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Heterogeneous Impact of Non-Tariff Measures through the Global Value Chains: Empirical Evidence from China

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Abstract

Over the last decades, the rising fragmentation of the production process across countries has been an increasingly key trend in international trade. On the other hand, technical standards and regulations in international trade are considered to have a potential effect on the organization and structure of the global value chains (GVC). By using firm-level customs data, manufacturing census data, and China's Input-Output Tables, this paper investigates the impact of non-tariff measure (NTM)'s stringency on Chinese firms' positioning in the GVC, which is measured by two types of GVC positioning indices, namely, output upstreamness and input downstreamness indices. We then estimate the impact of NTMs on various firm performance by paying special attention to how the impacts vary across firms with different positioning in the GVC. The empirical results show that NTMs imposed against and imposed by China could significantly reduce firms' linkages with foreign countries, thereby reducing the firms' importance within the GVC. We also find that stricter NTMs could even hinder firms' innovative activities and decrease exports and imports. Further analysis indicates that these negative impacts of NTMs on firms are heterogeneous across firms depending on their original position in the GVC; firms with higher output upstreamness or input downstreamness receive smaller effect than those with lower GVC positioning index.

JEL Classification: F14, F23, L11
Keywords: Global value chain, Non-tariff measure, Upstreamness, Downstreamness.

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1. Introduction

The rising fragmentation of production in the global value chain (GVC) has been an increasingly key trend in international trade and the division of labor in the GVC has been gradually replacing the traditional mode of division of labor. With the revolutionary breakthrough and cross-integration of information technology, new materials, new energy and other fields, the traditional world manufacturing development pattern has changed. That is, world production is now structured into global value chains. The regional decentralization of production led to the rise of intermediate goods trade (especially in the field of manufacturing), which promoted the transformation of the mode of production from “made in one country” to “made in the world”, and the mode of trade from “trade in goods” to “trade in tasks” (WTO & IDE-JETRO (2011)). Deeply involved in the division of global value chain, Chinese manufacturing industry has been rapidly developed. According to the World Input-Output Database (WIOD), China’s manufacturing industry has been growing at an average annual rate of 17.32% since 1995 the manufacturing output reached 175 billion US dollars in 2010, accounting for 14.10% of the world’s total manufacturing output.

Research on the positioning in the GVC has been made progress in recent years. In Antràs and Chor (2013), which pioneered this field, the upstreamness index of an industry was measured by the number of production stages, up to the final consumer of the industry. Similarly, Fally (2012) composed the GVC measure based on the concept that “if the product of the industry is used in an industry far from the final consumer in the value chain, the industry is located upstream”. Antràs et al. (2012) proved that Fally (2012)’s composition was identical with that of Antràs and Chor (2013). By using the upstreamness index, one can analyze the spillover effects of economic shocks in one country on the economy of another. For example, if a major industry in a country is located upstream in the GVC, production and exports in that country will be more susceptible to demand shocks in countries located downstream of GVC. Therefore, in order to consider the impact of these external economic shocks on the country’s economy, it is important to understand which country is located downstream of the country in the GVC of the country. In addition, it is important to compare the positioning of each country in the GVC with the benefits obtained from the trade in that country in examining the competitiveness of the industry at the national level.

On the other hand, in the past decade, while import tariff increases have been constrained by multilateral and regional trade agreements, non-tariff measures (NTMs) have spread in the world, certainly in those developing countries such as China. The imposition of NTMs can raise the variable costs of producing the exported goods: technical standards require upgrading or at least adaptation of products or packaging, and varying standards across destinations reduce opportunities for economies of scale. However, this additional cost may also become a fixed cost thereby discouraging intermediate suppliers from serving markets with stricter NTMs. Taking China as an example, since Chinese firms have been playing a leading role in the world processing trade, the imposition of NTMs would have a significant effect on the trade pattern of Chinese firms: when the NTMs imposed against China by a foreign country are stricter than those of China, it is more difficult for the downstream firms in the foreign country to import intermediate inputs from Chinese suppliers. Also, stricter NTMs imposed by China will hinder the upstream suppliers in foreign countries export intermediate inputs to the Chinese buyers. The farther position in the GVC away from the Chinese market (i.e. the more upstream the supplier is or the more downstream the demander is from the point of view of Chinese firms), the more difficult to grasp the components subject to NTM regulations because the longer distance in the GVC indicates the more markets with different environment of NTMs are held between China and the traders, in other words, the harder for one to foresee the net effect of NTMs. What makes the question more complex is that even facing the same environment of NTMs, the effect of NTMs on firms would vary across depending on firms' positioning in the GVC. For a specific firm, while it can choose to export and import different types and different amount of goods to foreign countries so that each firm may have a unique positioning in the GVC, it is the government who decide what type and how strict of the NTMs to impose. Under this situation, firms facing the same type and the same stringency of NTMs will receive different impact if they have different compositions and values of export or import.

This paper aims to shed light on whether the stringency of NTMs would have a latent effect on firms' role in the GVC. By using firm-level customs data, manufacturing census data, and China's Input-Output Tables, this paper investigates the impact of NTM on Chinese firms' positioning in the GVC, which is measured by two types of GVC positioning indices, namely, output upstreamness and input downstreamness indices. We then estimate the impact of NTMs on various firm performance by paying particular attention to how the impacts vary across firms with different positioning in the GVC. The empirical results show that NTMs imposed against and imposed by China could significantly reduce firms' linkages with foreign countries so that decrease firms' importance within the GVC. We also find that stricter NTMs could even hinder firms' innovative activities and decrease exports and imports of Chinese firms. Further analysis indicates that these negative impacts of NTMs on firms are heterogeneous across firms depending on their original position in the GVC; firms with higher output upstreamness or input downstreamness receive smaller effect than those with lower GVC positioning index.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the background. Section 3 presents the estimation models and the data used. Section 4 provides the estimation results and discussion. Section 5 concludes.

2. Background

2.1 NTM Regulations

During the past decades, there has been an increasing number of trade disputes related to NTMs. The rapid growth of NTMs has induced a large literature on their effects on trade and development, much of those has treated NTMs as pure trade barriers and advocated the removal for welfare improvement. While early studies warned about the dangers of marginalization of the poor with increasing standards, recent studies document mostly positive effects on household income, reduced risk and income variability, technology adoption and quality of produce (Beghin et al. (2015)). In order to understand the comprehensive effects of NTMs, it is important to know how they affect the organization and structure of value chains and in particular the endogeneity of vertical coordination.

Previous studies have provided different measures to reflect the changing environment in terms of NTMs. These measures include: (1) the price-wedge-ad valorem equivalent method, which measures the NTM regime by its impact on price; (2) inventory-based frequency and count measures, which simply counts the number or frequency of NTMs affecting a given market; (3) measures of stringency and heterogeneity across countries for SPS and standard-like NTMs regimes, using maximum residue limits and other policies that can be aggregated in a meaningful manner, and (4) measures of transparency and harmonization. The existing studies have applied these measures to analyze how the NTMs could affect trade focusing on various aspects. For example, Devadason et al. (2018) applied the same type of measures with this paper to examine the coverage, frequency, and diversity of NTMs for the food sector in Malaysia, and then estimates their impact on food imports from ASEAN.

Beghin et al. (2015) made a comprehensive review on the literatures on various effect of NTMs. The existing evidence from the studies investigating the effect of NTMs on welfare, trade, industrial organization and labor markets, is mixed in a sense that NTMs can promote or impede trade and economic growth, possibly reflecting their complex effects on industries and firms.

2.2 Global Value Chain

Research on the international competitiveness of manufacturing industry can be roughly divided into two categories according to different trade accounting systems: first, analysis of traditional trade index. Balassa (1965) proposed to use the revealed comparative advantage index to measure the international competitiveness of a country's industry. Since this approach ignored the import factor, later studies further proposed the trade competitiveness index, which measures the international competitiveness of a country's industry by the proportion of the net trade of a country's industry to the total trade. The second category is the value-added trade index analysis. Hummels et al. (2001) proposed that vertical specialization index (including forward and backward vertical specialization index) can be used to measure the division of labor position of a country's industry in the GVC. Koopman et al. (2010) put forward the GVC Participation index and GVC positioning index to measure the division of labor position of a country's industry in the global value chain[1], which has been developed by Wang et al. (2017) in which proposed a pair of GVC participation indices that improves upon the measures in the existing literature. Antràs & Chors (2013) estimated the average position of a country's industry in the GVC by constructing industry upstreamness and downstreamness index on the basis of the US input and output table.

