On predicting ESG ratings using dynamic company networks

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Environmental, social and governance (ESG) considerations play an increasingly important role due to the growing focus on sustainability globally. Entities, such as banks and investors, utilize ESG ratings of companies issued by specialized rating agencies to evaluate ESG risks of companies. The process of assigning ESG ratings by human analysts is however laborious and time intensive. Developing methods to predict ESG ratings could alleviate such challenges, allow ESG ratings to be generated in a more timely manner, cover more companies, and be more accessible. Most works study the effects of ESG ratings on target variables such as stock prices or financial fundamentals of companies, but few works study how different types of company information can be utilized to predict ESG ratings. Previous works also largely focus on using only the financial information of individual companies to predict ESG ratings, leaving out the different types of inter-company relationship networks. Such inter-company relationship networks are typically dynamic, i.e., they evolve across time. In this paper, we focus on utilizing dynamic inter-company relationships for ESG ratings prediction, and examine the relative importance of different financial and dynamic network information in this prediction task. Our analysis shows that utilizing dynamic inter-company network information, based on common director, common investor and news event-based knowledge graph relationships, can significantly improve ESG rating prediction performance. Robustness checks over different time-periods and different number of time-steps in the future further validate these insights.

CCS Concepts: • **Computing methodologies** → **Neural networks**; **Artificial intelligence**; **Knowledge representation and reasoning;**

Additional Key Words and Phrases: Sustainability, ESG, dynamic networks, knowledge graphs, machine learning, econometric, panel models

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1 INTRODUCTION

Motivation. Sustainability is an increasingly important topic, as evidenced by the growing global focus on this area through initiatives such as United Nations **Sustainable Development Goals (SDG)** [10], **United Nations Principles for Responsible Investments (UN PRI)** [9], and the **Network for Greening the Financial System (NGFS)** [3]. **Environmental, social and governance (ESG)** factors refer to a wide range of issues relating to the environment such as carbon emissions, social responsibilities such as labor rights, and governance such as board diversity. Evaluating companies' performance on such ESG factors helps determine the sustainability of their business practices, and plays an increasingly important role in international trade, investments, and supply chains [2]. ESG evaluation is however not an easy task due to the myriad of factors involved, and as there are no harmonized standards for assessing ESG performance for these factors.

To evaluate how companies perform on ESG matters, governments, financial institutions and investors rely on ESG ratings of companies [50, 53, 60] issued by specialized rating agencies which include Sustainalytics, RobecoSAM, and Bloomberg. These ESG ratings have been utilized by governments for evaluating companies' ESG practices and standards for policy-making or regulatory purposes; or by financial institutions and investors for evaluating ESG risks when deciding whether to lend to or invest in companies. To determine the ESG ratings of companies, rating agencies typically focus on ESG-related events that companies may be involved in, including the nature of companies' businesses, their policies, financial and non-financial disclosures, based on the rating agencies' research and interactions with these companies [45]. Hence, the process of generating ESG ratings, undertaken by rating analysts, is not only laborious and time intensive, but also non-transparent and highly dependent on the analysts' expertise and experience [11].

Methods to predict ESG ratings using different types of publicly available company data could help to address the above challenges. If these methods can accurately predict ESG ratings, they will facilitate sustainability efforts by (i) reducing the effort required to generate ESG ratings (e.g., by having the rating analysts adjust the predicted ESG ratings based on their expert knowledge, instead of them determining the ratings from scratch); (ii) enabling ESG ratings to be available in a more timely manner as the ESG rating prediction process can be automated; hence iii) allowing ESG ratings to be generated for more companies which may not be covered by the current scope of ESG rating agencies; and iv) improving the accessibility of ESG ratings by external stakeholders.

Information and Mechanisms. We focus on two main types of variables for predicting ESG ratings in this work - financial information, which serve as control variables, and network information, particularly dynamic network information, which serve as the variables of interest. Financial information, which could include company stock prices and financial fundamentals such as price to earnings, could reflect market consensus, as well as potential insider information, on the ESG profiles of companies. Such information are therefore useful for ESG rating prediction [34, 55]. Network information based on different types of relationships between companies may also influence the ESG profiles of companies via several different mechanisms. First, inter-company relationship networks arising from common stakeholders may influence ESG ratings as common stakeholders may assert similar values and expectations on the related companies. For example, common directors on multiple company boards or common mutual funds with investments in the same set of companies, can influence the behavior of companies in ESG-related areas. Specifically, companies that share common directors as stakeholders may have a more closely aligned position on ESG issues [49]; while companies with common mutual fund investors may face common pressures on ESG issues [71]. Secondly, inter-company relationship networks (e.g., two companies sharing common stakeholders, parent-subsidiary, or supply chain relationships), could serve as information propagation mechanisms through which ESG-related knowledge and practices spread [49, 71]. Inter-company relationship networks may also influence ESG rating predictions as a change in the ESG rating of one company can lead to the re-assessment of the ESG rating of another company related to it. From the perspective of an ESG analyst, inter-company relationship networks (e.g., common director, common investor, same business, same sector, supply chain relationships or other underlying relationships that can be deduced from companies being commonly associated in news or events), may be used to facilitate investigations on the ESG risks of companies [45, 51]. For example, a corruption scandal relating to the board of Company A may lead to investigations on Company B's ESG risks if they share common directors; the parent company of a subsidiary may also be investigated on its ESG risks if its subsidiary is accused of pollution. During the 2022 invasion of Ukraine by Russia, several companies in different sectors and businesses were frequently mentioned in the same news articles for ESG risks caused by their operations in Russia [6].

Existing Research Gaps and Proposed Approach. Most existing ESG-related works focus on methods that use ESG ratings to predict other target variables such as stock returns or construct investment portfolios [36, 48, 52, 56, 64, 79]. Very few works study prediction of ESG ratings. Even for the very few ESG ratings prediction works, they usually utilize financial information of individual companies, such as their financial fundamentals, and leave out the dynamic network information [15, 34, 51, 55].

While there are orthogonal works that study the use of financial and network information to predict other types of financial-related variables, e.g., stock prices or credit ratings [16, 17, 59, 61, 76], ESG ratings are however different from these financial-related variables as the process of generating ESG ratings is typically less transparent, e.g., the process of assessing the stock price or credit rating of a company based on its balance-sheet information is typically more transparent compared to the process of assessing the social impact of a company's business activities. Furthermore, reputational risks, which are hard to quantify, may play a more important role in determining ESG ratings [43].

Due to the non-transparent nature of ESG rating processes and the lack of a harmonized set of standards, the effects of different financial and network information on ESG rating predictions is also unclear. A deeper understanding of the effects of these information on ESG rating predictions could facilitate better decision-making. Similarly, most existing works in this area focus on the influence of ESG ratings on a range of target variables, such as the returns and risks of individual stocks or portfolios [22, 24, 25, 30, 36, 40, 57, 70, 72, 73], credit risks [52], or adverse news events [28] of companies. Again, there are very few works that examine the effects of different types of information on ESG rating predictions [34, 39].

In addition to companies' financial fundamentals [34], network information based on different types of relationships between companies may also influence ESG ratings via different mechanisms as described earlier. A few works have studied the effects of static inter-company networks on ESG-related information, e.g., the occurrence of ESG-related events [15, 19, 51]. However, inter-company relationships, as well as ESG ratings, are not static in real world settings, as they evolve across time.

To address the above-mentioned challenges and gaps in existing research, as well as understand the underlying mechanisms influencing ESG ratings, we examine the following two research questions in this paper:

- RQ1 **Can dynamic network information improve ESG rating prediction performance?**
- RQ2 **Which types of dynamic network information are important for ESG rating predictions?**

To answer these research questions, we first select a subset of important financial variables from a relatively large initial set of financial variables as control variables. Next, we assess if the use of network variables, based on network centrality features from different types of dynamic networks, can improve ESG rating prediction performance. We then evaluate the importance of different network variables for ESG rating predictions, relative to each other and the selected financial variables. To ensure the robustness of our analysis, we utilize a range of machine learning and econometric methods for each of these steps. To better understand the influence of each of the key dynamic network variables of interest relative to the financial control variables, we also examine dynamic network effects on ESG ratings with a dynamic panel data model.

We construct a novel dataset that includes multiple types of publicly available static and dynamic inter-company network information from a wide range of sources to study their effects on ESG ratings. These include inter-company relationships between companies sharing common directors and with common investors. We also construct inter-company relationship networks based on information mined from two rich **knowledge graphs (KG)** - Wikidata [12] and the **Global Database of Events, Language and Tone (GDELT) Global Knowledge Graphs (GKG)** [8]. Inter-company relationships extracted from Wikidata, one of the largest and most active collaboratively constructed KGs, represent different types of knowledge-based relationships between companies that were provided by contributors to Wikidata, e.g., parent-subsidiary relationships. From GKG, we extract inter-company relationships arising from the co-occurrence of companies across different news events. We compute key network features of companies in these networks and study these network features as the variables of interest in this paper. The dataset also includes a large number of non-network variables as control variables, specifically stock price-related and financial fundamentals. The dependent variables - total ESG ratings, and the underlying environmental, social and governance ratings - are obtained from an established ESG rating agency - Sustainalytics [7].

To evaluate the importance of different information and select key variables to include in our model specifications, we examine different measures of feature importances, as well as Granger causalities. To predict ESG ratings and compare performance across different model specifications, we adopt a state-of-the-art machine learning XGBoost model [31], as well as fixed and random effects panel models [32, 33, 65]. We also utilize panel models to analyze the effects and statistical significance of selected variables. To ensure validity of our results, we conduct a series of robustness tests on overall ESG ratings, as well as underlying environmental, social and governance ratings. We also examine differences in model performance for ESG ratings of companies listed on two exchanges (NYSE and NASDAQ), across different time-periods, and at different number of time-steps in the future.

From our experiments, we find that dynamic inter-company networks can significantly improve ESG rating prediction performances across both machine learning and econometric methods. We find that dynamic inter-company networks based on relationships between companies that share common directors and investors, as well as relationships extracted from dynamic news event-based knowledge graphs play an important role in improving ESG rating predictions, and that such effects are statistically significant.

Contributions. To our knowledge, this is the first work to examine if dynamic inter-company network information can improve ESG rating predictions, and evaluate the importances of different dynamic inter-company network features. Our findings provide strong evidence on the effects of different types of dynamic network information on ESG rating predictions, and a better understanding of how dynamic network information may influence ESG ratings.

The paper is organized as follows. Section 2 covers related works. Section 3 describes the dataset and methods to be utilized for this study. Section 4 presents the results and robustness tests. Finally, Section 5 offers key insights and concludes the paper.

2 LITERATURE REVIEW

ESG-Related. Among past ESG-related works, many either utilize ESG ratings to predict a range of other target variables or analyze the effects of ESG ratings on other target variables, instead of predicting ESG ratings or examining the effects of different information on ESG ratings.

In particular, several works focus on methods that utilize ESG ratings or ESG-related information to predict stock returns, risks or filter stocks for the construction of investment portfolios [36, 48, 56, 64]. [64] proposed to learn decision rules for predicting stock returns with ESG information. [56] utilized decision trees for portfolio allocation optimization and selected the most important ESG indicators for this task. [48] fused ESG-related news textual representations and sentiment scores and utilized the fused features with Bayesian inference to predict stock volatilities. [36] developed machine learning techniques to predict financial fundamental ratios with ESG indicators and other economic measures. [57] leveraged a change in ESG rating methodology that non-linearly inverts ESG ratings for companies in a natural experiment to examine the effects of ESG ratings on stock prices and investments. [72] found evidence of ESG ratings being predictive of future ESG news and stock returns, but that the predictive power varied based on the degree of consensus between ESG rating agencies. [24] introduced a correction procedure to address the noisiness of ESG ratings and found that the effect of ESG performance on stock returns were stronger after the procedure. [25] found that ESG disclosures were associated with improved portfolio returns. [40] found that European firms with higher ESG ratings were associated with higher stock returns and lower volatility during the Covid-19 crisis period. [73] discovered that European funds with high ESG ratings demonstrated significantly higher returns. [70] validated the existence of ESG risk premium, i.e., ESG as a source of risk that can influence the expected returns of investment portfolios. [22] similarly found that portfolios constructed using ESG momentum scores generate returns better than the market. They also found linkages between the SDG footprint of a company (determined based on structured and unstructured data) and its ESG scores. [30] introduced ESG exposures as an additional optimization objective in the portfolio allocation optimization process. The effects of ESG ratings on other variables have also been studied. [36] used an ordered logistic regression model and found a positive relationship between ESG practices and the financial fundamental ratios of companies. [52] examined the effects of ESG ratings on corporate bond data, and found that environmental ratings, when interacted with firm size, had a significant effect on bond returns. [28] examined the relationship between ESG ratings and adverse ESG events. While these works have established strong linkages between ESG ratings or ESG-related information with a range of different target variables, they do not provide insights on information and methods that are useful for predicting ESG ratings.

In contrast, very few works study methods for predicting ESG ratings or examine the effects of different information on ESG ratings [20, 34, 51, 55, 67]. [34] examined the importance of a range of financial fundamentals when predicting ESG ratings using random forest and generalized linear models, but limited their study to a few financial fundamentals: the ratio of sales to assets, earnings before interest and tax to sales, net income to sales, price to earnings, current assets to current liabilities, debt to total assets and dividend yields. [44] similarly studied the use of a few financial fundamentals of companies, specifically returns on assets, earnings per share, market capitalization, debt to equity ratio, stock beta and volumes to predict ESG ratings of European companies with a rough set model. [55] proposed a heterogeneous ensemble model, comprising feedforward neural network, CatBoost [38] and XGBoost [31] models, to predict companies' ESG ratings using their fundamental financial data. The study utilized a large number of company financial fundamental information but did not disclose the list of variables used, or analyze the importance of the different financial fundamentals. While such works have provided evidence on the usefulness of using financial fundamentals to predict ESG ratings, they either consider only a few financial fundamentals which may not be adequate for the task, or apply machine learning methods on a large set of financial fundamentals without examining the importance or statistical significance of these financial fundamentals.

Next, we review works that examine the effects of network information on ESG ratings, and those that examine the underlying mechanisms explaining how network information could influence ESG ratings. [21, 29, 63, 68, 80] analyze different inter-company network information or utilize inter-company network information for different predictive tasks, but do not study such information in relation to ESG ratings. Different types of relationships between companies may influence ESG ratings [51], which we described in Section 1. A few works have studied the effects of static inter-company networks on ESG-related information [15, 19, 51]. For example, [51] constructed heterogeneous static networks based on different types of relationships, e.g., parent-subsidiary, trade, common shareholder relationships, and used them to predict the occurrences of different types of adverse ESG-related events. [51] posited that such relationships are predictive of ESG-related events as they are used by analysts to investigate the ESG risks of companies. Some works relating to ESG or **corporate social responsibility (CSR)** have also studied other underlying mechanisms that could potentially explain how network information could influence ESG ratings. The need to consider the interests of common stakeholders between companies could drive common ESG-related behaviors in different companies. This mechanism is closely related to two well-known frameworks on social issues in management literature - stakeholder theory [42], which argues that companies need to consider the interests of all stakeholders, and CSR [37], which relates to how companies operate in a socially responsible manner. The ESG performance of a company is known to be closely related to CSR performance [35], and surveys of ESG and CSR-related literature [14, 35] have found that stakeholder theory is an important underlying theme in works that study key drivers of ESG or CSR performance. Common stakeholders can include common directors, CEOs or investors. [49] found strong relationships between board director network centrality and ESG performance of companies, while [26] found strong relationships between CEO social network centrality and CSR performance of companies. [71], which studied the importance of mutual fund networks on CSR behaviours, found that pressure and information propagation mechanisms arising from common mutual fund investors positively influence the CSR performance of companies. However, all the above works do not focus on the use of dynamic network information for ESG rating prediction.

