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SUPPLY CHAIN NETWORKS AND RETURN PREDICTABILITY

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Abstract

I use network theory to construct a set of long-short strategies for 65 companies, connected to the tire industry via trade relationships. I find that companies that are more central to the supply chain network earn higher returns that peripheral firms (Information Ratio of 0.72). A plausible explanation to this is that central firms are exposed to more shocks and, therefore, command a higher risk premium. Empirical evidence for this sector also suggests marginal return predictability for supply chain networks (for the revenues and market data), however, it does not outperform the benchmarks due to fast information diffusion across the network.[1]

[1] Source code can be found at: https://github.com/anna-averina/Thesis; the password for the data files is "thesis2019novasbe".

Contents

I. Introduction

Firms do not exist in isolation. Instead, they are interconnected through supply chain links, sector exposures, strategic partnerships, and a variety of other material relationships. In the evermore interconnected global economy, this implies a greater deal of exposure to shocks — from specific customer-supplier disturbances to macroeconomic fluctuations. A simple example of large production cuts by leading oil producers hurting financial results of internet retailers illustrates this spillover effect. (Ahern, 2013) First, resource-dependent economies cut oil production to balance their budgets, then refineries manufacture fewer oil products, next — shipping firms are forced to increase costs to sustain operating profits, which ultimately hits cash flows of internet retailers. This simplistic example demonstrates the importance of understanding and researching transmission mechanisms within supply chain networks, between sectors, and in the context of a wider economy.

In this paper, I focus on the former — supplier-customer relationships. I examine how shocks to one firm affect other companies in their supply chain network through two main channels: a) percentage of revenues attributed to a particular trading partner; b) variations in the stock market prices. As such, under channel "a)" I study the propagation of shocks from a customer to their supplier: for instance, if revenues of Micron Technology Inc, a semiconductor company, are caught in the crossfire of the U.S. — China trade war, how fast and how severe would that hit the stock price (perception of future revenues plunge) of Micron's biggest supplier, Lam Research Corporation? Similarly, in the channel "b)", if we see a hard Brexit in March 2019, up to which degree suppliers, customers, and competitors of Gecina SA, one of the largest French office real estate firms, would see a rise in their stock price? Admittedly, these two channels might seem similar on first sight, the key difference between them lies in the network specifications.

A network is an analytical tool that came to finance from physics, biology, and computer science. It helps to structure complex asymmetric relationships and, with advancements of computing power of modern software, it provides insights into investment analysis with increasing accuracy and diversity of techniques. I use this tool to formalize the supply chain network of firms, where the companies are interconnected either based on their revenues exposure (channel "a)"), or through the correlations of their stock returns (channel "b)"). This bi-directional analysis allows to separate trade-prompted fluctuations in the stock price (so-called pure "customer-supplier effect") from variations that are caused by all information available in the market, including supply chain links.

Under such setup, I examine the degree of market efficiency in the network comprised of 13 markets; I build a set of long-short equity strategies that are designed to:

i) take long positions in central elements of the network (based on betas, correlations, and covariances) and short positions in peripheral firms as the former are more exposed to inter-sectoral shocks and, therefore, command a higher risk premium;

ii) take long positions in firms with highest revenue link to the rest of the network and short companies with the lowest percentage of revenues coming from the network which is similar to the centrality-based rationale of higher risk premium;

iii) take long and short positions in stocks to construct a passive strategy based on cross-section betas as the market is assumed to contain information about trade flows. This adds up to 5 separate networks used for the analysis (3 networks under channel “i)”, 1 under channel “ii)” and 1 under channel “iii)”).

This paper contributes to two pillars of academic literature. First, it adds to the existing literature on investment analysis of supply chains. Hong and Stein (1999), Hou and Moscowitz (2005), Cohen and Frazzini (2008) explored stock price patterns between customer-supplier companies in the events of earnings announcements. They find that supplier companies are affected by the positive/negative news from customers with a time lag due to limited investor attention. These studies are largely focused on inter-sectoral propagation effects and use the input-output data from CRSP/COMPUSTAT for the U.S. firms since the Statement of Financial Accounting Standards (SFAS) No.131 requires public companies to report information about customers who represent more than 10% of their annual revenues or sales. In my study, I use Bloomberg Supply Chain Monitor data to construct not a sector, but a firm-level network for the tire industry; the network covers 13 equity markets and includes customers, suppliers, and a peer group of Michelin SA, a central to the network firm. I have chosen Michelin SA, since it a single-product tire producer, which is exposed to commodity shocks via its suppliers (materials) and consumer sentiment shifts via its customers (auto, air industries), which makes it an interesting industry for analysis that involves indirect assessment of shocks’ spillovers. Another contribution to the existing body of literature under the first pillar lies in the specification of the baseline long-short strategy: I depart from testing supply chains’ diffusion effects during earnings announcements and hypothesize that companies with higher betas to the rest of the network firms are more exposed to supply chain shocks than companies with lower betas. Thus, in one of the hypotheses, I infer that a long-short strategy with baskets of high (long) and low (short) beta companies outperforms the benchmarks (Section IV. Hypotheses).

Second, my thesis contributes to research on the network theory applied to investment analysis. Existing literature finds contradictory evidence regarding the role of the network elements in the return predictability. A number of papers (Ahern (2013), Anjos and Fracassi (2015)) find that higher network centrality is positively related to stock outperformance: long-short portfolios with a long position in top central stocks and a short position in bottom central stocks generate alpha. At the same time, Ramirez (2014) and Herskovic (2018) find the opposite to be true: due to higher risk premium and lower exposure to shocks, peripheral firms tend to outperform central companies. Intrigued by this dichotomy of academic findings, I test whether the central companies indeed outperform peripheral firms and evaluate the network topology based on centrality, connectivity, and density measures.

The remainder of this paper is organized as follows: Section 2 discusses supply chain investing, market psychology, and network theory literature. Section 3 describes the methodology used in this paper as well as the theoretical background of the network theory. Section 4 embarks on the research hypotheses on: i) delays of information diffusion through complex supply chain networks and ii) network topology which both are hypothesized to yield financial benefits under the long-short equity strategies. Section 5 provides an overview of the data. Section 6 presents the model. Section 7 introduces the results of empirical tests, and Conclusion discusses the future direction of the research.

II. Literature overview

In my thesis, I attempt to align supply chain analysis with the network theory. As to the former, prior research of return predictability for supply chain-linked companies provides empirical evidence of such due to constraints of information acquisition and limited investor attention. One of the pioneer papers in the field from Cohen and Frazzini (2008) utilizes customer-supplier relationships to build a long-short equity strategy of buying firms whose customers experienced positive news in the previous month and selling firms whose customers underwent negative developments. They find that this strategy of "customer momentum" yields alpha of 155 basis points on a monthly basis over the period span from 1980 to 2004. Authors link this result to constraints of investor attention: in the world of tremendous information availability, investors are bounded by a scarce cognitive capacity, and therefore they are forced to select few information sources for their decision-making process.

