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WHITEPAPER: BY METE TEPE | PER THASTROM | ROBERT CHANG

How Do ESG Activities Affect Default Risk of Firms?

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Introduction

It is an open question as to how default risk is affected by Environmental, Social, and Governance (ESG) activities. Investing in ESG activities may increase default risk because ESG activities come with a price tag, requiring cash outflows and creating uncertainty. Firms may need to make significant changes to their strategy, operations, assets, and capital structure. Conversely, investing in ESG activities may decrease default risk by addressing climate-related risks, improving brand equity, attracting capital from ESG investors, improving operational efficiency, and attracting and retaining talent. This paper explores both the risk-driving and risk-mitigating impacts of ESG on default risk. It empirically models the impact of ESG activities on default risk using a sample of 240 publicly traded large U.S. firms between 2012 and 2018.

Our results support the hypothesis that firms with strong ESG, measured by their ESG rating, have a lower probability of default. In other words, strong ESG is a form of credit enhancement. However, our analysis raises several important questions for further research. First, do our results extend to a more heterogeneous portfolio that includes small and mid-size firms? Second, instead of looking at the combined ESG rating, what is the relationship between the separate E, S, and G pillars and default risk? Do the results hold when using ESG ratings from different data providers? Third, how do business cycles affect the relationship between ESG ratings and default? ESG activities seem to have a non-linear effect on default risk, and the benefits of ESG depend on the firm type, lifecycle stage, and specific type of ESG-activity being measured. And finally, how can financial institutions better manage the impact of ESG activities on their portfolios?

We highlight three areas where institutions should focus:

Focus Area	Description
Data Capture/ Measurement	▪ ESG data is not yet standardized. Perform due diligence on ESG rating companies and understand their methodology ▪ Focus on data quality, distinguish between quantitative ESG metrics and subjective scores ▪ Consider developing an in-house ESG rating system if ESG rating companies' coverage of your portfolio is limited
Assessing Impact	▪ ESG has non-linear impacts on default risk, be aware of model limitations, explore machine learning approaches if necessary ▪ It is difficult to isolate the effect of ESG on default risk due to confounding variables that are correlated with both ESG and the default risk (e.g., firm size) ▪ Qualitative approaches can support quantitative approaches, until ESG data becomes more consistent and standardized
Governance/ Integration	▪ ESG risk management must be aligned with the business strategy and integrated into corporate governance, policies, and controls

ESG is set to become an integral part of financial modeling as market participants and regulators are becoming increasingly aware of ESG's potential use in managing risks emanating from policy, technology, and market changes as well as reputational and physical risks. Some of the recent actions and initiatives taken by regulators and supervisors in the ESG space are listed below.

March 4, 2021

1

U.S. Securities and Exchange Commission (SEC)

Established Enforcement Task Force on Climate to develop initiatives to identify ESG-related misconduct, hereunder also analyze disclosure and compliance with issues relating to advisers and fund ESG strategies.

March 17, 2021

2

Commodity Futures Trading Commission (CFTC)

Established Climate Risk Unit to focus on the role of derivatives in understanding, pricing and addressing climate-related risk and transitioning to a low-carbon economy.

May 10, 2021

3

Federal Deposit Insurance Corporation (FDIC)

Acknowledges that entities under supervision are considering ESG risk mitigation in the 2021 Risk Review report

Oct. 21, 2021

4

Financial Stability Oversight Council (FSOC)

FSOC releases Report on Climate-related Financial Risk with 30 recommendations including on potential new regulation.

Dec. 16, 2021

5

Office of the Comptroller of the Currency (OCC)

OCC requests feedback on draft Principles for Climate-Related Financial Risk Management for Large Banks

Dec. 27, 2021

6

Federal Housing Finance Agency (FHFA)

The agency included climate risk in the 2022 conservatorship scorecards

Mar. 21, 2022

7

U.S. Securities and Exchange Commission (SEC)

Proposed rule changes require registrants to include information about climate-related risks that are reasonably likely to have a material impact on their business in their registration statements and periodic reports.