3 DATA AND METHODS

3.1 Data

We construct a novel dataset from a diverse range of publicly available data sources for this research.

3.1.1 Control Variables - Financial Information. We first want our dataset to cover financial fundamental information of companies, especially those have been used in previous works to predict ESG ratings [34, 44, 55]. The importance of features derived from this financial fundamental information will also be evaluated. These financial variables, including stock price-related and financial fundamental ratios, serve as control variables in our study. We collect a large number of financial variables - monthly means (*Mean*) and standard deviations (*Std.*) of stock prices from the **Center for Research in Security Prices (CRSP)**, and 71 financial fundamentals from Compustat, a database published by Standard and Poor's. We compute the percentage changes for the financial fundamentals so that they share similar scales. We collectively refer to this set of 73 variables as *Fin.All*. Instead of using all 73 variables as control variables, we select the most important variables based on Granger causalities, multiple measures of feature importance, and an analysis of multicollinearity. This results in 24 financial variables, which we refer to as *Fin.Sub*. As a robustness check, we also compare the performances of machine learning XGBoost and econometric panel models with Fin.All and Fin.Sub. More details on the selection of these financial control variables are provided in Section 3.2. The time frequencies of all financial control variables are monthly. The list of all 73 financial variables is provided in the Appendix. Missing data are imputed by forward filling, so that we do not leak data from the future to the past.

3.1.2 Variables of Interest - Network Information. To assess the usefulness of network information in predicting ESG ratings, we construct four types of static and dynamic networks from a wide range of information sources.

- *Dir.Net*: For inter-company relationships between companies sharing common directors (*Dir.Net*), we obtain directorship information from **Morgan Stanley Capital International (MSCI)**. The update frequency of common director relationships is annual.
- *MF.Net*: For inter-company relationships between companies sharing common mutual fund investors (*MF.Net*), we utilize companies from CRSP and only add an edge between two companies if they share common mutual funds that overweight the company's stock relative to the weight of the stock in the fund's benchmarks. The update frequency of common investor networks is monthly.
- *WK.Net*: Following [18, 41], we extract inter-company relationship networks from Wikidata. Wikidata is one of the largest and most active collaboratively constructed KGs, comprising *entities* with *properties* that represent different types of relationships between entities. For example, companies such as Google, Apple and Microsoft are present within the Wikidata KG as entities, and relationships between them (e.g., Alphabet as a parent company of Google (first-order), both Apple and Microsoft in the same sector (second-order), etc.). We extracted 57 first and second-order relationship-types identified by [41]. Examples of first-order relationship-types include *owned-by* and *subsidiary-of* relationships, while examples of second-order relationship-types include common *product or material produced* relationships. To extract the networks (*WK.Net*), we utilized the Wikidata datasets [13] from 2014 till 7 January 2019. Earlier data were not used as we found that networks from them were too sparse to be useful for our analyses. We also did not use more recent Wikidata data as they would fall outside the March 2015 to April 2019 time-period covered in our analyses. Hence, WK.Net is a static network, which allows us to compare the importance of different dynamic networks with a static network.
- *GKG.Net*: We also construct inter-company relationship networks based on information mined from the **Global Database of Events, Language and Tone (GDELT) Global Knowledge Graphs (GKG)** [8]. The GKG dataset is used to construct a rich set of dynamic inter-company relationship networks based on co-occurrences in news events. GDELT is a research collaboration that monitors newspapers of 65 different languages globally and is updated every 15 minutes, resulting in 2.5TB of data annually [8]. The GDELT Global Knowledge Graph (GKG) processes GDELT data and extracts entities such as persons, organizations, locations, dates, themes and emotions [58]. To our knowledge, there are other papers that utilized GDELT or GKG data [19, 46, 47, 75, 77], but they have not been used for predicting ESG ratings. We retrieve GKG data for the period March 2015 to April 2019 via BigQuery from the public GKG dataset available on the Google Cloud Platform. To construct

Table 1. Network Statistics: Table Shows the Average (Avg.) and Standard Deviations (Std.) of These Network Statistics Across the Time-periods

		NYSE			NASDAQ				
		num_edges	density	mean_deg	num_edges	density	mean_deg	Type	Frequency
Dir.Net	Avg.	4664	0.0145	11.63	616	0.0102	3.53	Dynamic	Annual
	Std.	2335	0.0073	5.82	411	0.0068	2.36		
MF.Net	Avg.	3628	0.0113	9.05	379	0.0063	2.18	Dynamic	Monthly
	Std.	424	0.0013	1.06	62	0.0010	0.36		
WK.Net	Avg.	8482	0.0264	21.15	3436	0.0566	19.69	Static	-
	Std.	0	0.0000	0.00	0	0.0000	0.00		
GKG.Net	Avg.	145808	0.4500	363.58	84154	1.3858	482.26	Dynamic	Monthly
	Std.	39886	0.1300	99.47	18742	0.3086	107.41		

There are 802 company nodes in the NYSE dataset, and 349 company nodes in the NASDAQ dataset.

inter-company networks from GKG data (*GKG.Net*), we first build a look-up table of stock symbols and variations of their common names. We then use Levenshtein Distance [4] to calculate the similarities between the different names of organizations in the GKG dataset with the common names in the look-up table, and tag the news event with the corresponding stock symbol if the similarity score is above a threshold of 0.75, determined by experimentation. Given the size of the GKG dataset, the relatively high threshold of 0.75 allows us to reduce the noisiness of the processed dataset while still obtaining a large number of samples that have been tagged at high confidence levels. Dynamic inter-company relationship networks are then constructed based on co-occurrences of tagged company stocks in GKG records using monthly aggregates to match the frequency of ESG ratings.

After constructing the four networks, we compute the following distinct network features for each company: *degree centrality*, which is the fraction of other company nodes the company is directly connected to; *closeness centrality*, which is the reciprocal of the average shortest path distance from the company node to all other reachable company nodes in the network; *eigenvector centrality*, which is based on the centrality of the company node based on random walk; *PageRank*, which is similar to eigenvector centrality and ranks the nodes in the network based on the structure of their links; and *betweenness centrality*, which is the fraction of all-pairs shortest paths that pass through the company node. We choose these network centrality features as they represent different characteristics of the company nodes in the respective networks that relate to the potential mechanisms described in Section 1. These network centrality measures could indicate the number of common stakeholders (e.g., higher degree centrality means more common stakeholders), information propagation (e.g., higher closeness centrality means greater ease of information propagation), and influence how analysts generate ESG ratings (e.g., analysts may start with more important companies with higher eigenvector, PageRank, or betweenness centralities).

Across four types of networks and five network features, we have a combined total of 20 network features. Similarly, missing data are imputed by forward filling, so that we do not leak data from the future to the past. Key statistics relating to such network information are provided in Table 1. We can see from Table 1 that these networks differ significantly, allowing us to evaluate a diverse set of networks.

3.1.3 Dependent Variables - ESG Ratings. Monthly ESG ratings - overall total ratings (*Tot.*), and the underlying environmental (*Env.*), social (*Soc.*) and governance (*Gov.*) ratings - are obtained from

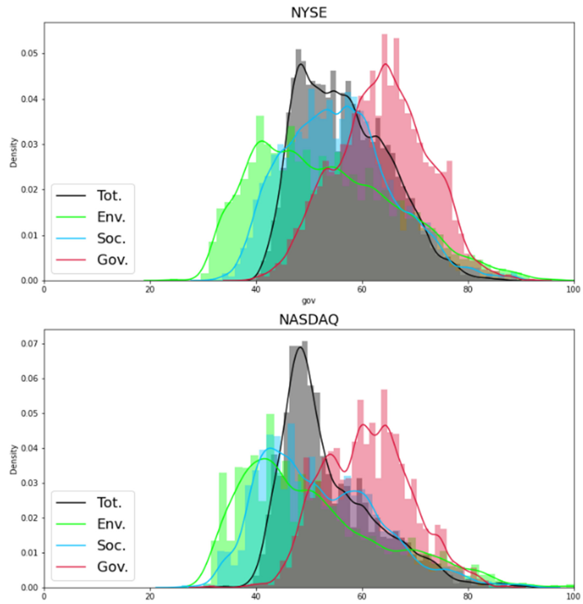

Fig. 1. ESG rating distributions.

an established ESG rating agency - Sustainalytics [7]. Based on the intersection of the time-span and companies covered within the financial and network variables and the ESG ratings data, we utilize ESG ratings from March 2015 to April 2019, covering 802 companies listed on the NYSE and 349 companies on NASDAQ. Not all companies have updated ESG ratings for every month within this time period. This could happen for two reasons: i) the company had not been included within the scope of companies covered by Sustainalytics at that point in time (e.g., company A might have obtained its first ESG rating in June 2016); or ii) the ESG ratings of a specific company might not have been updated in certain months (possibly due to the labor and time-intensive nature of the ESG rating process described in Section 1). In the former case, we do not impute any values for the ESG ratings of the company. In the latter case, we assume that no notable event or changes had necessitated a change in the ESG rating of a company and we retain the last known ESG rating of the company for that month, i.e., we forward-fill missing ratings during the imputation process. This is a reasonable assumption since ESG events or changes that could trigger a change in ESG ratings would have been picked up by the ESG analysts since they monitor news on the companies they cover as part of the rating process [45]. Hence, our dataset is unbalanced. We obtain 36,391 observations for each of the ESG rating types across companies listed on the NYSE exchange, and 14,648 observations for each of the ESG rating types across companies listed on the NASDAQ exchange. We analyze the NYSE and NASDAQ datasets (i.e., for companies listed on NYSE and NASDAQ exchanges) separately to examine if there are any differences in our findings for the two distinct datasets, and as a robustness check.

In Figure 1, we visualize the distributions of the different ESG ratings. All four types of ratings are skewed for both exchanges. However, we observe that overall total (Tot.), environmental (Env.) and social (Soc.) ratings are skewed in a different direction from the governance (Gov.) ratings. Based on the rating distributions, we can see that there are more observations with higher Gov. ratings, compared to Tot., Env. and Soc. ratings. This could be due to corporate governance issues,

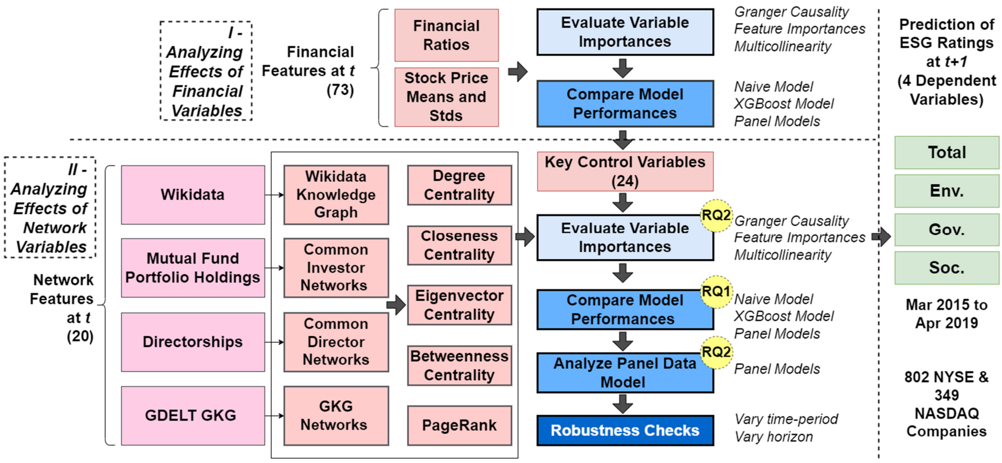

Fig. 2. Proposed framework: *Part I* - Analyzing Effects of Financial Variables focuses on the use and effects of financial control variables (at t) for predicting ESG ratings (at $t+1$). *Part II* - Analyzing Effects of Network Variables focuses on the use and effects of network variables of interest (at t) for predicting ESG ratings (at $t+1$).

that have been studied for a longer period compared to environmental and social issues, being more well-defined and hence better managed by companies [1].

3.2 Framework and Methods

We apply a range of machine learning methods across different steps to evaluate the importances and effects of a wide range of different network and financial information, and examine if network information can improve ESG rating predictions across different models. To strengthen the robustness of our analysis, we also apply econometric methods at each step and compare results from both machine learning and econometric methods. We present our proposed framework in Figure 2.

The first part of our framework (*Part I* - Analyzing Effects of Financial Variables) focuses on the effects of 73 financial control variables (see Section 3.1) for predicting ESG ratings. We predict ESG ratings of the following month, i.e., we utilize financial control variables at t to predict ESG ratings at $t+1$. This enables us to more clearly determine the effects of financial variables on ESG ratings. This also matches with the general approach of analysts using information at t to assign ESG ratings at $t+1$. While [34, 44] have examined the use and effects of fundamental financial variables for predicting ESG ratings, these works only study six to seven financial fundamental variables. [55] covers a large number of company financial fundamental information but did not disclose the list of variables used, nor analyze the importance of the different financial fundamentals. Hence, to ensure a robust set of financial variables, our study focuses on selecting a subset of key financial variables (Fin.Sub) that, when utilized for predicting ESG ratings across different machine learning and econometric models, leads to model performances that are on par with or better than the full set of financial variables (Fin.All).

Next, the second part of our framework (*Part II* - Analyzing Effects of Network Variables) focuses on the effects of the network variables of interest for predicting ESG ratings, comprising the 20 network variables described in Section 3.1. Similarly, we utilize network variables at t to predict ESG ratings at $t+1$ to better determine the effects of network variables on ESG ratings. We also analyze and compare the statistically significant panel model coefficients for both financial and network variables to understand how they influence ESG rating predictions, and conduct robustness checks on the key findings.

To evaluate variable importance, we utilize four different methods:

- Granger causalities (with a linear model as the backbone);
- Feature importance based on gain (i.e., the improvement in performance introduced by a feature);
- Feature permutation; and
- **Shapley Additive Explanations (SHAP)** [62].

