative abnormal returns of around 1.22%.

[13] Mitchell, 1989 cites a source estimating that the cost for Johnson & Johnson to achieve as much airtime and print space as it did after the 1982 Tylenol poisonings would have been around $1 billion. This corresponds to 43% of Dowdell et al., 1992's estimate of the total loss in market capitalization from the Tylenol incident, which was $2.31 billion (approximately -29% of market value).

Privacy and data security concerns form another key facet of the Product Safety score. The protection of privacy and data security is becoming increasingly crucial. Technology and internet companies, for instance, process significant amounts of user data on platforms such as social media and e-commerce websites. Similarly, pharmaceutical companies and healthcare providers handle sensitive patient information, while banks and insurance companies store substantial volumes of financial and personal data. The literature finds the adverse impact on firm value from data breaches (Kamiya et al., 2021), privacy breaches (Tripathi & Mukhopadhyay, 2022), and hacker attacks (Hinz et al., 2015).[14]

Consumer financial protection concerns and responsible investing concerns are the final two facets considered in the Product Safety score, with both elements being relevant specifically for the financial industry. To the best of our knowledge, there is no comprehensive academic study that investigates the effect of consumer financial protection breaches on a financial institution's value. However, convincing anecdotal evidence can be seen in the losses associated with Wells Fargo's fraudulent bank accounts scandal, where it was ordered to pay $3.7 billion in fines in addition to suffering significant reputational damage.[15] Regarding responsible investing issues, Akyildirim et al., 2023 find that greenwashing scandals are associated with negative abnormal returns.

In summary, the discussion suggests that all the issues covered by the Product Safety score relate to the risks faced by a firm.[16] Therefore, alleviating these issues could help mitigate the risk of significant reputational and financial losses. Consequently, in the absence of any mispricing, we would expect firms with superior product safety to exhibit safer cash flows and earn lower average returns, consistent with their lower risk if such risks are material.

[14] Spanos and Angelis, 2016 review the literature, documenting a negative impact of security breaches on affected firms in 20 out of 28 studies, with another five studies showing a negative but insignificant effect.

[15] See, e.g., "Wells Fargo to pay $3.7bn over loan violations", J. Franklin and S. Chavez, 20 December 2022, *Financial Times*.

[16] Edmans, 2023 argues that "some ESG factors may be best thought of as risks rather than assets", and Product Safety seems to fit into that category.

2.3 Data and empirical methodology

2.3.1 Data

In this subsection, we describe all the data used in our study.

Social scores

Our data on the aggregate social scores and their components are sourced from the MSCI ESG Ratings database. We focus on firms with International Securities Identification Numbers (ISIN) starting with 'US'. To address data gaps, we use the last available information to fill in gaps for up to 24 months.

The MSCI aggregate S scores (Social scores hereafter) are derived from four sub-component scores (dubbed theme scores in MSCI documentation): Human Capital, Product Safety, Social Opportunities, and Stakeholder Opposition. As previously mentioned, our analysis concentrates on the two primary components, Human Capital and Product Safety, with data availability starting in 2013. Data for the aggregate Social scores is available from 2007, but coverage is limited before 2013. Data for the other two sub-components is only available from 2016 onwards but is limited to only a few industries and firms; we, thus, omit these sub-components from our primary analysis.[17] Hence, our sample period spans from 2007 to 2022 for the aggregate Social score, and from 2013 to 2022 for its components, which is slightly longer than the period examined by Pástor et al., 2022 for their analysis of E.

Firms' ratings are based on their exposure to and management of industry-relevant social risks, relative to their peers. Different industries face unique social risks. For example, in the communication services sector, privacy and data security are critically important, accounting for around 49% of the social score, whereas in the materials sector, this risk is not weighted at all. Conversely, health and safety issues represent a significant risk in the health care sector, contributing to around 40% of the social score, while such

[17] Summary statistics for these sub-components are available in the Internet Appendix.

concerns are not applicable to information technology firms.

MSCI ESG ratings are derived from public and macro-level data relevant to the company and its operating sector. This data includes corporate disclosure documents, datasets from governments, regulatory bodies, and NGOs, as well as media sources. To calculate sub-component scores, MSCI evaluates two to five key issues per industry, with industries classified according to the Global Industry Classification Standard (GICS). All scores are rated on a scale of 0 to 10. Therefore, scores for social score sub-components such as Product Safety are calculated as a weighted average of the underlying key issue scores. These sub-component scores are then combined into an aggregate social score using a weighted methodology for aggregation. Notably, since the rating methodology is tailored to each industry, these aggregate social scores (and their sub-components) are not absolute values and should, thus, be interpreted relative to the scores of industry peers. High scores denote industry leadership, whereas low scores suggest falling behind industry standards.

Social scores data coverage

Figure 2.1 displays the evolution of firm coverage from January 2007 to December 2022. Panel A shows the number of firms with non-missing data in the CRSP-Compustat merged dataset, as well as those reporting Social, Human Capital, and Product Safety scores. Initially, the dataset includes 3,549 firms, decreasing to 3,016 by December 2022. This downward trend is similar to findings of Lindsey et al., 2023, with minor discrepancies in firm counts likely due to different criteria for firm characteristics between our studies. Initially, only 387 firms report the aggregate Social score, increasing to 1,547 firms by the end of 2012, aligning with MSCI ESG's expanded coverage to include smaller firms, a trend also observed in Pástor et al., 2022.[18] Post-2012, the firm count in our sample stabilizes around the 1600s, peaking at 1,760 in 2021. Starting in 2013, MSCI begins

[18] The surge in coverage reflects MSCI's inclusion of the U.S. Investible Market Index, predominantly comprising smaller US firms. Prior to this, MSCI primarily focused on the largest 1,500 firms in the MSCI World Index and large firms in the UK and Australia MSCI indexes.

reporting scores for the Human Capital and Product Safety scores. By December 2013, 1,633 firms report the Human Capital score, and this number generally remains in the 1500s and 1600s, reaching a maximum of 1,758 in 2021 before slightly decreasing in 2022. While most firms reporting the Social score also report Human Capital, fewer report Product Safety. In December 2013, 1,142 firms report the Product Safety score, which sees a decline in 2014 and 2015, followed by stability until 2018. The count then gradually increases to around 1,300 in 2021 and 2022.

Panel B of Figure 2.1 shows the total market capitalization of firms in the CRSP-Compustat dataset, along with those reporting Social, Human Capital, and Product Safety scores. Since the start of coverage in 2007, the total market capitalization of the firms in the CRSP-Compustat dataset and those with aggregate Social scores are closely matched. By 2022, the market capitalization of both converged to around $30 trillion. The market capitalization trajectory of firms with Human Capital scores closely mirrors those with Social scores, indicating a significant overlap in reporting entities. The market capitalization of firms with Product Safety scores was initially lower but reaches $23.4 trillion by December 2022.

Analyzing the total market capitalization of firms across different market capitalization tertiles yields further insights.[19] Figure 2.2 illustrates the distribution of firms by market cap categories, while Figure 2.3 presents their respective total market capitalizations. Notably, the coverage of the largest firms is extensive, encompassing the majority of the market capitalization of the largest listed stocks and, thus, a substantial portion of the overall market capitalization. Essentially, the dataset provides almost complete coverage based on the market capitalization criterion. The addition of small-cap stocks towards the end of 2013 further minimized any discrepancies in market cap coverage.

[19] Firms reporting Social, Human Capital, and Product Safety scores are classified into three market cap categories: small-cap, mid-cap, and large-cap, using market equity breakpoint data from Kenneth French's website. This dataset employs all NYSE stocks with share codes 10 or 11 to compute market equity percentiles from 5% to 100%, spanning from December 1925 to June 2023. The cutoff percentiles for constructing market cap buckets are the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles.

In Figure 2.4, we illustrate the distribution of firms reporting Social, Human Capital, and Product Safety scores, categorized by economic sector using GICS two-digit codes. Upon examining the CRSP-Compustat dataset, we observe that sectors like health care, finance, and information technology boast the highest number of firms. In contrast, sectors such as real estate, utilities, communication services, and materials feature a lower number of firms. The distribution of firms reporting Social and Human Capital scores mirrors the market's industry distribution. Firms with Product Safety scores generally also match the market's industry distribution, with some notable exceptions in sectors like Industrials, Energy, Materials, and Utilities (due to Product Safety's focus on consumer-facing products, its coverage is reduced in primary sectors like energy and materials).

Stock returns and firm characteristics

We obtain monthly stock prices, returns, and shares outstanding from CRSP and incorporate firm-level accounting data from Compustat. To clean and merge the CRSP and Compustat datasets, we follow the standard procedures described in Bali et al., 2016.

Given the limited guidance from the existing literature regarding the determinants of social scores, our choice of control variables in our analyses largely mirrors Bolton and Kacperczyk, 2021, which includes key predictors of returns in the cross-section of stock returns. Monthly stock returns from CRSP are adjusted for delistings and winsorized at the 0.1% level following Edmans et al., 2023. Beta refers to the CAPM beta, calculated using the WRDS Beta Suite with daily returns, employing a one-year rolling window, and requiring a minimum of 200 observations. The Momentum of firm i at time t is the cumulative monthly stock return over the year from month t˘12 to month t˘1. Volatility of firm i at time t is the standard deviation of monthly returns over the same period. For the construction of accounting ratios, we follow Jensen et al., 2023. Log Size is the natural logarithm of a firm's market capitalization (share price multiplied by the shares outstanding), and BM is the book-to-market ratio, both calculated as of year-end. Leverage is the book value of debt to the book value of assets ratio, and Investments is the capital expenditure to the book value of assets ratio. Log PPE is the natural logarithm of the firm's net plant, property, and equipment. ROE, return to equity ratio, is computed as net income to book value of equity. Sales Growth is the annual sales change to the one-month lagged market capitalization ratio. EPS Growth is the annual change in earnings per share, excluding extraordinary items, to the share price ratio. HHI is the Herfindahl-Hirschman Index, computed using sales data from the Compustat Segments database. Following Bolton and Kacperczyk, 2021, we winsorize BM, Leverage, and Investments at 2.5%, and Momentum, Volatility, Sales Growth, and EPS Growth at 0.5%.

Best Company indicator, and product controversies and sentiment

In our analyses to validate the Human Capital score, we use the variable from Edmans, 2011 and Boustanifar and Kang, 2022 that identifies firms featured in Fortune's annual Best Companies list, derived from independent and anonymous employee surveys.[20] This variable, Best Company indicator, is assigned a value of one for any year a company is included in this top 100 list, and zero otherwise.

To validate the Product Safety score, we relate it to future product controversies. Finding a comprehensive database of product controversies is challenging. However, a start-up, Market Psych, in partnership with Refinitiv, developed an algorithm to sift through a vast corpus of news and social media sources to score market sentiments on individual firms' various issues, including those related to products. They claim to exclude media sources controlled by firms, such as press releases and company-owned Twitter accounts. Following Aggarwal et al., 2024, who use the Market Psych database to gauge public sentiments about companies on various issues, we use this database to measure product controversies and product sentiment in order to validate the Product Safety score.

[20]Each January, Fortune magazine publishes this list, which is compiled by The Great Place to Work Institute. The data is publicly available. We thank Hamid Boustanifar for providing us the data from Boustanifar and Kang, 2022. We then extend the dataset to include the years 2021 and 2022.

Sample and descriptive statistics

We analyze US companies over the sample period from January 2007 to December 2022. We merge the S scores from the MSCI ESG Ratings database with CRSP-Compustat using the date and the first six digits of the CUSIP.[21] Out of the 7,964 US firms in the MSCI ESG Ratings database, we match 3,580 with CRSP-Compustat. The unmatched firms are mostly not listed on the three major exchanges covered by CRSP (NYSE, Amex, and Nasdaq).

Panel A of Table 2.1 presents descriptive statistics for the aggregate Social score and the sub-component scores of Human Capital and Product Safety, as well as aggregate environmental and governance scores (Environmental Score and Governance Score hereafter). The aggregate Social score's mean and median is 4.37 and 4.30, respectively, with extreme values being less common as 90% of observations fall between 2 and 6.9. The means and medians for Human Capital (4.16 and 4.10, respectively) and Product Safety (4.64 and 4.50, respectively) are similar. The distributions of all the scores are symmetrical, as evidenced by the close proximity of mean and median values. Product Safety score shows the greatest variability, with a standard deviation of 2.24.[22]

Table 2.2 presents the correlations between the different ESG scores and firm size. By construction, the Human Capital Score and Product Safety Score are correlated with the Social Score (correlation coefficients of 0.60 and 0.69, respectively). However, it is noteworthy that the Human Capital Score and Product Safety Score are slightly negatively correlated (-0.22), suggesting that the two measures capture different information. Moreover, the Human Capital Score is not correlated with either the Environmental Score or the Governance Score. The Product Safety Score is slightly positively correlated with the Environmental Score (correlation coefficient of 0.20). None of the scores appear strongly correlated with firm size, with the largest correlation coefficient being 0.29 for the Environmental Score.

[21] The first six digits of the CUSIP identify the firm. To ensure that the merge does not yield incorrect matches, we perform string cleaning and fuzzy matching on company names and manually check the few companies that match by CUSIP but not by names.

[22] Descriptive statistics for social scores by year and by industry are presented in the Internet Appendix.

Panel B of Table 2.1 presents the descriptive statistics for firm characteristics and stock returns. The average monthly return is 1.02%, with a standard deviation of 12.14%. The firms in our sample have a slightly higher market risk than the overall market, with an average beta coefficient of 1.15. There are stocks in our sample with notable momentum, with the 5^{th} and 95^{th} percentiles of cumulative returns being -49% and 95%, respectively. The average return volatility measure is 0.10. The mean log market capitalization is 8, and the mean log PPE is 5.74. The average book-to-market ratio is 0.52, and the mean leverage is 23%. Nearly half (45%) of the sample firms are concentrated in a single business segment, with an HHI across all firms at 0.76. Sales growth averages at 3%, with a notably high standard deviation of 57%. Over our sample period, the average EPS growth for our sample of firms is slightly negative, at -1%. The Internet Appendix reports pairwise correlations among the different variables used in our tests, with few noteworthy correlations (we note that Human Capital and Product Safety scores are slightly negatively correlated, -0.21, and both scores are slightly positively correlated with firm size, 0.10).

Panel C of Table 2.1 presents the descriptive statistics for the sentiment measures. Product Controversy is a sentiment measure of product-related controversies firm *i* has in year *t* across news and social media sources. Product Sentiment is a sentiment measure of media sentiment related to a firm's products in each year across news and social media sources. Both sentiment scores can range from -1 to 1. However, for Product Controversy, negative values are rare. They typically refer to discreet revaluations of the variable such as a sudden decline in product controversies. A higher value of Product Controversy score signals worse perception regarding a firm's product-related controversies, whereas a higher Product Sentiment score reflects better product quality and customer satisfaction. The summary statistics highlight that there is meaningful cross-sectional variation in the two variables, particularly in Product Controversy, which we use for our primary analysis.

2.3.2 Empirical methodology

Our empirical methodology is standard, largely following Bolton and Kacperczyk, 2021 and Bolton and Kacperczyk, 2023.

For our main analysis, we examine the relationship between a firm's social scores and its future stock returns, controlling for other known predictors. Specifically, we estimate pooled OLS regressions of the following form:

$$\mathrm{R}_{i,t} = \beta^{\mathrm{S}}\mathrm{S}_{i,t-1} + c' X_{i,t-1} + \gamma_{\text{industry}} + \gamma_{\text{time}} + \varepsilon_{i,t}, \tag{2.1}$$

where the dependent variable, $R_{i,t}$, is the stock returns of firm i in month t. $S_{i,t-1}$ denotes a social score variable (referring to Social score, Human Capital score or Product Safety score) of firm i in month $t-1$. $X_{i,t-1}$ is a vector of controls. Controls typically include firm characteristics like Log Size, Book-to-Market ratio, Investment, Leverage, Log PPE, ROE ratio, Sales Growth, EPS Growth and business segments HHI; as well as stock characteristics such as: CAPM Beta, Momentum and Volatility. We always include industry fixed effects, γ_{industry}, as social scores are constructed as within-industry scores. We also include time fixed effects, γ_{time}. We follow Abadie et al., 2023 in our choice of standard errors. In particular, we cluster standard errors at the level that captures the most variation in our variable of interest – the social scores. Given that these scores predominantly vary across firms, we cluster standard errors at the firm level.

In Section 2.4, we evaluate whether the MSCI social scores can predict relevant validating variables like product controversies. We use similar regression specifications to equation (2.1) for that analysis, with key differences including a change in the dependent variable, the use of annual instead of monthly data, and the use of logistic regression in cases where the dependent variables are binary.

2.4 Validation of social score measures

In this section, we assess whether MSCI social scores accurately capture what they are intended to capture. We do this by examining if the scores forecast a firm's future social outcomes. Specifically, we gather future outcome indicators related to human capital and product safety from independent sources. For each social outcome, we regress its future value in years $t+1$, $t+2$, or $t+3$ against the social scores, controlling for industry and year fixed effects, along with multiple firm characteristics described previously.

2.4.1 Validation of Human Capital score

To validate the Human Capital score, we examine whether it predicts a firm's likelihood of appearing in Fortune's Best Companies list. The finance literature on employee satisfaction, initiated by Edmans, 2011, has shown that this indicator meaningfully reflects a firm's human capital and has significant implications for firm value. Accordingly, if the Human Capital score accurately captures a firm's human capital, it should positively and strongly correlate with the firm's inclusion in the Best Companies list. Conversely, as a placebo test, we do not anticipate the Product Safety score to have a similar predictive power for this list.

Table 2.3 presents the logistic regression results. In each specification we regress the Best Company indicator in year $t+1$, $t+2$, or $t+3$ on social scores and controls. Column (1) shows that the aggregate Social score is positively and significantly associated with a firm's likelihood of being in the Best Companies list in one year ahead. Columns (2) and (3) show that the overall positive and significant relation is primarily attributed to the human capital component of the social score. Specifically, the coefficient on the Human Capital score is 0.301 (significant at the 1% level), indicating that a one standard deviation higher in the Human Capital score is associated with a 73% ($e^{0.301\times 184}-1$) increase in the odds of a firm being designated as a Best Company the following year. In contrast, the coefficient on the product safety score is statistically indistinguishable from zero. Similar results are observed for predicting the Best Company two and three years ahead, columns (4) to (9). In sum, the results indicate that the MSCI social scores effectively capture significant variations in a firm's human capital, and importantly, for the relevant dimension of the social scores.

2.4.2 Validation of Product Safety score

To validate the Product Safety score, we examine whether it predicts a firm's product-related controversies in the future. Specifically, we use the product controversies score and the product sentiment score from Refinitiv Market Psych as our validating indicators of the Product Safety score. A higher value of the product controversies score reflects worse sentiment regarding a firm's product-related controversies, whereas a higher product sentiment score reflects better product quality and customer satisfaction. Product controversy and sentiment scores from Refinitiv Market Psych range from -1 to 1; however, for clarity in the regression tables, we rescale them to be between -100 and 100.

Table 2.4 presents the regression results for predicting the product controversies score. It indicates that a higher aggregate social score correlates with fewer controversies related to a firm's products in the subsequent one, two, and three years (columns 1, 4, and 7), achieving statistical significance at the 1% or 5% level. This significant relation is attributed solely to the product safety aspect of the social score. Specifically, the Product Safety score significantly predicts sentiment regarding a firm's product-related controversies one, two, and three years ahead, unlike the Human Capital score. The economic impact is notable: a one standard deviation increase in the product safety score corresponds to up to a 6% standard deviation decrease in the product controversies score. Similar patterns emerge in predicting the product sentiment score, where a higher Product Safety score predicts improved product sentiment in the future (see the Internet Appendix). Thus, the Product Safety score effectively captures variations in a firm's product safety, while the Human Capital score does not. Overall, the MSCI aggregate social score and its components successfully capture variations in a firm's human capital and product safety, accurately reflecting the intended dimensions.