A similar conclusion was reached by Huberman and Regev (2001) who study the surge of the stock price of EntreMed, a company specializing on the cancer treatment, after the release of an article on the cancer breakthrough research in New York Times that was published in Nature journal five months prior to the NYT release. Other theoretical (Hong and Stein (1999)) and empirical (Hou and Moscowitz (2005)) studies also find that information propagates through markets with a time lag due to delays in investor recognition, generating return predictability.

Further direction of research on implications of customer-supplier relations for return predictability focuses mostly either on special situations, such as quarterly earnings announcements or on cross-industry analysis. An example of the former bulk of studies, Pandit et al. (2011) find evidence of information externalities for supplier firms in the time of customers earnings announcements; the market-adjusted returns are found to be affected more severely when the strength of economic links between suppliers and customers increases and the quarterly results are below the consensus.

Building up onto Cohen and Frazzini (2008) findings, Madsen (2017) shows that anticipation of supplier earnings announcements stimulates acquisitions of customer information which contributes to the price discovery and reduces the "limited investor attention" bias. He finds that customer news predict suppliers three-day pre-announcement returns, however failing to predict three-day post-announcement returns.

Finally, Evans and Outlaw (2018) show that sophisticated investors can capture informational asymmetries in supply chains. They show that short sellers place their trades on the suppliers/customers, whose customers/suppliers are only yet to undergo disappointing public announcements ("only yet to undergo" here is approximated by the open short interest on the customers/suppliers), exploiting limited attention span by less informed investors.

Academic literature on supply chain arbitrage also goes beyond the special situations studies and aggregates customer-supplier interdependencies to the level of industry spillover analysis. Menzly and Ozbas (2006), for example, find strong positive cross-autocorrelation among industries that are closely related to each other along the supply chain, documenting the effect as "cross-industry momentum." The annual alpha generated by this strategy is $\sim$6%.

Since the global financial crisis and up until recent years, the network theory was predominantly applied to the analysis of the financial system, contagion in the banking sector, and business cycle studies. As such, network theory in the context of return predictability for supply chain-linked companies is an emerging but fast-growing academic pillar. For instance, Ahern (2013) suggests that industries that are more central to intersectoral trade earn higher returns than less central industries as they have greater exposure to sectoral shocks, market, and future consumption growth. He builds a CMP (central minus peripheral) portfolio and finds that correlation between the returns of close industries increases in 1-3 months, while the diffusion of shocks through the peripheral industries takes as long as 10-12 months.

Around the same time, Ramirez (2014) points out that the topology of the firm network determines risk premia: central to the network firms command lower risk premium that peripheral companies as the latter rely more strongly on their existing supply chain links, thus, experiencing larger damage when their major counterparties undergo adverse developments. Constructing a long-short portfolio (long position in the lowest degree of centrality), the author obtains 0.8% alpha on a monthly basis and controls for the contagion risk of peripheral firms.

Herskovic (2018) finds that the network concentration and network sparsity (degree of input specialization) are the two metrics that influence asset prices in multi-sector input-output networks. His two models buy high i) sparsity, ii) concentration beta stocks while selling low i) sparsity, ii) concentration beta stocks, achieving 4.6% (i) and -3.2% (ii) return spreads, respectively.

Apart from exploring networks based on sectoral topology, another line of research focuses on investor networks. For example, Ozsoylev et al. (2013) show that investors positioned more centrally tend to outperform peripheral investors, based on the Istanbul Stock Exchange data. Receiving early information signals, central investors trade in the direction of subsequent stock movement before their peripheral peers, such that one standard deviation increase in centrality leads to 0.7%-1.8% increase in monthly returns, depending on specification.

III. Methodology

Network theory provides insights into investment analysis of equities which are interconnected by economic, financial, or other significant relationships; it allows to examine systematic interdependencies between standalone securities and contributes to the classic historic price analysis (i.e., backtesting). A network, in principle, is a set of nodes and links. Nodes can be presented as companies, investors, analysts, or any other entities. Nodes are connected by links — price correlations, betas, supply chains relationships, or common exposure to other factors. Links commonly have weights that determine the strength of the relationship between two given nodes; stronger weights in this paper are graphically depicted as thicker lines. The edge is comprised of the node j, node k, and the link between j and k. The neighbors of a node are all the nodes to which it has a link and the shortest path is the number of links it takes to get from node j to node k, assuming all nodes in between are distinct. (Soramki et al., 2006) The average shortest path length is computed as follows:

$$a = \sum_{j,k \in V} \frac{d(j,k,)}{n(n-1)}, \quad \text{where}$$

V is a set of nodes in the network, $d(j,k)$ is the distance between the nodes j and k, and n is the total number of nodes. (Hagberg et al., 2008) The average shortest path length $\in [0,+\infty]$, such that the higher the number the nodes involved in travel between j and k, the lower the indicator.

Average shortest path allows to assess the lags associated with information spillover across the network and will come to the forefront when estimating return predictability of supply chains within the confines of delayed investor reactions to the market updates.

The network properties that allow assessing its topology in this paper are given by density, sparsity, connectivity, and centrality. For the network with n nodes and m links, connectivity defines the number of links relative to the possible number of links and is given as $p = \frac{m}{n(n-1)}$, where $p \in [0,n]$, such that if $p \to n$, then all possible nodes are connected and a network is considered to be complete and dense. (Santos and Cont, 2010) If $p \to n$, the network is considered to be sparse. As such, density and sparsity represent the degree of the network's connectivity. Economically, higher connectivity is consistent with fast propagation of idiosyncratic shocks through the network.

Centrality metrics identify important hubs that are better connected to the rest of the network. One of such measures is degree centrality $(di) \in [0,1]$ which calculates the number of links attained to node j, giving equal importance to all links. (Freeman, 1977) The higher the metric $(di \to 1)$, the more central position the node takes.

IV. Hypotheses

Previous findings present controversial results regarding the role of network centrality in return predictability — Ahern (2013), Anjos and Fracassi (2015) versus Ramirez (2014) and Herskovic (2018). As such, this paper attempts to determine the relation between network centrality and stock performance:

> *Hypothesis 1.* Central to supply chain network companies earn higher returns than peripheral firms.