Recent studies have developed various theoretical frameworks, emphasizing the operation and influence of the rise of the GVC on the general equilibrium model of international trade. These measures envision a world in which production in the GVC features some element of sequentiality, among them is the term "snakes" given by Baldwin and Venables (2013) to refer to purely sequential value chains, in which each production stage obtains its inputs from a unique upstream stage. The other term of "spiders" they introduced described a flatter GVC in which each production stage sources from several upstream suppliers simultaneously. The measures of GVC positioning we employed in this paper are defined in a general way such that they can be computed for production processes that have both "snake" and "spider" type features.

2.3 Chinese Manufacturing Firms

Since its accession to the WTO in 2001, China's export growth has been remarkable. According to the WTO's statistics, the China's share in world exports grew from 3.3% in 1997 to 8.7% in 2007, and the China's share in total world trade in manufactured goods jumped from 4.7% in 2000 to 12% in 2007, making the country now the largest exporter in the world today. China's development has been inducing scholars to carry out a large number of empirical studies on productivity, international trade and other aspects. Shi (2011) indicates that China's export growth is mainly driven by quantity growth, that is the growth in intensive margin, which accounts for about 70% of overall export growth. Previous studies also found that export was beneficial for

[1] Studies related to the GVC participation index who referred to Koopman et al. (2010) include, for example, Sun et al. (2019). Sun et al. (2019) evaluated the carbon efficiency and the GVC position index and further analyzed the impact of position of manufacturing in GVC on carbon efficiency using the panel data of 60 countries from 2000 to 2011.

firms to improve their productivity, suggesting that there was a “learning effect” of export. Brandt et al. (2012) supported the growth of productivity, in which they found that the average annual productivity growth of Chinese manufacturing firms for incumbents is 2.85% for a gross output production function and 7.96% for a value-added production function over 1998-2007, which is among the highest compared to other countries. Regarding the role in the GVC, China consistently occupies the most upstream (resp. downstream) position along the global output supply (resp. input demand) chain, mainly due to a large share of manufacturing industry’s output in its gross output (Miller and Temurshoev (2017)). While the value-added export scale of China's manufacturing industry has achieved significant growth during the recent years, its export was dominated by low-tech manufacturing industry and it was not until recent years that has shifted to the medium- and high-tech manufacturing industry.

During the process of empirical analysis, some China’s databases have been frequently employed, among those is the Annual Survey of Industrial Firms (ASIF) database. As a database collected by the National Bureau of Statistics of China, the ASIF database has the advantages of large sample size, numerous indicators and long time series. The ASIF database has been applied to topic related to the spill-over effect of foreign direct investment (FDI). Xu and Sheng (2012) examined the spillover effects on Chinese domestic manufacturing firms and found evidence of positive spillovers arise from forward linkages where domestic firms purchase high-quality intermediate goods or equipment from foreign firms in the upstream sectors. Lu et al. (2017) then improved on the strategy to identify the spillover effect of horizontal FDI.

Some studies further examined topics related to value-added exports by combining the ASIF database with the database of the Chinese Customs Trade Statistics (CCTS). Kee and Tang (2016) provided micro-level evidence of China’s rising ratio of domestic value added in exports to gross exports. Upward et al. (2013) provided an assessment of the Chinese export boom from 2000 to 2007. They tried to measure the share of domestic value-added in China’s manufacturing exports by using a modification of a method proposed by Hummels et al. (2001) which takes into account the prevalence of processing firms, and further measured the skill-and technology-intensity of the firms which produce those exports. Lu et al. (2018) calculated the foreign value-added ratio to measure the GVC participation of Chinese exporting firms from 2000 to 2006. They found that productivity increased foreign value-added ratio, and that the rise in productivity led to an increase in foreign value-added ratio for both first-time and continuous exporters, while financial constraints only significantly affect first-time exporters.

3. Data and Methodology

3.1 GVC Positioning Index

In this paper, we employ measures of GVC positioning introduced in Antràs and Chor (2018), whose framework referred to Miller and Temurshoev (2017), Fally (2012) and Antràs and Chor (2013). We employed the WIOD database for the 2000-2014 period[2 3] to calculated the GVC positioning index. The WIOD database is built on national accounts data that were developed within the Seventh Framework Program of the European Commission. Using the input-output table from the WIOD, one can devise measures of the extent to which a particular industry in China is relatively upstream or downstream in the GVC. The following Figure 1 is prepared based on a schematic version of an input-output table from the WIOD. This figure covers the economy of the whole world with *J* countries (indexed by *i* or *j*) and *S* industries (indexed by *r* or *s*). Typically, the WIOD database covers 28 EU countries, 15 other major countries in the world and 56 industries based on the NACE (Nomenclature of Economic Activities) Rev. 1 classification for each country. In its top left $J \times S$ by $J \times S$ block, the table contains information on intermediate purchases by industry s in country j from industry r in country i (denoted by Z_{ij}^{rs}). The right of this block on the table contains an additional $J \times S$ by J block with information on the final-use expenditure in each country j on goods originating from industry r in country i (denoted by F_{ij}^{r}). The last row of Figure 1 shows that gross output in that industry and country (denoted by Y_i^r) equals to the sum of all intermediate purchases made from source industries r in countries i and F_{ij}^{r}. That is, we can define Y_i^r as:

$$Y_i^r = \sum_{s=1}^{S}\sum_{j=1}^{J} Z_{ij}^{rs} + \sum_{s=1}^{S} F_{ij}^{r} = \sum_{s=1}^{S}\sum_{j=1}^{J} Z_{ij}^{rs} + F_i^r. \quad (1)$$

Here, we denote the total final use of output originating from industry r in country i by $F_i^r = \sum_{j=1}^{J} F_{ij}^{r}$.

In the same way, gross output in industry s in country j (denoted by Y_j^s) also equals to the sum of (1) all intermediate purchases made from source industries r in countries i and (2) country j's value-added employed in the production of industry s itself (denoted by VA_j^s). That is, Y_j^s can be defined as:

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[2] The WIOD Input-output database is documented in Timmer et al. (2015) and is available at < http://www.wiod.org>. In this paper, we utilize the World IO Tables released in 2016. For a detailed description of the database construction, see Timmer et al. (2016).

[3] A global IO table has also been developed by the Institute of Developing Economies-Japan External Trade Organization (IDE-JETRO). Although the IDE-JETRO international IO table covers other Southeast Asian countries, including Thailand, and is available from 1985, it is only available at five year intervals (2005 is the latest year available). Its industry classification is less detailed (covering 24-26 industries) than that of the WIOD (which covers 56 industries) and is not harmonized throughout the period. Consequently, this paper utilizes the WIOD.

$$Y_j^s = \sum_{s=1}^{S} \sum_{j=1}^{J} Z_{ij}^{rs} + VA_j^s. \quad (2)$$

The WIOD database contains information on linkages in a full production network of the world, where each country-industry could potentially be traversed in a large number of production chains. Based on this setting, the measures of GVC positioning described below will seek to capture the average position of each country-industry in the production chains in which it is involved. Although our further goal is to convert the industry-level measures into the firm-level using the micro data from China, the world's input-output table is necessary for us to capture the linkages of China with the world. Thus, we need to derive the GVC positioning measures of all countries and then extract those of Chinese industires for further calculation.

Figure 1. The Structure of the WIOD's Input-output Table

			Input use & value added							**Final use**			**Total use**
			Country 1			…	Country J			Country 1	…	Country J	
			Industry 1	…	Industry S	…	Industry 1	…	Industry S				
Intermediate inuts supplied	Country 1	Industry 1	Z_{11}^{11}		Z_{11}^{1S}	…	Z_{1J}^{11}	…	Z_{1J}^{1S}	F_{11}^{1}	…	F_{1J}^{1}	Y_1^1
		…	…	Z_{11}^{rs}	…	…	…	Z_{1J}^{rs}			…	…	…
		Industry S	Z_{11}^{S1}	…	Z_{11}^{SS}	…	Z_{1J}^{S1}	…	Z_{1J}^{SS}	F_{11}^{S}	…	F_{1J}^{S}	Y_1^S
	…	…	…	…	…	Z_{ij}^{rs}	…	…	…	…	F_{ij}^{r}	…	Y_i^r
	Country J	Industry 1	Z_{J1}^{11}	…	Z_{J1}^{1S}	…	Z_{JJ}^{11}	…	Z_{JJ}^{1S}	F_{J1}^{1}	…	F_{JJ}^{1}	Y_J^1
		…	…	Z_{J1}^{rs}	…	…	…	Z_{JJ}^{rs}	…	…	…	…	…
		Industry S	Z_{J1}^{S1}	…	Z_{J1}^{SS}	…	Z_{JJ}^{S1}	…	Z_{JJ}^{SS}	F_{J1}^{S}	…	F_{JJ}^{S}	Y_J^S
Value added			VA_1^1	…	VA_1^S	VA_j^s	VA_J^1	…	VA_J^S				
Gross output			Y_1^1	…	Y_1^S	Y_j^s	Y_J^1	…	Y_J^S				

Source: Figure. 1 of Antràs and Chor (2018), which referred to the WIOD database.

