THE UNIVERSITY OF HONG KONG
Faculty of Business and Economics

HSBC | HexaNet

Supply Chain and Trade War Analysis

2019 MSBA Capstone Project Report

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0. Executive Summary

This report summaries the HKU MsBA capstone project cooperating with HSBC commercial banking division. The main objectives are identifying potential customers and investigating the impact of the trade war on different listed companies. There are two data sources used to tackle the above problems, supply chain data and financial data. As the trade war widely impacted the whole world economy, this study only focused on the automobile industry and mainly targeted the firms from the United States and China. In dealing with the first challenge, we visualised the network of the supply chain via the business intelligence tool to enable HSBC to track the linkage. Within the network, centrality measurements were used to determine the most prestigious companies which provided a way to prioritise. HITS algorithm was suggested to be the most effective one that can determine which suppliers/ manufacturers have the most business partners within the network. In the study of trade war impact, event study technique with a three-factor model was used. This model estimated the expected financial performances of listed companies as if there was no trade war. The result revealed that their inventories and debt-to-equity ratio increased more than expected, and their cash holding tends to fall below than expected. This result suggested the operation efficiency decreased during the trade war, and financial leverage increased accordingly. From these findings, a set of scoring system is created to access the business opportunities and risk and represented in the business intelligence tool. This methodology provided a framework for HSBC to study the effect of the economic event in the future.

1. Company Background

HSBC is the leading and global recognised international bank. It owns more than 50% of group client revenue related to international clients. The access to high-growth markets to high-growth developing markets in Asia, the Middle East and Latin America help HSBC seize the growth opportunity. Besides, substantial capital and liquidity position and low earning volatility also support HSBC to develop stably. As the core business in HSBC, commercial banking division (CMB) serves around 1.5 million customers ranging from small enterprises to global corporations in 53 countries and regions. The adjusted annual revenue for HSBC CMB in 2018 is 14,885 million, increased by 12%, 27.6% of the total revenue. Catering to both retail and corporate banking, HSBC CMB facilitates corporate customers in trade and plays an essential role in promoting economic growth. It mainly provides products like working capital, term loans, payment services and international trade facilitation, as well as expertise in mergers and acquisitions, and access to financial markets.

Company Challenges

Same as other big cooperations, to sustain the steady growth, they have similar challenges when dealing with their clients. In general, the key aspects are identifying new potential customers, growing existing ones and preventing attrition.

The core of a commercial bank's competitive strategy is to absorb and maintain customers and expand its market share. Nowadays, with the globalization of economy and finance and the intensification of competition in the bank industry, whoever has more customers, especially those with high value and added value, will have the initiative to compete. As for banks, institutional customers are the primary source of commercial banks' business income. Therefore, it is an essential task for HSBC to obtain a list of potential customers with a minimum loss under the premise of compliance and risk control.

Besides the internal challenges, the banking industry is susceptible to global economic trend. While the regulation becomes tighter, risk control requirement is stricter, which increases the need to predict the clients' performances better and avoid acquiring high-risk customers. Many economic events and government policy have launched from time to time, for example, one belt-one road and trade war. There is no doubt that in these economic events, some companies will be benefited more, and some of them will not. If HSBC wants to continue to maintain its superior position, they have to general better client insight than their peer competitors such as Standard Chartered and Citi group. The most critical pain point for them is how to identify the additional effect of these economic events on their clients.

Some specific requests from HSBC:

Company Network building and segmentation

To identify potential customers, HSBC believed that a company network would able them to complete the tasks. As for the network building, we need to consider some related data sources. In many public and accessible financial database, our mission is to discover the relevant and reliable data source for HSBC to use. The optimistic output will be a sustainable and automated data source.

High-standard visualization

Company network data is useless if there is no practical way to visualize it. The raw data structure is complex and hard to interpret. HSBC requested an interactive and easy to use business intelligence tool to demonstrate the company network. Potentially, the business intelligence tool should have relevant filters and rankings to prioritize potential clients.

Discover The Effect Of Trade War

As previously mentioned, the economic event played an important role in company financial performances. HSBC recognized this issue and requested provide an analytical framework to investigate this issue. As the heated topic of trade war these days, they hope we can discover and quantify the effect of the trade war on the existing and potential clients. The ideal solutions will enable them to balance the risks and opportunities when choosing a relevant client.

Customer propensity models

For effective client acquisition, HSBC expected a scoring system that can help them to prioritize the customers. Ideally, we need to provide a scoring system on which customer will be our target one, and we also need a propensity model on the impact of the Trade War on the companies and related parties in their network.

2. Analytical Challenges

Despite network analysis is a favourite research topic, most of them emphasized on social media and web network recently. The problem of analyzing company network is relative less. Most of the analysis that has included company network analysis such as Wasserman (1994) used centrality concept to measure the most prestigious companies. Comparably, the methodologies adopted in social media network are suitable in analyzing the company network. The goal of the network analysis is to find the most influential company within the system then hope to get more benefits through this big company.

Before we discuss the methodology on inspecting the trade war impact, we reviewed what has happened during the trade war. China and the United States have been engaged in a trade war through increasing tariffs and other measures since 2018. It is no wonder that this trade war has some impacts on the international economy and the supply chain network.

US President Donald Trump had complained about China's trading practices since before he took office in 2016. The US launched an investigation into Chinese trade policies in 2017. It imposed tariffs on billions of 'dollars' worth of Chinese products on March 22nd, 2018, and China retaliated in kind. This date is the official beginning of the US-China trade war. After months of hostilities, both countries agreed to halt new trade tariffs in December 2018 to allow for talks. Optimism had grown over the prospect of a deal, but that faded, and now the US has more than doubled tariffs on $200bn (£153.7bn) worth of Chinese products. China retaliated three days later with tariff hikes on $60bn of US goods.

During 2018, the US imposed three rounds of tariffs on more than $250bn worth of Chinese goods. The duties of up to 25% cover a wide range of industrial and consumer items - from handbags to railway equipment. China hit back with tariffs on $110bn of US goods, accusing the US of starting “the largest trade war in economic history”. China has targeted products including chemicals, coal and medical equipment with levies that range from 5% to 25%. It has also targeted products made in US districts with strong support for the Republicans, and goods that can be purchased elsewhere, such as soybeans. After agreeing on a truce in December, both sides began to talk. However, at the beginning of May in 2019, the US raised tariffs on $200bn of Chinese products to 25% from 10%. China retaliated, but officials say the countries are still talking. The US has also started the process for hitting an additional $300bn of Chinese goods with tariffs.

Here are some important dates we must be aware of when analyzing the trade war: First is March 22nd, 2018, the US started the trade war by imposing tariffs on some Chinese products. Second is July 6th, 2018, both US and China implemented their first official tariffs list. The third is August 23rd, 2018, both US and China second official tariffs list take into effect. Then, one month later, September 24th, their List 3 take into effect. Last is May 5th this year, the trade war resume as Trump post a twitter claiming to impose another round of tariffs on Chinese products. The trade war is still going on, and the world is watching it.

The early trade literature discussed the motives behind and economic impact of trade wars. The traditional view is that a country can reap terms-of-trade gains by raising tariffs as long as it is trading partners will not retaliate: the “optimal tariff” argument, see Johnson (1951) for a very early contribution. This argument is supported by the very ambitious recent empirical analysis undertaken by Ossa (2014). However, Caliendo and Parro (2015) give a dissenting view: they show that the optimal tariff may be harmful once production linkages and intermediate goods are taken into account. The seminal work of Johnson (1953) first analyzed the “beggar-thy-neighbour” incentives to increase trade tariffs but showed that in a trade war a country could gain by imposing an optimal duty even when others retaliate. Ossa (2014) disagrees and argues there will be substantial global and individual country losses in a full-scale tariff war with retaliation. From this part of the literature, we could see from previous research that scholars hold different views on the impact of the trade war. They mostly talk about the macroeconomic effects like the impact of a trade war on output, employment, or intertemporal trade positions. There are little academic literatures that analyzed the effect of the trade war on the international supply chain. Moreover, giving quantitative assessments on this field is quite innovative and challenging.

