Systematic Risk in Global Supply Chain Networks: A Country-Level ESG Analysis

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Abstract

Using data from both the U.S. and China, we present new empirical findings on the systematic risk in the global supply chain network. Specifically, we document that, in the U.S., Environmental risk (E-risk) is positively associated with both stock volatility and bond volatility, while Governance risk (G-risk) and Social risk (S-risk) are negatively associated with stock volatility but not bond volatility. In China, both E-risk and G-risk factors are negatively (positively) associated with stock volatility (bond volatility), while the S-risk factor is positively associated with both stock volatility and bond volatility. Regarding the relationship between ESG risk factors and supply chain centrality, we find that G-risk and S-risk factors are positively (negatively) associated with supply chain centrality in the U.S. (China). Lastly, the U.S. and China exhibit opposite relationships between supply chain centrality and stock/bond volatility, with a negative association in the U.S. and a positive one in China. Our findings highlight different systematic risk management implications regarding the supply chain centrality and ESG risk in the U.S. and China.

Keywords: ESG Risk, Global Trade Networks, Systematic Risk, Sovereign Bond, Refinitiv MarketPsych Analytics

1. Introduction

Fluctuations of industry production output represent an important source of systematic risk that propagates through the supply chain network (Osadchiy, Gaur, and Seshadri 2016). Therefore, the global supply chain linkage may be vital to a country's systematic risk. Countries that are more central in the global trade network are associated with higher risk premia (Richmond 2019) and are also more sensitive to environmental, social, and governance (ESG) shocks. Furthermore, global warming, the COVID-19 global pandemic, the Russia-Ukraine war, etc. have highlighted the vulnerability of this linkage to severe disruptions caused by global public crisis and ESG risk throughout the supply chain (Ernst & Young research 2023). Hence, a thorough analysis of ESG risk in a global supply chain context is vital to understanding this distinct source of systematic risk. Thus, this study aims to illustrate how systematic risk can be traced through a country's ESG risk within the global supply chain framework (i.e., supply chain centrality). Specifically, our research question is further divided into three questions. First, we investigate whether the risk of stock and sovereign bond markets is influenced by ESG risk in the U.S. and in China. Second, we examine whether their export network centrality affects the risk of stock and sovereign bond markets in these two countries. Third, we explore whether the effect of ESG risk on the systematic risk of stock and sovereign bond markets is channeled through those two countries' global trade network centrality.

According to Freeman (1984)'s stakeholder theory, corporate managers should consider the interests of all stakeholders, such as employees, society, suppliers, and customers, in their decision-making. ESG risk related studies find that good ESG practices can reduce firm's residual risk (Sharfman and Fernando 2008; Dunn, Fitzgibbons, and Pomorski 2018) and mitigate country-level credit risk (Hübel 2022). Along with the stakeholder theory, we predict a positive link between

ESG risk and systematic risk. Regarding the supply chain centrality and systematic risk, Osadchiy et al. (2016) propose and testify the aggregation hypothesis, which implies that a more dispersed customer base (i.e., a more centered supply chain) is associated with higher systematic risk at the industry and firm levels. Richmond (2019) further confirms the positive association between supply chain centrality and systematic risk at the inter-country level. These prior findings collectively predict a positive association between ESG risk and systematic risk. However, the literature on the relationship between supply chain structure and sustainability finds that supply chain centrality is negatively associate with ESG risk (Gualandris, Longoni, Luzzini, and Pagell 2021). Therefore, no definitive conclusion cannot be drawn regarding the relationship between ESG risk and supply chain centrality.

To answer our first research question, we construct systematic risk proxies of stock and sovereign bond indices for the China and US based on realized volatilities of Chian CSI300 Index and U.S. S&P500 Index as well as average volatilities of the China and US 10-year treasury bond indices. We then take advantage of Refinitiv MarketPsych Analytics (RMA) indicators and construct original ESG risk factors. The actual ESG risk factors that we use are available in Appendix A. Next, we employ a Partial Least Squares (PLS) regression to find the PLS-derived ESG risk factor and use OLS to estimate each E-risk, S-risk, and G-risk factor on the overall systematic risk. To answer our second and third research question, we use a two-stage least squares (2SLS) regression with least absolute shrinkage and selection operator (LASSO) dimensionality reduction. Specifically, we first estimate the ESG risk factor's effect on the supply chain centrality and then use the predicted supply chain centrality value to estimate its effect on systematic risk and bond volatility.

Our results based on the S&P500 (U.S. stock market) document that E-risk factor leads to an increase in the systematic risk, while G-risk factor and S-risk factor are related with decreased systematic risk. The results based on CSI300 Index (China's stock market) show that E-risk factor and G-risk factor are related with decreased systematic risk while S-risk factor are associated with increased systematic risk. These results imply that only G-risk factor in both U.S. and China can decrease systematic risk and further indicate that the stock market implications of E-risk factor and S-risk factor are different in the U.S. and China. Based on these results, our answer to the first research question is yes, the risks of China and US stock market are influenced by the environmental, social, and governance risk (ESG risk) of those two countries; and no, the impact is not the same for these two countries. Our results based on bond market shows that E-risk factor is significantly and positively related to both U.S. bond volatility and Chinese bond volatility, and that S-risk factor and G-risk factor are also significantly and positively related to Chinese bond volatility. Different from the divergent evidence on the stock market in the U.S. and China, evidence on the bond market consistently show that ESG risk factor leads to an increased bond volatility.

We further find that G-risk factor and S-risk factor are positively associated with supply chain centrality in the U.S., while they are negatively associated with supply chain centrality in China. E-risk factor does not load on the centrality test. These results answer our third research question, and the answer is yes, i.e., the effects of S-risk and G-risk on the systematic risk of China and US stock markets are channeled through those two countries' global trade network centrality.

Our last pair of test shows that the predicted supply chain centrality is negative (positive) associated with systematic risk in stock/bond market of U.S. (China). Thus, our answer to the second research question is another yes, i.e., the risk of China and US stock market is affected by their supply chain centrality; and no, i.e., the association is of opposite directions for China and U.S. We find a significant and negative (positive) association between supply chain centrality and stock/bond volatility in the U.S.

Our research has at least two major contributions. First, we contribute by documenting how national level ESG risk factor might be related to national level systematic risk based on both the developed market and the developing market. To our humble knowledge, we are the first to conduct a national level analysis and to directly compare the different patterns between China's market and the U.S.'s market. Our research complement and extend Osadchiy et al. (2016)'s investigation and further document that G-risk and S-risk factors could further contribute to the systematic risk in supply chain networks. Our research also answer to Alinaghian, Qiu, and Razmdoost (2020)'s call for future research to collect and construct real-world large-scale sustainable supply chain network datasets to investigate how network members achieve their sustainability goals across their supply chain.

