A HIERARCHIC FRAMEWORK FOR THE PROPAGATING IMPACTS OF THE CHINA-U.S. TRADE WAR ON VOLUME OF CHINESE CONTAINERIZED EXPORTS

BIN YU1,2,3,∗, MENGYAN HAO1, YONGLEI JIANG4 AND LIANJIE JIN5,∗

1 School of Transportation Science and Engineering
Beihang University, Beijing, 100191, China
2 Beijing Advanced Innovation Center for Big Data and Brain Computing
Beihang University, Beijing, 100191, China
3 Civil Engineering Department
Dalian University of Technology, Dalian, 100191, China
4 School of Traffic and Transportation
Beijing Jiaotong University, Beijing, 100044, China
5 Transport Planning and Research Institute
Beijing, 100028, China

(Communicated by Gerhard-Wilhelm Weber)

ABSTRACT. The China-U.S. trade war between the world’s two largest economies has received increasing attention. Due to the existing interdependencies within economic sectors, the trade war could bring about ripple effects and cause more damaging impacts than intuitive thoughts. By integrating Inoperability Input-output Model (IIM) and Partial Least Squares Regression (PLSR), we developed a hierarchic IIM-PLSR framework in this study to unravel the ripple effects of the China-U.S. trade war on volume of Chinese containerized exports. The results show that the China-U.S. trade war will affect the operability and output value of not only the tariff-targeted industries but the other interdependent industries. Contrary to expectations, the results show that the China-U.S. Trade War have an insignificant influence on the volume of containerized exports. Even in the worst scenario, the reduction percentage of containerized exports due to China-U.S. trade war is only 0.335%. This study brings fresh insights to stakeholders in the port industry for the implementation of rational port planning policies.

1. Introduction. The trade war between China and the U.S. has become a big concern for both sides, for not only have the two countries engaged in mutual placement of tariffs but the tension of trade disputes seems to be intensifying [25]. When the U.S. Government announced a tariff list of total $50 billion on imports from China on 3 April 2018 [36] and the Chinese responded with a retaliatory tariff list of the same amount [31], a tipping point for a potential trade war between the two countries was initiated. In the meantime, there exist frequent trade contact and close economic relationship between the world’s two largest economies. The China Statistical Yearbook 2018 [32] reveals that the U.S. increased its share in exports of China by 0.62 percentage in 2017 and reached a market share of 18.98 percent of
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total export value in China, remaining as the biggest destination for China exports. Therefore, the China-U.S. trade war could induce a serious string of consequences, slashing the Chinese exports volume to the U.S. and causing an abatement of the global economic activities.

On the other hand, owing to the existing interdependencies within economic sectors, trade war could bring about ripple effects to protagonist countries and cause more damaging impacts to the countries’ welfare than intuitive thoughts [20]. In other words, suppliers and customers of sectors involved in the trade war are directly affected; moreover, the product of one sector is used as an input in the production of another sector so that the impacts diffuse indirectly throughout the various sectors in the entire economic system. Despite global attention the China-U.S. trade war has received and the potential in causing enormous impact, scant literature has carried out the relevant impact analysis, especially in a quantitative method, indicating the existence of a research gap. Simultaneously, there are empirical evidences reflecting a coupled relationship between maritime sector and macroeconomic trends, which has caught increasing attention since the maritime sector slowed down due to the financial crisis in 2008 [41]. The economic connection of maritime transportation arises from the fact that most of the foreign trade has been carried out by sea with the development of containerized cargo transport [26]. Therefore, the China-U.S. trade war could set off a series of critical changes on maritime sector. While this has triggered particular attention to port related stakeholders, few researches have investigated the issue with respect to how the China-U.S. trade war affect port traffic and profits, mainly due to complexity of dealing with this subject and scarcity of related sample data.

To fill the research gap in the literature, this paper aims to analyze the propagating impact of the China-U.S. trade war on maritime transportation, specially focusing on volume of Chinese containerized exports. Since 2000 the proportion of total global freight that is containerized has steadily increased and as of 2017 containerized goods make up 15.7% of total freight (billion tonne-miles), according to the Shipbuilders Association of Japan [48]. It is noteworthy that China has dominated the container trade for over a decade, principally as an exporter. For this reason, forecasting volume of containerized exports in China could provide a pivotal reference for policy makers, researchers, as well as the maritime industry, including ports and shipping.

To perform the quantitative analysis, we developed a hierarchic Inoperability Input-output Model-Partial Least Squares Regression (IIM-PLSR) framework to unravel the ripple effects of the China-U.S. trade war on volume of Chinese containerized exports by integrating a risk-based multi-sector impact model with a multi-variate data analysis method. To be specific, we adopt the Inoperability Input-output Model (IIM) to describe interdependencies within economic sectors and take the Partial Least Squares Regression (PLSR) method to analyze the correlated variables. IIM is an extension of the input-output model, capable of modeling not only economic interdependency but interdependency in broader infrastructure sectors [8]. This model is widely accepted for estimating the economic consequences of hazard events, and was included in the 10 Most Important Accomplishments in Risk Analysis: 1980–2010 [14]. In this study, we have examined the propagating impacts of the China-U.S. trade war on 17 sectors using the proposed framework. By comparing the output dynamics of 17 sectors under various trade war simulation scenarios, the disruption can be obtained to measure the impact due to the
China-U.S. trade war and provide parameters for estimations of containerized export fluctuation. This study brings fresh insights to stakeholders in the port industry for the implementation of rational port planning policies.

This paper differs from existing literature in twofold: (1) proposing a novel framework (IIM-PLSR) to study disruptions in maritime transportation. Most studies applied network analysis or breaking-down rationale. According to [40], such network approaches are computationally intensive, so our framework provides a less-burden perspective. The breaking-down rationale focus on the operation process of ports, paying less attention to connections with other sectors. Hence, we take advantage of the input-output modelling to quantify the effects of interdependencies [49]; (2) providing three China-U.S. trade war scenarios. The scenarios are designed by varying the value of commodities involved in the trade war. Then in each scenario, inoperability and economic loss of all sector in China are analyzed, and the volume of containerized exports is estimated.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on disruptions in maritime transportation and economic-maritime relationship. Section 3 presents the research methodology and the conceptual framework developed to predict volume fluctuation of containerized exports. In Section 4, the case study and data are introduced and three scenarios considering various sources of uncertainties relating to trade war are presented. We discuss results in Section 5 and conclusion in Section 6.

