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Earnings Propagation Effects through the Global Supply Chain Network

Shimon Tsuchiya, CMA

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Senior Fund Manager, Investment Technology Fund Management Department, Nikko Asset Management Co., Ltd. After working for Dai-ichi Kangyo Asset Management Co., Ltd, he joined Nikko Asset Management in 2004. He graduated from Waseda University in 1999, and obtained a MBA from University of Tsukuba in 2009.

Abstract: We examine earnings propagation effects through the global supply chain by measuring the lead-lag structure of quarterly earnings. We find that propagation effects stem not only from direct trading partners, but also from indirectly linked firms, such as customers of customers. We also discuss the effectiveness of using network centrality to estimate the impact of each firm on other firms in the supply chain. Our results suggest that weighting by degree of network centrality can be effective for capturing propagation effects from indirectly linked firms.

1. Introduction

A supply chain is a network of business relationships between firms that extends from the procurement of raw materials to the sale of products and provision of services to final consumers. Against the backdrop of globalized competition among firms, the global supply chain is becoming more sophisticated and complex every year. Efficiency has become the key to surviving intensifying international competition; firms have concentrated management resources in areas where they have a competitive edge, opting to use external resources in other areas. As a result, international specialization among firms has expanded, resulting in a more sophisticated and complex supply chain. With the environment surrounding the corporate management of firms growing increasingly uncertain, building an efficient and adaptable supply chain in order to respond to unexpected changes in market structure and to minimize inventory costs has also become important. The competitiveness of the supply chain has come to affect the competitiveness of the firm itself.

Against this backdrop, customer-supplier ties have evolved beyond the traditionally simple relationship between a product supplier and its customer. Customers and suppliers sometimes share information and other management resources beyond organizational boundaries to add value to products and services by optimizing the entire supply chain. Firms in this type of relationship are in effect collaborating and have strong economic ties. Even among companies that are not in such collaborative relationships, there have been cases when firms and their trading partners are both impacted by price shocks caused by changes in the market prices of their products and services, resulting in economic ties. The increasing sophistication and complexity of supply chains thus strengthen economic ties between firms in various aspects.

In recent years, the development of databases containing records of business transactions between firms around the world has made it possible to analyze the impact of the global supply chain on corporate earnings. The main purpose of this paper is to use such business transaction data to examine the existence of earnings propagation effects through the global supply chain network. If propagation effects on the earnings of suppliers and customers do exist, such that the earnings of one affect the earnings of the other following a time lag, they could be applied to earnings forecasting and the development of investment strategies.

2. Previous Research

Aobdia et al. (2014) discuss earnings propagation effects through trading networks at the industry level. They define trade networks by the Input-Output Accounts published by the US Department of Commerce's Bureau of Economic Analysis (BEA) and analyze how the network structure affects the transmission of information and economic shocks across industries. The results show that the earnings of industries located in the center of the network are more strongly affected by macroeconomic indicators than non-central industries, and that the earnings and stock returns of central industries have predictive power for those of non-central industries. Although this study does not focus on earnings propagation among individual firms, it shows that at the industry level, the earnings of a central industry propagate to peripheral industries through the trading networks.

Most of other previous research on customer-supplier relationships focuses on the predictability of stock returns. Cohen and Frazzini (2008) analyze the predictability of stock prices for firms in customer-supplier relationships in the US. The study points out that the risk-adjusted returns of an investment strategy that buys suppliers with high return customers and sells suppliers with low return customers are positive with statistical significance.

Menzly and Ozbas (2010) and Shahrur et al. (2010) both define suppliers and customers by using Input-Output Accounts data from the BEA and examine the lead-lag relationship in stock returns; they report that customer returns lead supplier returns.

Hamuro and Okada (2018) point out that, in the US market, a sudden rise in the price of an individual stock is significantly propagated to other stocks that have trading relationships with it. They also find that propagation is observed in both directions–from suppliers to customers and vice versa.

Isogai et al (2019) discuss the predictability of stock returns from cross-momentum among firms linked by trading networks in the Japanese stock market, and show that a statistically positive relationship exists between news about a customer firm and a supplier firm’s future stock returns. Furthermore, they find that this cross-momentum effect predicts sell-side analysts' future earnings forecasts. They thereby argue that stock return predictability reflects the limits of investor attention and information processing capabilities.

Aobdia et al. (2014) discuss the propagation of earnings at the industry level, and Isogai et al. (2019) report on the relationship with analysts' earnings forecasts, but most studies about the supply chain are focused on relatively short-term cross-momentum effects, and there are few that examine the propagation effects of individual firms' earnings. The main purpose of our paper is to examine whether a lead-lag relationship is also observed at the earnings of individual firms linked by the supply chain, and if so, what its characteristics are. If a lead-lag relationship is observed in earnings, whether the earnings of supply chain-linked firms have predictive power for future stock returns is also discussed.