We also enrich literature on the consequences of ESG risk. When we review the history of ESG, we find that companies considered ESG strategies largely as tools to mitigate risk and that ESG strategies are associated with covering downside risk (such as, Christensen (2016) and Krüger (2015)). However, ESG could be a risk by itself, according to Park, Yoon, and Zach (2022), which define ESG risk as "the probability that firms experience a reduction in actual or expected value and reputation, emanating from actions or inactions pertaining to factors related to the Environmental, Social, and/or Governmental aspects of firms' operations." Our study based on national level of ESG risk factor further shows that these factors are related to systematic risk via supply chain centrality. These findings contribute to the emerging research field of ESG risk.

The remainder of this paper is organized as follows. Section 2 reviews related literature and develops the hypotheses. Section 3 introduces the data and construction. Section 4 discusses methodology. Section 5 presents empirical results. Section 6 provides a summary of concluding remarks.

2. Literature review and hypothesis development

Our focus is on the network level, and we examine how the national-level ESG risk is associated with national-level systematic risk through the properties and characteristics of the supply-chain network, such as centralization, betweenness, and closeness (Provan, Fish, and Sydow 2007). Therefore, our study is mainly based on three areas of research: studies related to supply chain network structure, those on the relationship between ESG risk and supply chain network characteristics, and those on ESG risk and systematic risk. We summarize each of the literature below. Figure 1 presents our analysis framework.

[Insert Figure 1 Here]

2.1 ESG risk and systematic risk

Since the conceptualization of ESG, the relationship between ESG factors and systemic market risk has emerged as a significant focal point of scholarly attention. Sahut and Pasquini-Descomps (2015) incorporate additional ESG factors into a multifactor model and find that there is a notable adverse influence of ESG factors on monthly stock performance in the UK market. Sassen, Hinze, and Hardeck (2016) analyze the impact of ESG factors on market-based firm risk by employing three risk measures—systematic, idiosyncratic, and total risk. The impact of corporate ESG factors on firm risk is significant. Therefore, from a national perspective, what is the relationship between a country's overall ESG risk and systemic risk? Hübel (2022) investigates the role of countries' ESG performance in sovereign CDS markets and identifies a discernible risk mitigation effect associated with ESG. Abdul Razak, Ibrahim, and Ng (2023) find that improvements in ESG performance, especially in its governance pillar, reduce credit risk.

Based on the literature presented above, ESG performance has a risk mitigation effect. We present our hypothesis as below:

H1: The systemic risk of a country is positively correlated with ESG risk.

2.2 Supply chain network structure and systematic risk

Traditionally setting firms' boundaries involved strategic decisions about "which business activities should be brought within the boundary of the firm? And which business activities should be outsourced?" (Barney 1999). In today's "international production networks", the competition is not only focused on the "final" goods and services but also involves the entire intermediate supply chain of products and services (de Mello-Sampayo 2017). The integration of supply chain into local actors of the network of goods and services completes the "firms' ecosystem" (Taglioni and Winkler 2016).

These network connections create synergies that enhanced firms' competitive advantage through elevating the firms' dynamic capabilities (Petricevic and Verbeke 2019). Based on this argument, Lavassani and Movahedi (2021) measure the centrality of global supply chain network structure and find that firms that are more strategically integrated into the industry supply chain will have a higher financial performance level, become more resilient due to their dynamic capabilities and thus have lower market value volatility and market beta. Wu (2015) defines and constructs the centrality of a supplier in the whole supply chain network, then he documents that supplier-central portfolios tend to be more volatile than average, and the stock performance of supplier-central portfolios tends to predict the movements of the overall stock market. Osadchiy, Gaur, and Seshadri (2016) directly document that the aggregation of orders from multiple customers in a supply chain network and the aggregation of orders over time result in the amplification of correlation upstream in supply networks and systematic risk in supply chain.

Based on this literature, it is possible that the supply chain centrality is positively associated with systematic risk. We present our hypothesis as below:

H2: supply chain centrality is positively associated with systematic risk.

2.3 ESG risk and supply chain centrality

Current literature on supply chain structure (including centrality) and ESG is mainly focus on investigating the influence of network structure characteristics on sustainable behavior and performance (Alinaghian et al. 2020). For instance, Saunders, Tate, Zsidisin, and Miemczyk (2019) examine how network brokers, such as local non-governmental organizations (NGOs), affect the development, adoption, and diffusion of sustainability initiatives. Cole and Aitken (2020) study how supply chain intermediaries supported the establishment of a sustainable supply chain through information transfer, knowledge development, risk management, and capability support.

Based on these studies, we predict that ESG risk is negatively associated with supply chain centrality. However, if supply chain centrality is the mediator between ESG risk and systematic risk, and if the ESG risk and systematic risk is positively associated (H1) and the supply chain centrality is positively associated with systematic risk (H2), then we will expect a positive association between ESG risk and supply chain centrality, as it is only possible mathematically. Therefore, we present one set of hypotheses as below:

H3a: ESG Risk is negatively associated with supply chain centrality.

H3b: ESG Risk is positively associated with supply chain centrality.

3. Empirical design

3.1 Systematic risk

The following three indicators are chosen as proxies for systematic risk: stock index volatility, stock market jumps, and the volatility of ten-year government bonds.

3.1.1 Stock index volatility

We utilize the realized variance (RV) statistic to quantify stock market volatility, which was first proposed by Andersen and Bollerslev (1998). We use five-minute prices of the CSI300 Index and S&P500 Index to construct the realized volatility estimators. This sampling frequency is widely adopted in the construction of realized estimators and strikes a balance between market microstructure noise and estimation accuracy. The CSI300 Index ranges from January 4, 2010, to December 30, 2022, encompassing 3,159 effective trading days, and the data source is the WIND Database (wind.com.cn). The S&P500 Index spans from January 3, 2006, to December 30, 2022, encompassing 4150 effective trading days, and the data source is "Pi Trading.com".[1]

For a given day *t*, we divide the time interval [0, 1] into *n* subintervals of length, where $M = 1/\Delta$ and Δ is the sampling frequency. Consequently, realized volatility is quantified by aggregating the squared returns at high-frequency intraday intervals. The formulation is articulated as follows:

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2$$

where $r_{t,i}$ represents the day t of i-th of intraday return. Based on the theory of Barndorff-Nielsen and Shephard (2004), RV_t can be satisfied when $\Delta \to 0$ as follows:

$$RV_t \to \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1 \le s \le t} k_s^2$$

where $\int_{t-1}^{t} \sigma_s^2 ds$ is the continuous component, referred to as continuous volatility. When $\Delta \to 0$, this part is equal to the realized bipower variation (BPV_t).

[1] The data is available for download at https://pitrading.com/.

$$BPV_t = u_1^{-2} \sum_{j=2}^{M} |r_{t,j}||r_{t,j-1}|$$

where $u_1 \approx 0.7979$. $\sum_{t-1 \le s \le t} k_s^2$ is the discontinuous component, abbreviated as jump volatility.