Modeling ESG and Default Risk

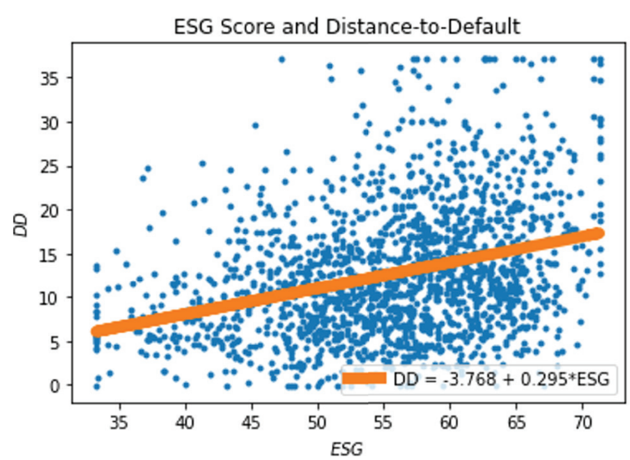
Academic research on the role of ESG on default risk has been limited and has not yet formed a consensus view. Two positions have emerged. the "ESG-positive" perspective argues that firms with high ESG ratings are better insulated from default risk. The ESG-positive perspective maintains that ESG activities provide tangible benefits, such as higher brand equity and customer loyalty, leading to stronger sales, which lowers the probability of default. Higher customer loyalty comes with a better ability to weather adverse events, so ESG provides a form of downside protection. The opposing "ESG-negative" position argues that firm performance suffers when the costs of ESG activities are underestimated or benefits are overstated, increasing a firm's default risk. This position is also tied to "greenwashing," the practice of using marketing and P.R. tactics to overamplify ESG efforts. Since managers may seek personal benefits, such as public recognition by engaging in ESG activities, "overinvestment" in ESG activities fails to add value to the firm and the financial performance deteriorates.

We empirically investigate the relation between ESG activities and default risk using a sample of 240 publicly traded U.S. firms between fiscal years 2012 and 2018 (240 x 7 = 1,680 observations).[2] We measure the firms' level of ESG-activity through their ESG rating. This third-party measurement scores each firm on factors such as resource use, greenhouse gas emissions, waste management, employee engagement, community involvement, and more. There are many subscription-based ESG data providers including, but not limited to, ISS, Moody's, MSCI, S&P Global, and Sustainalytics. We used ESG Book, a free ESG data platform, to collect the ESG ratings. ESG Book has coverage of over 9,000 companies with 22 sub-topics under the E, S, and G pillars. ESG Book sub-topics include emissions (E), resource use (E), water (E), diversity (S), community relations (S), human rights (S), business ethics (G), transparency (G) and capital structure (G). A complete description of ESG Book's rating system can be found in the ESG Book (2021) methodology paper.[3]

We start our sample period in 2012, as our ESG data source coverage begins in 2012, and end our sample period in 2018, so the COVID-19 market turmoil does not affect the analysis. To measure firm default risk, we use Merton's distance to default (D.D.) measurement, with higher values of D.D. implying lower default risk.[4] There are several advantages to using Merton's model to measure default risk. For instance, Merton's model relies on financial statements and stock return data which is publicly available and easily accessible. Also, the model does not require actual firm defaults. Firms that have experienced actual default tend to be smaller firms that may not have reliable ESG ratings over the 2012-2018 period.

We first look at a simple regression to understand the relationship between ESG ratings and default risk (see Figure 1). We observe a statistically significant relationship between D.D. and ESG (correlation of 0.32, $p < 0.01$). This simple relationship may suggest that firms with higher ESG ratings have higher distance-to-default (i.e., lower default risk).[5] This is, however, only a tentative finding and contingent on controlling for other explanatory factors that affect default risk.