2.5 Cross-sectional asset pricing results

In this section, we relate companies' social scores to their corresponding stock returns in the cross-section. Table 2.5 presents the cross-sectional regression results, estimating equation (2.1) on the cross-section of US stock returns. Our coefficient of interest is β^{S}, which we estimate for the three different scores related to the social dimension, the aggregate Social score and the two subcategories Human Capital and Product Safety.

Perhaps surprisingly, we find no effect of a firm's aggregate Social score on its returns, regardless of whether we include the controls (columns 1 and 4). In fact, the estimated coefficients are economically very close to zero.

In contrast, we observe a positive estimate for the Human Capital score, which is statistically significant at the 1% level (columns 2 and 5). In a specification that includes all the controls, the estimate is 0.0427, which corresponds to around 1% higher annual return for stocks with one standard deviation higher Human Capital scores. These results align with the findings of Boustanifar and Kang, 2022, who, expanding on Edmans, 2011, find that firms on the Best Companies list outperform by around 2% per year.[23] Our results support the hypothesis that firms with superior human capital have higher average returns. This result is consistent with existing literature but suggests that markets do not fully price in the value of human capital.

Additionally, we find a negative estimate for the Product Safety score, which is statistically significant at the 1% level (columns 3 and 6). Notably, the absolute magnitude of the point estimate for the Product Safety score coefficient, -0.0457, is essentially equal to that of the Human Capital score. This similarity accounts for the negligible effect of the aggregate Social Score, as it represents an average of two variables exerting opposite effects on future stock returns. Economically, the estimate translates to around 1.2% lower annual return for stocks with one standard deviation

[23] Both our methodology and our sample periods differ substantially from existing studies, hence we do not expect to find identical point estimates. However, given that Edmans, 2011 considers only 100 best ranked firms per year, a more suitable comparison would be firms within two standard deviations higher Human Capital scores, which would amount to a premium of exactly 2% per year aligning with the findings of prior research.

higher Product Safety scores. Our results corroborate the hypothesis that firms with superior product safety exhibit lower average returns, consistent with financial intuition, where lower risk typically necessitates lower expected return.

The estimated coefficients on the control variables have the expected signs and align with prior literature (e.g., larger stocks tend to have lower returns, on average). Both the Human Capital and Product Safety score estimates decrease slightly with the inclusion of the controls but still remain highly statistically significant. Given the comprehensive set of control variables included, this reinforces our conclusion that Human Capital and Product Safety scores provide incremental information not captured by other characteristics.

In Figure 2.5, we plot the time series of the cumulative values of the estimated human capital and product safety premiums. Specifically, the social premiums are estimated at each month t from the cross-sectional regression in equation (2.1). Because different social scores have varying ranges, we express the magnitudes in terms of the unit standard deviation of each score at each cross-section in time. This approach ensures that the plots of the cumulative effect display comparable numbers in terms of economic significance. The figure suggests that the premiums remain consistent over time.

Next, we evaluate whether the estimated social premiums may be partially driven by other ESG factors, namely E or G. Specifically, we add Environmental and Governance scores as additional controls. Table 2.6 presents the regression results. In a larger sample of firms reporting aggregate Social scores and Human Capital scores, the estimates for both the Environmental and Governance scores appear positive and statistically significant, in line with prior studies (e.g., Pástor et al., 2022). However, the coefficients for Environmental and Governance scores lose statistical significance in a smaller sub-sample of firms that report Product Safety scores. Importantly, controlling for Environmental and Governance scores, jointly or separately, has no discernible effect on the estimated coefficients for Human Capital and Product Safety scores. Hence, as was suggested by the correlations in Table 2.2, Human Capital and Product Safety capture different information compared to the other ESG scores.

Lastly, we evaluate whether the predictive power of the social scores is maintained with the inclusion of the Best Company indicator, which is known as a robust predictor of positive performance and also reflective of the human capital dimension. Table 2.7 presents the cross-sectional regression results. All the specifications include the full set of controls. In line with the extant literature (Boustanifar & Kang, 2022; Edmans, 2011) and despite differences in our methodology and sample, we find that the Best Company indicator is a positive and statistically significant predictor of future stock returns (column 1). The inclusion of the aggregate Social score does not alter the estimate for the Best Company indicator. However, when we instead control for the Human Capital score, the Best Company indicator estimate decreases by around 30% and loses statistical significance. Conversely, the Human Capital score remains statistically significant at the 1% level, and its magnitude is unaffected by the inclusion of the Best Company indicator. Therefore, the Human Capital score supersedes the explanatory power of the Best Company indicator. This is consistent with the fact that the Human Capital score considers employee satisfaction surveys in its calculation, and our findings that the Human Capital score predicts the Best Company indicator several years in advance. Additionally, in a specification including both the Best Company indicator and Product Safety score in column (4), both variables are statistically significant with minimal effect on the point estimates. This suggests that Product Safety captures distinct firm information from the Best Company indicator.

In sum, our findings indicate that the two main components of the S score are significant return predictors in the cross-section of stocks, though they operate in opposite directions.

2.6 Conclusion

Our analysis illuminates the impact of the S dimension of ESG on future stock returns. We find that the aggregate S score does not affect stock returns. However, the two main components of the S score exert significant, yet opposite, effects on returns. Specifically, higher human capital scores are associated with higher returns, aligning with previous research and suggesting that markets may not fully price in firms' human capital. Conversely, higher product safety scores are associated with lower average returns, consistent with the risk-based explanation that firms with safer products exhibit safer cash flows, reduced risk, and therefore, lower expected returns. This divergence questions the practice of combining varied ESG factors into a single score, which can mask the distinct risk and return implications of each component. Our findings underscore the complexity and diversity within ESG factors, particularly the social dimension, advising investors and practitioners to consider ESG criteria's individual aspects in investment decisions.

Table 2.1: Descriptive statistics

The table presents summary statistics for firm social scores, returns, characteristics, and product controversies and sentiment measures. The table reports the mean, 5th percentile (P5), median, 95th percentile (P95), standard deviation (SD), and the number of firms for which data is available (N Firm). Social Score, Human Capital Score, and Product Safety Score are MSCI's social scores. Environmental Score and Governance Score are MSCI's aggregate environmental and governance scores. Return is the monthly stock return (in %), Log Size is natural log of end-of-year firm market capitalization, BM is the ratio of the book value of equity to the market value of equity; Investment is the ratio of capital expenditure (capex) to the book value of assets; Leverage is the ratio of the book value of debt to the book value of assets; Log PPE is the natural log of the firm's plant, property and equipment; ROE is a profitability measure computed as the ratio of net income to the book value of equity (in %); Beta is the CAPM (market) beta; Momentum is the cumulative stock returns over a one year period from $t-12$ to $t-1$; Volatility is the standard deviation of stock returns over a one-year period from $t-12$ to $t-1$; Sales Growth is the ratio of change in annual sales to the one-month lagged market capitalization; EPS Growth is the change in basic earning per share scaled by the share price; and the HHI is the Herfindahl–Hirschman index computed using a firm's sales over different business segments. Product Controversy is a sentiment measure of product-related controversies firm i has in year t across news and social media sources. Product Sentiment is a sentiment measure of media sentiment related to a firm's products in each year across news and social media sources. Both measures are from Refinitiv MarketPsych. The sample period runs from January 2007 to December 2022.

	Mean	P5	Median	P95	SD	N Firms
Panel A: MSCI social scores						
Social Score	4.37	2.00	4.30	6.90	1.51	3,154
Human Capital Score	4.16	1.20	4.10	7.30	1.84	3,029
Product Safety Score	4.64	1.00	4.50	8.50	2.24	2,336
Environmental Score	4.52	1.10	4.50	8.20	2.15	3,154
Governance Score	5.41	2.70	5.40	8.50	1.75	3,153
Panel B: Firm and stock characteristics						
Return	1.02	−17.28	0.92	19.46	12.14	3,154
Log Size	8.00	5.83	7.85	10.82	1.55	3,154
BM	0.52	0.07	0.42	1.27	0.39	3,154
Investment	0.04	0.00	0.02	0.13	0.05	3,154
Leverage	0.23	0.00	0.21	0.58	0.19	3,154
Log PPE	5.74	2.23	5.72	9.49	2.18	3,154
ROE	5.22	−50.41	9.16	39.79	32.91	3,154
Beta	1.15	0.54	1.10	1.92	0.43	3,154
Momentum	0.16	−0.49	0.10	0.95	0.51	3,154
Volatility	0.10	0.04	0.09	0.21	0.06	3,154
Sales Growth	0.03	−0.21	0.02	0.32	0.57	3,154
EPS Growth	−0.01	−0.13	0.00	0.11	0.73	3,154
HHI	0.76	0.29	0.89	1.00	0.27	3,154
Panel C: Product controversies and sentiment						
Product Controversies	0.13	0.01	0.09	0.43	0.15	2,422
Product Sentiment	0.03	−0.01	0.02	0.11	0.04	2,548

Figure 2.1: Coverage over time

This figure shows the coverage of firms in the MSCI database compared to the CRSP and Compustat merged dataset over time. Panel A displays the number of firms as of December each year, and Panel B displays the firm market capitalization as of December each year. For inclusion in this plot, all firm and stock variables must be non-missing. The sample period is from January 2007 to December 2022.

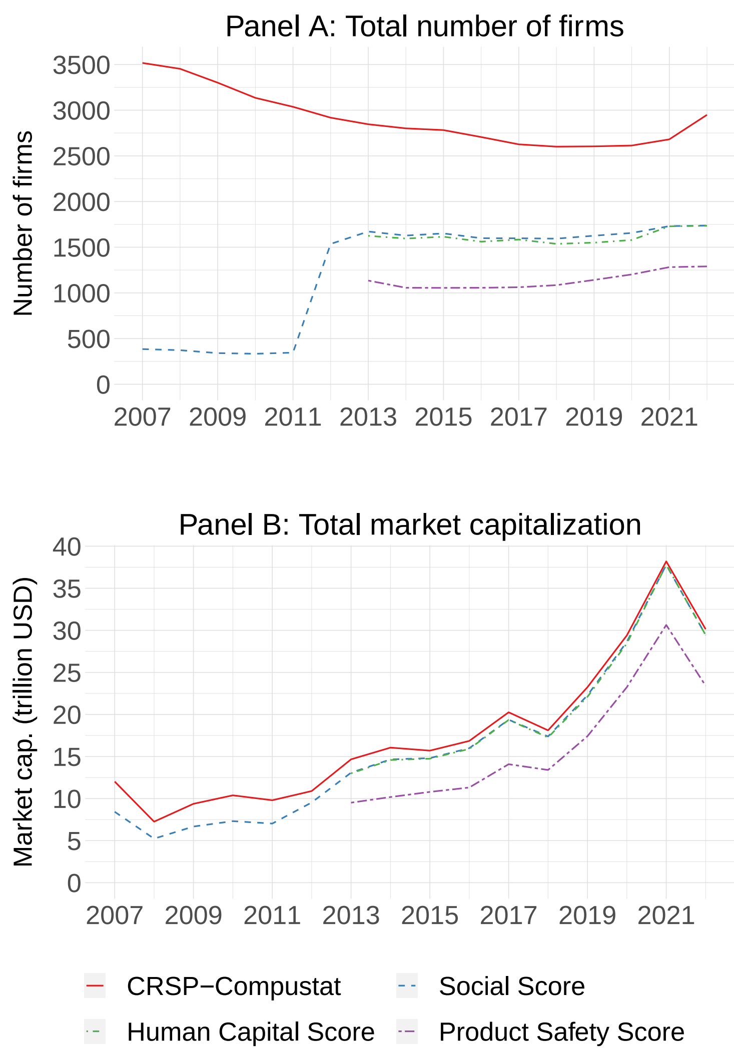

Figure 2.2: Total number of firms in each market capitalization bucket

This figure shows the total number of the firms that report the MSCI aggregate and sub-component social scores in each market capitalization bucket as of December each year. The breakpoints for constructing these buckets are based on the Kenneth French's market equity 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles. For inclusion in this plot, all firm and stock variables must be non-missing. The sample period is from January 2007 to December 2022.

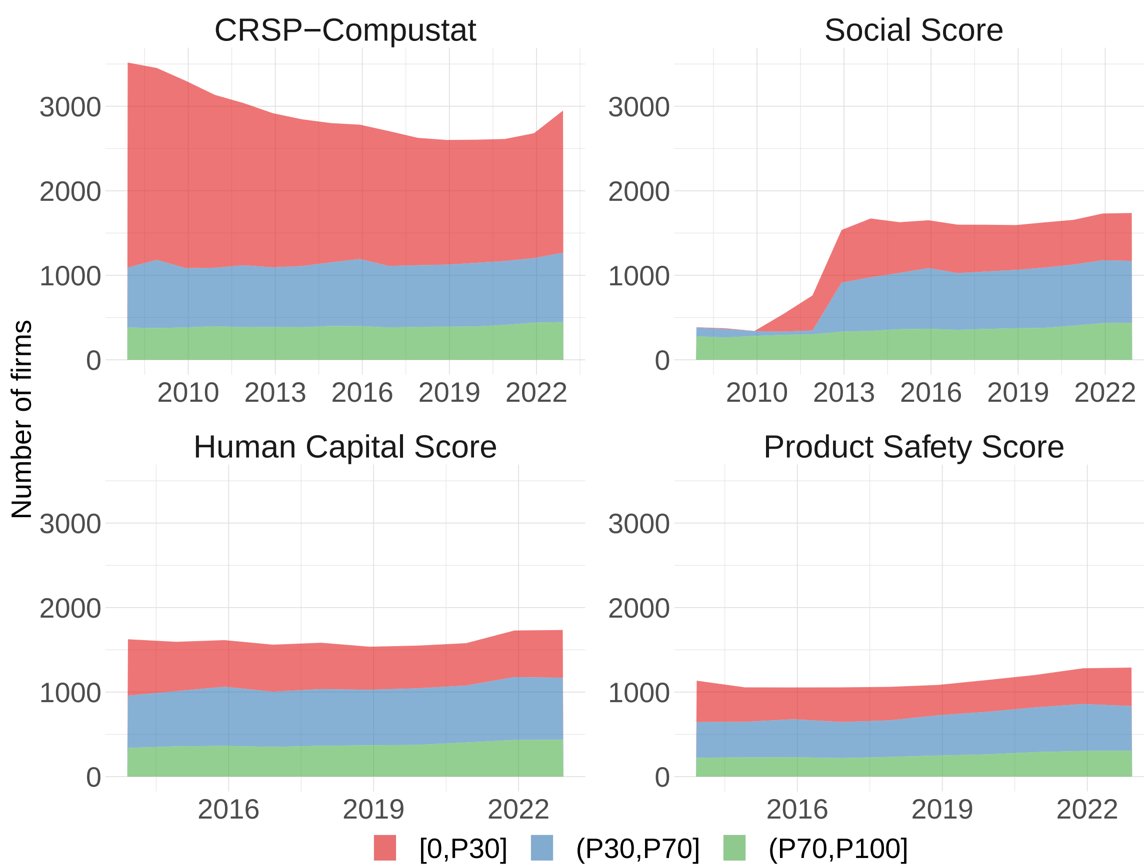

Figure 2.3: Total market capitalization in each market capitalization bucket

This figure shows the total market capitalization of the firms that report the MSCI aggregate and sub-component social scores in each market capitalization bucket as of December each year. The breakpoints for constructing these buckets are based on the Kenneth French's market equity 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles. For inclusion in this plot, all firm and stock variables must be non-missing. The sample period is from January 2007 to December 2022.

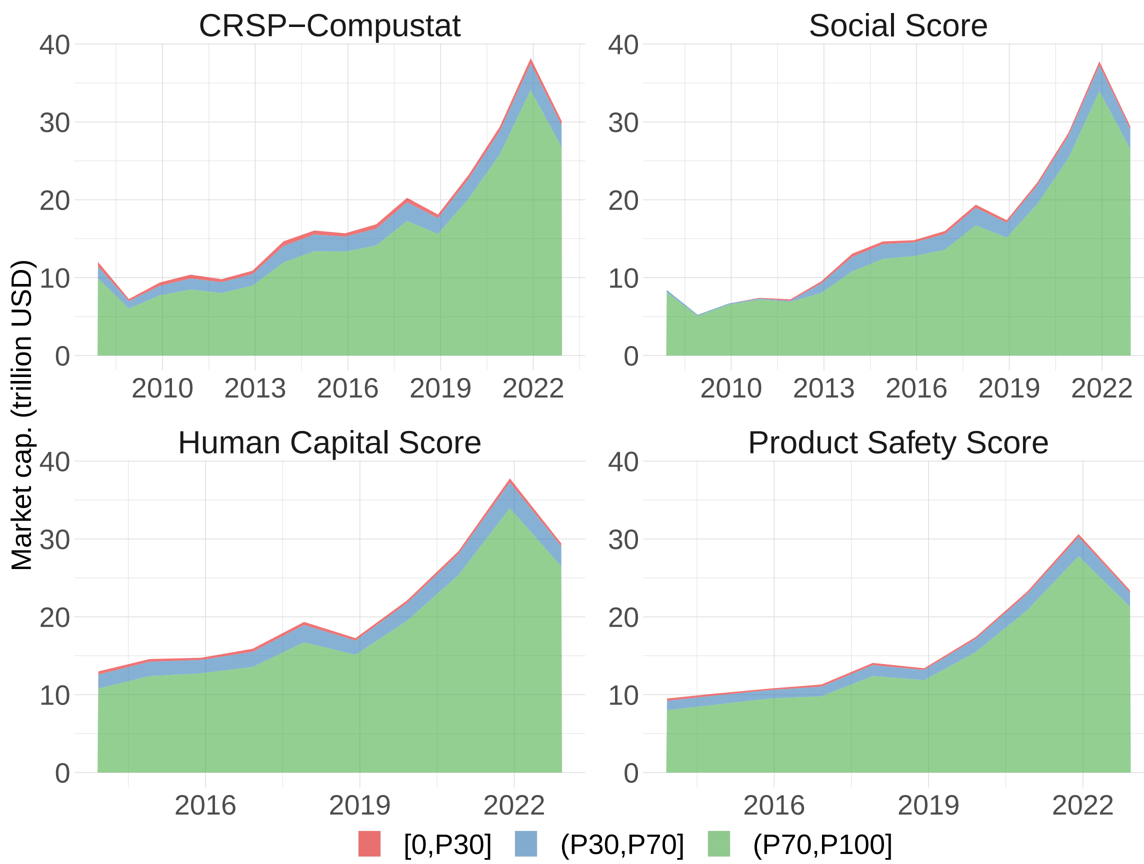

Figure 2.4: Coverage by industry

This figure displays the number of firms reporting MSCI aggregate and sub-component social scores as of December each year, categorized by GICS 2-digit codes that identify sectors. For inclusion in this plot, all firm and stock variables must be non-missing. The sample period is from January 2007 to December 2022.

