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ESG ratings and portfolio Selection: A network approach

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Abstract

This thesis explores the role of Environmental, Social, and Corporate Governance (ESG) ratings in portfolio selection and investigates the connectivity patterns of institutions based on ESG classes. The study addresses the gap in understanding the relationship between ESG ratings and stock returns/volatility. ESG scores are extracted from Bloomberg, categorizing companies into four ESG classes. The thesis employs a multilayer network analysis and constructs different investment strategies. The findings suggest that ESG scores play a limited role in connectivity patterns in the volatility network. The relevance of ESG scores in portfolio selection depends on the complexity of the network structure and the investor's risk tolerance. The proposed ESG portfolio strategies underperform compared to traditional Markowitz. This thesis contributes to understanding the complexities and trade-offs involved in incorporating ESG information in investment decision-making.

Keywords: ESG scores, Connectedness, Multilayer networks, Portfolio optimization.

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CHAPTER 1

Introduction

In recent years, there has been growing interest in Environmental, social, and corporate governance (ESG) based investments in the financial industry. ESG ratings provide a standardized framework for evaluating companies' sustainability performance, taking into account their environmental impact, social responsibility, and governance practices. In 2016, over 190 countries created the Paris Agreement which is a major ESG initiative to reduce carbon emissions and limit the global temperature increase. This initiative has led to numerous research which seeks to study the impact of the Paris Agreement on assets' financial performance and how to integrate carbon risk into financial products Agliardi et al. (2023).

A few such research has explored the impact of ESG ratings on financial performance, including the work of Engelhardt et al. (2021) who provided evidence that European firms with high ESG ratings exhibited higher abnormal returns and lower stock volatility amid the COVID-19 crisis. However, there is still a gap in understanding the intricate relationship between ESG ratings and stock returns or volatility. For instance, La Torre et al. (2020) investigated how ESG components affect the stock returns of companies in the Eurostoxx50 index and found no significant evidence supporting this claim. The study's findings indicated that the performance of Eurostoxx50 companies appeared unaffected by their ESG commitments. Likewise, Shanaev and Ghimire (2022) demonstrated that high ESG ratings do not necessarily correspond to high stock returns. Instead, they found that ESG rating upgrades were associated with positive abnormal returns of approximately 0.5% per month, albeit inconsistently significant.

One of the interesting lines of research that extend from the Paris Agreement is analyzing the role of ESG scores on portfolio selection. It is known that investors play a vital role in the objectives of the Paris Agreement based on their investment and portfolio selection strategies. An investor is more likely to invest in sustainable companies or investments if it is profitable. The work of Zehir and Aybars (2020) showed that ESG ratings or SRI investments plays no significant role in portfolio performance, while Cesarone et al. (2022) on the other hand showed that ESG investments became more profitable after the introduction of the Paris Agreement in 2016. This thesis seeks to investigate the role of ESG ratings or ESG scores on portfolio selection using network analysis.

There have been some concerns about how to evaluate the ESG performance of companies and this has led to a significant increase in the availability of non-financial data on ESG factors. Li and Polychronopoulos (2020) explains that there are as many as 70 different providers of ESG rating scores as of 2019. This also has raised issues about the ambiguity and discrepancies among ESG scores as a measure of ESG performance. A general principle adopted is that firms receive high ESG scores for exhibiting ESG-responsible behavior, while low scores are given for insufficient adherence to ESG standards. In this thesis, ESG scores of companies are extracted from Bloomberg in which we categorize companies into four main ESG classes (A, B, C, and D) with A representing the high ESG class and D low ESG class.

The purpose of this thesis is in two folds. (1) We aim to investigate the connectivity patterns of institutions in different ESG classes or categories. A pairwise granger dynamic multilayer network is extracted for both the daily returns and volatility of companies in the S&P 100. We analyze the multilayer network by studying the intra-layer connectedness which represents the connectivity patterns of companies belonging to a specific ESG class. Our analysis showed that companies in the High ESG class exhibit higher levels of connectivity and represent the central nodes or stocks in the financial market in terms of returns. However, the finding also showed that ESG scores play little role in the connectivity patterns of companies in the volatility network, signifying that ESG scores may be irrelevant in risk patterns in the financial system and even during the COVID crisis.

(2) Secondly, the thesis seeks to investigate the role of ESG scores on portfolio selection and to analyze the performance of our investment strategies. For this analysis, we construct four indexes, with each index representing an ESG class. These indexes are constructed using the network centrality measure of the company and the returns of that company in a particular ESG class. Different investment strategies are constructed based on the kind of network information we choose to incorporate into the portfolio optimization problem. The three main investment strategies include (1) *Simple Network Markowitz (NM)* strategy, (2) *Complex Network Markowitz with risk aversion parameter strategy* and (3) *Complex Network Markowitz with inter-layer connectivity as trading*

signals (NTS). Our optimal Portfolio allocation shows that the role and relevance of ESG scores in portfolio selection depend on the complexity of the network structure we incorporate into the Portfolio Optimization problem. This means that in the case where we only use simple network structure or no network information, ESG scores are vital in portfolio selection. However when we incorporate the complex network structure into the portfolio optimization, then the relevance of the ESG scores in portfolio selection depends on the risk tolerance of the investor. The more risk-averse the investor is, the more he diversifies his asset overall class of ESG and so ESG ratings are irrelevant.

The performance of these strategies is compared with other corporate investment strategies where we do not factor in ESG information. The out-of-sample performance shows traditional investment strategies such as Markowitz performs better than the proposed ESG portfolio strategies. The thesis is structured as follows. Chapter 2 provides a detailed review of network theory, multilayer networks, and the methodology behind how we extract our multilayer network. Chapter 3 discusses the model for portfolio construction and the application of network connectivity on portfolio construction. Chapter 4 discusses the data, the connectivity patterns of the ESG class, the ESG investment strategies, and the performances of these strategies. Finally, Chapter 5 concludes.

CHAPTER 2

Network Analysis

2.1 Network Theory

A network is a group of points (known as nodes) connected by lines (edges) Newman (2010). A network is a tool used to study the relationship between objects. Network theory or graph theory has been applied in various fields such as biology, computer science, sociology, transportation, and many more. In the last few years, there has been a growing interest in the application of networks in economics and finance for studying pairwise relationships between financial assets and depicting patterns or features of a market or an economy Tsankov (2021).

Definition 1. *A Graph is defined as the ordered pair of sets $G = (V, E)$, where $V = \{1, 2, ..., n\}$ is the set of vertices or nodes and $E \subset V \times V$ the set of edges or links.*

A network or a graph can be directed or undirected. The former is when an edge has a source node and a target node that is, the edge points from one node to another. The latter on the other hand is when there is no specific direction assigned to edges, meaning that going from node i to node j is indistinguishable from going from node j to node i. A network can be presented by a matrix known as the Adjacency matrix defined as :

$$A_{ij} = \begin{cases} 1 & \text{if} \quad (i,j) \in E \\ 0 & otherwise \end{cases}$$

with $i, j \in V$. We do not allow self-loops in the network i.e. $(i, i) \notin E, i \in V$. If A_{ij} is symmetric then the graph is undirected, otherwise, it is directed. In this thesis we will represent a network as an Adjacency matrix and all the network measures will be expressed in terms of the Adjacency matrix.

2.1.1 Multilayer Network

A multilayer network is a type of network used to study the relationships between complex systems or systems with multiple relationships. A multilayer network usually involves a collection of networks and the relationships that exist between these networks. Similar to a regular network or graph, a multilayer network comprises a set of nodes (V). However, unlike a single-layer network, multilayer networks require multiple sets of layers to account for the diverse aspects they encompass.

Definition 2. *A multilayer network is represented as $\mathcal{M} = (\mathcal{G}, \mathcal{C})$, where $\mathcal{G} = \{\mathbf{G}_\alpha; \alpha \in \{1, ..., M\}\}$ denotes a collection of graphs $\mathbf{G}_\alpha = (V_\alpha, E_\alpha)$ (called the layers of $\mathcal{M}$), referred to as the layers of $\mathcal{M}$. These graphs can be either directed or undirected, and weighted or unweighted. The set*

$$\mathcal{C} = \{E_{\alpha\beta} \subseteq V_\alpha \times V_\beta; \alpha, \beta \in \{1, ..., M\}, \alpha \neq \beta$$

represents the interconnections between nodes in different layers $\mathbf{G}_\alpha$ and $\mathbf{G}_\beta$ (where $\alpha \neq \beta$). The interconnections between layers are known as crossed layers, while the connections within each layer E_α are referred to as intralayer connections. This description is based on Boccaletti et al. (2014).

We denote the set of nodes in each layer $\mathbf{G}_\alpha$ as $V_\alpha = \{v_1^\alpha, .., v_{N_\alpha}^\alpha\}$ and the adjacency matrix of each layer $\mathbf{G}_\alpha$ will be denoted as $A^{[\alpha]} = (a_{ij}^\alpha) \in \mathbb{R}^{N_\alpha \times N_\alpha}$, where

$$a_{ij}^\alpha = \begin{cases} 1 & if \quad (v_i^\alpha, v_j^\alpha) \in E_\alpha \\ 0 & otherwise \end{cases}$$

for $1 \leq i, j \leq N_\alpha$ and $1 \leq \alpha \leq M$. The interlayer adjacency matrix corresponding to $E_{\alpha\beta}$ is the matrix $A^{[\alpha,\beta]} = (a_{ij}^{\alpha\beta}) \in \mathbb{R}^{N_\alpha \times N_\beta}$, given by

$$a_{ij}^{\alpha\beta} = \begin{cases} 1 & if \quad (v_i^\alpha, v_j^\beta) \in E_{\alpha\beta} \\ 0 & otherwise \end{cases}$$

Now the projection network of $\mathcal{M}$ is the graph $proj(\mathcal{M}) = (V_\mathcal{M}, E_\mathcal{M})$, where

$$V_\mathcal{M} = \bigcup_{\alpha=1}^{M} V_\alpha, \quad E_\mathcal{M} = \left(\bigcup_{\alpha=1}^{M} E_\alpha\right) \bigcup \left(\bigcup_{\alpha,\beta=1}^{M} E_{\alpha\beta}\right).$$

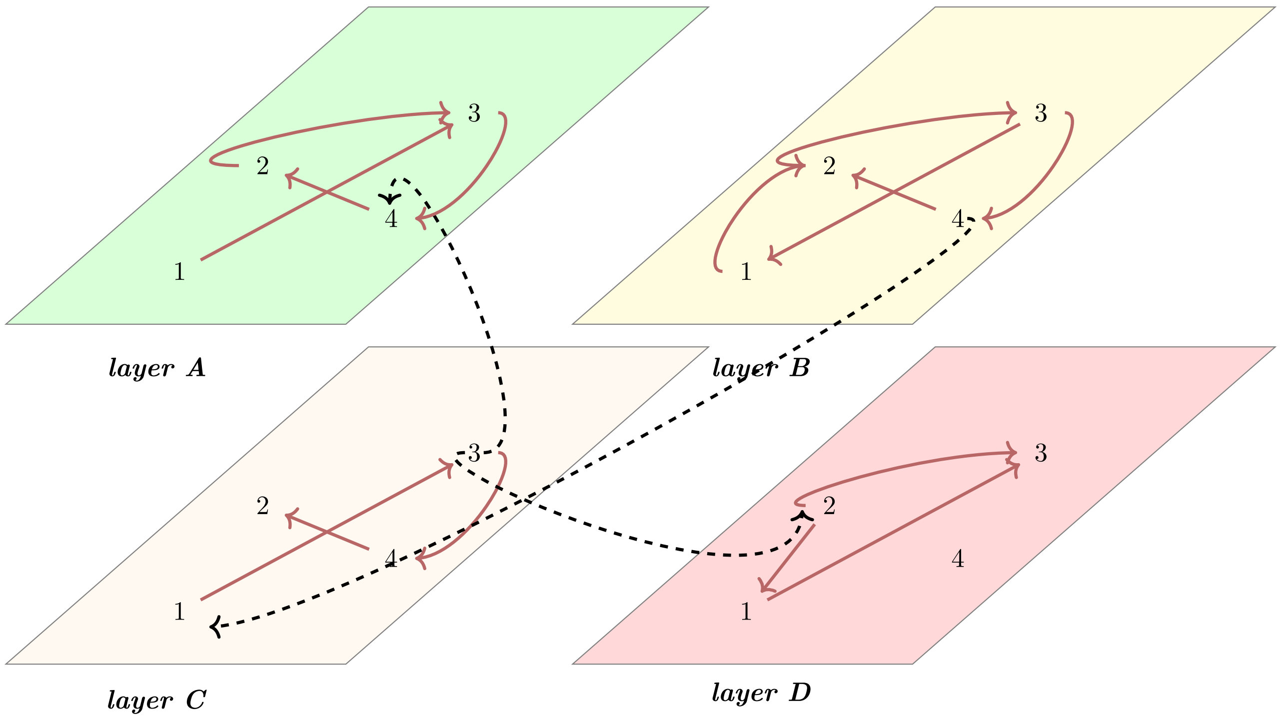


Figure 2.1: Example of a Multilayer Network

Figure 2.1 represent a diagrammatic example of a multilayer network with four layers. The red arrows represent the intra-layer connections within each layer while the dashed black arrows represent the inter-layer connections moving from nodes in one layer to other nodes in another layer. This network allows us to study the multiple relationships within a system in which we observe connections within layers and between layers.

2.1.2 Temporal Networks

We have assumed that networks are static up to this point, and this assumption fails to capture the changing relationships between objects over time. To address the constraints of static network models, we study temporal networks or time-varying networks, which allow us to investigate how objects interact over time and how the network structure responds and even changes over time. We will be able to watch how the network's nodes and edges evolve over time, which is known as node dynamics and edge dynamics.

Definition 3. *A temporal network (or time-varying network) $\mathcal{G}$ is a collection of networks $\mathcal{G} = (G_t)_t = (V, E_t)_t$ for each time $t = 1,...,T$. The network connectivity at time $t = 1,...,T$ can be* *represented by an Adjacency matrix* A_{ij}^t

$$A_{ij}^t = \begin{cases} 1 & if \quad \{i,j\} \in E_t \\ 0 & otherwise \end{cases}$$

We explore the dynamics of the network across time, which includes two major forms known as Edge dynamics and Vertex dynamics

1. Edge dynamics regards the evolution of the connections between nodes in a network. In this type of dynamics, the network's edges change, such as the creation, deletion, or rewiring of a connection, while the nodes remain constant. Consider figure 2.2 , with the nodes fixed over time, we can observe how new edges are formed in time t = 2, and how edges are also deleted and rewired at t = 3 and so on.

2. Vertex dynamics, on the other hand, focus on the changes that occur within the individual entities (or nodes) of a network. This type of dynamics involves changes in the attributes, states, or characteristics of the nodes themselves, while the edges remain unchanged. Figure 2.2 shows the node dynamics over time. Note that the node dynamics automatically implies edge dynamics since the introduction of a new node can lead to the rewiring of the network if the new node is important.