Figure 1.
Scatter Plot and Linear Regression Line for ESG and D.D.



[1] See Atif and Ali (2021), Gillan, Koch, and Starks (2021), Razak, Ibrahim, Ng (2020), Gerard (2019), and Rizwan, Obaid, and Ashraf (2017).
[2] We choose the largest 30 firms (in terms of average market capitalization in 2012-2018 period) from each GICS sector. We exclude Financials, Utilities, and Real Estate, as these firms' reporting standards for debt are not suitable for the standard KMV-Merton model and/or they are highly regulated (see Technical Appendix). We require the firms to have non-missing financial and ESG data for the entire sample period to have a balanced panel setting. Choosing the largest firms allows us to minimize missing data and reduce the small-firm effect on our results.

[3] https://www.arabesque.com/docs/sray/marketing/Arabesque20SRay20Methodology20Guide_November202021.pdf

[4] See Technical Appendix for a detailed discussion of distance-to-default (DD).

We introduce certain control variables that can predict default risk and be related to ESG ratings.[6] First, we control for firm size by LnAssets (natural logarithm of total assets). In general, we expect that larger firms are associated with higher distance-to-default (i.e., lower default risk), as they have a more stable business and are more established in debt markets. However, this relationship may be less pronounced as our sample is already weighted toward larger firms.[7] Our second control variable is profitability, which is measured by ROA (net income / total assets). It measures the firm's ability to generate returns and service its debt obligations; more profitable firms are expected to be associated with higher D.D. Lastly, we control for financial leverage by DebtRatio (debt / total assets). Firms with large debt loads have lower D.D. (higher risk of default). To reduce the influence of outliers on our results, we winsorize[8] all our variables at the 1% level. We then check for multi-collinearity issues that might bias our results (see Table 1). Using a rule-of-thumb of 0.6 to indicate potential multi-collinearity issues, we find no multi-collinearity issues in our analysis (highest correlation is 0.391 between D.D. and ROA).

Table 1. Pairwise Correlations

	DD	ESG	LnAssets	ROA	DebtRatio
DD	1.000				
ESG	0.320	1.000			
LnAssets	-0.114	0.002	1.000		
ROA	0.391	0.284	-0.166	1.000	
DebtRatio	-0.356	-0.296	-0.037	-0.082	1.000

Analyzing and Interpreting the Model Results

Table 2 indicates that we may run into problems in our statistical interpretation if we simply regress D.D. on ESG. For instance, there is a significant negative correlation between DD and DebtRatio (-0.356, $p < 0.01$) and a significant negative correlation between ESG and DebtRatio (-0.296, $p < 0.01$). Therefore, we may explain the positive relation between D.D. and ESG as firms with higher financial leverage have lower ESG ratings and lower D.D. simultaneously. We estimate the following general regression model to investigate this (see Table 3).

$$DD_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Controls_{it} + FirmFE_i + YearFE_t + \epsilon_{it}$$

Our main coefficient of interest is β_1, which we expect to be positive if firms with higher ESG ratings are associated with lower default risk (i.e., higher D.D.). In each of Column (1), (2), and (3) of Table 2, we introduce additional control variables one-by-one to the regression and continue to find a positive and statistically significant coefficient estimate for β_1.[9] While the positive relation between ESG and D.D. holds for different control variables, other firm- or year-specific variables may be driving both ESG ratings and default risk. For instance, although unlikely, a macroeconomic event in a certain year may have caused a positive or negative trend both in ESG and D.D. We use year fixed-effects to account for time-dependent trends, and firm-fixed effects to handle any time-invariant feature of a firm (i.e., firm's headquarter location, state of incorporation, industry). Controlling for such effects in Columns (4), (5), and (6) in Table 2, we continue to find that β_1 is still positive and statistically significant, suggesting that firms with higher ESG ratings have lower default risk.