3.1.1 Output Upstreamness Index

The GVC positioning measures are based on the idea that an industry that sells disproportionately to final consumers would appear to be downstream in the GVC, while an industry that sells little to final consumers is more likely to be upstream in the GVC. Invoking equation (1), we first define $a_{ij}^{rs} = Z_{ij}^{rs}/Y_j^s$ as the dollar amount of industry *r*'s output from country *i* needed to produce one dollar worth of industry s's output in country *j*. With this notation, equation (1) can be rewritten as:

$$Y_i^r = \sum_{s=1}^{S} \sum_{j=1}^{J} a_{ij}^{rs} Y_j^s + F_i^r. \quad (3)$$

Iterating this identity, we can express industry *r*'s output in country *i* as an infinite sequence of terms which reflect the use of this country-industry's output at different positions in the GVC, which can be expressed as the following equation:

$$Y_i^r = F_i^r + \sum_{s=1}^{S} \sum_{j=1}^{J} a_{ij}^{rs} F_j^s + \sum_{s=1}^{S} \sum_{j=1}^{J} \sum_{t=1}^{S} \sum_{k=1}^{J} a_{ij}^{rs} a_{jk}^{st} F_k^t + \cdots. \quad (4)$$

Building on this identity, Antràs and Chor (2013) suggested to calculate the (weighted) average position of a country-industry's output in global value chains by multiplying each of the terms in

(4) by its respective production-staging distance from final use plus one, and dividing by Y_i^r, or we can derive the Output Upstreamness for industry *r* of country *i* (OU_i^r) index as:

$$OU_i^r = 1 \cdot \frac{F_i^r}{Y_i^r} + 2 \cdot \frac{\sum_{s=1}^{S}\sum_{j=1}^{J} a_{ij}^{rs} F_j^s}{Y_i^r} + 3 \cdot \frac{\sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{t=1}^{S}\sum_{k=1}^{J} a_{ij}^{rs} a_{jk}^{st} F_k^t}{Y_i^r} + \cdots. \quad (5)$$

One can easily see that $OU_i^r \geq 1$, and that larger values are associated with relatively higher levels of upstreamness of the output originating from industry *r* in country *i*.

The *OU* index is identical to industries' total forward linkages in terms of gross output. Industries that have a high total forward linkage supply a significant part of their output as intermediate inputs to other industries, and that is precisely what places industries in an upstream position in the output supply chain with respect to many industries buying inputs from that industry.

3.1.2 Input Downstream Index

Based on the identity in 3.1.1, we now turn to the direction of the downstreamness measure from the perspective of a country-industry pair's use of intermediate inputs and primary factors of production. The downstreamness index is defined based on the idea that other things equal, it seems plausible that production processes that embody a larger amount of intermediate inputs relative to their use of primary factors of production will be relatively downstream in value chains. By defining $b_{ij}^{rs} = Z_{ij}^{rs}/Y_i^r$ as the share of industry *r*'s output in country *i* that is used in industry *s* in country *j*, equation (2) can be rewritten as:

$$Y_j^s = \sum_{r=1}^{S}\sum_{i=1}^{J} b_{ij}^{rs} Y_i^r + VA_j^s. \quad (6)$$

Iterating the identity in Eq. (4), we have:

$$Y_j^s = VA_j^s + \sum_{r=1}^{S}\sum_{i=1}^{J} b_{ij}^{rs} VA_i^r + \sum_{r=1}^{S}\sum_{i=1}^{J}\sum_{t=1}^{S}\sum_{k=1}^{J} b_{ki}^{tr} b_{ij}^{rs} VA_k^t + \cdots. \quad (7)$$

With reference to Antràs and Chor (2013), we define the Input Downstreamness (ID_j^s) index for industry *s* of country *j*, which captures a given country-industry pair from primary factors of production as:

$$ID_j^s = 1 \cdot \frac{VA_j^s}{Y_j^s} + 2 \cdot \frac{\sum_{r=1}^{S}\sum_{i=1}^{J} b_{ij}^{rs} VA_i^r}{Y_j^s} + 3 \cdot \frac{\sum_{r=1}^{S}\sum_{i=1}^{J}\sum_{t=1}^{S}\sum_{k=1}^{J} b_{ki}^{tr} b_{ij}^{rs} VA_k^t}{Y_j^s} + \cdots. \quad (8)$$

ID_j^s measures are identical to the total backward linkage expressed in terms of gross output. Contrary to OU_i^r, industries that have a high total backward linkage purchase a significant part of their inputs in the form of intermediate inputs from other industries that are located more upstream than them, and this kind of purchase places industries that have a high total backward linkage in a downstream position in the input demand chain with respect to many other suppliers exporting inputs to these industries.

3.1.3 Convert Industry-level GVC Positioning Index to Firm-level Ones

After deriving the industry-level *OU* and *ID* indices, next we move on to converting these indices into firm-level indices based on Chor et al. (2014). The upstreamness of firm *f*'s exports (OU_{ft}^{X}) and its imports (OU_{ft}^{M}) are computed as:

$$OU_{ft}^{X} = \sum_{r=1}^{N} \frac{X_{frt}}{X_{ft}} OU_{i}^{r}, \quad OU_{ft}^{M} = \sum_{r=1}^{N} \frac{M_{frt}}{M_{ft}} OU_{i}^{r}. \ (9)$$

Here, $X_{ft} = \sum_{r=1}^{N} X_{frt}$ and $M_{ft} = \sum_{r=1}^{N} M_{frt}$ are respectively the total exports and imports within industry *r* of firm *f*, respectively. In other words, Chor et al. (2014) took a weighted average of the upstreamness across industries, using the export shares (respectively, import shares) of each industry to capture the importance of that industry in firm *f*'s export (respectively, import) mix. For example, when one observes changes in say the export upstreamness of a particular firm, these stem from changes in the underlying composition of its exports as reflected by the set of export shares, i.e. $\frac{X_{frt}}{X_{ft}}$.

Based on the same theory, the downstreamness of firm *f*'s exports (ID_{ft}^{X}) and its imports (ID_{ft}^{M}) are defined as:

$$ID_{ft}^{X} = \sum_{s=1}^{N} \frac{X_{fst}}{X_{ft}} ID_{j}^{s}, \quad ID_{ft}^{M} = \sum_{s=1}^{N} \frac{M_{fst}}{M_{ft}} ID_{j}^{s}. \ (10)$$

Here, $X_{ft} = \sum_{s=1}^{N} X_{fst}$ and $M_{ft} = \sum_{s=1}^{N} M_{fst}$ are respectively the total exports and imports within industry *s* of firm *f*.

As discussed in Miller and Temurshoev (2017), *OU* and *ID* are expected to be strongly positively correlated[4]. The observed positive correlation indicates that an industry that is close to (resp. far away from) final uses as final *ou*tput users turns out to be, on average, also close to (resp. far away from) final uses as suppliers of primary inputs.

Table 1 (corresponds to Table 1 of Miller and Temurshoev (2017)) gives the interpretation of the values of *OU* and *ID* measures. For example, an industry with larger OU should have (i) a larger share of intermediate output in its gross output; (ii) intermediates output supply links that are stronger and more highly interconnected with industries that have the same two characteristics. Eq. (5) fully captures the complexity and size of industry *i*'s entire output supply network.

[4] According to Miller and Temurshoev (2017), the corresponding correlations for each year range between (0.36, 0.43), while the overall correlation coefficient for all pairwise observations is 0.40. As for this paper, the correlation coefficient for all pairwise observation is 0.28 in terms of exports and 0.17 in terms of imports.