3. Research Design

（1）Supply Chain Database

The supply chain data used in our analysis was obtained from the FactSet Revere Supply Chain Relationships database. This database contains customer, supplier, competitor, and partner relationships for firms and organizations around the world, based on information sources such as the SEC’s 10-K annual reports, investor presentations, and press releases. In this paper, we focus on the relationship between customers and suppliers[1].

[1] FactSet Revere Supply Chain Relationships contains data from 2003 onwards.

Our sample universe consists of firms that have one or more customers or suppliers in the database, with firms included regardless of their country or region. This is because today's supply chain is globally interlinked, and to discuss its impact it is necessary to take as wide a range of samples as possible. However, the database includes firms and organizations for which financial statements are not available, such as unlisted firms and public institutions. As we cannot measure the earnings propagation effects (the purpose of this paper) for such firms, we exclude them and focus on firms for which quarterly corporate earnings and market capitalization are available[2]. The reason for limiting the sample universe to firms that announce their results each quarter is that earnings propagation effects may be observed more clearly in a short time horizon. In addition, there would be some overlap in the measurement period of corporate earnings if we include firms with differing fiscal year-end periods in our analysis. We therefore focus on firms with quarter fiscal year-ends in March, June, September, and December. This makes it possible to measure propagation effects without any overlap in the measurement period of earnings. The analysis period is 64 quarters, from the last quarter of 2003 to the third quarter of 2019 inclusive and the sample data covers a total of 275,342 quarters and firms3. The summary of the sample data is shown in Table 1.

Table 1 Data Summary

Manufacturing / Non-manufacturing	Region	Total Sample (Quarters × Firms)	Avg. Market Cap(per issue)	Composition Ratio		Market Cap Percentile		
				No.of Issues	Market Cap	25%	50%	75%
Manufacturing	North America	45,517	7,893	36.8%	50.8%	130	730	3,346
	Europe	10,960	13,116	8.9%	20.3%	345	1,928	9,541
	Japan	19,340	4,436	15.6%	12.1%	207	768	3,396
	Asia(exJPN)	36,256	2,088	29.3%	10.7%	153	485	1,503
	Else	11,738	3,661	9.5%	6.1%	120	438	2,140
	All Region	123,811	5,714	100.0%	100.0%	159	656	2,781
Non-manufacturing	North America	75,174	7,315	49.6%	59.5%	246	1,158	4,651
	Europe	12,641	9,087	8.3%	12.4%	349	1,851	8,672
	Japan	14,839	4,004	9.8%	6.4%	133	464	2,458
	Asia(exJPN)	28,173	4,208	18.6%	12.8%	188	705	2,471
	Else	20,704	3,957	13.7%	8.9%	182	734	2,860
	All Region	151,531	6,102	100.0%	100.0%	208	934	3,865

(Market cap in millions of dollars)

(2) Regression Models

In this paper, we discuss earnings propagation effects by measuring the lead-lag structure of quarterly earnings through regression analysis. The dependent variable is operating profit and not net profit, which is affected by taxes and extraordinary gains and losses; in addition, year-on-year change is used for seasonal adjustment. The independent variable is the year-on-year change in operating profit of the

[2] We obtained earnings and market capitalization data from Thomson Reuters Quantitative Analytics.

[3] The supply chain network is updated once a year at the end of December, and the network is applied for the following year.

customer/supplier a quarter earlier[4]. In the case of multiple customers/suppliers, the average value is used as the independent variable. In addition to customer/supplier firms directly linked to their counterparties (defined as distance 1), we also discuss the propagation effects from indirectly linked firms such as the customers of customers and the suppliers of suppliers (defined as distance 2). Given the time lag, it is possible that the propagation effects of firms located further away in the supply chain could be larger. Therefore, in the regression model we decided to include firms up to the distance 2 classification as independent variables. We conduct a regression analysis with these independent variables on a quarterly basis and discuss the propagation effects by statistical significance of the coefficient estimates[5]. In this paper, we separate the regression model that examines propagation from customers and the regression model that examines propagation from suppliers and then estimate the coefficients of the following two regression models:

$$P_{i,t} = \alpha_{0,t} + \alpha_{1,t}P_{i,t-1} + \alpha_{2,t}M_{i,t-1} + \alpha_{3,t}D_i + \alpha_{4,t}C_{i,t-1} + \alpha_{5,t}CC_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

$$P_{i,t} = \alpha_{0,t} + \alpha_{1,t}P_{i,t-1} + \alpha_{2,t}M_{i,t-1} + \alpha_{3,t}D_i + \alpha_{4,t}S_{i,t-1} + \alpha_{5,t}SS_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

$P_{i,t}$: YoY change in operating profit for firm i, period t

$M_{i,t-1}$: Log market cap for firm i, period t-1

D_i : Dummy variable that takes 1 if firm i is from a developed country and 0 otherwise.