3.1.2 Stock market jumps

High-frequency returns in intraday continuous time may experience abrupt and significant changes, commonly referred to as jumps. The popular BNS test proposed by Barndorff-Nielsen and Shephard (2004) is used to estimate the jump component in RV in this study. The BNS test treats small jumps as measurement errors and uses the following Z_t statistic to detect significant daily jump:

$$Z_t = \sqrt{M} \frac{(RV_t - BPV_t)RV_t^{-1}}{((\frac{\pi^2}{4} + \pi - 5)\, max(1, TQ_t BPV_t^{-2}))^{1/2}} \rightarrow N(0,1)$$

where TQ_t is the realized tri-power quarticity: $TQ_t = M\mu_{4/3}^{-3} \sum_{j=3}^{M} |r_{t,j}|^{4/3} |r_{t,j-1}|^{4/3} |r_{t,j-2}|^{4/3}$, with $\mu_{4/3} = 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$. The jump component is: $J_t = I(Z_t > \Phi_\alpha)(RV_t - BPV_t), t = 1, \dots T$, where $I(\cdot)$is the indicator function.

The BNS test detects 274 daily jumps at the 1% significance level within the 3,159 trading days in the China market, and 1,209 daily jumps within the 4,150 trading days in the U.S. market. We compute the monthly average of daily RV series and jump series as the monthly volatility and jump in the Chinese and U.S. markets.

3.1.3 The volatility of ten-year government bonds

We then compute the volatility of the 10-year government bond by using historical volatility, which is defined as the square of the standard deviation of daily bond returns measured on a monthly time scale. The calculation equation is as follows.

$$Historical\ Volatility = \frac{\sum(Daily\ Returns - Mean\ of\ Daily\ Returns)^2}{N}$$

We obtain daily prices of the US and China 10-year sovereign bond indices from Global Financial Database. The U.S. 10-year treasury bond data ranges from January 2, 2000, to December 30, 2022. The China 10-year treasury bond data spans from January 2, 2008, to December 30, 2022.

3.2 Other measurements

We obtain the international trade data comes from the Direction of Trade Statistics - IMF. We then get ESG-related data from Refinitiv MarketPsych Analytics Data App (marketpsych.com). Refinitiv MarketPsych Analytics (RMA) analyze news and social media in real-time. The buzz fields represent a sum of entity-specific words and phrases used in RMA computations. Monthly data is derived from daily data and weighted using the buzz field.

4 Data and Methodology

4.1 Partial Least Squares (PLS) regression

To effectively capture the relationship between multiple ESG risk factors and systemic risk, we employ a Partial Least Squares (PLS) regression to derive the systemic risk indicators on month $t+1$. The PLS regression models the systemic risk indicator $ESG_{j,t}$ which is influenced by the stock index's realized volatility on month $t+1$, as expressed in the following equation:

$$ESG_{j,t} = \pi_0 + \pi_1 RV_{m,t+1} + \mu_{j,t}$$

where $ESG_{j,t}$ represents the ESG risk factors' influence on the systemic risk of month t, π_0 and π_1 are the coefficients, $RV_{m,t+1}$ denotes the realized volatility of the market index on month $t+1$, and $\mu_{j,t}$ is the error term.

In addition, an OLS regression is used to estimate the coefficients that define the relationship between the systemic risk indicator and the individual ESG risk factors, leading to the following equation:

$$\widehat{ESG}_{j,t} = c_t + \hat{\pi}_j ESG_t^{PLS} + v_{j,t}$$

In this equation, $\widehat{ESG}_{j,t}$ is the estimated influence of ESG risk factors on the systemic risk for month t, ESG_t^{PLS} is the systemic risk indicator derived from the PLS regression of month t, and $v_{j,t}$ is the error term.

The PLS-derived ESG risk indicator ESG_t^{PLS} is then utilized in the construction of the systemic risk model, informed by the following equation:

$$ESG_t^{PLS} = w^T X_t$$

In this equation, X_t represent the vector of environmental, social, and governance (ESG) risk factors, respectively. Following the methodological precedents set by Pástor, Stambaugh, and Taylor (2015) and the subsequent adaptations by Jiang and Zhu (2017), the model integrates the ESG risk indicator into the wider systemic risk analysis framework. This comprehensive approach allows for a nuanced understanding of how ESG risks contribute to overall market volatility.

4.2 Two-Stage Least Squares Regression with LASSO Dimensionality Reduction

To investigate the impact of the supply chain centrality on market risk, we utilize a two-stage least squares (2SLS) regression framework. In the first stage, we address the potential endogeneity of the supply chain centrality by using the ESG risk variables as instrumental variables. The high dimensionality of the ESG risk variables poses a challenge for the analysis. To overcome this, we implement a Least Absolute Shrinkage and Selection Operator (LASSO) regression technique to reduce dimensionality while retaining the most informative predictors.

4.2.1 Stage One: LASSO Regression

In the initial stage, we apply LASSO regression to select the most significant ESG risk variables that serve as predictors for supply chain centrality. The LASSO technique imposes a penalty on the absolute size of the regression coefficients, effectively shrinking less important variable coefficients to zero, thus performing both variable selection and regularization:

$$\hat{\beta}^{LASSO} = \underset{\beta}{argmin}\left\{\frac{1}{2N}\sum_{i=1}^{N}(y_i - X_i\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right\}$$

where y_i denotes the measure of supply chain centrality, X_i represents the matrix of ESG risk variables, β_j is the vector of coefficients, *N* is the number of observations, p is the number of predictors, and λ is the tuning parameter that controls the degree of regularization.

To find the λ with best predictability. We involved lassoCV function. The lassoCV function implements leave-one-out cross-validation (LOOCV), a method where the dataset is split into two parts: a single observation as the test set and the remaining data as the training set. For a dataset with n samples, this process is repeated n times, each time fitting the model on (*n*-1) samples and predicting the value of the excluded sample. This approach systematically cycles through each data point, ensuring that each observation is used as a validation point exactly once.

$$\{(x_1, y_1), \cdots, (x_{i-1}, y_{i-1}), (x_{i+1}, y_{i+1}), \cdots, (x_n, y_n)\}$$

Using the training set, a linear regression model is fitted, and then the independent variable x_i is inputted into the trained model to obtain the predicted value of the dependent variable $\widehat{y_i}$. Subsequently, calculations are performed based on these predictions.

$$MSE_i = (y_i - \widehat{y_i})^2$$

This process is repeated n times, yielding n mean squared errors for $i = 1,2, \dots n$. Consequently, we can obtain the mean of these n mean squared errors (MSE_i).

$$CV(\lambda) = \frac{1}{n}\sum_{j=1}^{n} MSE_j$$

For each parameter value within a predefined range, we calculate a corresponding cross-validation (CV) value, CV(i), We then select the optimal λ parameter based on the principle of minimizing the CV value.

$$\widehat{\lambda_{Loocv}} = argmin_{\lambda}\, C\, V(\lambda)$$

Under the CV criterion, we refine the leave-one-out cross-validation (LOOCV) method to k-fold cross-validation. The underlying principle remains the same. However, k-fold cross-validation divides the sample into k subsets. Each iteration uses one subset for testing and the remaining (k-1) subsets for training. Similarly, for each iteration, we can calculate a mean squared error MSE, and obtained CV_k, as follows:

$$CV_k = \frac{1}{k}\sum_{j=1}^{k} MSE_j$$

4.2.2 Stage Two: 2SLS Regression

In the second stage, we perform a 2SLS regression to estimate the effect of the predicted supply chain centrality, obtained from the first stage, on market risk. The 2SLS estimator provides a consistent estimate of the impact, adjusting for potential endogeneity.

$$\hat{\gamma}^{2SLS} = (\tilde{Z}^T Z)^{-1} \tilde{Z}^T Y$$

where $\tilde{Z}$ is the matrix of fitted values from the first-stage LASSO regression, Z is the matrix of instrumental variables, and Y is the vector of market risk measures.