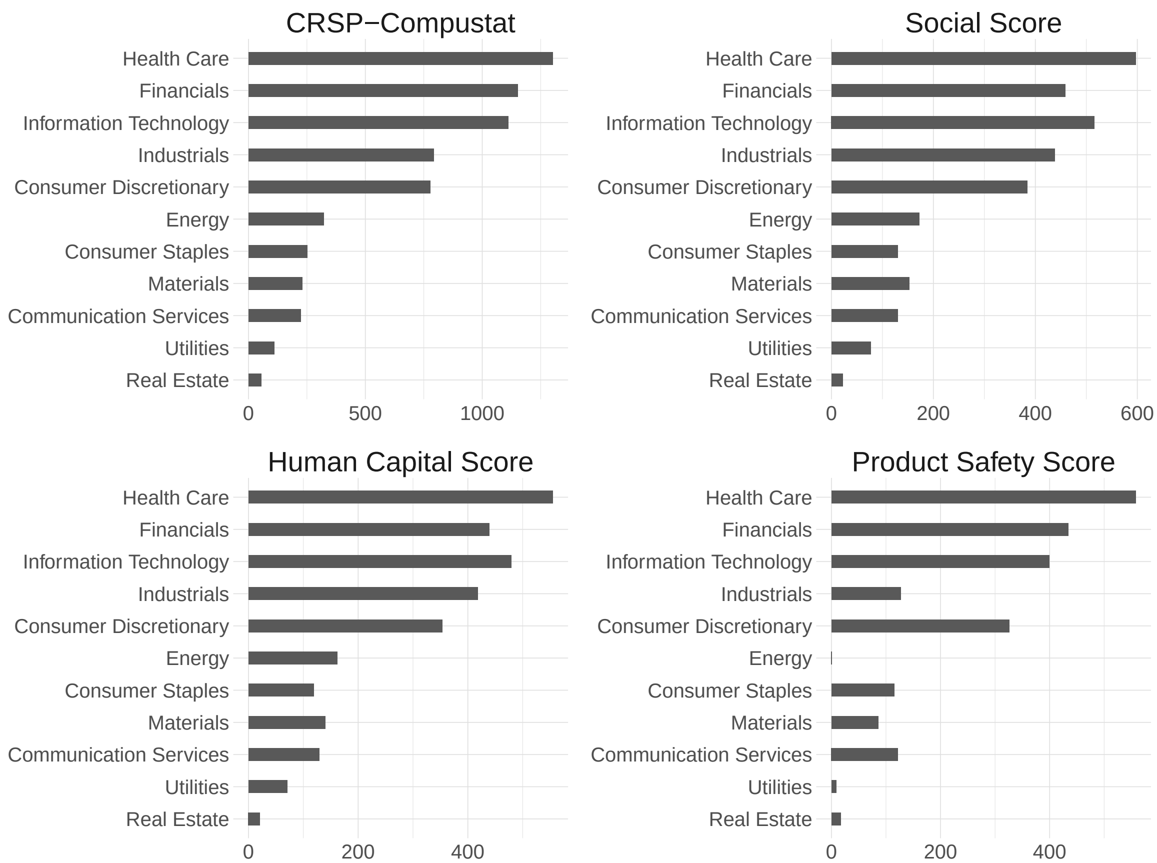

Figure 2.5: Social premiums over time

This figure displays the cumulative values of social scores premiums estimated from the cross-sectional regressions of monthly returns on lagged standardized Human Capital and Product Safety scores, respectively. The regressions include the same set of controls as in Table 2.5. The sample period is from January 2013 to December 2022.

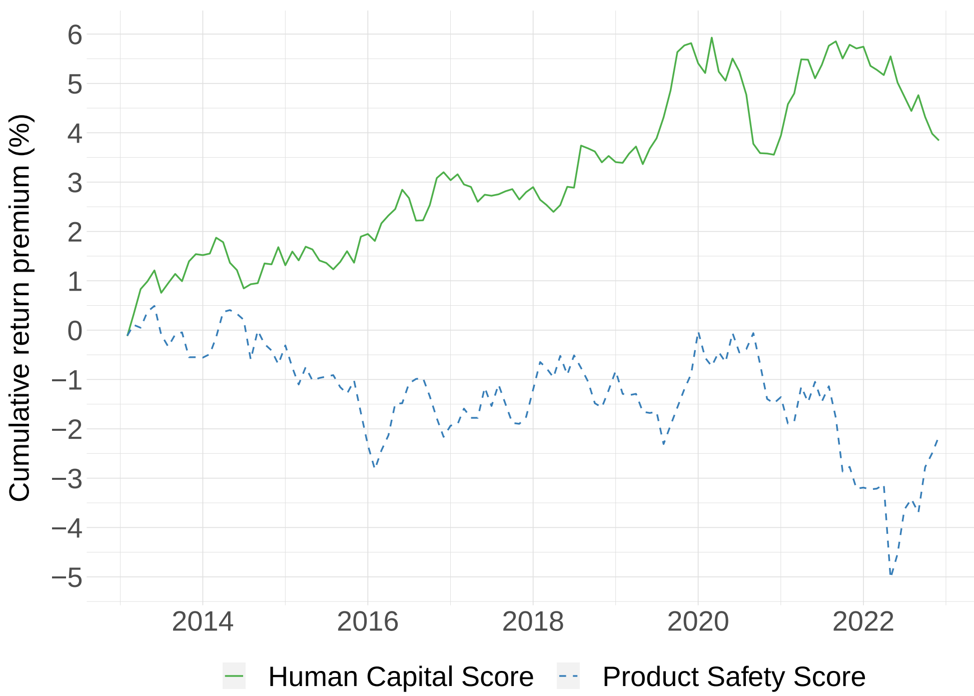

Table 2.2: Correlations

The table presents correlation coefficients for firm ESG scores and size. Social Score, Human Capital Score, and Product Safety Score are MSCI's social scores. Environmental Score and Governance Score are MSCI's aggregate environmental and governance scores. Size is natural log of end-of-year firm market capitalization. The sample period runs from January 2007 to December 2022.

	Social	Human Capital	Product Safety	Environmental	Governance	Size
Social Score	1.00					
Human Capital Score	0.60	1.00				
Product Safety Score	0.69	−0.22	1.00			
Environmental Score	0.16	0.00	0.20	1.00		
Governance Score	0.00	0.01	−0.12	−0.05	1.00	
Size	0.11	0.10	−0.03	0.29	0.05	1.00

Table 2.3: Validating MSCI human capital score: predicting Best Company

The table presents logit regression results estimating the ability of MSCI social scores to predict a firm's inclusion in Fortune's annual list of "Best Companies to Work For". The independent variable is an indicator taking the value of one if a firm belongs to the Best Companies list in a given year and zero otherwise. The key predictors are Social Score, Human Capital Score, and Product Safety Score. Controls include each firm's log end-of-year market capitalization (Log Size), book-to-market ratio (BM), ratio of capital expenditure to the book value of assets (Investment), ratio of the book value of debt to the book value of assets (Leverage), log value of property, plant and equipment (PPE), ratio of net income to book value (ROE, in %), ratio of change in annual sales to the one-month lagged market capitalization (Sales Growth), change in basic earning per share scaled by the share price (EPS Growth), and the Herfindahl–Hirschman index (HHI) computed using a firm's sales over different business segments. All regressions include industry and year fixed effects. Standard errors in parentheses are clustered by firm. R^2 denotes the pseudo R^2. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The data are annual and the sample period runs from January 2007 to December 2022.

	1-year forecast			2-year forecast			3-year forecast		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Score	0.278***			0.267**			0.226**		
	(0.101)			(0.106)			(0.107)		
Human Capital Score		0.301***			0.310***			0.275***	
		(0.064)			(0.075)			(0.076)	
Product Safety Score			0.095			0.101			0.111
			(0.089)			(0.103)			(0.108)
Log Size	0.684***	0.631***	0.434**	0.623***	0.575**	0.396*	0.604***	0.585**	0.431*
	(0.199)	(0.214)	(0.213)	(0.215)	(0.225)	(0.232)	(0.228)	(0.232)	(0.243)
BM	−0.231	−0.454	−0.624	−0.067	−0.347	−0.363	−0.042	−0.218	−0.120
	(0.452)	(0.590)	(0.659)	(0.505)	(0.649)	(0.721)	(0.563)	(0.679)	(0.749)
Investment	5.490*	2.531	−1.996	5.021	3.072	−0.905	3.530	3.320	−0.589
	(3.244)	(3.666)	(5.265)	(3.474)	(3.885)	(5.903)	(3.804)	(4.042)	(6.429)
Leverage	0.267	0.415	0.096	0.493	0.699	0.352	0.355	0.516	0.171
	(0.959)	(1.005)	(1.042)	(1.002)	(1.045)	(1.087)	(1.064)	(1.101)	(1.131)
Log PPE	0.156	0.252	0.437**	0.165	0.246	0.401*	0.180	0.217	0.330
	(0.171)	(0.202)	(0.212)	(0.189)	(0.217)	(0.231)	(0.202)	(0.223)	(0.238)
ROE	−0.003	−0.003	−0.002	−0.001	−0.001	0.000	−0.003	−0.002	−0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Sales Growth	−0.013	0.029	0.109	0.078	0.108	0.139*	0.134	−0.031	−0.014
	(0.116)	(0.139)	(0.099)	(0.076)	(0.070)	(0.080)	(0.084)	(0.163)	(0.228)
EPS Growth	0.082**	0.059	0.038	0.021	0.015	0.012	0.047	0.052	0.026
	(0.041)	(0.040)	(0.044)	(0.048)	(0.043)	(0.049)	(0.046)	(0.038)	(0.042)
HHI	0.259	0.730	0.590	0.081	0.526	0.177	−0.148	0.231	−0.237
	(0.641)	(0.726)	(0.851)	(0.650)	(0.745)	(0.871)	(0.658)	(0.716)	(0.838)
R^2	0.345	0.357	0.325	0.350	0.366	0.337	0.350	0.354	0.325
Observations	18,474	16,345	11,423	15,485	13,862	9,594	12,995	11,784	8,112

Table 2.4: Validating MSCI product safety score: predicting product controversies

The table presents regression results estimating the ability of MSCI social scores to predict product controversies. The dependent variable is Product Controversy a sentiment measure of product-related controversies firm i has in year t across news and social media sources, from Refinitiv MarketPsych. Higher Product Controversy measure corresponds to worse controversies for a firm. The key predictors are Social Score, Human Capital Score, and Product Safety Score. Controls include each firm's log end-of-year market capitalization (Log Size), book-to-market ratio (BM), ratio of capital expenditure to the book value of assets (Investment), ratio of the book value of debt to the book value of assets (Leverage), log value of property, plant and equipment (PPE), ratio of net income to book value (ROE, in %), ratio of change in annual sales to the one-month lagged market capitalization (Sales Growth), change in basic earning per share scaled by the share price (EPS Growth), and the Herfindahl–Hirschman index (HHI) computed using a firm's sales over different business segments. All regressions include industry and year fixed effects. Standard errors in parentheses are clustered by firm. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The data are annual and the sample period runs from January 2007 to December 2022.

	1-year forecast			2-year forecast			3-year forecast		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Score	−0.3414***			−0.3467**			−0.3316**		
	(0.1244)			(0.1363)			(0.1423)		
Human Capital Score		0.0623			−0.0013			−0.1366	
		(0.1029)			(0.1086)			(0.1239)	
Product Safety Score			−0.3072***			−0.3897***			−0.2418*
			(0.1011)			(0.1139)			(0.1267)
Log Size	−1.103***	−0.7968***	−0.8601***	−1.495***	−1.152***	−1.133***	−1.748***	−1.631***	−1.680***
	(0.2155)	(0.2188)	(0.2450)	(0.2452)	(0.2453)	(0.2811)	(0.2645)	(0.2832)	(0.3103)
BM	0.4101	0.9810	1.174*	−0.2700	0.0097	0.2132	−0.8843	−0.6380	−0.8148
	(0.5784)	(0.6097)	(0.6871)	(0.6315)	(0.6656)	(0.7839)	(0.6863)	(0.7611)	(0.8826)
Investment	−6.997	−2.571	−4.281	−6.988	−1.787	2.362	−8.345	−1.110	4.529
	(6.167)	(6.453)	(7.579)	(6.765)	(7.059)	(9.116)	(7.446)	(7.992)	(10.75)
Leverage	1.448	1.519	1.791*	1.437	1.892*	1.869	1.243	2.012	2.268*
	(1.012)	(1.023)	(1.080)	(1.108)	(1.128)	(1.210)	(1.183)	(1.256)	(1.334)
Log PPE	0.3754*	0.2330	0.0551	0.4393**	0.2318	0.0180	0.5072**	0.3278	0.1949
	(0.1964)	(0.2018)	(0.2117)	(0.2222)	(0.2255)	(0.2497)	(0.2366)	(0.2551)	(0.2741)
ROE	0.0103***	0.0075**	0.0076*	0.0154***	0.0112***	0.0107***	0.0185***	0.0174***	0.0134***
	(0.0037)	(0.0037)	(0.0039)	(0.0039)	(0.0039)	(0.0040)	(0.0041)	(0.0042)	(0.0044)
Sales Growth	0.0723	−0.3419	−0.1163	0.0413	−0.3130	−0.0396	−0.0225	0.1100	−0.2143
	(0.1125)	(0.2371)	(0.2986)	(0.0957)	(0.2046)	(0.2169)	(0.0762)	(0.2009)	(0.2730)
EPS Growth	0.0647	0.0996*	0.1897	0.0020	0.0750	0.0996	0.0246	0.0906	0.0389
	(0.0585)	(0.0598)	(0.1272)	(0.0510)	(0.0509)	(0.1094)	(0.0925)	(0.1124)	(0.1549)
HHI	2.195**	1.758*	2.176**	2.348**	1.904*	2.445**	2.130**	2.273**	2.337*
	(0.8860)	(0.9169)	(1.014)	(0.9623)	(0.9871)	(1.116)	(1.019)	(1.114)	(1.276)
Adjusted R^2	0.137	0.111	0.115	0.149	0.132	0.141	0.145	0.152	0.156
Observations	14,894	12,015	8,411	14,602	11,821	8,200	13,966	11,524	7,934

Table 2.5: Social scores and stock returns

This table reports pooled OLS regression results estimating the relation between MSCI social scores and stock returns. The dependent variable is the monthly stock return, $r_{i,t}$ (in %), of firm i at time t. All the independent variables are measured at time $t-1$. The key independent variables are Social Score, Human Capital Score, and Product Safety Score. Controls include each firm's log end-of-year market capitalization (Log Size), book-to-market ratio (BM), ratio of capital expenditure to the book value of assets (Investment), ratio of the book value of debt to the book value of assets (Leverage), log value of property, plant and equipment (PPE), ratio of net income to book value (ROE, in %), beta with respect to the aggregate market (Beta), cumulative stock returns over a one-year period from $t-12$ to $t-1$ (Momentum), standard deviation of stock returns over a one-year period from $t-12$ to $t-1$ (Volatility), ratio of change in annual sales to the one-month lagged market capitalization (Sales Growth), change in basic earning per share scaled by the share price (EPS Growth), and the Herfindahl–Hirschman index (HHI) computed using a firm's sales over different business segments. All regressions include industry and year-month fixed effects. Standard errors in parentheses are clustered by firm. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample period runs from January 2007 to December 2022.

	(1)	(2)	(3)	(4)	(5)	(6)
Social Score	0.0047			−0.0030		
	(0.0163)			(0.0162)		
Human Capital Score		0.0576***			0.0427***	
		(0.0148)			(0.0147)	
Product Safety Score			−0.0561***			−0.0457***
			(0.0154)			(0.0160)
Log Size				−0.2184***	−0.2035***	−0.1366***
				(0.0403)	(0.0432)	(0.0494)
BM				0.0829	0.0704	0.2890**
				(0.1048)	(0.1146)	(0.1355)
Investment				−6.229***	−6.466***	−2.586*
				(0.8699)	(0.9460)	(1.417)
Leverage				−0.2094	−0.0935	−0.0829
				(0.1843)	(0.1994)	(0.2304)
Log PPE				0.2162***	0.2078***	0.1275***
				(0.0352)	(0.0377)	(0.0438)
ROE				0.0035***	0.0026*	0.0038**
				(0.0014)	(0.0015)	(0.0016)
Beta				−0.4094***	−0.5368***	−0.2638**
				(0.1008)	(0.1101)	(0.1338)
Momentum				0.1407*	0.1506*	0.0693
				(0.0741)	(0.0784)	(0.0952)
Volatility				3.407***	3.091***	2.070*
				(0.9388)	(1.021)	(1.174)
Sales Growth				0.0017	0.0145	−0.0456
				(0.1005)	(0.1074)	(0.1625)
EPS Growth				−0.0611	−0.0832	−0.7339***
				(0.0863)	(0.1722)	(0.2244)
HHI				0.0290	−0.0160	0.0179
				(0.0915)	(0.1018)	(0.1197)
Adjusted R^2	0.215	0.207	0.192	0.216	0.208	0.192
Observations	223,678	190,439	134,043	223,678	190,439	134,043
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.6: Social scores and stock returns, controlling for environmental and governance scores

This table reports pooled OLS regression results estimating the relation between MSCI social scores and stock returns, controlling for the Environmental and Governance scores. The dependent variable is the monthly stock return, $r_{i,t}$ (in %), of firm i at time t. All the independent variables are measured at time $t-1$. The key independent variables are Social Score, Human Capital Score, Product Safety Score, and the Environmental and Governance scores. Controls include each firm's log end-of-year market capitalization (Log Size), book-to-market ratio (BM), ratio of capital expenditure to the book value of assets (Investment), ratio of the book value of debt to the book value of assets (Leverage), log value of property, plant and equipment (PPE), ratio of net income to book value (ROE, in %), beta with respect to the aggregate market (Beta), cumulative stock returns over a one-year period from $t-12$ to $t-1$ (Momentum), standard deviation of stock returns over a one-year period from $t-12$ to $t-1$ (Volatility), ratio of change in annual sales to the one-month lagged market capitalization (Sales Growth), change in basic earning per share scaled by the share price (EPS Growth), and the Herfindahl–Hirschman index (HHI) computed using a firm's sales over different business segments. All regressions include industry and year-month fixed effects. Standard errors in parentheses are clustered by firm. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample period runs from January 2007 to December 2022.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Score	−0.0059			−0.0036			−0.0065		
	(0.0163)			(0.0162)			(0.0163)		
Human Capital Score		0.0415***			0.0436***			0.0424***	
		(0.0148)			(0.0147)			(0.0148)	
Product Safety Score			−0.0454***			−0.0457***			−0.0454***
			(0.0160)			(0.0161)			(0.0160)
Environmental Score	0.0276*	0.0273*	−0.0095				0.0271*	0.0280*	−0.0095
	(0.0142)	(0.0162)	(0.0194)				(0.0142)	(0.0162)	(0.0194)
Governance Score				0.0315**	0.0438***	0.0000	0.0311**	0.0442***	0.0000
				(0.0131)	(0.0147)	(0.0178)	(0.0131)	(0.0147)	(0.0178)
Adjusted R^2	0.216	0.208	0.192	0.216	0.208	0.192	0.216	0.208	0.192
Observations	223,665	190,439	134,043	223,654	190,436	134,040	223,654	190,436	134,040
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7: Social scores and stock returns, controlling for Best Company

This table reports pooled OLS regression results estimating the relation between MSCI social scores and stock returns, controlling for the Best Company indicator. The dependent variable is the monthly stock return, $r_{i,t}$ (in %), of firm i at time t. All the independent variables are measured at time $t-1$. The key independent variables are Social Score, Human Capital Score, Product Safety Score, and the Best Company indicator. The Best Company indicator takes the value of one if a firm is included in Fortune's annual list of "Best Companies to Work For" in a given year, and zero otherwise. Controls include each firm's log end-of-year market capitalization (Log Size), book-to-market ratio (BM), ratio of capital expenditure to the book value of assets (Investment), ratio of the book value of debt to the book value of assets (Leverage), log value of property, plant and equipment (PPE), ratio of net income to book value (ROE, in %), beta with respect to the aggregate market (Beta), cumulative stock returns over a one-year period from $t-12$ to $t-1$ (Momentum), standard deviation of stock returns over a one-year period from $t-12$ to $t-1$ (Volatility), ratio of change in annual sales to the one-month lagged market capitalization (Sales Growth), change in basic earning per share scaled by the share price (EPS Growth), and the Herfindahl–Hirschman index (HHI) computed using a firm's sales over different business segments. All regressions include industry and year-month fixed effects. Standard errors in parentheses are clustered by firm. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample period runs from January 2007 to December 2022.