$C_{i,t-1}$: YoY change in operating profit for customers of firm i, period t-1

$CC_{i,t-1}$: YoY change in operating profit for customers of customers of firm i, period t-1

$S_{i,t-1}$: YoY change in operating profit for suppliers of firm i, period t-1

$SS_{i,t-1}$: YoY change in operating profit for suppliers of suppliers of firm i, period t-1

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[4] The year-on-year change in operating profit is calculated using the following formula:
(Operating profit for the current period - Operating profit for the same period the previous year)/{(|Operating profit for the current period|+|Operating profit for the same period the previous year|)/2}

[5] We do not take into account the timing of earnings announcement dates. We forecast earnings for the fiscal year ending June using linked firms' earnings for the fiscal year ending March, and forecast earnings for the fiscal year ending September using linked firms' earnings for the fiscal year ending June, and so on.

Equation (1) is the model for analyzing propagation from customers (hereinafter referred to as the 'customer model') and equation (2) that for analyzing propagation from suppliers (hereinafter referred to as the 'supplier model'). In both equations, the following variables are added as control variables: year-on-year operating profit for the previous period ($P_{i,t-1}$), log market capitalization ($M_{i,t-1}$), and a dummy variable for developed countries (D_i) that takes 1 for firms in developed countries and 0 for others[6]. The reason for adopting the previous period's earnings, $P_{i,t-1}$, as a control variable is to control the portion of the current period's earnings that is explained by earnings in the previous period. Our interest in this analysis focuses on the significance of coefficients α_4 and α_5. Here, manufacturing firms, which are mainly located upstream in the supply chain, and non-manufacturing firms, which are mainly located downstream, might be affected differently by their counterparty firms. Therefore, in this paper, we divide the sample into the manufacturing industry and the non-manufacturing industry and estimate the coefficients separately[7].

4. Regression Results

Table 2 shows the means and t-statistics of the regression coefficients for the manufacturing industry. Model 1 to Model 3 are the customer models and Model 4 to Model 6 are the supplier models. Looking at the whole, we can see that the t-statistic of α_1 is the highest, indicating own earnings in the previous period have the highest explanatory power. Also, the coefficient of determination of the customer models is slightly higher, indicating that the customer models fit better than the supplier models.

First, we look at the results of the customer models. The coefficients α_4 and α_5, the key interest of this paper, are significant at the 5% level in both models, indicating that customer earnings still have additional predictive power after adjusting for previous period earnings. Comparing α_4 and α_5, the t-statistic of α_4 is higher and significant at the 1% level for both Model 1 and Model 3, indicating that the earnings propagation effects from directly linked customers/suppliers are stronger. Although the t-statistic for α_5 is lower than that for α_4, it is significant at the 1% level for Model 2. In Model 3, which uses customer earnings at distance 1 and distance 2 simultaneously, α_5 remains significant at the 5% level, indicating the existence of propagation effects from firms at distance 2. It is one of the key findings of this paper that earnings propagation from indirectly linked firms exists even after adjusting directly linked firms' earnings.

Next, we look at the results of the supplier models. Coefficients α_4 and α_5 are significant at the 1% level for both Model 4 and Model 6, indicating the existence of earnings propagation from suppliers

[6] We defined the MSCI World Index constituent countries as developed countries.
[7] The classification of manufacturing and non-manufacturing industry is based on the North American Industry Classification System (NAICS).

at distance 1. On the other hand, α_5 is not significant even at the 10% level, showing that propagation from suppliers at distance 2 cannot be observed in this model. Comparing customer and supplier models, the t-statistics of customer models are higher in all models when they are compared at the same distance, indicating that earnings propagation effects are relatively larger from customers. These results are consistent with previous studies that indicated that customer returns lead supplier returns.

Table 3 shows the means of coefficient estimates and their t-statistics for the non-manufacturing industry. Although the two industries follow similar trends, the overall levels of t-statistics for α_4 and α_5 for non-manufacturing are lower than those for manufacturing, indicating that the propagation effect is relatively small. This may be due to differences in the functions of supply chains in the manufacturing and non-manufacturing groups. The strong ties that exist between component manufacturers and manufacturers of finished products are relatively rare in the non-manufacturing industry, and the small propagation effect could be a reflection of this difference.

The results of the customer model show that α_4 remains significant at the 1% level for both Model 1 and Model 3, confirming the propagation effects from direct customers, as was the case in the manufacturing industry. On the other hand, unlike the manufacturing industry, α_5 is non-significant at the 5% level for both Model 2 and Model 3, indicating that the propagation from customers at distance 2 is relatively small.

Next, results of the supplier model show that, as in the customer model, α_4 is significant for Model 4 and Model 5, indicating the existence of propagation from direct suppliers. Although α_5 is slightly non-significant at the 5% level in Model 5, it is significant in Model 6. The propagation trend from suppliers at distance 2 is somewhat different from that of the manufacturing industry, where it is non-significant. A comparison of the customer model and the supplier model shows that their α_4 and α_5 t-statistic levels are within close proximity. This suggests that suppliers have a comparable influence to that of customers. Non-manufacturing industries, such as retail, are often located downstream in the supply chain, therefore subject to greater impact from the upstream compared to manufacturing industries.