This two-step procedure allows for a robust assessment of the causal influence of supply chain centrality on market risk, with the first step ensuring that only the most relevant dimensions of ESG risk variables are used as instruments.

4.3 Data Description

In Figure 2, we present the monthly time series of the volatility of U.S. 10-year bonds, stock market volatility, and jump components. The three systemic risk indicators exhibit a high degree of correlation. An exceptional point in the U.S. bond market volatility is observed in March 2020, attributed to the heightened financial market tensions triggered by the global spread of the COVID-19 pandemic. The U.S. bond market experienced a widespread sell-off as a result of the global market turmoil during that period. From Figure 2, it is evident that the U.S. market experienced significant fluctuations during the Global Financial Crisis in 2008 and the COVID-19 pandemic in 2020. Additionally, notable volatility occurred during the Eurozone Debt Crisis and the 2016 U.S. presidential election, reflecting heightened market turbulence during these periods. Figure 2 also illustrates the supply chain structure of the U.S. in October 2008, August 2011, and March 2020. Influenced by the Eurozone Debt Crisis, the share of the European Union in the U.S. supply chain structure decreased in August 2011. Since 2018, amid the U.S.-China trade tensions, there has been a decline in China's significance in the U.S. supply chain structure.

[Insert Figure 2 Here]

In Figure 3, we present the monthly time series of volatility for China's 10-year bond, stock market, and jump components. Figure 2 shows that there is a strong correlation among the three systemic risk indicators. Figure 2 also depicts the supply chain structure in China during the months of June 2015 (stock market crisis), March 2018 (the initiation of the U.S.-China trade war), and March 2020 (the COVID-19 pandemic). In June 2015, the Chinese stock market witnessed a significant crash, characterized by increased volatility, subsequently affecting the bond market. Additionally, there was a rise in the amplitude and frequency of extreme fluctuations (jumps). In the initiation of the 2018 U.S.-China trade war, the supply chain structure in China experienced disruptions, consequently impacting both the stock and bond markets, leading to an increase in volatility. In March 2018, the initiation of the U.S.-China trade war led to disruptions in China's supply chain structure, affecting both the stock and bond markets and consequently resulting in heightened volatility. In March 2020, due to the impact of the COVID-19 pandemic, all three systemic risk indicators experienced an uptick. During these three periods, the characteristics of China's supply chain structure exhibited variations. The significance of the U.S. in China's supply chain structure gradually diminished, while the importance of Emerging and Developing Asia gradually increased in China's supply chain configuration.

[Insert Figure 3 Here]

5. Empirical Analysis

5.1 US market

Table 1 presents the regression analysis based on the U.S. market. It provides an insightful perspective on the influence of ESG factors on market volatility. The model reveals a significant positive coefficient for the environmental risk factor (β_1 in stock market) with respect to stock market volatility, sitting at 0.3541 with a *t*-value of 3.134, which indicates a clear statistical significance. This impact is even more pronounced in the bond market, where the coefficient for environmental risk (β_1 in bond market) rises sharply to 11.5127, accompanied by a robust *t*-value of 9.665, underscoring the acute sensitivity of bond markets to environmental considerations.

Governance and social factors show a different pattern. In the stock market, governance risk (β_2 in stock market) is negatively associated with market volatility, with a coefficient of -0.1964 and a significant *t*-value of -2.499, suggesting a stabilizing effect. However, this significance does not carry over to the bond market, where the governance factor (β_2 in bond market) has a coefficient of -0.7113 and a non-significant *t*-value of -0.968. Similarly, the social factor (β_3 in stock market) shows significance in the stock market with a coefficient of -0.4494 and a *t*-value of -4.431, but not in the bond market, implying that these ESG dimensions may be interpreted differently by investors across asset classes.

These results are in line with scholarly discussions about the importance of ESG considerations in financial markets. For example, the demonstrated relationship between environmental risk and market volatility is supported by Schoenherr and Speier-Pero (2015), who highlight the impact of ESG factors within supply chain management. Additionally, Barrot and Sauvagnat (2016) draw attention to how supply chain disturbances can translate into broader market risks, a concept mirrored in the sensitivity of market volatility to environmental risks observed in our findings.

Overall, our results provide partial support for H1, i.e., the E-risk factor is positively associated with systematic risk.

This nuanced understanding of the variable impact of ESG factors across different market types provides a baseline for cross-market comparisons and anticipates an engaging juxtaposition with the forthcoming analysis of the China Market.

[Insert Table 1 Here]

To further investigate the relationship between ESG risk factors and supply chain centrality, we utilize scaled exports as a proxy for supply chain centrality and report the estimation results in Table 2. G- and S- risk factors demonstrate a positive and statistically significant influence on supply chain centrality, with coefficients of 0.0006 ($t = 3.258$) and 0.0008 ($t = 3.186$) respectively, signifying their importance in the central positioning within supply networks. These results support H3b. These results also align with the findings of Schoenherr and Speier-Pero (2015), which posit that robust governance structures and social engagement can enhance a firm's operational and strategic capabilities within the supply chain.

In contrast, environmental factors indicated by β_1 in bond market exhibit a non-significant relationship with supply chain centrality (coefficient = -0.0006, t = -1.895). This suggests that, in the context of U.S. supply chain, environmental concerns may not be as pivotal to central positioning as governance and social factors. This nuanced understanding adds depth to the discourse on supply chain finance and management, where the emphasis is often placed on the operational efficiency and risk mitigation afforded by strong governance and social practices, a sentiment echoed in the comprehensive review by Gelsomino, Mangiaracina, Perego, and Tumino (2016).

[Insert Table 2 Here]

Lastly, we estimate the predicted supply chain centrality on the systematic risk measurements and report the results in Table 3.

This table, rooted in the study's hypothesis development, distinctly explores the conduit through which national-level ESG risks percolate into systematic risk via supply chain centrality. The regression findings with US stock index's risk, which highlights the realized volatility of the US stock index, resonate with the hypothesis that supply chain centrality is positively associated with systematic risk (H2). The significant negative coefficient of supply chain centrality indeed underscores a pivotal aspect of our theory: that heightened ESG risk factors, as reflected through supply chain centrality, contribute to a discernible decrease in systemic risk within the equity market.

The results with US bond's risk, focusing on the historical volatility of US bonds, echo this sentiment, further reinforcing the notion that supply chain centrality, as influenced by ESG risk factors, wields a tangible impact on systemic risk. This is in line with hypothesis H3a, where ESG risk is conjectured to be negatively associated with supply chain centrality, and thus a mitigating force against systemic risk.