Briefly formed, this hypothesis is underpinned by three main assumptions. Firstly, it assumes that prices contain updated information about trade relationships between companies. Secondly, it assumes that reduced networks replicate properties of the wider network proportionally. Finally, it assumes that shocks within the network do not cancel out through diversification. I discuss these assumptions below in greater detail. The first assumption refers to informational market efficiency, implying that not only price correlations contain information about trade links between firms, but also that the release of new information immediately updates the prices. This assumption is key to my analysis as I construct the networks based on correlations, covariances, and betas of stock returns. As such, information about supply chain topology is transmitted to the test network through correlations, covariances, or betas. This confirms the validity of hypothesis 1 specification: given the information about cross-company correlations, covariances, or betas, it is possible to test whether central firms in supply chain networks earn higher returns than peripheral companies.

The second assumption implies that the selected network of companies is a reduced version of a global economy network that is interconnected through cross-border and cross-sector linkages. An easy example to grasps this idea is to think about fractals — mathematical sets that repeat its patterns at increasingly small scales, indefinitely and recursively. (Mandelbrot, 1982) Although economic networks exhibit little similarity to fractal topology, this comparison captures the gist of the underlying assumption. In the absence of feasibility to construct a global economy network with high accuracy and precision as well as to estimate the properties (e.g., centrality) of such network, I assume that features attributed to the clusters of the global economy networks replicate respective features of the wider network. These clusters can be identified as national economies, sectors, or supply chains. As such, estimating network properties on the trade links between a given set of firms would provide valid inference regarding generalized network properties.

Finally, the third assumption is crucial to ascertain the gist of hypothesis 1 — why would central firms earn higher returns than peripheral companies. The myopic macroeconomic idea that negative shock in one industry would be canceled by a positive shock in another industry, and hence, keeping the economy and volatility unaffected, has long been a prevailing view Acemoglu et al. (2012) find that supply chain networks in the U.S. are asymmetric: some elements of the networks have more input-output links than the others. The asymmetric nature of the economic networks also implies that the shocks occurring in different parts of the trade system do not cancel each other out. Instead, they aggregate to the economy-level volatility. This suggests that network elements that are more interconnected (higher centrality) with other network elements have greater exposure to the shocks and systematic volatility. Given that these shocks cannot be canceled through the diversification, central companies are hypothesized to earn higher returns than peripheral firms to compensate for greater exposure to systematic risks. (Ahern, 2013)

The body of research (Huberman and Regev (2001), Cohen and Frazzini (2008), Pandit et al. (2011) and others (referred to in the literature overview section)) has shown that due to the lags in investor reaction to new information, long-short strategies for the firms linked through supply chain can earn superior risk-adjusted returns. These studies, however, restricted their analysis in multiple ways: first, they examined pairs of firms (supplier-customer) instead of a simultaneous complex network of companies; second, they tied trading windows to earnings announcement events. In this thesis, I attempt to overcome these restrictions and examine if return predictability holds in a continuous sample (not centered around earnings events) for the trade network of companies in its complexity.

> *Hypothesis 2.* Due to the limited attention of investors, supply chain networks exhibit return predictability.

The second hypothesis is based on three assumptions. Firstly, there is a limit to the market efficiency due to cognitive capacities of participating investors. Secondly, net betas provide insight into supply chain network topology. Finally, information about percentages of revenues to a particular supplier/customer can approximate respective supply chain links.

The first assumption sends us back to hypothesis 1 — assumption 1. In this case, however, we infer that stock prices do not reflect all available information as investors delay price discovery due to their limited cognitive capacities. Psychological studies show that attention is a scarce resource, which is why attention to one responsibility requires allocation of all available resources from another responsibility. (Kahneman, 1973) As such, in a world of tremendous informational flows and high pace of change, it is rational for investors to choose a limited number of information sources as most investment management roles involve multitasking. Hence, market players attention span is limited. Note, however, that this assumption does not override assumption 1 of hypothesis 1 (prices do contain information about supply chain topology), as behavioral finance is a complement but not a substitute to traditional finance.

The second assumption refers to the second part of assumption 1 of hypothesis 1 — information about supply chain topology is transmitted to the test network through betas. Betas are preferred to correlations and covariances, as they provide directionality of the relationship. As such, if prices reflect information about network topology, then betas (and therefore — net betas, whose derivation will be provided in section VI.Model) will transmit this information as well, preserving original directionality. Assuming that investors are characterized by limited cognitive capacity, it is possible to use net betas to assess whether supply chains exhibit return predictability.

Finally, I assume that the data regarding percentages of sales attributed to a particular customer/supplier is optimal to approximate trading links between firms. I infer this as in the tire industry, direct sales account for most of the money transfers in the supply chain, such that few sales are made on credit (source: financial statements of Michelin SA and other tire pure-play producers). Apart from that, the Statement of Financial Accounting Standards No.131 obliges public firms to disclose information about customers that comprise more than 10% of their annual sales for the purposes of monitoring supply chains, which also validates this assumption.

V. Data

The data is obtained from Bloomberg Professional Services — Supply Chain Monitor and historic pricing databases. Supply chain monitor data represents the percentage of revenues of suppliers attributed to particular customers. Historical pricing data covers the period between 10/07/2000 and 04/12/2018 and is comprised of 3563 data points for each of the 65 companies in the network.

The final network is reduced from 91 companies until 65 due to the loss of information. Deleted companies had up until 3136 missing values, thus reducing the analyzed period for the entire network to 427 days, with windows of missing values as long as several years. Therefore, it was decided to select a cutoff value 65 (firms) as this number was consistent the highest increase in time span, as is demonstrated in Appendix 1.

The dataset is further divided into the training and test sets. (Gareth, 2013) Training dataset is used to fit the parameters of the model, in other words, to calculate betas, correlations, covariances, and the network topology metrics (connectivity, centrality) that will be used to design the long-short strategy. The test set is used to provide an unbiased estimation of the final strategy specification; simply put, it is a time period for which the strategy is applied to returns data to assess the annualized performance metrics (mean, standard deviation, information ratio). I have selected ½ proportion split between the training and test datasets (training: 10/07/2000 — 06/10/2009, test: 06/10/2009 — 04/12/2018).

To assess the performance of the strategies relatively to equity indices, I identify three different benchmarks. One would argue that the performance of the U.S. equity would suffice; I, however, complement the set with two more indices: i) sectoral ETFs index, weighted by participation in my network ii) regional ETFs index, weighted by the regions of largest revenues of my network. As such, the former is based on consumer discretionary ($\sim$ 62%), industrials ($\sim$ 14%), materials ($\sim$ 9%), and information technology ($\sim$ 9%) ETFs, as they cover operating activities of 61 out of 65 companies in the network. Selected ETFs come from the umbrella of Vanguard funds

— VCR US Equity, VIS US Equity, VAW US Equity, and VGT US Equity, respectively to the order in the previous sentence. The second commingled benchmark is given by EMEA equity ETFs (IEV US Equity — Europe, XMEA GY Equity — EM EMEA) in sum totaling in $\sim 31\%$; the Americas (SPY US Equity and ILF US Equity for the U.S. and LatAm regions) that, respectively, comprise $\sim 39\%$ of the final benchmark; and Asia Pacific (AAXJ US Equity, $\sim 28\%$). These geographies cover the largest revenue regions for 63 out of 65 companies in the network.