	(1)	(2)	(3)	(4)
Best Company	0.2495**	0.2526**	0.1820	0.3003**
	(0.1174)	(0.1174)	(0.1302)	(0.1409)
Social Score		−0.0047		
		(0.0162)		
Human Capital Score			0.0421***	
			(0.0147)	
Product Safety Score				−0.0469***
				(0.0160)
Adjusted R^2	0.216	0.216	0.208	0.192
Observations	223,678	223,678	190,439	134,043
Industry F.E.	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

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Chapter 3

Sovereign Bond Spreads and Economic Activity

Abstract

There is considerable empirical evidence that corporate bond credit spreads are good predictors of real economic activity. This paper[1] examines the ability of credit spreads of sovereign bonds issued by emerging countries to predict economic activity and stock market returns of these countries. It finds that sovereign credit spreads are significant predictors of economic activity and stock market returns over a one-quarter-ahead horizon. We decompose bond credit spreads into default risk and risk premium components, and find that both components contribute to the predictability of economic activity. The risk premium component plays a particularly important role in predicting stock returns.

[1]This paper was written under the supervision of Alexandre Jeanneret.

3.1 Introduction

Since the global financial crisis that began in 2007, the relationship between financial conditions and economic prospects has received a lot of attention.[2] Disturbances in the financial sector have serious repercussions for real activity. As a result of this link between the credit market and the broader economy, movements in credit spreads provide significant signals of the outlook of the economy. Motivated by Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012), several papers examine the predictability of economic activity using credit spreads.[3] While these papers examine economic activity in the US and in Europe, we do not have evidence for emerging markets.

Credit spreads are forward looking and they capture the risk of default. When there is a high risk of default, the economy is expected to slowdown. So higher credit spreads predict lower aggregate output growth, lower industrial production growth and higher unemployment. On the other hand, lower credit spreads predict higher aggregate output growth, higher industrial production growth and lower unemployment. In our paper, we use spreads of sovereign debt issued by emerging countries and examine their relationship with economic activity. In the case of emerging countries, sovereign default spreads are more accurate measures of credit risk compared with corporate spreads because they are less likely to be contaminated with idiosyncratic variations. We find that sovereign credit spreads are significant predictors of economic activity of emerging countries. A 1% increase in credit spreads predicts an 0.360% decline in GDP growth in emerging countries over a one-quarter-ahead horizon.

Stock returns are highly related to economic activity. Thus, if credit spreads predict economic activity variables, it is possible that they predict stock returns as well. We examine the predictability of local stock returns using credit spreads and find that credit spreads are significant negative predictors of stock market returns. A 1% increase in

[2]Federal reserve officials discussed the economic and policy implications of the disturbances in the financial sector for the global economy in many occasions (see B. Bernanke, 2007a, 2007b; Mishkin, 2007a, 2007b).

[3]See, for instance, Faust et al. (2013), Bleaney et al. (2016) and Gilchrist and Mojon, 2018.

credit spreads predicts a 7.5% decline in stock market returns of emerging markets over a one-quarter-ahead horizon. We also construct a credit spread index by equally weighting credit spread data of individual countries and examine the predictability of the returns of MSCI World and MSCI Emerging Market stock market indexes using our index. We find favorable evidence of the predictability of the returns of MSCI Emerging market and MSCI World stock market indexes. A 1% increase in our credit spread index predicts a 4.08% decline in MSCI Emerging Market Returns and a 2.095% decline in MSCI World returns.

A natural question to ask is whether the predictive content of bond credit spread is due to the available country-specific information on default risk or to the residual component that represents variation in the pricing of default risk, the risk premium. Thus, we follow Gilchrist and Zakrajšek, 2012 and extract the credit spread component that is independent of the risk premium using the model of Jeanneret, 2018. The risk premium part is the difference between the credit spreads and the default risk part. We then substitute the credit spreads in our models by the default risk and risk premium parts and examine the predictability of economic activity variables using the spread components. Our results show that both spread components play an important role in predicting economic activity variables. A 1% increase in the default risk component predicts an 0.64% decline in output growth, a 4.654% decline in the growth of industrial production and an 0.282% increase in unemployment over the next quarter. A similar increase in the risk premium component predicts an 0.391% decline in output growth, an 0.550% decline in industrial production growth and an 0.044% increase in unemployment over the next quarter. We examine the predictability of local stock market returns using the spread components and find that a 1% increase in default risk part leads to a 13.126% decline in stock returns. A similar increase in the risk premium part leads to a 7.572% decline in stock returns.

To the extent of our knowledge, research to date studies the relationship between bond credit spreads and economic activity in the US and in the Euro area. Little work is done on emerging markets. While this paper contributes to the existing literature by examining the predictive power of sovereign credit spreads and their components in emerging markets, a direct comparison with previous studies reveals some important distinctions. Unlike the work of Caballero et al. (2019), which also investigates emerging markets, our study not only focuses on sovereign rather than corporate spreads but also decomposes these spreads into default risk and risk premium components. This decomposition allows for a more nuanced understanding of the mechanisms driving the predictive relationship between spreads and economic activity. In contrast, earlier studies, such as Gilchrist and Zakrajšek (2012), have primarily concentrated on developed economies and corporate spreads, highlighting the role of the excess bond premium in forecasting economic activity. Our findings suggest that both the default risk and risk premium components of sovereign spreads are significant predictors of economic activity and stock returns in emerging markets. This contrasts with the results from developed economies, where the excess bond premium tends to dominate the predictive power of spreads. In comparison, our findings are more restricted in scope, as we only find evidence for the predictability of sovereign credit spreads for economic activity over the short-term horizon in emerging markets. This difference may be attributed to the unique characteristics of emerging market economies, such as greater volatility and different financial market dynamics. Overall, our study adds a new dimension to the literature by elucidating the role of sovereign spread components in emerging markets, thereby offering a more comprehensive understanding of the relationship between financial conditions and economic outcomes in these economies, albeit primarily in the short term.

Our paper is organized as follows. Section 3.2 provides a brief review of the literature. Section 3.3 describes the data, the econometric specification and the main results. Section 3.4 describes the spread decomposition and presents the results of estimating the models with the spread components. Section 3.5 provides some further insights about the results. Finally, section 3.6 concludes.

3.2 Literature Review

There is a large literature on predicting economic activity using asset prices. J. Stock and Watson (2003) provide an extensive survey of this literature. This paper groups financial variables into two categories: Monetary variables such as short term interest rates and term spread, and default variables such as Corporate-Treasury bond spreads.

One strand of literature focuses on the predictive content of monetary variables for real economic activity. Among the early works that find evidence supporting the information content of short term interest rates with respect to future output are Sims (1980) and B. Bernanke and Blinder (1992) -the commercial paper rate and the federal funds rate, respectively. Subsequent research finds that the level (or change) of short term interest rates has little marginal predictive content for output once interest rate spreads are included. The term spread has been a widely used predictor of economic activity, but its ability to predict economic activity has been declining since the mid 1980s.[4] One possible explanation of the lack of predictive power of the term spread since the mid-1980s is that; the monetary policy in the US has been more stabilizing with the Federal Reserve reacting systematically to expected fluctuations in either inflation or real output (J. Stock & Watson, 2003).

Another strand of literature focuses on the predictive content of default spreads for real economic activity. Different authors measure these spreads differently and needless to say these differences are important. Among the default spreads examined are the Baa-Treasury bond spread (B. S. Bernanke, 1983), investment grade spread (Chan-Lau & Ivaschenko, 2001, 2002), the high yield bond spread (Gertler & Lown, 1999; Mody & Taylor, 2004), the Commercial Paper-Treasury Bill spread (Friedman & Kuttner, 1992; J. H. Stock & Watson, 1990) and the Baa-Aaa spread -the spread between corporate bonds of high and low quality (J. Stock & Watson, 2003). Up to this point, it remained an unexplored territory whether all credit spreads have the same predictive power, and if not, which spreads should be selected for forecasting purposes. Here is where Mueller (2009)

[4]See, among others, Laurent (1988), Laurent et al. (1989), Harvey (1988), Harvey (1989), J. H. Stock and Watson (1990), N.-F. Chen (1991), Estrella and Hardouvelis (1991) and Estrella and Mishkin (1997).

contributes to this stream of literature by exploring the information content of the whole term structure of credit spreads and across different rating classes.

More recent research on the relationship between bond credit spreads and real activity has been performed by Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012) using US bond market data. The novelty of these works lies in employing a bottom-up approach that entails the careful selection of bonds to construct a credit spread index that is not distorted by embedded options or illiquidity (See Duca, 1999). Gilchrist et al. (2009) find that credit spreads are robust predictors of economic activity, using a sample of credit spreads constructed using secondary bond prices of outstanding senior unsecured debt of a large sample of US non-financial firms. The constructed spreads solve the problem of maturity mismatch that plagues older work. To compute the spreads this paper compares the price of each bond to a synthetic risk-free rate that matches the cash flows of the bond. Gilchrist et al. (2009) also construct matched portfolios of equity returns, which enables them to examine the information content of bond spreads that is independent of the information content of stock prices for the same sample of firms. The main findings of this paper is that corporate bond credit spreads contain substantial predictive power for economic activity especially at longer term horizons and that they outperform widely used credit spread measures. Gilchrist and Zakrajšek (2012) decompose the credit spreads to two components: one that reflects the available firm-specific information on default risk and a residual component, the excess bond premium, that represents variation in the pricing of default risk. Gilchrist and Zakrajšek (2012) use the same ground-up approach used in Gilchrist et al. (2009) to construct a credit spread index which they call “the GZ spread”, using outstanding bond data that dates back to 1973. Then they decompose the spread into the two components described above. Basically, the excess bond premium component captures the variation in the price of the exposure to corporate credit risk above what investors in the corporate bond market require as compensation for expected default. Gilchrist and Zakrajšek (2012) find that the GZ credit spread is a significant predictor of economic activity at one-quarter-ahead and four-quarter-ahead forecast horizons. In addition, in the period 1985-2010, the forecasting power of the GZ spread to economic activity is entirely attributable to the excess bond premium component.

One way to get additional evidence on the relationship between credit spreads and economic activity is to examine evidence for other countries. Bleaney et al. (2016) apply the same ground-up approach used in Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012) to a panel of European data on 500 corporate bonds for 8 European countries, in order to evaluate the relationship between credit spreads and real activity at the country level, and find a robust and consistent negative relationship between bond credit spreads and real activity. Gilchrist and Mojon (2018) use a similar approach to construct credit risk indicators for banks and non-financial corporations in the euro area. These indicators expose the extent to which the 2008 financial crisis increased the cost of funds in the euro area for banks and non-financial corporations, and caused a divergence in credit spreads of financial firms across countries in the euro area. Credit spreads of financial firms in periphery countries such as Spain and Italy widened considerably compared to their counterparts in core countries such as France and Germany. This pattern reflects rising concerns of sovereign default of periphery countries which later spilled over into the corporate sector. Gilchrist and Mojon (2018) show that credit spreads can predict economic activity for the euro area as a whole as well as for individual countries. As far as we know, there are not any papers that examine the ability of credit spreads to predict economic activity in emerging countries. Also existing studies exploit corporate bond data not sovereign bond data. Our contribution to the literature is to examine the predictability of economic activity in emerging countries using sovereign bond spreads. We also decompose the credit spreads and examine the predictability of economic activity using the spread components.

3.3 Data and Methodology

The following section examines the predictability of economic activity and stock returns in emerging markets using sovereign bond credit spreads. We begin by describing the data and the econometric specification. After that we present the main results.

3.3.1 Data

Sovereign Bond Data

The empirical investigation of this paper examines the ability of sovereign credit spreads to predict economic activity. The measure of credit spread is J.P. Morgan Emerging Market Bond Index (hereafter EMBI). This series consists of monthly data that starts in early 1994 and covers a sample of 60 emerging market countries. We download this data from Datastream.

Table 3.1 reports summary statistics of spread data by country from 1994 to early 2018. The largest regional group is made up of countries in Latin America and Caribbean with 20 countries. The data set also includes 11 countries in Sub-Saharan Africa, 7 countries in East Asia and Pacific, 17 countries in Europe and Central Asia, 4 countries in Middle East and North Africa, and 2 countries in South Asia. There is a great variation in spreads both across countries and over time.

Table 3.1 [about here]

We use individual country data as well as a credit spread index that we construct by equally-weighting the credit spread data of the individual countries. Figure 3.1 shows a time series of the equally-weighted EMBI credit spread data of our sample of 60 emerging countries from January 1994 to June 2018. It is sensible to expect the credit spread index to increase during economic crises. Indeed, from Figure 3.1, there are observable spikes in the index level in the periods 1994-1995, 1997-1999, 2007-2009, 2012-2013 and 2014-2016. These spikes precede the Mexican crisis, the Russian crisis, the Great Recession, the European debt crisis and most recently the oil bust in 2014.

Figure 3.1 [about here]

Dependent Variables

Two different sets of dependent variables are used in this paper: macroeconomic variables and price index data for a number of stock market indexes. The macroeconomic variables used are country-level GDP, industrial production and unemployment rate. We also use local stock market price index data for EMBI constituent countries , as well as MSCI World and MSCI Emerging Markets stock market indexes. Stock market data is from Datastream, while country-level variables data is from the World Bank website. Tables 3.2 and 3.3 provide descriptive statistics as well as data definitions and sources.

Tables 3.2 and 3.3 [about here]

Control Variables

Building on Gilchrist and Zakrajšek (2012) we control for two key indicators of the stance of monetary policy in the US: the term spread and the real federal funds rate. The *term spread* is the slope of the treasury yield curve which is defined as the difference between the three-month and the ten-year constant maturity yield. The *real federal funds rate* in period t is the average effective federal funds rate during the period less realized inflation.

In addition to that, following Caballero et al. (2019) we include two proxies for global financial risk: the VIX and the US Baa-Aaa spread. The *VIX* serves as a proxy for uncertainty and risk aversion emanating from the implied volatility of S&P500 index options. While the *Baa-Aaa spread*, one of the widely used default risk indicators in the US, is the spread on indexes of Baa- and Aaa-rated seasoned industrial corporate bonds. Rey (2015) describes the VIX factor as one that exhibits strong comovement with the global financial cycle in cross border capital flows. Akıncı (2013) finds that shocks to Baa-Aaa spread lead to adverse economic outcomes in a sample of emerging economies. The data for US variables is downloaded from FRED website and the VIX data from Datastream.

3.3.2 Methodology

To examine the predictability of economic activity using credit spreads, we estimate the following model:

$$\nabla^h Y_{t+h} = \alpha_1 + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 \Delta CS_t + \gamma_2 \Delta TS_t + \gamma_3 \Delta FFR_t + \gamma_4 \Delta VIX_t + \gamma_5 \Delta Baa_t + \varepsilon_{t+h}, \tag{3.1}$$

where $\nabla^h Y_{t+h} \equiv \frac{c}{h} ln \frac{Y_{t+h}}{Y_t}$, such that Y_t denotes the macroeconomic variables or the stock market index prices[5], c is a scaling constant that takes the value of 400 for quarterly data, $h = 1$ is the one-quarter-ahead forecast horizon, the number of lags is $p = 4$. The credit spread is denoted as CS_t, and the set of control variables used are denoted as TS_t, FFR_t, VIX_t and Baa_t, γ are slope coefficients and ε_{t+h} is the forecast error.[6] The credit spread and all the controls enter the equation as a first difference. In this framework, we examine the predictive content of CS_t for Y_{t+h} above what is contained in the past values of Y_{t+h} and after controlling for several factors that affect economic activity in emerging countries.

To exploit the cross section of the data, we use country-level economic variables and local stock market index prices to estimate equation (3.1) using a panel fixed effects model. We use Driscoll and Kraay (1998) standard errors to allow for auto-correlated errors across countries with an auto-correlation structure of a maximum of four lags. In addition, we examine the predictability of the returns of MSCI World and MSCI Emerging Markets stock market indexes using a credit spread index constructed by equally weighting the credit spread data of all countries of our sample.

[5] All variables are transformed that way except for unemployment rate the first difference is used.

[6] As mentioned in J. Stock and Watson (2003), the h-step-ahead projection method is the standard approach used in the literature on asset prices as predictors of economic activity. An alternative to that method is to perform some joint one-step ahead model for X_t and Y_t, then iterate this model forward for h periods. A vector-autoregression (VAR) model could be a reasonable choice. If the VAR is correcly specified, then opting for this choice would be more efficient asymptotically. However, the h-step ahead projection forecast reduces the effect of specification error in the model.

3.3.3 Using Credit Spreads to Predict Economic Activity and Stock Market Returns

This section presents the results of using credit spreads of sovereign bonds issued by emerging countries to predict economic activity of emerging countries. Then, it presents the results of using these credit spreads to predict the local stock market returns of emerging countries as well as the returns of MSCI Emerging Markets and MSCI World indexes.

Increasing credit spreads, as well as a flat or inverted yield curve signal the deterioration of economic conditions -slowdown of output and industrial production, as well as increase in unemployment-. The federal funds rate impacts monetary and financial conditions, which in turn affects employment, growth, and inflation. It also indirectly influences short-term interest rates. Hence, a higher federal funds rate signals an economic slow-down. Since the VIX and the Baa-Aaa spread are proxies for financial risk, these variables are negatively related to economic activity.

Using Credit Spreads to Predict Economic Activity

Panel A of Table 3.4 presents the results of using country-level credit spread data to predict country-level GDP over a one-quarter-ahead horizon. Indeed, credit spreads are statistically significant negative predictors of GDP growth over a one-quarter-ahead horizon using the four different model specifications considered. A 1% increase in credit spreads leads to about an 0.3% decline in GDP growth over the short-term. The results of Model (2) show that both the term spread and the federal funds rate are significant, however their signs are not correct. Models (3) and (4) show that Baa-Aaa spread is also a significant negative predictor of GDP growth. A 1% increase in Baa-Aaa spread leads to about a 2% decline in GDP growth.

Tables 3.4 [about here]

Using Credit Spreads to Predict Stock Market Returns

In addition to being reliable indicators of the economy, credit spreads have traditionally been reliable indicators of the stock market returns as well. In theory, increasing credit spreads signal bearish stock markets. We examine the predictability of the returns of local stock market indexes of emerging countries using credit spreads. Panel B of Table 3.4 shows that credit spreads are highly statistically significant predictors of local stock market returns of emerging countries using the four model specifications considered. A 1% increase in the credit spreads leads to close to a 7.5% decline in stock returns.