Table 1. The Interpretations of OU and ID Index

	OU measure	ID measure
Large	(a) Large (small) share of intermediate output (final demand) in gross output (b) Strong intermediate output supply links with similar industries	(a) Large (small) share of intermediate input (value added) in gross input (b) Strong intermediate input demand links with similar industries
Small	(a) Small (large) share of intermediate output (final demand) in gross output (b) Weak intermediate output supply links with similar industries	(a) Small (large) share of intermediate input (value added) in gross input (b) Weak intermediate input demand links with similar industries

3.2 Coverage Ratio / Frequency Index

To measure the regulatory intensity of NTM incidence, we employ the import coverage ratio[5] (*CR*) and the frequency ratio (*FI*) for the products covered by NTMs with respect to China's export and import. The coverage ratio of each industry *s* in year *t* are then calculated as the export or import shares of product items covered by NTMs in the product group category. The *CR* (and *FI*) reflects the relative value (number of transactions) of affected export/import, varies between 0% (no coverage) and 100% (all products covered), and is expressed as follows:

$$CR_{st} = \left[\frac{\sum D_{mt}V_{mt}}{\sum V_{mt}}\right], \quad (11)$$

where *s* denotes the industry, *m* denotes the product category of the HS6-digit level, D_{mt} is a dummy variable for the product *m* with NTM in year *t* (1 if there is an NTM measure and 0 otherwise), and V_{mt} is China's exports/imports of product item *m* in year *t*, and

$$FI_{st} = \left[\frac{\sum D_{mt}M_{mt}}{\sum M_{mt}}\right], \quad (12)$$

where M_{mt} is a dummy variable that is equal to 1 if there is an export/import of product *m* in year *t* and 0 otherwise.

These measures can provide a useful indication of the stringency and frequency of NTMs imposed on Chinese firms' export and imposed by China against the imports to China. However, they do not indicate the deterrent effect that NTMs may have on exporters' pricing and exporting decisions. As for the dataset, we employ the UNCTAD TRAINS database[6]. This database covers NTMs imposed/affecting specific country during 2000-2018. They are based on the classification

[5] The coverage ratio and the frequency index only indicates the extent of NTM coverage on export and import. It does not take specific effect of some NTM into consideration. That is, although the stringency and impact of NTMs may vary, the coverage ratio and frequency index only consider the number of NTMs.
[6] The database is available at < https://trains.unctad.org>.

of import measures by UNCTAD (2013), which includes 15 chapters, comprising technical and nontechnical measures. The UNCTAD TRAINS database contains information on the effectively applied non-tariff measures at HS 2-digit, 4-digit, 6-digit, 8-digit and 10-digit product aggregations. However, to be consistent with the CCTS database described later, we first unified the HS codes to 6-digit ones. To derive the industry-level NTM stringency indices, we then need to allocate the HS 6-digit NTM regulation information to industries that are based on NACE Rev.1 classification. Finally, we have the industry-year specific databases covering the period 2000-2014 which include all the industry-year combinations with non-missing information on input-output and NTM imposition.

3.3 Data

3.3.1 Industry-level Input-output Data and NTM Data

As mentioned at the previous section, we employ the WIOD database for the industry-level input-output table. The WIOD provides panel information on the global Input-output tables for the 27 EU countries, 13 other major countries and the rest of the world (ROW)[7]. These tables are constructed on the basis of the officially published input-output tables, in conjunction with the national accounts and international trade statistics. Table A1 shows the codes and the descriptions of all the contained industries.

As for NTM regulations, the UNCTAD TRAINS database includes 15 chapters, comprising technical and nontechnical measures. One limitation is that UNCTAD database only provides cross-sectional information on NTMs in force at the time of data collection (data on China is collected in 2016), indicating that NTMs those issued and then revoked before 2016 are not captured. Fortunately, information on the effective date of each NTM is available, so even though it might be a strong assumption given China has been going through substantial reform following WTO accession, we can convert the cross-sectional data into a panel one that covers our sample period by ignoring the revoked NTMs. Tables 2 and 3 respectively show the calculated coverage ratio and frequency index of NTMs related to exports (i.e. NTMs imposed against China) and NTMs related to imports (i.e. NTMs imposed by China) during the sample period. We can confirm that for all industries, the stringency of NTMs imposed against China is significantly higher than that of NTMs imposed by China. Further, the stringency of NTM regulations also vary across industries. Another fact is that, industries with higher coverage ratio also have relatively higher frequency index values with some exceptions such as industry number C29 (i.e. manufacture of

[7] The 13 countries include non-EU OECD member countries, including Japan and the US, and emerging economies including China, Indonesia and Mexico. The detailed list for countries is given by Table A2.

machinery and equipment), whose coverage ratio (=62.3%) is about twice higher than its frequency index (=30.3%) than that of imports.

Table 2. Coverage Ratio and Frequency Index of NTMs Imposed against Each Chinese Industry

	Coverage Ratio			Frequency Index		
	N	mean	sd	N	mean	sd
A01	10,368	0.942	0.0298	10,368	0.935	0.0327
A02	277	0.909	0.173	277	0.703	0.0883
A03	3,075	0.759	0.185	3,075	0.956	0.0284
B	2,796	0.378	0.100	2,796	0.394	0.0943
C10-C12	11,179	0.937	0.0479	11,179	0.939	0.0249
C13-C15	79,182	0.721	0.256	79,182	0.627	0.277
C16	11,404	0.718	0.126	11,404	0.634	0.0793
C17	22,441	0.403	0.167	22,441	0.275	0.147
C18	7,839	0.260	0.183	7,839	0.229	0.126
C19	436	0.726	0.159	436	0.627	0.138
C20	23,138	0.735	0.0667	23,138	0.652	0.104
C21	2,190	0.889	0.175	2,190	0.943	0.0629
C22	50,125	0.744	0.104	50,125	0.440	0.0996
C23	159	0.509	0.297	159	0.471	0.144
C24	40,680	0.486	0.135	40,680	0.357	0.138
C25	20,359	0.367	0.126	20,359	0.245	0.0945
C26	79,956	0.645	0.150	79,956	0.639	0.148
C29	12,557	0.915	0.0397	12,557	0.833	0.0475
C30	667	0.947	0.0572	667	0.709	0.127
C31-C32	51,926	0.608	0.0895	51,926	0.395	0.0689

Source: Author’s calculations based on UNCTAD TRAINS and World Input-Output Database.

Table 3. Coverage Ratio and Frequency Index of NTMs Imposed by Each Chinese Industry

	Coverage Ratio			Frequency Index		
	N	mean	sd	N	mean	sd
A01	7,215	0.540	0.303	7,215	0.509	0.253
A02	1,191	0.443	0.456	1,191	0.244	0.180
A03	1,856	0.291	0.1000	1,856	0.564	0.177
B	8,347	0.169	0.262	8,347	0.0985	0.0926
C10-C12	5,479	0.360	0.165	5,479	0.469	0.319
C13-C15	62,135	0.335	0.303	62,135	0.320	0.321
C16	7,466	0.377	0.281	7,466	0.216	0.132
C17	56,301	0.0633	0.0517	56,301	0.0308	0.0182
C18	19,503	0.0477	0.125	19,503	0.0524	0.0764
C19	8,152	0.312	0.332	8,152	0.152	0.0909
C20	69,970	0.127	0.0649	69,970	0.141	0.0484
C21	1,041	0.698	0.280	1,041	0.420	0.189
C22	100,940	0.0735	0.0360	100,940	0.0749	0.0299
C23	1,943	0.0100	0.0173	1,943	0.0539	0.0712
C24	67,480	0.0543	0.0457	67,480	0.0568	0.0328
C25	45,516	0.0274	0.0221	45,516	0.0343	0.0352
C26	106,777	0.159	0.0971	106,777	0.146	0.0544
C29	9,073	0.623	0.191	9,073	0.303	0.157
C30	365	0.383	0.390	365	0.304	0.178
C31-C32	54,793	0.135	0.0610	54,793	0.109	0.0167

Source: Author's calculations based on UNCTAD TRAINS and World Input-Output Database.

3.3.2 Panel Data on Industrial Firms

With the industry-level trade and NTM data, we next convert them into firm-level. This study draws on two main sources of Chinese firm data. The first data used is from the Annual Survey of Industrial Firms (ASIF) which is conducted by the National Bureau of Statistics of China for the 2001-2007 period[8]. These surveys cover all of state-owned enterprises (SOEs) and non-SOEs with annual sales over 5 million Chinese yuan. As the first two columns of Table 4 show, from 2001 to 2007, the database includes more than 1.7 million observations, and the sample size of each year increases from about 169,000 in 2001 to about 337,000 in 2007. While about 550,000 firms made the list in the seven-year sample period, only 46,000 firms (accounting for about 8%) appeared on the list for more than two consecutive years due to various reasons such as bankrupt, restructuring and reorganization. The number of firms covered in the surveys varies from approximately 162,000 to 270,000. Though the exact number varies across years, the data set of each year has more than 100 variables, which providing the basic information for each surveyed firm, including the firm's identification number, location code, industry affiliation, ownership structure, and the financial and

[8] To be exact, the ASIF database after 2008 is also available. Most literatures only use the data collected from 2000-2007, because there is a significant change in statistical methods and dimensions for data collected after 2008 and there is also criticism of the data reliability. Refer to Hsieh and Klenow (2009) and Chen (2018) for details.

operational information extracted from accounting statements, such as sales, employment, R&D expenditure, fixed assets, and total wage bill.