Both analyses are consistent with the literature that suggests a country's leading role in the global trade network can amplify its exposure to ESG shocks. However, our regression results elucidate that this centrality, in conjunction with ESG risk factors, may indeed have a buffering effect on systemic risk as measured by market volatility indicators. This insight lends substantial credence to our empirical hypothesis and aligns with the overarching narrative of our research, which posits that the structure of the supply chain and its ESG risk profile are instrumental in shaping systematic risk profiles.

[Insert Table 3 Here]

5.2 China market

We next move to examine the relationships between ESG risk factors and systematic risks in the China Market.

Table 4 presents the results of the first regression. In examining the regression outputs for the China Market, we observe a nuanced interplay between ESG risk factors and systemic risk. The results highlight how the principal components derived from PLS regression, associated with ESG risk factors, variably influence market volatility.

The negative coefficients of β_1 and β_2 in stock market in the first regression output, pertaining to realized volatility, suggest that environmental and governance dimensions of ESG may serve as mitigating factors to systemic risk. This is coherent with the premise that sound environmental policies and robust governance structures can serve as risk abatement mechanisms, potentially leading to a reduction in the cost of equity capital (Sassen et al. 2016). In contrast, the positive of

β_3 in stock market could be indicative of the social dimension of ESG contributing to systemic risk, potentially reflecting the economic cost of social risks not being managed effectively within corporate strategies (Dunn et al. 2018).

The second regression output, focusing on historical volatility, presents a contrasting scenario with positive coefficients across all ESG factors. This could imply that the bond market, with its inherent long-term investment horizon, may view ESG risks as contributory to systemic volatility, thereby demanding a higher risk premium. This perspective is underpinned by the literature which postulates that ESG factors, particularly in the context of bonds, are predictive of long-term financial risks and may affect discount rates and cash flow stability (Sahut and Pasquini-Descomps 2015).

The divergence in the direction of the coefficients for the stock and bond markets underscores the distinct ways in which these markets internalize ESG information. While equity markets may reward firms for managing ESG risks, bond markets may penalize firms for the perceived increase in long-term risk associated with ESG factors. This distinction is reflective of the inherent differences in risk profiles and investment horizons between equities and bonds (Wu 2015). The positive association in the bond market resonates with the hypothesis that supply chain centrality, influenced by ESG risk factors, could be associated with elevated systemic risk, necessitating a reevaluation of the discount rates to account for the ESG risk premium (Lavassani and Movahedi 2021).

These empirical findings contribute to the burgeoning discourse on ESG risk and systemic volatility, suggesting that ESG factors, through the lens of supply chain centrality, have a differential impact on market volatility. This has significant implications for how firms manage their ESG profiles in relation to their positioning within the supply chain, and for investors who seek to align their portfolios with ESG considerations.

[Insert Table 4 Here]

Same as in the U.S. market, we move to test ESG risk factors on supply chain centrality. Table 5 presents the results. The regression analysis demonstrates a baseline positive level of supply chain centrality for Chinese exports, with ESG factors influencing this centrality to varying degrees. The positive coefficient for environmental factors (β_1 in bond market), though not statistically significant, suggests a potential but indistinct relationship between environmental practices and supply chain centrality. Governance (β_2 in bond market) and social factors (β_3 in bond market), both negatively associated with centrality, indicate that higher perceived risks in these areas may lead to a more decentralized supply chain. This is consistent with the economic principle of risk diversification, where firms mitigate risk by avoiding over-reliance on central nodes within the supply chain that exhibit higher governance and social risks (Markowitz 1952). Such strategic decentralization can enhance resilience and minimize the impact of potential disruptions (Williamson 1981).

[Insert Table 5 Here]

In the empirical analysis of the China Market, the role of supply chain centrality, as measured by scaled exports, emerges as a salient factor in the context of systemic risk. The regression model examining historical volatility does not establish a significant relationship, with a positive but statistically insignificant coefficient (0.0255, *t*-value 0.318) for the predicted supply chain centrality. This suggests that while supply chain centrality may have an influence on the historical volatility of bonds, the effect is not robust enough within the confines of the model used.

Conversely, the analysis of realized volatility in the stock market reveals a markedly different picture. The significant positive coefficient (0.6771, *t*-value 5.794) for the predicted supply chain centrality underscores a strong association with systemic risk, indicating that as Chinese firms' centrality in the global supply chain increases, so does their susceptibility to systemic market fluctuations. This finding resonates with the economic theory that central agents in a network may bear more risk due to their pivotal role and potential to propagate systemic shocks (Granovetter 1985).

Comparatively, this relationship contrasts with that observed in the US market, where supply chain centrality exhibited a negative correlation with systemic risk indicators. The divergent outcomes between the two markets may reflect underlying differences in market structures, regulatory frameworks, and the specific nature of ESG risks inherent to each economic context. Notably, the significant positive relationship in the Chinese stock market suggests a unique interplay between supply chain centrality and systemic risk, potentially offering insights into the distinct economic mechanisms at play within China's rapidly evolving market landscape.

[Insert Table 6 Here]

5.3 Robustness Test

The regression analysis for the US market includes a robustness test using *Jump* as an additional dependent variable, representing a jump component of realized volatility. This component acts as a proxy for extreme market movements and is used to test the robustness of the relationship between supply chain centrality and systemic risk.

[Insert Table 7 Here]

The regression coefficient for *Jump*, the jump component, reveals significant relationships with predicted supply chain centrality. The negative coefficients indicate that an increase in supply chain centrality, as measured by predicted scaled exports, is associated with a decrease in both regular and jump volatility in the US market.

The large negative *t*-statistics for predicted supply chain centrality in the regressions suggest that the findings are robust and statistically significant, reinforcing the conclusion that supply chain centrality plays a substantial role in systemic risk within the US market. This relationship is consistent with economic theories that central players in a network can be key propagators of systemic risk due to their interconnectedness and influence (Granovetter, 1985). The robustness check using *Jump* confirms the negative association with systemic risk, suggesting that supply chain centrality also correlates with the likelihood or magnitude of extreme market movements.

The robustness test for the China Market uses *Jump* as the dependent variable, representing the jump component of realized volatility, which is a proxy for extreme market movements. The regression model aims to test the stability of the relationship between supply chain centrality and systemic risk.

[Insert Table 8 Here]

The regression coefficient for China's predicted supply chain centrality is positive (0.011863) and statistically significant (*t*-statistic = 3.445702), suggesting that an increase in the centrality of China's supply chain, as approximated by scaled exports, is positively related to the magnitude of market jumps. This result implies that more central positions in the supply chain network might be associated with greater susceptibility to sudden, significant changes in market volatility.

The significant *t*-statistic reinforces the conclusion that supply chain centrality is an influential factor in systemic risk within the China Market, echoing the findings from the realized and historical volatility models. This robustness check, therefore, confirms the initial observations and suggests that the relationship between supply chain centrality and systemic risk is consistent, even when considering extreme market movements.