3. Analytical Solutions

Since there are more than thousands of millions of companies in the world, identifying potential new customers and studying potential financial impacts became challenging if we do not minimize the scope. By reducing the scope, we aimed at constructing a framework and generalized methodology for HSBC to adopt in the future. After a round of consideration, we decided to study the automobile industry as our starting point. There are three reasons behind. Firstly, it has many suppliers in the automobile industry. The types of suppliers are also diversified, which ranged from auto parts to microchips. We can inspect the market impact in a high-level point of view. Secondly, the automobile industry is vital to country economics. It contributed to 3 to 3.5% of GDP in the US and around 5 to 10% GDP of developed countries (Hill, 2010). If the automobile industry collapsed, it could widely affect the world economy. Thirdly, it involved a lot of international trade opportunities. The principal suppliers of automobile industry spread all over the world, from engineering in Japan, raw material processing in China, to technology services in the United States. The impact of a trade war should then be more prominent compared to the other industry. Besides, this characteristic implied the foreign exchange product need is, which means a business potential for commercial banking.

Data

As the strict usage of HSBC internal data, we related our data externally. The data we collected can be classified into two main categories, namely, supply chain data and financial data. The companies in our dataset included the following: 1. Manufacturers of the automobile industry that are located in the United States and China; 2. The first-tier suppliers of manufacturers of the automobile industry that are located in the United States or China; 3. The second-tier suppliers of manufacturers of the automobile industry that are located in the United States or China; 4. The customers of manufacturers of the automobile industry that are located in the United States or China.

We explored several different data sources before we started to collect our data, including Bloomberg, Eikon, Compustat, Cninfo and Wharton Research Data Services (WRDS). Every data source has its pros and cons.

Bloomberg: It has complete data and provides excellent customer service, but we cannot directly extract the supply chain data. The export function is prohibited by Bloomberg and can be manually obtained row by row to excel.

Eikon and Compustat: Supply chain data can be able to extract the data directly but requires a subscription. However, the information is not complete compared to Bloomberg. For example, in Bloomberg supply chain data, Tesla Inc. has around 100 suppliers, while in Eikon, it only has approximately ten suppliers.

Cninfo and WRDS: Financial data can be extracted directly, but Cninfo and WRDS lack some information outside China and the United States, respectively.

After considering the pros and cons above, we decided to collect both supply chain data and financial data from Bloomberg to have a consistent dataset. Supply chain data can be found in Bloomberg terminal by using SPLC function. Therefore, we dragged the data from Bloomberg Terminal to an Excel file row by row. We collected quarterly data from 2017 quarter 4 to 2019 quarter 1. In the dataset, we have the supplier information of 45 manufacturers and 952 first-tier suppliers. Therefore there are 4210 second-tier suppliers. We got more than 85,000 rows of supply chain data in our dataset. It was around 400 hours of manual work in total with the help from the research assistants. For financial data, we collected financial data of all 5,207 companies whatever they are listed. We collected quarterly data from 2014 quarter 1 to 2019 quarter 1 using Bloomberg excel add-in function. We directly exported the balance sheet, income statement and cash flow statement financial metrics we needed to an Excel file. The detailed variable lists attached in the appendix.

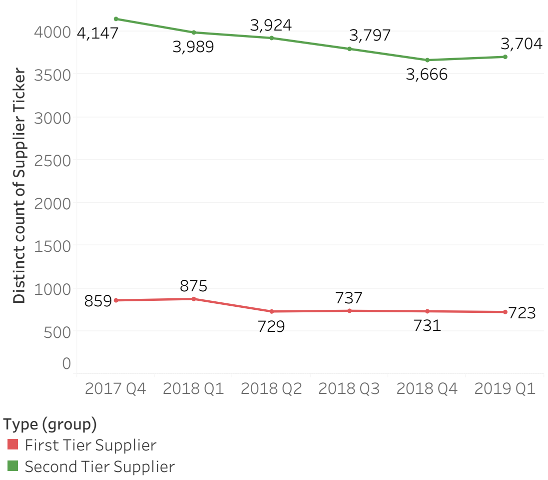
Data Handling

As the data format of the Bloomberg data is not suitable for analyzing, we have done several steps to complete the dataset.

1. Converting the money value to USD, we researched the FX rate to convert the value
2. Standardize the ticker code. Since in the supply chain data, we have some private companies' information, they do not have ticker information. We standardize the ticker code by adding some distinctive identifier to make sure it is a unique key.
3. Research the company location. Some companies do not have their country information in Bloomberg supply-chain dataset. We researched ourselves to make sure all companies have country information.

EDA

There are some exciting findings from the supply chain data we have found. Firstly, we found that the total number of suppliers, both first tier and second tier suppliers, dropped during the trade war period (figure 1). Secondly, we found that their supplier structure also changed rigorously in 2018Q2 (figure 2) compared to the other quarters. This information was shown by a quarter over a quarter change of our self-developed index, Degree of Supplier Change (DSC). This index ranged from 0 to 1, and when the number is higher, it means the supplier structure changed more.



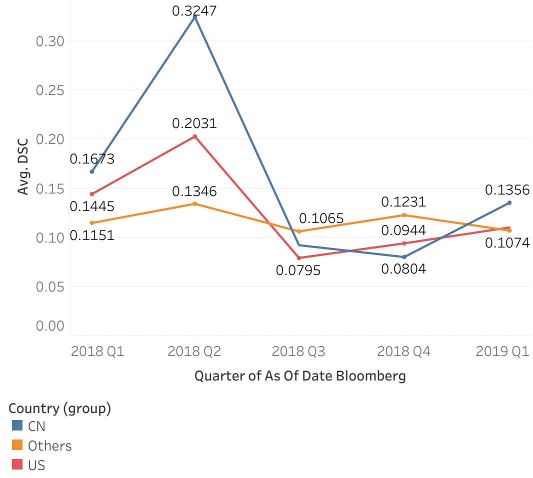


Figure 1 Total number of suppliers in automobile industry

Figure 2 Degree of Supplier Change

Degree of supplier change determines the how much of their suppliers have changed.

Mathematical Equation:

$$DSC = \frac{\sum Abs(Change\ of\ proportion\ count\ of\ supplier)}{Sum\ of\ Before\ Period\ and\ After\ Period\ proportion}$$

For example, a hypothetical company ABC has 2 suppliers in 2017 and 2019. We first calculate their how many suppliers they have in proportion. Next, we will get the absolute change of the proportion change of its respective suppliers. We added up those absolute changes then divided by 2 (sum of before period and after period proportion). Below summarise the example:

Company ABC's Suppliers	**2017 Count of suppliers**	**2019 count of suppliers**	**Absolute Change**
A	1 (0.5)	0	0.5
B	1 (0.5)	1 (0.5)	0
C	0	1 (0.5)	0.5
Total	2 (1)	2 (1)	1

Therefore, the company ABC has its degree of supplier change from 2017 to 2019 is 0.5. Note that the above calculation is using count of suppliers but it can be changed to monetary value. If using monetary value, it will better represent the change. However, as the data sources has some limitation which will be discussed later, we had to adopt the count of suppliers only.

With the supply chain dataset, we understood of the supplier locations. On an aggregate level, both United States and Chinese firms heavily rely on local suppliers. From figure 3, US firms' suppliers are more international with second largest supplying country is Japan, while for Chinese firms second largest supplying country is United States.