VI. Model

Hypothesis 1 — Model

The baseline model for the test of hypotheses 1 is built on covariances, correlations, and betas networks. Although similar, each of these metrics has its own drawbacks and advantages, which is why it was decided to start with three baseline models. One can argue that covariance is better suited for analysis of time-varying models as it accommodates for the change of scale, which is possible in a form of a structural shift (for example, in 2008). At the same time, covariance is bounded by $[-\infty;+\infty]$ which, in presence of extreme events, would skew the topology properties, e.g. centrality. Correlation remediates this deficiency and indicates the strength of the relationship between two variables, however, it does not provide the insights into the causality. Finally, betas are obtained from regression analysis of generic specification:

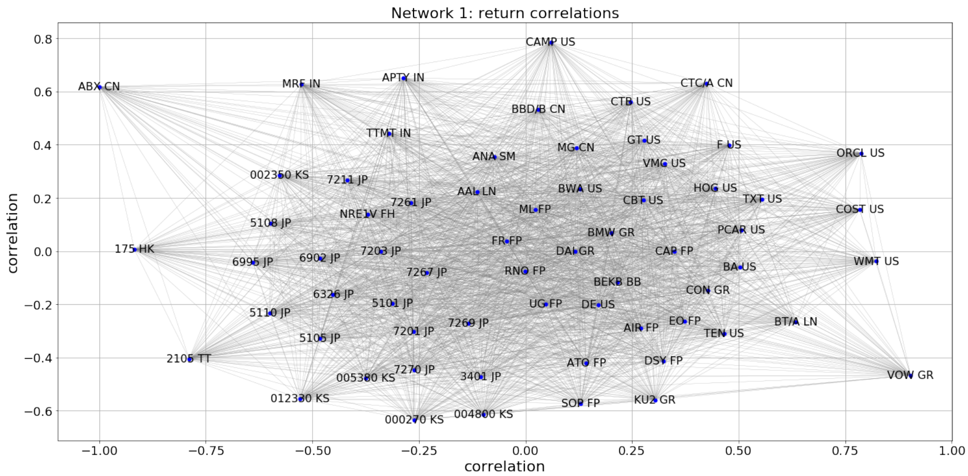
$$y_i = \alpha + \beta_1 \cdot x_i + u, \quad \text{where} \tag{1}$$

y_i are the returns of the company y at time i and x_i are returns of the company x at time i. For such specification, I use ordinary least squares method of obtaining coefficient for the regressor (returns company x). I also do not explicitly account for the market risk premium in the equation as, given the presence of 13 markets in the network, it increases the noise, e.g, variation in data that does not add explanatory power.

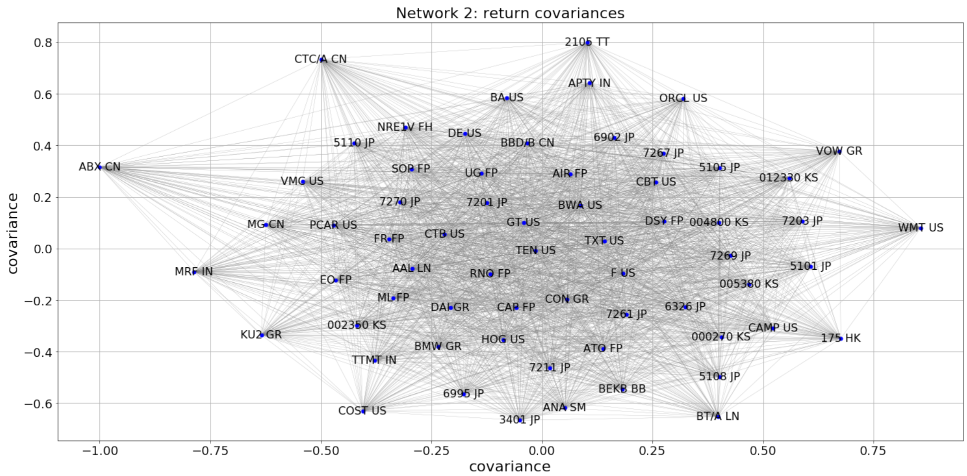
To further reduce the noise in the network, I establish thresholds for absolute values of correlation and covariance (to eliminate $\sim 20\%$ of lowest metrics), which are: 0.03 and 0.004, respectively. For betas, I use a cutoff of 0.05 for p-value to select only statistically significant betas for the network analysis. I also place an absolute value cap on the beta coefficient itself equal to 3 as some companies exhibit tremendous volatility: for example, in some of the eliminated regressions, a basis point increase in returns of the regressand would need to be matched by '000 basis points increase/decrease in regressors. These restrictions help to remove meaningless relationships between the companies as well as to scale the variables, which in turn reduces the volatility of the final results.

Using NetworkX package (Python), I visualize the networks that are used to validate hypothesis 1. Figure 1 presents the network graphs, where nodes are given by network companies and links are represented by a) correlations, b) covariances, and c) betas:

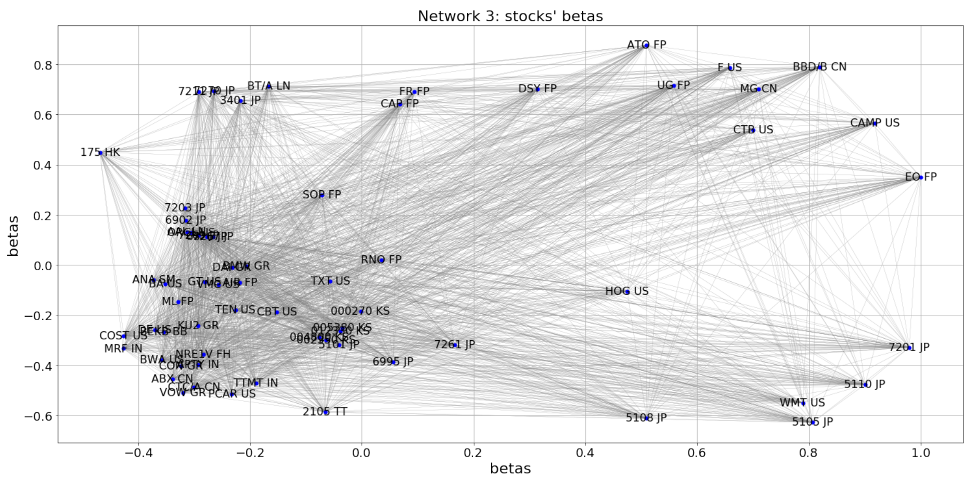
Figure 1: Networks



(Figure 1.a) Network 1 — Return Correlations



(Figure 1.b) Network 2 — Return Covariances



(Figure 1.c) Network 3 — Stocks' Betas

As could have been noticed, the shapes and density (thickness and number of links) of the networks above differ. This attributes to the differences in selected thresholds and dimensions of loadings' (correlations, covariances, and betas) values. Overall, the density metrics for all networks are high: ~ 0.979 for a), ~ 1.030 for b), and ~ 0.947 for c). Density above 1 is possible when the network has self-loops. (Hagberg et al., 2008)