Table 2 Regression Coefficients (Manufacturing)

	Customer Model			Supplier Model		
	Model1	Model2	Model3	Model4	Model5	Model6
α_0 : Intercept	0.018	0.046	0.347	0.034	0.054 *	0.057 *
	(0.64)	(1.31)	(1.18)	(0.88)	(1.73)	(1.81)
α_1 : Own Earnings_{t-1}	0.342 ***	0.349 ***	0.347 ***	0.328 ***	0.331 ***	0.328 ***
	(33.91)	(34.57)	(33.71)	(32.12)	(30.45)	(29.82)
α_2 : Log Market Cap	0.000	−0.002	−0.002	−0.001	−0.001	−0.003
	(−0.12)	(−0.61)	(−0.60)	(−0.31)	(−0.44)	(−0.95)
α_3 : Developed Country Dummy	0.011	−0.009	−0.513	0.000	−0.968	−0.375
	(0.62)	(−0.33)	(−0.51)	(0.02)	(−0.97)	(−0.37)
α_4 : $\text{Distance1Earnings}_{t-1}$	0.058 ***		0.073 ***	0.037 ***		0.035 ***
	(6.97)		(6.37)	(5.07)		(3.85)
α_5 : Distance2 Earnings_{t-1}		0.039 ***	0.038 **		0.009	0.004
		(3.24)	(2.61)		(1.08)	(0.45)
No. of Samples	84,074	66,961	62,075	74,232	57,362	51,205
Adjusted R^2	0.130	0.131	0.136	0.121	0.120	0.121

***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 3 Regression Coefficients (Non-Manufacturing)

	Customer Model			Supplier Model		
	Model1	Model2	Model3	Model4	Model5	Model6
α_0 : Intercept	0.039	0.044	0.298	0.042	0.037	0.047
	(1.25)	(1.13)	(1.56)	(1.03)	(1.43)	(1.64)
α_1 : Own Earnings_{t-1}	0.292 ***	0.298 ***	0.298 ***	0.270 ***	0.271 ***	0.267 ***
	(33.14)	(30.64)	(30.75)	(29.77)	(30.38)	(29.22)
α_2 : Log Market Cap	0.003	0.002	0.002	0.002	0.001	0.001
	(1.34)	(0.81)	(0.74)	(0.83)	(0.55)	(0.58)
α_3 : Developed Country Dummy	−0.025	−0.015	−1.513	−0.017	−0.008	−0.680
	(−1.29)	(−0.62)	(−1.51)	(−1.18)	(−0.01)	(−0.68)
α_4 : $\text{Distance1Earnings}_{t-1}$	0.024 ***		0.022 ***	0.017 ***		0.016 **
	(3.66)		(2.70)	(3.21)		(2.42)
α_5 : Distance2 Earnings_{t-1}		0.016	0.020 *		0.015 *	0.018 **
		(1.60)	(1.68)		(1.87)	(2.19)
No. of Samples	86,914	66,370	61,585	98,588	77,164	69,090
Adjusted R^2	0.091	0.094	0.095	0.078	0.078	0.076

***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

5. Network Centrality Weighting

（1）Network Centrality

In handling cases of multiple customers/suppliers, so far in this paper we have used the simple average of their year-on-year change in earnings as independent variables. In reality, indirectly linked firms (such as customers of customers), could include firms that have little or no impact on a company's earnings. When the number of indirectly linked firms is large, the less relevant firms become noise, thereby making it more difficult to capture propagation effects. To improve explanatory power, it is desirable to focus more on firms that are considered important in the supply chain. Therefore, in this section we discuss the effectiveness of using network centrality to determine which firms should be given more weight. Hamuro and Okada (2018) report that applying edge betweenness centrality to the supply chain network to weight purchase volume can improve return on investment strategies that use information propagation from suppliers to customers. Aobdia et al. (2014) apply network centrality to inter-industry trading networks and show that the accounting performance of the central industries predicts the accounting performance of non-central industries. These results suggest that network centrality may also be effective in improving the earnings predictability of this paper.

In this paper, we examine the effectiveness of two centrality indices: degree centrality and betweenness centrality. Degree centrality gives higher centrality to nodes (in this paper, the nodes represent firms) that have many edges (in this paper, edges represent relationships with other firms). We consider degree centrality to be effective since firms with many edges are likely to be suppliers of competitive parts or customers with highly effective sales forces. Betweenness centrality gives higher centrality to nodes that are often located on the shortest path in the network and is an indicator of a hub function in a network. We consider betweenness centrality to be effective because the movement of a firm that acts as a hub in a supply chain network affects many other firms around it.

We will specifically observe the characteristics of these two network centralities using a real supply chain network. Here, for convenience, we take a small network from the global supply chain and observe which firms and industries are given high centralities by these two network centralities. Figures 1 through 3 take MSCI Japan Index constituents from the global supply chain as of the end of December 2019 and graph only the edges that exist between these stocks. Figure 1 shows a market capitalization-weight graph as a comparison for network centrality, where the size of the circles at the nodes is proportional to market capitalization. In the graphs in figures 2 and 3, the circles are proportional to the centrality assigned to the firm, showing that firms with larger circles have higher centrality.