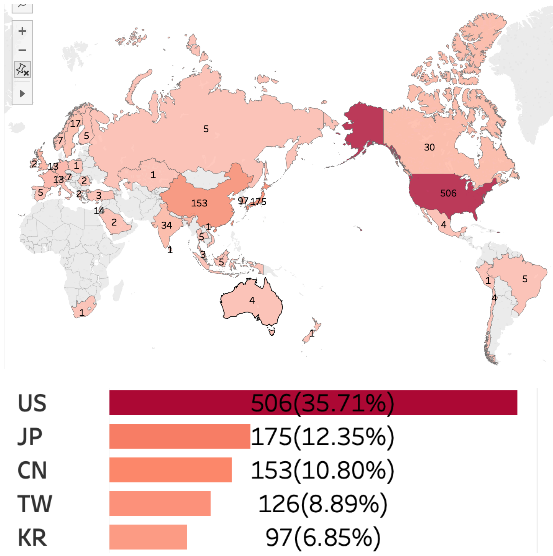


Figure 3 Suppliers locations of US firms as of 2019Q1

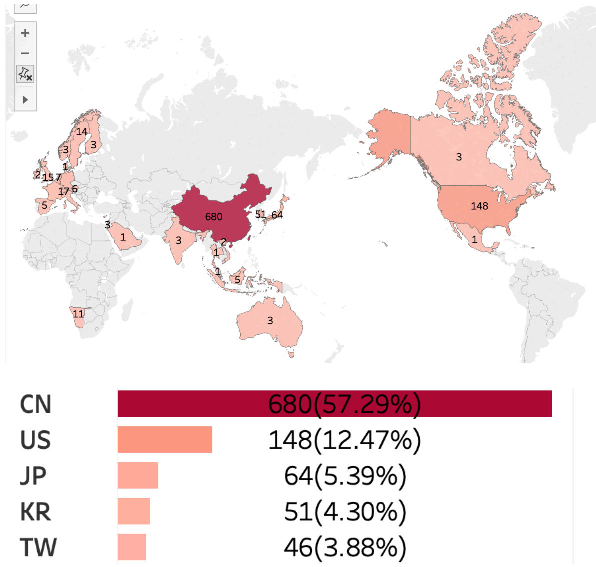


Figure 4 Suppliers locations of Chinese firms as of 2019Q1

We focused on the portion of trade value by regions. Surprisingly, for both Chinese and United States firm, the trade value portions on the counter party countries increased. Especially, Chinese firms in total increased the trade amount with United States from 9.3% before trade war to 16.0% post trade war (Figure 6). One possible explanation is that Chinese firms were enjoying much subsidies from Chinese government. The firms do not afraid of the new tariff imposed. However, this measurement might be biased as discussed in the limitation session.

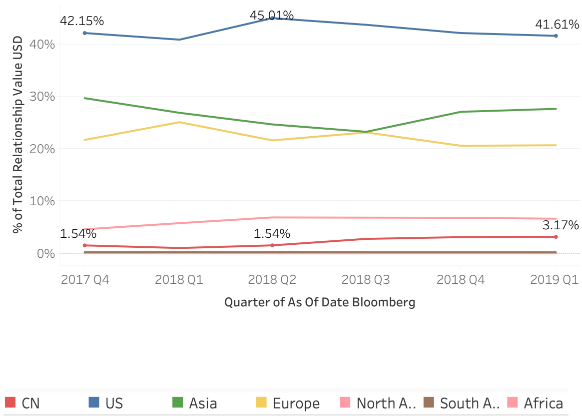


Figure 5 Portion of Relationship Value from Different Regions of US Firms

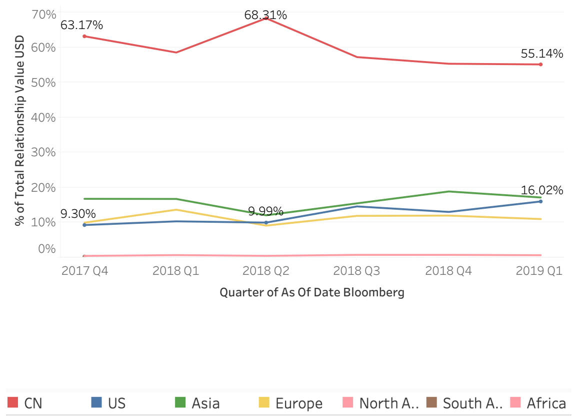


Figure 6 Portion of Relationship Value from Different Regions of Chinese Firms

4. <u>Analytical Methods</u>

Identify New Customers

Since we have the supply chain data, we can visualise and construct this in a company network. Every company represents a node, and the link is developed whenever there is a trade that happened between them. To identify a new customer, we can utilise this linkage and assume information will be transferred through this trade linkage. The cooperating bank information would be transferred within the link. For example, consider Ford Motor used HSBC to handle their transaction. Ford’s supplier will receive the money through HSBC financing and realised that the superior banking services provided by HSBC. Therefore, from this network, we can connect all the companies, and if one of the companies is HSBC client, we can understand which companies could be brought to HSBC as a new client. In this regard, the first function of our Business Intelligence tool is to visualise the network and able to navigate within the whole network. You can track a particular company network or choose to visualise it at a macro level.

However, as previously mentioned, a sole industry already has 1,000 first tier suppliers and 5,000-second-tier suppliers. Even with the robust sales team in HSBC, it is impossible to target all the companies at a time. As a result, we will need priority rules on companies list. To construct this list, we adopted the concept of centrality.

Analysing the company network can be compared as analysing a social media network. In analysing the social media network, we utilised the concept of centrality to identify the most important nodes (Persons). In a company network, the same idea is adopted while we use different centrality measurement to find out the most important company. Priority will be given to the most centred company which is believed to bring more connections and benefits to HSBC through the supply chain network. There are some popular centrality measurements available. We have included degree centrality, closeness centrality, betweenness centrality and HITS algorithm.

Degree Centrality

It measures how many neighbours a company has, which implies how many companies are directly dealing business with them. In that sense, the higher degree centrality, the more important of a node is because it has many companies link to it.

Mathematical Equation:

$$C_{deg}(v) = \frac{d_v}{|N| - 1}$$

Closeness Centrality

It measures its average farness to all other nodes. In other words, it represents on average the number paths a company need to path through in order to reach the other companies. The higher the score means the node have the shortest distance to all other nodes.

Mathematical Equation:

$$C_{close}(v) = \frac{|N| - 1}{\sum_{u \in N \setminus \{v\}} d(v, u)}$$

From the equation here we can see that if a company can reach all the other companies with one step only, it will have the centrality score 1; hence, it is the most centred company.

Betweenness Centrality

It measures the amount of influence a node has over the flow of information in a graph. It can be imaged every company is acting as a bridge. Every time there is an information flow, it has to walk through the bridge. If a company is important, it will be walked by more than the others. In here, the higher the score, the easier it was treated as a bridge; hence, it is more important within the network.

Mathematical Equation:

$$C_{btw}(v) = \Sigma_{s,t \in N} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}}$$

$\sigma_{s,t}$ $is\ total\ number\ of\ the\ shortest\ paths\ from\ node\ s\ to\ node\ t$

$\sigma_{s,t}(v) is\ the\ number\ of\ thosepaths\ that\ pass\ through\ v$

HITS Algorithm

This measurement is a link analysis algorithm that rates the web pages developed by Jon Kleinberg (1999). The measurement is only suitable to directed graph. This algorithm separated the nodes into two categories, hubs and authorities. It has 2 scores to represent the relative importance of the two concept. The higher authorities score means the company being connected with more companies towards them (supply to). The higher hub score means the company connected with more companies outward (supply from). To simplify the algorithm mechanism, in the first step, we will assign each company having a authority score and hub score of 1. The next step is updating the company's authority score by using the sum of the hub scores that other companies point to it. Meanwhile, hub score is also updated by using the sum of the authority scores that the company point to. The third step is to normalise the score by dividing each score by the square root of the sum of all the score. Repeating the steps many times until the score reach a stable state. From this algorithm, the scores we obtained have more implications than the above 3 centrality measurement. First, it separated the importance of suppliers and manufacturers. The higher the authorities score means it is a more important manufacturers. Secondly, it provided the insights to both direct and indirect linkage, as it has their scores cascade to the other companies. Thirdly, it weighted more for those large manufacturers and suppliers in terms of the number of connections. Therefore, in the business implications, for the high authority score, it is a manufacturer with many suppliers. As such, it should have more payment need. Likewise, the higher hub score, it represents a supplier supplied to many companies. They are more influential and have connections with many other firms.