Different methods for evaluating variable importances have different limitations. Granger causalities are suitable for time-series information but assume that underlying distributions are linear and stationary [74]. Feature importance based on gain and permutation measure the contribution of variables to prediction accuracy whereas SHAP measures the contribution of variables to the prediction output [78]. Therefore, the use of multiple methods for evaluating variable importances and variable selection allows us to select a more robust set of variables, while reducing the risk of important variables being dropped leading to omitted variable bias. We also conduct checks on multi-collinearities based on correlations and ***variance inflation factors*** **(VIF)**. VIF is obtained by regressing each independent variable on all other independent variables and checking how much of it is explained by these other variables. To avoid multi-collinearities, the general practice adopted by researchers [75] is to select sets of independent variables with VIFs of less than 5. To compare model performances, specifically ESG rating prediction performances for different model specifications (i.e., different sets of variables), we adopt a state-of-the-art machine learning **XGBoost (XGB)** model [31], as well as econometric models - **fixed (FE)** and **random (RE) effects** panel models [32, 33, 65]. XGB is a more regularized version of the gradient boosting approach, an additive model with multiple fitting steps, where a regression tree is fit on the negative gradient of the given loss function at each step. We choose XGBoost as it is an established machine learning method that has been used in a variety of contexts and shown to perform consistently well. FE models capture the constant characteristics of individual (i.e., the companies in our dataset) or time groups in a panel (i.e., time-series) dataset, while RE models assume that the individual-specific effects for all individuals are distributed around a common mean value and estimate different variances for different individual groups. For the econometric panel models, we apply F-tests (fixed versus pooled effects) and Breusch-Pagan Lagrange Multiplier test [27] (random versus pooled effects). The tests return p-values of less than 0.05, indicating that pooled effects models are not appropriate. We also choose to use individual effects and not time-period effects as $T \ll N$ in this case, where T is the number of time-steps (50 in our paper) and N is the number of individuals (300 to 800 companies in our paper). We also compare the performances of XGB, FE and RE models against a naive model (Naive) that uses the mean of ESG ratings in the training dataset as predictions for the testing dataset. Across all models, we conduct experiments with 10-fold cross validation with the **root mean squared error (RMSE)** metric, and use the average of RMSE (Avg.) to compare performances of different models. We assess the statistical significance of differences in model performances for RMSE with Nadeau and Bengio's corrected t-test [66]. We also compare the percentage change (Δ%) in the performances of XGB, FE and RE models relative to the Naive model. We analyze the panel model coefficients to understand the statistical significance and effects of the different financial and network variables.

To ensure the robustness and validity of our results, we conduct model evaluations on overall ESG ratings, as well as underlying environmental, social and governance ratings. We also examine differences in model performance for ESG ratings of companies (i) across the NYSE and NASDAQ

Table 2. VIFs of Key Financial Control Variables

Variables	NYSE	NASDAQ
Std	1.00	1.03
Book to Market	1.02	1.06
PE Diluted Incl EI.	1.11	1.06
Price to Sales	1.22	1.36
Operating Profit Margin Before Depreciation	1.01	1.00
After-tax Return on Invested Capital	1.02	1.02
Interest Average to Long-term Debt	1.02	1.01
Cash Balance to Total Liabilities	1.10	1.19
Inventory to Current Assets	1.09	1.13
Short Term Debt to Total Debt	1.02	1.01
Long Term Debt to Total Liabilities	1.05	1.02
Total Debt to Total Assets	1.28	1.29
Total Debt to Capital	1.28	1.19
Interest Coverage Ratio	1.02	1.02
Current Ratio	1.20	1.14
Cash Conversion Cycle Days	1.00	1.01
Payables Turnover	1.01	1.02
Research and Development to Sales	1.04	1.07
Labor Expenses to Sales	1.00	1.09
Price to Book	1.04	1.30
Trailing PE to Growth	1.03	1.00
Dividend Yield	1.17	1.13
Forward PE to 1 Year Growth	1.02	1.00
Forward PE to Long Term Growth	1.10	1.02

exchanges, (ii) across a shorter and more recent two year time-period; and (iii) for prediction at 3, 6, and 12 months time-steps in the future.

4 RESULTS AND FINDINGS

4.1 Part I - Analyzing Effects of Financial Variables

In this section, we first select the key financial variables that will serve as our control variables in the subsequent parts of the study. We also compare the performances of both machine learning and econometric models for all financial variables (Fin.All) and the selected subset of financial variables (Fin.Sub) against a naive (Naive) model.

Evaluate Variable Importances: Based on the methodology described in Section 3 for evaluating the importances of different variables (based on Granger causalities, feature importances based on gain, feature permutation and SHAP, as well as analyses of multi-collinearity), we select 24 financial variables (from 73 financial variables). For Granger causalities, we include all variables that are determined to be statistically significant at 5% (X^{gc}) after applying **Benjamini–Hochberg (BH)** multiple hypothesis corrections [23] for a maximum lag of 3. For feature importances, we include all variables that are among the top ten in any of the feature importance methods for Tot. ESG ratings and at least one of the other underlying ESG ratings (X^{fi}). The union of both sets of variables, i.e., $X^{gc} \cup X^{fi}$ are selected as the final set of variables. We show the resultant VIFs of the financial variables that we select as the key control variables for both the NYSE and NASDAQ datasets in Table 2. The VIFs are less than 1.5 for all the selected financial control variables.

Compare Model Performance: We compare the performances of XGB, FE and RE models with the full set of 73 financial variables (Fin.All) and the selected set of 24 financial variables (Fin.Sub),

Table 3. Part I: Model Performances (RMSE) with Financial Variables

	NYSE								NASDAQ							
	Tot.		Env.		Soc.		Gov.		Tot.		Env.		Soc.		Gov.	
Model	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%
Naive	8.12	0.00	13.05	0.00	9.77	0.00	8.60	0.00	8.74	0.00	13.05	0.00	10.99	0.00	8.33	0.00
XGB (Fin.All)	7.88*	−2.96	12.88	−1.30	9.45*	−3.28	8.34*	−3.02	8.61	−1.49	13.08	0.23	10.55	−4.00	8.56	2.76
XGB (Fin.Sub)	7.89*	−2.83	12.91	−1.07	9.49*	−2.87	8.38	−2.56	8.62	−1.37	13.00	−0.38	10.52	−4.28	8.59	3.12
FE (Fin.All)	8.16	0.49	13.13	0.61	9.87	1.02	8.69	1.05	9.00	2.97	13.58	4.06	11.12	1.18	9.29	11.52
FE (Fin.Sub)	8.12	0.00	13.07	0.15	9.77	0.00	8.61	0.12	8.74	0.00	13.14	0.69	10.96	−0.27	8.41	0.96
RE (Fin.All)	8.14	0.25	13.08	0.23	9.80	0.31	8.61	0.12	8.78	0.46	13.09	0.31	11.06	0.64	8.40	0.84
RE (Fin.Sub)	8.13	0.12	13.06	0.08	9.79	0.20	8.61	0.12	8.77	0.34	13.06	0.08	11.02	0.27	8.37	0.48

Avg. refers to the average RMSE performance of the model over the 10-fold cross validation. Lower is better for Avg.; Δ% refers to the percentage change in the performance of the XGB, FE and RE models relative to the Naive model, a negative % change indicates an improvement in performance relative to the Naive model. If the performance of the respective XGB, FE or RE models compared to the Naive model is better and statistically significant at the 5% confidence level with Nadeau and Bengio's corrected t-test [66], we indicate this with a * next to the average RMSE result.

and a naive model (Naive) that uses the mean of ESG ratings in the training dataset as predictions for the testing dataset, as described in Section 3. The results, based on 10-fold cross validation, are shown in Table 3.

Across the different models (XGB, FE, RE), we observe that the use of the selected set of 24 financial variables (Fin.Sub) either improved model performance, or did not lead to a significant difference in model performance. This provides additional assurance on the subset of financial variables that we selected as control variables. We also observe that predicting Env. and Soc. ratings is more difficult than predicting Gov. ratings, based on the average RMSE (Avg.). Predicting ESG ratings for companies listed on NASDAQ also appears to be more difficult than predicting ESG ratings for companies listed on NYSE. Intuitively, this could be due to Env. and Soc. ESG risks being relatively newer areas than Gov. ESG risks [1]. As there are more growth companies on the NASDAQ, their ESG risks may be more volatile and hence harder to predict. This could also be due to the smaller number of observations available for the NASDAQ dataset. Nonetheless, the ESG ratings prediction performance for companies listed on the NYSE and NASDAQ are generally consistent.

4.2 Part II - Analyzing Effects of Network Variables

In this section, we examine the importances of the different groups of network variables alongside the selected financial control variables. We then compare the performances of both machine learning and econometric models for different model specifications. Finally, we examine the coefficients of the panel models to understand the effects of the different variables.

Evaluate Variable Importances: We first evaluate the importances of the Dir.Net, MF.Net, WK.Net and GKG.Net groups of network variables based on the methodology described in Section 3. To provide an idea of the importance of network variables, we show the SHAP importances of the top variables in Figure 3, and also the set of variables that Granger cause at least one of the ESG ratings types across both markets in Table 4. While the top variables based on different methods differ, the importance of dynamic Dir.Net and GKG.Net network variables across both machine learning and econometric methods provides greater assurance on their importances. This is in line with the key mechanisms we discussed in Section 1, particularly the importance of common directors as common stakeholders, inter-company relationship networks serving as information propagation mechanisms, and a change in the ESG rating of one company potentially

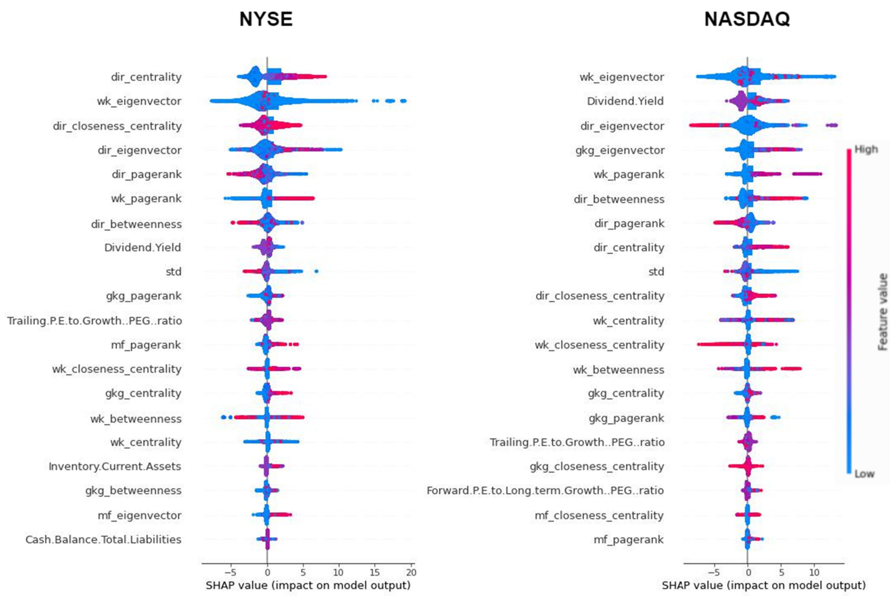

Fig. 3. SHAP importances shown as beeswarm plots for Tot. ESG Ratings for NYSE and NASDAQ datasets. Beeswarm plots show all the SHAP values, grouped by the features on the y-axis, with the SHAP values on the x-axis. The SHAP values indicate how much each factor contributed to the model's prediction when compared to the mean prediction. More positive or more negative SHAP values indicate that the feature had a significant positive or negative impact on the model's prediction. For each group, the colour of the points is determined by the value of the feature. For example, for dir_centrality for NYSE, we see that higher values of the dir_centrality features (more reddish shade) correspond to more positive SHAP values, while lower values of the dir_centrality features (more blueish shade) correspond to more negative SHAP values. The features are ordered by the mean SHAP values, i.e., more important features are at the top.

leading to the re-assessment of the ESG rating of another company related to it. Interestingly, the dynamic MF.Net network variables do not appear as frequently in the list of top variables for both SHAP importances and the Granger causalities, but the static WK.Net network variables do. This suggests that mutual fund investors as common stakeholders may not play as important a role, but that inter-company relationships, even when static, could still serve as important information propagation mechanisms.

Compare Model Performances: Next, we compare the performances of the XGB, FE and RE models with different model specifications (CON, BM1 to BM5, and NET). The set of variables included in each of the model specifications are listed in Table 5. While there are other possible combination of variables that could be combined as additional model specifications, we select these model specifications as they are the most promising based on the variable importances and empirical experiments. The performances of the different models (i.e., XGB, FE and RE) with different model specifications (i.e., CON, BM1 to BM5, and NET) are shown in Table 6. The BM5 and NET model specifications include all network variables except the WK.Net group of network variables as we found that model performances either did not improve or dropped when the WK.Net group of network variables were included under the BM3 model specification. This could be due to the network variables in WK.Net coming from a static network.

For the XGB and FE models, we observe a significant improvement in performances of models with the network variables for most ESG ratings across both NYSE and NASDAQ datasets, e.g.,

Table 4. Part II: Variables with Granger Causalities that are Statistically Significant at 5% Confidence Levels after Applying Benjamini–Hochberg (BH) Corrections for at Least One of the ESG Ratings Types and Across both Markets

	NYSE								NASDAQ							
	Tot.		Env.		Soc.		Gov.		Tot.		Env.		Soc.		Gov.	
Variables	p-val	BH	p-val	BH	p-val	BH	p-val	BH	p-val	BH	p-val	BH	p-val	BH	p-val	BH
Book to Market	0.176	F	0.991	F	0.103	F	0.038	F	0.000	T	0.000	T	0.000	T	0.000	T
Price to Sales	0.415	F	0.330	F	0.001	T	0.080	F	0.310	F	0.661	F	0.014	F	0.041	F
Operating Profit Margin Before Depreciation	0.568	F	0.336	F	0.959	F	0.608	F	0.002	T	0.496	F	0.095	F	0.000	T
After-tax Return on Invested Capital	0.022	F	0.476	F	0.228	F	0.000	T	0.981	F	0.913	F	0.876	F	0.451	F
Inventory to Current Assets	0.047	F	0.074	F	0.179	F	0.043	F	0.043	F	0.742	F	0.001	T	0.384	F
Short Term Debt to Total Debt	0.411	F	0.921	F	0.009	T	0.555	F	0.827	F	0.876	F	0.924	F	0.761	F
Long Term Debt to Total Liabilities	0.394	F	0.242	F	0.947	F	0.326	F	0.009	T	0.622	F	0.000	T	0.414	F
Total Debt to Capital	0.926	F	0.735	F	0.282	F	0.929	F	0.000	T	0.170	F	0.001	T	0.000	T
Current Ratio	0.933	F	0.940	F	0.757	F	0.383	F	0.001	T	0.003	T	0.050	F	0.359	F
Cash Conversion Cycle Days	0.553	F	0.553	F	0.805	F	0.001	T	0.869	F	0.998	F	0.744	F	0.953	F
Research and Development to Sales	0.672	F	0.761	F	0.479	F	0.493	F	0.000	T	0.808	F	0.000	T	0.000	T
Labor Expenses to Sales	0.000	T	0.016	F	0.102	F	0.000	T	0.464	F	0.000	T	0.042	F	0.016	F
Dividend Yield	0.304	F	0.028	F	0.408	F	0.003	T	0.288	F	0.107	F	0.107	F	0.585	F
dir_centrality	0.000	T	0.000	T	0.000	T	0.000	T	0.000	T	0.000	T	0.000	T	0.022	F
dir_closeness_centrality	0.000	T	0.000	T	0.000	T	0.000	T	0.000	T	0.000	T	0.001	T	0.008	T
dir_eigenvector	0.000	T	0.000	T	0.000	T	0.000	T	0.197	F	0.910	F	0.178	F	0.082	F
dir_betweenness	0.000	T	0.000	T	0.000	T	0.004	T	0.000	T	0.000	T	0.076	F	0.184	F
dir_pagerank	0.000	T	0.000	T	0.000	T	0.000	T	0.024	F	0.000	T	0.226	F	0.009	T
mf_eigenvector	0.145	F	0.008	T	0.069	F	0.010	T	0.786	F	0.424	F	0.907	F	0.175	F
wk_centrality	0.000	T	0.002	T	0.000	T	0.087	F	0.128	F	0.064	F	0.150	F	0.006	T
wk_closeness_centrality	0.000	T	0.001	T	0.000	T	0.026	F	0.353	F	0.122	F	0.277	F	0.024	F
wk_eigenvector	0.000	T	0.000	T	0.000	T	0.060	F	0.082	F	0.020	F	0.095	F	0.017	F
wk_betweenness	0.032	F	0.083	F	0.092	F	0.123	F	0.032	F	0.264	F	0.353	F	0.000	T
wk_pagerank	0.000	T	0.000	T	0.000	T	0.024	F	0.091	F	0.040	F	0.058	F	0.006	T
gkg_centrality	0.652	F	0.003	T	0.232	F	0.040	F	0.110	F	0.001	T	0.031	F	0.823	F
gkg_closeness_centrality	0.065	F	0.737	F	0.000	T	0.009	T	0.005	T	0.130	F	0.001	T	0.165	F
gkg_eigenvector	0.198	F	0.000	T	0.757	F	0.028	F	0.838	F	0.695	F	0.482	F	0.560	F
gkg_betweenness	0.651	F	0.071	F	0.765	F	0.222	F	0.000	T	0.000	T	0.003	T	0.307	F
gkg_pagerank	0.111	F	0.000	T	0.521	F	0.180	F	0.192	F	0.401	F	0.099	F	0.840	F