2. Literature review.

2.1. Economic-maritime relationship. The container throughput may fluctuate due to global economy and trade event, resulting in the complexity and volatility [1, 53]. The literature also presents the efforts to investigate the relationship between economic activity and maritime freight to forecast port traffic. Estache et al. [10] has considered macro-economic trends and reforms as one of the main factors when forecasting freight traffic, such as trade liberalization, trade agreements (such as the Transatlantic Trade and Investment Partnership (TTIP)), openness of the economy and evolution of industrial production. Chou [7] has taken into account the relationship between the volumes of im/export containers and the economic variables when establishing a mixed fuzzy expert system and regression model for forecasting the volumes of Taiwan’s import containers. Zondag et al. [55] presented a new approach to model port competition, which emphasizes on the negative impact in the short-run caused by the financial crisis. Artuso et al. [2] provided future scenarios for the EU shipping sector based on the macroeconomic conditions and the EU-global maritime trends to analyze the geographical trade relationships of container shipping expressed in volumes of manufactured products. This report showed that relationship between economic growth and trade developments is of crucial importance to maritime trade. Rashed et al. [41] studied how will the aggregate container throughput in the Hamburg-Le Havre range develop until 2050 under different scenarios. They developed a three-step approach by combining the autoregressive distributed lag model with economic scenarios to capture the potential impact of specific risks. A cointegration relationship between the economic indicators and the container throughput is found, which is in line with earlier literature.

As for China-U.S. trade war, Gong et al. [12] investigated how the volume of the China-U.S. trade influences the contagion risk between the shipping freight rate
and stock markets, by employing Markov regime-switching copula model. They found that, in most cases, the contagion risk between the two markets increases due to the reduction in China-U.S. trade volume. However, insufficient academic studies have considered the interdependencies within economic sectors and conducted inter-sectoral analysis to dig into the economic-maritime relationship. In any case, explaining the behavior of different sectors is extremely challenging since they are numerous, they usually overlap, may compete indirectly and interact differently to various shocks [39]. For China-U.S. trade war could be a huge shock to port industry, an inter-sectoral analysis is considered crucial since it provides evidence for aggregate fluctuations. So, this study performed a quantitative analysis under various China-U.S. trade war scenarios to capture and assess the propagating impact on volume of Chinese containerized exports.

2.2. Disruptions in maritime transportation. Maritime sectors are exposed to disruption events from both man-made events (e.g. macro-economic trends, policy, daily operation, terrorist acts) and natural hazards (e.g. tsunami, earthquake, climate extremes) [34]. Given the crucial role shipping plays in international trade, disruptions in maritime transportation has drawn the attention from different fields and communities. These studies investigated the topic by diversified methods and frameworks, and several key research clusters can be identified including: 1. From a breaking-down operation process perspective. The main activities within seaport system were decomposed into different subsystems based on operation process. For instance, the subsystems include (1) navigation and berthing, (2) materials and handling, (3) vehicles and movement, (4) goods storage and (5) transport and supply chain. Then the risk and impact analysis were conducted for each subsystem [3, 17, 19]. Gou and Lam [13] integrated breaking-down the operation process and State Transition model to analyze risk of marine cargoes and ports to natural hazards. 2. From a complex network perspective. Studies showed that the maritime transportation network shared the characteristics of other networks found in nature and sciences: (1) it was a scale-free network; (2) it was a ‘small-world’ network; (3) a giant node could be found in the network. Based on network analysis, disruptions could be simulated by the shutdown of selected ports which means the relevant nodes and links disappear [9, 21, 52]. In the study of Calatayud et al. [5], the network metrics (e.g. total degree, betweenness centrality, average clustering coefficient) from complex network theory was applied to analyze the impact of targeted disruptions.

In this study, we propose an IIM-PLSR framework to analyze the impact of trade war on maritime transportation. As a powerful interdependency analysis technique, the IIM and its extensions have been successfully applied to study multi-sector impacts of changes in supply and demand [8, 15, 24, 42], including transportation system [8, 18, 40, 46]. These available databases of interdependency statistics, such as National Bureau of Statistics of China (NBS), the U.S. Bureau of Economic Analysis (BEA) database of national I-O accounts and the Organization for Economic Co-operation and Development (OECD), provide an essential foundation for applying the IIM. On the other hand, PLSR has enjoyed large popularity and gained close attention in a wide range of fields, mainly because it is designed to cope with such a situation that there are many possible correlated prediction variables, with relatively few samples [30]. Originating from chemistry [27, 50], PLSR has been broadly applied many other fields covering transportation [54], ecology [6], environmental development [45], food engineering [11]. Compared to other methods, PLSR can
analyze samples with strongly correlated, noisy, and multiple X-variables, allowing us to investigate more complicated problems than before, and analyze available data in a more pragmatic way [51].

3. Methodology.

3.1. Model structure. A flowchart of the proposed hierarchic IIM-PLSR framework for propagating impacts of the China-U.S. trade war on volume of Chinese containerized exports is shown in Figure 1. In the first stage, we apply IIM to study multi-sector impacts, which is a powerful interdependency analysis technique. In the second stage, we need to deal with multi-sector inputs so we adopt PLSR for it can analyze samples with strongly correlated, noisy, and multiple X-variables.

The methodology presented in this paper consists of two main elements: (1) the first stage: to expound on ripple effects attributed to interdependencies within economic sectors and (2) the second stage: to handle strong collinearity in explanation variables (economic sectors) while predicting Chinese containerized exports volume.