In short, among all the four centrality measurements, we recommended the usage of HITS algorithm as it provided a holistic view of the supply chain network and the scores have a business implications on the client priorities. HSBC can use hubs score and authorities score to rank the priority solely on based on supply chain information.

Link Predictions

After the priority list of the clients, HSBC can target the companies according to their interests and strategic positions. We may want to get the confidence in terms of the likelihood of acquiring a particular customers through the existing connection. This likelihood can be produced using Adamic-Adar Index. The conceptual idea of this index is to calculate the amount of shared links between two companies, where it is believed that the fraction of "resource" will be sent through common neighbours. We can hypothetically assume HSBC has business with some companies within the existing network and the weighting of each link are the same. Therefore, we use the sum of the inverse logarithmic degree centrality of the neighbours shared by HSBC and the other companies.

Mathematical Equation:

$$adamic_{adar(X,Y)} = \sum_{u \in N(x) \cap N(Y)} \frac{1}{\log (|N(u)|)}$$

This measurement the information can be transferred by the common friends discounted by the total friends a friend has. For example, if company A and company B can be connected through company C and company D. If company C has lesser total connection, then company C is more effective in connecting company A and company B, because the information is not dispersed during referral.

However, this method is not a golden rule. There are three reasons. Firstly, it assumed the weight of the link is the same. It could be the case for social network, however, in company network. Link weighting are not the same. It depends on various factor, for instance the deal size, the reliability of the material, director relationships of the two companies, etc. One can imagine that if the relationship manager is closer with a company, they will have higher probability to convert. Secondly, the type of relationship are different. Some type of relationship are COGS, some are SG&As which made the fundamental of the importance of the relationship form and its strongness. Thirdly, we do not have the competitors information. An existence of competitor potentially affects the possibility that companies could form a relationship with the others. It is possible that if a company has a long-term banking relationship that will make it relatively difficult to change its cooperative bank unless the credit of that bank fell suddenly. Based on these limitations, we cannot directly adopt this method but only use this as a base to amend the formula. However, due to the time limitations of this project, we cannot further investigate the possibility. To develop a relatively more perfect solution, it requires more data such as subsidiaries, director information and cooperating bank information. We hope this could give a better insight for HSBC and the next year capstone project.

Trade War Impact

Unfortunately, although we all understand that the trade war affected the world economy to some extent, there is no variables or index to indicate whether a company is truly affected by the trade war. Moreover, for some companies if the management team are wise enough to predict this, they can react beforehand to reduce the impact. This made the whole analysis more complicated. Despite the difficulty given, we tried to create an index that could represent the potential exposure degree to the trade war. Logically, when we are talking about the United States-China trade war, those firms in United States have many trade with Chinese firms and firms in China have many trade with US firms should have be impacted more. Hence, the first index to create is the US/CN degree.

Exposure Degree I – US/CN degree

The idea is simple. In the supply chain dataset, we are given the country of origin of the firms and their related suppliers. Therefore, for every companies we have, we aggregate their suppliers' country of origin. Therefore, we calculate the percentage of suppliers from united states and china respectively. For the US manufacturers, the exposure degree is how much percentage of Chinese suppliers they have; for the Chinese manufacturers, the exposure degree is how much percentage of US suppliers they have. Next, we are trying to add the cascade effect of trade war through supply chain network. In the original dataset, we also obtained the second-tier supplier's data. For first-tier suppliers, they would experience the same degree of trade war impact if their suppliers (second-tiers) are from China or United States. Therefore, first-tier materials price may increase proportionally to the additional cost raised. Hence, it will impact the manufacturers cost not only because of the additional tariffs. As a result, for all first-tier supplier, their US/CN degree are also calculated. To cascade the effect, we assume the second-tier effect will proportionately be reflected in the first-tier supplier. Therefore, we can multiply the second-tier effect with the first-tier supplier proportion. For example, assume a US manufacturer have 30% suppliers are from China, 60% of suppliers are from United States. Of those Chinese suppliers, 50% have their suppliers (Second-Tier) from United States and for those United States suppliers, 30% have their suppliers (Second-Tier) from China. As a consequence, the first-tier exposure degree is 0.3. The second-tier exposure degree is 0.3x0.5 = 0.15 for first-tier Chinese suppliers; 0.6*0.3 = 0.18 for first-tier United States suppliers. As a result, the total exposure degree for that particular manufacturer is 0.3+0.15+0.18 = 0.63. In the calculation methodology the range for the degree will be from minimum 0 to maximum 2.

Exposure degree II – Revenue - Cost (RC) Degree

For the above exposure degree I, we have just focused on the supply side trade war effect. In fact, the revenue side, which means the customer supply chain, would have effect on the company financial performances. Rationally, if the tariff is being imposed, the buy-side company may reduce the buying volume from affected countries. Then, it harms the financial impact of that particular companies. RC degree is created to capture such effect. However, with the limited data we have, we can only do the RC Degree for first-supplier manufacturers and particularly within automobile industry customers. Mathematically, we used the similar idea of exposure degree I. We assume the proportion of United States or Chinese suppliers and customers represented the exposure degree of a firm. Again, on every first-tier supplier, we calculate their proportion of supplier on country level. Next step, we did the same calculation on customer side. However, a little difference is that the calculation used proportion of relationship value, which is provided by Bloomberg supply chain dataset as previously mentioned, but not solely on count since we do not have full customer list of the first-tier supplier. As a result, we have the supply side exposure degree and the customer side exposure degree. To aggregate two exposure, we took the particular firm cost of goods sold structure.

Mathematical Equation

$$RC\ Degree = Supply\ side\ Exposure\ \left(\frac{COGS}{Revenue}\right) + Customer\ Side\ Exposure\ \left(1 - \frac{COGS}{Revenue}\right)$$

We assume a firm cost of goods sold fully captured the increased tariffs cost and profit margin captured the changed customer buying impact.

Despite the two exposure degrees are logically presented, there are some limitations with the usage. Firstly, the supply data chain is not complete and relationship value is not readily reliable. This limitation limited the use of relationship value while it should able to provide more insights to the exposure. Detailed explanation will be provided in the limitations part. Secondly, we rely on country of origin of that companies, which is the headquarter location. Yet, for the large multinational cooperate, they have factories and offices all over the world. Simply using the country of origin cannot tell the story behind. Detailed explanation will be provided in the limitations part. Thirdly, the actual product flow is unknown. While calculating the exposure degree, we assume the goods must flow from company A country of origin and company B country of origin. However, this is not the case if company A has some offshore factories that is the same as company B, in which company B goods did not actually export to the other countries. These limitations limited the validity of the exposure degree, yet, this still possess a reasonable thought on inspecting the trade war effect. We will try to utilize these degrees to look at the impact in the result part.

Financial Performances

Financial performances is one of the key metrics to determine how a company performing. The challenging part is how to represent the trade war impact to indicate whether it has affected the financial performances. In here, we have adopted the event study methodologies by Kothari (2004). In the original event study, Kothari (2004) inspected the stock price changes after the outburst of some economic events or company news. The idea behind is simple, Kothari (2004) modelled the time series stock price to discover the normal stock price performances as if there is no economic shock. Therefore, he observed the actual differences to calculate whether the differences is significant or not.