Next we examine the predictability of MSCI World and MSCI Emerging Markets returns using the credit spread index constructed by equally-weighting the credit spread data of the individual countries. Table 3.5 shows that credit spreads are significant negative predictors of MSCI Emerging Markets index using the four model specifications considered. A 1% increase in credit spreads leads to about a 4% decline in MSCI Emerging Markets index returns over a one-quarter-ahead horizon. Similarly, Table 3.6 shows that credit spreads are significant negative predictor of MSCI World returns. A 1% increase in credit spreads, leads to approximately a 2% decline in MSCI World returns.

Tables 3.5 and 3.6 [about here]

3.4 The EBP and the decomposition

In this section, we decompose the credit spreads into a component associated with the idiosyncratic default risk of firms and a risk premium component which Gilchrist and Zakrajšek (2012) call the excess bond premium EBP. To do the decomposition, we use the structural model in Jeanneret (2018) to get the credit spread implied by the model, then we use the difference between the credit spread and the predicted value of the spread as the risk premium.

3.4.1 Decomposing the Credit Spreads

To compute the model-implied credit spread, we use country-level GDP as the state variable in the model instead of fiscal revenues that is used in the original model. To remove the effect of the trend from the GDP data and maintain positive values, we disentangle the trend component and the cyclical component of the GDP data using Hodrick and Prescott (1997), then we divide the GDP data by the trend. We use the following equations to compute the spread [7]:

$$C = \frac{X_0}{\varphi}\left[\phi(1-\beta) - \frac{\beta\gamma^{\kappa} r}{\mu}\right]^{1/\beta} \tag{3.2}$$

$$\varphi = \frac{\phi\beta(r-\mu)}{r\lambda\gamma(\beta-1)} \tag{3.3}$$

$$X^{D*} = C\varphi \tag{3.4}$$

$$CS(X) = r\left[1-\phi\left(\frac{X}{X^D}\right)^{\beta}\right]^{-1} - r \tag{3.5}$$

Such that X denotes GDP, which evolves according to a geometric Brownian motion with constant mean μ and volatility σ. The coupon is expressed as C. The default boundary X^D at which it is optimal for the government to default, occurs at time $T^D = inf\{t \geq 0 | X_t \leq X^D\}$. The level of government effectiveness in collecting fiscal revenues is $\gamma = [0,1]$, with the average economy having $\gamma = 0.5$. A government's decision to default represents a trade-off between *default gains* $\phi \in [0,1]$ which is the proportion of debt service that the government gets to save in the event of debt restructuring, and *default loss* $\lambda \in [0,1]$ which is the proportion of output lost as a result of default. Investment incentives is denoted by κ, $\beta = \frac{-2r}{\sigma^2}$, and CS is the model-implied credit spread.

[7] We only present the parts of the model that we use to compute the spread. Please refer to Jeanneret (2018) for more details.

To calculate the model-implied spread, we use the input parameters of the base case environment of Jeanneret (2018), which are as follows: The risk-free rate $r = 5\%$, the government gets to save $\phi = 60\%$ of its debt obligation, the contraction of output in the event of default is $\lambda = 5\%$, investment incentives $\kappa = 0.5$, the level of government effectiveness $\gamma = 0.5$ the growth rate and volatility of output growth are $\mu = 1.08\%$ and $\sigma = 27.4\%$ respectively. I get the default boundary such that it reduces the RMSE between the EMBI spread and the model-implied spread.

3.4.2 Predicting Economic Activity Using Spread Components

This section examines the predictability of economic activity using the credit spread components: the risk premium and the default risk components. Figure 3.2 plots the actual spread against the default risk component of the spread, and shows that the default risk component captures the overall trend of the credit spread data. Figure 3.3 plots the risk premium component of the credit spread over the period 1994-2018. Similar to the pattern exhibited by the credit index plotted in Figure 3.1, the risk premium component increases significantly during most of the cyclical downturns that occurred in the 1994-2018 period. The plot shows that the the risk premium component was at its lowest level during the 2005-2006 period, which was the period preceding the financial crisis, then it starts to increase in early 2007. This upward movement precedes the economic slowdown that occurred a few months later, hence this could be viewed as evidence that the the risk premium component captures investor sentiment during the period leading to the financial crisis.

Figure 3.2 and 3.3 [about here]

We examine the predictability of emerging countries output growth using credit spread components: risk premium and default risk parts. From Panel A of Table 3.7, we observe that the predictability of output growth is non-attributable to one of the spread components in particular; both components are significant negative predictors of country

GDP growth. Since the credit spread components are derived from a model that uses GDP as the state variable, we present the results of predicting the growth of other economic activity variables as a robustness check. Table 3.8 presents the results of examining the predictability of industrial production growth and the growth of unemployment in emerging countries over a one-quarter-ahead horizon. The default risk part is a significant negative predictor of industrial production growth using the four different model specifications considered, however the risk premium part shows a weaker statistical significance compared to the default risk part. We obtain similar results by examining the predictability of unemployment using the credit spread components, with the spread components being positive predictors of the growth of unemployment.

Tables 3.7 and 3.8 [about here]

3.4.3 Predicting Stock Returns Using Spread Components

We examine the predictability of stock returns of local stock market indexes of emerging countries and the returns of MSCI World and MSCI Emerging Markets indexes using indexes of the credit spread components. We construct indexes of the risk premium component and the default risk component by equally weighting the data for the individual countries.

Panel B of Table 3.7 presents the results of using country-level local stock market data. It is evident that both components of the spread contribute to the predictability of local stock market returns. The same results hold for MSCI Emerging Markets index, presented in Table 3.9. In the case of MSCI World index presented in Table 3.10, we observe that the predictability MSCI World index returns is only attributable to the risk premium component.

Tables 3.9 and 3.10 [about here]

3.5 Discussions

Similar to the results of other papers that examine the predictability of economic activity using corporate credit spreads, this paper finds evidence in favor of sovereign credit spreads. Theoretically, two mechanisms link credit conditions to macroeconomic outcomes. Firstly, financial frictions on the borrowers' side imply that their cost of borrowing includes an additional premium above the relevant risk-free rate that is influenced to a great extent by the borrower's net worth compared to the amount borrowed. During economic slowdowns, this premium increases with the fall in asset prices and rise in leverage. Consequently, borrowing costs increase, and expenditure by households and firms decline, further exacerbating the downturn. Secondly, fluctuations in credit supply reflect a shift in the supply of funds offered by financial intermediaries. A worsening in the capital position of intermediaries leads to a weakening in the supply of funds, an increase in borrowing costs, and a widening of credit spreads. As a result, spending and production activity in the economy will slow down (B. Bernanke & Gertler, 1989b, 1995; B. Bernanke et al., 1996, 1999).

The results of this study could be improved further if the way the index is constructed is revised. Since bond issue-level data was not used to construct the spreads (for instance, as in Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), Gilchrist and Mojon (2018), and Bleaney et al. (2016)), probably the index constructed by this paper is a distorted measure of bond credit spreads. The excess spread of bonds over treasury bonds of comparable maturities includes three risk measures: prepayment risk, liquidity risk, and credit risk. Hence, investment-grade bonds are likely to have a lower proportion of the excess spreads as compensation for credit risk compared with non-investment-grade bonds. This kind of information is lost when individual bond spreads are aggregated to form country-level spreads. Constructing a credit spread index using bond issue-level data helps overcome these drawbacks. In addition, variations in bond characteristics could be exploited to enrich the results of this paper: bond credit rating, maturity, default probability, etc. Another possibility is to perform the analysis using CDS data since they are a better measure of credit risk compared to bond spreads. Longstaff et al. (2005) list several reasons why CDS spreads are a better measure of credit risk compared to bond spreads. Mizen et al. (2014) and Daula (2011) examine the information content of CDS spreads for predicting economic activity. Compared to using individual bond level data, using CDS is simpler and less model-dependent.

In addition to data quality issues, the liberalization of economies in several emerging countries since the 1990s presents an important contextual factor that may influence the relationship between sovereign credit spreads and economic activity. Economic liberalization, characterized by deregulation, privatization, and the opening up of markets to foreign investment, can significantly impact the financial stability and economic growth of these countries. In our analysis, it is crucial to consider the timing and extent of liberalization policies, as they can affect the risk perceptions of investors and, consequently, sovereign credit spreads. One way to address this in our analysis is by incorporating liberalization indices or policy reform indicators as control variables to capture the effects of economic liberalization. Additionally, conducting a sub-sample analysis based on the degree of liberalization or dividing the sample period into pre- and post-liberalization phases could provide insights into how the relationship between sovereign credit spreads and economic activity has evolved in response to liberalization policies. By accounting for the impact of economic liberalization, our analysis can offer a more nuanced understanding of the dynamics between sovereign credit spreads and economic activity in emerging markets.

Data issues in emerging markets can significantly affect the analysis of sovereign bond spreads and economic activity. Emerging markets often suffer from less comprehensive and lower-quality data compared to developed markets, which can lead to difficulties in obtaining accurate measures of economic variables and bond spreads. Additionally, the frequency and timeliness of data updates in these markets can be problematic, with longer publication lags reducing the ability to perform timely analysis. Variations in accounting standards, economic measurement techniques, and reporting practices across different emerging markets can further lead to inconsistencies, making cross-country comparisons challenging. Expropriation risk, the likelihood that a government might seize private assets without fair compensation, can lead to higher sovereign bond spreads as investors demand a risk premium for holding such assets. This risk increases the default risk component of the credit spread, leading to higher premiums required by investors and affecting the predictability of economic activity. Political risks, including political instability, changes in government policies, and political unrest, can significantly impact the economic environment in emerging markets. These risks lead to increased uncertainty and volatility, which are reflected in the risk premium component of the credit spreads. Consequently, sudden shifts in investor sentiment due to political events can impact bond spreads and their ability to predict economic activity and stock returns.

Countries with higher expropriation and political risks tend to have higher sovereign spreads due to the increased default risk and risk premium demanded by investors. The predictive power of credit spreads for economic activity may be weakened in emerging markets due to the higher and more volatile risk components. Both the default risk and risk premium components may be more variable and subject to sudden changes in response to political events. Decomposing the credit spreads into default risk and risk premium components, as outlined in this paper, helps in understanding the individual contributions of these risks. In emerging markets, it is particularly important to account for the higher variability and potential biases introduced by expropriation and political risks. Adjusting models to explicitly account for these risks, for example, by including political risk indices or expropriation risk measures as additional controls, could help in isolating their effects on sovereign spreads and economic activity. In conclusion, while the methodology and findings of this paper highlight the significant predictive power of sovereign credit spreads, it is crucial to recognize the additional layers of complexity introduced by data issues, expropriation, and political risks in emerging markets. These factors not only affect the level of credit spreads but also their components and, consequently, their ability to predict economic activity and stock returns.

Examining crisis periods such as sovereign debt defaults or other major shocks, whether global or specific to the sample of 60 emerging countries in the EMBI index, is crucial for understanding their impact on sovereign bond spreads and economic activity. Notable events during our sample period include the Asian Financial Crisis of 1997-1998, which caused widespread economic turmoil in East Asia and led to significant increases in credit spreads. The Russian Financial Crisis in 1998 resulted in a sovereign default and substantial market disruptions. The Argentine debt default in 2001 was another major event, leading to severe economic decline and soaring credit spreads. The Global Financial Crisis of 2007-2009 had a profound impact worldwide, causing credit spreads to spike dramatically as risk aversion increased. The European Debt Crisis from 2010 to 2012 also influenced emerging markets, particularly through contagion effects and heightened risk perceptions. More recently, the 2014-2016 oil price shock significantly affected commodity-exporting countries within the sample, leading to increased economic instability and widened credit spreads. Ignoring these periods can lead to an underestimation of risk and volatility in the analysis. Crisis periods often result in significant spikes in credit spreads due to heightened risk aversion and increased default risk. These spikes can distort the relationship between credit spreads and economic activity if not properly accounted for, leading to biased estimates and potentially misleading conclusions.

To incorporate crisis periods into future analysis, several approaches can be considered. Firstly, including dummy variables for known crisis periods in the regression models can help capture the impact of these events. This allows for isolating the effect of crises from the overall trend, providing a clearer picture of the underlying relationships. Secondly, using interaction terms between crisis dummy variables and credit spreads can help assess how the predictive power of spreads changes during crises. Additionally, employing regime-switching models can allow for different relationships between variables during normal and crisis periods. These models can identify structural breaks and accommodate shifts in the economic environment, providing more robust estimates. Furthermore, it would be beneficial to conduct a detailed event study analysis around crisis periods to examine the immediate impact of shocks on credit spreads and economic activity. This can provide insights into the dynamics of spreads during crises and improve the understanding of their predictive power in turbulent times. Incorporating these approaches into future research will enhance the robustness of the findings and provide a more comprehensive understanding of the relationship between sovereign credit spreads and economic activity in emerging markets.

3.6 Conclusion

This paper examines if sovereign bond credit spreads issued by emerging countries predict economic activity and stock market returns of these countries, using a forecasting specification that has been largely used by the literature of predicting economic activity using asset prices. After that, it examines if the ability of credit spreads to predict economic activity and stock market returns could be attributed to one of the spread components in particular. The main findings of this paper are that credit spreads are significant predictors of economic activity and stock market returns of emerging countries, as well as of the returns of MSCI Emerging Markets and MSCI World stock market indexes. This paper also finds that both components of the credit spreads influence their ability to predict economic activity. The risk premium component plays a particularly important role in predicting stock returns.

There are several ways the work performed in this paper could be developed. One possibility is to estimate the models for a smaller sample of countries individually instead of for aggregated countries. This allows for customizing the forecast models to the individual countries. Secondly, it is important to examine how the forecasting model performs out of sample and to assess forecast accuracy (Gilchrist et al., 2009; Mueller, 2009; J. Stock & Watson, 2003). Thirdly, it could be useful to examine how country credit rating impacts the ability of its credit spreads to predict economic activity. Mueller (2009) and Gilchrist and Zakrajšek (2012) find that for corporate bonds in the US market, credit spreads of borrowers with intermediate rating have a higher information content for economic activity compared to borrowers with other credit ratings. But to the extent of our knowledge, nobody has examined this on a country-level.

3.7 Figures and Tables

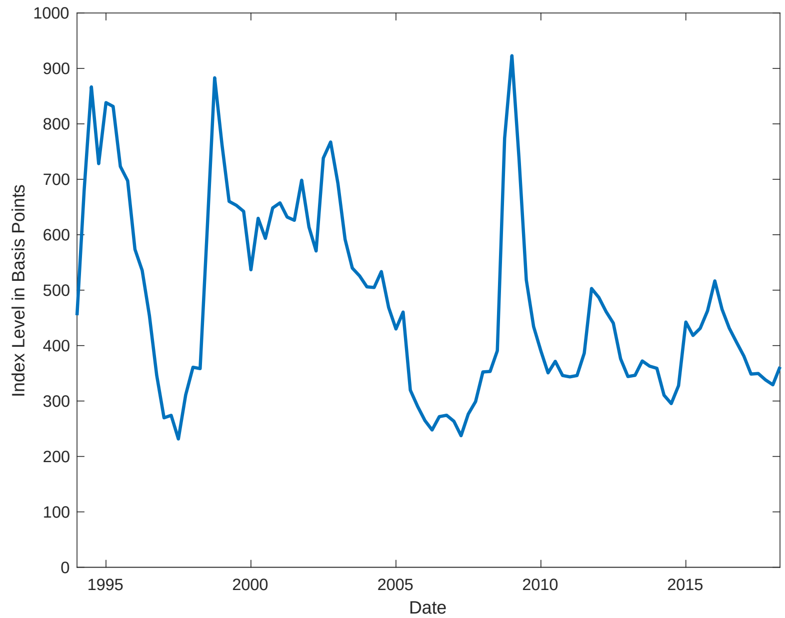

Figure 3.1: **Credit Spread Index from January 1994 to June 2018.**
This figure plots the credit spread index constructed by equally-weighting EMBI data from January 1994 to June 2018. This data set is provided by J.P. Morgan and it consists of monthly data of credit spreads of sovereign US dollar denominated debt issued by 60 emerging countries. Table 3.1 provides summary statistics of the credit spread data for the individual countries.

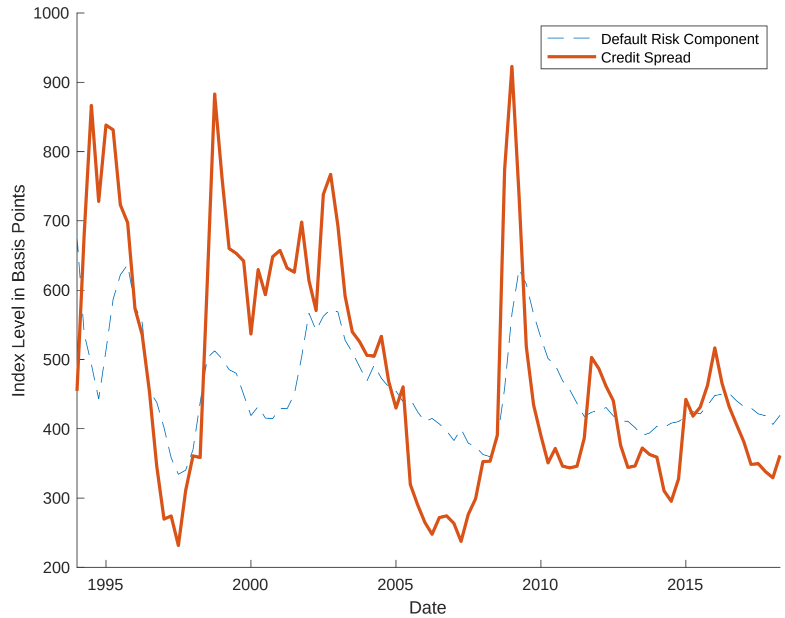

Figure 3.2: **The Credit Spread Index and the Default Risk Component of the Index from January 1994 to June 2018.**
This figure plots the credit spread index constructed by equally-weighting the EMBI data against the default risk component of the index from January 1994 to June 2018. The components of the credit spread are disentangled using the model in Jeanneret (2018). The process of decomposing the spread is described in Section 3.4 of the paper. The risk premium component is plotted in Figure 3.3. Various descriptive statistics of the credit spread index and both of its components are reported in Panel A of Table 3.2.

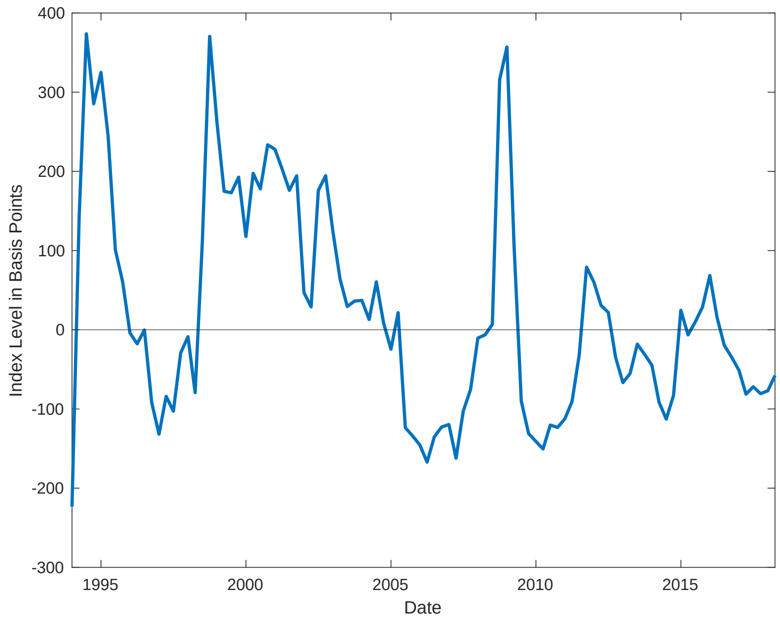

Figure 3.3: **The Risk Premium Component of the Credit Spread from January 1994 to June 2018.**
This figure plots the risk premium component of the credit spread index constructed by equally-weighting the EMBI data from January 1994 to June 2018. The components of the credit spread are disentangled using the model in Jeanneret (2018). The process of decomposing the spread is described in Section 3.4 of the paper. The credit spread index and the default risk component of the index are plotted in Figure 3.2. Various descriptive statistics of the credit spread index and both of its components are presented in Panel A of Table 3.2.