Hypothesis 1 — Test

To test the hypothesis that central to supply chain network companies earn higher returns than peripheral firms, I utilize networks a), b), and c) from the previous section. I construct a long-short portfolio, in which I buy companies with the highest centrality values and I sell firms with the lowest centrality values, for the training period of 10/07/2000 — 06/10/2009. The long leg is comprised of a greater number of firms than the short leg (the numbers can be found in section VII.Results) to approximate the long bias and adhere to the limit on leverage (maximum of $4x$), as correlations, covariances, and betas distributions are skewed to the right. (Appendix 2)

Assuming static network topology, generic centrality strategy is given by:

$$[AB]_{i,j} = a_j^T \cdot B_{i,j}, \quad \text{where}$$

$[AB]_{i,j}$ is the resulting matrix of returns filtered through the strategy. Transposed vector a_j^T is a generic form of the strategy matrix, consisting of signals $= \{-1, 0, 1\}$ for sell, no action, and buy operations, respectively. The signals a_j^T are based on measures of degree centrality for each node i (sorted in descending order), which, in turn, differ for networks based on correlations, covariances, and betas. $B_{i,j}$ is a 1781×65 matrix of returns for companies $j = \{1, \ldots, 65\}$ and test dataset $i = \{1, \ldots, 1781\}$. $[AB]_{i,j}$ is then used to compute the performance metrics associated with the strategy. One of them, an annualized mean return is computed as:

$$\mu = \frac{\sum_{i=1}^{N} \log(\frac{P_{t+1}}{P_t})}{N} \cdot 250, \quad \text{where}$$

N is number of trading days in a given year and 250 is an average number of trading days in a year, used to annualize the returns. The standard deviation of the portfolio returns is given by:

$$\sigma = \frac{\sum_{i=1}^{N} (\log(\frac{P_{t+1}}{P_t}) - \mu)^2}{N-1} \cdot \sqrt{250}, \quad \text{where}$$

$N-1$ is the number of trading days in the year less one, as ς is a sample statistic. Finally, the Information Ratio is used to evaluate the performance and is calculated as:

$$\text{Information Ratio} = {}^{\mu}/_{\sigma}.$$

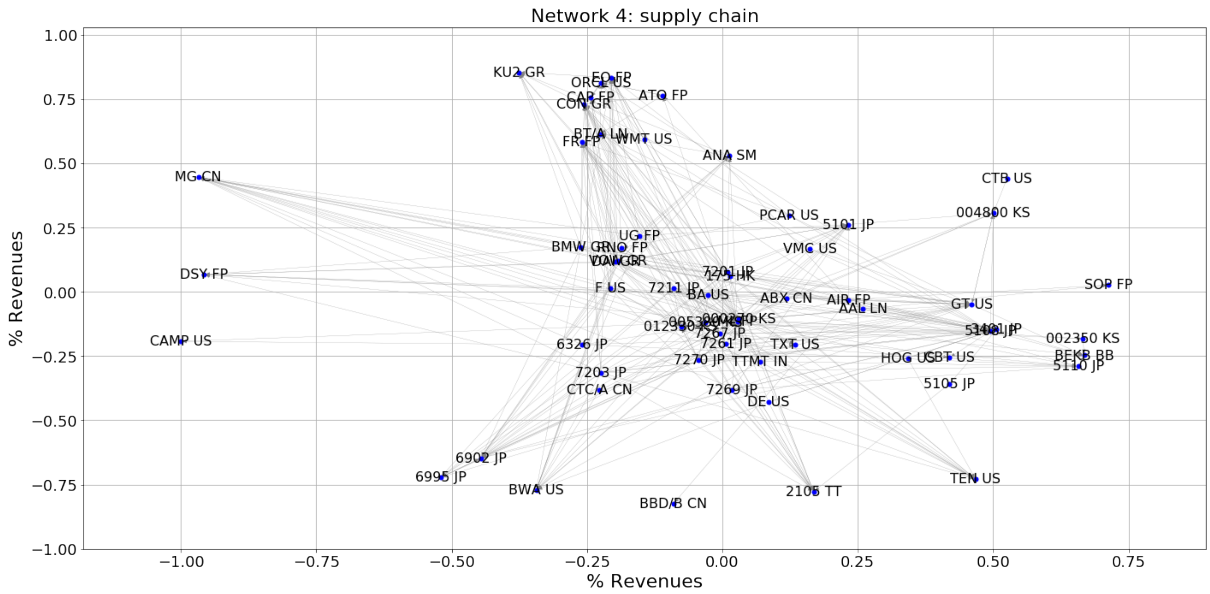
I favor Information Ratio to Sharpe Ratio for the sole purposes of this analysis since it is more suitable for evaluation of the model against the equity benchmark (and not cash return). Information ratio is also preferable when evaluating consistency with which the strategy generates returns, which is of interest in this paper as my strategies adopt a buy and hold investment approach.

Hypothesis 2 — Model

To test whether supply chain networks exhibit return predictability due to limited attention of investors, I construct two networks: one accounts for the supply chain data explicitly, while another model is based on the market data.

The first network is comprised of customers and suppliers as nodes, and the links are weighted against the percentages of revenues between trade partners for 65 companies of the network. As in assumption 3 of hypothesis 2, I selected revenue figures for approximation of the trade interdependencies between firms as: i) those account for most of money transfers in the supply chain (few sales are made on credit) and ii) the data is easily accessible the (Statement of Financial Accounting Standards (SFAS) No.131 disclosure requirements). It was chosen to use percentages of revenues instead of absolute values to mitigate the scale effects of the operating results (Figure 2). The resulting network is drawn in Figure 2:

Figure 2: Network 4 — Supply Chain



As can be seen in the graph, the resulting network has lower measures of density (~ 0.086) and the average node connectivity (Appendix 3) than networks 1, 2, and 3, which is indicative of the higher sparsity, hence, longer information diffusion. This is confirmed by the longer average path length (~ 0.354) than in the previous networks, which suggests that customer-supplier networks have a lag until the shocks propagate across the entire supply chain.