In this trade war analysis, we modified a bit from the original event study. Firstly, we inspect the differences of all the financial variables we have but not the stock prices. Secondly, we used a three factor model to model the financial performances rather a time series model. As mentioned previously, we have obtained all listed firms quarterly financial performances from 2014 till 2019 Quarter 1. On all 30 financial variables we had, we run a linear regression model to get the expected financial performances. In the linear regression model, we used three factors, industry average; quarter; company size (market capitalisation). Intuitively, industry average neutralised the firm risk and specific event and solely represented the market risks. Company size mattered as larger company should have larger earning abilities or else larger spending. Company financial performances like revenue and cost should be cyclical. The generally acknowledged start date of US-China trade war is 22nd March 2018, where Donald Trump announced he was going to impose the tariff. Therefore, we separated the time series data into two windows, estimation window and event window. While estimation window included 2014 to 2017 data and event window included 2018Q2 to 2019Q1. The reason for dropping 2018Q1 data was to exclude the bias that some firms have acted on beforehand and this data point is too embarrassing to be classified in either windows.

Similar to Kothari (2004), we inspected the abnormal changes of the financial metrics. We used the deviations of actual performances to expected performances in percentage form. To validate the accuracy of the three-factor model, we also use the estimation window data to check the deviations. After we get these abnormal changes, we shall able to see how those companies performed during the trade war period.

5. <u>Results</u>

HITS Algorithm

By analysing the current supply chain data, we identified several important firms. Below we provided the top 10 important suppliers and manufacturers. Detailed ranking will be in appendix.

Rank	Company Name	Hub Score	Company Name	Authority Score
1	Dassault Systemes SE	0.003950	General Motors Co	0.04529
2	Magna International Inc	0.003594	Samsung Electronics Co Ltd	0.04447
3	International Business Machines Corp	0.003594	Ford Motor Co	0.04384
4	Aptiv PLC	0.003486	Volkswagen AG	0.04321
5	Aisin Seiki Co Ltd	0.003477	Nissan Motor Co Ltd	0.04109
6	CIE Automotive SA	0.003462	Honda Motor Co Ltd	0.03980
7	thyssenkrupp AG	0.003390	Fiat Chrysler Automobiles NV	0.03894
8	Sensata Technologies Holding PLC	0.003355	Panasonic Corp	0.01760
9	Kongsberg Automotive ASA	0.003335	Geely Automobile Holdings Ltd	0.01734
10	KUKA AG	0.003296	Denso Corp	0.01653

Three-factor Model Validation T-test

In the financial analysis part, before we fully adopted the three-factor model, we had verified the accuracy of the three-factor model. Essentially, we have calculated the expected performances using the original dataset and getting the abnormal financial changes of estimation window. After that we performed t-test to see whether the abnormal changes are different from 0 or not. For most of the variables, we cannot reject the hypothesis that the abnormal change is 0 (See table 1). The models for inventories, short term debt and long term debt, may not enough could be due to too much missing variables. If we take a stricter confidence level, only short term debt model was not adequate enough.

Variables	t-test	p-value	Variables	t-test	p-value
Cash	-0.8295	0.4068	Inventories	-2.2654	0.0235*
D/E Ratio	-0.0218	0.9826	Net Income	-0.0232	0.9815
COGS	-0.9998	0.3175	Revenue	-0.0932	0.9259
EPS	1.007	0.3139	EBIT	0.9731	0.3305
Operating Expense	1.5523	0.1206	Total Liabilities	0.7628	0.4456
Total Equity	0.9026	0.3668	Gross Profit	0.7760	0.4378
Short term debt	-3.612	0.000**	Long term debt	2.167	0.0303*

Table 1, t-test results for financial variables

Financial Abnormal Changes

We summarize the financial abnormal changes on an aggregate level. Generally, the financial performances have been deteriorated since the trade war has happened. From the below graph we can see that the cash holding, inventories and D/E ratios for the firms have been more than expected. Average abnormal cash holding has a trend to be less than expected lately. Table 2 summarized 2018Q4 and 2019Q1 abnormal financial change.

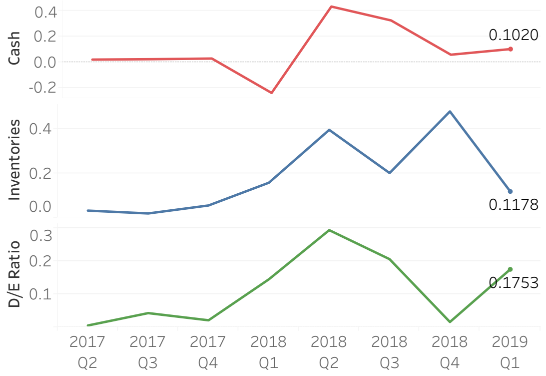


Figure 7 Abnormal Changes of financial performances

	2018Q4	2019Q1
Cash	5.84%	10.20%
Inventories	47.79%	11.78%
D/E Ratio	1.56%	17.53%
EBIT	-308.65%	-0.65%
Operating Expense	41.46%	37.88%
EPS	320.21%	19.10%
COGS	54.63%	-41.04%
Total Liabilities	37.12%	22.58%
Total Equity	7.40%	8.48%

Table 2 2018Q4 and 2019Q1 abnormal financial change

US and CN firms have different extent of impacts during trade war when we are looking at the country level. Chinese firms have increased inventories compared to US firms in the same period. However, D/E ratio increased consistently a lot for US firms in the same period while Chinese firms have fluctuate ratio.

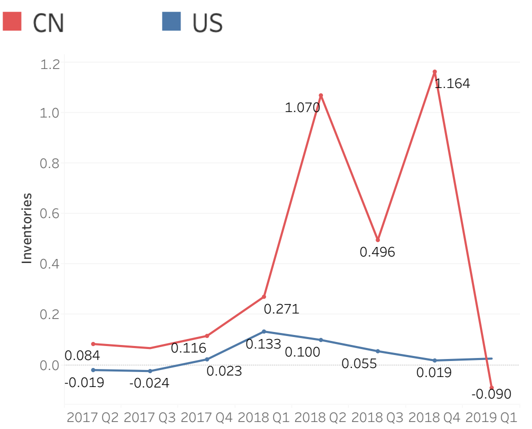


Figure 9 Average abnormal Inventories change of US and China

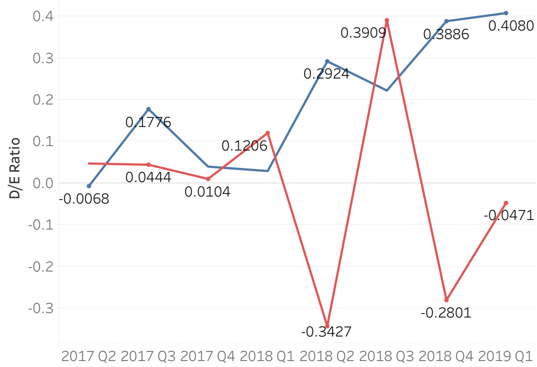


Figure 10 Average abnormal DE Ratio change of US and China

HexaNet Scoring System

Based on these findings, there are still lacking of business implications. As a result, we created a scoring system to measure a company's need to borrow money, risk and need for foreign exchanges.

Borrow need score:

$$= Abnormal\ change\ of\ inventories - abnormal\ change\ of\ cash$$

The rationale behind this score is that increasing inventories and decreasing cash may imply the company's operation is not efficient. Therefore, the company turnover ability decrease to keep on existing business scale, they may need to borrow more money.

Risk score:

$$= Abnormal\ change\ of\ debt - to - equity\ ratio$$

When debt-to-equity ratio increase, the company' financial flexibility may decrease. In this situation, the company may have higher risk that it cannot repay its debt. In the banking perspective, it should pay more attention in lending money to those companies.

Foreign Exchange Score:

$$= \text{number of foreign suppliers}$$

If a company has more suppliers from other countries, meaning that it has higher foreign exchange opportunities.

After the calculation, we've also done some standardization to transform the scores to range of zero to one. The scores here mean relative but not absolute value.