[5] We choose "distance-to-default (DD)" rather than "probability of default (PD)" as our response variable, as DD's statistical properties are better-suited for a regression analysis. First, DD is not theoretically bounded from above and below, while PD is bounded between zero and one. Second, DD has a more symmetrical and "bell-shaped" sample distribution (i.e., approximating normal distribution), whereas the sample distribution of PD is highly skewed to the right.

[6] It is virtually impossible to account for every variable that can explain default risk. We choose the ones that are most relevant and widely used in public company setting (i.e., size, profitability, and capital structure).

[7] Although our subsequent analysis reveals a negative pairwise correlation between firm size and DD, we remind the reader that our sample is heavily tilted towards large firms, and our a-priori assumption may not hold in this specific sample. Additionally, a latent variable (e.g., debt maturity) that is correlated with both firm size and default risk may be responsible for the observed correlation.

[8] In other words, we set the values that are above (below) the 99th percentile (1st percentile) of the sample distribution equal to 99th percentile (1st percentile) of the sample distribution.

[9] We use White standard errors (i.e., robust standard errors) to account for potential heteroskedasticity in the error terms.

Table 2.
Regression Results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ESG	0.295*** (14.722)	0.212*** (10.691)	0.134*** (6.585)	0.056** (2.058)	0.144*** (7.532)	0.077*** (3.002)
LnAssets	-0.789*** (-5.137)	-0.426*** (-2.925)	-0.500*** (-3.618)	-2.314*** (-5.606)	-0.426*** (-3.157)	-1.770*** (-4.397)
ROA		37.257*** (13.442)	37.099*** (13.787)	5.091* (1.885)	37.239*** (14.009)	6.239** (2.439)
DebtRatio			-13.520*** (-12.825)	-21.809*** (-11.967)	-12.462*** (-12.249)	-18.179*** (-10.250)
Constant	4.189** (2.240)	2.557 (1.436)	11.959*** (6.288)	39.418*** (8.588)	10.288*** (5.625)	31.566*** (6.698)
Firm FE?	No	No	No	Yes	No	Yes
Year FE?	No	No	No	No	Yes	Yes

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. t-statistics are given in the parenthesis and calculated using robust standard errors.

Challenges and Solutions

We have provided evidence that ESG rating is a potential explanatory factor for default risk both in terms of statistical results and economic rationale. These results are robust to different regression specifications, including year and firm fixed effects.

However, there are complexities to modeling ESG ratings and their impact on default risk. One such complexity is that the ESG rating and default risk relationship is likely conditional on other factors. For example, the effect of ESG on D.D. can be greater for more mature and larger firms, as these firms are more likely to be monitored closely by their stakeholders and have more resources to invest in ESG activities. Another dependency is the firm's industry. For example, it may be more worthwhile for oil firms to mitigate regulatory risks through ESG investments than for technology companies. Therefore, segmentation or adding interaction terms to the model is needed to account for these dependencies.

Another challenge is that the relationship between ESG rating and default risk is likely non-linear. For example, the strength and direction of the relationship may differ when ESG ratings are relatively low as opposed to when the ESG rating is already high. For example, this type of behavior could suggest that ESG activities benefit firms to a point, but then "over-investment" in ESG activities leads to increased default risk. Additional segmentation, adding polynomial terms, or exploring machine learning approaches, may be necessary to handle non-linearities between ESG rating and default risk.

Additionally, ESG ratings reflect the aggregate rating of three main dimensions (E, S, and G), and each dimension affects each industry differently (e.g., Environmental rating for an oil extraction firm vs. Social rating for an online retailer). The different dimensions may also work on different time horizons (e.g., governance risks could be quicker to materialize than environmental risks). In these instances, applying domain specific knowledge to select the most relevant ESG components or developing custom ESG ratings to suit the business purpose may improve the model.