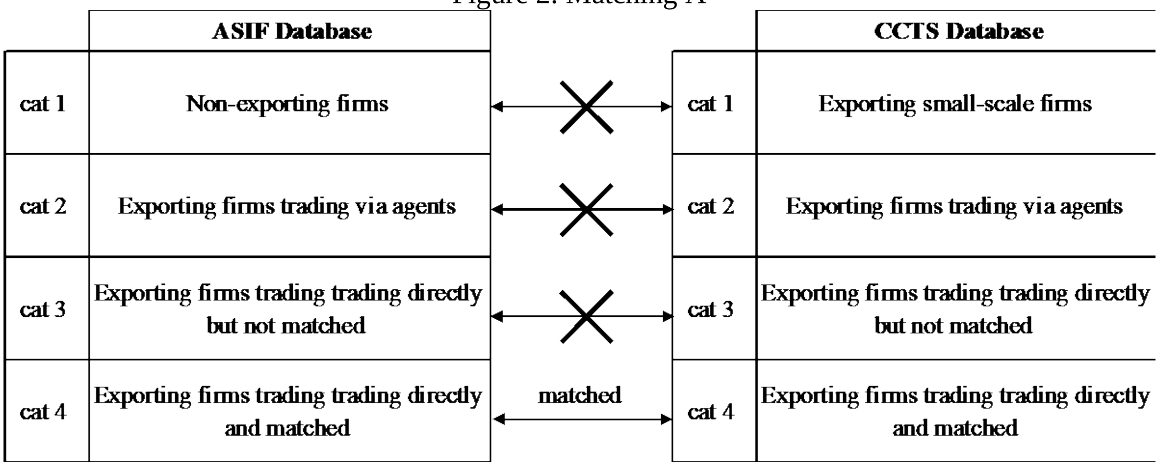
3.3.3 Firm-level Data on Trade

The second data source is the database of the Chinese Customs Trade Statistics (CCTS) collected by the General Administration of Customs of China. The CCTS database covers monthly records of all merchandise transactions passing through Chinese customs from 2001 to 2013, including firm identification (name, address, ownership), HS product code, value of imports and exports, quantity of goods, customs regimes, means of transportation, customs code, origin, and destination country. We collapse the data to annual data to make it consistent with the firm-level ASIF data. The product codes of traded goods are HS8-digit codes and we convert them to HS6-digit ones. The export and import values are reported as free-on-board (FOB) values in US dollars. Table 4 gives the observed number of Chinese firms who had export and import records during 2001-2007. From the middle two columns, we can see that the number of exporting firms kept increasing from about 67,000 in 2001 to about 177,000 in 2007 so that comes to an aggregated number of about 800,000 during the sample period. In terms of the importing firms, the number also consistently increased from about 66,000 to about 120,000 during the seven years. Both the increased number of Chinese exporting and importing firms implies that China has been enhancing the connection with the GVC since 2001, in which China just joined the WTO.

3.3.4 Matching Industrial Firm Data with the Trade Data

We matched the ASIF and CCTS data by firm name, because firm names are relatively more available and consistent over time compared with the other possible identifiers. The two data sets do not completely match for the following reasons. First, the ASIF data includes a large number of non-trade firms, which do not appear in the CCTS data. Second, firms who export via trading agents are reported as exporters in the ASIF data, but their exports will be recorded under the name of the trading agent in the CCTS data. Third, the ASIF data only includes larger firms in the manufacturing industry, while the CCTS data records all trade transactions including those made by small firms and firms outside the manufacturing industry. These inconsistencies are illustrated in Fig. 2. Table 5 respectively gives the sample size of the exporting and importing firms in the matched data for each year. For both exporting and importing firms, the annual number of observations slowly increased from less than 20,000 in 2001 to more than 50,000 for export and more than 32,000 for import in 2007. Totally, the number of exporting firms is slightly larger than that of importing firms, and the aggregated sample size of exporting firms is about 240,000 and that of importing firms is about 180,000.

Figure 2. Matching A



SIF and CCTS Database

Table 6 further gives information about the proportion of firms appear in the ASIF and CCTS databases which also appear in the matched ASIF-CCTS data. We can see that only less than 15% of firms in the ASIF database appear in the matched data, mainly because about one-quarter of firms that export to foreign countries. Though not listed in the table, only half of the exporting firms in the ASIF appear in the matched data. The most plausible explanation is that the remaining firms classified as exports in the ASIF data were actually exported via trading agents, just like the Cat 3 of Fig. 2 demonstrates. As for the percentage of firms appear in the CCTS data which also appear in the matched ASIF-CCTS data, the matched data contains less than 30% of all customs-registered firms. The proportion of firms in either the ASIF and the CCTS data which are in the matched data has not significantly changed during the sample period, and has kept relatively a flat and low level. One possible reason is that the cleaned CCTS data contains the population of all non-service trade, and therefore includes trade by small-scale firms whose annual sale are not high enough to be included in the ASIF data. Another explanation is that the cleaned CCTS data includes trade by the agricultural industry, which are excluded from the cleaned ASIF data.

Table 4. Sample Size of the ASIF and CCTS Database

	ASIF		CCTS			
			Export		Import	
	N	Percent	N	Percent	N	Percent
2001	168,958	9.7%	67,216	8.4%	65,925	10.3%
2002	181,488	10.5%	74,952	9.4%	73,111	11.4%
2003	196,152	11.3%	89,611	11.2%	81,813	12.7%
2004	278,991	16.1%	109,054	13.7%	91,982	14.3%
2005	271,766	15.7%	116,479	14.6%	90,529	14.1%
2006	301,877	17.4%	162,939	20.4%	119,446	18.6%
2007	336,665	19.4%	177,116	22.2%	119,201	18.6%
Total	1,735,897	100.0%	797,367	100.0%	642,007	100.0%

Table 5. Sample Size of the Matched ASIF-CCTS Dataset

	Export		Import	
	N	Percent	N	Percent
2001	18,534	7.6%	16,575	9.1%
2002	21,536	8.8%	18,635	10.2%
2003	25,440	10.4%	20,663	11.3%
2004	39,281	16.1%	30,490	16.7%
2005	40,400	16.6%	29,263	16.0%
2006	47,698	19.6%	33,903	18.6%
2007	50,564	20.8%	32,987	18.1%
Total	243,453	100.0%	182,516	100.0%

Table 6. Percentage of Firms in the ASIF and CCTS Database Which Appear in the Matched ASIF-CCTS Dataset

	ASIF		CCTS	
	Export	Import	Export	Import
2001	11.0%	9.8%	27.6%	25.1%
2002	11.9%	10.3%	28.7%	25.5%
2003	13.0%	10.5%	28.4%	25.3%
2004	14.1%	10.9%	36.0%	33.1%
2005	14.9%	10.8%	34.7%	32.3%
2006	15.8%	11.2%	29.3%	28.4%
2007	15.0%	9.8%	28.5%	27.7%
Average	14.0%	10.5%	30.5%	28.4%

3.4 Estimation Strategies

This paper aims to investigate the following two questions: (1) whether NTM imposed against (by) China may affect Chinese firm’s GVC positioning which is represented by our GVC positioning indices- *OU* and *ID*; (2) whether the effect of NTM imposed against (by) China may vary across firms that are located at different positioning in the GVC. We examine these questions separately in our analyses.

3.4.1 NTM Regulations and Firms' GVC Positioning

We first investigate the relationship between NTM regulations and firms' GVC positon with the with the following regression specification.

$$\{OU_{ft}^{X}, OU_{ft}^{M}, ID_{ft}^{X}, ID_{ft}^{M}\} = \alpha + \beta_t\{CR_{st}, FI_{st}\} + \gamma_t Year_t + \delta_t Z_{ft} + \varepsilon_{ft}. \quad (13)$$

The outcome variables of interest are the four indices of firms' positioning in the GVC: the average upstreamness of firms' exports (OU_{ft}^{X}), the average upstreamness of firms' imports (OU_{ft}^{M}), the average downstreamness of firms' export (ID_{ft}^{X}), and the average downstreamness of firms' import (ID_{ft}^{M}). These GVC positioning indices are calculated in firm-level. The explanatory variables include the coverage ratio (CR_{st}), the frequency index (FI_{st}) which is calculated in industry-level. The other explanatory variables are the year dummy ($Year_t$) and firm characteristics, Z_{ft}, which consist of firm *f*'s total stock, paid-up capital and ownership type. The error term, ε_{ft}, captures the correlated shocks within firm *f* over year *t*. During the estimation, all the continuous dependent and independent variables are converted to the logarithmic scale, so that the estimated coefficients can be interpreted into the NTM regulation elasticities of the GVC positioning.