Table 3.1: **Descriptive Statistics of Credit Spread Data**

This table presents descriptive statistics of the credit spread data of individual countries. The credit spreads used are the EMBI credit spreads provided by J.P. Morgan and consist of monthly data of credit spreads of sovereign US-dollar-denominated debt issued by 60 emerging countries for the period January 1994 to June 2018. We report the mean, standard deviation, various percentile statistics and the number of months for which credit spread data is available for each country.

Variables	Mean	StdDev	P5	P25	P50	P75	P95	N
Angola	544.75	203.08	275.02	368.95	518.76	728.06	875.43	68
Argentina	1100.40	1143.42	295.07	449.06	618.69	1008.47	3899.79	294
Armenia	382.74	99.48	239.80	307.00	366.48	465.86	544.80	56
Azerbaijan	314.66	84.17	206.00	252.46	297.42	354.14	471.36	74
Belarus	701.80	304.97	325.08	463.45	652.90	906.42	1236.94	93
Belize	234.80	71.16	80.20	202.10	239.97	290.88	335.05	67
Bolivia	471.82	310.96	173.13	233.39	365.44	649.55	1043.32	290
Brazil	360.60	364.81	67.99	76.55	215.23	522.23	1176.92	287
Bulgaria	152.98	52.57	77.92	120.06	147.91	182.31	244.46	229
Chile	134.32	58.08	58.35	83.93	132.63	166.40	238.51	291
China	327.42	192.50	142.11	181.94	242.16	453.94	722.89	256
Colombia	382.82	74.62	261.42	333.19	372.12	421.94	514.44	71
Costa Rica	1560.42	962.75	365.83	503.61	1498.42	2440.10	2963.19	242
Côte d'Ivoire	265.49	149.18	145.34	145.34	226.77	315.38	600.13	262
Croatia	494.92	300.90	228.68	329.49	395.81	513.04	1152.80	199
Dominican Republic	966.73	570.88	485.67	630.20	817.82	1096.28	1922.63	280
Ecuador	298.52	170.26	49.91	136.41	335.24	421.72	576.88	203
Egypt	370.82	137.76	174.88	270.23	361.34	444.84	641.77	194
El Salvador	456.04	212.25	247.97	310.46	389.88	510.74	932.41	126
Gabon	479.22	334.18	213.55	330.43	384.99	467.33	1318.68	120
Georgia	585.86	245.81	349.10	409.19	523.48	648.65	1150.65	128
Ghana	236.27	40.47	183.05	201.88	234.29	266.25	308.77	72
Guatemala	423.28	121.75	255.50	336.84	426.85	472.70	683.21	62
Hungary	180.77	137.60	35.90	74.11	137.23	250.58	490.02	233

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Table 3.1 Continued from previous page

Variables	Mean	StdDev	P5	P25	P50	P75	P95	N
India	180.44	54.97	112.29	147.60	163.22	200.37	290.29	68
Indonesia	268.31	114.79	170.23	201.07	246.89	294.10	427.13	165
Iraq	584.32	196.65	355.78	462.48	532.05	641.74	1037.37	146
Jamaica	501.41	164.21	297.56	387.37	459.85	592.87	794.69	128
Kazakhstan	387.49	222.72	208.35	259.23	325.28	422.13	839.09	132
Latvia	109.98	50.64	34.84	70.38	104.30	147.75	194.90	69
Lebanon	423.63	167.75	201.38	342.10	398.96	480.19	778.44	242
Lithuania	187.92	110.68	56.11	106.90	142.69	277.44	416.52	103
Malaysia	243.08	99.50	101.24	154.33	228.38	345.03	396.49	260
Mexico	230.79	75.56	135.64	175.97	217.34	271.51	380.06	246
Mongolia	125.06	19.99	104.84	111.22	116.77	135.35	164.38	73
Morocco	250.41	211.01	57.63	57.63	203.71	392.58	670.94	246
Mozambique	1178.97	520.30	469.72	651.10	1192.71	1581.90	2046.56	55
Namibia	260.82	51.10	186.23	224.26	247.61	290.25	357.87	79
Nigeria	500.91	405.98	29.77	249.50	404.42	704.30	1369.53	294
Pakistan	613.60	409.15	181.38	315.13	519.86	716.10	1499.71	204
Panama	277.50	121.20	139.58	179.77	230.00	375.61	501.90	263
Paraguay	261.29	45.32	193.84	225.18	262.33	293.43	338.31	64
Peru	315.52	191.90	133.10	167.57	216.02	448.78	695.50	255
Philippines	288.67	156.98	102.61	152.93	252.58	422.94	585.10	246
Poland	159.03	100.76	51.83	83.11	144.61	195.85	378.21	284
Romania	209.16	84.82	128.33	163.10	180.80	224.53	414.54	76
Russia	632.78	1025.29	115.95	199.54	273.15	527.75	3277.42	246
Senegal	455.68	101.36	302.18	386.22	429.94	525.85	647.20	85
Serbia	353.28	180.73	132.41	236.76	307.64	432.44	631.77	156
Slovakia	119.96	8.16	104.76	113.71	122.76	126.03	128.60	58
South Africa	239.69	115.15	88.04	163.64	231.87	285.32	432.25	282
South Korea	130.15	98.80	71.35	96.56	96.56	113.33	278.47	294
Tanzania	463.79	122.81	353.89	371.72	409.16	520.15	731.69	61
Tri and Tobago	260.89	77.49	160.02	213.38	249.17	292.93	421.51	58
Turkey	377.86	201.48	186.35	236.95	300.63	476.73	863.51	264
Ukraine	830.63	705.81	176.94	364.78	647.96	932.97	2290.79	217

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Table 3.1 Continued from previous page

Variables	Mean	StdDev	P5	P25	P50	P75	P95	N
Uruguay	346.27	263.31	154.03	195.62	248.19	361.04	917.74	205
Venezuela	1095.36	881.91	234.52	551.03	869.07	1180.24	3005.93	294
Vietnam	286.93	133.05	123.28	201.56	272.12	339.96	509.12	151
Zambia	579.63	212.72	361.06	431.52	497.99	691.10	1002.94	68

Table 3.2: **Descriptive Statistics**

This table presents descriptive statistics of the variables used in this study. Panel A includes country variables, Panel B includes emerging region variables, Panel C includes world variables and panel D includes US variables. We report the mean, standard deviation and various percentile statistics. In Panel A we report the number of country quarters for each variable, and in Panels B,C and D we report the number of quarters. For data-sets with non-missing observation, 5880 country quarters are available; 60 countries between January 1994 and June 2018. Table 3.3presents variable definitions and data sources.

Variables	Mean	Std. Dev.	P5	P25	P50	P75	P95	N
Panel A: Country Variables								
GDP (in Mn USD)	72,197.46	229,479.89	1,497.07	5,476.13	13,410.90	47,626.90	301,317.00	5880
Industrial Production (in Mn USD)	14,879.56	43,443.41	343.13	1,080.00	4,473.33	9,170.00	43,320.00	2778
Unemployment Rate (%)	9.39	5.06	3.04	6.00	8.40	11.67	19.63	2054
Local Stock Market Price Index	543.05	848.27	31.08	108.21	275.02	621.78	1,854.40	3407
Credit Spread (in bps)	441.71	500.52	78.16	180.05	302.06	505.65	1,199.48	3428
Default Risk (in bps)	446.23	353.17	131.40	241.92	335.02	512.05	1,126.93	3488
Risk Premium (in bps)	0.00	359.03	-407.19	-124.03	-28.82	66.32	465.09	3488
Panel B: Emerging Region Variables								
MSCI EM Price Index	700.59	295.08	292.56	436.75	633.83	969.25	1,135.40	98
Equally-Weighted Credit Spread (in bps)	471.31	169.11	263.96	338.30	427.86	613.87	771.20	98
Equally-Weighted Default Risk (in bps)	458.62	70.49	365.60	411.00	438.08	501.15	599.95	98
Equally-Weighted Risk Premium (in bps)	22.43	136.57	-143.79	-82.67	-5.22	105.52	303.56	98
Panel C: World Variables								
MSCI World Price Index	1,228.81	367.78	644.78	959.31	1,206.01	1,492.55	1,862.46	98
Panel D: US Variables								
Term Spread (%)	1.72	1.08	-0.10	0.84	1.71	2.64	3.35	98
Federal Funds Rate (%)	2.60	2.30	0.09	0.18	1.75	5.24	5.80	98
CBOE Volatility Index (VIX)	19.62	7.53	11.82	13.73	17.43	23.21	30.37	98
Baa-Aaa spread (%)	0.96	0.41	0.60	0.70	0.87	1.08	1.42	98

Table 3.3: **Variable Definitions and Sources**

This table defines the variables used in this study and provides the data sources. Panel A includes credit spread variables, Panel B includes control variables and Panel C includes dependent variables. Table 3.2 reports descriptive statistics of these variables. Section 3.3.1 presents a more detailed description of the variables used.

Variable	Definition	Source
Panel A: Credit Spread		
EMBI	Credit spread of sovereign US-dollar-denominated debt of 60 emerging countries.	Datastream
Panel B: Control Variables		
Term Spread	The slope of the treasury yield curve (the difference between the three-month and the ten-year constant maturity yield).	FRED
Federal Funds Rate	The average effective federal funds rate during the period less realized inflation.	FRED
CBOE Volatility Index (VIX)	A measure of the implied volatility of S&P500 index options.	Datastream
Baa-Aaa spread	The spread on indexes of Baa- and Aaa-rated seasoned industrial corporate bonds (a quality spread).	FRED
Panel C: Dependent Variables		
GDP	Country-level GDP (constant 2010 prices) in $US, adjusted for seasonality.	World Bank
Industrial Production	Country-level industrial production (constant 2010 prices) in $US, adjusted for seasonality.	World Bank
Unemployment Rate	Total unemployment rate as a percentage of total labor force (national estimate).	Datastream
Stock Market Index	MSCI or Standard and Poor local stock market index in USD.	Datastream
MSCI Emerging Market Index	The MSCI Emerging Markets Index captures large and mid cap representation across 26 emerging countries.	Datastream
MSCI World Index	A market cap weighted stock market index of 1,644 stocks from companies all over the world.	Datastream

Table 3.4: **Credit Spreads, Real GDP Growth and Stock Returns of Individual Emerging Countries**

This table presents results from our dynamic fixed effects panel regressions investigating the ability of sovereign credit spreads to predict real GDP growth and stock returns of a sample of 60 emerging countries. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable in Panel A is the annualized log of the first difference of country real GDP, while the dependent variable in Panel B is the annualized log of the first difference of country local stock market index price. Model (1) includes 4 lags of the dependent variable (not reported) and credit spreads as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3 presents variable definitions and sources. All regressors other than the lagged dependent variable are in first difference. Driscoll and Kraay standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Panel A: GDP Growth				
	(1)	(2)	(3)	(4)
Variables				
Credit Spread	-0.447***	-0.360***	-0.290**	-0.264**
	(0.13)	(0.12)	(0.12)	(0.12)
TS		1.356***		0.653*
		(0.37)		(0.38)
FFR		2.491***		1.505***
		(0.42)		(0.41)
VIX			0.052	0.047
			(0.04)	(0.04)
Baa-Aaa			-2.154***	-1.832***
			(0.45)	(0.46)
Observations	3,351	3,351	3,351	3,351
R^2	11.00%	11.90%	12.60%	12.90%
Panel B: Stock Returns				
	(1)	(2)	(3)	(4)
Variables				
Credit Spread	-8.105***	-7.995***	-7.279***	-7.246***
	(1.67)	(1.66)	(1.57)	(1.57)
TS		-1.866		-9.330**
		(3.56)		(3.84)
FFR		12.072***		2.707
		(4.34)		(4.70)
VIX			2.472***	2.570***
			(0.45)	(0.46)
Baa-Aaa			-36.912***	-37.568***
			(4.76)	(4.96)
Observations	2,474	2,474	2,474	2,474
R^2	15.80%	16.30%	18.20%	18.60%

Table 3.5: **Bond Spreads and the Emerging Country Region Stock Returns.**
This table presents results from our OLS regressions investigating the ability of sovereign credit spreads to predict stock returns of the emerging country region. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable is the annualized log of the first difference of the MSCI emerging markets index price. Model (1) includes 4 lags of the dependent variable (not reported) and credit spreads as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3 presents variable definitions and sources. All regressors other than the lagged dependent variable are in first difference. Newey-West standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	MSCI Emerging Market Returns			
	(1)	(2)	(3)	(4)
Variables				
Credit Spread	-4.096***	-4.082***	-4.193***	-4.205***
	(0.58)	(0.58)	(0.58)	(0.57)
TS		-2.894		-0.69
		(11.52)		(12.51)
FFR		10.889		18.639
		(14.04)		(15.24)
VIX			1.107	1.327
			(0.92)	(0.94)
Baa-Aaa			8.183	17.542
			(17.52)	(17.61)
Observations	93	93	93	93
R^2	56.60%	57.80%	57.90%	60.00%

Table 3.6: **Bond Spreads and World Stock Returns**

This table presents results from our OLS regressions investigating the ability of sovereign credit spreads to predict stock returns of the world. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable is the annualized log of the first difference of the MSCI world index price. Model (1) includes 4 lags of the dependent variable (not reported) and credit spreads as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3 presents variable definitions and sources. All regressors other than the lagged dependent variable are in first difference. Newey-West standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	MSCI World Returns			
	(1)	(2)	(3)	(4)
Variables				
Credit Spread	-2.091***	-2.095***	-2.100***	-2.117***
	(0.54)	(0.55)	(0.52)	(0.53)
TS		-8.408		-7.11
		(6.47)		(6.90)
FFR		6.034		8.017
		(8.56)		(9.38)
VIX			1.096	1.094
			(0.71)	(0.76)
Baa-Aaa			-10.719	-3.936
			(11.14)	(11.28)
Observations	93	93	93	93
R^2	50.30%	54.00%	51.70%	55.40%

Table 3.7: **Bond Spread Components, Real GDP Growth and Stock Returns of Individual Emerging Countries**

This table presents results from our dynamic fixed effects panel regressions investigating the ability of the sovereign credit spread components (the default risk part and the risk premium part, derived using the model in Jeanneret (2018)) to predict real GDP growth and stock returns of emerging countries. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable in Panel A is the annualized log of the first difference of country real GDP, while the dependent variable in Panel B is the annualized log of the first difference of country local stock market index price. Model (1) includes 4 lags of the dependent variable (not reported) and the credit spread components as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3 presents variable definitions and sources. All regressors other than the lagged dependent variable are in first difference. Driscoll and Kraay standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Panel A: GDP Growth				
	(1)	(2)	(3)	(4)
Variables				
Default Risk	-0.754**	-0.640**	-0.607**	-0.561*
	(0.30)	(0.29)	(0.30)	(0.29)
Risk Premium	-0.484***	-0.391***	-0.306**	-0.280**
	(0.14)	(0.14)	(0.14)	(0.13)
TS		1.311***		0.633*
		(0.38)		(0.38)
FFR		2.405***		1.451***
		(0.43)		(0.41)
VIX			0.052	0.047
			(0.04)	(0.04)
Baa-Aaa			-2.122***	-1.813***
			(0.45)	(0.46)
Observations	3,351	3,351	3,351	3,351
R^2	11.20%	12.10%	12.80%	13.10%

Panel B: Stock Returns				
	(1)	(2)	(3)	(4)
Variables				
Default Risk	-13.479***	-13.126***	-12.514***	-12.381***
	(2.63)	(2.69)	(2.56)	(2.59)
Risk Premium	-7.618***	-7.572***	-6.832***	-6.799***
	(1.56)	(1.56)	(1.47)	(1.47)
TS		-3.564		-11.781***
		(3.56)		(3.85)
FFR		9.033**		-1.815
		(4.29)		(4.69)
VIX			1.792***	1.882***
			(0.41)	(0.42)
Baa-Aaa			-31.007***	-32.472***
			(4.51)	(4.75)
Observations	2,515	2,515	2,515	2,515
R^2	16.10%	16.50%	18.00%	18.40%

Table 3.8: **Bond Spread Components, Industrial Production Growth and Unemployment Rate Growth of Individual Emerging Countries**

This table presents results from our dynamic fixed effects panel regressions investigating the ability of the sovereign credit spread components (the default risk part and the risk premium part, derived using the model in Jeanneret (2018)) to predict the growth of industrial production and unemployment rate of emerging countries. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable in Panel A is the annualized log of the first difference of country industrial production, while the dependent variable in Panel B is the first difference of country unemployment rate. Model (1) includes 4 lags of the dependent variable (not reported) and credit spread components as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3 presents variable definitions and sources. All regressors other than the lagged dependent variable are in first difference. Driscoll and Kraay standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Panel A: Industrial Production Growth				
	(1)	(2)	(3)	(4)
Variables				
Default Risk	-4.884***	-4.654***	-4.087***	-4.069***
	(0.76)	(0.71)	(0.65)	(0.66)
Risk Premium	-0.555*	-0.550*	-0.163	-0.2
	(0.33)	(0.33)	(0.29)	(0.30)
TS		0.478		-1.662
		(1.38)		(1.41)
FFR		4.897***		1.847
		(1.49)		(1.47)
VIX			0.162	0.176
			(0.14)	(0.14)
Baa-Aaa			-5.817***	-5.653***
			(1.55)	(1.63)
Observations	1,922	1,922	1,922	1,922
R^2	9.20%	10.20%	11.10%	11.60%
Panel B: Unemployment Growth				
	(1)	(2)	(3)	(4)
Variables				
Default Risk	0.302***	0.282***	0.283***	0.277***
	(0.07)	(0.08)	(0.08)	(0.08)
Risk Premium	0.047**	0.044*	0.039	0.042*
	(0.02)	(0.02)	(0.03)	(0.02)
TS		-0.06		-0.041
		(0.15)		(0.16)
FFR		-0.471***		-0.441**
		(0.17)		(0.20)
VIX			-0.001	0
			(0.02)	(0.02)
Baa-Aaa			0.136	0.038
			(0.16)	(0.17)
Observations	1,510	1,510	1,510	1,510
R^2	15.40%	16.00%	15.50%	16.00%

Table 3.9: **Bond Spread Components and Emerging Country Region Stock Returns**
This table presents results from our OLS regressions investigating the ability of the sovereign credit spread components (the default risk part and the risk premium part, derived using the model in Jeanneret (2018)) to predict stock returns of the emerging country region. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable is the annualized log of the first difference of the MSCI emerging markets index price. Model (1) includes 4 lags of the dependent variable (not reported) and credit spreads as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3 presents variable definitions and sources. All regressors other than the lagged dependent variable are in first difference. Newey-West standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	MSCI Emerging Markets Returns			
	(1)	(2)	(3)	(4)
Variables				
Default Risk	-3.563**	-3.477**	-3.786**	-3.657**
	(1.48)	(1.45)	(1.52)	(1.47)
Risk Premium	-4.107***	-4.087***	-4.274***	-4.288***
	(0.73)	(0.73)	(0.74)	(0.74)
TS		-2.881		0.09
		(10.99)		(12.02)
FFR		8.321		17.475
		(13.35)		(14.65)
VIX			1.538*	1.739*
			(0.90)	(0.95)
Baa-Aaa			8.185	16.484
			(17.92)	(18.38)
Observations	93	93	93	93
R^2	56.50%	57.30%	58.70%	60.50%

Table 3.10: **Bond Spreads Components and World Stock Returns**
This table presents results from our OLS regressions investigating the ability of the sovereign credit spread components (the default risk part and the risk premium part, derived using the model in Jeanneret (2018)) to predict stock returns of world. The series is composed of quarterly data from January 1994 to June 2018. The dependent variable is the annualized log of the first difference of the MSCI world index price. Model (1) includes 4 lags of the dependent variable (not reported) and credit spreads as regressors, Model (2) augments Model (1) by adding the term spread and the federal funds rate as regressors, Model (3) augments Model (1) by adding CBOE volatility index (VIX) and the Baa-Aaa spread to the list of regressors, and Model (4) augments Model (1) by adding all the additional regressors used in Models (2) and (3). Table 3.2 presents the variables' descriptive statistics and Table 3.3presents variable definitions and sources. All regressors other than the lagged dependent variables are in first difference. Newey-West standard errors are used with an autocorrelation structure of 4 lags. Standard errors in parenthesis and $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	MSCI World Returns			
	(1)	(2)	(3)	(4)
Variables				
Default Risk	-1.27	-1.372	-1.355	-1.475
	(0.89)	(0.88)	(0.96)	(0.93)
Risk Premium	-2.329***	-2.289***	-2.338***	-2.309***
	(0.60)	(0.61)	(0.58)	(0.58)
TS		-6.953		-5.643
		(6.65)		(7.03)
FFR		6.104		8.056
		(8.79)		(9.63)
VIX			1.197*	1.21
			(0.72)	(0.77)
Baa-Aaa			-11.424	-5.303
			(10.99)	(11.20)
Observations	93	93	93	93
R^2	52.40%	55.30%	54.00%	56.90%

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General Conclusion

The three articles collectively contribute to the field of empirical asset pricing with a focus on the predictive powers and implications of various financial factors.