Then we use these three basic scores to create an aggregated HexaNet score to measure a company's overall potential to be a new customer. Formula:

$$HexaNet\ Score = \sqrt{((Borrow\ Need\ )\hat{}2 + (FX\ Need)\hat{}2 + (1 - Risk)\hat{}2\ )}$$

Higher HexaNet Score means that the company may have higher borrow need, higher FX Need and lower risk, therefore, higher HexaNet Score represents higher business opportunity for HSBC. Detailed list of the score in appendix.

Scoring System Validation

This scoring system although is logically put through, it is quite hard to be validated its effectiveness as we do not have the actual borrowing information to quantify it. However, we have found news or some ratings to support this.

We have found Tesla's borrow need score increases to 0.8295 in 2019 Q1 from 0.7083 in 2018 Q2. Its risk score drops to 0.1348 from 0.2555. And its FX need score increases to 0.19397 from 0.13793. The according news reported that in 2019 February "Tesla reached an agreement with a group of Chinese banks to secure over $500 million in loans". This corresponds to its borrow need score increase at this quarter. And Tesla's bond price rise from 95 dollars in March 2018 to 110 dollars in January 2019, which may imply that Tesla has lower risk because the market has confidence in it. And also, in 2019 February, there is a news saying that Tesla is going to build its first Gigafactory in China Shanghai, showing its increasing need for overseas business.

Moreover we used Moody ratings to see if they matched with our scoring systems. We randomly found 6 companies to cross check. Please see the below table:

Company Name	HexeNet Risk	Moody's Rating
Yamaha Motor Co Ltd	0.14083	A3
Volkswagen AG	0.42196	A3
Panasonic Corp	0.30488	A3
LG Electronics Inc	0.4612	Baa3
ABB Ltd	0.7863	A2
Magna International Inc	0.6964	A3

Comparatively, our scores do not quite agree with moody rating. One that agree perhaps LG electronics Inc which has relatively lower rating while our risk scores suggesting higher risk. This is predictable as our scoring mechanism is not the same as Moody and we only consider financial performances and within the automobile industry. It would be surprised if our simple scoring can compete with a sophisticated financial rating firms.

Cascading Trade War Effect

In this session, we first inspect the relationship of exposure degree and financial abnormal changes. We plotted the scatter plot on degree with the need score.

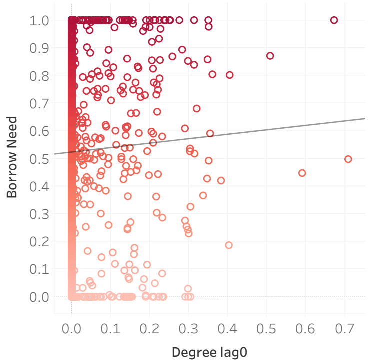


Figure 11 Borrow need with exposure degree

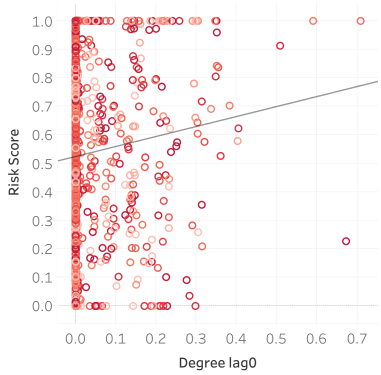


Figure 12 Risk score with exposure degree

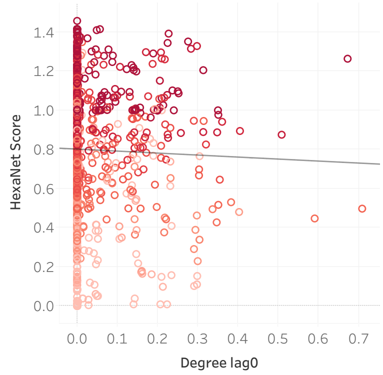


Figure 13 HexaNet score with exposure degree

We found that for the high exposure, the risk we calculated tends to be higher. The overall HexaNet score is less when the exposure degree is high. This is logical since they should impacted if they have high exposure score in trade war.

To cascade the score we utilised the supply chain information, we used relationship value as a proportion of effect being transferred. We compared the cascaded effect and the original effect calculated. The association is relatively low between cascaded and non-cascaded. However, we are able to see a little positive relationship between cascaded risk and non-cascaded risk.

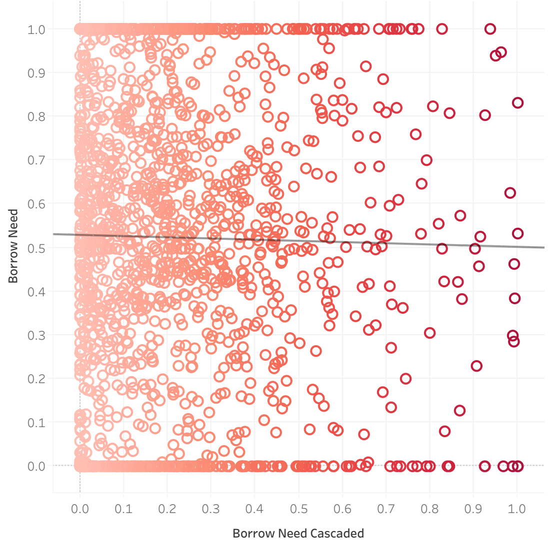


Figure 14 Relationship of Cascaded Borrow Need and Non-Cascaded Borrow Need (Pearson correlation coeff = -0.02)

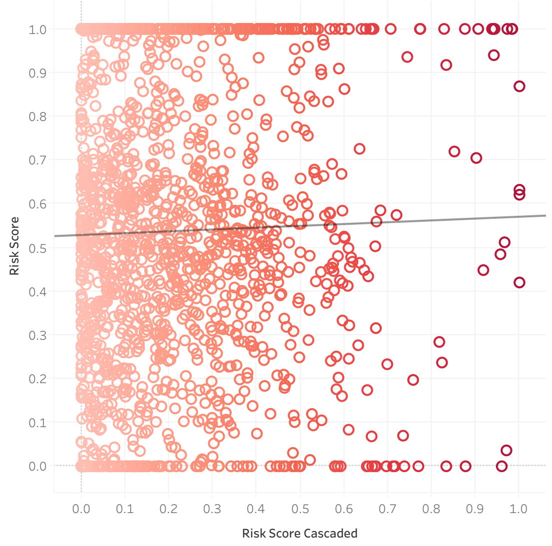


Figure 15 Relationship of Cascaded Risk Score and Non-Cascaded Risk Score (Pearson correlation coeff = 0.019)

Business Intelligence Tool

As mentioned before, we need an effective visualisation tool. As such, we have created an online business intelligence for HSBC to visualise our research findings. Please access to http://hexanet.live and see attached manual for more details.

6. Limitations and Potential Improvement

After we completed the analysis, we have found several limitations that it could not be solved at this stage.

Supply Chain Data:

Although Bloomberg provided a relatively completed supply chain list than other data sources, it still have its limitations. Firstly, not all the records are quantified. We have done a rough calculations that only 50% of all records are quantified. Secondly, the actual calculation of the relationship value is unknown. While there are some articles described the methodologies of Bloomberg on how they estimate the relationship value, the key models behind have not been revealed. As such, we cannot validate the value. Hypothetically, the relationship value shall be similar to at least 70% to 80% of a company COGS if we believe supply chain data recorded all raw materials expenses. However, we found that the total relationship value in a quarter from Bloomberg supply chain data only contained 40-45% of quarterly COGS of US firms and

25%-35% of Chinese firms. These findings revealed the unreliable usage of relationship value. These are also the reasons why we do not use relationship value in most of our analysis.