![Figure 1. Structure of the proposed hierarchic framework](image)

Firstly, we give a description of procedures before entering the first stage of the hierarchic framework. The notations are introduced in Table 1. The tariff imposed by the U.S. on imports from China can be obtained, once a trade war is started. For imports, an increase in prices decreases demand [22]. Then according to the definition of import demand elasticity [29], we can achieve import demand fluctuation in U.S. illustrated by equation (1)-(3).

\[
E_i = \frac{\Delta quantity_i}{\Delta price_i} \times \frac{price_i}{quantity_i}, \tag{1}
\]

\[
\frac{\Delta quantity_i}{quantity_i} = E_i \frac{\Delta price_i}{price_i}, \tag{2}
\]

where \(E_i\) is the import demand elasticity of sector \(i\). When good price gets changed, the demand fluctuation in terms of value can be deduced by equation (3).

\[
\xi_i = \frac{(quantity_i + \Delta quantity_i)(price_i + \Delta price_i) - quantity_i \cdot price_i}{quantity_i \cdot price_i}, \tag{3}
\]

where \(\xi_i\) is the demand change percentage in terms of value of sector \(i\). A tariff imposed on import goods of sector \(i\) will increase the price and reduce the demand.
Table 1. Overview of notations used in the IIM-PLSR framework

| Notation | Description |
|----------|-------------|
| \(a_{ij}\) | proportion of sector \(i\)'s input used by sector \(j\) with respect to total production of sector \(j\) |
| \(A\) | matrix of technical coefficient |
| \(A^*\) | demand-based interdependency matrix |
| \(b_0\) | vector of offset coefficients |
| \(B\) | matrix of regression coefficients |
| \(c_j\) | final demand for sector \(j\) |
| \(C\) | vector of final demand |
| \(c^*_i\) | normalized degraded demand for sector \(i\) |
| \(c^*\) | vector of normalized degraded demand |
| \(\hat{c}_i\) | value of nominal final demand of sector \(i\) |
| \(\hat{c}\) | vector of nominal final demand |
| \(\tilde{c}_i\) | value of degraded final demand of sector \(i\) |
| \(\tilde{c}\) | vector of degraded final demand |
| \(E_i\) | import demand elasticity of goods of sector \(i\) |
| \(F\) | matrix of residuals |
| \(p_i\) | total output of sector \(i\) |
| \(P\) | vector of sector output |
| \(p_{ij}\) | input from sector \(i\) to sector \(j\) |
| \(\hat{p}_i\) | the nominal output of sector \(i\) |
| \(\hat{p}\) | vector of nominal output |
| \(\tilde{p}_i\) | the degraded output of sector \(i\) |
| \(\tilde{p}\) | vector of degraded output |
| \(q_i\) | normalized output loss of sector \(i\) |
| \(Q\) | vector of normalized output loss |
| \(t_i\) | tariff rate for goods of sector \(i\) |
| \(T\) | latent variables |
| \(V_i\) | value of commodities of sector \(i\) |
| \(X\) | matrix of predictor variables |
| \(Y\) | matrix of response variables |
| \(\xi_i\) | demand change percentage of sector \(i\) |

Given the assumption that the tariff rate is equivalent to the rate of price change \((t_i = \frac{\Delta\text{price}_i}{\text{price}_i})\), the demand change in terms of value can be expressed as:

\[
\xi_i = t_i + E_i t_i + E_i t_i^2,
\]

where \(t_i\) is the tariff rate for goods of sector \(i\), depending on the circumstances of the trade war. Then the import demand change caused by tariffs in U.S. can be calculated according to equation (4), which equals the corresponding export demand change caused by tariffs in China. With this, preliminary process of the first stage has been finished.

3.2. Inoperability Input-Output Model (first stage). The Inoperability Input-Output Model (IIM) is an extension of the input-output economic model, for which Leontief [23] won a Nobel Prize. This risk-based interdependency model [43,
shapes the propagation of inoperability and quantifies the proportional extent to which industries are out of operation due to perturbations in final consumption through interconnected sectors.

In the traditional economic input–output model, the economy consists of $n$ interdependent sectors. Under a static equilibrium the total output of the $i$th sector is distributed to all sectors and satisfies external demand. The balance equation is expressed as equation (5), which suggests that the total output of sector $i$ is consumed as two forms: intermediate consumption ($p_{ij}$) or final consumption ($c_i$).

$$ p_i = \sum_{j=1}^{n} p_{ij} + c_i \Leftrightarrow p_i = \sum_{j=1}^{n} a_{ij} p_j + c_i \Leftrightarrow \mathbf{P} = \mathbf{AP} + \mathbf{C}, $$

where $\mathbf{P}$ is the vector of sector output; $\mathbf{A}$ is called the matrix of technical coefficient or Leontief coefficient, and $\mathbf{C}$ is the vector of final demand or external demand. The technical coefficient matrix can be obtained on the basis of Input-Output Table.

The IIM establishes the interdependency matrix, which represents the probability of inoperability due to interconnectedness of the infrastructures, to assess the direct and indirect economic impacts of disruptive events throughout the various sectors in the nation. Several studies have been conducted to analyze the impacts of anthropogenic and natural catastrophes using the IIM. The fundamental of the IIM lies in the definition of inoperability as the degraded normalized production loss of Sector $i$, given as

$$ q_i = \frac{\hat{p}_i - \tilde{p}_i}{\hat{p}_i} \quad \forall i, $$

where $\hat{p}_i$ is the nominal or “as planned” output of sector $i$ and $\tilde{p}_i$ is the degraded output of sector $i$ after catastrophe. $\hat{p}_i - \tilde{p}_i$ describes a deviation from the initial production due to catastrophe. The inoperability of an sector lies between 0 and 1, where $q_i = 0$ is a measure of a perfectly operational sector $i$, and $q_i = 1$ is a measure of a completely ineffective sector $i$. Then the Leontief I-O Model can be expressed as