In this thesis, we extract a dynamic multilayer network, that enables us to capture and study the

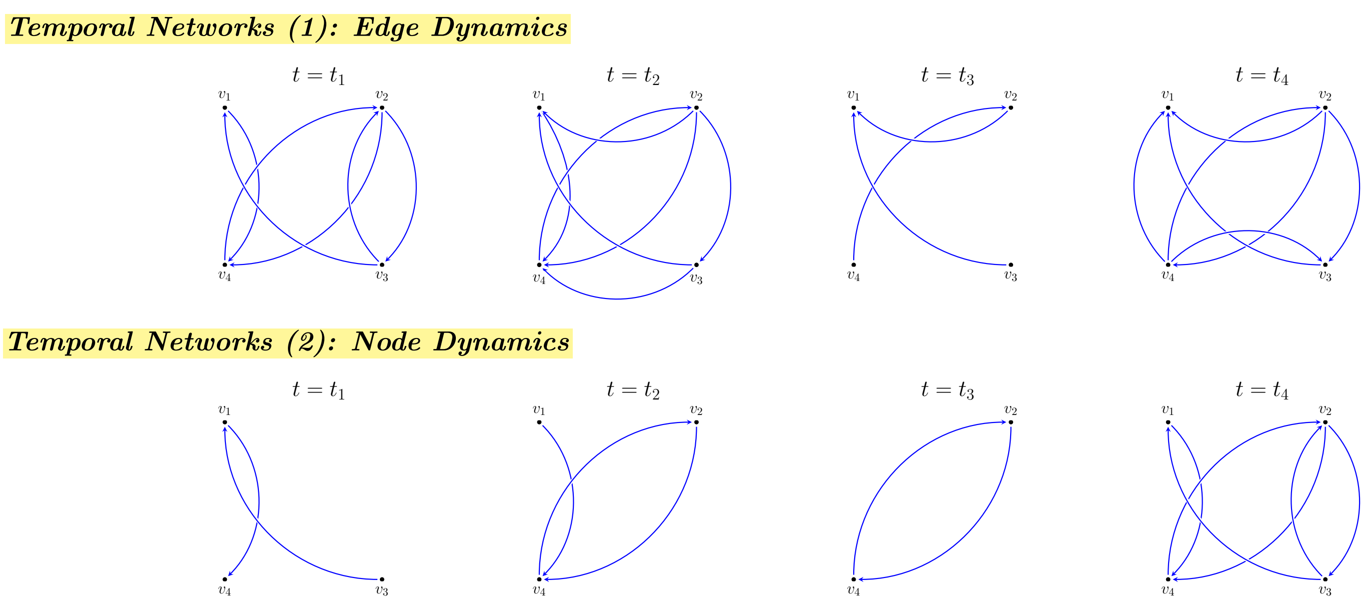


Figure 2.2: Node dynamics and Edge dynamics of a temporal network.

complexity of the network over time. Our approach to constructing the multilayer network involves four layers of networks, each representing the intra-relationship between institutions of the same ESG class. The network is extracted using a rolling window estimation to capture the time-varying relationships between the layers and within each layer. Because an institution representing a node can change from one ESG class to another at each time t, involving both the creation and deletion of a node within ESG classes, we can examine both node and edge dynamics. Additionally, the rewiring, addition, or deletion of edges in the network is a direct result of node dynamics, which also influences edge dynamics.

2.2 Financial Network Extraction methods

In economics, networks are essential for comprehending the relationships and interdependencies between different economic units. The fact that these networks cannot be directly observed, however, presents a problem for researchers and analysts. To Overcome these limitations, specific techniques have been created to extract financial networks from accessible data sources using econometric tools. Researchers have demonstrated a strong interest in the extraction of unobserved networks from time series data in the field of finance. This topic has gained attention from various scholars, including Billio et al. (2012) and Diebold and Yılmaz (2014). Other researchers such as the work of Barigozzi and Brownlees (2019) and Bräuning and Koopman (2020) also proposed different methodologies in estimating financial networks from time-series returns of firms.

Most networks extracted for financial series study are correlation-based networks where the relationships between the objects are based on the correlation coefficient between these two objects. Assume N assets and a correlation matrix **C** of returns represent the Adjacency matrix given as:

$$\mathbf{C} = \begin{cases} \rho_{ij} & for \quad i \neq j \\ 0 & if \quad i = j \end{cases}$$

Correlation networks are fully connected networks and this makes it difficult to analyze such a network. This limitation can however be solved by filtration techniques which remove the noise from the correlation matrix and create a more parsimonious representation of the network using statistical tools Vỳrost et al. (2015). There are two main filtering methods adopted by researchers to identify important linkages in a correlation-based network. This includes:

Hierarchical methods comprising of the minimum spanning trees(MST) and Planar maximally-filtered graph (PMFG) algorithms, as discussed in Mantegna (1999) and Tumminello et al. (2005) respectively. The PMFG method generates a planar graph by iteratively adding the most significant edges while assuring that the resulting graph remains planar (no edges intersect). The MST approach builds a tree-like structure that connects all nodes in the network while minimizing the total sum of edge weights.

Threshold methods : With threshold approaches, a threshold is defined that specifies the minimal correlation value necessary for an edge to be deemed significant. Below this point, the network's edges are eliminated, creating a sparser one with stronger connections. The threshold can occasionally change, and statistical techniques are used to determine it.

According to Vỳrost et al. (2015), The primary drawback of hierarchical approaches is the lack of an economic or statistical basis for the topological limitations on these networks. The threshold approach, on the other hand, involves the selection of a crucial value (the threshold) for which edges in the network are kept, and this value is chosen carefully using statistical validation techniques. However, correlation does not imply causality, so correlation networks are not suitable to study causal relationships but rather employed to simulate undirected networks.

There are many network extraction techniques that capture the causal relationships between economic entities in order to get around the limitations of correlation-based networks, including Vector Autoregression (VAR) models, Bayesian Networks or Graphical Networks, Dynamic Conditional Correlation (DCC) models, Sims Causality approach, and many others. However, to extract causal network linkages between financial entities in this thesis, we use the Pairwise Granger Causality approach.

2.2.1 Pairwise and conditional Granger causality network

Following Billio et al. (2012), we extract the network of returns and volatility using a pairwise Granger causality test between two institutions. Consider a bivariate vector autoregressive (VAR) model of order one;

$$\begin{cases} y_{it} = \rho_{10} + \rho_{11} y_{it-1} + \rho_{12} y_{jt-1} + \epsilon_{it} \\ y_{jt} = \rho_{20} + \rho_{21} y_{it-1} + \rho_{22} y_{jt-1} + \epsilon_{jt} \end{cases} \tag{2.1}$$

$\forall i, j = 1, ..., n, i \neq j$, where ϵ_{it} and ϵ_{jt} are uncorrelated white noise processes. According to Granger (1969), a time series y_j is said to "Granger-cause" y_i if past values of y_j contain information that helps predict y_i above and beyond the information contained in past values of y_i alone. This definition enables us to extract a network of returns and volatilities such that if y_j granger causes y_i then there is a link or an edge from node j to i. Following VAR model definition in equation 2.1, the condition for the Granger causality between any pair of y_i and y_j is given as:

- if $\rho_{12} \neq 0$ and $\rho_{21} = 0$, then y_{jt} granger causes y_{it} and $a_{ji} = 1$;

- if $\rho_{12} = 0$ and $\rho_{21} \neq 0$, then y_{it} granger causes y_{jt} and $a_{ij} = 1$;
- if $\rho_{12} \neq 0$ and $\rho_{21} \neq 0$, then there is a feedback relationship among y_{it} and y_{jt} and $a_{ij} = a_{ji} = 1$; where a_{ij} is the element in the i_{th} row and j_{th} column of the adjacency matrix A.

As we mentioned before, to understand the dynamic interrelationships between any two institutions, we extract the dynamic pairwise Granger causality network. This is done by estimating the VAR model in a rolling window estimation, enabling us to obtain snapshots of the network over time. In this research, we consider a window size of 260 trading days, and a timestep of 20 days to estimate the VAR model. This is the general approach in which we extract the network. To build the Multilayer network of returns and volatilities, we follow the procedure below:

Step 1 : Following the VAR model in equation 2.1, we estimate the model in a rolling window estimation for return time series and volatility time series of 85 firms in the S&P 100. The pairwise Granger causality test is performed and we obtain 80 time-varying networks of returns and 80 time-varying networks of volatilities.

Step 2 Using a quantile threshold, we categorize the institutions in the S&P 100 into four main classes based on the average yearly ESG rating score of each firm. This is done in according to the rolling window estimation, which means that the class a company falls into at time t might change in time t+1. So if the average ESG rating of the company i (in a time window) is less or equal to the p^{th} percentile of all the averages, then the company is given a category. For instance if $E\bar{S}G_i \leq 25^{th}$ percentile, then company i falls in group D.

Step 3 Using the *Step 1* and *Step 2*, extract the time-varying networks of returns and volatilities for each ESG class in a rolling window estimation. This gives us 320 networks of returns and 320 networks of volatilities. In total, we have 640 networks just to study the intra-relationships between institutions in ESG classes. Adding to the networks extracted in *Step 1*, we obtain a total of 800 networks to analyze. At this stage we have a multiplex networks where each layer represents the ESG class and the relationship between companies in the ESG class represents the intra-relationship of the multiplex. The next step is to observe the relationships between companies from one layer (ESG class) to another layer. This is known as the inter-layer connectivity of the network. Observing the inter-layer connectivity implies we move from a multiplex to a multilayer network.

Step 4 To observe the interconnection between layers, we project the category network to a new network we call the ESG network. This network is represented by four nodes where the nodes are the ESG categories A, B, C, and D. The edges in the network represent the interconnections between each category. So this is extracted by counting the number of connections moving from companies in category u to companies in category v. This new network is a weighted directed network where the weights represent the number of connections and the diagonal of this network represents the number of connections within the category itself. So this new network is a projection of the category networks which is capturing the intra-connection and inter-connections among the category.

This represents the procedure under which we extract the dynamic multilayer network, used to study the intra-relationship and interrelationship between different institutions of different ESG classes. Now once we have extracted our multilayer network, it is important we analyze a study this network and to do that we rely on network measures and topologies such as connectivity and centralities which we study in the next section.

2.3 Network Connectedness and centralities

As important as a multilayer network is, which enables us to observe the complexity of a system, one may have noticed that such a network is difficult to visualize and study from its raw data. It is easy to make inferences and even study the connections and relationships in a simple network just by visualizing such a network. However, studying the connections both the intra-connections and inter-connections of a multilayer network is a complex task and cannot be simply done by visualizing the network, although visualization helps. Therefore, to analyze and study the relationships between entities in such a network, we rely on network measures which are mathematical metrics designed to simplify the network structure into interpretable and comprehensible measures Newman (2010).

A substantial body of research on networks has been dedicated to investigating network connectivity and centralities. The former refers to the degree to which nodes in the network are linked to each other while the latter quantifies the influence or importance of nodes in a given network. The connectivity and centrality measures do not just help us study the multilayer network but these measures are inferred and used to construct the ESG portfolio indexes which will be discussed in Chapter 3. There are several measures of network connectivity and centrality including the Degree centrality, the density of the network, and the Betweenness of a network. These are the three main network measures we rely on in analyzing the multilayer network and inferring these measures in constructing our portfolios.

2.3.1 Degree Centrality

Centrality is a measure of the importance of a node. As such we define the degree of a node as the number of edges connected to such a node. So the degree measures how important a node is based on the number of links or connections that node has. In a social network, the degree of a node could represent the number of followers a person (node) has on Twitter or Facebook. So the more followers you have, the more important you are in the social network. Mathematically we define the degree as follows:

Definition 4. *Consider a network $G = (N, V)$ with A_{ij} as the adjacency matrix. The degree centrality of asset i is defined as follows :*

$$d_i = \sum_{j=1}^{n} A_{ij}.$$

In a directed network such as ours, the degree of a node is decomposed into Indegree and Outdegree. The former refers to the number of edges or links directed from other nodes to that node. The latter on the other hand refers to the number of edges or connections directed from node i toward other nodes. In our social network example, the in-degree refers to the number of followers you have and the outdegree represents the number of handles or people you are following.

Although the degree is a centrality measure, the average degree of a network reflects the connectivity of the network. As mentioned earlier, the connectivity of a network measures the overall connectedness of the network. Taking the average of the degree is also a measure of the connectivity of the network as a higher average degree indicates a greater level of overall network connectedness Diebold and Yılmaz (2014). This measure has become a fundamental benchmark for assessing network connectedness in various studies such as Diebold and Yılmaz (2014). However, a more suitable measure of connectivity is the density of a network.

2.3.2 Density

The density of a network is a quantitative measure that indicates the proportion of observed edges within the network relative to the total number of potential edges. It is derived by dividing the actual number of edges in the network by the total number of possible edges. The density, denoted as ρ, can be calculated using the following formula:

$$\rho = \frac{m}{N(N-1)},$$

where m is the actual number of edges in the network. The density of a network strictly falls within the range of $0 \leq \rho \leq 1$, serving as a measure that signifies the probability of a randomly selected pair of nodes being connected by an edge Newman (2010). Additionally, a relationship exists between the density of a network and its average degree. In networks with a high average degree, a substantial number of edges interconnect the nodes, leading to a greater likelihood of denseness. However, it is crucial to consider the influence of the total number of potential edges, which is contingent upon the network's node count. Consequently, a network exhibiting a high average degree but possessing a limited number of nodes may still demonstrate a relatively low density.

2.3.3 Betweenness Centrality

The last network centrality measure we discuss is the Betweenness Centrality which basically measures the significance of a node within a network by considering the number of shortest paths that traverse through it. Nodes with high betweenness centrality act as pivotal connectors or bottlenecks, linking other nodes in the network and thus exerting control over the flow of information or resources.

Definition 5. *Let n^i_{st} denote the number of shortest paths from s to t that pass through i and we define g_{st} to be the total number of shortest paths from s to t. Then the betweenness centrality of node i on a general network is*

$$x_i = \sum_{st} \frac{n^i_{st}}{g_{st}},$$

where we adopt the convention $\frac{n^i_{st}}{g_{st}} = 0$ if both n^i_{st} and g_{st} are zero.

CHAPTER 3

Portfolio Analysis

3.1 Portfolio Construction

One of the core purposes of this thesis is the application of a Multilayer network to analyze the impact of ESG scores on Portfolio allocation strategies. The research question here is, Do ESG scores matter in investment decisions through the lenses of a multilayer network? As we have discussed in chapter 2, we classify institutions into four ESG classes i.e. (A, B, C, and D) and we study the relationship that exists between these institutions within and across ESG classes. Now we want to use our knowledge about the relationship between these institutions in constructing a portfolio and how this network relationship affects our investment decisions. The approach we adopt in this section involves

Step 1 Construct an ESG Portfolio index for each class of ESG. As we know, institutions are categorized into classes based on the ESG score and the idea here is to use the returns of each company that belong to a certain ESG class to build an ESG portfolio index for that class. These portfolio indexes are constructed in a rolling window estimation like before and the approach in constructing these portfolios is explained below in section 3.1.1.

Step 2 Develop a class of investment strategies using the portfolio indexes constructed in *Step 1* and intra-relationship and interrelationship of the multilayer network discussed in chapter 2. These investment strategies are built using the Markowitz framework. see section 3.1.2 .