Subsidiary Information:

Bloomberg supply chain data provided the information of the supplier company, however, they aggregated or can only provide the data in group level. They also provided the information of the country of origin of the mother companies. Nevertheless, an international corporate may have multiple factories or subsidiaries in many countries. For example, Ford Motor have 70% of its subsidiary not locating in United States and Aptiv plc, a global auto parts company headquartered in Dublin, Ireland, has more than 10% of its factories in China. Bloomberg supply chain data could not revealed this fact. It necessarily means that even if those products are shipped from China and the income earned by those Chinese subsidiaries, it will report as Ireland products in supply chain data. Despite the fact that for most listed companies their subsidiary listed can be obtained from annual report, we are unable to obtain the actual revenue distribution across all subsidiaries because they are not required to disclose. Due to this limitation, the customer information in supply chain data is also unreliable as automobile companies tend to sell their products through subsidiaries and we cannot track where those products actually shipped to.

Propensity Model:

In creating the propensity model, we used centrality measurement and provided a link prediction to HSBC. However, in order to validate this model or enhance this model, we need to have HSBC internal data to validate. In some literature reviews, they suggested centrality scores could be one of the independent variables in regressing the probability of client retention or identifying new customers. For more, in our current dataset we lack of operating banking information which make the propensity model less provable.

HexaNet Scoring:

According to the company financial performances, we have created three scores and an aggregated score. Although they are logically presented, however, they are yet to be perfect and are not statistically verified. For borrowing need, we have considered one aspect of the reasons only. Some strategical reasons like changing debt structure has not been considered. For FX need, the currency peg issues are not considered. If a currency pegged with a currency, such as HKD to USD, the FX product need for this currency pair is actually low. In our calculation, we have neglected this issue. Other issues could be the trade frequency of the currency pair could affect the volatility of the currency rate hence the hedging need. The calculation of the risk score was simple and do not consider different other factors. Therefore, it should not be comparable to the professional financial firms rating. Nonetheless, this scoring system is providing a framework only and can be improved in the future.

7. Conclusion

To sum up, based on the background of the trade war and the requirement from HSBC, we chose automobile industry as research field and Bloomberg supply chain data as our main data source to turn the task into reality. Firstly, we identified the potential customers by creating and visualizing a supply chain network and performed network analysis to rank the companies through centrality scores. Secondly, we explored the effect of trade war. We built a three-factor model to calculate the expected performance and used it to compare with the actual performances. From these abnormal changes, we then created the HexaNet scoring system to access business opportunities for HSBC. Lastly, we use business intelligence tool to visualize the changes of supply chain network, our scoring system and financial performance. Financial firms can search on their clients to see how trade war event impact them and access the opportunities and the risks. During the ongoing trade war, the business intelligence tool will help HSBC learn more and deeper from trade war as long as the data is updating continuously. Furthermore, this framework is not only focusing on trade war effect but also analysing other economic events potentially such as oil crisis and natural disaster.

8. Appendix

Appendix – List of Variables

Supply Chain Data

Variables Name	Description
Central Ticker	Listed Ticker of the central company
Central Company	Company Name of the central company
As Of Date Bloomberg	As of date of supplier information
Central Country	Domicile country of central company
Market_Cap_Central	Market Capitalisation of central company
Stock Number	Central company ticker number
Listed Country	Central company listed country
Supplier Registered Name	Official name of supplier name
Supplier Company	Supplier company name
Supplier Ticker	Listed Ticker of the supplier company
Relationship Type	Relationship Type, Supplier/ Customer
Supplier Country	Domicile country of supplier company
Supplier Market Cap	Market Capitalisation of supplier company
Latest Inv. Growth	Supplier inventories growth
% Revenue get from central	Estimated trade value/ suppliers total revenue
Relationship Value	Estimated trade value
Currency	Trade value currency
Account As Type	Trade type, COGS/ SG&A/ R&D
%Cost	Estimated trade value/ central company total COGS
Relationship Value USD	Converted relationship value in USD
Source	Sources that Bloomberg used to determine the trade value
As Of Date	The date that this trade has been identified

Financial Data

Variables Name	Description
Tickers	Ticker Name of the company
Company Name	
Country	Domicile country of the company
GICS SubInd Name	Sub Industry Code according to GICS
GICS Ind Name	Industry Code according to GICS
GICS Sector	Sector Code according to GICS
End Date	Financial performances as of date
Market_Cap	Market capitalisation of the company
Last Price	Last trading price as of end date
Long Term Debt	
Short Term Debt	
Total Equity	
EBIT	Earnings Before Interest and Tax
Interest Expense	
Total Liabilities	
Net Income/Net Profit (Losses)	
Free Cash Flow to Equity	
Free Cash Flow to Firm	
Operating Expenses	

Revenue	
Basic Earnings per Share	
Selling, General and Administrative Expense	
R&D Expense	
Inventories	
Gross Profit	
Cost of Goods & Services Sold	
Cash From Operations	
Return on Assets	
Accounts Receivable - Net	
Accounts Payable	
Cash	

APPENDIX – TRADE WAR TIMELINE

DATE	Trade War Events
2018.3.22	**US starts the war** US impose tariffs on Chinese products, worth about $60 billion.
2018.4.2	**China takes its first shot** China retaliates against the steel and aluminum duties with tariffs on about $3 billion worth of U.S. goods.
2018.4.3	**China List 1 announcement** China sets out its list of targets for possible retaliation, including key exports from the US such as soybeans and cars.
2018.6.15	**US List 1 finalized** USTR(United States Trade Representative) announced the initial list of products reduced and finalized. and is set to take effect on July 6, 2018.
2016.6.16	**China List 1 finalized** Beijing announces tariffs on $50 billion in U.S. products.
2018.7.6	**US List 1 takes into effect and list 2 announcement** US implements first China-specific tariffs. Meanwhile List 2 is under review. **China List 1 takes into effect** China imposes a 25 percent tariff on 545 goods originating from the US.
2018.7.10	**US List 3 announcement** The USTR releases a third list of tariffs of over 6,000 commodities originating in China (worth US$200 billion), which will be subject to a 10 percent tariff.
2018.8.3	**China List 3 announcement** China's Ministry of Commerce proposes a range of additional tariffs on 5,207 products originating from the US (worth US$60 billion).
2018.8.23	**US List 2 takes into effect** US implements a 25 percent tariff on 279 goods originating from China. **China List 2 takes into effect** China implements retaliatory 25 percent tariffs on 333 goods originating from the US.
2018.9.17	**US List 3 finalized** The USTR announceed the finalized list of tariffs on US$200 billion worth of Chinese goods.
2018.9.18	**China List 3 finalized** China says it will slap tariffs on $60 billion in U.S. products in response to the latest U.S. duties.
2018.9.24	**US List 3 takes into effect** The US implements tariffs on US$200 billion worth of Chinese goods. **China List 3 takes into effect** China responds to US tariffs by implementing tariffs on US$60 billion worth of US goods.
2018.12.1	**A temporary truce** Trump and Xi have dinner at the G-20 summit in Argentina. They set out to strike a trade deal within 90 days.
2018.12.30	**China, US president phone call** Both sides agree to make the effort to solve the issue. China announced paused the tariff on US automobiles and auto parts.
2019.1~4	**Trade War Negotiation** Within these 4 months, US and China have gone through 11 meeting and discussion on Trade war issue. Market anticipated positive result from the negotiation.
2019.5.5	**Trade War Resume** Trump twittered a post claiming to impose another round of tariffs on US$200 billion goods on 10 May.