$$ \left[ (\text{diag}(\hat{\mathbf{p}}))^{-1} (\hat{\mathbf{p}} - \tilde{\mathbf{p}}) \right] = \left[ (\text{diag}(\hat{\mathbf{p}}))^{-1} (\hat{\mathbf{p}} - \tilde{\mathbf{p}}) \right] \left[ (\text{diag}(\hat{\mathbf{p}}))^{-1} (\hat{\mathbf{c}} - \tilde{\mathbf{c}}) \right], $$

where $\hat{c}_i$ is the value of nominal final demand of sector $i$ and $\tilde{c}_i$ is the value of degraded final demand of sector $i$ due to catastrophe. Given the definition of $\mathbf{q}$, $\mathbf{A}^*$ and $\mathbf{c}^*$, the IIM can be illustrated by

$$ \mathbf{q} = \mathbf{A}^* \mathbf{q} + \mathbf{c}^* \Leftrightarrow \mathbf{q} = (\mathbf{I} - \mathbf{A}^*)^{-1} \mathbf{c}^*, $$

$$ \mathbf{q} = \left[ (\text{diag}(\hat{\mathbf{p}}))^{-1} (\hat{\mathbf{p}} - \tilde{\mathbf{p}}) \right], $$

$$ \mathbf{A}^* = \left[ (\text{diag}(\hat{\mathbf{p}}))^{-1} \mathbf{A} (\text{diag}(\hat{\mathbf{p}})) \right] $$

$$ \mathbf{c}^* = \left[ (\text{diag}(\hat{\mathbf{p}}))^{-1} (\hat{\mathbf{c}} - \tilde{\mathbf{c}}) \right], $$

where $\mathbf{q}$ is the vector of normalized output loss due to demand reduction; $\mathbf{A}^*$ is the demand-based interdependency matrix derived from I-O data (the 2015 Input-Output Table is used here); and $\mathbf{c}^*$ is the vector of normalized degraded demand
due to catastrophe (i.e. trade war). Thereupon, normalized degraded demand or demand perturbation for sector $i$ due to tariffs ($c^*_i$) can be obtained by

$$c^*_i = \frac{\hat{c}_i - \bar{c}_i}{p_i} = \frac{\xi_i \times V_i}{p_i},$$  \tag{12}$$

where $\xi_i$ is demand change percentage caused by tariffs of sector $i$. And $V_i$ is the value of commodities of sector $i$ involved in the trade war. For economic systems, $c^*_i$ is the measure of the change in demand as a proportion of the original production level in sector $i$, as shown in equation (11). The Inoperability Input–Output Model (IIM) extends the traditional economic input–output model to quantify how inoperability, not only commodity flows, propagate through interdependent sectors [40]. From the above, the economic losses or degraded value ($\tilde{p}_i$) and inoperability ($q_i$) to each sector can be acquired.

3.3. Partial Least Squares Regression (second stage). This stage is used to illustrate the relationship between economic sectors and containerized exports. As illustrated in the first stage, the economic sectors are physically and logically interdependent systems [16], resulting in strong collinearity in the regression analysis. In view of this challenge and the small sample size, Partial Least Squares Regression (PLSR) is adopted to cope with multiple possible correlated prediction variables.

The key thoughts of PLSR model lies on (1) extracting a few latent variables $T$ to summarize the interesting information in $X$, and (2) modelling both $X$ and $Y$ in terms of these latent variables, illustrated as:

$$T = w(X),$$  \tag{13}$$

$$[X, Y] = f(T) + F,$$  \tag{14}$$

where $w(\cdot)$ and $f(\cdot)$ represent functions, usually linear. The final obtained model may be summarized as a conventional linear regression model (equation (15)). More explicit details may be found in e.g. Martens and Martens [28].

$$Y = b_0 + XB + F,$$  \tag{15}$$

where $b_0$ is the offset coefficient vector, $B$ is the matrix of regression coefficients and $F$ is residual of $Y$. In this study, PLSR Model is introduced to analyze the volume change of containerized exports due to trade war, with all economic sectors’ output value as regressors (X-variables).

According to Martens and Martens [28], the cross-validation/jack-knifing procedure is used here. The “leave-one-product-out” cross-validation (CV) is aimed at describing the model’s ability to predict $Y$ from $X$ via latent variables, in new products of the same general type under the chosen experimental conditions. For PLSR, the components, also called Latent Variables (LVs), are obtained iteratively. Cross-validation (CV) are used in this model to determine the optimal number of components to consider. On the basis of jack-knife estimates of the uncertainty of the model parameters, useless or unreliable X- or Y-variables may be eliminated automatically, in order to diminish complexity in the final model and achieve high reliability. All X and Y variables are centered and normalized prior to the analysis (with mean = 0 and standard deviation = 1), to balance noise and to facilitate the interpretation. The computation is done in R version 3.5.2.
4. Data and scenario development.

4.1. Input data. Table 2 lists all the 17 sectors in China, according to the 2018 CHINA STATISTICAL YEARBOOK compiled by National Bureau of Statistics of China [32]. As the foundation for our measure of interdependency, 2015 Input-Output Table is used in the first stage to calculate economic losses and inoperability to interdependent sectors due to the China-U.S. trade war. In the second stage, output dynamics of 17 sectors and the annual volume of containerized exports are input variables into PLSR model. The data required for this study consist of: (1) import demand elasticity in U.S. as -1.10 according to Kee et al. [22]; (2) 2015 Input-Output Table which includes matrix of technical coefficient ($A$) and output value vector of each sector ($P$) from National Bureau of Statistics of China [32], scaled by producers’ prices into one common unit of dollars; (3) output value of all sectors in China from 2000 to 2015, shown in Table 3a and Table 3b, from [33]; (4) annual volume of containerized exports in China, shown in Table 4, from Transport Planning and Research Institute of Ministry of Transport (Unpublished data).