P-values (p-val) shown are before BH corrections. For BH, 'T' means that the Granger causality of the variable is statistically significant after BH corrections, while 'F' means that the Granger causality of the variable is not statistically significant after BH corrections. We only show variables that have Granger causalities that are statistically significant for at least one of the ESG ratings across the NYSE and NASDAQ markets.

for XGB(BM5) and FE(BM5) models, the performance improves as much as 10-11% (for Env. rating predictions for the NYSE dataset) compared to the Naive model. This demonstrates the usefulness of such network variables in improving ESG rating prediction performance. For XGB models, the difference in performances as we add more network variables, with the exception of WK.Net variables (for the BM3 model specification), is quite clear. For FE models, we observe that a large part of the performance improvement comes from the addition of Dir.Net variables, i.e., BM1 model specification. The RE models do not perform as well across all model specifications. The good performance of the FE models could indicate the presence of constant individual (i.e., company effects) which is being captured by the FE models. The performance of models for Gov. ratings for

Table 5. Benchmark Model Specifications

Model	Specification
CON	Fin.Sub
BM1	Fin.Sub + Dir.Net
BM2	Fin.Sub + Dir.Net + MF.Net
BM3	Fin.Sub + Dir.Net + WK.Net
BM4	Fin.Sub + Dir.Net + GKG.Net
BM5	Fin.Sub + Dir.Net + MF.Net + GKG.Net
NET	Dir.Net + MF.Net + GKG.Net

Table 6. Part II: Model Performances with Financial and Network Variables

	NYSE								**NASDAQ**							
	Tot.		**Env.**		**Soc.**		**Gov.**		**Tot.**		**Env.**		**Soc.**		**Gov.**	
Model	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%	Avg.	Δ%
Naive	8.12	0.00	13.05	0.00	9.77	0.00	8.60	0.00	8.74	0.00	13.05	0.00	10.99	0.00	8.33	0.00
XGB (CON)	7.89	−2.83	12.91	−1.07	9.49	−2.87	8.38	−2.56	8.62	−1.37	13.00	−0.38	10.52	−4.28	8.59	3.12
XGB (BM1)	7.76	−4.43	12.30*	−5.75	9.75	−0.20	8.85	2.91	8.65	−1.03	13.09	0.31	11.07	0.73	9.01	8.16
XGB (BM2)	7.66	−5.67	12.10*	−7.28	9.55	−2.25	8.88	3.26	8.66	−0.92	12.80	−1.92	11.04	0.45	9.02	8.28
XGB (BM3)	8.06	−0.74	12.70	−2.68	10.17	4.09	9.07	5.47	8.99	2.86	13.11	0.46	11.09	0.91	9.27	11.28
XGB (BM4)	7.65*	−5.79	12.05*	−7.66	9.59	−1.84	8.80	2.33	8.44	−3.43	12.39	−5.06	10.78	−1.91	9.07	8.88
XGB (BM5)	7.60*	−6.40	12.03*	−7.82	9.51	−2.66	8.79	2.21	8.33	−4.69	12.23	−6.28	10.87	−1.09	9.01	8.16
XGB (NET)	7.82*	−3.69	12.38*	−5.13	9.93	1.64	9.21	7.09	8.92	2.06	12.90	−1.15	11.74	6.82	9.40	12.85
FE (CON)	8.12	0.00	13.07	0.15	9.77	0.00	8.61	0.12	8.74	0.00	13.14	0.69	10.96	−0.27	8.41	0.96
FE (BM1)	7.34*	−9.61	11.73*	−10.11	9.31*	−4.71	8.43*	−1.98	8.19*	−6.29	12.28*	−5.90	10.67	−2.91	8.29	−0.48
FE (BM2)	7.32*	−9.85	11.65*	−10.73	9.31*	−4.71	8.43*	−1.98	8.15*	−6.75	12.12*	−7.13	10.64	−3.18	8.33	0.00
FE (BM3)	7.34*	−9.61	11.72*	−10.19	9.31*	−4.71	8.45*	−1.74	8.04*	−8.01	11.80*	−9.58	10.65	−3.09	8.37	0.48
FE (BM4)	7.30*	−10.10	11.62*	−10.96	9.31*	−4.71	8.41*	−2.21	8.21	−6.06	12.14	−6.97	10.74	−2.27	8.29	−0.48
FE (BM5)	7.29*	−10.22	11.56*	−11.42	9.31*	−4.71	8.42*	−2.09	8.22	−5.95	12.12	−7.13	10.72	−2.46	8.38	0.60
FE (NET)	7.29*	−10.22	11.55*	−11.49	9.31*	−4.71	8.41*	−2.21	8.22	−5.95	12.04	−7.74	10.74	−2.27	8.29	−0.48
RE (CON)	8.13	0.12	13.06	0.08	9.79	0.20	8.61	0.12	8.77	0.34	13.06	0.08	11.02	0.27	8.37	0.48
RE (BM1)	7.99*	−1.60	13.14	0.69	9.58*	−1.94	8.51*	−1.05	8.74	0.00	13.12	0.54	10.99	0.00	8.38	0.60
RE (BM2)	7.97*	−1.85	13.14	0.69	9.56*	−2.15	8.52*	−0.93	8.73	−0.11	13.15	0.77	10.98	−0.09	8.40	0.84
RE (BM3)	7.76*	−4.43	12.57*	−3.68	9.46*	−3.17	8.55*	−0.58	8.48	−2.97	12.36	−5.29	10.92	−0.64	8.48	1.80
RE (BM4)	7.97*	−1.85	12.99*	−0.46	9.58*	−1.94	8.52*	−0.93	8.74	0.00	12.99	−0.46	10.99	0.00	8.40	0.84
RE (BM5)	7.94*	−2.22	12.99*	−0.46	9.56*	−2.15	8.53*	−0.81	8.73	−0.11	13.02	−0.23	10.98	−0.09	8.41	0.96
RE (NET)	7.94*	−2.22	12.98*	−0.54	9.56*	−2.15	8.53*	−0.81	8.73	−0.11	13.01	−0.31	10.96	−0.27	8.41	0.96

Avg. refers to the average RMSE performance of the model over the 10-fold cross validation. Lower is better for Avg.; Δ% refers to the percentage change in the performance of the XGB, FE and RE models relative to the Naive model, a negative % change indicates an improvement in performance relative to the Naive model. If the performance of the respective XGB, FE or RE models with specifications BM1, BM2, BM3, BM4, BM5 and NET compared to XGB, FE or RE models with control variables only (i.e., CON) is better and statistically significant at the 5% confidence level with Nadeau and Bengio's corrected t-test [66], we indicate this with a * next to the model name.

the NASDAQ dataset is poor across all models. We can also see from models with the NET model specification that the improvement in model performance is driven by the network variables. In terms of the ESG rating prediction performance across different markets and types of ESG rating, we observe similar trends as Part I, i.e., predicting Env. and Soc. ratings is generally more difficult than predicting Gov. ratings; and predicting ESG ratings for companies listed on NASDAQ is more difficult than predicting ESG ratings for companies listed on NYSE. While we observe improvements in ESG rating prediction performances for the NASDAQ dataset when network variables are utilized, the significance of such improvements is lower than for the NYSE dataset. We also observe that it is more difficult to improve Gov. ratings with more information.

On **RQ1** (Can dynamic network information improve ESG rating prediction performances?), the performance of the XGB and FE models with dynamic network variables, in particular BM1, BM2, BM4 and BM5 model specifications, provides fairly strong evidence that dynamic company network variables can improve ESG rating prediction performance for both machine learning and econometric models. The difference in performance is significant in comparison to the Naive method, as well as model specifications using only the financial control variables (CON). While we see that the use of static network information, specifically WK.Net, can further improve ESG rating prediction performance in some cases, particularly FE (BM3) for Tot. and Env. rating predictions for the NASDAQ market, this is when WK.Net variables are used together with the dynamic network variables in Dir.Net. Based on our other empirical experiments, we had observed that the WK.Net variables do not improve ESG rating prediction performance as much when not used together with dynamic network information. When we only use Fin.Sub and WK.Net variables for the FE model for NASDAQ companies, the average RMSE is 8.48 for Tot. rating predictions (compared to 8.04 for BM3 for Tot. rating predictions for NASDAQ companies), and 12.39 for Env. rating predictions (compared to 11.80 for BM3 for Env. rating predictions for NASDAQ companies). Hence, while variable selection is still important for optimizing model performance across different rating types (i.e., Tot., Env., Soc., or Gov. ratings), markets (i.e., NYSE or NASDAQ), and models (i.e., XGB, FE or RE), we see that the use of dynamic network information generally plays an important role in improving ESG rating prediction performances.

On **RQ2** (Which types of dynamic network information are important for ESG rating predictions?), we see that network information that are more dynamic, specifically the Dir.Net, MF.Net, and GKG.Net groups of network variables, are more important (based on feature importances and Granger causalities), and also lead to better model performances when compared to the static WK.Net group of network variables and the financial control variables.

Nonetheless, for both RQ1 and RQ2, we note that the effects of the dynamic network features varies across the NYSE and NASDAQ datasets and the different types of ESG ratings, particularly for Gov. ESG rating predictions for companies listed on NASDAQ with the XGB model. A few reasons could explain this. First, unlike the FE and RE panel models, the XGB model does not address underlying company-specific features not included in the study. Second, corporate governance issues have been studied for a longer period compared to environmental and social issues, and are likely to be more well-defined. Hence, they may be better managed by companies [1], making them less sensitive to the influence of the public information we utilized to construct the dynamic networks. Third, we have significantly fewer observations for companies listed on NASDAQ, which makes it harder to train models such as XGB that require more data to model non-linear patterns. The differences in the effects of the financial and network variables on ESG rating prediction performances for NYSE and NASDAQ markets could also be due to the differences in the characteristics of companies listed on NYSE and NASDAQ. NYSE companies are typically in more traditional industries, while NASDAQ companies are typically in more growth-oriented sectors such as technology. The differences in ESG rating prediction performances could potentially reflect differences in the ESG risks of different types of companies, as well as differences in how analysts assign ESG ratings for different types of companies. Notwithstanding these differences, which make intuitive sense due to the significant differences in characteristics of the NYSE and NASDAQ companies, and as Env., Soc., and Gov. ratings measure different ESG risks, we see a general improvement in model performances when dynamic network variables are used.

Analyze Panel Data Model: Based on the significantly better performances of the FE panel model (compared to the RE panel model), as well as the results of F-tests and Breusch-Pagan Lagrange Multiplier tests [27] (as described in Section 3.2), we utilize the **fixed effects (FE)** panel model to analyze the model coefficients with robust standard errors. This allows us to better understand dynamic network effects on ESG ratings by evaluating the influence of each of the key dynamic network variables of interest relative to the financial control variables. Hence, we focus on the selected financial variables (Fin.Sub) and the dynamic network variables, i.e., Dir.Net, MF.Net, and GKG.Net. As the network variables are all measures of node centralities, we find that they are positively correlated to each other. Hence, we cannot include all of the network variables in a single model due to multi-collinearities.

Therefore, we first calculate the VIFs of the selected financial variables (Fin.Sub) and each of the network variables in Dir.Net, MF.Net, and GKG.Net to check if there are any multi-collinearities between the selected financial variables (Fin.Sub) and each of the network variables in Dir.Net, MF.Net, and GKG.Net. The VIFs, set out in Tables 3 to 8 of the Appendix, show that the VIFs are all below 1.5.

Next, we examine the coefficients of multiple FE panel models. Each of the FE panel models utilizes the selected financial variables (Fin.Sub) and one of the network variables in each of the Dir.Net, MF.Net, and GKG.Net groups of network variables as independent variables. Tables 7 to 12 present the coefficients of the respective FE panel models that are statistically significant for at least one of the dependent variables. Across all FE panel models for the NYSE and NASDAQ markets, we see that most of the dynamic network variables in Dir.Net, MF.Net, and GKG.Net are statistically significant. The level of statistical significance and the magnitude of the effects are comparable to or stronger than the financial variables. This is in line with the mechanisms we described earlier in Section 1, and our earlier observations relating to the importances of different variables. Among the dynamic network variables, we see more Dir.Net and GKG.Net network variables having significant effects on ESG ratings than MF.Net network variables for both the NYSE and NASDAQ markets. For both NYSE and NASDAQ datasets, we see that most of the dynamic network variables in Dir.Net and MF.Net have a positive effect (albeit with different levels of statistical significance) on ESG ratings. This could be due to common stakeholders influencing the behavior of companies in ESG-related areas, and serving as information propagation mechanisms, as mentioned in Section 1. Better managed companies (that also manage sustainability risks better) may also attract better directors who tend to sit on more boards, and more common mutual fund investors that emphasise the management of ESG risks. For the GKG.Net group of dynamic network variables, the significance and strength of the relationships implies that such relationships between companies due to different types of relationships and co-occurrences in news events have a strong effect on ESG ratings. As described earlier in Section 1, this could be due to analysts, journalists and the market, when investigating the ESG risks of companies, following the inter-connections between companies present across multiple types of relationships and news events.