Appendix – Centrality Ranking (Top 50)

Rank	Company Name	Hubs Score	Company Name	Authorities Score
1	Dassault Systemes SE	0.00395	General Motors Co	0.04529
2	Magna International Inc	0.00359	Samsung Electronics Co Ltd	0.04447
3	International Business Machines Corp	0.00359	Ford Motor Co	0.04384
4	Aptiv PLC	0.00349	Volkswagen AG	0.04321
5	Aisin Seiki Co Ltd	0.00348	Nissan Motor Co Ltd	0.04109
6	CIE Automotive SA	0.00346	Honda Motor Co Ltd	0.03980
7	thyssenkrupp AG	0.00339	Fiat Chrysler Automobiles NV	0.03894
8	Sensata Technologies Holding PLC	0.00336	Panasonic Corp	0.01760
9	Kongsberg Automotive ASA	0.00334	Geely Automobile Holdings Ltd	0.01734
10	KUKA AG	0.00330	Denso Corp	0.01653
11	Strattec Security Corp	0.00328	Siemens AG	0.01544
12	Oracle Corp	0.00325	Tesla Inc	0.01389
13	ANSYS Inc	0.00325	Continental AG	0.01375
14	Exedy Corp	0.00313	CNH Industrial NV	0.01283
15	Honeywell International Inc	0.00312	Hitachi Ltd	0.01255
16	TTM Technologies Inc	0.00308	Cummins Inc	0.01223
17	SKF AB	0.00302	SAIC Motor Corp Ltd	0.01198
18	ArcelorMittal	0.00301	Aptiv PLC	0.01189
19	Schaeffler AG	0.00298	FAW CAR Co Ltd	0.01186
20	BorgWarner Inc	0.00295	Intel Corp	0.01174
21	TI Fluid Systems PLC	0.00292	Mitsubishi Heavy Industries Ltd	0.01155
22	Faurecia SA	0.00292	Magna International Inc	0.01109
23	Dana Inc	0.00291	Honeywell International Inc	0.01098
24	Intel Corp	0.00290	ZF Friedrichshafen AG	0.01008
25	Infineon Technologies AG	0.00289	Textron Inc	0.00983
26	Cooper-Standard Holdings Inc	0.00287	Dongfeng Motor Group Co Ltd	0.00951
27	Toyoda Gosei Co Ltd	0.00287	Mitsubishi Electric Corp	0.00929
28	CTS Corp	0.00287	Great Wall Motor Co Ltd	0.00899
29	Kokusai Co Ltd	0.00287	Valeo SA	0.00816
30	NTN Corp	0.00285	Chongqing Changan Automobile Co Ltd	0.00803
31	Silicon Laboratories Inc	0.00284	Eaton Corp PLC	0.00797
32	Trelleborg AB	0.00281	International Business Machines Corp	0.00795
33	Visteon Corp	0.00280	Aisin Seiki Co Ltd	0.00786
34	Analog Devices Inc	0.00280	Alphabet Inc	0.00785
35	ZF Friedrichshafen AG	0.00275	BYD Co Ltd	0.00781
36	Shiloh Industries Inc	0.00274	Visteon Corp	0.00730
37	Tenneco Inc	0.00272	ABB Ltd	0.00676
38	Denso Corp	0.00271	Autoliv Inc	0.00662

39	Adient PLC	0.00270	BEIQI FOTON MOTOR CO LTD-A	0.00662
40	Valeo SA	0.00269	Faurecia SA	0.00659
41	Estic Corp	0.00268	Lear Corp	0.00655
42	Gentherm Inc	0.00267	Guangzhou Automobile Group Co Ltd	0.00649
43	Hirata Corp	0.00267	Ferrari NV	0.00641
44	ElringKlinger AG	0.00264	Schneider Electric SE	0.00627
45	TDK Corp	0.00264	thyssenkrupp AG	0.00589
46	JTEKT Corp	0.00263	Hon Hai Precision Industry Co Ltd	0.00566
47	Autoliv Inc	0.00263	BAIC Motor Corp Ltd	0.00561
48	Riken Corp	0.00262	JTEKT Corp	0.00551
49	Akka Technologies	0.00260	Harley-Davidson Inc	0.00534
50	PTC Inc	0.00259	Flex Ltd	0.00520

Appendix – HexaNet Score as of 2019Q1 Top 50

Rank	Company Name	Borrow Need	Risk Score	FX Need	HexaNet Score
1	Meritor Inc	1.0000	-	0.0426	1.4149
2	Goodyear Tire & Rubber Co/The	1.0000	-	0.0298	1.4145
3	Teradata Corp	1.0000	-	0.0043	1.4142
4	TPK Holding Co Ltd	1.0000	0.0145	0.0298	1.4043
5	Valhi Inc	0.9786	-	0.0043	1.3992
6	Schaeffler AG	0.9760	-	0.0511	1.3983
7	LyondellBasell Industries NV	1.0000	0.0360	0.0638	1.3905
8	Gentherm Inc	1.0000	0.0587	-	1.3734
9	Ningbo Huaxiang Electronic Co Ltd	1.0000	0.0733	0.0128	1.3634
10	Hankook Tire Co Ltd	0.9251	-	0.0213	1.3624
11	Suzhou Anjie Technology Co Ltd	1.0000	0.0873	-	1.3539
12	NSK Ltd	0.9070	-	0.0213	1.3502
13	Constellium NV	1.0000	0.1240	0.0128	1.3295
14	Iochpe Maxion SA	1.0000	0.1289	0.0085	1.3263
15	Albemarle Corp	1.0000	0.1295	-	1.3258
16	Tesla Inc	1.0000	0.1736	0.1915	1.3113
17	Qingdao Doublestar Co Ltd	1.0000	0.1568	0.0043	1.3081
18	Shiloh Industries Inc	1.0000	0.1770	0.0128	1.2952
19	Fiat Chrysler Automobiles NV	-	-	0.8213	1.2940
20	Hitachi Metals Ltd	1.0000	0.1985	0.0043	1.2816
21	American Axle & Manufacturing Holdings Inc	0.8004	-	0.0213	1.2811
22	Panasonic Corp	1.0000	0.3049	0.3872	1.2779
23	Volkswagen AG	0.6438	0.4220	0.9404	1.2779
24	Gentex Corp	0.7677	-	0.0043	1.2607
25	BorgWarner Inc	1.0000	0.2593	0.0681	1.2463
26	Aptiv PLC	1.0000	0.3418	0.2979	1.2337
27	Tenneco Inc	1.0000	0.3188	0.0340	1.2105
28	Steel Dynamics Inc	0.8774	0.1677	-	1.2094
29	Microsoft Corp	0.5367	-	0.4128	1.2077
30	Eaton Corp PLC	1.0000	0.3789	0.2596	1.2054
31	F-Tech Inc	0.7990	0.1026	-	1.2015
32	Mitsubishi Electric Corp	0.7323	0.0604	0.1191	1.1972
33	Samsung Electronics Co Ltd	0.2815	0.3841	0.9617	1.1762
34	GuangDong PaiSheng Intelligent Technology Co Ltd	1.0000	0.4077	0.0085	1.1623
35	Sherwin-Williams Co/The	1.0000	0.4304	0.0553	1.1522
36	Amada Holdings Co Ltd	1.0000	0.4334	0.0085	1.1494
37	Koito Manufacturing Co Ltd	0.6933	0.0851	0.0170	1.1480
38	Baoshan Iron & Steel Co Ltd	0.7396	0.1227	0.0298	1.1478
39	United States Steel Corp	0.5419	-	0.0213	1.1376

40	Shenzhen Sunshine Laser & Electronics Technology Co Ltd	1.0000	0.4650	-	1.1341
41	Dana Inc	1.0000	0.4776	0.0340	1.1288
42	NGK Insulators Ltd	0.9409	0.3782	0.0043	1.1278
43	Modine Manufacturing Co	1.0000	0.4793	0.0085	1.1275
44	Anhui Tongfeng Electronics Co Ltd	0.7363	0.1642	-	1.1139
45	Hitachi Ltd	0.4701	0.0349	0.2894	1.1119
46	China Jialing Industrial Co Ltd	0.4697	-	0.0043	1.1048
47	Wesco Aircraft Holdings Inc	1.0000	0.5411	0.0936	1.1042
48	KUKA AG	0.4668	-	-	1.1036
49	FAW CAR Co Ltd	1.0000	0.5400	0.0468	1.1017
50	Bayerische Motoren Werke AG	0.4458	0.3513	0.7660	1.0983

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