4.2. Scenarios. In consideration of uncertainty lying in the characteristics of trade war, multi-level scenarios have been analyzed by varying the value of commodities involved in the trade war. As shown in Table 5, three scenarios are designed based on China–U.S. trade war to dissect the direct and indirect impact on Chinese containerized exports, under different tariff policies. Scenario 1 refers to President Donald Trump’s announcement that steel imports would face a 25% tariff and aluminum 10% [4, 47]. According to the international trade data from U.S. Department of Commerce, U.S. Imports for Consumption of Steel Products from China reached 976 million dollars in 2017 and 902 million dollars in 2018. So, in the first scenario, the value of commodities involved in the trade war is set as 1 billion dollars in “Manufacture and Processing of Metals and Metal Products” sector. Then following Section 301 investigation, USTR published a proposed list of products imported from China, worth approximately $50 billion, which could be subject to additional tariffs of 25 percent [36]. Thereupon according to the proposed list, the value of commodities involved in the trade war in scenario 2 are set as 5 and 45 billion dollars respectively in “Manufacture and Processing of Metals and Metal Products” sector and “Manufacture of Machinery and Equipment” sector. As the trade war escalated, USTR began the process of imposing tariffs of 10 percent on an additional $200 billion of Chinese imports [35], with announcement to be increased to 25 percent [37]. Accordingly, the value of commodities involved in the trade war are set as 20 and 180 billion dollars respectively in scenario 3. To deduce the relatively serious consequence, we set the tariff rate as 25% according to the above tariff polices (ranging from 10% to 25%).

Assumptions: (1) The economic losses triggered by tariffs are equal to the summation of those triggered by a direct descent in demand for the affected sectors’ output and the expanding descent due to interdependencies between sectors; (2) This paper focuses on Chinese exports, so the potential retaliatory measures by Chinese government are not considered.

5. Results and discussion. Multi-level scenarios in China-U.S. trade war have been analyzed in terms of economic loss and inoperability through the Inoperability Input-Output Model. The results are based on assumption that the economic losses triggered by tariffs are equal to the summation of those triggered by a direct descent
Table 2. All 17 sectors in China

| Index | Sector                                                                 |
|-------|------------------------------------------------------------------------|
| 1     | Agriculture, Forestry, Animal Husbandry & Fishery                       |
| 2     | Mining                                                                 |
| 3     | Manufacture of Foods, Beverage & Tobacco                               |
| 4     | Manufacture of Textile, Wearing Apparel & Leather Products             |
| 5     | Coking, Gas and Processing of Petroleum                                 |
| 6     | Chemical Industry                                                      |
| 7     | Mineral Products                                                       |
| 8     | Manufacture and Processing of Metals and Metal Products                |
| 9     | Manufacture of Machinery and Equipment                                 |
| 10    | Other Manufacture                                                      |
| 11    | Production and Supply of Electric Power, Heat Power and Water          |
| 12    | Construction                                                           |
| 13    | Transport, Storage, Post, Information                                  |
| 14    | Wholesale and Retail Trades, Hotels and Catering Services              |
| 15    | Real Estate, Leasing and Business Services                             |
| 16    | Financial Intermediation                                               |
| 17    | Other Services                                                         |

Table 3. Output value of each sector in China (in billion dollars)

(A)

| Year | Output Value ($X_i$) |
|------|----------------------|
|      | $X_1$   | $X_2$   | $X_3$   | $X_4$   | $X_5$   | $X_6$   | $X_7$   | $X_8$   |
| 2000 | 424.64  | 129.788 | 235.226 | 274.376 | 133.6   | 346.593 | 100.75  | 252.498 |
| 2002 | 458.846 | 165.648 | 232.496 | 251.035 | 103.532 | 346.359 | 93.195  | 343.031 |
| 2005 | 631.891 | 312.606 | 415.481 | 450.87  | 214.574 | 642.728 | 246.616 | 675.398 |
| 2007 | 785.001 | 468.514 | 670.965 | 694.72  | 356.157 | 995.41  | 366.135 | 1265.196|
| 2010 | 1112.963| 780.927 | 1082.658| 911.499 | 484.051 | 1497.191| 643.248 | 1711.171|
| 2012 | 1345.703| 860.544 | 1412.234| 1064.191| 692.57  | 1943.109| 748.26  | 2285.335|
| 2015 | 1718.842| 864.351 | 1837.159| 1340.565| 710.367 | 2507.955| 1032.203| 2491.578|

(B)

| Year | Output Value ($X_i$) |
|------|----------------------|
|      | $X_9$   | $X_{10}$ | $X_{11}$ | $X_{12}$ | $X_{13}$ | $X_{14}$ | $X_{15}$ | $X_{16}$ | $X_{17}$ |
| 2000 | 668.386 | 143.308  | 136.844  | 355.742  | 169.719  | 271.888  | 177.297  | 82.929   | 231.551  |
| 2002 | 713.382 | 223.037  | 136.121  | 451.684  | 234.515  | 390.004  | 278.252  | 117.429  | 493.718  |
| 2005 | 1459.226| 350.667  | 311.768  | 683.392  | 562.924  | 547.33   | 330.367  | 164.755  | 777.982  |
| 2007 | 2339.123| 585.645  | 524.45   | 1007.028 | 681.737  | 789.79   | 426.421  | 312.777  | 967.112  |
| 2010 | 3766.195| 794.671  | 766.34   | 1643.172 | 1061.82  | 1038.7   | 833.196  | 518.377  | 1465.646|
| 2012 | 4147.833| 895.583  | 809.107  | 2225.493 | 1397.658 | 1533.136 | 1225.254 | 947.499  | 2093.395|
| 2015 | 5198.017| 1196.406 | 987.575  | 3241.663 | 1915.727 | 2169.057 | 1902.89  | 1416.748 | 2887.539|

in demand for the affected sectors’ output and the expanding descent due to interdependencies between sectors. Moreover, inoperability to each sector are given, which can be explained as a decrease in the ability of the system to accomplish
Table 4. Annual volume of containerized exports in China

| Year | Volume (in 1000 TEU) |
|------|----------------------|
| 2000 | 25500                |
| 2001 | 28800                |
| 2002 | 33000                |
| 2003 | 41700                |
| 2004 | 51000                |
| 2005 | 58200                |
| 2006 | 68400                |
| 2007 | 79400                |
| 2008 | 83300                |
| 2009 | 77000                |
| 2010 | 91740                |
| 2011 | 96240                |
| 2012 | 97700                |
| 2013 | 98650                |
| 2014 | 102430               |
| 2015 | 104960               |