The second network used to estimate whether supply chains exhibit predictable returns is based on betas, where it was assumed that prices entail information about customer-supplier relationships. The usage of betas however entails a hidden trap for the network analysis under hypothesis 2, as betas are bi-directional: while covariances and correlations suggest a single number to describe the relationship between i and j, there are two betas from i regressed on j and j regressed on i. This presents a computational challenge as in my study, network analysis does not explicitly account for the direction of the relationship between two nodes since directionality of the network would result in excessive trading, which harms profits through trading costs. To overcome this issue, I derive the net beta — a single weight based on a summation of beta coefficients across the set of possible permutations for companies. I use permutations to count the set of regressions for companies instead of combinations since the order of elements does matter in a regression analysis.

As such $P_k^n = \frac{n!}{(n-k)!}$ computes the ordered subset of k elements from a set of n elements, in other words, a number of regressions based on generic form $(1) = P_k^n = \frac{65!}{(65-2)!} = 4160$ regressions. For each of these regressions, parameter θ is defined as:

$$\theta = \begin{cases} 0, & \text{if p-value} > 0.05 \\ 1, & \text{if p-value } < 0.05 \end{cases}$$

Therefore:

$$\text{Net } \beta_i = \sum_{n=1}^{N} \theta - \sum_{m=1}^{M} \beta_1 \cdot \theta, \quad \text{where}$$

N is the total number of times company i appears as a regressand and M is a total number of times company i appears as a regressor.

Hypothesis 2 — Test

The test for the relevance of the second hypothesis is similar to the strategy described for hypothesis 1. I build a long-short portfolio, sorting the stocks based on degree centrality: I buy 45 companies and sell 5 companies (where $X > Y$ and $X/Y < 4$ in underlying metric terms) to comply with leverage restrictions and approximate long bias, due to excess positive skew of % Revenues distribution. (Appendix 4)

The network centrality strategy, as before, is defined through $[AB]_{i,j}$ matrix and performance statistics are given by annual μ, σ, and Information Ratio. A similar test is performed with net betas, however, the long position is given by 8 stocks, while short position is given by 21 securities.

VII. Results

In this section we present the performance measures for the strategies specified in V.Model: H1-betas (H1_betas), H1-correlations (H1_corrs), H1-covariances (H1_covs), H2-supply chain (H2_sc), H2-net betas (H2_betas), where H1 and H2 refer to the tests of hypotheses 1 and 2, respectively:

Table 1: Performance of the strategies

	H1_betas	H1_betas*	H1_corrs	H1_corrs*	H1_covs	H1_covs*	H2_sc	H2_sc*	H2_betas	H2_betas*
Mean	0.726994	-0.726994	2.933894	-2.933894	5.382654	-5.382654	4.387850	-4.387850	-0.901093	0.901093
Std	2.561943	2.561943	7.106074	7.106074	7.425410	7.425410	8.312524	8.312524	4.084022	4.084022
Info Ratio	0.283767	-0.283767	0.412871	-0.412871	0.724897	-0.724897	0.527860	-0.527860	-0.220639	0.220639

As is seen from the table, returns and standard deviations are given by high values, which is consistent with the leverage restrictions (maximum of 4). As is indicated by Information Ratio, all strategies outperform Benchmark 2, weighted against regional returns (Table 2). H1_covs also outperforms SPY US Equity, while no strategy outperformed sector-weighted Benchmark 1.

It is a call of a researcher to define a benchmark and state the conditions under which the hypothesis is accepted or rejected. For the purposes of this paper, I reject a hypothesis if it does not outperform all the benchmarks. This provides evidence against hypotheses 1 and 2. Hypothesis 1, however, can be partially reanimated, given that H1_covs outperforms a major equity market — the U.S. ($\sim 2.5\%$ annual spread), as well as other regional indices (Benchmark 1). The validity of H1 is further confirmed when obtaining results for the contrary strategy — going long peripheral firms and selling central firms, which is indicated by "$*$" superscript after the strategy's name (Table 1). As is shown in the table, such model specification produces negative returns, which weakly supports my hypothesis regarding higher return compensation returns for larger exposure of central elements to systematic risk. This, however, is insufficient evidence in favor of hypothesis 1, because these results underperform different specifications of the benchmark: SPY US Equity, participation-weighted sectoral ETFs, and geography-weighted equity indices' ETFs during the test period (06/10/2009 — 04/12/2018):

Table 2: Benchmarks' performance

	SPY US Equity	Benchmark 1 (sectors)	Benchmark 2 (regions)
Mean	0.103419	0.123815	0.026064
Std	0.147929	0.154916	0.204924
Info Ratio	0.699108	0.799242	0.127189

As has been already mentioned, the results presented in table 1 correspond to the constraint of maximum leverage equal to 4. For most of the strategies, this is executed through the leverage on the long leg, with only exception — strategy H2_betas(*). As such, the models depart from market neutrality in favor of long or short bias, as it produces higher risk-adjusted returns. With this, for example, for strategy H1_covs to comply with leverage restrictions and achieve the highest Information Ratio, available within the strategy specifications, it needs to go long 45 companies and short 5 firms. In net covariance terms (derivation is similar to net betas), it is given as $\sum_{n=1}^{45} net\ nov\ j,k$ for the long leg and $\sum_{n=1}^{5} net\ nov\ j,k$ for the short leg, namely: 982.64509 and 256.98729, respectively. The ratio of long and short positions gives the leverage level of $982.64509/256.98729 =\sim 3.8$. A similar exercise can be performed for all other strategies (with exception of H2_sc, as it is based on relative values:

Table 3: Description of positions and leverage

	H1_betas	H1_corrs	H1_covs	H2_betas
Long position in equity	16	40	41	8
Short position in equity	5	10	5	21
Long position in underlying metric	620.642790	830.721606	982.645092	507.348106
Short position in underlying metric	163.072118	317.416170	256.987292	150.808731
Leverage	3.805940	2.617137	3.823710	3.364182

Within the confines of the strategy validation process, I have tested the performance of the constructed models out of the sample. The out-of-sample tests were delivered in two variations: i) enlarging the learning period (training set accounts for 2/3 of the whole data points and test set takes final 1/3 of the dataset), and ii) removing the period of extreme volatility, associated with the Global Financial Crisis (from the onset of 2008 until late 2009). These adjustments generate marginal improvements in the performance statistics for some strategies:

Table 4: Out-of-sample analysis (2/3 for the training period, 1/3 for the test period)

	H1_betas	H1_betas*	H1_corrs	H1_corrs*	H1_covs	H1_covs*	H2_sc	H2_sc*	H2_betas	H2_betas*
Mean	0.885130	-0.885130	2.798097	-2.798097	5.387414	-5.387414	4.294977	-4.294977	-1.014304	1.014304
Std	2.203852	2.203852	5.839528	5.839528	6.341514	6.341514	8.312524	8.312524	4.056711	4.056711
Info Ratio	0.401629	0.401629	0.479165	-0.479165	0.849547	-0.849547	7.497715	-7.497715	-0.250031	0.250031