In summary, the statistical significance of the coefficients of the dynamic network variables in Dir.Net, MF.Net, and GKG.Net support our earlier findings that the use of dynamic network variables can improve ESG rating predictions; and that network information that are dynamic in nature are important for ESG rating predictions.

4.3 Robustness Checks

The results presented in Section 4.2 show that the inclusion of dynamic network variables under model specification BM5 (which include Fin.Sub, Dir.Net, MF.Net and GKG.Net groups of variables) led to significant improvements in performances across the different machine learning and econometric models. To check the robustness of this core observation, we examine the performance of the XGB, RE and FE models for the BM5 model specification and the CON model specification (i.e., the subset of financial control variables only) on Tot. ESG rating predictions for i) a shorter and more recent two year time-period, and ii) at different number of time-steps in the future.

Table 7. Statistically Significant Fixed Effects Panel Model Coefficients for NYSE Dataset with Dir.Net

	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.
dir_centrality	24.642***	−52.362***	75.624***	51.255***																
	(2.330)	(3.798)	(3.554)	(3.070)																
dir_closeness_centrality					−0.150	−4.372***	1.190***	3.236***												
					(0.173)	(0.279)	(0.252)	(0.230)												
dir_eigenvector									1.310	−12.450***	6.420***	10.031***								
									(1.085)	(1.795)	(1.639)	(1.481)								
dir_betweenness													38.963***	−117.047***	103.616***	151.473***				
													(6.960)	(11.443)	(10.566)	(9.854)				
dir_pagerank																	−2.133	−447.901***	77.712**	454.046***
																	(25.430)	(42.173)	(37.770)	(34.211)
Std.	0.004	0.010	−0.005	0.017	0.007	−0.010	0.008	0.033**	0.007	0.005	0.003	0.022	0.006	0.007	0.001	0.019	0.007	0.006	0.004	0.021
	(0.014)	(0.017)	(0.022)	(0.013)	(0.014)	(0.018)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.022)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)
Book to Market	0.029	−0.081	0.201***	−0.027	0.013	−0.113	0.174***	−0.010	0.017	−0.069	0.167***	−0.041	0.020	−0.067	0.171***	−0.035	0.015	−0.095	0.165***	−0.011
	(0.049)	(0.087)	(0.062)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.062)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)
Price to Sales	0.036	0.068	−0.202	0.339***	0.003	0.031	−0.264**	0.351***	0.009	0.108	−0.280**	0.296**	0.014	0.109	−0.272**	0.306**	0.006	0.080	−0.282**	0.329**
	(0.088)	(0.129)	(0.129)	(0.130)	(0.088)	(0.130)	(0.130)	(0.131)	(0.088)	(0.129)	(0.130)	(0.130)	(0.087)	(0.129)	(0.128)	(0.130)	(0.088)	(0.129)	(0.130)	(0.131)
After-tax Return on Invested Capital	−0.001	0.001	−0.003*	0.0003	−0.001	0.001	−0.003*	0.0003	−0.001	0.001	−0.003*	0.0001	−0.001	0.001	−0.003*	0.0003	−0.001	0.001	−0.003*	0.0003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Interest Average to Long-term Debt	0.059*	0.073*	0.040	0.082*	0.053	0.081*	0.024	0.073*	0.054	0.081*	0.025	0.073*	0.055	0.081*	0.027	0.075*	0.054	0.083**	0.024	0.073*
	(0.035)	(0.041)	(0.074)	(0.043)	(0.035)	(0.042)	(0.075)	(0.042)	(0.035)	(0.042)	(0.075)	(0.043)	(0.034)	(0.042)	(0.075)	(0.042)	(0.035)	(0.041)	(0.075)	(0.042)
Total to Debt Capital	0.130*	0.006	0.245***	0.077	0.131*	0.002	0.248***	0.080	0.131*	0.003	0.248***	0.080	0.129*	0.010	0.242***	0.071	0.131*	0.010	0.246***	0.073
	(0.074)	(0.145)	(0.091)	(0.126)	(0.074)	(0.146)	(0.091)	(0.125)	(0.074)	(0.145)	(0.092)	(0.126)	(0.074)	(0.146)	(0.091)	(0.125)	(0.074)	(0.145)	(0.092)	(0.125)
Interest Coverage Ratio	0.004**	0.009***	0.003	0.0003	0.005**	0.008**	0.004	0.001	0.005**	0.008**	0.004	0.001	0.005**	0.008**	0.004	0.001	0.005**	0.008***	0.004	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Research and Development to Sales	−0.149	−0.366*	−0.030	0.031	−0.131	−0.365*	0.011	0.039	−0.135	−0.377*	0.009	0.046	−0.136	−0.391*	0.012	0.051	−0.132	−0.382*	0.018	0.046
	(0.162)	(0.215)	(0.327)	(0.256)	(0.167)	(0.210)	(0.343)	(0.255)	(0.166)	(0.215)	(0.337)	(0.257)	(0.166)	(0.212)	(0.341)	(0.255)	(0.167)	(0.213)	(0.341)	(0.255)
Labor Expenses to Sales	−0.480	−1.656**	−1.287	1.759*	−0.254	−1.682**	−0.753	1.885*	−0.295	−1.850**	−0.769	1.993**	−0.309	−1.981**	−0.747	2.039**	−0.267	−1.756**	−0.699	1.845*
	(0.659)	(0.785)	(1.269)	(0.969)	(0.661)	(0.772)	(1.277)	(0.987)	(0.661)	(0.796)	(1.269)	(0.985)	(0.664)	(0.783)	(1.279)	(0.966)	(0.662)	(0.779)	(1.273)	(0.980)
Dividend Yield	0.407***	0.514**	0.833***	−0.331*	0.501***	0.501*	1.055***	−0.276	0.488***	0.395	1.068***	−0.202	0.471***	0.398	1.040***	−0.240	0.495***	0.431*	1.085***	−0.253
	(0.149)	(0.260)	(0.209)	(0.187)	(0.148)	(0.261)	(0.210)	(0.187)	(0.148)	(0.261)	(0.210)	(0.187)	(0.148)	(0.259)	(0.210)	(0.187)	(0.148)	(0.262)	(0.210)	(0.188)
Forward PE to Long-term Growth	0.005*	0.006	0.005	0.002	0.005*	0.006	0.005	0.002	0.005*	0.005	0.006	0.002	0.005*	0.006	0.005	0.002	0.005*	0.006	0.006	0.002
	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)
F Statistic	5.619***	8.742***	23.118***	11.570***	1.043	10.538***	3.239***	8.322***	1.077	3.000***	3.085***	2.862***	2.207***	4.894***	6.355***	10.575***	1.013	5.850***	2.538***	8.172***

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 8. Statistically Significant Fixed Effects Panel Model Coefficients for NYSE Dataset with MF.Net

	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.
mf_centrality	4.017***	1.515	7.737***	0.493																
	(1.147)	(1.837)	(1.676)	(1.613)																
mf_closeness_centrality					1.304***	0.809	2.856***	−0.350												
					(0.354)	(0.572)	(0.521)	(0.493)												
mf_eigenvector									2.743***	−0.199	4.060***	3.374***								
									(0.688)	(1.147)	(0.982)	(0.997)								
mf_betweenness													70.320**	−20.299	130.004***	12.026				
													(32.135)	(55.768)	(41.461)	(40.562)				
mf_pagerank																	71.320***	−15.005	127.125***	78.833***
																	(15.725)	(25.563)	(22.500)	(22.177)
Std.	0.007	0.004	0.004	0.023*	0.007	0.004	0.004	0.023*	0.008	0.004	0.005	0.024*	0.007	0.004	0.004	0.023*	0.007	0.004	0.005	0.023*
	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)
Book to Market	0.016	−0.049	0.160**	−0.057	0.015	−0.050	0.157**	−0.057	0.016	−0.050	0.159**	−0.055	0.015	−0.050	0.158**	−0.057	0.017	−0.050	0.161**	−0.054
	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)
Price to Sales	0.002	0.129	−0.300**	0.277**	0.002	0.127	−0.302**	0.279**	0.001	0.131	−0.299**	0.271**	0.005	0.131	−0.295**	0.278**	−0.003	0.132	−0.307**	0.268**
	(0.088)	(0.129)	(0.129)	(0.130)	(0.088)	(0.129)	(0.129)	(0.131)	(0.088)	(0.129)	(0.130)	(0.130)	(0.088)	(0.129)	(0.130)	(0.130)	(0.088)	(0.129)	(0.129)	(0.130)
After-tax Return on Invested Capital	−0.001	0.001	−0.003*	0.00003	−0.001	0.001	−0.003*	0.00002	−0.001	0.001	−0.003*	0.00004	−0.001	0.001	−0.003*	0.00003	−0.001	0.001	−0.003*	0.0001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Interest Average to Long-term Debt	0.053	0.085**	0.023	0.070	0.053	0.085**	0.022	0.070	0.053	0.085**	0.023	0.070	0.053	0.085**	0.023	0.070	0.053	0.085**	0.022	0.070
	(0.035)	(0.042)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)
Total to Debt Capital	0.132*	0.005	0.249***	0.078	0.133*	0.006	0.252***	0.078	0.132*	0.005	0.249***	0.079	0.131*	0.005	0.247***	0.078	0.132*	0.005	0.248***	0.079
	(0.074)	(0.146)	(0.092)	(0.126)	(0.074)	(0.146)	(0.092)	(0.126)	(0.074)	(0.146)	(0.092)	(0.126)	(0.074)	(0.146)	(0.092)	(0.126)	(0.074)	(0.146)	(0.092)	(0.126)
Interest Coverage Ratio	0.005**	0.007**	0.004	0.002	0.005**	0.007**	0.004	0.002	0.005**	0.007**	0.004	0.002	0.005**	0.007**	0.004	0.002	0.005**	0.007**	0.004	0.002
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Research and Development to Sales	−0.127	−0.400*	0.031	0.066	−0.126	−0.398*	0.034	0.064	−0.130	−0.402*	0.024	0.068	−0.133	−0.401*	0.021	0.066	−0.126	−0.403*	0.031	0.072
	(0.167)	(0.211)	(0.342)	(0.255)	(0.166)	(0.211)	(0.340)	(0.255)	(0.167)	(0.211)	(0.342)	(0.255)	(0.167)	(0.211)	(0.343)	(0.255)	(0.166)	(0.211)	(0.341)	(0.254)
Labor Expenses to Sales	−0.259	−2.101***	−0.620	2.199**	−0.260	−2.100***	−0.621	2.196**	−0.250	−2.106***	−0.611	2.221**	−0.274	−2.103***	−0.649	2.197**	−0.253	−2.108***	−0.611	2.215**
	(0.662)	(0.808)	(1.271)	(0.996)	(0.662)	(0.808)	(1.272)	(0.997)	(0.662)	(0.807)	(1.271)	(0.994)	(0.662)	(0.807)	(1.273)	(0.997)	(0.662)	(0.806)	(1.271)	(0.994)
Dividend Yield	0.494***	0.327	1.101***	−0.148	0.493***	0.326	1.099***	−0.147	0.498***	0.327	1.108***	−0.144	0.493***	0.328	1.100***	−0.148	0.498***	0.327	1.109***	−0.144
	(0.147)	(0.263)	(0.210)	(0.186)	(0.147)	(0.262)	(0.210)	(0.187)	(0.147)	(0.263)	(0.210)	(0.186)	(0.148)	(0.263)	(0.210)	(0.186)	(0.147)	(0.263)	(0.210)	(0.186)
Forward PE to Long-term Growth	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003
	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)
F Statistic	1.571**	0.787	3.330***	0.825	1.617**	0.846	3.721***	0.844	1.778***	0.758	3.142***	1.442*	1.286	0.765	2.791***	0.825	1.997***	0.773	3.830***	1.467*

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 9. Statistically Significant Fixed Effects Panel Model Coefficients for NYSE Dataset with GKG.Net

	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.
gkg_centrality	−0.314	3.360***	−2.673***	−1.459***																
	(0.229)	(0.387)	(0.335)	(0.302)																
gkg_closeness_centrality					−0.683***	1.756***	−2.584***	−1.223***												
					(0.156)	(0.262)	(0.225)	(0.213)												
gkg_eigenvector									1.446***	4.470***	−0.677	1.490**								
									(0.551)	(0.926)	(0.755)	(0.759)								
gkg_betweenness													34.038***	63.626***	30.002***	8.911				
													(7.194)	(14.353)	(9.976)	(9.643)				
gkg_pagerank																	38.255***	129.014***	0.020	2.374
																	(10.996)	(19.596)	(14.799)	(15.942)
Std.	0.008	−0.008	0.013	0.028**	0.009	−0.002	0.013	0.027**	0.007	0.003	0.004	0.023*	0.004	−0.001	0.002	0.022*	0.005	−0.002	0.004	0.023*
	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)	(0.014)	(0.017)	(0.023)	(0.014)
Book to Market	0.017	−0.074	0.176***	−0.046	0.020	−0.063	0.176***	−0.048	0.014	−0.051	0.157**	−0.057	0.014	−0.051	0.156**	−0.057	0.015	−0.051	0.157**	−0.057
	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)	(0.049)	(0.087)	(0.063)	(0.076)
Price to Sales	0.007	0.122	−0.285**	0.282**	0.005	0.135	−0.299**	0.274**	0.005	0.126	−0.291**	0.277**	0.003	0.124	−0.294**	0.277**	0.008	0.136	−0.291**	0.278**
	(0.088)	(0.129)	(0.130)	(0.130)	(0.088)	(0.129)	(0.130)	(0.131)	(0.088)	(0.129)	(0.130)	(0.130)	(0.088)	(0.129)	(0.130)	(0.130)	(0.088)	(0.128)	(0.130)	(0.130)
After-tax Return on Invested Capital	−0.001	0.001	−0.003*	0.00002	−0.001	0.002	−0.003**	−0.0002	−0.001	0.001	−0.003*	0.00002	−0.001	0.001	−0.003*	0.00002	−0.001	0.001	−0.003*	0.00003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Interest Average to Long-term Debt	0.054	0.083**	0.025	0.071*	0.054	0.085**	0.023	0.070	0.053	0.082**	0.024	0.069	0.054	0.086**	0.024	0.070	0.052	0.080*	0.023	0.070
	(0.035)	(0.041)	(0.075)	(0.043)	(0.035)	(0.041)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)	(0.035)	(0.042)	(0.075)	(0.043)
Total to Debt Capital	0.131*	0.003	0.249***	0.079	0.131*	0.005	0.247***	0.078	0.131*	0.003	0.247***	0.078	0.129*	−0.0001	0.245***	0.078	0.131*	0.004	0.247***	0.078
	(0.074)	(0.145)	(0.093)	(0.126)	(0.074)	(0.146)	(0.093)	(0.126)	(0.074)	(0.146)	(0.092)	(0.126)	(0.073)	(0.145)	(0.091)	(0.126)	(0.074)	(0.146)	(0.092)	(0.126)
Interest Coverage Ratio	0.005**	0.007**	0.005	0.002	0.005**	0.007**	0.005	0.002	0.005**	0.007**	0.004	0.002	0.005**	0.007**	0.004	0.002	0.005**	0.007**	0.004	0.002
	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Research and Development to Sales	−0.131	−0.416**	0.033	0.072	−0.130	−0.406*	0.028	0.069	−0.133	−0.406*	0.022	0.064	−0.136	−0.409*	0.018	0.065	−0.135	−0.412*	0.021	0.065
	(0.167)	(0.211)	(0.346)	(0.255)	(0.167)	(0.211)	(0.342)	(0.255)	(0.166)	(0.212)	(0.343)	(0.255)	(0.165)	(0.212)	(0.340)	(0.255)	(0.165)	(0.211)	(0.343)	(0.255)
Labor Expenses to Sales	−0.279	−1.994**	−0.726	2.150**	−0.300	−2.023**	−0.759	2.141**	−0.265	−2.096***	−0.640	2.201**	−0.283	−2.132***	−0.651	2.194**	−0.267	−2.100***	−0.638	2.198**
	(0.662)	(0.808)	(1.274)	(0.999)	(0.662)	(0.806)	(1.271)	(0.998)	(0.661)	(0.809)	(1.273)	(0.996)	(0.662)	(0.805)	(1.273)	(0.997)	(0.657)	(0.807)	(1.272)	(0.996)
Dividend Yield	0.490***	0.381	1.060***	−0.171	0.486***	0.348	1.072***	−0.163	0.488***	0.306	1.106***	−0.155	0.482***	0.303	1.091***	−0.151	0.495***	0.327	1.103***	−0.148
	(0.148)	(0.260)	(0.209)	(0.186)	(0.148)	(0.262)	(0.210)	(0.187)	(0.148)	(0.260)	(0.210)	(0.187)	(0.148)	(0.263)	(0.210)	(0.187)	(0.147)	(0.257)	(0.210)	(0.187)
Forward PE to Long-term Growth	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003	0.005*	0.005	0.006	0.003
	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)
F Statistic	1.096	4.391***	5.189***	1.780***	1.683**	2.452***	6.894***	1.974***	1.401*	2.179***	2.389***	1.042	2.028***	2.116***	2.722***	0.858	1.636**	3.474***	2.349***	0.822