Table 5. Scenarios for the China-U.S. trade war

| Tariff rate | Sector                                      | Value of commodities involved in the trade war (billion $) |
|-------------|--------------------------------------------|----------------------------------------------------------|
|             | Scenario 1 | Scenario 2 | Scenario 3 |
| 25%         | Manufacture and Processing of Metals and Metal Products | 1 | 5 | 20 |
|             | Manufacture of Machinery and Equipment      | 0 | 45 | 180 |

its expected output due to China-U.S. trade war. At length, the ultimate impact of China-U.S. trade war on volume of Chinese containerized exports are analyzed based on PLS model.

5.1. Inoperability Input-Output Model (first stage). Here the relatively severe scenarios (with a 25% tariff) are deeply analyzed, for the reason that higher tariff rate leads to more serious and destructive consequences. The detailed output value and inoperability prediction of all interdependent sectors is listed in Table 6. The scenario 1 corresponds to situations when “Manufacture and Processing of Metals and Metal Products” sector suffers the primary perturbation in terms of both economic loss (0.16 billion dollars) and inoperability (6.54*10^{-5}), as we all preconceived. Conversely, it is not intuitive to see that “Mining” sector suffers the second serious disturbance, which indicates that a large number of commodities in “Manufacture and Processing of Metals and Metal Products” sector used by “Mining” sector intermediately. That is to say, there is a strong connection with these two industries. In this scenario, China would suffer a total economic loss of 0.37 billion dollars and an average inoperability of 0.0012% for each sector, suggesting a relatively mild shock of China-U.S. trade war.
Table 6. Output value (in billion dollars) and inoperability prediction in each scenario

| Index | Base Scenario | Scenario 1 | Scenario 2 | Scenario 3 |
|-------|---------------|------------|------------|------------|
|       | Output        | Inoperability | Output     | Inoperability | Output     | Inoperability |
| 1     | 1718.842      | 0.00035%    | 1718.538   | 0.01771%    | 1717.624   | 0.07086%    |
| 2     | 864.351       | 0.00413%    | 863.576    | 0.08965%    | 861.25     | 0.35872%    |
| 3     | 1837.159      | 0.00034%    | 1836.842   | 0.01728%    | 1835.889   | 0.06914%    |
| 4     | 1340.565      | 0.00031%    | 1340.339   | 0.01689%    | 1339.659   | 0.06755%    |
| 5     | 710.363       | 0.00160%    | 710.029    | 0.04696%    | 709.028    | 0.18789%    |
| 6     | 2507.955      | 0.00083%    | 2506.706   | 0.04978%    | 2502.96    | 0.19915%    |
| 7     | 1032.203      | 0.00051%    | 1031.958   | 0.02366%    | 1031.226   | 0.09465%    |
| 8     | 2491.578      | 0.00654%    | 2488.814   | 0.11094%    | 2480.517   | 0.43935%    |
| 9     | 5198.017      | 0.00051%    | 5190.058   | 0.15311%    | 5166.182   | 0.61243%    |
| 10    | 1196.406      | 0.00102%    | 1195.983   | 0.03535%    | 1194.714   | 0.14144%    |
| 11    | 987.575       | 0.00228%    | 986.953    | 0.06304%    | 985.084    | 0.25222%    |
| 12    | 3241.663      | 0.00003%    | 3241.617   | 0.00142%    | 3241.478   | 0.00570%    |
| 13    | 1915.727      | 0.00001%    | 1915.081   | 0.03375%    | 1913.141   | 0.13933%    |
| 14    | 2169.057      | 0.00005%    | 2168.329   | 0.03556%    | 2166.146   | 0.13423%    |
| 15    | 1902.89       | 0.00004%    | 1902.338   | 0.02901%    | 1900.682   | 0.11606%    |
| 16    | 1416.748      | 0.00104%    | 1416.166   | 0.04104%    | 1414.421   | 0.16420%    |
| 17    | 2887.539      | 0.00023%    | 2887.18    | 0.01245%    | 2886.101   | 0.04982%    |

Figure 2. Economic Loss and Inoperability due to China-U.S. Trade War in Scenario 2
Note: See Table 2 for Sector Index.

The scenario 2 (shown in Figure 2) begins to make a broader and deeper impact. Also intuitively, “Manufacture and Processing of Metals and Metal Products” sector and “Manufacture of Machinery and Equipment” sector bear the leading perturbation. Subsequently, “Mining” sector comes close behind just like the scenario 1 in
terms of inoperability, whereas “Chemical Industry” sector ranks ahead of “Mining” sector in terms of economic loss. It is because the output of “Chemical Industry” sector (2507.96 billion dollars) outstrips that of “Mining” sector (864.35 billion dollars). Therefore, to better understand what the impacts of the trade war will be and to facilitate effective management policy establishment, it is imperative to assess both economic loss and inoperability. In this scenario, China would suffer a total economic loss of 18.13 billion dollars and an average inoperability of 0.0456% for each sector. It can be seen from Figure 2 that the inoperability of four sectors exceeded the mean value significantly and seven sectors exceeded the median value significantly. As for economic loss, three sectors exceeded the mean value significantly and four sectors exceeded the median value significantly. These results contribute to strategic decisions on proactive investments to mitigate impact of China-U.S. trade war.