The market capitalization graph in Figure 1 shows that Toyota Motor has a large weight, but major telecommunications firms and major city banks also have relatively large weights. On the other hand, the degree centrality graph in Figure 2 shows that the weight of these firms has decreased, while the weight of machinery and electrical machinery has increased, indicating that the centrality of large manufacturing firms that have business relationships with many industries is highly weighted. Degree centrality is also characterized by smaller differences in weights among nodes than market capitalization weights. Regarding betweenness centrality in Figure 3, there is a large difference in evaluation among firms. This is mainly because, from the definition of betweenness centrality, firms located at the end of the network are not valued at all[8]. In terms of betweenness centrality, major electronics firms such as Toshiba, Sharp, and Sony were weighted higher than they were for the other two weights, indicating that these firms serve as hubs in the Japanese supply chain.

[8] In this analysis, when centralities of all customers/suppliers are 0, independent variables are calculated as equal weights.

Figure 1 Market Capitalization

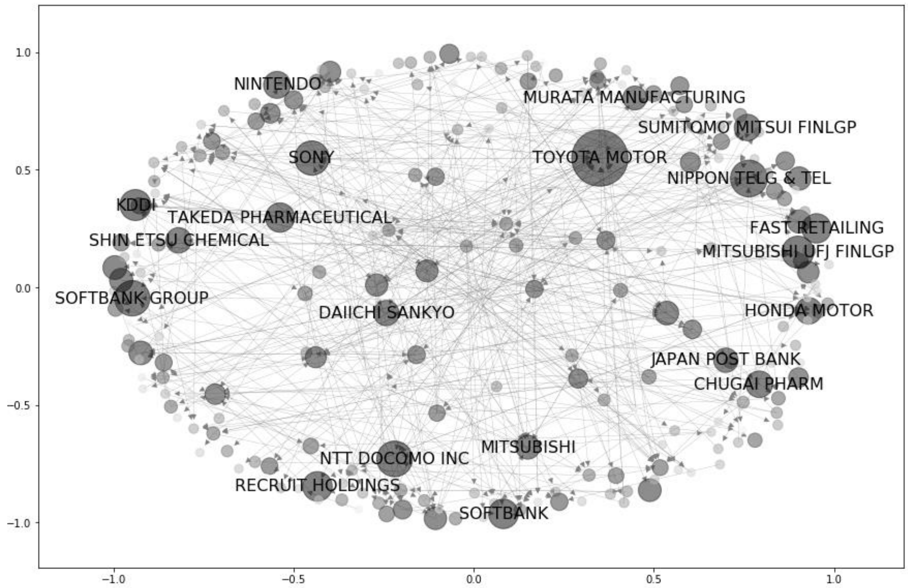


Figure 2 Degree Centrality

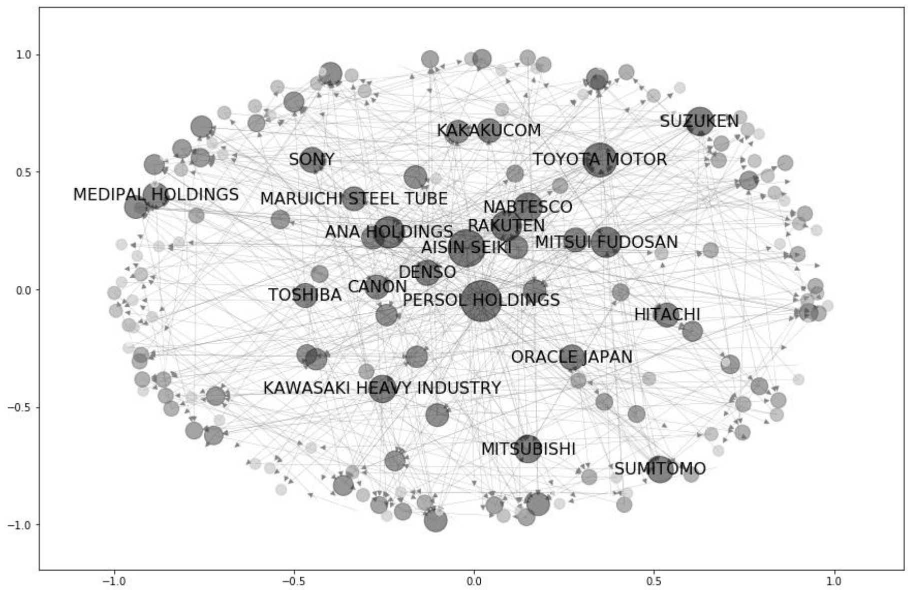
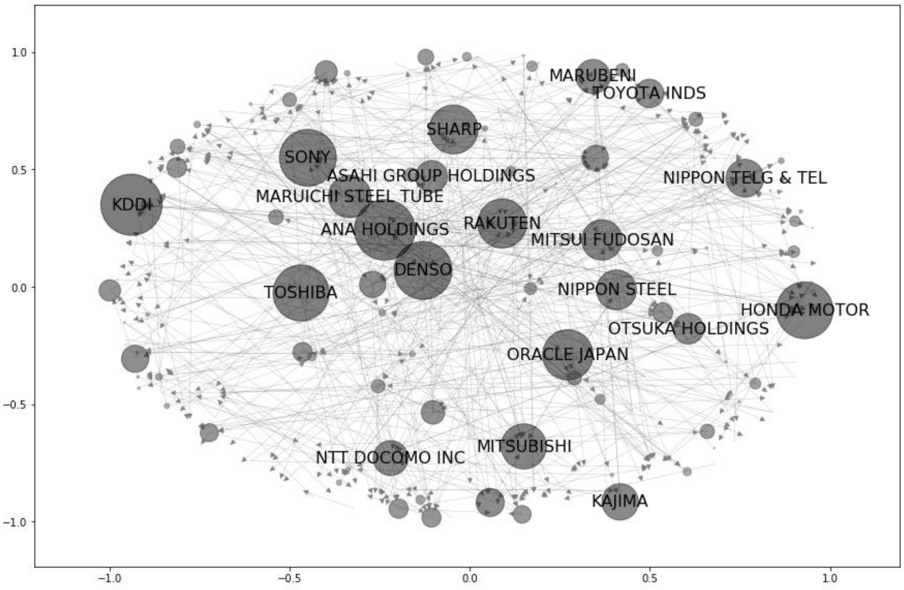