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 10. Statistically Significant Fixed Effects Panel Model Coefficients for NASDAQ Dataset with Dir.Net

	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.
dir_centrality	26.857***	−17.839***	36.655***	60.493***																
	(3.247)	(4.944)	(5.055)	(4.275)																
dir_closeness_centrality					1.757***	−1.509*	2.059***	4.942***												
					(0.485)	(0.775)	(0.714)	(0.624)												
dir_eigenvector									3.074***	1.442**	0.782	7.814***								
									(0.502)	(0.676)	(0.846)	(1.180)								
dir_betweenness													9.098**	−14.534**	9.362	29.862***				
													(4.044)	(5.744)	(6.482)	(4.765)				
dir_pagerank																	21.567*	−77.116***	−39.521**	222.500***
																	(12.220)	(18.400)	(18.043)	(16.847)
Std.	0.402***	0.397***	0.546***	0.326*	0.440***	0.378***	0.604***	0.395**	0.469***	0.350***	0.640***	0.477***	0.457***	0.374***	0.626***	0.436**	0.460***	0.390***	0.661***	0.371**
	(0.083)	(0.123)	(0.132)	(0.181)	(0.083)	(0.122)	(0.133)	(0.179)	(0.083)	(0.121)	(0.133)	(0.179)	(0.083)	(0.122)	(0.133)	(0.181)	(0.083)	(0.122)	(0.134)	(0.181)
PE Diluted Incl EI.	0.004	−0.004	0.014	0.002	0.005	−0.004	0.015*	0.004	0.005	−0.004	0.015*	0.004	0.005	−0.004	0.015*	0.003	0.005	−0.004	0.015*	0.002
	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)
Operating Profit Margin Before Depreciation	−0.017*	−0.005	0.010	−0.080**	−0.016	−0.005	0.012	−0.077**	−0.015	−0.007	0.014	−0.075**	−0.015	−0.006	0.013	−0.075**	−0.015	−0.005	0.014	−0.077**
	(0.010)	(0.025)	(0.017)	(0.034)	(0.010)	(0.025)	(0.016)	(0.033)	(0.010)	(0.025)	(0.016)	(0.034)	(0.010)	(0.026)	(0.016)	(0.034)	(0.010)	(0.026)	(0.016)	(0.033)
Interest Average to Long-term Debt	0.049	0.164**	−0.001	−0.035	0.048	0.164**	−0.003	−0.036	0.045	0.165**	−0.005	−0.043	0.047	0.164**	−0.004	−0.039	0.046	0.164**	−0.006	−0.037
	(0.032)	(0.082)	(0.039)	(0.046)	(0.032)	(0.082)	(0.039)	(0.045)	(0.032)	(0.083)	(0.039)	(0.045)	(0.032)	(0.082)	(0.039)	(0.045)	(0.032)	(0.082)	(0.039)	(0.046)
Inventory to Current Assets	−0.010	−0.0005	0.188	−0.319*	−0.021	0.004	0.171	−0.336**	−0.038	0.014	0.155	−0.382**	−0.023	−0.002	0.167	−0.337**	−0.027	−0.010	0.142	−0.299*
	(0.100)	(0.195)	(0.141)	(0.167)	(0.100)	(0.195)	(0.141)	(0.169)	(0.100)	(0.195)	(0.141)	(0.171)	(0.100)	(0.195)	(0.141)	(0.168)	(0.100)	(0.195)	(0.141)	(0.167)
Long-term Debt to Total Liabilities	0.005	−0.002	0.008	0.011*	0.004	−0.002	0.007	0.009*	0.004	−0.002	0.007	0.008	0.004	−0.002	0.007	0.009*	0.004	−0.002	0.006	0.010*
	(0.008)	(0.009)	(0.017)	(0.006)	(0.008)	(0.009)	(0.017)	(0.005)	(0.008)	(0.010)	(0.017)	(0.005)	(0.008)	(0.009)	(0.017)	(0.005)	(0.008)	(0.009)	(0.017)	(0.006)
Total Debt to Total Assets	−0.012	−0.756*	0.388	0.455	−0.011	−0.758*	0.388	0.459	−0.017	−0.755	0.383	0.442	−0.018	−0.750	0.380	0.437	−0.014	−0.757*	0.382	0.455
	(0.309)	(0.458)	(0.439)	(0.436)	(0.309)	(0.458)	(0.439)	(0.439)	(0.308)	(0.459)	(0.439)	(0.440)	(0.308)	(0.459)	(0.439)	(0.436)	(0.308)	(0.458)	(0.439)	(0.434)
Labor Expenses to Sales	1.422*	3.416**	−0.349	1.656	1.419*	3.433**	−0.340	1.608	1.496*	3.373**	−0.254	1.824*	1.462*	3.417**	−0.285	1.715*	1.449*	3.522**	−0.177	1.374
	(0.763)	(1.663)	(0.819)	(1.023)	(0.770)	(1.659)	(0.823)	(1.043)	(0.769)	(1.662)	(0.823)	(1.035)	(0.768)	(1.661)	(0.825)	(1.019)	(0.768)	(1.661)	(0.822)	(1.017)
Price to Book	−0.134	−0.003	−0.279**	−0.102	−0.135	−0.002	−0.279**	−0.104	−0.131	−0.002	−0.277**	−0.095	−0.135	−0.001	−0.280**	−0.106	−0.132	−0.008	−0.280**	−0.089
	(0.108)	(0.156)	(0.138)	(0.105)	(0.108)	(0.156)	(0.137)	(0.106)	(0.108)	(0.156)	(0.137)	(0.107)	(0.108)	(0.156)	(0.137)	(0.108)	(0.108)	(0.157)	(0.137)	(0.105)
Trailing PE to Growth	−0.004	−0.001	−0.010***	0.002	−0.004	−0.001	−0.010***	0.002	−0.004	−0.002	−0.010***	0.003	−0.004	−0.001	−0.010***	0.003	−0.004	−0.001	−0.010**	0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)
Forward PE to Long-term Growth	−0.001	−0.006	−0.005	0.014*	−0.001	−0.006	−0.005	0.015*	−0.001	−0.006	−0.006	0.014	−0.001	−0.006	−0.006	0.014	−0.001	−0.006	−0.006	0.015*
	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)
F Statistic	3.094***	0.984	3.220***	8.531***	1.230	0.743	1.441*	3.652***	1.516**	0.669	1.129	4.319***	0.943	0.815	1.219	2.669***	0.839	1.175	1.302	9.196***

*p<0.1; **p<0.05; ***p<0.01.

Table 11. Statistically Significant Fixed Effects Panel Model Coefficients for NASDAQ Dataset with MF.Net

	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.
mf_centrality	3.288*	−0.082	3.713	3.067																
	(1.816)	(2.892)	(2.710)	(2.507)																
mf_closeness_centrality					3.651***	3.308**	4.614***	0.961												
					(0.938)	(1.457)	(1.373)	(1.194)												
mf_eigenvector									0.861	−2.618***	2.479***	1.084								
									(0.541)	(0.907)	(0.822)	(0.783)								
mf_betweenness													23.602	33.638	−37.146	97.388**				
													(32.762)	(42.200)	(50.332)	(45.621)				
mf_pagerank																	8.334	−3.995	−4.430	22.779**
																	(8.059)	(12.298)	(12.077)	(10.992)
Std.	0.474***	0.351***	0.645***	0.486***	0.479***	0.358***	0.650***	0.485***	0.473***	0.346***	0.646***	0.485***	0.472***	0.352***	0.640***	0.485***	0.473***	0.350***	0.640***	0.487***
	(0.083)	(0.121)	(0.133)	(0.179)	(0.083)	(0.121)	(0.133)	(0.179)	(0.083)	(0.121)	(0.133)	(0.179)	(0.083)	(0.121)	(0.133)	(0.179)	(0.083)	(0.121)	(0.133)	(0.179)
PE Diluted Incl EI.	0.005	−0.004	0.015*	0.004	0.005	−0.005	0.015*	0.004	0.005	−0.004	0.015*	0.004	0.005	−0.004	0.015*	0.003	0.005	−0.004	0.015*	0.004
	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.007)
Operating Profit Margin Before Depreciation	−0.015	−0.006	0.014	−0.074**	−0.014	−0.005	0.015	−0.074**	−0.015	−0.007	0.014	−0.074**	−0.015	−0.006	0.014	−0.074**	−0.015	−0.007	0.014	−0.074**
	(0.010)	(0.025)	(0.016)	(0.034)	(0.010)	(0.025)	(0.016)	(0.033)	(0.010)	(0.026)	(0.016)	(0.034)	(0.010)	(0.025)	(0.016)	(0.034)	(0.010)	(0.025)	(0.016)	(0.033)
Interest Average to Long-term Debt	0.046	0.166**	−0.005	−0.041	0.045	0.165**	−0.006	−0.041	0.046	0.165**	−0.005	−0.041	0.046	0.166**	−0.005	−0.041	0.046	0.166**	−0.005	−0.041
	(0.031)	(0.083)	(0.039)	(0.045)	(0.031)	(0.083)	(0.039)	(0.045)	(0.032)	(0.083)	(0.039)	(0.045)	(0.032)	(0.083)	(0.039)	(0.045)	(0.032)	(0.083)	(0.039)	(0.045)
Inventory to Current Assets	−0.035	0.016	0.154	−0.375**	−0.034	0.016	0.155	−0.374**	−0.034	0.015	0.156	−0.373**	−0.034	0.016	0.155	−0.372**	−0.034	0.016	0.155	−0.374**
	(0.100)	(0.195)	(0.141)	(0.170)	(0.100)	(0.195)	(0.140)	(0.170)	(0.100)	(0.195)	(0.140)	(0.170)	(0.100)	(0.195)	(0.141)	(0.170)	(0.100)	(0.195)	(0.141)	(0.170)
Total Debt to Total Assets	−0.015	−0.754	0.384	0.447	−0.017	−0.755*	0.381	0.446	−0.013	−0.760*	0.389	0.449	−0.016	−0.755	0.384	0.444	−0.015	−0.754	0.383	0.447
	(0.308)	(0.459)	(0.439)	(0.438)	(0.308)	(0.459)	(0.439)	(0.438)	(0.308)	(0.460)	(0.438)	(0.438)	(0.309)	(0.459)	(0.439)	(0.439)	(0.308)	(0.459)	(0.439)	(0.438)
Labor Expenses to Sales	1.504*	3.370**	−0.240	1.823*	1.529**	3.405**	−0.208	1.821*	1.495*	3.359**	−0.244	1.816*	1.494*	3.375**	−0.260	1.824*	1.497*	3.368**	−0.258	1.829*
	(0.769)	(1.662)	(0.823)	(1.035)	(0.769)	(1.662)	(0.823)	(1.035)	(0.769)	(1.661)	(0.822)	(1.035)	(0.769)	(1.662)	(0.823)	(1.035)	(0.769)	(1.662)	(0.823)	(1.035)
Price to Book	−0.133	−0.003	−0.278**	−0.101	−0.134	−0.004	−0.279**	−0.101	−0.133	−0.005	−0.276**	−0.100	−0.133	−0.003	−0.279**	−0.099	−0.133	−0.003	−0.278**	−0.100
	(0.108)	(0.156)	(0.137)	(0.107)	(0.108)	(0.155)	(0.137)	(0.107)	(0.108)	(0.156)	(0.136)	(0.106)	(0.108)	(0.156)	(0.137)	(0.107)	(0.108)	(0.156)	(0.137)	(0.107)
Trailing PE to Growth	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)
F Statistic	0.852	0.606	1.187	1.262	1.440*	0.820	1.657**	1.221	0.814	0.932	1.492*	1.284	0.735	0.620	1.127	1.388*	0.762	0.610	1.110	1.395*

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 12. Statistically Significant Fixed Effects Panel Model Coefficients for NASDAQ Dataset with GKG.Net