3.1.1 Constructing ESG Portfolio Indexes

Given that we have four ESG classes i.e. (A, B, C, and D), we construct four portfolio indexes for each ESG class which we refer to as the ESG class index. There are two main approaches we use in constructing these indexes. One is the naive Equally weighted approach where each asset in each ESG class has the same weights and contributes equally in the ESG index. In this approach, the ESG indexes are constructed without any network measure or relationships. Let n_k represent the number of assets in ESG class for $k = 1, 2, 3, 4$.

Definition 6 (case 1)**.** *Let φ_k represent the ESG index for class k. The ESG portfolio index for class k is defined as*

$$\varphi_k = \frac{1}{n_k} \sum_{i=1}^{n_k} \mathcal{I}_{k(i)} \cdot r_i, \tag{3.1}$$

where r_i represents the returns of asset i in category k and $\mathcal{I}_{k(i)}$ is an indicator function which is 1 if the asset i belongs to the ESG class k.

The other approach in constructing the Portfolio index for each ESG category is to use the node centrality measure from the simple network of returns. In this case, we construct the ESG index as a linear combination of the node centrality of asset i in ESG class k and the returns of that asset i in ESG class k.

Definition 7 (case 2)**.** *Let φ_k represent the ESG index for class k, r_i represent the returns of asset i and x_i represent the centrality measure of asset i. The ESG portfolio index for class k is defined as*

$$\varphi_k = \sum_{i=1}^{n_k} \mathcal{I}_{k(i)} \cdot r_i \frac{x_i}{\sum x_i}, \tag{3.2}$$

where $\mathcal{I}_{k(i)}$ is an indicator function which is 1 if the asset i belongs to the ESG class k.

In this case, the weight of each asset in the ESG index is dependent on the centrality measure of that asset. So if an asset i has a higher centrality measure then asset i contribute more to the ESG index compared to an asset with a low centrality measure. In this approach, we incorporate the centrality information of the asset in constructing the ESG index. There have been several research that investigated the relationship between network centrality measures in portfolio construction strategies. The work of Pozzi et al. (2013) demonstrates that low central assets outperform high central nodes because high central assets in a network widely spread shocks in the portfolio. This finding was formally proven by Peralta and Zareei (2016) who showed that there is a negative relationship between the centrality of assets within a network and the optimal weights in Markowitz portfolio construction. This means that to properly diversify your portfolio, investors rather select outer node assets rather than core assets. This is because high central assets, due to their extensive connections, can easily spread shocks within the portfolio. As a result, a shock to one of these major assets can potentially affect the performance of other assets and hence the portfolio. This theoretical result of Peralta and Zareei (2016) is given as a proposition in this thesis without proof[1].

Proposition 1. *Consider the Markowitz mean-variance portfolio optimization problem with the expected returns vector given as* μ *and the covariance matrix,* $\Sigma = [\sigma_{ij}]$*. The mean-variance portfolio optimization problem is given as:*

$$\min_{w} \sigma_p^2 = w^T \Sigma w \quad \textit{subject} \quad \textit{to} \quad w^T \mu^e = R^e.$$

The optimal weights are given as:

$$w_{mv}^* = \frac{R^e}{\mu^{eT} \Sigma^{-1} \mu^e} \Sigma^{-1} \mu^e,$$

can also be written as

$$\hat{w}_{i,mv}^* = \varphi_{mv} \Omega^{-1} \hat{\mu}^e,$$

$$\textit{where } \hat{w}_{i,mv}^* = w_{i,mv}^* \sigma_i, \quad \varphi_{mv} = \tfrac{R^e}{\mu^{eT} \Sigma^{-1} \mu^e}, \quad \hat{\mu}_i^e = \tfrac{\mu_i^e}{\sigma_i} \ .$$

The relationship between the optimal portfolio weights and the asset centralities is given in proposition 2.

Proposition 2. *Consider the financial market network* $FMN = (N, \Omega)$ *where* $\{v_i, ..., v_n\}$ *and* $\{\lambda_1, ..., \lambda_n\}$ *accounts for the sets of eigenvectors and and eigenvalues of* Ω*, respectively.*

$$\hat{w}_{mv}^* = \varphi_{mv} \hat{\mu}^e + \varphi_{mv} (\frac{1}{\lambda_1} - 1) \hat{\mu}_M^e v_1 + \Gamma_{mv}, \tag{3.3}$$

$$\textit{where,} \quad \hat{\mu}_M^e = v_1^T \hat{\mu}^e \quad \textit{and} \quad \Gamma_{mv} = \varphi_{mv} [\textstyle\sum_{k=2}^n (\frac{1}{\lambda_k} - 1) v_k v_k^T] \hat{\mu}^e \ .$$

Taking this theoretical result into consideration, we construct the ESG index from definition 7 by adopting a simple inverse transformation of the node centrality such that

$$x_i^* = \frac{1}{x_i},$$

$$\text{where } x_i^* = 0 \text{ whenever } x_i = 0$$

Given this inverse transformation, low central nodes in the network are weighted more in the index while high central nodes are weighted less. This will not only help diversify the portfolio but also improves our investment strategies.

[1]The proof to proposition 2 can be found in section 2 of Peralta and Zareei (2016) research work.

3.1.2 Intra-layer Network Connectivity as Portfolio Risk

Given that we have constructed the ESG portfolio indexes, the objective is to devise an investment allocation strategy in which we choose optimally a class of ESG index to invest in while minimizing risk and maximizing returns. Using the ESG indexes as assets in the Markowitz Portfolio optimization problem, we are able to analyze the impact of ESG scores in investment allocation and observe if ESG scores matter in portfolio selection. We also observe the role multilayer network plays in portfolio selection and ESG ratings. As such different Markowitz portfolio optimization is implemented, each representing an investment strategy, and one of these investment strategies involve incorporating the intra-connectivity of the multilayer network into the Optimization problem.

We build the investment strategy using the Markowitz optimization framework and one of the ways to incorporate the intra-layer network connectivity into our investment strategy is by decomposing the portfolio variance into two components, contemporaneous and intra-layer network risk. The former measures the risk associated with simultaneous movements in ESG index returns, and the latter explains the risk stemming from the connectivity of the intra-layer network. We solve the following Portfolio optimization problem:

$$\min_{\omega} \omega^{\mathbf{T}} \mathbf{\Sigma}^{*} \omega + \lambda \sum_{k=1}^{4} \rho_k^2 \omega_k^2, \tag{3.4}$$

subject to

$$\begin{cases} \sum_{k=1}^{4} \omega_k \varphi_k \leq \mu_P \\ \sum_{k=1}^{4} \omega_k = 1 \end{cases}$$

where ω is the vector of portfolio weights to which we invest in the ESG class indexes, Σ^* represents the contemporaneous risk that is obtained from the simultaneous movements of the ESG portfolio indexes returns while the second term of the objective function measures the risk associated from the intra-layer network structure. So ρ_k represents the density of each ESG class network and λ represent the risk aversion parameter to this level of risk. Generally, portfolios built upon traditional Markowitz theory are such that risk is minimized for given expected returns using as input the variance-covariance matrix of the asset returns. Our investment strategy is built on two-step portfolio construction, in which we first construct ESG class portfolio indexes and use these indexes as returns and the connectivity in each of these ESG classes as an additional measure of risk in the financial system.

3.1.3 Inter-layer connectivity and Portfolio Investment strategy

Incorporating the intra-layer connectivity into the Portfolio optimization is just one way to observe the role the multilayer network plays in the ESG investment allocation. One other way is to incorporate inter-layer connectivity which basically measures the relationship between institutions in different ESG classes. We use the interconnectivity of the multilayer network as a trading signal to the investor, informing them to take a LONG or SHORT position on a particular ESG index.

The inter-layer network connectivity is obtained by computing the number of connections moving from asset i in category k to asset j in category l. With this approach, we obtain a weighted network that is fully connected but not symmetric. This means that for instance, the number of connections from ESG class A to ESG class B differs from the number of connections from ESG class B to ESG class A. This information on inter-layer connectivity is filtered by considering the net connectivity between any two ESG classes.

Definition 8. *Let A_{uv} represent the weighted adjacency matrix containing the number of connections from one ESG class to the other. Let $a_{uv} \in A_{uv}$ represent the number of connections from ESG class u to ESG class v, then the net connectivity of a_{uv} is defined as:*

$$\hat{a}_{uv} = sign(a_{uv} - a_{vu})$$

$$and$$

$$\hat{a}_{uv} = \begin{cases} 1 & if \quad u \to v \\ -1 & if \quad v \to u \end{cases}$$

Trading Signals

Using the definition above, a good trading strategy is to take a LONG position on ESG index u and a SHORT position on index v if $\hat{a}_{uv} = 1$. However, given that there are four ESG classes (A, B, C, and D), for each index, there exist three different signals which can be opposing and counter-interactive. For instance, it is possible that for ESG index A, $\hat{a}_{AB} = 1 \implies$ taking a LONG position on index A but if $\hat{a}_{AC} = -1$ then this lead to opposing signals as $\hat{a}_{AC} = -1 \implies$ take a SHORT position on index A.

To deal with these opposing signals, we adopt a simple convention where the signal of an index u, is given as a linear combination of the net connectivity of any other index and index u. This is defined as follows:

$$
\begin{aligned}
signal_A &= sign(\varepsilon_1 \hat{a}_{AB} + \varepsilon_2 \hat{a}_{AC} + \varepsilon_3 \hat{a}_{AD}) \\
signal_B &= sign(\varepsilon_1 \hat{a}_{AB} + \varepsilon_2 \hat{a}_{BC} + \varepsilon_3 \hat{a}_{BD}) \\
signal_C &= sign(\varepsilon_1 \hat{a}_{AC} + \varepsilon_2 \hat{a}_{BC} + \varepsilon_3 \hat{a}_{CD}) \\
signal_D &= sign(\varepsilon_1 \hat{a}_{AD} + \varepsilon_2 \hat{a}_{BD} + \varepsilon_3 \hat{a}_{CD})
\end{aligned}
$$

$$
\text{where, } \varepsilon_1 = \varepsilon_2 = \varepsilon_3 = 1 \text{ and}
$$

$$
signal_k = \begin{cases} 1 \implies LONG \\ 0 \implies OUT \\ -1 \implies SHORT \end{cases}
$$

Now this concludes the chapter on Portfolio Analysis. The next chapter is our Empirical analysis which is mainly in two parts. The first part discusses the network analysis of our Multilayer network, which helps establish the relationship between the connectivity of each ESG class. The second part involves the application to Portfolio construction, where we analyze the role of ESG scores in Portfolio allocation.

CHAPTER 4

Empirical Analysis

4.1 Data Description

The dataset used for this empirical analysis comprises daily time series of ESG scores of 100 companies in the standard and poor (S&P) 100. The original data comprises the individual time series of the environmental, social, and governance ratings of the ESG. However, we are simply interested in the impact of the general ESG scores on portfolio selection. Additionally, the daily prices and volatilities of these companies are also extracted, all from the Bloomberg Finance terminal. The dataset ranges from 04 January 2016 to 07 February 2023 with over 1850 observations of 100 companies in the S&P 100. However, some companies lack substantial data on the ESG scores component and hence were removed from the analysis. These companies include 'MCD', 'CSCO', 'INTC', NVDA', TXN', 'BK', 'AMD', 'AAPL', 'AVGO', 'QCOM', 'SBUX', 'DOW', 'LIN', and 'EXC', leaving us a total of 85 companies to work with and about 1850 observations. The empirical analysis is two main parts: i.e. (1) Comprehensive analysis of the Multilayer network analysis and (2) Application to portfolio selection strategies. In the Portfolio selection strategy, the data is split into in-sample and out-of-sample analyses where a window size of 200 days is used for in-sample while the remaining 60 days are for out-of-sample analysis. This enables us to observe the performances of the various investment strategies.

4.2 Network Analysis

4.2.1 Analyze the main network of returns and volatilities

Following the network extraction procedure discussed in section 2.2, we first extract the general network of returns and volatilities in a rolling window estimation as defined in step 1. We analyze the connectedness and centrality such as the density, the betweenness centrality, and the degree of the network of returns and volatilities as discussed in section 2.3. The idea here is to compare the network of the volatility and returns defined over time and identify possible key companies that are central in the network as we know that the central nodes have the potential to propagate risk in the network.

Figure 4.1, shows the density of the network returns and volatility and we can observe some interesting events in these two densities. Firstly, the volatility network is way more dense and highly connected as compared to the network returns. This suggests a higher level of interconnectedness and information flow in the volatility dynamics compared to the return dynamics. Additionally, The higher density in the network of volatilities suggests a greater potential for volatility spillovers or contagion effects. When a highly volatile company experiences significant changes in its volatility, it is more likely to transmit those shocks to other connected companies, leading to heightened market volatility. Investors should be aware of these spillover effects as they can impact the overall risk and stability of the financial system.

One of the benefits of observing dynamic networks is to capture notable changes in the interconnectedness of the network in time changes and this is well captured during the Covid-19 crisis. We can observe significant changes in both the density of the network volatility and returns. The density of the volatility increased by almost 150% while the density of the returns declined instead. The sharp increase in the density of the volatility indicates that financial institutions become highly interconnected during systematic risk as also shown by Billio et al. (2012).

Moreover, the measure of connectedness such as the clustering coefficient in Figure 4.2 also indicates the volatility network is highly interconnected as compared to the network of returns. The high clustering coefficient of the volatility network shows that the volatility of institutions tends to form clusters or groups, and we can notice how the clustering coefficient of the volatility network has increased dramatically during the Covid crisis. This demonstrates once more how financial institutions tend to form groups or clusters during a systematic risk.

The measure of connectedness analyses the network from a macro point of view by observing key changes in the dynamic of the network and its connectivity. The centrality measures on the hand allow us to observe central nodes in the network and how these central nodes change over time. One of the fascinating centrality measures to observe is the outdegree centrality and betweenness centrality of the network.