Figure 3　Betweenness Centrality



（2）Propagation Effects in the Manufacturing Industry

First, we discuss the effectiveness of network centrality in the manufacturing industry. Table 4 shows the results of regression analysis using the independent variables calculated with market capitalization weighting, degree centrality weighting, and betweenness centrality weighting [9]. Comparing the results of the customer model with the results of equal weighting in Table 2, the significance of α_5 in the degree centrality weighting exceeds equal weighting, but the other coefficients are inferior to equal weighting. Many of the results of the supplier model are also inferior, and we cannot find any clear effectiveness of network centrality weighting. This result indicates that it is difficult to improve the explanatory power of linked firms' earnings in the manufacturing industry, even when weighting by network centrality.

[9] Only the results for α_4 and α_5 are shown. Trends for α_0 through α_3 are the same as in Table 2.

Table 4　Network Centrality Weighting (Manufacturing)

		Customer Model			Supplier Model		
Weight	Variables	Model1	Model2	Model3	Model4	Model5	Model6
Market Cap	$\alpha 4$: Distance1Earnings$_{t-1}$	0.042 ***		0.042 ***	0.034 ***		0.032 ***
		(5.48)		(4.02)	(5.50)		(4.68)
	$\alpha 5$: Distance2 Earnings$_{t-1}$		0.036 ***	0.035 **		0.006	0.000
			(2.92)	(2.44)		(0.87)	(0.01)
Degree Centrality	$\alpha 4$: Distance1Earnings$_{t-1}$	0.045 ***		0.048 ***	0.031 ***		0.026 ***
		(6.03)		(4.68)	(4.95)		(3.27)
	$\alpha 5$: Distance2 Earnings$_{t-1}$		0.044 ***	0.044 ***		0.007	0.004
			(3.53)	(2.92)		(0.91)	(0.45)
Betweenness Centrality	$\alpha 4$: Distance1Earnings$_{t-1}$	0.035 ***		0.036 ***	0.029 ***		0.023 ***
		(5.34)		(4.03)	(5.17)		(3.26)
	$\alpha 5$: Distance2 Earnings$_{t-1}$		0.034 ***	0.031 **		0.007	0.006
			(2.87)	(2.27)		(1.14)	(0.83)

***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

(3) Propagation Effects in the Non-manufacturing Industry

Table 5 shows the results of regression analysis for the non-manufacturing industry[10]. Comparing the results of the customer models with the results of equal weighting in Table 3, we can see that the t-statistics of α_4 and α_5 have improved in both market capitalization weighting and network centrality weighting. In particular, the significance of α5 is greatly improved by using network centrality. We can see that propagation from the customer at distance 2, which is not significant in equal weighting, becomes significant with network centrality weighting. In addition, α_5 remains significant at the 5% level for Model 3, confirming that customer earnings at distance 2 have the additional predictive power even after adjusting for customer earnings at distance 1.