Table 5: Out-of-sample analysis (excluding 2008-2009 in the training and testing sets)

	H1_betas	H1_betas*	H1_corrs	H1_corrs*	H1_covs	H1_covs*	H2_sc	H2_sc*	H2_betas	H2_betas*
Mean	0.749124	-0.749124	3.073066	-3.073066	5.024295	-5.024295	4.006634	-4.006634	-0.943809	0.943809
Std	2.157220	2.157220	7.083655	7.083655	7.383992	7.383992	8.308021	8.308021	3.892706	3.892706
Info Ratio	0.347264	-0.347264	0.433825	-0.433825	0.680431	-0.680431	0.482261	-0.482261	-0.242456	0.242456

In the out-of-sample that divides the data into 2/3 — 1/3 proportion, the results of all strategies under H1 see improvement, while H2 Info Ratios deteriorate, which witnesses the benefit of including high-volatility periods into training samples. Under this sample, strategy H1_covs outperforms all three benchmarks. When selecting low volatility periods (Table 5), the improvements can be seen for H1_betas, H1_corrs, and H2_betas* strategies. It was achieved by a mix of reduction in volatility and an increase in returns. As a final remark, I have decided not to include transaction costs since the strategies already underperform the benchmarks.

VIII. Conclusion

This paper contributes to the body of academic literature on investment analysis using the network topology for firms linked via supply chains as well as to the research on asset return predictability. It was first hypothesized that firms that are more central to the network command higher risk premia due to a larger exposure to systematic shocks, contrary to their peripheral counterparties. Secondly, an inference was made regarding the return predictability within supply chains, stemming from the limited attention of investors.

The main insight of my thesis is that while central network elements indeed earn higher returns, the long-short strategy based on buying central firms and selling peripheral does not generate returns high enough to outperform the all established equity benchmarks in the base training/test sample, even though it does so in out-of-sample tests. I do not consider the out-of-sample outperformance sufficient to validate my hypothesis, as it is coincident with the longest bull run in equity markets, a unique situation that excludes turbulent environments. I also find that trade-related firms do not exhibit return predictability when departing from *i*) special situations (e.g., earnings announcements), *ii*) basing the strategy on the entire network and not pair-wise regressions, and *iii*) working with Bloomberg datasets instead of commonly used COMPUSTAT fillings. Other novelties of my work include: *i*) application of the network theory to investment analysis of supply chains on the firm level for the tire industry, *ii*) development of the net beta methodology, and *iii*) assessment of long-short strategies against the degree centrality measure based on covariances, correlations, and betas with the leverage limit of 4.

My findings provide grounds for further discussion on the market efficiency of the chosen equity industry. An absence of return predictability might indicate shortcomings of model specifications; alternatively, it can provide evidence in favor of a high degree of market efficiency in the tire industry, where extracting superior returns is impossible since all new information is immediately reflected in the prices. For the network, the latter implies that any shocks diffuse across the system without time lags, hence, yielding hypothesis 2 irrelevant. The first hypothesis, however, is unaffected by this finding, as it already assumes informational efficiency. It is the exposure to different firms (and therefore — sectors, and generally, economy) that is inferred to generate good performance. A number of model limitations can be an explanation to poor returns: *i*) dynamism of the strategy, *ii*) use of undirected networks, *iii*) allocation process, *iv*) number of network elements.

While modern software, such as NetworkX package for Python enables the dimension of analysis unimaginable in Microsoft Excel, it is bounded by the computational capacity of the PC. As such, the long-short strategies, once established on the training dataset, were applied to test dataset without subsequent dynamic modifications, mimicking a buy-and-hold investment approach. However as confirmed by an overwhelming number of academic sources, in presence of manager skill, active strategies help to enhance performance when compared to the buy-and-hold approach. (Gupta-Mukherjee, 2013, Cremers, 2017) In case of my model, active investing would imply updating correlations, covariances, and betas once new information is released to the market, such that the upper bound of the training set would expand at each $t+1$. Unfortunately, for betas, it would imply rerunning 4160 regressions for each $t+1$, which is not feasible for my hardware. Another limitation attained to the dynamism of the strategy is given by the structure of percentages of revenues data, which is time-variant and labor-intensive in processing. As such, it was assumed that supply chain links between the companies remain unchanged for the training and test periods, which could have been another reason for compromising findings. With regards to "*ii*) use of undirected networks", the model structure has neglected link directionality in favor of comparability (across strategies) and simplicity. Further improvements to the model would entail the adoption of directed networks when analyzing betas and supply chains, as under these settings the flows are directional. The methodology of the allocation process can also provide potential possibilities for improvement — my current model allocates between assets based on their notional; switching to the risk parity method would help to enhance performance in high volatility environments (Maillard et al., 2010). Finally, the size of the current network could be enlarged to provide a better approximation of the industry groups. My current network is comprised of 65 companies, which is limited and truly centered around one company — Michelin SA. In attempts for further improvement, it could be expanded until 918 companies (number of network elements when accounting for reduced (Bloomberg limit of 25) supply chains of suppliers, customers, and competitors of Michelin SA.

To sum up, the network theory is a powerful tool in application to investment research, as it provides a more sophisticated framework than the regression analysis yet allows for the involvement of a financial professional, unlike the fully auto-piloted machine learning techniques, i.e., neural networks. As I have shown in my thesis, some of the long-short strategies for supply chain networks outperform $^2/_3$ or $^3/_3$ restrictive benchmarks. This is a positive indicator for future research on the return predictability in the supply chain networks.

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Appendices

1. Data Preparation

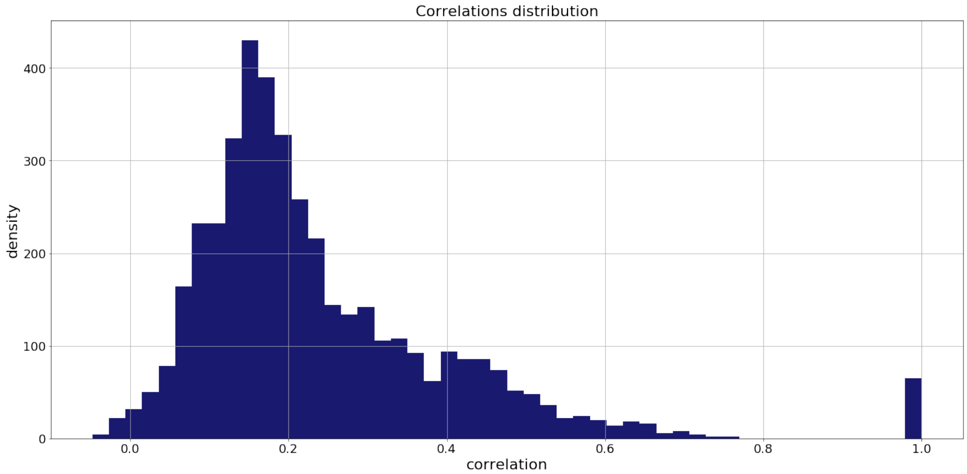
Selection of the optimal number of companies and time horizon: columns from left to right; row number, number of data points, number of the companies in the network