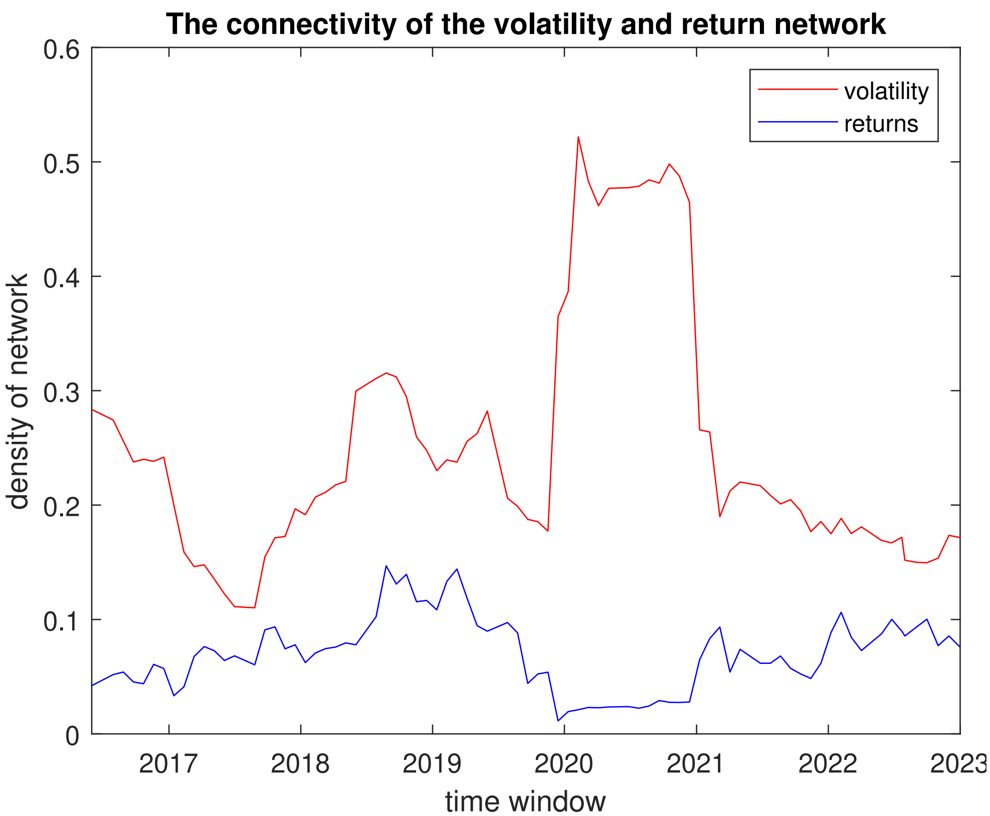


Figure 4.1: The density of the network of returns and volatility over time. Observe that the volatility is highly connected over time as compared to a network of returns. An interesting period in the changes in the dynamic of the network is 2020 during the period of the Covid-19 crisis.

The analysis of outdegree and betweenness centrality in the networks of returns and volatilities provides valuable insights into the influence and connectivity of companies within the financial system. In terms of outdegree, higher values indicate that a company's performance has a significant impact on the returns or volatilities of many other institutions in the network. This implies that these companies have the potential to steer the market positively or negatively as their actions affect the performances of other companies. Figure A.1 and Figure A.2 represent the heatmap of the outdegree of returns and volatility respectively.

Similarly, the betweenness centrality indicates the extent to which a company could serve as a bridge, especially in the dissemination or spread of information, shocks, or risk. Companies with high betweenness centrality in the volatility network can be critical in terms of systematic risk assessment. They have the potential to propagate volatility shocks to other companies, leading to contagion effects and amplifying market-wide volatility. Monitoring the betweenness centrality of companies in the volatility network helps in identifying important companies that may contribute to the overall risk levels in the financial system. Figure A.3 and Figure A.4 also represent the heatmap of the betweenness centrality returns and volatility networks respectively.

This analysis provides meaningful insights into the influence and interconnectedness of companies in terms of their impact on returns and volatilities. It highlights the companies that are pivotal in the network returns or volatility and suggests their potential significance in the overall market dynamics. Understanding these centrality measures aids in risk assessment, identifying systemically important companies, and guiding investment decisions. Table 4.1 presents the institutions that exhibit the highest centrality measures in terms of outdegree and betweenness for each year in both networks. Tracking these high central nodes or institutions provides valuable insights and trading opportunities to the investor. Notably, companies such as 'BKNG', 'SO', 'COST', 'CVS', and 'GD' emerge as significant central nodes, exhibiting both high outdegree and betweenness centrality in relation to both performance and volatility dynamics in the financial market.

Additionally, we provide a visualization of the network of returns for the beginning part of 2018 in Figure 4.3 where the node size represents the Outdegree of the node in the network, and the colors of the node are based on the cluster or group that a node belongs to using the modularity

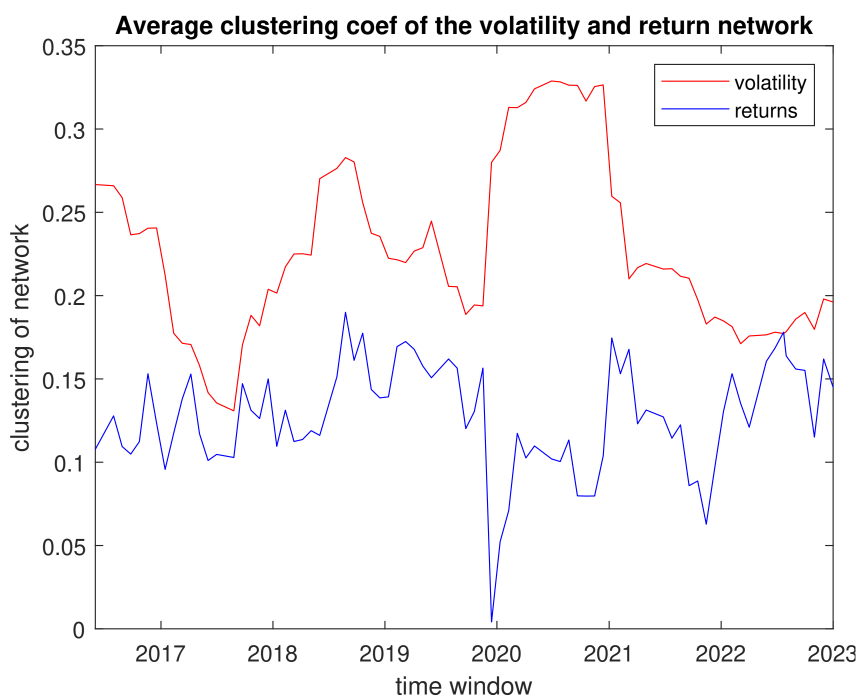


Figure 4.2: The average clustering coefficient of the network returns and volatility.

algorithm index. One can observe that a few of the largest nodes in the network includes "PM", "P", and "TMO" which also are the highest central nodes in 2018 on average. see table .4.1. This provides some consistency in our analysis.

In the next section, we discuss and analyze the intra-connectivity and relationships of the multilayer network. The goal of the next section is to study the relationship that exists between the intra-layer networks i.e. the connectivity that exists between the different ESG classes.

Outdegree centrality of Network Returns						
2016	2017	2018	2019	2020	2021	2022
'BKNG'	'BKNG'	'PM'	'LOW'	'F'	'AXP'	'NFLX'
'COST'	'BMY'	'TMO'	'COF'	'RTX'	'BKNG'	'TGT'
'BMY'	'UPS'	'P'	'SO'	'SPG'	'GM'	'MSFT'
Outdegree centrality of Network Volatility						
2016	2017	2018	2019	2020	2021	2022
'BKNG'	'TGT'	'GOOGL'	'MSFT'	'AIG'	'RTX'	'LMT'
'CVS'	'OVS'	'MSFT'	'MA'	'MSFT'	'MMM'	'MRK'
'TMUS'	'BKNG'	'GD'	'AT&T'	'USB'	'USB'	'MMM'
Betweenness centrality of Network Returns						
2016	2017	2018	2019	2020	2021	2022
'COST'	'AIG'	'UPS'	'KHC'	"	'SO'	'MMM'
'NKE'	'BMY'	'KO'	'SO'	"	'TSLA'	'WMT'
'TGT'	'UPS'	'XOM'	'ABBV'	"	'META'	'ADBE'
Betweenness centrality of Network Volatility						
2016	2017	2018	2019	2020	2021	2022
'CL'	'CVS'	'CVX'	'COST'	'WMT'	'LMT'	'KHC'
'CVS'	'BKNG'	'GM'	'SPG'	'NFLX'	'BLK'	'CRM'
'GILD'	'EMR'	'GD'	'SO'	'SCHW'	'IBM'	'DUK'

Table 4.1: Key nodes or institutions central in the network of returns and volatility across years. Shaded institutions represent institutions with consistently high levels of centrality across time, networks type, and measures.

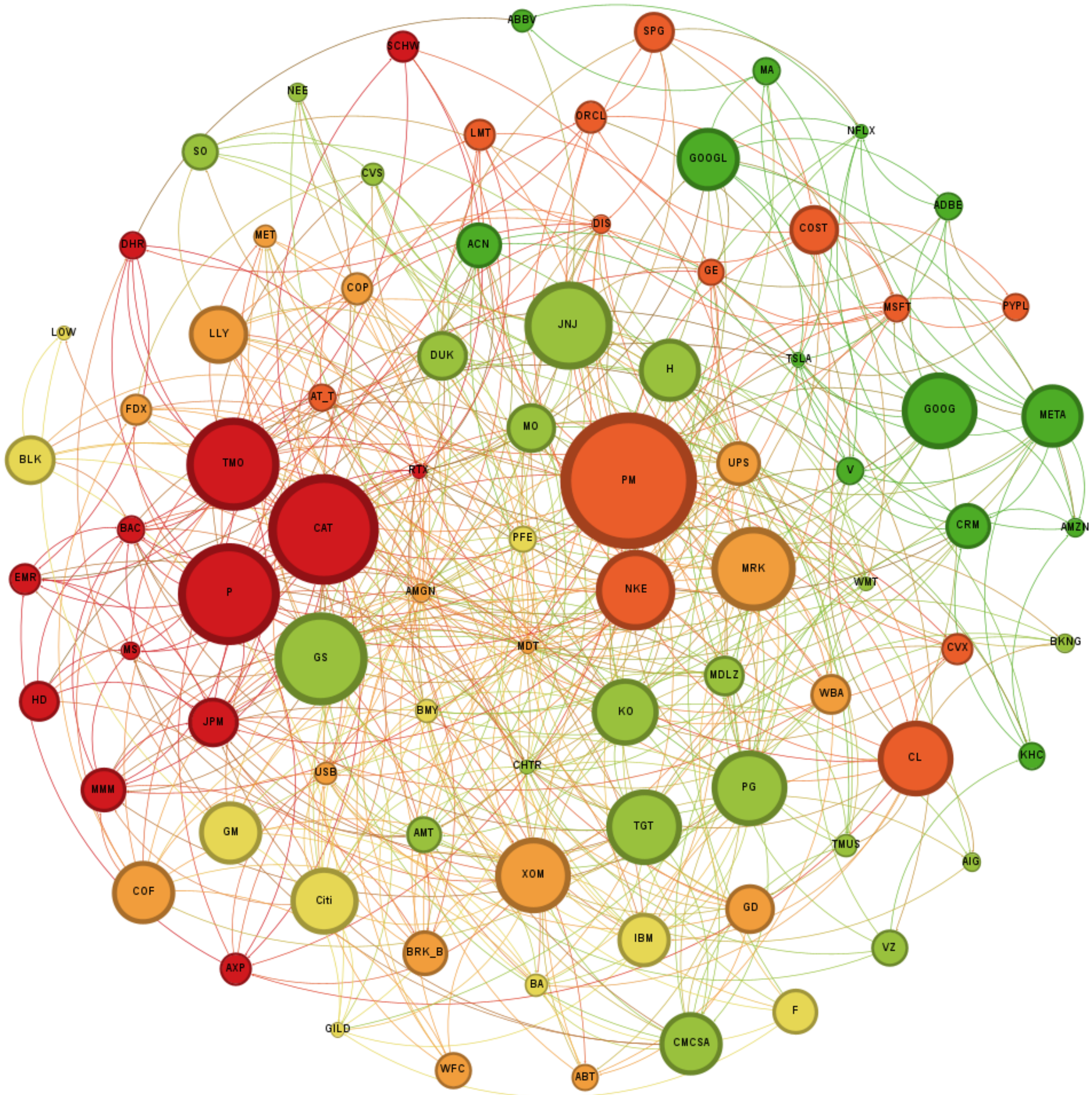


Figure 4.3: The network of returns for the latter part of 2017. The node size represents the Out-degree measure of the node and the node color represents the groups of clusters in the network.

4.2.2 Intra-connectivity of the Multilayer network

In this section, we seek to analyze the connectivity of the intra-layer network, enabling us to compare the level of connectedness in each ESG class. This analysis will inform us of the connectivity patterns of each ESG class and how this connectivity pattern changes over the years and during the COVID-19 period. This level of connectivity is studied in both the network of returns and the volatility as the level of connectivity in each ESG class depends on the kind of relationship that exists between institutions in that class. We study this level of connectivity using both the connectivity and centrality measures discussed in chapter 2.

Connectednes

Given that we are interested in the connectivity pattern of each ESG index, it is difficult to observe the comparison between the connectivity patterns of each class with a line plot. As a result, we compute the yearly average connectedness of each ESG index and we use a Bar plot to observe the connectivity patterns between each ESG class at each year. Figure 4.4 represents the yearly average density of the four ESG classes, where A represents the high ESG class and D represents the Lowest ESG class for both the returns network and volatility network respectively. From this Bar chart, it is easy to observe that high ESG classes such as A and B have the highest level of connectivity in the years 2017, 2018, 2019, and 2021 in the network of returns. This is not a surprising result because the latter of 2016 to 2019 represents the prime years of the introduction of significant ESG policies and their impact on financial institutions and investment policies. For example, the Paris Agreement was enforced in November 2016 with over 190 countries agreeing to reduce carbon emissions and limit global temperature and there has been a growing discussion on the impact of such policies on financial performance and how this is integrated into financial products Agliardi et al. (2023).

According to Forbes, the latter part of 2017 to 2018 marked a significant turning point for ESG investments, characterized by a surge in news coverage and information related to ESG investments, and strong ESG initiatives and increased investor preference for sustainable investing and as well as the emergence of roles such as "ESG Analysts." The introduction of these policies in these years actually explains the high level of connectivity among high-class ESG companies. Consider a company say in the Automobile industry that adopts ESG policy by introducing products that reduce carbon emissions, this affects not only the performance of the company but also the performance of its competitors. Because for the competitor to compete it must adopt such low ESG policies as its stakeholders or investors or even consumers will potentially choose products with low carbon emissions and this will therefore affect the performance of its competitors. So a company's ESG policies have the potential to affect its returns and granger cause the returns of competitors and so this means that companies in the same ESG class will have a high level of connectivity.

However, the year 2020 represents a fascinating and interesting turn of events. One can observe that the connectivity level in 2020 is low compared to other years as we have seen above. Additionally, the level of connectivity across all classes of ESG is low and about the same, implying the possibility that ESG scores were irrelevant in the event of the crisis. To understand better the connectivity level in 2020, we analyze the volatility network as we know that there is a high level of connectivity in the volatility network than in the returns.

In general, one may notice a similar level of connectivity among all ESG classes across all years even during the prime ESG period in the volatility network. This observation informs that there is the same level of connectedness among companies in both the high ESG class and the low ESG class when the relationship between them is their volatility. This means that the ESG ratings or classes play very little role in the volatility relationships between institutions even in 2020 during the COVID crisis. We observed the surge in the connectivity of the volatility of companies in all ESG classes, however with similar levels of connectivity. Billio et al. (2012) showed that financial institutions become highly connected during systematic risk and this could explain why the level of connectivity between high ESG and low ESG classes are similar and high in 2020. However, our analysis concludes that ESG scores or classes are irrelevant and play very little role in the connectivity of the volatility of financial institutions.