Next Steps

How can financial institutions better manage the impact of ESG activities on their portfolios? We highlight three areas where institutions should focus:

Data Capture/Measurement: Prepare for due diligence on ESG rating companies. There are myriad companies to choose from with distinct methodologies for determining ratings. ESG data is not yet standardized and lack of agreement amongst vendors on how to rate ESG performance is a major challenge.[10] Certain providers may be more suitable to the composition and coverage of your portfolio. ESG ratings are generally for public firms, ESG ratings for private firms are still in their infancy. Data quality will continue to be a challenge for ESG, as will distinguishing between quantitative ESG metrics and subjective scores. Depending on the composition of your portfolio, it may be worthwhile to construct your own ESG rating system, but this may require higher effort and costs. However, climate data for example, is in many cases publicly available. ESG-related disclosures can be sourced from financial statements and other filings. Credit rating agencies are integrating ESG components into their credit rating but be sure to understand the agency's data sources and methodology.

Assessing Impact: Numerous challenges are present when using ESG data for modeling or analytics. ESG data is often incomplete and requires imputation to fill in the gaps. Many ESG initiatives are conducted with a long-term view in mind, and financial performance may suffer in the short-term before rebounding. As our model demonstrated, it is difficult to isolate the effect of ESG on default risk, and the influence of control variables and unobserved variables needs to be addressed. The non-linear and asymmetric effect of ESG on default risk needs consideration in any impact assessment. It is possible that instead of a purely linear relationship, ESG confers a form of "downside protection" for firms, and "over-investment" in ESG provides diminishing benefits. Qualitative approaches can also be used in conjunction with quantitative approaches, until ESG data becomes more consistent and standardized.

Governance/Integration: ESG risk management objectives must be aligned with the overarching business strategy. This requires ESG objectives to be fully integrated into corporate governance, reporting, and controls. Is ESG accounted for in the risk appetite framework, and is ESG considered when measuring diversification benefits and identifying concentrations? If ESG risk responsibility and accountability are not integrated into the existing organizational structure, new roles must be created. Risk committees should establish monitoring procedures for key ESG risks, as determined by a formal risk identification process. ESG should be integrated into the overall risk profile so thresholds and limits can be established.

[10] Brandon, Krueger, and Schmidt (2021) document that the average pairwise correlation among the ESG ratings of the seven providers is only about 0.45.

Technical Appendix

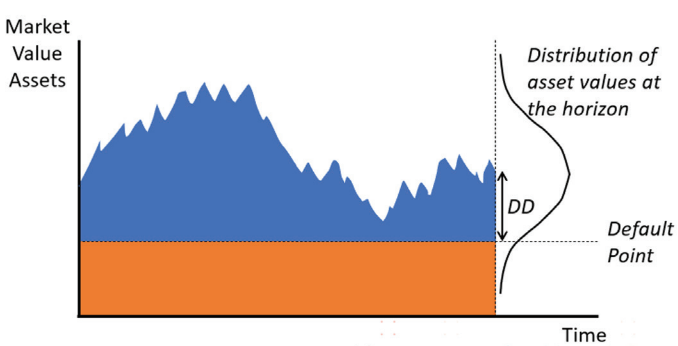
We measure default risk by distance to default (D.D.) of KMV-Merton model. Under this framework, the firm's equity is modeled as a call option where the underlying is the firm's asset value and the strike price is equal to the face value of the firm's debt. Then, the probability of default under the KMV-Merton model assumptions is

$$\pi_{KMV} = N\left(-\left(\frac{ln(V/F) + (\mu_V - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)\right) = N(-DD)$$

where V is the value of the firm, F is the face value of debt, μ_V and σ_V is the drift and volatility of asset value (where the stochastic process is modeled as a Geometric Brownian Motion with constant drift and volatility), T is the forecasting horizon for default, and N is the cumulative distribution function of the standard normal distribution.

The $D.D.$ measure is drawn from Merton's (1974) seminal paper **On the Pricing of Corporate Debt**. In this "structural" framework, we find the perspective of the owners when viewing the equity as a call option on the asset values with the debt value as the strike price. The perspective of the creditor is the corresponding downside risk. The larger the positive distance between firm value and firm liabilities, the lower the probability of default. The idea is also depicted in Figure 2.