In our matched ASIF-CCTS trade statistics, the sample comprises more than 430,000 exporter-industry-year observations with data on OU_{ft}^{X} and ID_{ft}^{X}, along with more than 635,000 importer-industry-year observations with data on OU_{ft}^{M}, and ID_{ft}^{M}. When we are to use information from firms' balance sheets for variables in Z_{ft}, the sample will significantly decline for both exporters and importers, which mainly because that the ASIF database is an unbalanced database. Importantly, this variation in sample sizes across specifications does not appear to generate estimation bias.

3.4.2 Transmission of NTM through GVC on Firm Performance

We then estimate how the NTMs affect firms' performance with the following specification.

$$Perf_{ft} = \varphi + \theta_t\{CR_{st}, FI_{st}\} + \delta_t\{CR_{st}, FI_{st}\} * \{OU_i^r, ID_i^r\} + \rho_t Year_t + \sigma_t Z_{ft} + \nu_{ft}. (14)$$

For the dependent variable, we choose variables reflecting firm's performance including total sale ($Sale_{ft}$), R&D expenditure ($R\&D_{ft}$), sale of new product ($NewPro_{ft}$), annual export amount (Exp_{ft}) and annual import amount (Imp_{ft}) at year *t*. The explanatory variables include the coverage ratio (CR_t), the frequency index (FI_t), the year dummy ($Year_t$) and firm characteristics, Z_{ft}. The variable set Z_{ft} includes firm *f*'s total stock, paid-up capital and ownership type, which is identical with those of Section 3.4.1. Similar with the first stage estimation, all the continuous dependent and independent variables are converted to the logarithmic scale. To capture the potential heterogeneity of the impact across different firms' positioning in the GVC, we additionally use the interaction term of the GVC index and the NTM regulation index. It should be noted that, because the firm-level *OU* and *ID* indices are related to the stringency of NTM regulations, CR_{st}, and FI_{st}, we cannot directly include them as explanatory variables due to the endogeneity problem. Thus, instead of the firm-level indices, here we use the industry-level ones, OU_i^r, ID_i^r, to generate the interaction term.

3.4.3 Descriptive Statistics

Table 7 shows the country-level descriptive statistics of the key variables in this paper -GVC positioning measures and NTMs stringency indices. Unlike the firm-level data, the country-level indices have a longer span of sample period which is from 2000 to 2014 for the GVC positioning indices and from 2001 to 2018 for the NTM variables. For the GVC positioning indices, we can see that the output upstreamness idex, *OU*, ranges between 2.6 and 3.0 during the sample period and the mean is 2.8. The input downstreamness index, *ID*, has a similar value range to *OU*, and has a slightly lower mean of 2.7[9]. For NTMs regulations, the coverage ratio and frequency index of NTMs imposed against China (i.e. *CR_Exp* and *FI_Exp*) are about three times higher than NTMs imposed by China (i.e. *CR_Imp* and *FI_Imp*), indicating that Chinese firms tend to be easier to purchase intermediates from foreign countries than to provide their goods as a supplier in the GVC.

Tables 8 gives summary statistics of the variables used in the empirical analysis. As mentioned above, the sample period for the firm-level estimation should be matched with that for the ASIF database as the ASIF database only provides reliable statistics during the 2001-2007 period. From the perspective of *OU* and *ID* indices, we can see that while the firm-level indices are not significantly changed from the country-level ones, the *ID* index has slightly increased from 2.7 to around 3.2 while the firm-level indices are not significantly changed from the country-level ones. This change indicates that Chinese firms had lost their total backward linkage to some extent after 2008, which is somewhat puzzling because China has been rapidly developing and because it has become one of the largest importers (and, of course, one of the largest exporters as well) during the past decade. One possible explanation would be that the frim-level *ID* lost its value because it takes account of the variation of firms' heterogeneous choice of export and import amount. As the firms-level *ID* index is calculated using the trade records of only the middle- and

[9] This result corresponds to Antràs and Chor (2018), in which employed the same database to obtain China's output uptreamness (equals to 2.819) and input downstreamness (equals to 2.900) at the year of 2011.

large-scale firms only, it would have reflected those firms' flexible choice on export and import and ignored those small-scale firms' trade strategies. As for NTMs regulations, both the coverage ratio and frequency index have smaller mean values compared to the country-level ones, which indicates that Chinese firms had been facing looser regulations when making international trade before the year of 2007 than those from 2008 to 2018.

Table 7. Descriptive Statistics of Country-level Coverage Ratio, Frequency Index and *OU*, *ID* Index

Variable	Obs	Mean	Std. Dev.	Min	Max
CR_Exp	18	0.763	0.164	0.438	0.955
CR_Imp	18	0.252	0.160	0.001	0.611
FI_Exp	18	0.667	0.184	0.194	0.906
FI_Imp	18	0.222	0.126	0.002	0.479
OU	15	2.827	0.135	2.629	3.031
ID	15	2.754	0.111	2.555	2.889

Source: Author's calculations based on UNCTAD TRAINS and World Input-Output Database.

Table 8. Descriptive Statistics of Firm-level Coverage Ratio, Frequency Index and *OU*, *ID* Index Regarding Export Records

Variable	Obs	Mean	Std. Dev.	Min	Max
CR	430,754	0.649	0.216	0.000	1.000
FI	430,754	0.536	0.240	0.053	1.000
OU	430,754	2.672	0.594	1.005	4.893
ID	430,754	3.165	0.361	1.280	3.635

Source: Author's calculations based on UNCTAD TRAINS and World Input-Output Database.

Table 9. Descriptive Statistics of Firm-level Coverage Ratio, Frequency Index and *OU*, *ID* Index Regarding Import Records

Variable	Obs	Mean	Std. Dev.	Min	Max
CR	635,543	0.143	0.181	0.000	0.954
FI	635,543	0.128	0.156	0.000	0.851
OU	635,543	2.862	0.569	1.024	4.893
ID	635,543	3.237	0.283	1.154	3.635

Source: Author's calculations based on UNCTAD TRAINS and World Input-Output Database.

Tables 10 and 11 describes the dependent variables in the estimation of the effect of NTMs on firm's performances. All the variables are in units of one thousand Chinese yuan. Generally speaking, Chinese firms tend to spend about 0.001% of their annual sales on R&D activities and the outcome of R&D, the sale of new products, accounts for about 20% of their annual sales.

Table 10. Descriptive Statistics of Firm Performances Regarding Export Records

Variable	Obs	Mean	Std. Dev.	Min	Max
NewPro	233,301	54977.8	1068544.0	0.0	110000000.0
R&D	239,253	2494.4	70309.8	-47894.0	7142497.0
Sale	319,215	251500.8	2941316.0	-54.0	669000000.0
Export	430,754	11600000.0	170000000.0	1.0	23200000000.0

Source: Author's calculations based on ASIF and CCTS databases.

Table 11. Descriptive Statistics of Firm Performances Regarding Import Records

Variable	Obs	Mean	Std. Dev.	Min	Max
NewPro	371,182	74449.0	1084099.0	0.0	110000000.0
R&D	298,955	3083.5	63560.3	-47894.0	7142497.0
Sale	516,553	332100.5	2824274.0	-54.0	731000000.0
Import	635,543	13100000.0	140000000.0	1.0	21800000000.0

Source: Author's calculations based on ASIF and CCTS databases.

4. Empirical Result

4.1 Effect of NTM on GVC Positioning

We now present our estimation results. Table 12 shows the effect of the two measures of NTM regulations, CR_t and FI_t, on firms' positioning in the GVC. Columns 1-4 of the table correspond to the effect of CR_t on firms' GVC positioning in terms of export, OU_{ft}^X, while the first two columns are for the output upstreamness (OU_{ft}^X) based on the ordinary least squares (OLS) and fixed-effects model estimation and the latter two columns are for the input downstreamness (ID_{ft}^X) using the OLS and fixed-effects model, respectively. The results suggest a significant and negative effect of NTM regulations on both firms' output upstreamness and input downstreamness, where the stringency of NTM regulations are measured by the coverage ratio. These results are robust against the choice of estimation models, and indicates that exported goods by Chinese firms have a smaller share of intermediate input and output in gross output. The results also indicate weaker intermediate output supply or input demand links with similar industries when facing stricter NTM regulations. Columns 5-8 shows the effect of FI_t on firms' GVC positioning in terms of import. Columns 5-6 are for the output upstreamness (OU_{ft}^X) based on the OLS and fixed effects estimation and Columns 7-8 are for the input downstreamness (ID_{ft}^X) using the OLS and fixed effects model. The results show that the signs and the magnitudes of the coefficients remain unchanged even when the NTM regulations are measured by the frequency index, which confirms the negative effect of NTM regulations on GVC positioning.