Centrality

This finding and results are also observed in our comparison of the intra-layer network in terms of the average centrality measures. Although the connectedness of the network shows how companies or institutions in the ESG class interact and build interrelationships, the centrality shows the relative importance of an institution in the network and the role that institutions play in the spread of risk or flow of information. Due to the complexity of our network, we analyze the average node centrality of the network, specifically the average betweenness centrality which provides insights into the importance of individual companies in facilitating the flow of information or risk within their respective ESG categories.

Figure 4.5 provides a Bar chart of the average yearly betweenness centrality of the network returns and volatility across ESG classes. Notably, one may observe that companies in the high ESG class consistently exhibit high betweenness centrality across 2017,2018,2019, 2021, and 2022 in the network of returns. This is to say that not only are the high ESG class of companies highly connected but also the companies in this high ESG class are more likely to be the central nodes and institutions in the financial network. Overall, one may suggest that the high level of connectivity and average centrality in the network returns among high ESG companies is due to the similarity in ESG-related initiatives adopted by these firms.

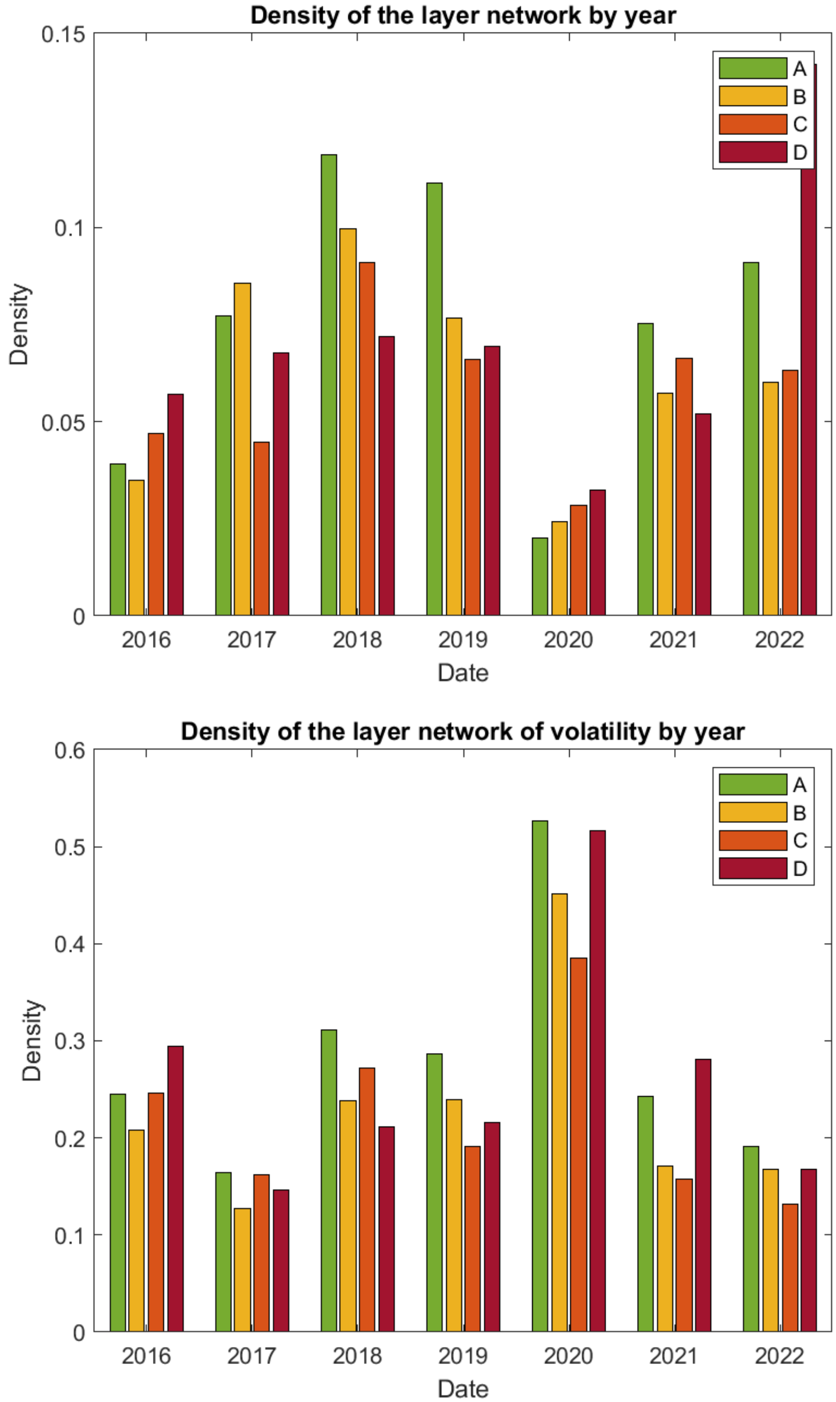


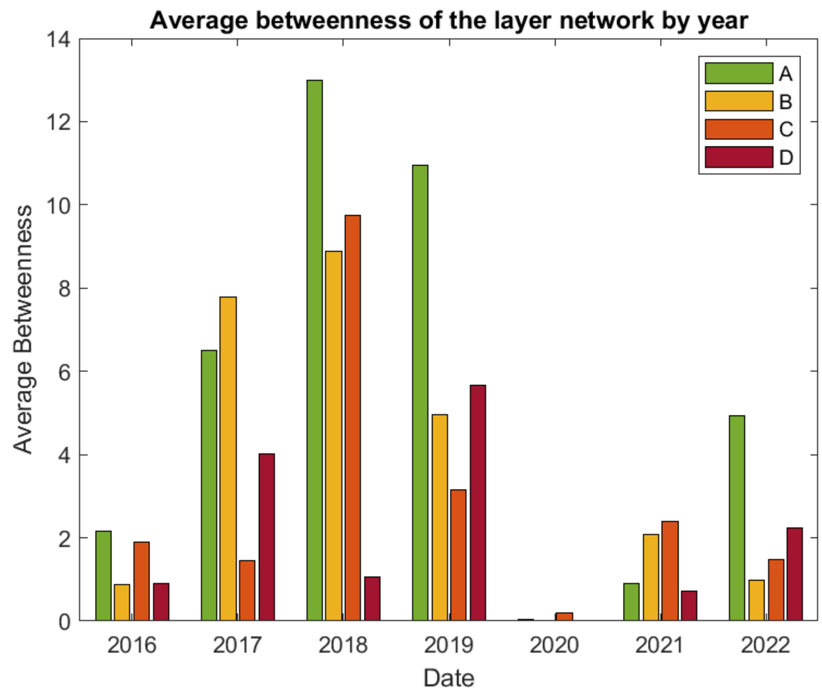
Figure 4.4: The Density of the ESG classes (A, B, C, D) of both network of returns and volatility.

Additionally, We provide in Figure 4.6 a visualization of one of the temporal networks of returns in the beginning part of 2018 for all ESG classes. The node size represents the degree of the node and the color represents the closeness centrality of the node i.e. green for high centrality and blue for low centrality. One may notice right away the networks of Class A and Class B are highly connected compared to Class C and Class D. In addition, class A and Class B have many bigger nodes than Class C and Class D showing that there are more central nodes in the high ESG class compared to the low ESG class. This is in line with our analysis of how high ESG companies are more connected and highly central in the network compared to the low ESG class of companies.

Lastly, the average betweenness of the returns in 2020 is almost zero and so we are unable to observe how companies behave in the network returns in 2020. Moving to the average betweenness of the volatility network, one may observe just as before that the betweenness across all ESG classes is the same showing that ESG plays very little role in the average centrality of the volatility network. Lastly, we may observe also a decline in the betweenness centrality of the volatility network in all ESG classes for the year 2020 just as it is in the network of returns. This is in line with the betweenness centrality of the overall network in Figure A.4 in Appendix A. In general, there is a decline in the betweenness centrality of the volatility network during the COVID-19 crisis. This shows that the COVID-19 crisis led to a decline in the number of assets that were bridges in the volatility network and have the potential to propagate risk.

In summary, our findings from an intra-layer network analysis of returns and volatility reveal that:

- High ESG class companies are highly connected and highly central in the network of returns for the years 2017,2018,2019 and 2021.
- During the Covid-19 crisis, ESG scores or ratings are not so relevant in the connectivity patterns of both returns and volatility since there is a similar level of connectedness during the COVID crisis.
- ESG scores and ratings play very little role in the connectivity of the Volatility network as regardless of the ESG class, institutions of any ESG class exhibit similar levels of connectivity and centrality patterns in the network.



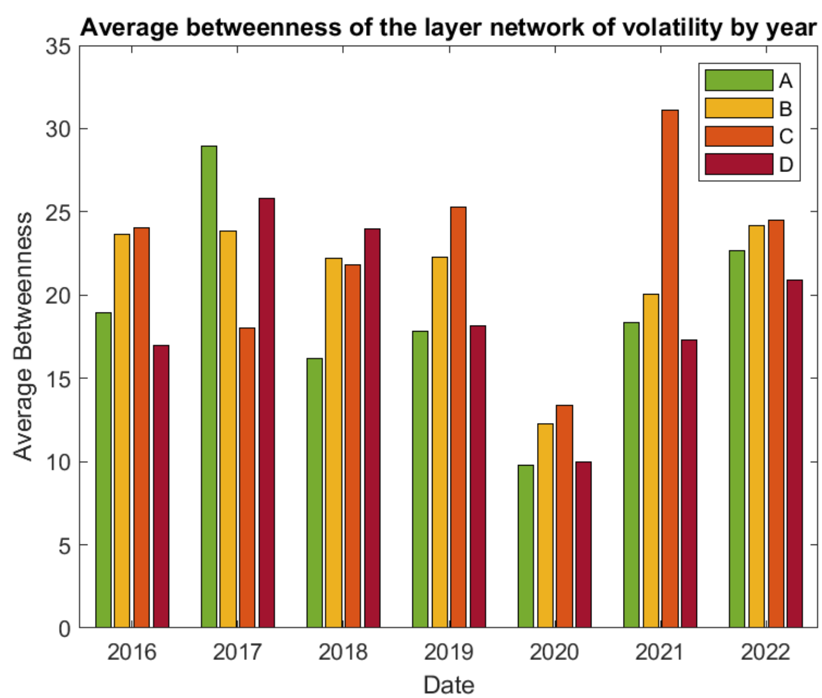


Figure 4.5: Average Betweenness of the multilayer network of returns and volatility. Each layer corresponds to the ESG class (A, B, C, D).

4.3 Portfolio Construction with Multilayer Network

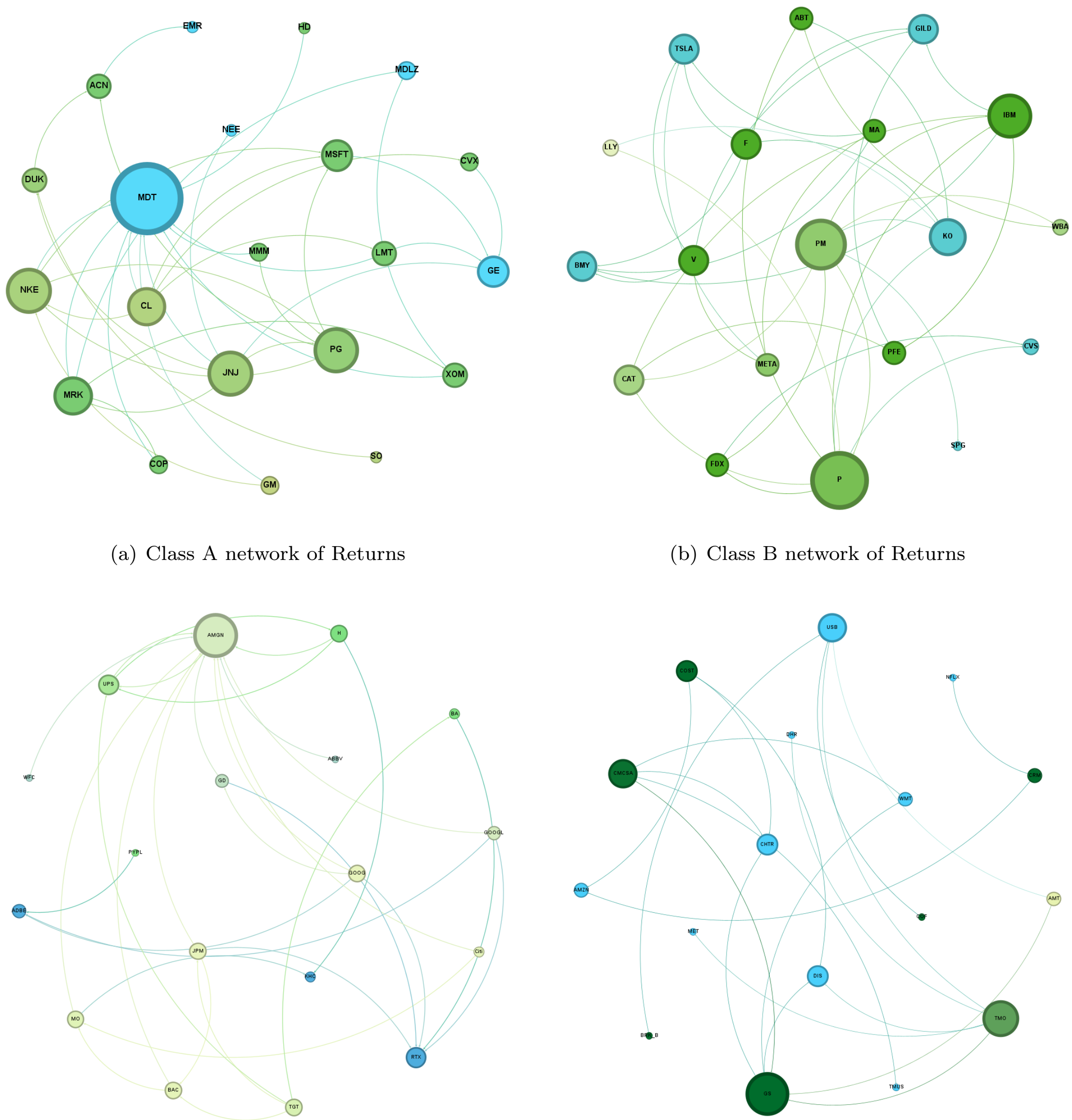
As we discussed in the methodology in section 3.1, we construct portfolio ESG indexes for each ESG class which is a linear combination of the outdegree centrality measure of the asset i in an ESG class k. We provide summary statistics of these portfolio indexes and plot the normalized return of each of these indexes. Table 4.2, provides some basic descriptive statistics of the extracted ESG indexes. One may notice that these basic statistics about our ESG indexes are in line with the stylized facts about asset returns, discussed by Cont (2001). We observe the average daily returns to be about 3% and the indexes are negatively skewed with fat tails, depicting that these indexes are non-Gaussian. Figure 4.7 provides the dynamic behavior of the indexes over time depicting the normalized return indexes. One can observe that the low ESG class index seems to have higher returns or values compared to the high ESG class. This is due to the transformation we adopted, where we gave more weight to low central nodes in the index and less weight to high central nodes. And as we have seen earlier, the most central assets are in the high ESG class, and as such the low ESG index seems to perform better in this sense compared to the high ESG index.