6 Conclusion

Using both US' and China's datasets, we construct a battery of national level Environmental, Social and Governance (ESG) risk factors, national level systematic risk / sovereign bond volatility, and national level supply chain centrality measurements. Without controlling any other control variables, we find some preliminary results on the systematic risk in the global supply chain network. Specifically, we document that Environmental (E-risk) risk is positively associated with systematic risk in the U.S., while Governance (G-risk) and Social (S-risk) risk is negatively associated with systematic risk in the U.S. In China's market, we report a different pattern, specifically, we find that both E-risk and G-risk factors are negatively associated with systematic risk while S-risk factor is positively associated with systematic risk. However, results based on bond volatility show some consistence between the U.S. and China, which is a positive and significant relationship between E-risk factor and bond volatility. We also find evidence showing that S-risk factor and G-risk factor are both positive and significant related to the China's sovereign bond volatility. In terms of the relationship between ESG risk factors and supply chain centrality, we find that G-risk and S-risk factors are positively associated with supply chain centrality in the U.S., while they are negatively associated with supply chain centrality in China. Lastly, we find that US and China present opposite directions on the relationship between supply chain centrality and the systematic risk / bond volatility, where US shows a negative relationship and China shows a positive one.

Our results consistently point to the one direction where in a mature market such as US, the G-risk and S-risk factors decrease systematic risk through increased centrality. In a developing market such as China, G-risk factor and S-risk factor shows different patter. First, the G-risk factor decreases systematic risk through decreasing centrality. Second, the S-risk factor increases systematic risk through decreasing centrality. Third, the overall centrality is positively associated with systematic risk. The different pattern between US and China might be of interest for further academic research.

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Appendix A
Description of TRMI ESG Risk Indices

Panel A: National Environmental Risk		
Index	Meaning	Range
coldWave	unusually cold weather	0 to 1*
drought	lack of rain with environmental consequences	0 to 1*
earthquake	seismic activity	0 to 1*
fire	forest, brush, and structural fires	0 to 1*
flood	rising water levels with economic consequences	0 to 1*
heatwave	unusually hot weather	0 to 1*
humanInfectiousDisease	presence and outbreaks of contagious or epidemic diseases	0 to 1*
hunger	human caloric deficiency	0 to 1*
volcanicActivity	volcanic eruption	0 to 1*
windStorm	cyclonic storms and extreme wind weather events	0 to 1*
Panel B: National Social Risk		
Index	Meaning	Range
socialInequality	social inequality	0 to 1*
socialUnrest	social unrest and calls for political change	0 to 1*
cyberCrime	cyberattacks, data leaks, and electronic espionage	0 to 1*
terrorism	terrorist threats and activities	0 to 1*
violentCrime	criminal violence	0 to 1*
war	war and militant activity	0 to 1*
agriculturalStress	agricultural failures and production deficiencies	0 to 1*
Panel C: National Governance Risk		
Index	Meaning	Range
governmentAnger	anger and disgust about government officials and departments	0 to 1*
governmentCorruption	fraud, deceit, and corruption in government	0 to 1*
governmentInstability	governmental instability, net of references to governmental stability	-1 to 1
politicalSentiment	positive sentiment expressed about political parties and institutions net of negative sentiment	-1 to 1
regimeChange	regime change	0 to 1*
sanctions	sanctions or embargoes emanating from or against a country	0 to 1*
tradeWar	references to trade conflict	0 to 1*
tradeTalks	references to trade negotiations	0 to 1*