Table 13 shows the effect of NTM regulations on GVC positioning in terms of Chinese firms' imports. The results are quite similar to the export case. Again, we can find a negative effect of NTM stringency on both firms' output upstreamness and input downstreamness. This means that imported goods by Chinese firms have smaller share of intermediate input and output in gross output when facing stricter regulations of NTM. Recall that *OU* and *ID* respectively indicates firm's total forward and backward linkages in the GVC. This result indicates that higher pressure of NTM regulations results in a decrease of total forward and backward linkages in terms of gross output. According to Miller and Temurshoev (2017), total forward linkage measures are often used as indicators of firm's importance or keyness in the supply chain. A Firm with high total forward linkage is interpreted as a more appropriate target for economic stimulation purposes because it will bring more benefit to the entire economy than a firm with lower total forward linkage. In the meanwhile, a firm with high total backward linkage is interpreted as a more suitable target for an economic stimulation, because it purchases a significant part of its inputs in the form of intermediate inputs from other firms so that will lead other firms to also expand their outputs in order to meet that firm's increased intermediate demands. As long as the estimation results indicate, we can say that the negative effect of NTM regulations on firms' output upstreamness and input downstreamness would hinder Chinese firms from purchasing intermediate or providing output to other firms so that further decreases their importance and competitiveness in the GVC.

In summary, it can be said that the NTM regulations will act as an obstacle in the way of Chinese firms to get accessed with the world's production chains. The analysis uncovered the fact that facing stricter NTM regulations, firms will choose to purchase the intermediate from firms located closer to the midstream and also provide their outputs to firms located closer to the midstream of the GVC. This conclusion can also be translated as the strict NTM regulations will drive firms to decrease their linkages with the world's production chains.

Table 12. Estimated Effect of NTMs Imposed against China on Firms' Positioning in the GVC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OU	OU	ID	ID	OU	OU	ID	ID
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
CR	-0.0236***	-0.00509***	-0.0130***	-0.00167***				
	(0.000688)	(0.000374)	(0.000369)	(0.000161)				
FI					-0.0654***	-0.00787***	-0.0229***	-0.00130***
					(0.000833)	(0.000500)	(0.000503)	(0.000215)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y
Observations	255,347	255,347	255,347	255,347	255,347	255,347	255,347	255,347
R-squared	0.050	0.349	0.143	0.726	0.067	0.349	0.146	0.726
Number of N	135,898	135,898	135,898	135,898	135,898	135,898	135,898	135,898

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13. Estimated Effect of NTMs Imposed by China on Firms' Positioning in the GVC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OU	OU	ID	ID	OU	OU	ID	ID
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
CR	-0.0107***	-0.00156***	-0.00310***	-0.000365**				
	(0.000204)	(0.000115)	(9.01e-05)	(5.31e-05)				
FI					-0.0130***	-0.00320***	-0.00673***	-0.00168***
					(0.000279)	(0.000196)	(0.000123)	(9.04e-05)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y
Observations	406,045	406,045	406,045	406,045	406,045	406,045	406,045	406,045
R-squared	0.054		0.237		0.053		0.241	
Number of N	206,200	206,200	206,200	206,200	206,200	206,200	206,200	206,200

Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 Effect of NTM on Firm Performance

The findings of the negative impact of NTM on firms' GVC positioning in the previous subsection motivate us to further examine the relationship between NTM regulations and various firm performances in consideration of the difference in the GVC positioning. As mentioned above, as we regard the firms' GVC positioning as an endogenous variable, instead of the firm-level GVC positioning measure, we use the industry-level ones to capture the heterogeneous effect of NTM regulations. We first examine how NTM regulations affect the firms' import and export amount. Table 14 presents the estimated effect of NTMs imposed against China on firms' export. It shows strong evidence that stricter NTM regulations results in less export activities of firms. These results, regardless of which measure of NTM regulations we employ, suggest that manufacturers located outside of China typically are more willing to outsource processing activities to China when the

NTM regulations imposed against China are not very strict. When we include the interaction term of NTM regulation and GVC positioning index, we find that the negative effect of NTM regulations on exports vary depending on the GVC positioning. The positive coefficient of the interaction term, along with the smaller magnitude than that of NTM regulation index, indicates that the larger the firms' output upstreamness and input downstreamness are, the less negative is the effect of the NTM regulations.

Table 15 shows the effect of NTM regulations on firms' imports. Similarly, the results again indicate that foreign firms typically outsource processing activities to China when China imposes looser NTM regulations. The opposite sign of the interaction terms with the NTM index also tell the same story that the more firms located near both ends of the GVC, the less negative is the effect of NTM regulations impose on firms' processing activities.

We then examine how NTM regulations affect firms' R&D activities. Table 16 shows the results of how NTM regulations imposed against China can affect Chinese firms' innovative activities. Columns 1-6 correspond to the relationship between NTM and firms' R&D expenditures and Columns 7-12 shows the effect on firms' sale of new products. Here, one can regard the sale of new products as kind of the outcome of the R&D activities. We find strong evidence that NTM regulations are negatively related with firms' innovative activities. For both R&D expenditures and sales of new products, one percent increase in NTM regulations against China will bring a decrease by 0.1-0.2 percent, regardless of the measure of NTM regulation. This implies that Chinese firms facing stricter NTMs may be compelled to cut the budget for innovative activities in order to comply with the NTM regulations. As for the total sales, as Columns 13-18 indicate, the NTM regulations imposed against China also hinder Chinese firms' production activities. The interaction terms between NTM regulations and GVC positioning further show us that the negative effect vary across firms regarding their positioning in the GVC. The results coincide with the previous case, that is, the positive and smaller magnitudes of the coefficients indicate that firms with higher output upstreamness and input downstreamness seem to be less affected by NTM regulations imposed against China and (Columns 1-6). For the rest columns of Table 16, we can see how NTM regulations affect firms' annual sales. Again, we get the similar conclusion that the more firms are located at the edges of GVC, the smaller negative effect they receive from NTM regulations.

In contrast to Table 16, Table 17 shows how NTM regulations imposed by China can affect Chinese firms. Surprisingly, the results indicate that stricter NTM regulations imposed by China may stimulate Chinse firms to arrange more R&D activities (Columns 7-12). However, when we recall that NTMs imposed against China are found to hinder firms' R&D activities, this result can be reasonable. Unlike the previous case, the positive impact on R&D expenditures as well as the sales of new products indicates the NTM plays a roll of protectionism policy as we now use the measures of NTMs that are imposed by China (i.e. against countries whoever want to export to China).

Finally, let us take a look at how NTM regulations will affect firms' total sales. Columns 13-18 of Tables 16 and 17 show that the NTM regulations imposed against China as well as NTMs imposed by China may decrease the firms' total sales, due possibly to the above-mentioned negative effects on firms' export and import activities. Without exception, the negative effects are found to vary across firms according to which position the firm is located in the GVC. Thus, the findings from the analyses so far suggest that NTM regulations tend to suppress firms' performance from various aspects and the effect is quite heterogeneous with firms' positioning in the GVC.

4.3 Robustness Checks

To check the heterogeneous impact of NTM regulations on firms' performance, we conduct a robustness check by dividing the sample into 20 groups according to firms' *OU* and *ID* index and run Eq. (14) using these subsamples. Tables 18 and 19 show the results of robustness check for the heterogeneous effect of NTMs. Here, we suppress the results of the subgroups whose observation is less than 100. For each subgroup with more than 100 observations, the coefficients and the significance levels are reported. Despite some exceptions, we can generally observe that firms with lower output upstreamness and input downstreamness in the GVC tend to receive the greater negative effect of NTM regulations.

5. Conclusion

The rising fragmentation of production in the global value chain has been a key trend in international trade thus, it is critical for researchers to elucidate how changes in the economic environment are likely to affect the specialization of countries within the GVC. By combining firm-level customs data, manufacturing census data, and China's Input-Output Tables, this paper investigates the impact of NTM's stringency on Chinese firms' positioning in the GVC, which is measured by two types of GVC positioning indices, namely, output upstreamness and input downstreamness indices. We then estimate the impact of NTMs on various firm performance by paying special attention to how the impacts vary across firms with different positioning in the GVC.

The empirical results show that NTMs imposed against and imposed by China could significantly reduce firms' linkages with foreign countries, thereby reducing the firms' importance within the GVC. We also find that stricter NTMs could even hinder firms' innovative activities and decrease exports and imports. Further analysis indicates that these negative impacts of NTMs on firms are heterogeneous across firms depending on their original position in the GVC; firms with higher output upstreamness or input downstreamness have smaller effect than those with lower GVC positioning indices.