Summary statistics of ESG class indexes				
Class	Mean	Std	Skewness	Kurtosis
'A'	0.02432	0.01078	-0.94693	26.50293
'B'	0.03429	0.01155	-0.90313	20.17077
'C'	0.03597	0.01241	-0.86574	22.13722
'D'	0.03749	0.01207	-0.76051	17.79766

Table 4.2: Summary statistics of the ESG portfolio indexes of each ESG class (A, B, C, D).

4.3.1 Portfolio Strategies

In this subsection, we illustrate the results related to the proposed portfolio strategies discussed above. Here it is important to observe how the proposed strategy leads to different findings based on the level of complexity of the network we incorporate into the optimization problem. The proposed strategies include (1) *Simple Network Markowitz (NM)* strategy where the portfolio ESG index is constructed using the asset node centrality measure. In this case, we rely on just the centrality measure of the asset without incorporating the complexity of the connectivity of the Multilayer network. (2) *Complex Network Markowitz with risk aversion parameter strategy*. In this case, we incorporate the complexity of the multilayer network in the portfolio optimization problem by adding an additional risk, the connectivity of the intra-layer of the network. Without



(a) Class A network of Returns

(b) Class B network of Returns

(c) Class C network of Returns

(d) Class D network of Returns

Figure 4.6: The intra-layer network of Returns for different ESG class (A, B, C, D)

loss of generality, we propose different values of network risk aversion parameter λ, where $\lambda = 0.005, 0.025, 0.05, 0.1, 0.25, 1$. The case where $\lambda = 0$ indicates no aversion and represents the case of the Network Markowitz Strategy. (3) *Complex Network Markowitz with inter-layer connectivity as trading signals (NTS)*. We believe that the importance of ESG score in portfolio allocation depends on the complexity of the network structure which is allowed or incorporated into the Markowitz Portfolio Optimization problem.

Optimal Portfolio Allocation with Simple Network Measure

Consider the first investment strategy with simple network Markowitz portfolio optimization, discussed in section 3.1, equation 3.4. In this strategy, we rely on incorporating the simple asset centrality measure of the network in constructing the ESG indexes. Figure 4.8 represent the composition of the optimal portfolio of the ESG indexes that are optimally selected from the Optimization problem. From this result, one may conclude that ESG scores play a vital role in portfolio

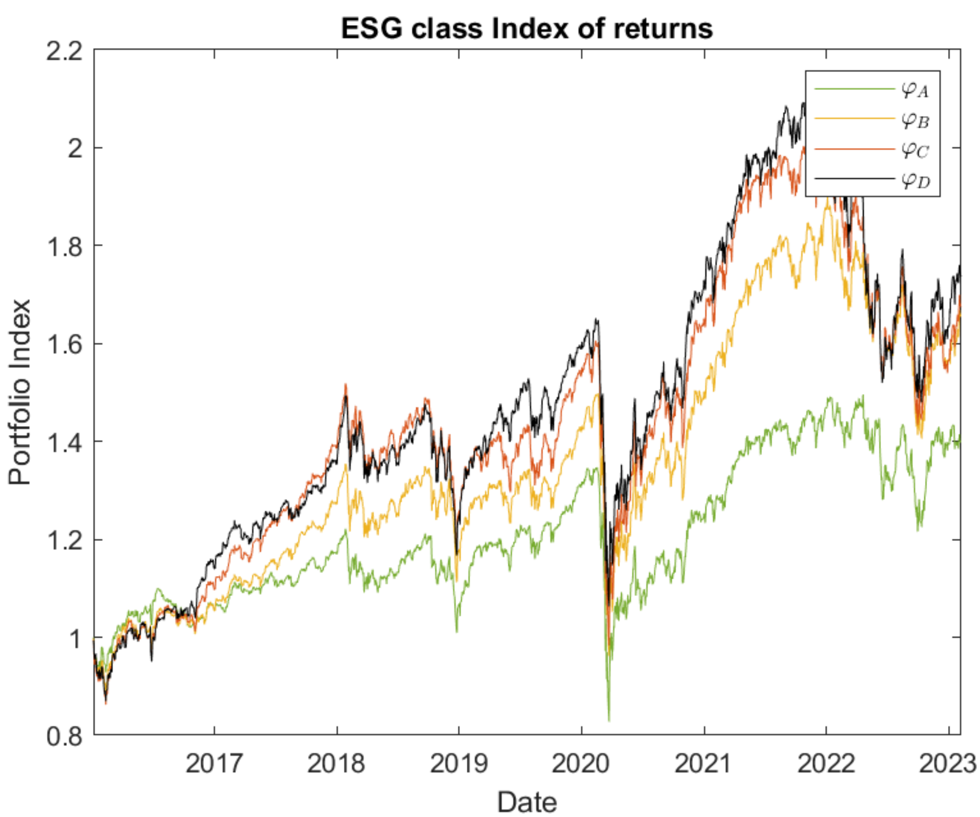


Figure 4.7: The Portfolio ESG indexes for each ESG class (A, B, C, D).

allocation strategy and investors should allocate their resources to companies that have high ESG scores, especially in the periods of boom and stable market conditions such as 2017 to 2022 except for 2020 during the crisis. This finding suggests that one may invest in low ESG class companies during periods of crisis as good ESG scores during the crisis do not matter.

These results and findings are supported by the case where we do not incorporate any network measure into the portfolio selection period. This investment strategy is the case where the ESG index is constructed using equal weights for all assets in an ESG class. In this investment strategy, no network measure is incorporated, and figure B.1 shows similar results with the simple network Markowitz strategy. These two strategies inform the investor to allocate the resources to companies with High ESG scores except for periods of crisis.

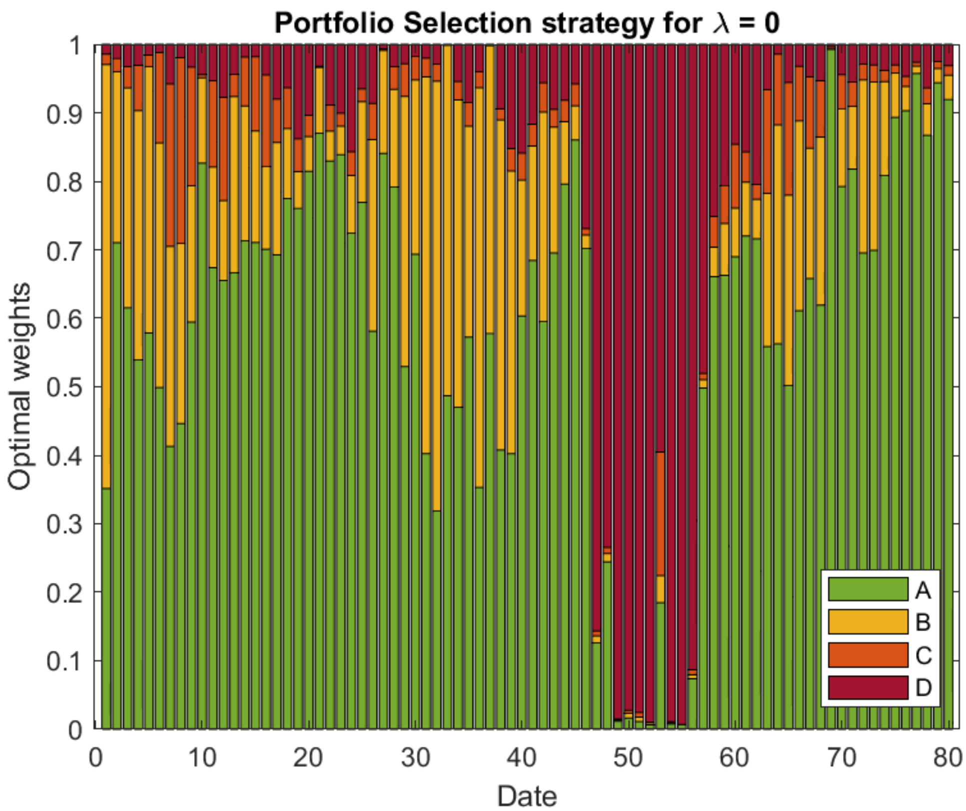


Figure 4.8: Optimal ESG portfolio selection with simple network Markowitz strategy.

Optimal Portfolio Allocation with Complex Network Measure

Recall in section 4.2.2, we analyzed the multilayer network for each class of ESG and we observed that companies in the high ESG class are highly connected and are central nodes in the network. We know that investing only in an index or class that is highly connected is not a good investment strategy as companies in this class are correlated and do not represent a good diversification strategy. Taking this into consideration, the additional risk component from the network connectivity in equation 3.4 serves as a penalizing factor, which penalizes highly connected indexes so as to create a more diversified portfolio. Additionally, this penalizing factor also serves as the risk that the network connectivity imposes on the portfolio since highly connected indexes have a higher risk compared to low connected indexes.

Figure 4.9, presents the optimal weight allocation to ESG investments for $\lambda = 0.25$. One can observe this strategy creates a more diversified portfolio across all classes of ESG indexes as compared to the Simple Network Markowitz strategy. The intra-layer connectivity of the network then enables us to obtain a more diversified investment depending on the risk tolerance of the investor from investing in high concentrated ESG index. So by incorporating a complex network structure into the portfolio optimization problem, the role of ESG ratings in portfolio selection, therefore, depends on the risk aversion parameter to the network risk. So if an investor can tolerate the risk from the intra-layer connectivity of the network, then ESG scores are vital and the strategy is to invest in high ESG rating companies but if the investor is risk averse then he diversifies his portfolio across all ESG classes so as to avoid the risk from network structure.

In summary, to answer the question of the relevance of ESG scores on portfolio selection, one has to consider the complexity of the network structure and the risk tolerance to the network risk. A simple network structure or no network structure suggests ESG scores are vital in portfolio selection while a complex network structure suggests that the relevance of the ESG scores is dependent on the risk tolerance of the investor to network risk.

The next section discusses the performance of our strategies.

4.3.2 Strategy Performance

The performance of these strategies is compared with the following traditional investment strategies including (1) Equally weighted naive approach (EW), (2) Traditional Markowitz Portfolio selection with no ESG information or network structure (TD), and (3) Traditional Markowitz with ESG class index (TESG). This is the case where we construct the ESG index with no network measure that is each asset is equally weighted in the ESG index and we construct a Markowitz portfolio selection approach. We use 40 weeks of trading periods as the in-sample period where we compute the optimal portfolio weights, and the remaining 12 weeks of the trading year to evaluate the out-of-sample performance of our strategies. The performance of our strategy is based on the Portfolio returns, Sharpe Ratio, and the value at risk (VaR).

Table 4.3 presents the portfolio returns of the various strategy stated above, including the simple Network Markowitz strategy (NM), the complex Markowitz network strategy, and the strategy with the inter-layer connectivity as trading signals (NTS). It is worth noting that the returns of these strategies are very close with very small deviations. From the table, the complex network Markowitz strategy seems to perform better in terms of portfolio returns compared to the simple network Markowitz and even in the Traditional Markowitz, especially in 2017. However, on average the Traditional Markowitz seems to perform quite well above most of the strategies. This can be confirmed by observing the Sharpe Ratios and the Value at Risk in Table 4.4 and Table B.1 respectively. It is easy to observe that the Traditional Markowitz which does not take into consideration the ESG ratings at all, seems to outperform all other strategies in which ESG information is incorporated. Although the portfolio returns are very close among all strategies, the Sharpe Ratios is significantly higher for the traditional Markowitz as compared to the other strategies. This means that the portfolio risk of the proposed strategies is higher compared to the traditional Markowitz. One may observe from the Value at risk in Table B.1, showing that the proposed ESG investment strategies are riskier and have a higher risk. And even more, incorporating the complex network structure also increases the risk of the portfolio. see table B.2 in the Appendix.

These results from the Sharpe ratio and the Value at Risk shows that the traditional investment strategy with no ESG information or scores is more profitable and less risky compared to the investment strategies with ESG scores. Our results, therefore, show that ESG investments are more risky, regardless of the network structure, and have the same level of returns as the traditional Markowitz. To complete our analysis, we compare the performance of the different ESG investment strategies and observe which of these strategies performs better if the investor is to take into consideration the ESG information in investment decisions.

Comparing ESG investment strategies, we compute a bar chart of the Sharpe ratio and Value at Risk of the proposed strategies (1) Traditional Markowitz with ESG index (TESG), (2) Simple Network Markowitz strategy (NM), (3) Network Markowitz with Trading signals (NTS) and (4) The complex network Markowitz with chosen $\lambda = 0.25$. Figure 4.10 shows the Sharpe Ratios for the aforementioned strategies. One can observe that the complex network Markowitz has the worst performance among these four strategies with the simple Network Markowitz and the Traditional ESG strategies performing way better, especially in 2016 and 2017. One can also observe that the Network Markowitz with the inter-layer connectedness as trading signals also performs very well among these strategies. In summary, the complexity of the network structure increases the risk of the portfolio in out-of-sample.