Figure 2.
KMV-Merton Model



Since the firm's asset value and asset volatility are not directly observable, computing the probability of default requires a numerical solution to two non-linear equations. To keep things simple, we use Bharath and Shumway (2008) 's naïve approach, where the asset value is equal to the sum of market value of equity and face value of debt, asset volatility is computed as the weighted average volatility of equity and debt capital, and the drift of asset value is estimated via the drift of equity (μ_e). The probability of default under the Naïve model is

$$\pi_{Naive} = N\left(-\left(\frac{ln((E+F)/F) + (\mu_E - 0.5Naive\ \sigma_V^2)T}{Naive\ \sigma_V\sqrt{T}}\right)\right) = N(-Naive\ DD)$$

$$Naive\ \sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}Naive\ \sigma_D$$

$$Naive\ \sigma_D = 0.05 + 0.25\sigma_E$$

Face value of debt is defined as the sum of short-term debt and one-half of long-term debt on the balance sheet, while the market value of equity is defined as the stock price times the number of outstanding shares. We estimate the equity volatility and drift using the past year's monthly returns. Lastly, we set T equal to one year.

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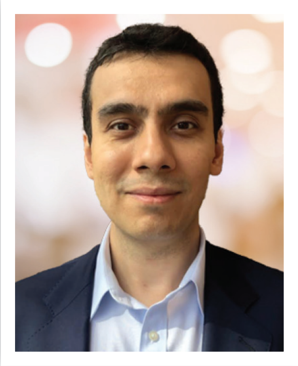
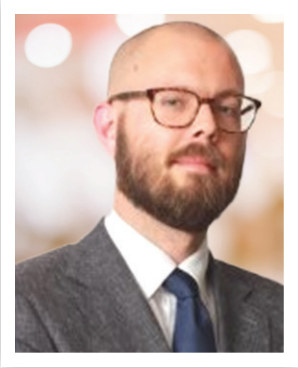


Author: Mete Tepe

Mete has both academic and industry experience in corporate finance, particularly in the areas of corporate governance, institutional investors, and financial and econometric modeling. Before joining FI as a Senior Consultant, he worked as a research analyst at ISS, providing proxy vote recommendations for institutional investors on corporate governance and executive compensation topics. He also published his corporate governance research in peer-reviewed academic journals. Mete holds a PhD degree in Finance from Virginia Tech, a Master's degree in Financial Mathematics from Middle East Technical University, and is a CFA charterholder.