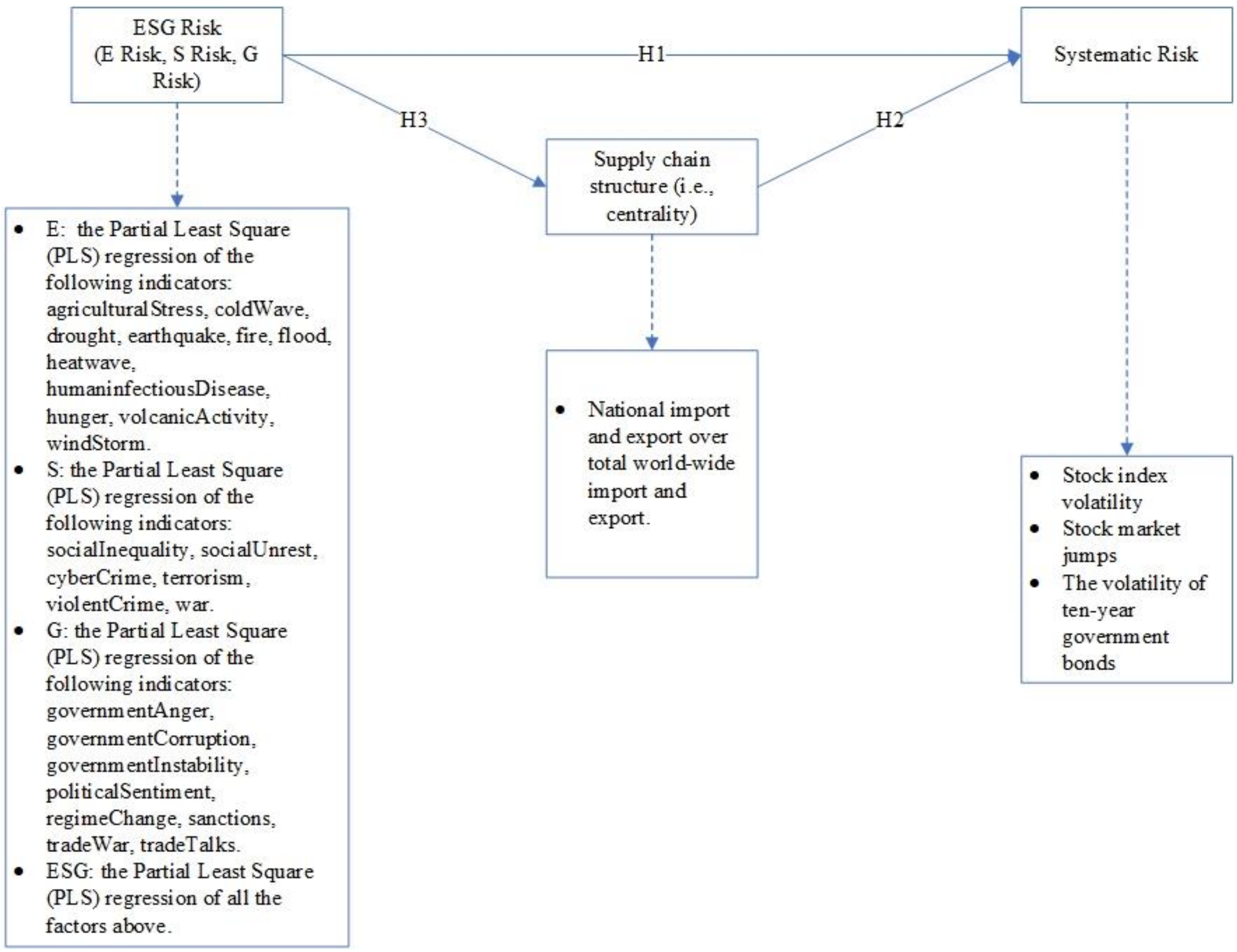

Figure 1 Analysis Framework

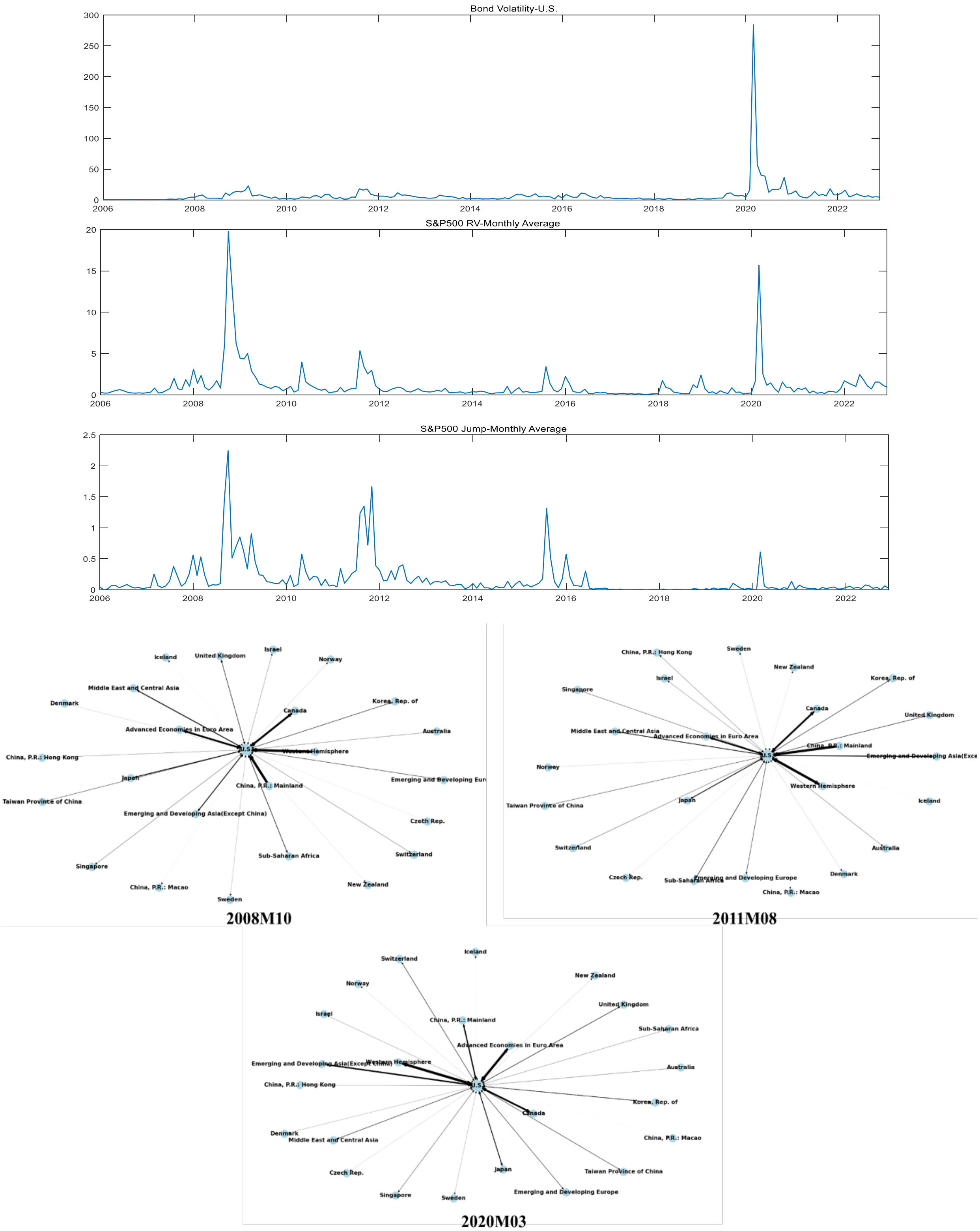

Figure 2 Systematic Risk Measures and Supply Chain Network in U.S.

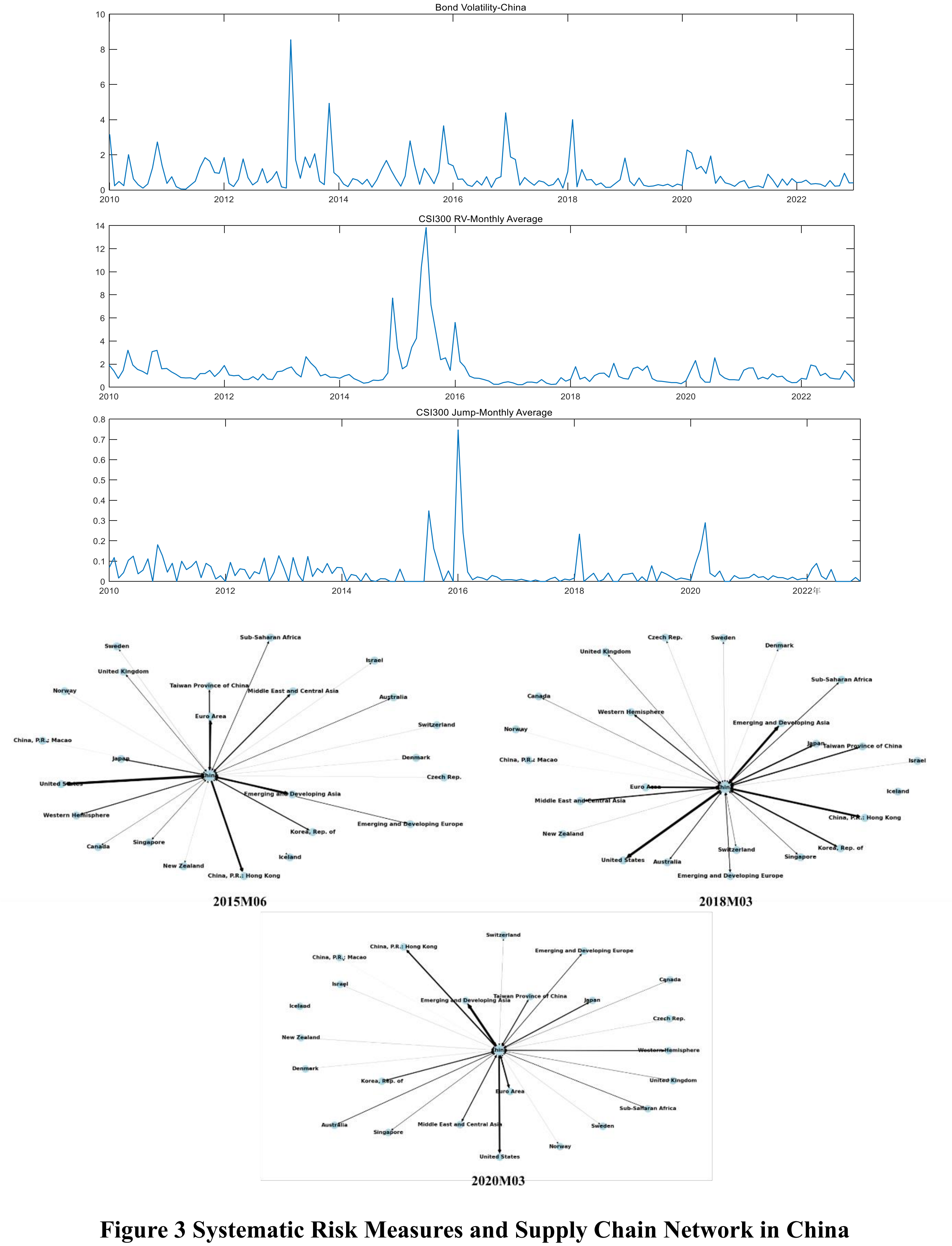

Figure 3 Systematic Risk Measures and Supply Chain Network in China

Table 1 Regression Results for Market Volatility and ESG Factors in the U.S. Market