The conclusion of the first article emphasizes the role of primary dealers in sophisticated asset markets and enhances our understanding of their liability structures and the market pricing of their leverage. The constructed debt factor, derived from intermediary cost of funding proxies and debt composition data, is proven to explain variability in asset returns across multiple classes when included in a multifactor model.

The second article sheds light on the S dimension of ESG and its complex impact on stock returns. It demonstrates that while the aggregate S score does not influence returns, its individual components—human capital and product safety—have significant and contrasting effects. This finding advocates for a more nuanced approach in ESG investing, where the distinct implications of individual ESG criteria are recognized rather than amalgamated into a single score.

The third article establishes that credit spreads of sovereign bonds from emerging markets are significant predictors of economic activity and stock market returns, and both components of credit spreads—the default risk and risk premium—are critical to this predictive capacity. It suggests future research avenues for a more tailored forecasting model, the examination of out-of-sample performance, and the impact of country credit ratings on prediction accuracy.

Through rigorous empirical analysis, this thesis advances the understanding of financial indicators as tools for forecasting and their broader implications on asset pricing. From the intricacies of financial intermediaries' leverage to the multifaceted nature of ESG components and the predictive strength of sovereign bond credit spreads, these studies highlight the necessity for a detailed and differentiated approach to financial evaluation. They collectively underscore the importance of considering each financial factor's unique contribution rather than relying on aggregated indices, thereby enhancing the strategy and insight of investors, policymakers, and scholars in the realm of financial markets. The thesis stands as a testament to the need for continuous refinement in asset pricing models, advocating for a granular examination of financial factors to accurately reflect the complexity of market dynamics.

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Appendix A – Appendix to the First Article

Additional Tables

Table A1: **List of New York Fed Primary Dealers over January 2001 to January 2021.**

This table provides details about the New York Fed primary dealers over our sample period. It lists the primary dealer, its holding company, the start and end date of being a primary dealer (P.D. From and P.D. To) and the start and end date of inclusion in our factor construction. Some primary dealers undergo name changes over the P.D. From and P.D. To period. This is handled by listing the most recent names under the Primary Dealer column.

Holding Company	Primary Dealer	P.D. From	P.D. To	Start Date	End Date
ABN AMRO Bank, N.V.	ABN AMRO Bank, N.V., New York Branch	1998-09-29	2006-09-15	-	-
Aladin Secured Lending, Inc.	ASL Capital Markets Inc.	2022-04-04	Current	-	-
Amherst ASG Holdings, LLC	Amherst Pierpont Securities LLC	2019-05-06	Current	-	-
Bank of America Corporation	Merrill Lynch, Pierce, Fenner & Smith Inc.	1999-05-17	2019-05-13	2001-01-01	2019-05-13
Bank of America Corporation	BofA Securities, Inc.	2019-05-13	Current	2019-05-13	2021-02-01
BMO Nesbitt Burns Corp	BMO Nesbitt Burns Corp	2000-02-15	2002-04-01	-	-
Bank of Montreal	BMO Capital Markets Corp.	2011-10-04	2021-12-13	2011-10-04	2021-02-01
Bank of Montreal	Bank of Montreal, Chicago Branch	2021-12-13	Current	-	-
Bank of Nova Scotia	Bank of Nova Scotia, New York Agency	2011-10-04	Current	2011-10-04	2021-02-01
Bank One Corporation	Banc One Capital Markets, Inc.	1999-04-01	2004-08-02	2001-01-01	2004-08-02
Barclays PLC	Barclays Capital Inc.	1998-04-01	Current	2001-01-01	2021-02-01
Bear Stearns Companies, Inc.	Bear, Stearns & Co., Inc.	1981-06-10	2008-10-01	2001-01-01	2008-10-01
BNP Paribas	BNP Paribas Securities Corp.	2000-09-15	Current	2001-01-01	2021-02-01

Continued on the next page

Holding Company	Primary Dealer	P.D. From	P.D. To	Start Date	End Date
Canadian Imperial Bank of Commerce	CIBC World Markets Corp.	1996-03-27	2007-02-08	2001-01-01	2007-02-08
Cantor Fitzgerald & Co.	Cantor Fitzgerald & Co.	2006-08-01	Current	-	-
Citigroup Inc.	Citigroup Global Markets Inc.	1961-06-15	Current	2001-01-01	2021-02-01
Countrywide Bank	Countrywide Securities Corporation	2004-01-14	2008-07-15	2004-01-15	2008-07-15
Credit Suisse Group AG	Credit Suisse Securities (USA) LLC	1993-10-12	2017-11-13	2001-01-01	2017-11-13
Credit Suisse Group AG	Credit Suisse AG, New York Branch	2017-11-13	Current	2017-11-13	2021-02-01
Daiwa Securities Group, Inc.	Daiwa Capital Markets America Inc.	1986-12-11	Current	2001-01-01	2021-02-01
Deutsche Bank AG	Deutsche Bank Securities Inc.	1990-12-13	Current	2001-01-01	2021-02-01
Dresdner Bank	Dresdner Kleinwort Securities LLC	1997-05-08	2009-06-26	-	-
Goldman Sachs Group, Inc.	Goldman Sachs & Co. LLC	1974-12-04	Current	2001-01-01	2021-02-01
HSBC Holdings PLC	HSBC Securities (USA) Inc.	1994-05-09	Current	2001-01-01	2021-02-01
Jefferies & Company, Inc.	Jefferies LLC	2009-06-18	Current	2009-06-18	2021-02-01
JPMorgan Chase & Co.	J.P. Morgan Securities	1960-05-19	Current	2001-01-01	2021-02-01
Lehman Brothers Holdings Inc.	Lehman Brothers Inc.	1976-11-25	2008-09-22	2001-01-01	2008-09-22
Merrill Lynch & Co.	Merrill Lynch Government Securities Inc.	1960-05-19	2009-02-11	2001-01-01	2009-02-11
MF Global Holdings Ltd	MF Global Inc.	2011-02-02	2011-10-31	-	-
Mizuho Financial Group, Inc.	Mizuho Securities USA Inc.	2002-04-01	Current	2002-04-01	2021-02-01
Morgan Stanley	Morgan Stanley & Co. LLC	1978-02-01	Current	2001-01-01	2021-02-01
NatWest Group PLC	NatWest Markets Securities Inc.	2009-04-01	Current	2009-04-01	2021-02-01
Nomura Holdings, Inc.	Nomura Securities International, Inc.	1986-12-11	2007-11-30	2001-01-01	2007-11-30
Nomura Holdings, Inc.	Nomura Securities International, Inc.	2009-07-27	Current	2009-07-27	2021-02-01
Royal Bank Holding Inc.	RBC Capital Markets, LLC	2009-07-08	Current	2009-07-08	2021-02-01

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Holding Company	Primary Dealer	P.D. From	P.D. To	Start Date	End Date
Societe Generale	SG Cowen Securities Corporation	1999-07-01	2001-10-31	-	-
Societe Generale	SG Americas Securities, LLC	2011-02-02	2015-12-07	2011-02-02	2015-12-07
Societe Generale	Societe Generale, New York Branch	2015-12-07	Current	2015-12-07	2021-02-01
Toronto-Dominion Bank	TD Securities (USA) LLC	2014-02-11	Current	2014-02-11	2021-02-01
UBS Group AG	UBS Securities, LLC	1989-12-07	Current	2001-01-01	2021-02-01
Wells Fargo & Co.	Wells Fargo Securities, LLC	2016-04-18	Current	2016-04-18	2021-02-01
Zions Bancorporation	Zions First National Bank	1993-08-11	2002-04-01	2001-01-01	2002-04-01

Table A2: **Correlation Matrices of Cost of Funding Proxies Across Countries.**
This table presents correlation matrices of repo rates, LOIS spreads and bond yield across countries. Repo rate and LOIS spread data are for the following currencies: USD, CAD, GBP, EUR and JPY. GBP and EUR repo rates and LOIS spreads are averaged and are represented as "Europe" in panels A and B. In panel C, bond yields of banks in each country are averaged before calculating the correlation coefficients. Bond yield is computed as the yield of a local government bond plus the bank's CDS spread.

Panel A: Repo Rate Correlation Matrix				
	Canada	Europe	Japan	USA
Canada	1.00	0.92	0.38	0.89
Europe	0.92	1.00	0.49	0.79
Japan	0.38	0.49	1.00	0.29
USA	0.89	0.79	0.29	1.00
Panel B: LOIS Correlation Matrix				
	Canada	Europe	Japan	USA
Canada	1.00	0.46	0.25	0.63
Europe	0.46	1.00	0.84	0.83
Japan	0.25	0.84	1.00	0.70
USA	0.63	0.83	0.70	1.00
Panel C: Bond Yield Correlation Matrix				
	Canada	Europe	Japan	USA
Canada	1.00	0.88	0.11	0.88
Europe	0.88	1.00	0.45	0.85
Japan	0.11	0.45	1.00	0.23
USA	0.88	0.85	0.23	1.00

Table A3: **Three-Factor Model: Liability-Weighted Moving Average Proportions Debt Factor, HKM Equity, and Market, Monthly.**
Estimates of the prices of risk for shocks to the intermediary debt factor, HKM equity factor and the market's excess return factor. The intermediary debt factor is constructed using the primary dealers' bond discount rates, the repo rates and LOIS spreads of the countries where the holding companies of our primary dealers are located, guided by Capital IQ funding composition data. HKM equity is the intermediary equity return factor and the market factor is the excess return on the market. Risk prices are the mean slopes of the cross-sectional regressions of portfolio excess returns on risk exposures (betas) , expressed in percentage terms. Betas are calculated in a first-stage time series regression. The monthly sample is from February 2001 to February 2021. GMM t-statistics, reported in parenthesis, correct for cross-asset correlation in the residuals and time series beta estimate error. The measures of goodness of fit reported are R^2 and MAPE. Assets and Months represent the number of portfolios in each asset class and the number of months used in the estimation, respectively.

	FF25	US bonds	Sov. Bonds	Options	CDS	Comod.	FX	All
Debt Factor	-2.57*	-6.98**	-6.17	-7.7*	-9.23**	-6.77**	-12.47*	-4.53***
	(-1.68)	(-2.36)	(-1.48)	(-1.80)	(-2.50)	(-2.31)	(-1.77)	(-3.22)
HKM Equity	-0.02	0.00	2.97**	-0.30	3.59*	2.03	3.14	1.34**
	(-0.02)	(0.00)	(2.19)	(-0.05)	(1.94)	(1.33)	(1.28)	(2.07)
Market Factor	0.12	0.21	0.49	0.05	-0.35	-0.38	-0.93	0.64**
	(0.23)	(0.42)	(0.38)	(0.04)	(-0.39)	(-0.33)	(-0.61)	(2.13)
Intercept	0.77*	0.11***	0.03	-0.37	-0.14***	0.00	-0.45	-0.11
	(1.89)	(3.62)	(0.10)	(-0.33)	(-3.11)	(0.01)	(-1.11)	(-1.31)
R^2	12.00%	81.00%	90.00%	98.00%	82.00%	55.00%	67.00%	52.00%
MAPE	0.13%	0.06%	0.07%	0.06%	0.05%	0.35%	0.07%	0.26%
Assets	25	15	6	18	20	23	10	117
Months	241	239	123	132	143	241	237	241

Additional Figures

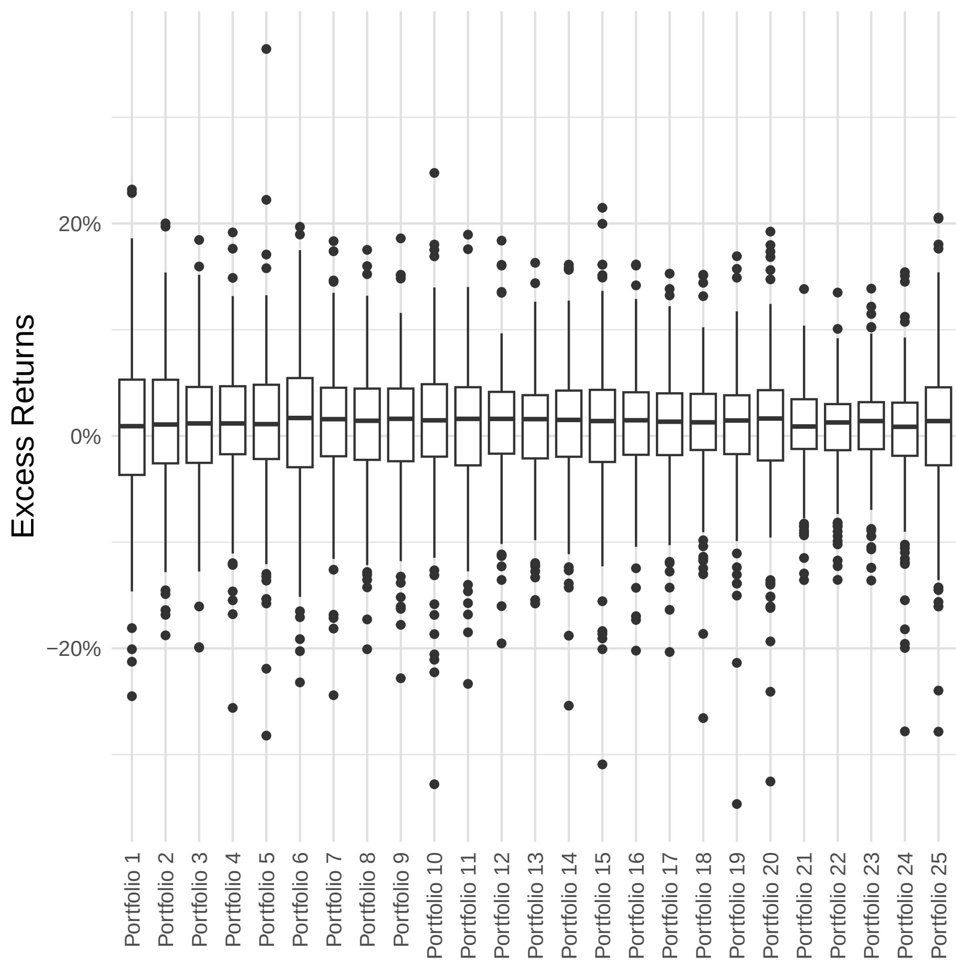

Figure A1: **Equity Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 25 US equity test asset portfolios. The portfolio includes Fama and French (1993) Size and Book-to-Market equity portfolios. The sample is from February 2001 to February 2021. The data is sourced from Ken French website.

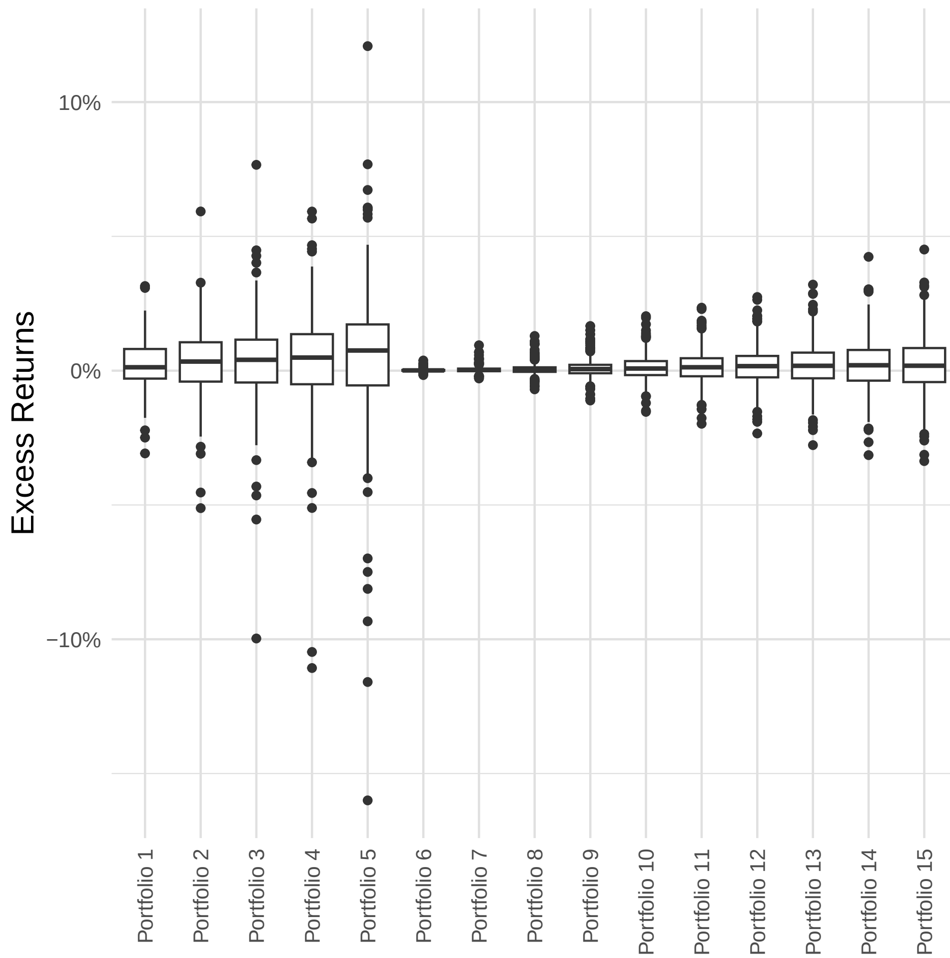

Figure A2: **US Bonds Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 15 US bonds test asset portfolios. The portfolio includes five U.S. corporate bond portfolios and ten U.S. sovereign bond portfolios. The corporate bond portfolios are five Bloomberg corporate bond indexes classified by rating and the government bonds are ten maturity-sorted ”Fama Maturity Portfolios” from CRSP with maturities in six month intervals up to five years. The data is from February 2001 to February 2021.