Next, we compare the results of the supplier model with the results of equal weighting. For α_4, the results are inferior to equal weighting for all weighting methods. Because they are direct trading partners, the number of firms at distance 1 is limited; furthermore, their economic ties are plain to see. Due to these reasons, there is not much point in weighting them, and it might be reasonable to treat them equally. On the other hand, the significance of α_5 shows that market capitalization weighting and degree centrality weighting results have improved from equal weighting. Although the degree of improvement is smaller than that of the customer model, the fact that Model 5, which was not significant in equal weighting, becomes significant at the 5% level indicates some degree of effect. These results suggest that for the non-manufacturing industry, weighting by network centrality can improve the predictive power of linked firms' earnings, especially from indirect customers. In the equal weighting results, the propagation effects of the non-manufacturing industry are smaller than those of the manufacturing industry. As we mentioned earlier, one possible reason for this is that there are fewer examples of strong inter-firm ties in the non-manufacturing industry compared to the manufacturing

[10] Only the results for α_4 and α_5 are shown. Trends for α_0 through α_3 are the same as in Table 3.

industry. In the non-manufacturing industry, more business relationships generate noise in relative terms when we measure earnings propagation, and that may have made it difficult to observe earnings propagation in equal weighting. We infer that this noise is mitigated by placing more emphasis on the central firms in the supply chain network through network centrality, allowing us to better observe the propagation effects. One of the key contributions of this paper is that it shows the potential of using network centrality to capture earnings propagation from indirectly linked firms, which in some cases is difficult to observe.

Table 5 Network Centrality Weighting (Non-Manufacturing)

		Customer Model			Supplier Model		
Weight	Variables	Model1	Model2	Model3	Model4	Model5	Model6
Market Cap	$\alpha 4$: Distance1Earnings$_{t-1}$	0.023 ***		0.019 **	0.013 **		0.010
		(3.91)		(2.46)	(2.41)		(1.34)
	$\alpha 5$: Distance2 Earnings$_{t-1}$		0.018 *	0.021 *		0.017 **	0.020 ***
			(1.84)	(1.88)		(2.39)	(2.73)
Degree Centrality	$\alpha 4$: Distance1Earnings$_{t-1}$	0.023 ***		0.019 **	0.012 **		0.008
		(4.29)		(2.58)	(2.24)		(1.11)
	$\alpha 5$: Distance2 Earnings$_{t-1}$		0.022 **	0.028 **		0.016 **	0.022 **
			(2.42)	(2.63)		(2.00)	(2.62)
Betweenness Centrality	$\alpha 4$: Distance1Earnings$_{t-1}$	0.021 ***		0.020 ***	0.008		0.003
		(4.24)		(2.93)	(1.54)		(0.47)
	$\alpha 5$: Distance2 Earnings$_{t-1}$		0.017 **	0.022 **		0.014 *	0.019 **
			(2.04)	(2.30)		(1.88)	(2.63)

***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

6. Stock Return Predictability

Even if earnings propagation effects exist among firms and the earnings of firms they are linked with are able to predict their own future earnings, we should not find a significant relationship between the published earnings of linked firms and future stock returns if the market is efficient and stock prices are formed by incorporating the earnings propagation from linked firms. In particular, the earnings of firms with high centrality are more likely to be incorporated into stock prices because they attract investor attention, and their predictive power for future stock returns might not be significant. In this section, we conduct a regression model in which the dependent variable is future stock returns and the independent variables are the linked firms' earnings (year-on-year change in operating profit) up to distance 2, and discuss whether linked firms' earnings have predictive power for future stock returns.

The risk factors to be controlled are market beta (BETA), market capitalization (SIZE), and book-to-market (BTM) proposed by Fama and French (1993), plus the momentum factor (MOM) proposed by Carhart (1997)[11]. In line with the analysis so far in this paper, the sample universe is firms for which

[11] The 36-month MSCI AC World Index beta is used as BETA, and log-market capitalization is used as SIZE.

market capitalization and quarterly earnings are available. The analysis period is also from the last quarter of 2003 to third quarter of 2019 inclusive, and the coefficients are estimated separately for the manufacturing and non-manufacturing industries. In order to examine the relationship with stock returns, in this analysis we take into account earnings announcement dates and conduct these regression models that explain stock returns in the following month using only information available at that point in time.

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}C_{i,t-1} + \alpha_{2,t}CC_{i,t-1} + \alpha_{3,t}BETA_{i,t-1} + \alpha_{4,t}BTM_{i,t-1} + \alpha_{5,t}SIZE_{i,t-1} + \alpha_{6,t}MOM_{i,t-1} + \varepsilon_{i,t} \qquad (3)$$

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}S_{i,t-1} + \alpha_{2,t}SS_{i,t-1} + \alpha_{3,t}BETA_{i,t-1} + \alpha_{4,t}BTM_{i,t-1} + \alpha_{5,t}SIZE_{i,t-1} + \alpha_{6,t}MOM_{i,t-1} + \varepsilon_{i,t} \qquad (4)$$

Equation (3) is a customer model using customer earnings as the independent variable, and equation (4) is a supplier model using supplier earnings as the independent variable. $R_{i,t}$ is the stock return of stock i in period t. Table 6 shows the means of the coefficient estimates and their t-statistics. Coefficients α_1 and α_2, the main point of interest of this analysis, show that although they are positive in most cases, statistically significant coefficients are found only in the manufacturing industry's customer model. This result is consistent with previous studies that argue that customer returns lead those of suppliers. Significant coefficients do not exist in the non-manufacturing industry, but the coefficients of distance 1 and distance 2 are all positive in both customer and supplier models, and there is a possibility that information of the linked firms' earnings are not fully incorporated in stock prices.