The scenario 3 leads to similar outcomes as the scenario 2, but the impact (both economic loss and inoperability) is four times what it is in the scenario 2. We can see that the economic loss of “Manufacture of Machinery and Equipment” sector and “Manufacture and Processing of Metals and Metal Products” sector is up to 31.83 and 11.06 billion dollars. In this scenario, China would suffer a total economic loss of 72.54 billion dollars and an average inoperability of 0.1825% for each sector. For this worst-case scenario, industries in China will receive harsh damage and a series of consequences may happen in succession such as employment problem. Thus, relevant management measures should be taken to ease the tensions between China and the U.S. and to prevent the international trade situation getting worse.

**Figure 3.** Comparison of with/without considering the interdependencies (InterD) in Scenario 3

*Note: See Table 2 for Sector index.*
Table 7. Preliminary fitting results in PLS model

| CV  | (Intercept) | 1 component | 2 components | 3 components | 4 components |
|-----|-------------|-------------|--------------|--------------|--------------|
| RMSEP | 1.095 | 0.5619 | 0.3028 | 0.3306 | 0.3297 |

To shed some lights on the importance of considering the interdependencies among sectors, a contrastive illustration is shown in Figure 3. Without considering the interdependencies in scenario 3, the economic loss and inoperability of sectors bear the main shock are underestimated by 83.04% (Sector 8) and 46.99% (Sector 9) respectively. Besides, the propagating impact of China-U.S. on other sectors is ignored. In fact, there exists strong reciprocation among multiple sectors through supply chain. The comparison shows that including the interdependencies dramatically improves the estimation power of the IIM.

5.2. Partial Least Squares Regression (second stage). The cross-validation /jack-knifing procedure is conducted and the validation results here are Root Mean Squared Error of Prediction (RMSEP). That is to cross-validate the model with various number of factors, then choose the component number with minimum prediction error on the validation set. The RMSEP of the cross-validated predictions are shown as equation (16), where \( \text{cvp}_i \) and \( y_i \) are the prediction and actual data in the ith subset. That is to say, RMSEP is a measure of prediction error obtained by testing the ith subset with the PLSR model based on k-1 groups (suppose sample size is k). Table 7 lists preliminary fitting results in PLS model. According to CV results and the percentage of variance explained by latent variables, 2 components are set for PLS model.

\[
RMSEP = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\text{cvp}_i - y_i)^2},
\]  

As shown in Table 8, the useless or unreliable variables are eliminated from PLS model with appropriate significance (p < 0.1). This level is chosen as a relatively moderate and pragmatic requirement [28]. The remaining active X-variables are \( X_2, X_6, X_8 \) and \( X_9 \), i.e. the output value of “Mining” sector, “Chemical Industry” sector, “Manufacture and Processing of Metals and Metal Products” sector and “Manufacture of Machinery and Equipment” sector. Then in order to better explain the impact mechanism of trade war on the volume of containerized exports, these four active X-variables are put into next iteration, results shown in Table 9. The optimal number of components is determined as 1 likewise. Table 10 lists the jack-knifed test results when number of components is 1 in the second iteration.

We can see from Table 10 that all 4 variables are retained in the final PLSR model, which manifests that there is a significant correlation between output value of these four industries and the volume of containerized exports. The results above
Table 8. Jack-knifed test results when number of components is 2

| Variable | Coefficient | Std. Error | Df  | t value | Pr(>|t|) |
|----------|-------------|------------|-----|---------|----------|
| X1       | 0.022995    | 0.066024   | 5   | 0.3483  | 0.741817 |
| X2       | **0.275605**| **0.094744**| 5   | **2.9089**| **0.033441**|
| X3       | 0.032528    | 0.030684   | 5   | 1.0601  | 0.337592 |
| X4       | 0.162531    | 0.131415   | 5   | 1.2368  | 0.27109  |
| X5       | 0.174269    | 0.120794   | 5   | 1.4427  | 0.208691 |
| X6       | **0.053442**| **0.010296**| 5   | **5.1908**| **0.003494**|
| X7       | 0.071065    | 0.057688   | 5   | 1.2319  | 0.272759 |
| X8       | **0.183614**| **0.08237**| 5   | **2.2291**| **0.076248**|
| X9       | **0.160552**| **0.055204**| 5   | **2.9083**| **0.033464**|
| X10      | 0.122573    | 0.113811   | 5   | 1.077   | 0.330685 |
| X11      | 0.251876    | 0.140159   | 5   | 1.7971  | 0.132254 |
| X12      | -0.068757   | 0.053546   | 5   | -1.2841 | 0.255396 |
| X13      | 0.015483    | 0.064637   | 5   | 0.2395  | 0.820203 |
| X14      | -0.110264   | 0.057606   | 5   | -1.9141 | 0.113786 |
| X15      | -0.176734   | 0.135578   | 5   | -1.3036 | 0.249177 |
| X16      | -0.149952   | 0.102439   | 5   | -1.4638 | 0.203121 |
| X17      | -0.074279   | 0.040517   | 5   | -1.8333 | 0.126235 |

Signif. Codes: 0 '****' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1

are obtained from centered and normalized X and Y variables, so the final PLS model illustrating the pattern between initial X and Y variables are obtained below (equation (17)). The coefficients of the output value of “Mining” sector, “Chemical Industry” sector, “Manufacture and Processing of Metals and Metal Products” sector and “Manufacture of Machinery and Equipment” sector is 24.1224, 8.9991, 8.5403, 4.3317 respectively, with all coefficients positive. It is accordant with ordinary conception that higher output of industries contributes to larger volume of containerized exports.

\[
Y = 24753.038 + 24.122X_2 + 8.999X_6 + 8.540X_8 + 4.332X_9.
\]  

(17)