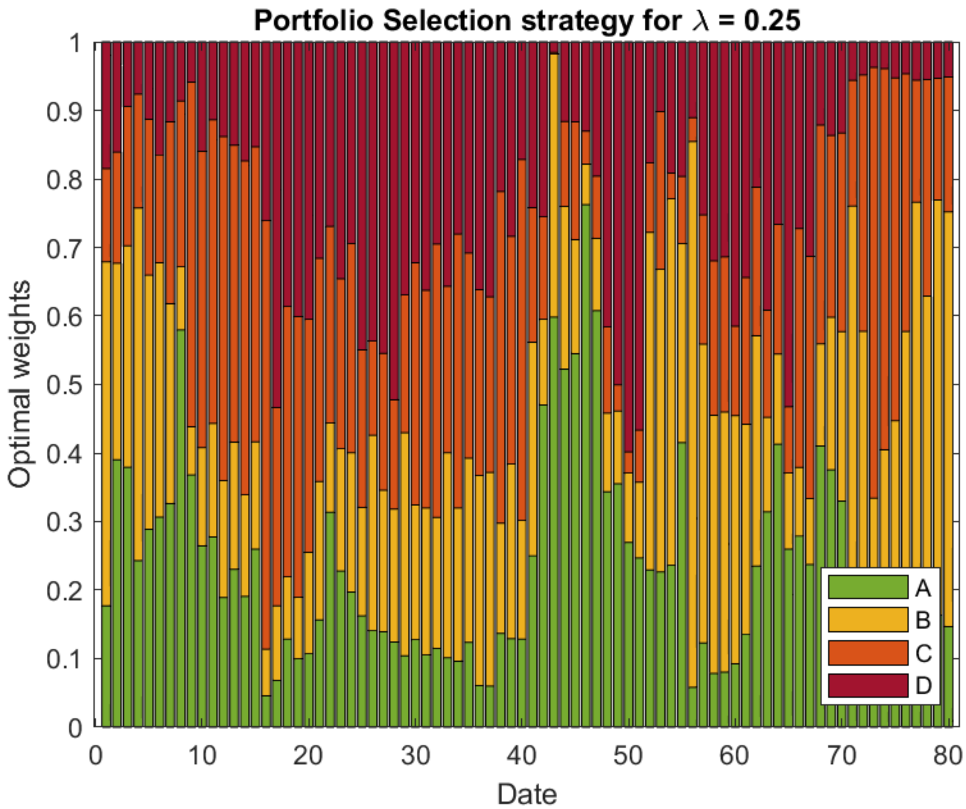


Figure 4.9: Optimal ESG portfolio selection with complex network structure

Portfolio Returns for different Investment strategy											
Year	EW	TD	TESG	NM	NTS	$\lambda = 0.005$	$\lambda = 0.025$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.25$	$\lambda = 1$
2016	0.074	0.077	0.060	0.060	0.058	0.062	0.065	0.066	0.066	0.067	0.067
2017	0.040	0.015	0.020	0.033	0.037	0.040	0.042	0.042	0.042	0.042	0.042
2018	0.016	0.038	0.026	0.016	0.026	0.016	0.012	0.012	0.011	0.011	0.011
2019	-0.010	0.026	-0.016	-0.014	-0.017	-0.009	-0.008	-0.007	-0.007	-0.007	-0.006
2020	0.107	0.102	0.095	0.099	0.0110	0.098	0.098	0.099	0.098	0.097	0.094
2021	0.068	0.070	0.077	0.050	0.058	0.064	0.067	0.067	0.067	0.066	0.066
2021	-0.046	-0.023	-0.035	-0.004	-0.039	-0.012	-0.024	-0.027	-0.029	-0.030	-0.031

Table 4.3: Portfolio returns of the portfolio optimization problem for different strategies

Sharpe Ratio for different Investment strategy											
Year	EW	TD	TESG	NM	NTS	$\lambda = 0.005$	$\lambda = 0.025$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.25$	$\lambda = 1$
2016	37.23	90.26	37.81	37.58	26.46	32.86	23.31	17.38	11.58	5.84	1.69
2017	34.66	45.26	29.87	33.20	34.17	25.26	14.14	9.52	5.85	2.77	0.77
2018	10.56	30.41	13.05	10.95	11.36	7.12	3.54	2.20	1.24	0.53	0.14
2019	13.73	30.84	13.48	14.52	13.56	12.32	8.12	5.83	3.71	1.62	0.10
2020	10.43	18.45	11.07	12.84	11.13	12.25	11.09	10.32	9.33	7.54	4.11
2021	12.32	23.60	15.89	12.45	10.11	12.94	9.87	7.66	5.42	3.03	1.01
2022	-2.39	4.47	-2.66	-0.23	-1.98	-0.40	-0.82	-0.84	-0.73	-0.50	-0.18

Table 4.4: Sharpe Ratio of the portfolio optimization problem for different strategies

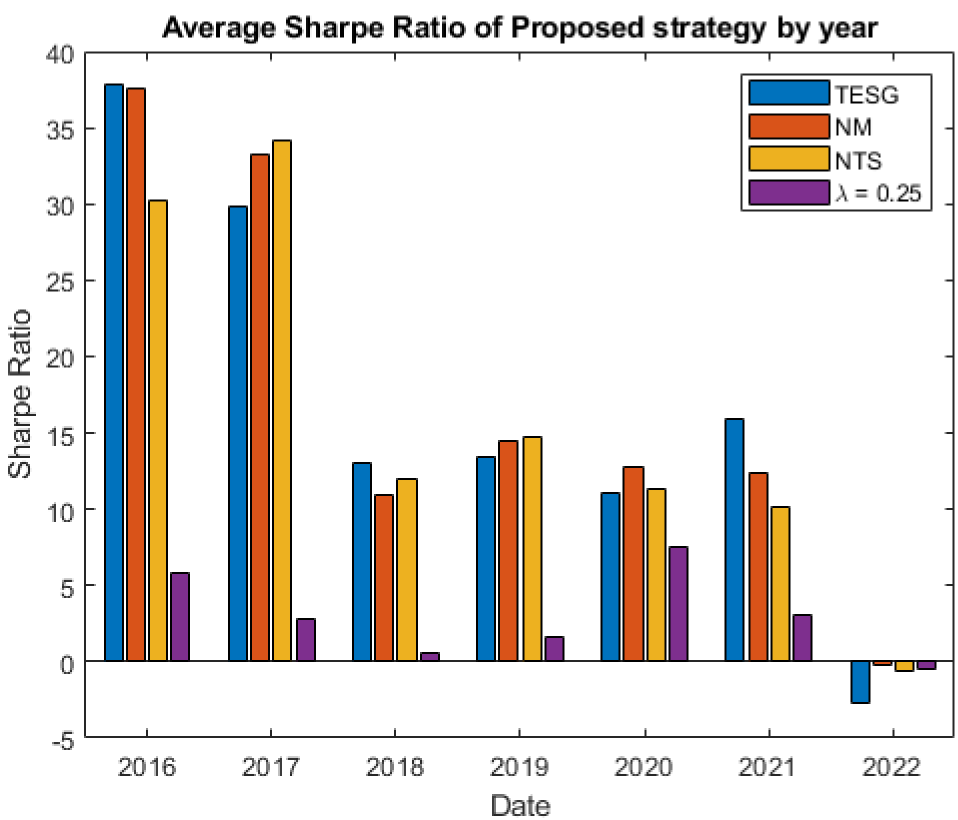


Figure 4.10: The Value at Risk for the proposed strategies TESG, NM, NTS and $\lambda = 0.25$

CHAPTER 5

Conclusion

In this thesis, we proposed different investment strategies that examine the role of ESG scores in Portfolio selection through the lenses of Network analysis. In particular, we extract a multilayer network that studies the connectivity patterns of institutions in different ESG classes and how these connectivity patterns affect ESG investment strategies. We apply our model using the ESG scores, daily returns, and volatilities of companies in the S&P 100. We have shown that the role of ESG scores in portfolio selection depends on the complexity of the network structure and the investor risk aversion parameter.

Our empirical findings show that institutions in the High ESG class are highly connected and are likely to be the central nodes in the network of returns. However, our findings also show that ESG scores may be irrelevant in the connectivity patterns of the volatility of firms and ESG plays no role in the risk component of firms even during COVID-19. We apply the connectivity patterns to devise different investment strategies to observe the role of ESG ratings on portfolio selection and our empirical results show that ESG scores are vital in portfolio selection if we assume simple network connectivity patterns or no network measures in the Portfolio selection process. However, if we adopt a complex network structure, then the relevance of ESG factors depends on the investor's risk aversion parameter to the network risk.

Lastly, we compare the out-of-sample performance of our proposed investment strategies and traditional corporate investment strategies such as the Traditional Markowitz portfolio strategy, and our results show Tradional Corporate Investments strategies with no ESG information perform better compared to ESG investment strategies.

APPENDIX A

Appendix

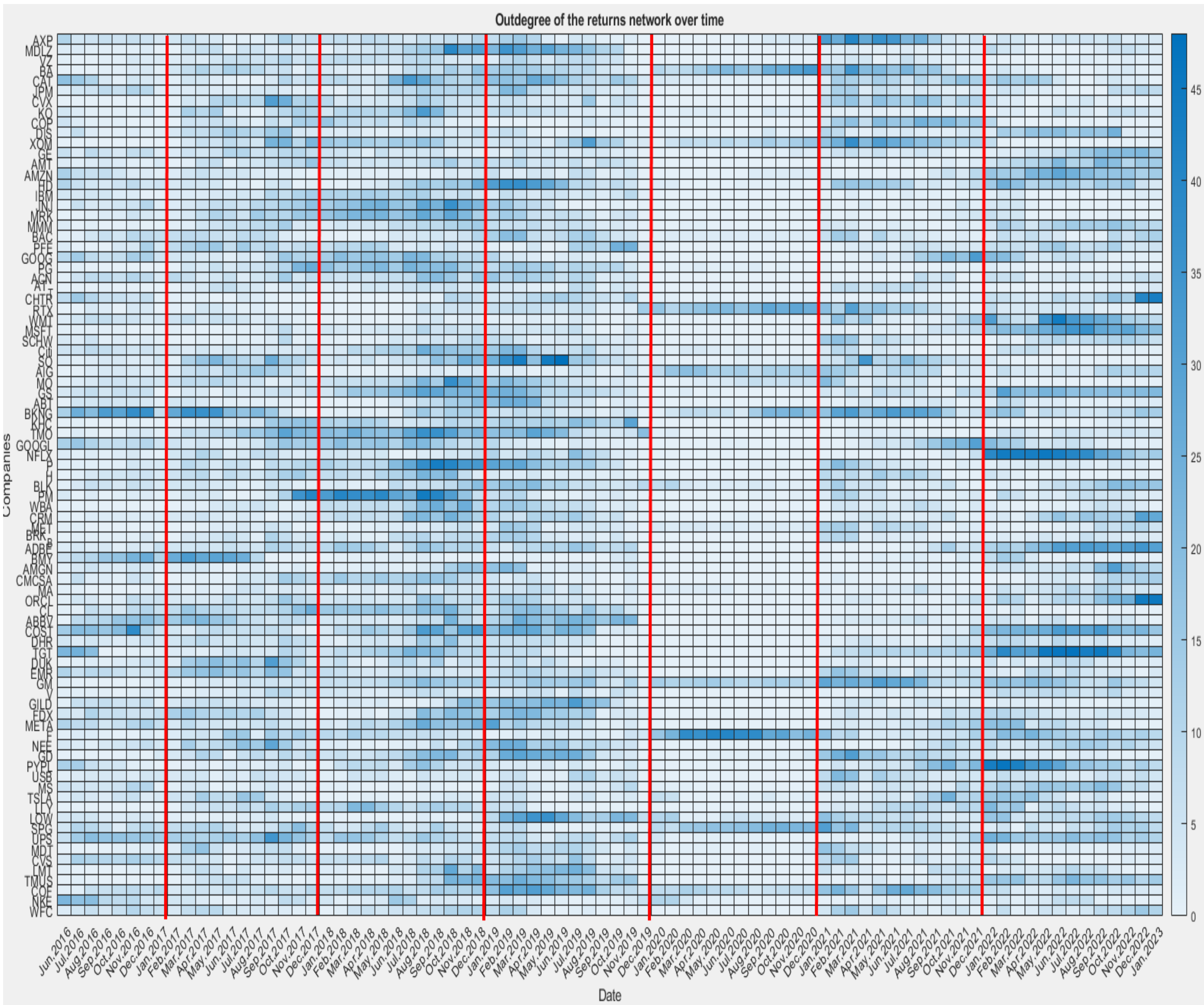


Figure A.1: Outdegree of network returns. We capture key nodes with great impact in terms of years since the central nodes change in time.

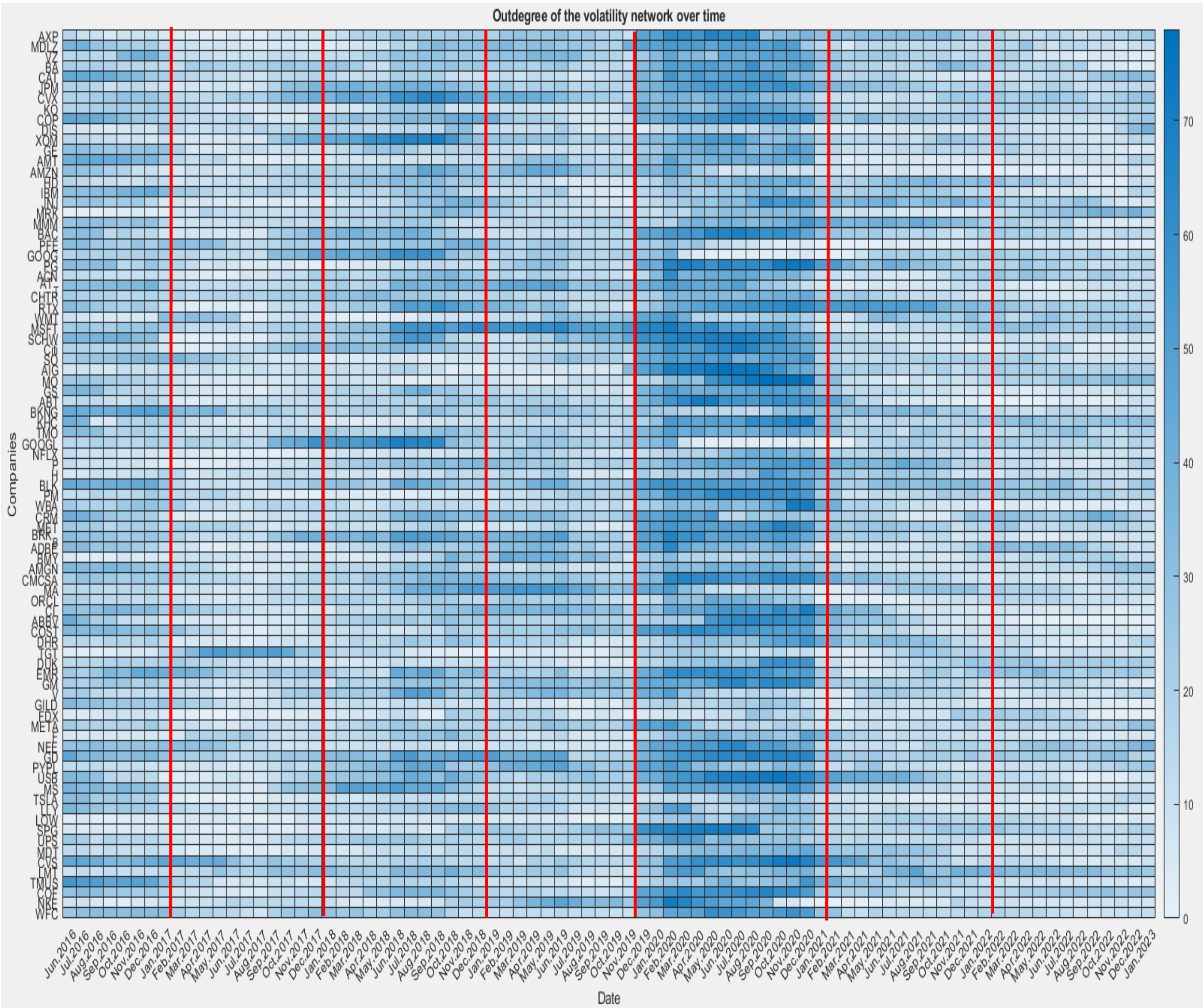


Figure A.2: Outdegree of volatility networks. These nodes could represent sources of risk or shocks in the network. Ideally, these nodes have the ability to spread risk in the network and could represent a great opportunity for investors.