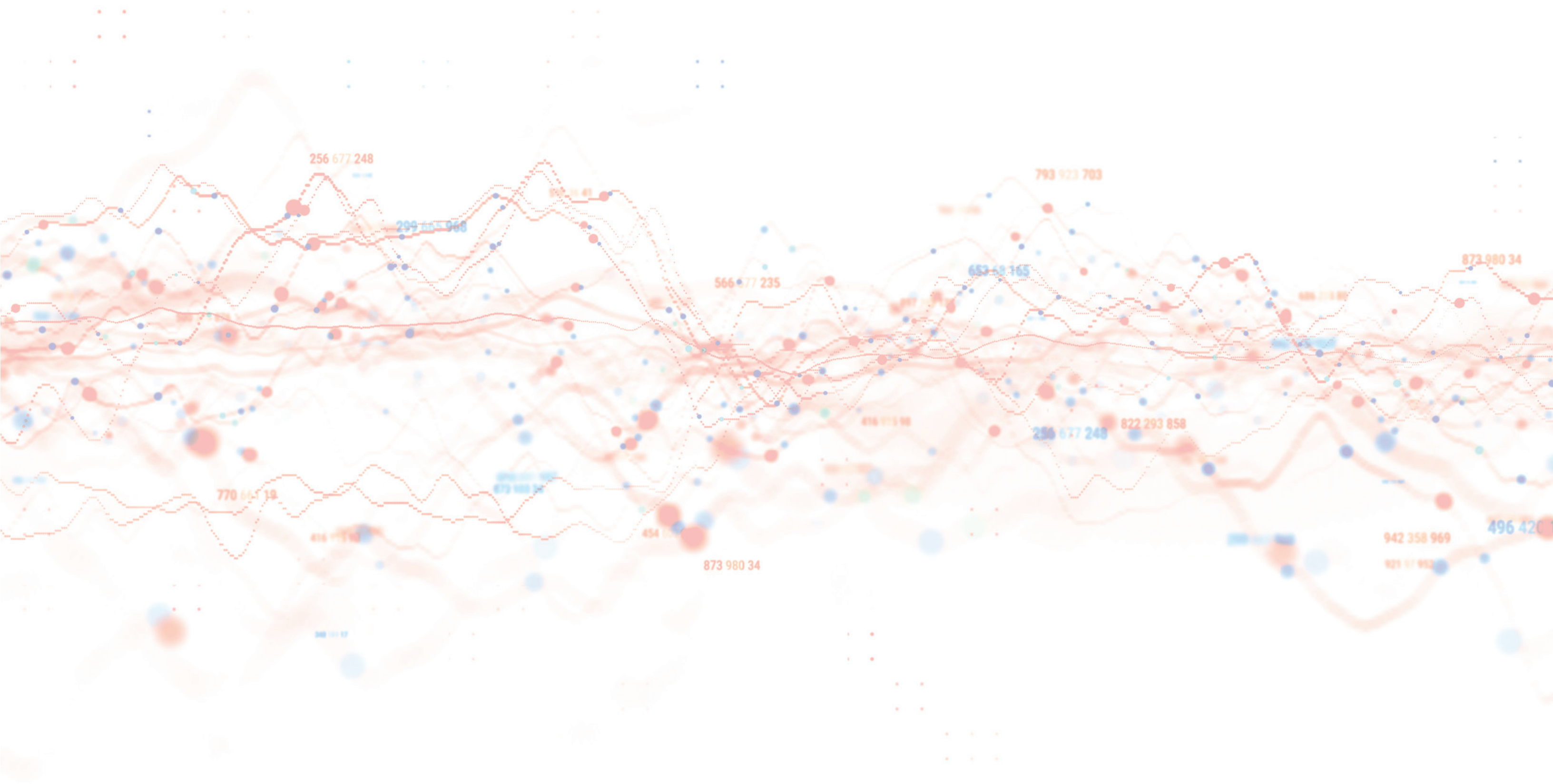
Author: Per Thastrom

Per has extensive financial industry experience from European top tier institutions as well as Big Four consulting experience. Recent roles include Executive Advisor to the Group Chief Risk Officer of a $600B institution, Country Chief Risk Officer of a $165B business and Program Manager in a 400 FTE model redevelopment program. As a consultant, Per has managed several projects spanning internal risk model development, including managing the regulatory risks, as well as leading assurance projects in the financial risk space. Per holds a Master of Science in Engineering from Uppsala university as well as a Sustainability and Climate Risk Certificate from GARP.

Author: Robert Chang

Robert leads Model Development and Model Validation projects for Commercial and Federal financial institutions, including Capital One Bank, Northern Trust Bank, Freddie Mac, the Federal Housing Administration (FHA), and the U.S. Department of Treasury. Robert was previously a Financial Engineer and Exotic Options Trader at several hedge funds and banks in London, Singapore and Hong Kong. Robert holds a Master's degree in Mathematics of Finance from Columbia University, a Master's degree in Information Management Systems from the Harvard Extension School, and is a Certified FRM.

If you are interested in learning more about how FI Consulting can support your organization in developing effective end-to-end ESG risk strategies, please email contact@ficonsulting.com or call us at 571.255.6900.



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