As for the effectiveness of network centrality, the results show that it is difficult to find superiority over equal weighting in both distance 1 and distance 2. We infer that network centralities do not always work effectively for predicting future stock returns since the predictive power for future stock returns is affected not only by the predictive power of future earnings but also by the extent of investor attention.

Table 6 Stock Return Predictability

Manufacturing / Non-manufacturing	Customer/Supplier	Weighting	Distance 1(α_1)		Distance 2 (α_2)		BETA(α_3)		BTM(α_4)		SIZE(α_5)		MOM(α_6)	
			Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Manufacturing	Customer Model	Equal	0.153	2.39 **	0.268	2.62 ***	−0.041	−0.41	0.421	5.06 ***	0.026	0.28	0.148	1.58
		Market Cap	0.147	2.40 **	0.133	1.36	−0.044	−0.44	0.421	5.06 ***	0.020	0.22	0.152	1.62
		Degree Centrality	0.129	2.16 **	0.160	1.69 *	−0.039	−0.39	0.421	5.07 ***	0.024	0.26	0.152	1.63
		Betweennes Centrality	0.113	2.10 **	0.095	1.22	−0.042	−0.42	0.421	5.08 ***	0.021	0.23	0.155	1.66 *
	Supplier Model	Equal	0.040	0.78	−0.080	−0.88	0.034	0.32	0.295	3.56 ***	0.015	0.17	0.239	2.30 **
		Market Cap	0.036	0.69	−0.105	−1.31	0.033	0.32	0.291	3.50 ***	0.015	0.16	0.236	2.26 **
		Degree Centrality	0.030	0.59	−0.101	−1.15	0.039	0.37	0.292	3.52 ***	0.016	0.18	0.235	2.25 **
		Betweennes Centrality	0.052	1.15	−0.065	−0.92	0.039	0.37	0.293	3.54 ***	0.016	0.17	0.237	2.27 **
Non-manufacturing	Customer Model	Equal	0.060	0.86	0.060	0.61	−0.021	−0.22	0.126	1.76 *	−0.078	−0.89	0.096	0.95
		Market Cap	0.010	0.15	0.019	0.22	−0.021	−0.21	0.132	1.85 *	−0.076	−0.87	0.097	0.96
		Degree Centrality	0.032	0.46	0.042	0.46	−0.018	−0.19	0.126	1.76 *	−0.077	−0.88	0.096	0.95
		Betweennes Centrality	0.060	0.98	0.020	0.27	−0.018	−0.18	0.128	1.78 *	−0.077	−0.88	0.097	0.96
	Supplier Model	Equal	0.058	1.09	0.052	0.68	−0.040	−0.38	0.138	1.99 **	−0.108	−1.27	0.174	1.74 *
		Market Cap	0.011	0.21	0.108	1.43	−0.039	−0.37	0.136	1.96 *	−0.110	−1.30	0.172	1.72 *
		Degree Centrality	0.032	0.61	0.070	0.91	−0.042	−0.40	0.137	1.99 **	−0.112	−1.31	0.175	1.75 *
		Betweennes Centrality	0.040	0.88	0.047	0.67	−0.043	−0.41	0.136	1.97 *	−0.114	−1.35	0.176	1.76 *

***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

7. Conclusion

This paper has examined earnings propagation effects through the global supply chain network. The results show that earnings propagation effects exist both from customers and suppliers. The results also suggest that when comparing the manufacturing and non-manufacturing industries, propagation is larger in the manufacturing industry, and when comparing customers and suppliers, propagation from customers is larger. The larger influence from customers is consistent with previous studies that argue that customer returns lead supplier returns. Looking at the effect of distance in the supply chain network on propagation strength, the results show that propagation effects are greater for directly linked firms, but they also show the existence of propagation effects from indirectly linked firms, such as customers of customers.

We have discussed whether weighting firms in a supply chain by their network centrality can improve earnings predictability. The results suggest that network centrality weighting has some effects on improving earnings predictability in the non-manufacturing industry. We have also examined stock return predictability and found that, in the manufacturing industry, customers' earnings have statistically significant predictive power for future stock returns even after they were risk-adjusted. This result indicates that a portion of customers' earnings aren't incorporated into stock prices.

The main contributions of this paper are the following: 1) we confirmed that there are earnings propagation effects among firms throughout the global supply chain, 2) we indicated the possibility that network centrality weighting can improve the predictive power of earnings of indirectly linked firms, which are sometimes difficult to observe, and 3) we discovered that linked firms' earnings have the power to predict future stock returns. At the same time, some issues have yet to be examined. Our analysis does not take into account the types of relationships that exist between customers and suppliers. Propagation effects may differ depending on factors such as the balance of power between the firms and whether they are in a long- or short-term relationship. Furthermore, it is possible that firms in a weaker position are forced to bear the risk stemming from changes in the external environment. Analyzing such relationships between firms may enable us to observe earnings propagation effects and predictive power for future stock returns in areas that this paper does not identify. Further research is needed on these issues.

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