	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.	Tot.	Env.	Soc.	Gov.
gkg_centrality	−0.987***	1.589***	−2.692***	−1.545***																
	(0.378)	(0.615)	(0.550)	(0.479)																
gkg_closeness_centrality					−1.583***	1.856***	−2.986***	−3.628***												
					(0.234)	(0.380)	(0.324)	(0.305)												
gkg_eigenvector									4.177***	4.299**	8.204***	−2.562								
									(1.221)	(1.928)	(1.597)	(1.617)								
gkg_betweenness													−12.465**	−8.550	−17.763**	−9.393				
													(4.858)	(7.020)	(7.055)	(5.856)				
gkg_pagerank																	14.485**	6.933	25.109***	3.110
																	(6.529)	(9.973)	(9.104)	(8.756)
Std.	0.503***	0.300**	0.727***	0.533***	0.500***	0.318***	0.695***	0.549***	0.474***	0.354***	0.647***	0.481***	0.477***	0.355***	0.649***	0.487***	0.464***	0.348***	0.629***	0.482***
	(0.083)	(0.122)	(0.134)	(0.180)	(0.083)	(0.121)	(0.132)	(0.178)	(0.083)	(0.121)	(0.133)	(0.178)	(0.083)	(0.121)	(0.133)	(0.179)	(0.083)	(0.121)	(0.133)	(0.179)
PE Diluted Incl EI.	0.005	−0.004	0.015*	0.004	0.005	−0.004	0.015*	0.003	0.005	−0.004	0.015*	0.004	0.005	−0.004	0.015*	0.004	0.005	−0.004	0.015*	0.004
	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.008)	(0.006)	(0.010)	(0.009)	(0.007)
Operating Profit Margin Before Depreciation	−0.015	−0.006	0.013	−0.075**	−0.016	−0.005	0.011	−0.077**	−0.015	−0.006	0.014	−0.074**	−0.015	−0.007	0.014	−0.074**	−0.015	−0.006	0.014	−0.074**
	(0.010)	(0.025)	(0.015)	(0.034)	(0.010)	(0.025)	(0.016)	(0.034)	(0.010)	(0.025)	(0.016)	(0.034)	(0.010)	(0.025)	(0.016)	(0.034)	(0.010)	(0.025)	(0.016)	(0.034)
Interest Average to Long-term Debt	0.046	0.166**	−0.006	−0.042	0.048	0.163**	−0.001	−0.036	0.046	0.166**	−0.005	−0.041	0.046	0.166**	−0.005	−0.041	0.046	0.166**	−0.005	−0.041
	(0.032)	(0.083)	(0.039)	(0.045)	(0.032)	(0.082)	(0.039)	(0.046)	(0.032)	(0.083)	(0.039)	(0.045)	(0.032)	(0.083)	(0.039)	(0.045)	(0.032)	(0.083)	(0.039)	(0.045)
Inventory to Current Assets	−0.029	0.008	0.169	−0.366**	−0.024	0.004	0.174	−0.351**	−0.031	0.019	0.162	−0.376**	−0.038	0.013	0.150	−0.376**	−0.033	0.016	0.157	−0.373**
	(0.100)	(0.195)	(0.141)	(0.170)	(0.100)	(0.195)	(0.141)	(0.169)	(0.100)	(0.195)	(0.141)	(0.170)	(0.100)	(0.195)	(0.141)	(0.170)	(0.100)	(0.195)	(0.141)	(0.170)
Long-term Debt to Total Liabilities	0.004	−0.001	0.006	0.008	0.004	−0.002	0.007	0.009*	0.004	−0.001	0.007	0.008	0.003	−0.002	0.006	0.008	0.004	−0.002	0.007	0.008
	(0.008)	(0.010)	(0.017)	(0.005)	(0.008)	(0.010)	(0.017)	(0.005)	(0.008)	(0.009)	(0.016)	(0.005)	(0.008)	(0.010)	(0.017)	(0.005)	(0.008)	(0.010)	(0.017)	(0.005)
Total Debt to Total Assets	−0.010	−0.762*	0.397	0.454	−0.018	−0.750	0.378	0.439	−0.010	−0.749	0.393	0.443	−0.011	−0.751	0.389	0.449	−0.012	−0.752	0.389	0.447
	(0.308)	(0.459)	(0.438)	(0.438)	(0.308)	(0.460)	(0.437)	(0.438)	(0.309)	(0.459)	(0.439)	(0.438)	(0.308)	(0.459)	(0.439)	(0.439)	(0.309)	(0.459)	(0.439)	(0.439)
Labor Expenses to Sales	1.451*	3.434**	−0.363	1.749*	1.402*	3.475**	−0.423	1.607	1.495*	3.375**	−0.247	1.809*	1.506**	3.381**	−0.233	1.823*	1.495*	3.373**	−0.248	1.812*
	(0.767)	(1.665)	(0.821)	(1.033)	(0.765)	(1.672)	(0.835)	(1.032)	(0.769)	(1.662)	(0.822)	(1.035)	(0.768)	(1.662)	(0.822)	(1.034)	(0.769)	(1.662)	(0.823)	(1.035)
Price to Book	−0.134	−0.002	−0.280**	−0.102	−0.127	−0.011	−0.265*	−0.085	−0.134	−0.003	−0.278**	−0.101	−0.136	−0.005	−0.281**	−0.103	−0.133	−0.003	−0.276**	−0.101
	(0.108)	(0.155)	(0.137)	(0.106)	(0.108)	(0.156)	(0.137)	(0.105)	(0.109)	(0.156)	(0.138)	(0.105)	(0.108)	(0.156)	(0.137)	(0.106)	(0.108)	(0.156)	(0.138)	(0.107)
Trailing PE to Growth	−0.003	−0.002	−0.010**	0.003	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003	−0.004	−0.002	−0.010***	0.003
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)
Forward PE to Long-term Growth	−0.001	−0.006	−0.005	0.014*	−0.001	−0.006	−0.006	0.014*	−0.001	−0.006	−0.006	0.014*	−0.001	−0.006	−0.006	0.014	−0.001	−0.006	−0.006	0.014
	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.009)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)	(0.012)	(0.023)	(0.008)	(0.009)
F Statistic	1.045	0.913	2.274***	1.676**	2.231***	1.358	3.688***	6.022***	1.127	0.763	1.863***	1.284	1.091	0.670	1.468*	1.319	0.885	0.620	1.346	1.195

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

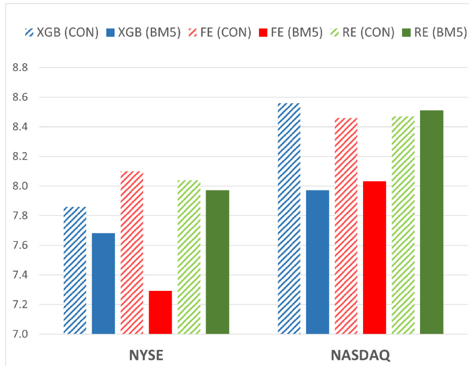

Fig. 4. Tot. ESG ratings predictions performance (avg. RMSE) from April 2017 to April 2019. Lower RMSE is better.

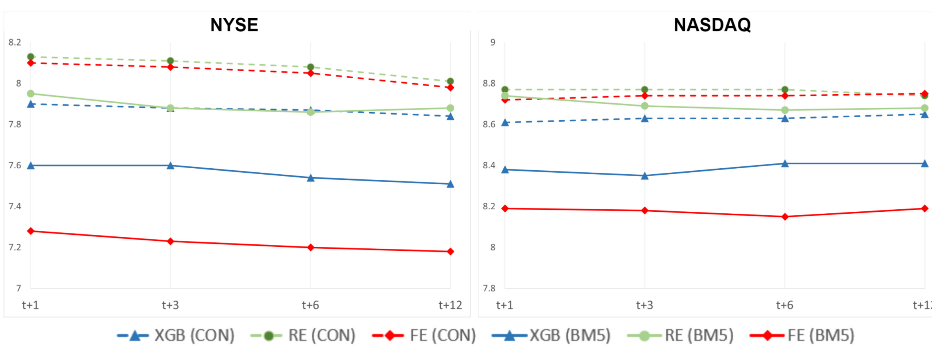

Fig. 5. Tot. ESG ratings prediction performance (avg. RMSE) at current time-step (t) and 3, 6, and 12 months in the future, i.e., $t + 3$ to $t + 12$ for XGB, RE, and FE models. Dotted lines for models with CON model specification; solid lines for models with BM5 model specification. Lower RMSE is better.

Varying the time-period: We evaluate Tot. ESG ratings predictions over a shorter time-period, from April 2017 to April 2019, instead of the March 2015 to April 2019 time-period covered in the prior sections. Figure 4 shows the performances of the models over this shorter time-period. We observe similar improvements in model performances for the BM5 model specification with network variables over the shorter time period.

Varying time horizons: With financial and network information at the current time-step (t), we further evaluate Tot. ESG ratings predictions 3, 6, and 12 months in the future, i.e., $t+3$ to $t+12$ for XGB, RE, and FE models. Figure 5 shows the performances of the models across the different time-steps. We observe similar improvements in model performances for the BM5 model specification with network variables over the different time-steps. Across all time-steps, we see that the BM5 model specification with network variables led to significant improvements in model performance compared to the model specification CON (i.e., with the subset of financial control variables only). We also observe a greater improvement in model performance on the NYSE dataset than the NASDAQ dataset. Interestingly, for the NYSE dataset, we observed better model performances for predictions that are further in the future, e.g., for the XGB(BM5) and FE(BM5) models, prediction performance at the $t + 12$ time-step is better than at the $t + 1$ time-step. This provides further evidence to support the informativeness of the variables selected.

Hence, based on the results of the analyses of the NYSE and NASDAQ datasets, as well as the robustness checks on a shorter and more recent two year time-period, and across different number of time-steps in the future, we are able to validate the key findings in this paper on the importance and usefulness of network variables for ESG rating predictions.

5 DISCUSSION AND CONCLUSION

Based on the results in this paper, we see that dynamic company networks contain rich information that can be utilized to significantly improve ESG rating prediction performance for both machine learning and econometric models. While the degree to which dynamic company network information can improve model performance depends on (i) the types of network variables selected, (ii) the type of ESG ratings to be predicted (i.e., total, environmental, social, or governance ratings), and (iii) the market (NYSE or NASDAQ) that the company is listed on, we find strong evidence from both machine learning and econometric perspectives that support the importance of network variables, particularly when compared to financial variables that had been utilized in past works [34, 44, 55]. We find that dynamic common director networks, as well as news event-based co-occurrence networks are the most important (based on multiple measures of feature importances), and statistically significant (based on robust standard errors of the fixed effects panel model estimation). The better performance of the network-based fixed effects panel models, when compared to the state-of-the-art XGBoost machine learning model, suggests the presence of strong individual (i.e., company) specific attributes that do not vary much across time. In addition, our paper extends past studies [34, 44, 55] that examined the use of financial information for predicting ESG ratings, and we show that models that utilize network information outperform models that only use financial information for predicting ESG ratings.

Regarding the external validity of the results, we studied companies listed on two major markets - NYSE and NASDAQ. As both markets are based in the US, the results may not be equally valid in other countries, e.g., Europe. However, this is mitigated by the leading role that the US plays in global capital markets, in ESG-related global forums, as well as continued efforts to harmonize ESG ratings globally [5]. With regards to internal validity, we examined the robustness of the results for a shorter and more recent two year time-period, and at different number of time-steps in the future. We find that results are equally valid under different time-periods and at different number of time-steps in the future. Interestingly, we find that the use of dynamic company network information can lead to better model performances for predictions that are further in the future, which implies that dynamic company network information can be utilized for forecasting ESG rating predictions.

As described in Section 1, our findings can help address key challenges involved in the current ESG ratings process, specifically the labor, time intensive, and non-transparent nature of the process [11]. Being able to predict ESG ratings from publicly available data that we used in this study can facilitate the work of ESG ratings analysts and improve the timeliness of ESG ratings. For investors and other market participants, being able to predict ESG ratings using publicly available data could improve accessibility by allowing them to evaluate ESG risks without having to wait for the ESG rating providers to issue their ratings, or to evaluate companies that are not covered by the ESG rating providers.

For future work, the effects of dynamic networks involving other entities, e.g., countries, other relationship-types, e.g., thematic relationships extracted from GKG, could be studied. The framework could also be extended to include other machine and deep learning methods that learn rich embeddings or representations of entities and relationships in the networks, e.g., using network embedding methods such as DeepWalk [69], or graph neural networks [54]. The effects of dynamic company networks on the ESG ratings of entities in other markets, e.g., in Europe or China, could also be an interesting future research topic.

APPENDIX

Table 1. All Financial Variables

No.	Financial Variables
1	**Mean** - mean of stock prices
2	**Std.** - standard deviation of stock prices
3	**Shillers Cyclically Adjusted PE Ratio** - gauge of stock value based on market price and earnings
4	**Book to Market** - book value relative to market value
5	**Enterprise Value Multiple** - total value (of equity, debt, and minority interests) relative to cash profits
6	**Price Operating Earnings Basic Excl EI.** - market price relative to operating earnings excluding extraordinary items
7	**Price Operating Earnings Diluted Excl EI.** - market price relative to operating earnings excluding extraordinary items with dilution (i.e., assuming convertible securities exercised)
8	**PE Diluted Excl EI.** - market price relative to earnings excluding extraordinary items with dilution
9	**PE Diluted Incl EI.** - market price relative to earnings including extraordinary items with dilution
10	**Price to Sales** - market price relative to sales revenues
11	**Price to Cash Flow** - market price relative to cash flows
12	**Dividend Payout Ratio** - dividends paid out relative to net income
13	**Net Profit Margin** - net profit relative to revenues
14	**Operating Profit Margin Before Depreciation** - operating profit margin before accounting for depreciation
15	**Operating Profit Margin After Depreciation** - operating profit margin after accounting for depreciation
16	**Gross Profit Margin** - revenue after accounting for cost of sales
17	**Pretax Profit Margin** - profit before accounting for taxes
18	**Cash Flow Margin** - cash flows relative to total sales revenue
19	**Return on Assets** - profitability relative to total assets
20	**Return on Equity** - profitability relative to equity
21	**Return on Capital Employed** - profitability relative to capital employed
22	**Effective Tax Rate** - total tax paid relative to pre-tax income
23	**After-tax Return on Average Common Equity** - profit after tax relative to average amount of equity over period
24	**After-tax Return on Invested Capital** - profit after tax relative to invested capital
25	**After-tax Return on Total Stockholders Equity** - profit after tax relative to total equity
26	**Pre-tax return on Net Operating Assets** - profit before tax relative to net operating assets
27	**Pre-tax Return on Total Earning Assets** - profit before tax relative to total earning assets
28	**Gross Profit to Total Assets** - gross profits relative to total assets
29	**Common Equity to Invested Capital** - common equity relative to invested capital (debt and equity)
30	**Long-term Debt to Invested Capital** - long-term (more than 12 months) debt relative to invested capital (debt and equity)
31	**Total Debt to Invested Capital** - total debt relative to invested capital (debt and equity)
32	**Capitalization Ratio** - level of debt in capital structure
33	**Interest Average to Long-term Debt** - average interest expense relative to long-term (more than 12 months) debt
34	**Interest Average to Total Debt** - average interest expense relative to total debt
35	**Cash Balance to Total Liabilities** - cash/cash equivalents relative to total liabilities
36	**Inventory to Current Assets** - inventory assets relative to all current assets
37	**Receivables to Current Assets** - receivable assets relative to all current assets
38	**Total Debt to Total Assets** - total debt relative to total assets
39	**Total Debt to EBITDA** - total debt relative to earnings before interest, taxes, depreciation and amortization
40	**Short-term Debt to Total Debt** - total short-term (12 months or less) debt relative to total assets

Table 2. All Financial Variables (Continued)