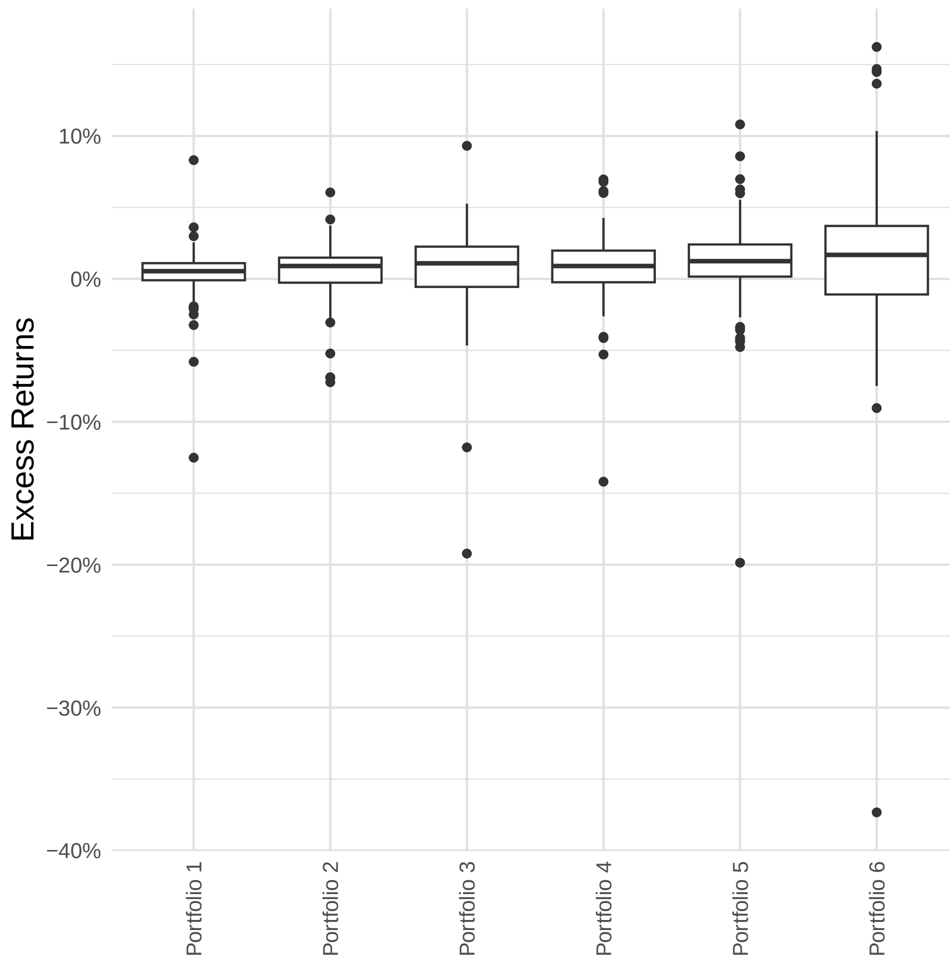

Figure A3: **Sovereign Bond Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 6 sovereign bonds test asset portfolio. The portfolio includes Borri and Verdelhan (2011) portfolios that are constructed using a two-way sort of the bond's beta to the US equity market return and the bond's S&P credit rating. The data is provided through the author's website and goes from February 2001 to April 2011.

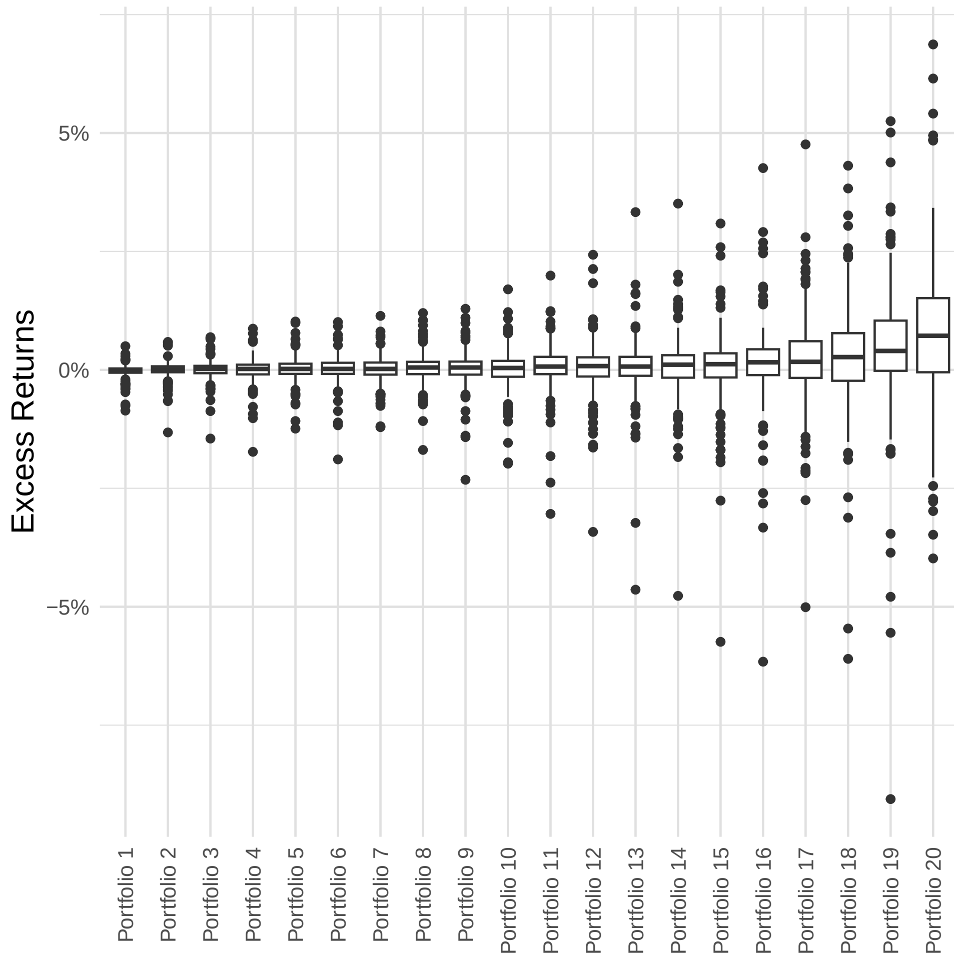

Figure A4: **CDS Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 20 CDS test asset portfolios. The CDS portfolios data is from He et al. (2017) and is composed of portfolios of single name CDS constructed using data from Markit and goes from February 2001 to December 2012.

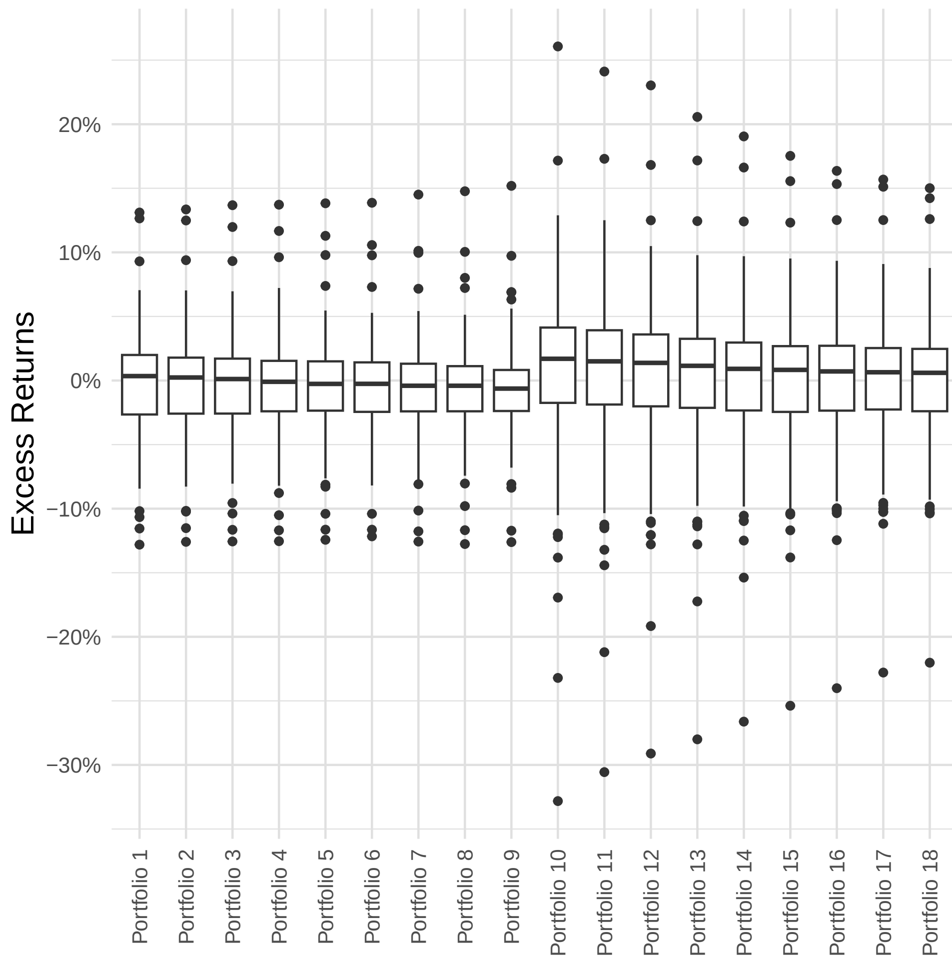

Figure A5: **Options Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 18 equity options test asset portfolios. The options portfolios aggregate data provided by Constantinides et al. (2013) and extend from February 2001 to January 2012.

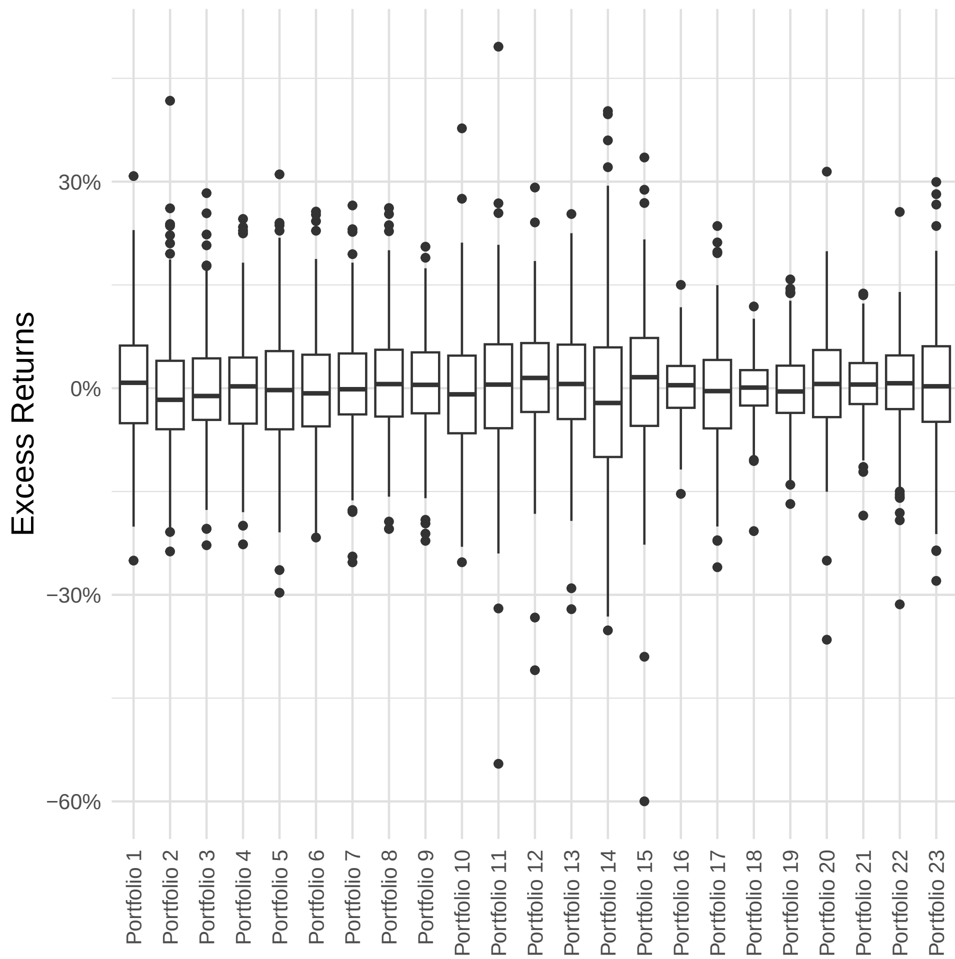

Figure A6: **Commodities Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 23 commodities test asset portfolios. The commodities portfolios is composed of 23 commodities total return indices from Bloomberg using the same comodities list from Yang (2013). Data is from February 2001 to February 2021.

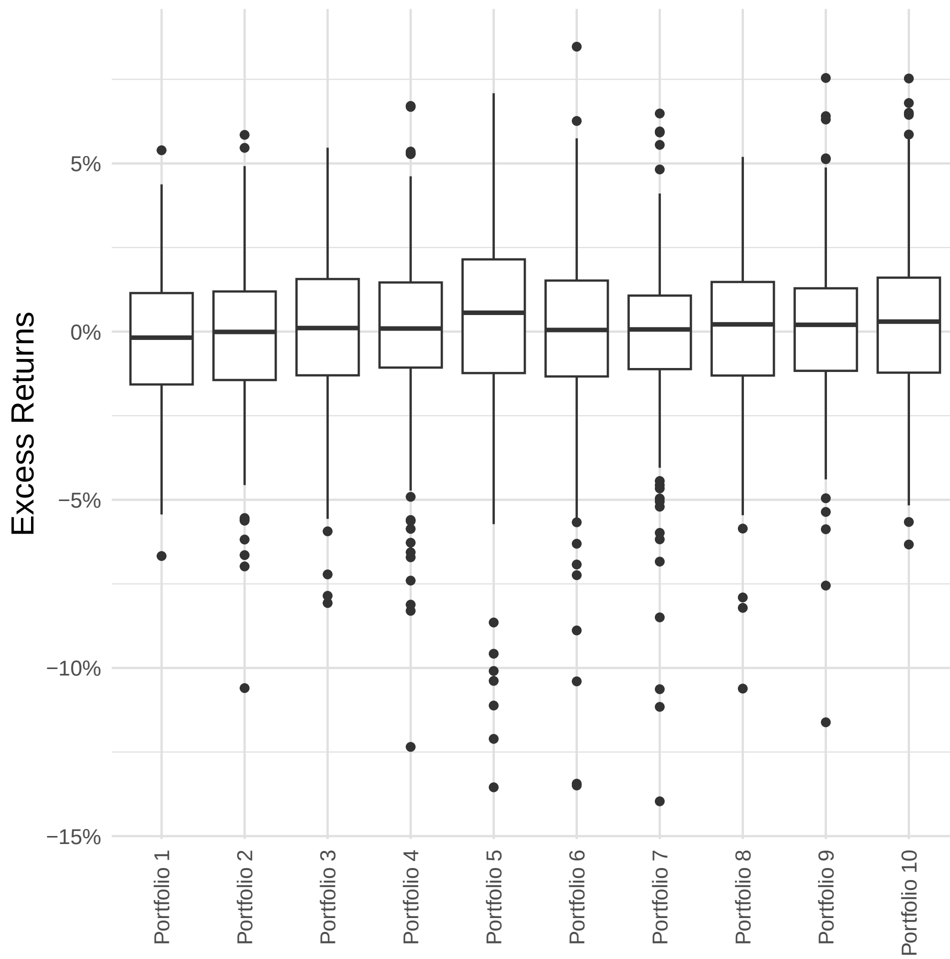

Figure A7: **FX Test Asset Portfolios Summary Statistics.**
This figure is a box plot of the excess returns of the 10 FX test asset portfolios. The FX portfolio include 5 carry portfolios and 5 momentum portfolios from Orłowski et al. (2021) that are constructed using 44 developed and emerging currencies. Data is from February 2001 to February 2021.

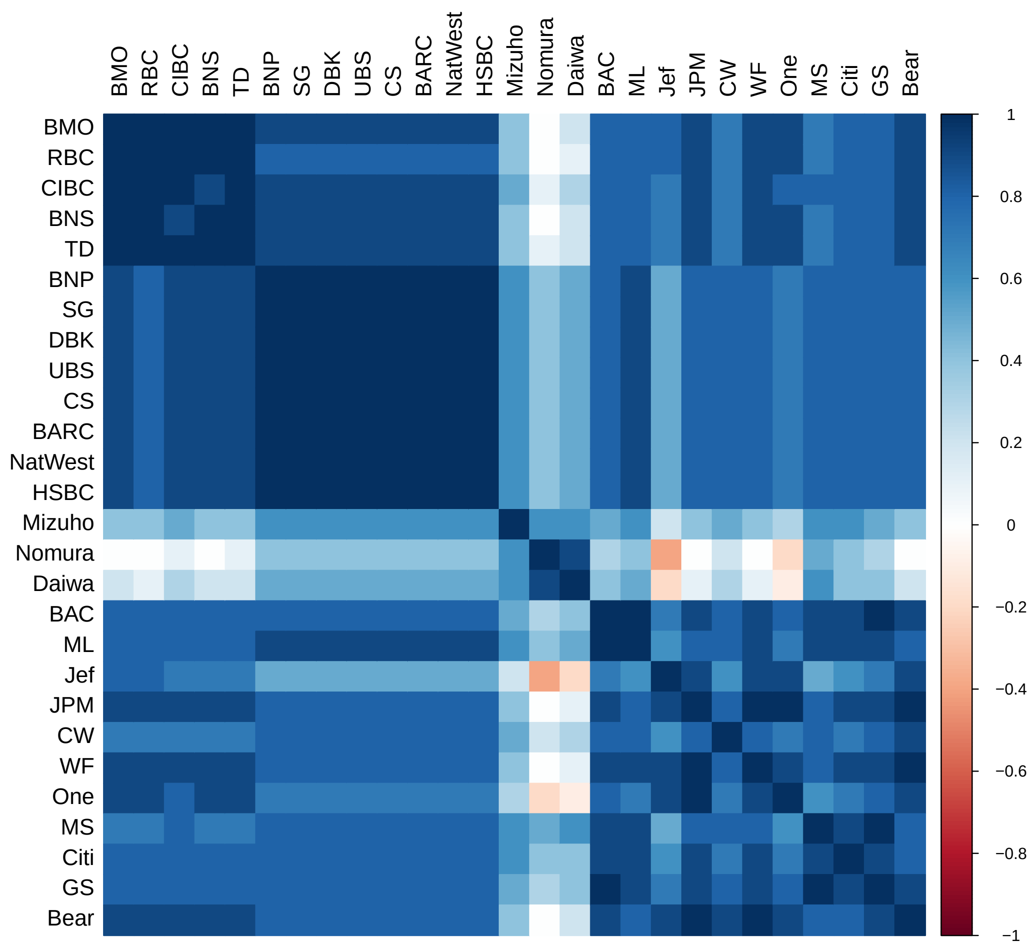

Figure A8: **Bond Discount Rate Correlation Matrix Plot**
This plot shows the correlation matrix of the bond yield of our sample of banks. Bond discount rates are computed as the yield of long-term government bonds plus the bank's CDS spread. Bond discount rates data are from Bloomberg and CDS data are from Markit.