Figure 3: Data preparation

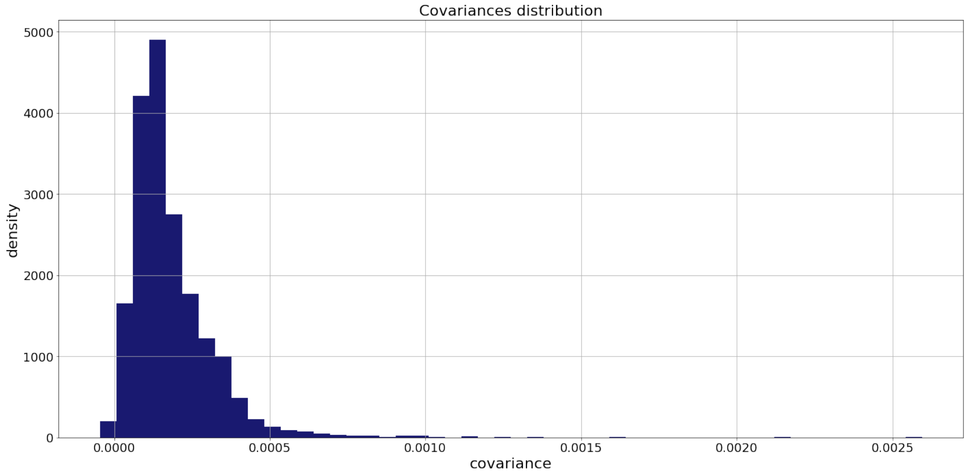
```
1 (427, 91)
2 (444, 90)
3 (518, 89)
4 (643, 88)
5 (720, 87)
6 (863, 86)
7 (896, 85)
8 (1153, 84)
9 (1236, 83)
10 (1236, 82)
11 (1393, 81)
12 (1657, 80)
13 (1866, 79)
14 (1915, 78)
15 (2055, 77)
16 (2075, 76)
17 (2098, 75)
18 (2098, 74)
19 (2334, 73)
20 (2586, 72)
21 (2694, 71)
22 (2801, 70)
23 (3027, 69)
24 (3191, 68)
25 (3259, 67)
26 (3407, 66)
27 (3563, 65)
28 (3563, 64)
29 (3564, 63)
30 (3564, 62)
31 (3564, 61)
32 (3564, 60)
33 (3564, 59)
34 (3564, 58)
35 (3564, 57)
36 (3564, 56)
37 (3564, 55)
38 (3564, 54)
39 (3564, 53)
40 (3564, 52)
41 (3564, 51)
```

2. Distribution graphs for correlations, covariances, and betas

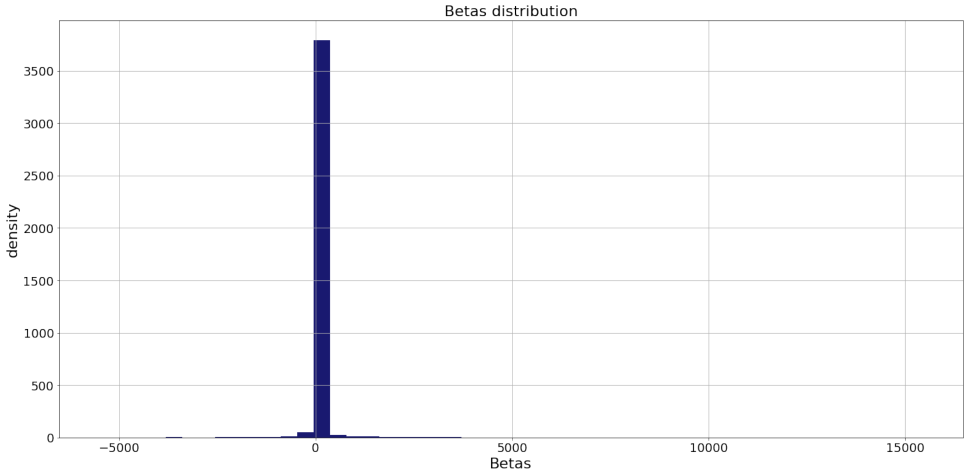
(Figure 4.a) Correlations' distribution



(Figure 4.b) Covariances' distribution



(Figure 4.c) Beta' distribution



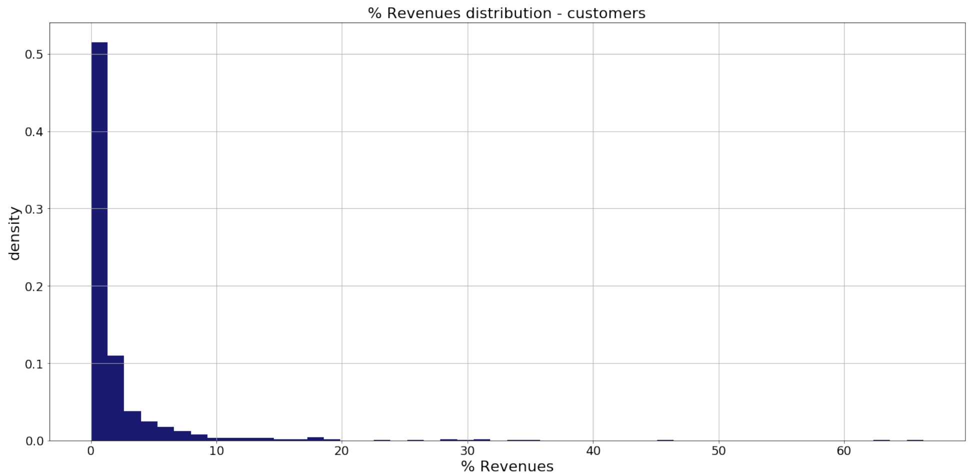
3. Network summary statistics

Table 6: Average shortest path, density, and average node connectivity for the networks

	Supply chain network	Covariance network	Correlation network	Betas network
Average shortest path	0.354098	1.0	1.020673	1.052884
Density	0.086066	1.030288	0.979327	0.947115
Average node connectivity	0.376503	64.0	61.710577	59.225

4. Revenue distribution for suppliers and customers

(Figure 5.a) Customers



(Figure 5.b) Suppliers