No.	Financial Variables
41	**Current Liabilities to Total Liabilities** - liabilities due in 12 months or less relative to total liabilities
42	**Long-term Debt to Total Liabilities** - debt due after 12 months relative to total liabilities
43	**Profit Before Depreciation to Current Liabilities** - profit before accounting for depreciation relative to liabilities due in 12 months or less
44	**Operating Cash Flow to Current Liabilities** - operating cash flows relative to liabilities due in 12 months or less
45	**Cash Flow to Total Debt** - cash flows relative to total liabilities
46	**Free Cash Flow to Operating Cash Flow** - cash flows net of operating and capital expenditures relative to operating cash flows
47	**Total Liabilities to Total Tangible Assets** - total liabilities relative to total physical assets
48	**Long-term Debt to Book Equity** - total long-term (more than 12 months) debt relative to equity
49	**Total Debt to Total Assets** - total debt relative to total assets
50	**Total Debt to Capital** - total debt relative to total capitalization
51	**Total Debt to Equity** - total debt relative to total equity
52	**After-tax Interest Coverage** - ability to pay interest on debt based on earnings after tax
53	**Interest Coverage Ratio** - ability to pay interest on debt based on earnings before tax
54	**Cash Ratio** - ability to meet short-term (12 months or less) obligations using cash/cash equivalents
55	**Quick Ratio Acid Test** - ability to pay short-term (12 months or less) obligations with liquid assets
56	**Current Ratio** - ability to pay short-term (12 months or less) obligations
57	**Cash Conversion Cycle Days** - number of days to convert cash spent on inventory back into cash via sales
58	**Inventory Turnover** - cost of goods sold relative to average inventory value over period
59	**Asset Turnover** - total sales relative to average assets over period
60	**Receivables Turnover** - number of times receivables converted to cash over period
61	**Payables Turnover** - number of times accounts payable paid off over period
62	**Sales to Invested Capital** - amount of sales relative to invested capital
63	**Sales to Stockholders Equity** - amount of sales relative to equity
64	**Sales to Working Capital** - amount of sales relative to working capital
65	**Research and Development to Sales** - research and development expenditure relative to sales
66	**Advertising Expenses to Sales** - advertising expenditure relative to sales
67	**Labor Expenses to Sales** - labor expenditure relative to sales
68	**Accruals to Average Assets** - accruals (revenue or expenses earned or incurred but not received or paid) relative to average assets over period
69	**Price to Book**- market price relative to book value of equity
70	**Trailing PE to Growth** - market price relative to past year's earnings divided by growth rate of earnings over period
71	**Dividend Yield** - dividends paid out relative to market price
72	**Forward PE to 1 year Growth** - market price relative to forecasted earnings divided by expected rate of earnings over 1 year period
73	**Forward PE to Long-term Growth** - market price relative to forecasted earnings divided by expected long-term rate of earnings

Table 3. VIFs of Dir.Net Variable of Interest and Key Financial Control Variables for NYSE

	dir_centrality	dir_closeness_centrality	dir_eigenvector	dir_betweenness	dir_pagerank
Network Variable of Interest	1.04	1.06	1.02	1.02	1.05
Std.	1.03	1.05	1.02	1.02	1.04
Book to Market	1.02	1.02	1.02	1.02	1.02
PE Diluted Incl EI.	1.11	1.11	1.11	1.11	1.11
Price to Sales	1.22	1.22	1.22	1.22	1.22
Operating Profit Margin Before Depreciation	1.01	1.01	1.01	1.01	1.01
After-tax Return on Invested Capital	1.02	1.02	1.02	1.02	1.02
Interest Average to Long-term Debt	1.02	1.02	1.02	1.02	1.02
Cash Balance to Total Liabilities	1.10	1.10	1.10	1.10	1.10
Inventory to Current Assets	1.09	1.09	1.09	1.09	1.09
Short-term Debt to Total Debt	1.02	1.02	1.02	1.02	1.02
Long-term Debt to Total Liabilities	1.05	1.05	1.05	1.05	1.05
Total Debt to Total Assets	1.28	1.28	1.28	1.28	1.28
Total Debt to Capital	1.28	1.28	1.28	1.28	1.28
Interest Coverage Ratio	1.02	1.02	1.02	1.02	1.02
Current Ratio	1.20	1.20	1.20	1.20	1.20
Cash Conversion Cycle Days	1.00	1.00	1.00	1.00	1.00
Payables Turnover	1.01	1.01	1.01	1.01	1.01
Research and Development to Sales	1.04	1.04	1.04	1.04	1.04
Labor Expenses to Sales	1.00	1.00	1.00	1.00	1.00
Price to Book	1.04	1.04	1.04	1.04	1.04
Trailing PE to Growth	1.03	1.03	1.03	1.03	1.03
Dividend Yield	1.18	1.18	1.18	1.18	1.18
Forward PE to 1 year Growth	1.02	1.02	1.02	1.02	1.02
Forward PE to Long-term Growth	1.10	1.10	1.10	1.10	1.10

Table 4. VIFs of MF.Net Variable of Interest and Key Financial Control Variables for NYSE

	mf_centrality	mf_closeness_centrality	mf_eigenvector	mf_betweenness	mf_pagerank
Network Variable of Interest	1.01	1.01	1.01	1.00	1.03
Std.	1.01	1.01	1.01	1.01	1.02
Book to Market	1.02	1.02	1.02	1.02	1.02
PE Diluted Incl EI.	1.11	1.11	1.11	1.11	1.11
Price to Sales	1.22	1.22	1.22	1.22	1.22
Operating Profit Margin Before Depreciation	1.01	1.01	1.01	1.01	1.01
After-tax Return on Invested Capital	1.02	1.02	1.02	1.02	1.02
Interest Average to Long-term Debt	1.02	1.02	1.02	1.02	1.02
Cash Balance to Total Liabilities	1.10	1.10	1.10	1.10	1.10
Inventory to Current Assets	1.09	1.09	1.09	1.09	1.09
Short-term Debt to Total Debt	1.02	1.02	1.02	1.02	1.02
Long-term Debt to Total Liabilities	1.05	1.05	1.05	1.05	1.05
Total Debt to Total Assets	1.28	1.28	1.28	1.28	1.28
Total Debt to Capital	1.28	1.28	1.28	1.28	1.28
Interest Coverage Ratio	1.02	1.02	1.02	1.02	1.02
Current Ratio	1.20	1.20	1.20	1.20	1.20
Cash Conversion Cycle Days	1.00	1.00	1.00	1.00	1.00
Payables Turnover	1.01	1.01	1.01	1.01	1.01
Research and Development to Sales	1.04	1.04	1.04	1.04	1.04
Labor Expenses to Sales	1.00	1.00	1.00	1.00	1.00
Price to Book	1.04	1.04	1.04	1.04	1.04
Trailing PE to Growth	1.03	1.03	1.03	1.03	1.03
Dividend Yield	1.17	1.17	1.17	1.17	1.17
Forward PE to 1 year Growth	1.02	1.02	1.02	1.02	1.02
Forward PE to Long-term Growth	1.10	1.10	1.10	1.10	1.10

Table 5. VIFs of GKG.Net Variable of Interest and Key Financial Control Variables for NYSE

	gkg_centrality	gkg_closeness_centrality	gkg_eigenvector	gkg_betweenness	gkg_pagerank
Network Variable of Interest	1.03	1.08	1.00	1.02	1.01
Std.	1.03	1.07	1.01	1.02	1.01
Book to Market	1.02	1.02	1.02	1.02	1.02
PE Diluted Incl EI.	1.11	1.11	1.11	1.11	1.11
Price to Sales	1.22	1.22	1.22	1.22	1.22
Operating Profit Margin Before Depreciation	1.01	1.01	1.01	1.01	1.01
After-tax Return on Invested Capital	1.02	1.02	1.02	1.02	1.02
Interest Average to Long-term Debt	1.02	1.02	1.02	1.02	1.02
Cash Balance to Total Liabilities	1.10	1.10	1.10	1.10	1.10
Inventory to Current Assets	1.09	1.09	1.09	1.09	1.09
Short-term Debt to Total Debt	1.02	1.02	1.02	1.02	1.02
Long-term Debt to Total Liabilities	1.05	1.05	1.05	1.05	1.05
Total Debt to Total Assets	1.28	1.28	1.28	1.28	1.28
Total Debt to Capital	1.28	1.28	1.28	1.28	1.28
Interest Coverage Ratio	1.02	1.02	1.02	1.02	1.02
Current Ratio	1.20	1.20	1.20	1.20	1.20
Cash Conversion Cycle Days	1.00	1.00	1.00	1.00	1.00
Payables Turnover	1.01	1.01	1.01	1.01	1.01
Research and Development to Sales	1.04	1.04	1.04	1.04	1.04
Labor Expenses to Sales	1.00	1.00	1.00	1.00	1.00
Price to Book	1.04	1.04	1.04	1.04	1.04
Trailing PE to Growth	1.03	1.03	1.03	1.03	1.03
Dividend Yield	1.17	1.18	1.17	1.18	1.17
Forward PE to 1 year Growth	1.02	1.02	1.02	1.02	1.02
Forward PE to Long-term Growth	1.10	1.10	1.10	1.10	1.10

Table 6. VIFs of Dir.Net Variable of Interest and Key Financial Control Variables for NASDAQ

	dir_centrality	dir_closeness_centrality	dir_eigenvector	dir_betweenness	dir_pagerank
Network Variable of Interest	1.15	1.27	1.02	1.07	1.22
Std.	1.17	1.29	1.05	1.10	1.24
Book to Market	1.06	1.06	1.06	1.06	1.06
PE Diluted Incl EI.	1.06	1.06	1.06	1.06	1.06
Price to Sales	1.36	1.36	1.36	1.36	1.36
Operating Profit Margin Before Depreciation	1.00	1.00	1.00	1.00	1.00
After-tax Return on Invested Capital	1.02	1.02	1.02	1.02	1.02
Interest Average to Long-term Debt	1.01	1.01	1.01	1.01	1.01
Cash Balance to Total Liabilities	1.19	1.19	1.19	1.19	1.19
Inventory to Current Assets	1.13	1.13	1.13	1.13	1.13
Short-term Debt to Total Debt	1.01	1.01	1.01	1.01	1.01
Long-term Debt to Total Liabilities	1.02	1.02	1.02	1.02	1.02
Total Debt to Total Assets	1.29	1.29	1.29	1.29	1.29
Total Debt to Capital	1.19	1.19	1.19	1.19	1.19
Interest Coverage Ratio	1.02	1.02	1.02	1.02	1.02
Current Ratio	1.14	1.14	1.14	1.14	1.14
Cash Conversion Cycle Days	1.01	1.01	1.01	1.01	1.01
Payables Turnover	1.02	1.02	1.02	1.02	1.02
Research and Development to Sales	1.07	1.07	1.07	1.07	1.07
Labor Expenses to Sales	1.09	1.09	1.09	1.09	1.09
Price to Book	1.30	1.30	1.30	1.30	1.30
Trailing PE to Growth	1.01	1.01	1.00	1.00	1.01
Dividend Yield	1.13	1.13	1.13	1.13	1.13
Forward PE to 1 year Growth	1.00	1.00	1.00	1.00	1.00
Forward PE to Long-term Growth	1.02	1.02	1.02	1.02	1.02

Table 7. VIFs of MF.Net Variable of Interest and Key Financial Control Variables for NASDAQ

	mf_centrality	mf_closeness_centrality	mf_eigenvector	mf_betweenness	mf_pagerank
Network Variable of Interest	1.03	1.05	1.02	1.01	1.12
Std.	1.06	1.07	1.05	1.04	1.15
Book to Market	1.06	1.06	1.06	1.06	1.06
PE Diluted Incl EI.	1.06	1.06	1.06	1.06	1.06
Price to Sales	1.36	1.36	1.36	1.36	1.36
Operating Profit Margin Before Depreciation	1.00	1.00	1.00	1.00	1.00
After-tax Return on Invested Capital	1.02	1.02	1.02	1.02	1.02
Interest Average to Long-term Debt	1.01	1.01	1.01	1.01	1.01
Cash Balance to Total Liabilities	1.19	1.19	1.19	1.19	1.19
Inventory to Current Assets	1.13	1.13	1.13	1.13	1.13
Short-term Debt to Total Debt	1.01	1.01	1.01	1.01	1.01
Long-term Debt to Total Liabilities	1.02	1.02	1.02	1.02	1.02
Total Debt to Total Assets	1.29	1.29	1.29	1.29	1.29
Total Debt to Capital	1.19	1.19	1.19	1.19	1.19
Interest Coverage Ratio	1.02	1.02	1.02	1.02	1.02
Current Ratio	1.14	1.14	1.14	1.14	1.14
Cash Conversion Cycle Days	1.01	1.01	1.01	1.01	1.01
Payables Turnover	1.02	1.02	1.02	1.02	1.02
Research and Development to Sales	1.07	1.07	1.07	1.07	1.07
Labor Expenses to Sales	1.09	1.09	1.09	1.09	1.09
Price to Book	1.30	1.30	1.30	1.30	1.30
Trailing PE to Growth	1.00	1.00	1.00	1.00	1.00
Dividend Yield	1.13	1.13	1.13	1.13	1.13
Forward PE to 1 year Growth	1.00	1.00	1.00	1.00	1.00
Forward PE to Long-term Growth	1.02	1.02	1.02	1.02	1.02

Table 8. VIFs of GKG.Net Variable of Interest and Key Financial Control Variables for NASDAQ

	gkg_centrality	gkg_closeness_centrality	gkg_eigenvector	gkg_betweenness	gkg_pagerank
Network Variable of Interest	1.18	1.46	1.01	1.08	1.02
Std.	1.21	1.48	1.04	1.10	1.05
Book to Market	1.06	1.06	1.06	1.06	1.06
PE Diluted Incl EI.	1.06	1.06	1.06	1.06	1.06
Price to Sales	1.36	1.36	1.36	1.36	1.36
Operating Profit Margin Before Depreciation	1.00	1.00	1.00	1.00	1.00
After-tax Return on Invested Capital	1.02	1.02	1.02	1.02	1.02
Interest Average to Long-term Debt	1.01	1.01	1.01	1.01	1.01
Cash Balance to Total Liabilities	1.19	1.19	1.19	1.19	1.19
Inventory to Current Assets	1.13	1.13	1.13	1.13	1.13
Short-term Debt to Total Debt	1.01	1.01	1.01	1.01	1.01
Long-term Debt to Total Liabilities	1.02	1.02	1.02	1.02	1.02
Total Debt to Total Assets	1.29	1.29	1.29	1.29	1.29
Total Debt to Capital	1.19	1.19	1.19	1.19	1.19
Interest Coverage Ratio	1.02	1.02	1.02	1.02	1.02
Current Ratio	1.14	1.14	1.14	1.14	1.14
Cash Conversion Cycle Days	1.01	1.01	1.01	1.01	1.01
Payables Turnover	1.02	1.02	1.02	1.02	1.02
Research and Development to Sales	1.07	1.07	1.07	1.07	1.07
Labor Expenses to Sales	1.09	1.09	1.09	1.09	1.09
Price to Book	1.30	1.30	1.30	1.30	1.30
Trailing PE to Growth	1.00	1.01	1.00	1.00	1.00
Dividend Yield	1.13	1.13	1.13	1.13	1.13
Forward PE to 1 year Growth	1.00	1.00	1.00	1.00	1.00
Forward PE to Long-term Growth	1.02	1.02	1.02	1.02	1.02

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