According to the output value prediction in each scenario (Table 6) and the final PLS model (equation (17)), we can answer the question to what extent the China-U.S. trade war will impact the volume of containerized exports. Table 11 presents the final forecasts on the annual volume of containerized exports reduction in each scenario. In the relatively severe China-U.S. trade war scenario, there is a reduction of 3, 88 and 352 thousand TEU respectively, which takes a percentage of 0.002%, 0.084% and 0.335% compared to the base volume of containerized exports in 2015. This result implies that even in the worst scenario (200 billion worth of commodities involved in the China-U.S. trade war subject to additional tariffs of 25 percent, i.e. Scenario 3), the reduction of containerized exports due to China-U.S. trade war is not significant. The average increment of 2644 thousand TEU in last five years could be mainly attributed to the growing prosperity in the Chinese economic situation and thriving propagation in international trade environment. Whereas, the China-U.S. trade war will hinder the harmony of trade environment and process and slash
Table 9. Preliminary fitting results in PLS model

| CV       | (Intercept) | 1 component | 2 components | 3 components | 4 components |
|----------|-------------|-------------|--------------|--------------|--------------|
|          | 1.095       | 0.4108      | 0.3903       | 0.5343       | 12.22        |

Table 10. Jack-knifed test results when number of components is 1

| Variance | Coefficient | Std. Error | Df | t value | Pr(>|t|)  |
|----------|-------------|------------|----|---------|----------|
| X2       | 0.245531**  | 0.072592   | 5  | 3.3823  | 0.019624 |
| X6       | 0.236153*** | 0.038451   | 5  | 6.1416  | 0.001663 |
| X8       | 0.244841*** | 0.052856   | 5  | 4.6322  | 0.005672 |
| X9       | 0.244020*** | 0.050796   | 5  | 4.8039  | 0.004867 |

Signif. Codes: 0 ‘****’ 0.001 ‘***’ 0.01 ‘**’ 0.05 ‘*’ 0.1 ‘ ’ 1

Table 11. Annual reduction of containerized exports due to China-U.S. trade war

| Scenario | Scenario1 | Scenario2 | Scenario3 |
|----------|-----------|-----------|-----------|
| Reduction (in 1000 TEU) | 3         | 88        | 352       |
| Reduction percentage    | 0.002%    | 0.084%    | 0.335%    |

the increment of containerized exports by 13.31% in the worst scenario (compared with the average increment of 2644 thousand TEU).

6. Conclusion. IIM scenario studies have been conducted to analyze the impacts of U.S. tariffs on plentiful commodities imported from China embraced in two industries (“Manufacture and Processing of Metals and Metal Products” sector and “Manufacture of Machinery and Equipment” sector). Sensitivity analysis of trade war scenarios are achieved by considering various sources of uncertainties relating to (1) tariff level, (2) total value of goods taxed, (3) sector involved in the trade war. For each China-U.S. trade war scenario, IIM metrics have been quantified (economic loss and inoperability) to determine the top 10 most impacted sectors. The proposed hierarchic IIM-PLSR framework is useful for analyzing the propagating impacts of trade war scenarios (and other catastrophe or attack scenarios) on the volume of containerized exports. Three implications are drawn according to our study results.

1) The China-U.S. trade war will affect the operability and output value of not only the tariff-targeted industries but the other interdependent industries. Consider
the most severe case, Scenario 3 with a 25% tariff, the top 5 affected industries in terms of inoperability are “Manufacture of Machinery and Equipment”, “Manufacture and Processing of Metals and Metal Products”, “Mining”, “Production and Supply of Electric Power, Heat Power and Water” and “Chemical Industry” sector. In terms of the economic loss, the top 5 industries are “Manufacture of Machinery and Equipment”, “Manufacture and Processing of Metals and Metal Products”, “Chemical Industry”, “Mining” and “Wholesale and Retail Trades, Hotels and Catering Services” sector, with a total loss of 72.536 billion dollars.

2) There is a strong correlation between four industries’ output value and the volume of containerized exports. These four industries are “Mining”, “Chemical Industry”, “Manufacture and Processing of Metals and Metal Products” and “Manufacture of Machinery and Equipment” sector, with coefficients in PLS model as 24.1224, 8.9991, 8.5403, 4.3317 respectively. The positive coefficients imply that higher output of these four industries contributes to larger volume of containerized exports. The inoperability and correlation relationship obtained from the proposed IIM-PLSR framework enables decisionmakers of Chinese government to easily identify the most critical sectors under multifold scenarios. Some suggestions about the risk management for critical sectors: (1) increment of supply chain flexibility, such as supplier and customer diversification; (2) inventory management, such as planning and optimization for delivery cycle; (3) risk mitigation, such as proactive measures to increase or decrease infrastructure investments.

3) The China-U.S. Trade War have an insignificant influence on the volume of containerized exports. The prediction results show that even in the worst scenario (200 billion worth of commodities involved in the China-U.S. trade war subject to additional tariffs of 25 percent, i.e. Scenario3), the reduction percentage of containerized exports due to China-U.S. trade war is only 0.335%. Albeit this, it is necessary for logistics companies to actively respond to the trend in international trade. These trends will shape the future competition in the international shipping industry. The shipping lines that respond to the trend effectively and successfully will create new opportunities to generate extra business value and profits.

We develop a hierarchic framework in this paper and calculate potential inoperability and output value step-down across economic sectors in China due to the China-U.S. trade war, and thus obtain a national view of the potential impact of the container shipping, which makes sense in a national level plan. This paper has addressed the potential implications of port and shipping developments in China on the future state of containerized exports in the aftermath of the China-U.S. trade war. On the one hand, given the impact obtained from this paper, the policymakers of Chinese government could reevaluate the logistics performance to determine a scientific strategy. According to Özceylan et al. [38], indicators from three aspects could be utilized to enable the evaluation, including Freight Transactions Factors (e.g. total freight transported by maritime), Transportation Capability Factors (e.g. proximity of ports to province center), Economic & Infrastructure Factors (e.g. export value). On the other hand, this would provide port system administrators and container terminal operators with new insights as to policy formulation and making strategic decisions. Proactive response measures could be utilized based on the containerized export estimation, such as optimization models for container truck paths and empty container management.
Acknowledgments. This research was supported in National Natural Science Foundation of China (7190137008 and U1811463), National Key Research and Development Project (2020YFE0201200) and this work is partially funded by Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University. The authors would also like to thank Bin Yu for the data which was attained during his doctoral research of Civil Engineering Department, Dalian University of Technology.

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