Variable	Stock	Bond
α	1.1003*** (8.300)	7.3992*** (6.381)
β_1	0.3541*** (3.134)	11.5127*** (9.665)
β_2	-0.1964** (-2.499)	-0.7113 (-0.968)
β_3	-0.4494*** (-4.431)	0.7158 (-0.740)

Notes: This table provides the results of the parameter estimates for the equation in the U.S. market.

$$Volatility_t^m = \alpha + \beta_1 E\_pls_t^m + \beta_2 S\_pls_t^m + \beta_3 G\_pls_t^m + \varepsilon_t$$

The stock market volatility is represented by the monthly average of realized volatility, while the bond market volatility is proxied by the monthly historical volatility. Sample period spans from January 2006 to December 2023. Numbers in parenthesis are *t*-statistics. *** and ** indicate that the coefficient is significant at the 1% and 5% levels, respectively.

Table 2 OLS Regression Results for Supply Chain Centrality and ESG Risk Factors

Variable	Coefficient
α	0.0851*** (283.532)
β_1	-0.0006 (-1.895)
β_2	0.0006** (3.258)
β_3	0.0008** (3.186)

Notes: This table provides the results of the parameter estimates for the equation in the U.S. market.

$$Supply\ Chain\ Centrality_t^m = \alpha + \beta_1\ E\_pls_t^m + \beta_2\ S\_pls_t^m + \beta_3\ G\_pls_t^m + \varepsilon_t$$

The Supply Chain Centrality is proxied by scaled Exports. Sample period spans from January 2006 to December 2023. Numbers in parenthesis are *t*-statistics. *** and ** indicate that the coefficient is significant at the 1% and 5% levels, respectively.

Table 3 Test of the role supply chain play in ESG affect systemic risk

Variable	Stock	Bond
α	223.7767***	17.6762**
	(3.133)	(2.375)
β_1	-2541.1802***	-194.6475**
	(-3.03)	(-2.228)

Notes: This table provides the results of the parameter estimates for the equation in the U.S. market.

$$Volatility_t^m = \alpha + \beta_1\ predicted\ supply\ chain\ centrality\ US_t^m + \varepsilon_t$$

The stock market volatility is represented by the monthly average of realized volatility, while the bond market volatility is proxied by the monthly historical volatility. Sample period spans from January 2006 to December 2023. Numbers in parenthesis are *t*-statistics. *** and ** indicate that the coefficient is significant at the 1% and 5% levels, respectively.

Table 4 Regression Results for Market Volatility and ESG Factors in the China Market

Variable	Stock	Bond
α	1.3871*** (11.147)	0.8481*** (11.039)
β_1	-0.2668** (-2.255)	0.1759** (2.565)
β_2	-0.2714*** (-2.785)	0.1729*** (2.786)
β_3	0.3619** (2.464)	0.135* (1.878)

Notes: This table provides the results of the parameter estimates for the equation in the China market.

$$Volatility_t^m = \alpha + \beta_1\, E\_pls_t^m + \beta_2\, S\_pls_t^m + \beta_3\, G\_pls_t^m + \varepsilon_t$$

The stock market volatility is represented by the monthly average of realized volatility, while the bond market volatility is proxied by the monthly historical volatility. Sample period spans from January 2010 to December 2023. Numbers in parenthesis are *t*-statistics. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% levels, respectively.

Table 5 The Impact of ESG Risk Factors on Supply Chain Centrality

Variable	Coefficient
α	0.1289*** (82.652)
β_1	0.0018 (1.321)
β_2	-0.0022* (-1.744)
β_3	-0.055*** (-3.749)

Notes: This table provides the results of the parameter estimates for the equation in the China market.

$$Supply\ Chain\ Centrality_t^m = \alpha + \beta_1\ E\_pls_t^m + \beta_2\ S\_pls_t^m + \beta_3\ G\_pls_t^m + \varepsilon_t$$

The Supply Chain Centrality is proxied by scaled Exports. Sample period spans from January 2010 to December 2023. Numbers in parenthesis are *t*-statistics. *** and * indicate that the coefficient is significant at the 1% and 10% levels, respectively.

Table 6 Test of the role supply chain play in ESG affect systemic risk

Variable	Stock	Bond
α	0.8104***	0.3686*
	(5.607)	(1.836)
β_1	0.0255	0.6771***
	(0.318)	(5.794)

Notes: This table provides the results of the parameter estimates for the equation in the China market.

$$Volatility_t^m = \alpha + \beta_1 \, predicted\ supply\ chain\ centrality\ CN_t^m + \varepsilon_t$$

The stock market volatility is represented by the monthly average of realized volatility, while the bond market volatility is proxied by the monthly historical volatility. Sample period spans from January, 2010 to December, 2023. Numbers in parenthesis are *t*-statistics. *** and * indicate that the coefficient is significant at the 1% and 10% levels, respectively.

Table 7 Using stock index jump as systemic risk to test the robustness of supply chain as a path in US market

Variable	Coefficient
α	1.278056
β_1	-13.111685*** (-54.195512)

Notes: This table provides the results of the parameter estimates for the equation in the U.S. market.

$$Jump_t^m = \alpha + \beta_1 \, predicted\ supply\ chain\ centrality\ US_t^m + \varepsilon_t$$

The monthly jump components are calculated by the monthly average of daily jump detected by the BNS test at 1% significance level. Sample period spans from January, 2006 to December, 2023. Numbers in parenthesis are *t*-statistics. *** indicate that the coefficient is significant at the 1% level.

Table 8 Using stock index jump as systemic risk to test the robustness of supply chain as a path in China Market

Variable	Coefficient
α	0.027737
β_1	0.011863***
	(3.445702)

Notes: This table provides the results of the parameter estimates for the equation in the China market.

$$Jump_t^m = \alpha + \beta_1 \, predicted \; supply \; chain \; centrality \; CN_t^m + \varepsilon_t$$

The monthly jump components are calculated by the monthly average of daily jump detected by the BNS test at 1% significance level. Sample period spans from January, 2010 to December, 2023. Numbers in parenthesis are *t*-statistics. *** indicate that the coefficient is significant at the 1% level.