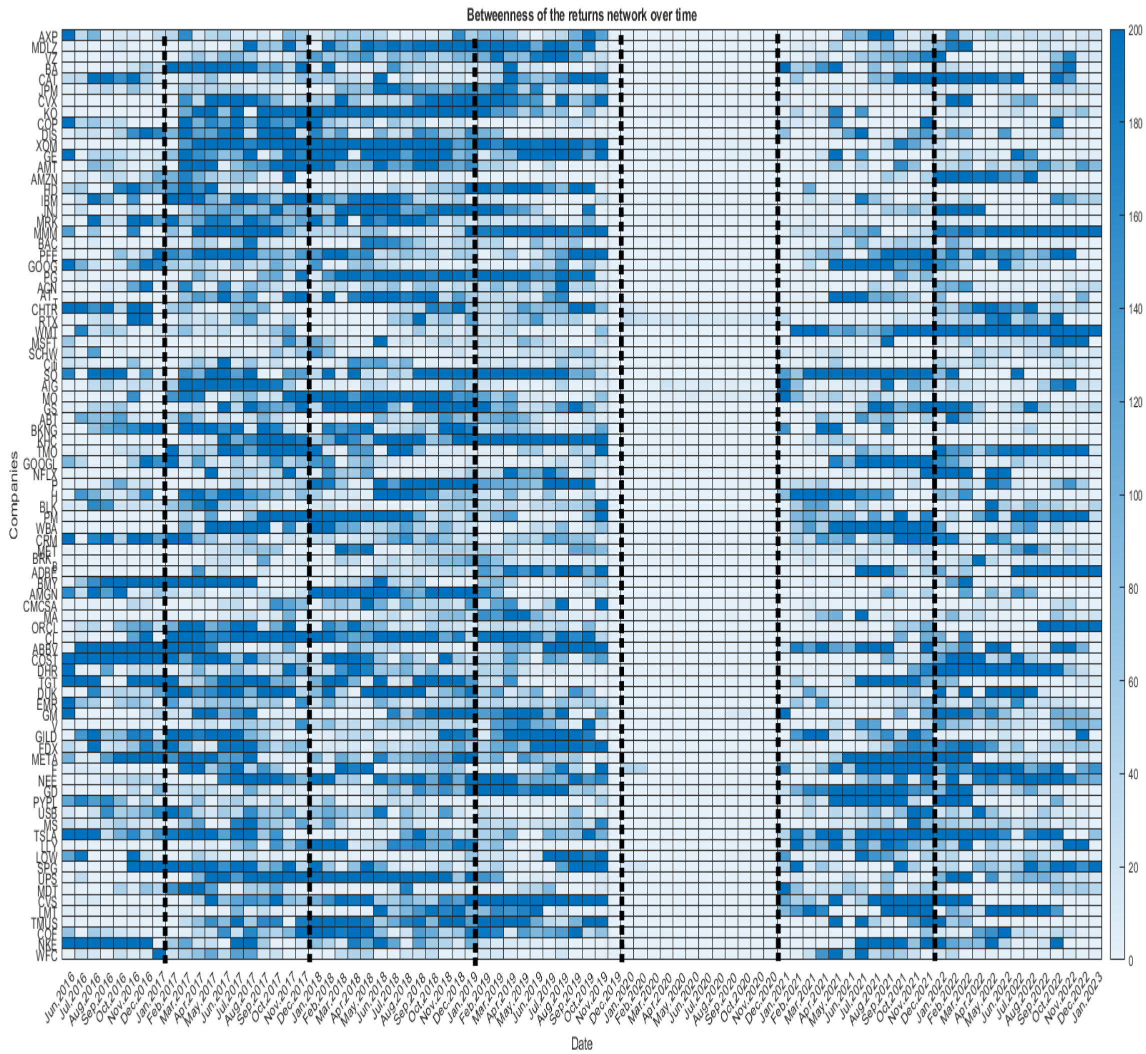


Figure A.3: Heatmap of the Betweenness centrality of the network returns where companies with darker color represent bridges that have a significant influence on the transmission of returns between other networks.

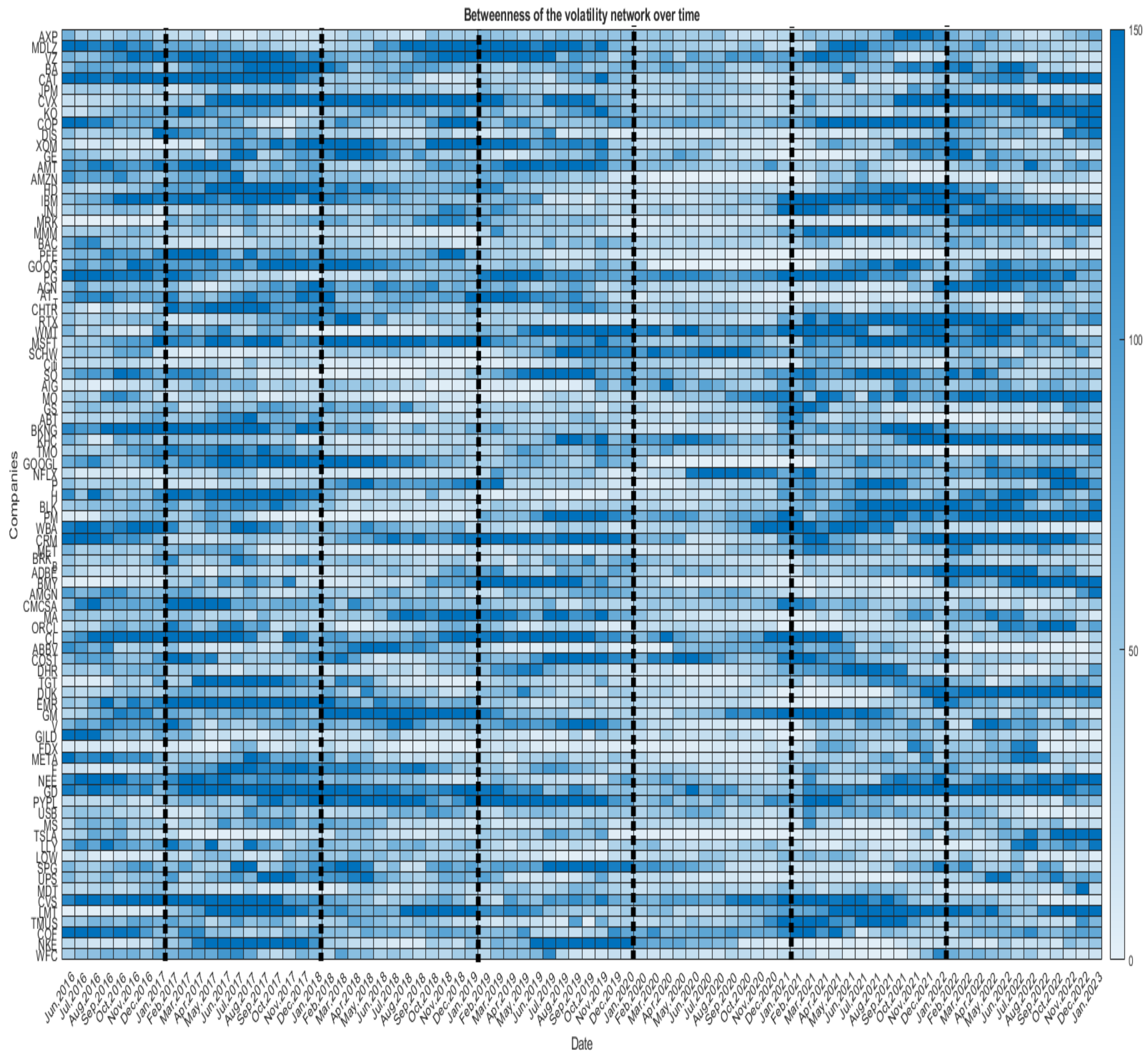


Figure A.4: Heatmap of the Betweenness centrality of the network volatility where companies with darker color represent bridges that have a significant influence on the transmission of shocks and risk between other networks

APPENDIX B

Appendix

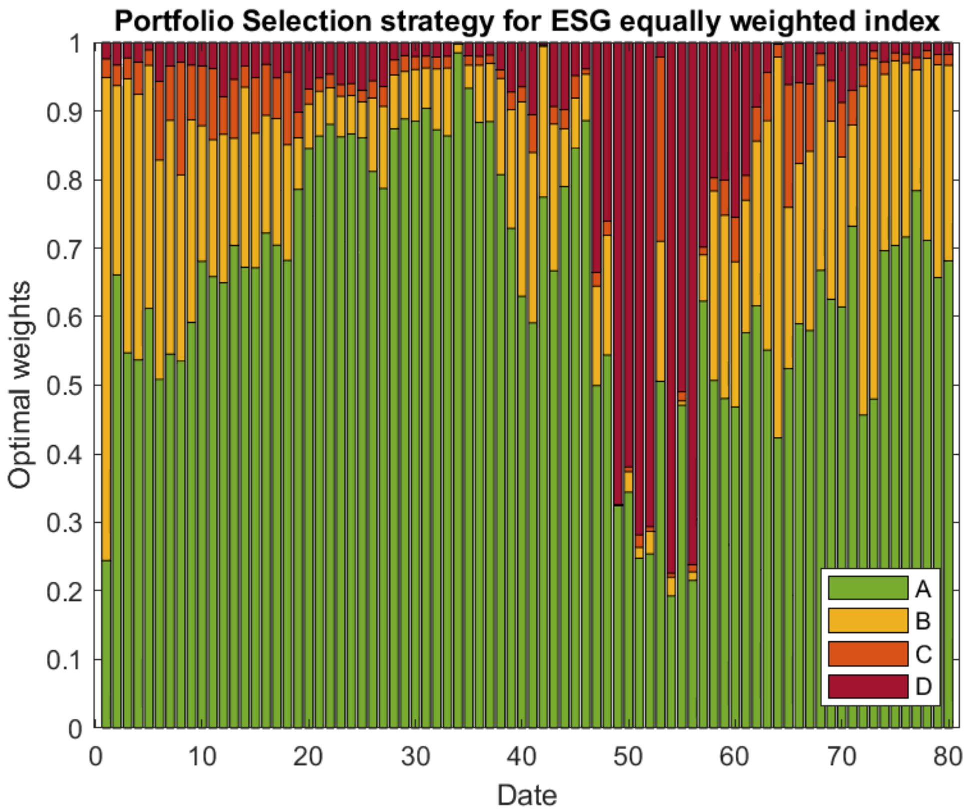


Figure B.1: Optimal ESG portfolio selection without Network measures

VaR for different Investment strategy											
Year	EW	TD	TESG	NM	NTS	$\lambda = 0.005$	$\lambda = 0.025$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.25$	$\lambda = 1$
2016	0.0008	0.0000	0.0011	0.0013	0.0047	0.0014	0.0017	0.0021	0.0030	0.0056	0.0251
2017	0.0254	0.0240	0.0226	0.0230	0.0233	0.0223	0.0244	0.0260	0.0287	0.0376	0.1203
2018	0.0388	0.0173	0.0308	0.0374	0.0326	0.0369	0.0433	0.0485	0.0580	0.0935	0.3424
2019	0.0784	0.0342	0.0747	0.0792	0.0841	0.0808	0.0821	0.0841	0.0888	0.1152	0.2948
2020	0.0922	0.0151	0.0921	0.0697	0.0691	0.0698	0.0703	0.0710	0.0735	0.0779	0.0855
2021	0.0104	0.0051	0.0046	0.0087	0.0105	0.0072	0.0085	0.0096	0.0113	0.0171	0.0841
2022	0.0902	0.0318	0.0739	0.0453	0.0762	0.0522	0.0639	0.0703	0.0806	0.1093	0.2614

Table B.1: Value at Risk of the Portfolio Optimization Problem for different strategies

Portfolio Risk for different Investment strategy											
Year	EW	TD	TESG	NM	NTS	$\lambda = 0.005$	$\lambda = 0.025$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.25$	$\lambda = 1$
2016	0.0021	0.0010	0.0017	0.0017	0.0023	0.0020	0.0030	0.0041	0.0064	0.0131	0.0466
2017	0.0054	0.0028	0.0043	0.0047	0.0048	0.0060	0.0081	0.0104	0.0149	0.0285	0.0962
2018	0.0086	0.0040	0.0068	0.0073	0.0078	0.0097	0.0144	0.0197	0.0300	0.0608	0.2147
2019	0.0142	0.0065	0.0130	0.0134	0.0148	0.0147	0.0180	0.0220	0.0298	0.0532	0.1702
2020	0.0435	0.0166	0.0412	0.0353	0.0366	0.0356	0.0364	0.0372	0.0386	0.0415	0.0523
2021	0.0056	0.0031	0.0048	0.0041	0.0054	0.0050	0.0070	0.0090	0.0131	0.0249	0.0841
2022	0.0175	0.0074	0.0145	0.0109	0.0158	0.0139	0.0179	0.0214	0.0278	0.0466	0.1400

Table B.2: Portfolio Risk of the Portfolio Optimization Problem for different strategies

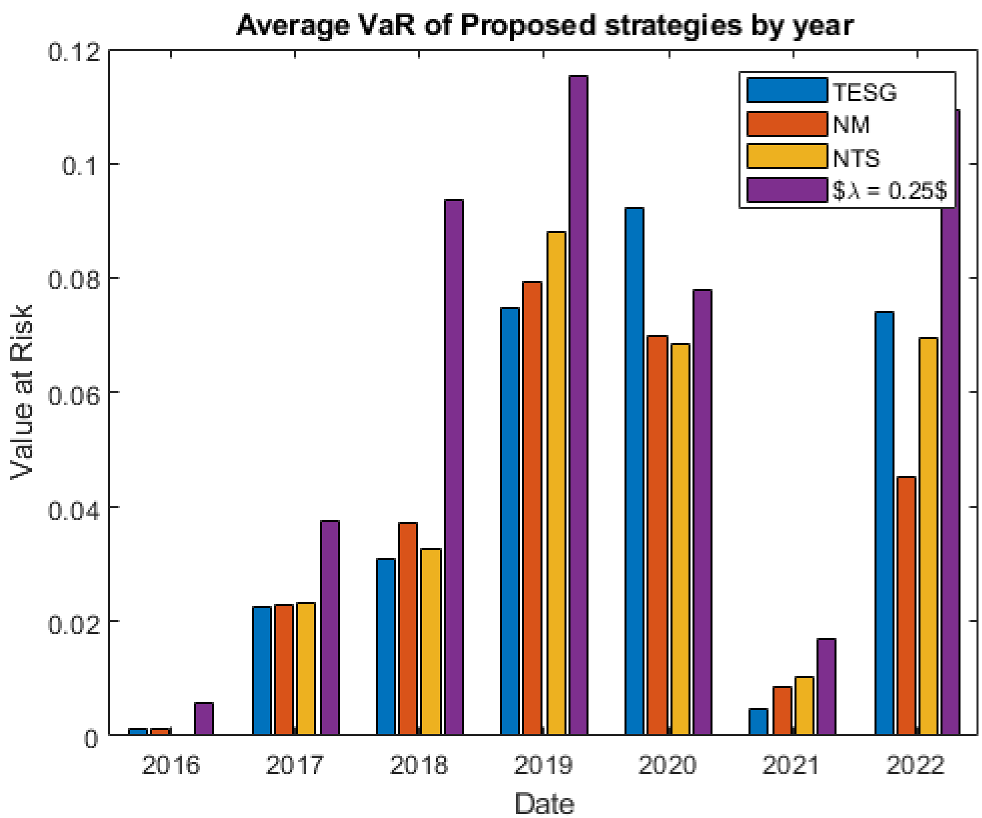


Figure B.2: The Value at Risk for the proposed strategies TESG, NM, NTS and $\lambda = 0.25$

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