Table 14. Estimated Effect of NTMs Imposed against China on Firms' Export

	(1)	(2)	(3)	(4)	(5)	(6)
			lnExport			
CR	-0.109***		-1.069***	-3.882***		
	(0.00554)		(0.0556)	(0.135)		
CR_OU			0.917***			
			(0.0528)			
FI		-0.270***			-1.061***	-2.795***
		(0.00773)			(0.0393)	(0.111)
Up_FI					0.767***	
					(0.0375)	
ID_CR				3.169***		
				(0.113)		
ID_FI						2.189***
						(0.0953)
Year dummy	Y	Y	Y	Y	Y	Y
Ownership FE	Y	Y	Y	Y	Y	Y
Observations	255,347	255,347	255,347	255,347	255,347	255,347
R-squared	0.112	0.115	0.113	0.115	0.116	0.116

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15. Estimated Effect of NTMs Imposed against China on Firms' Import

	(1)	(2)	(3)	(4)	(5)	(6)
			lnImport			
CR	-0.0414***		0.0723***	-0.627***		
	(0.00227)		(0.0212)	(0.0396)		
CR_OU			-0.106***			
			(0.0197)			
FI		-0.0497***			0.186***	-1.116***
		(0.00313)			(0.0260)	(0.0591)
Up_FI					-0.220***	
					(0.0243)	
ID_CR				0.505***		
				(0.0341)		
ID_FI						0.911***
						(0.0504)
Year dummy	Y	Y	Y	Y	Y	Y
Ownership FE	Y	Y	Y	Y	Y	Y
Observations	406,029	406,029	406,029	406,029	406,029	406,029
R-squared	0.273	0.273	0.273	0.273	0.273	0.273

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
			lnNewPro						lnR&D						lnSale			
CR	-0.199***		-0.357	4.979***			-0.110***		-0.527***	5.063***			-0.0386***		-0.0334	0.279		
	(0.0306)		(0.252)	(0.355)			(0.0100)		(0.187)	(0.331)			(0.0128)		(0.0933)	(0.171)		
FI		-0.106***			0.212	6.382***		-0.130***			-0.00934	4.072***		0.0529***			-0.122*	0.507***
		(0.0303)			(0.184)	(0.375)		(0.0160)			(0.138)	(0.264)		(0.0110)			(0.0676)	(0.163)
CR_OU			0.151						0.394**						-0.00507			
			(0.240)						(0.176)						(0.0908)			
FI_OU					-0.306*						-0.112						0.0674	
					(0.176)						(0.128)						(0.0655)	
ID_CR				-4.474***						-4.293***						-0.294*		
				(0.313)						(0.275)						(0.158)		
ID_FI						-5.843***						-3.524***						-0.519***
						(0.340)						(0.221)						(0.151)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ownership FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	86,559	86,559	86,559	86,559	86,559	86,559	108,328	108,328	108,328	108,328	108,328	108,328	67,304	67,304	67,304	67,304	67,304	67,304
R-squared	0.158	0.157	0.158	0.160	0.157	0.161	0.180	0.179	0.180	0.181	0.179	0.181	0.517	0.517	0.517	0.517	0.517	0.517

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
			lnNewPro						lnR&D						lnSale			
CR	0.0191***		0.0582***	0.223***			0.00603		0.0794***	0.265***			-0.00558***		0.0256***	0.0434***		
	(0.00502)		(0.0211)	(0.0348)			(0.00448)		(0.0187)	(0.0335)			(0.00175)		(0.00712)	(0.0120)		
FI		0.0189**			0.0137	0.319***		0.0158***			-0.106***	0.357***		0.00682**			0.0265***	-0.122***
		(0.00802)			(0.0269)	(0.0437)		(0.00588)			(0.0232)	(0.0393)		(0.00293)			(0.00926)	(0.0150)
CR_OU			-0.0305*						0.0637***						0.0157***			
			(0.0161)						(0.0134)						(0.00545)			
FI_OU					0.00382						0.0833***						0.0146**	
					(0.0188)						(0.0151)						(0.00649)	
ID_CR				-0.189***						-0.214***						0.0359***		
				(0.0322)						(0.0272)						(0.0113)		
ID_FI						-0.275***						-0.285***						0.109***
						(0.0399)						(0.0323)						(0.0140)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ownership FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	168,749	168,749	168,749	168,749	168,749	168,749	147,875	147,875	147,875	147,875	147,875	147,875	136,623	136,623	136,623	136,623	136,623	136,623
R-squared	0.156	0.156	0.156	0.156	0.156	0.156	0.187	0.187	0.187	0.187	0.187	0.187	0.555	0.555	0.555	0.556	0.555	0.556

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18. Robustness Check for the Heterogeneous Effect of NTMs Imposed against China

	Export					
	β(CR)					
	lnNewPro	*lnR&D*	*lnSale*	*lnNewPro*	*lnR&D*	*lnSale*
GVC	OU	OU	OU	ID	ID	ID
1						
1.2						
1.4						
1.6						
1.8						
2	-0.532*		-0.273***	-0.262		0.247**
2.2	-0.244***	-0.509***	-0.141***	-0.0644	0.0561*	0.263**
2.4	-0.130**	-0.0994***	-0.135***	-0.0650	0.0952	0.0339
2.6	-0.275***	-0.140***	-0.0548	0.000133	-0.0342	0.0629*
2.8	-0.135	-0.0538*	-0.117**	-0.0172	-0.0793***	0.0530
3	-0.133	-0.0128	0.0857	0.0621	-0.0318	0.112 ***
3.2	0.117	-0.107*	0.0748	-0.0171	-0.0168	-0.0381*
3.4	0.266**	0.0207	0 .0194	-0.209***	-0.0611***	-0.176***
3.6	0.158**	-0.0415	-0.00873	-0.132	-0.0388*	
3.8	0.469***	0.0216	0.0971***	0.0954*	-0.116***	
4	-0.120	0.00918	0.574			
4.2	-0.197	0.0816*	0 .166			
4.4	-0.138	-0.365				
4.6						
4.8	0.424	-0.519				
5						

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Robustness Check for the Heterogeneous Effect of NTMs Imposed by China

	Import					
	β(CR)					
	lnNewPro	*lnR&D*	*lnSale*	*lnNewPro*	*lnR&D*	*lnSale*
GVC	OU	OU	OU	ID	ID	ID
1						
1.2						
1.4						
1.6						
1.8						
2	-0.0172		0.0316	-0.0160		0.00742
2.2	.0178***	0.0301***	-0.000557	0.0371	-0.00672	0.0557***
2.4	0.0214*	0.00451	-0.0200***	-0.0162	-0.0692	-0.0343**
2.6	-0.00265	-0.0316**	-0.0149***	0.0178	-0.00522	0.00517
2.8	0.0254	0.0126	-0.00925	0.0456*	0.000904	-0.0179*
3	-0.00199	0.0155	0.00102	0.0154*	0.0191	0.000207
3.2	0 .0149	0.0180	0.00567	0.00626	0.0134	-0.000383
3.4	0.0161	-0.00254	0.000987	-0.0172	0.00133	-0.0204***
3.6	0 .0150	0.00469	-0.00532	0.0717**	0.0349***	
3.8	0.0376**	0.00997	-0.00405	0.0374	0.000831	
4	0 .0489	0.0378**	-0.0381			
4.2	0.0567	0.00192	0.00134			
4.4		0.0122				
4.6		0.0518				
4.8	0.483***	0.00296				
5						

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table A1. Manufacturing Industry Classification of World Input-Output Tables

Code	Industry	Code	Industry
A01	Crop and animal production, hunting and related service activities	C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
A02	Forestry and logging	C22	Manufacture of rubber and plastic products
A03	Fishing and aquaculture	C23	Manufacture of other non-metallic mineral products
B	Mining and quarrying	C24	Manufacture of basic metals
C10-C12	Manufacture of food products, beverages and tobacco products	C25	Manufacture of fabricated metal products, except machinery and equipment
C13-C15	Manufacture of textiles, wearing apparel and leather products	C26	Manufacture of computer, electronic and optical products
C16	Manufacture of wood and of products of wood and cork, except furniture	C27	Manufacture of electrical equipment
C17	Manufacture of paper and paper products	C28	Manufacture of machinery and equipment n.e.c.
C18	Printing and reproduction of recorded media	C29	Manufacture of motor vehicles, trailers and semi-trailers
C19	Manufacture of coke and refined petroleum products	C30	Manufacture of other transport equipment
C20	Manufacture of chemicals and chemical products	C31-C32	Manufacture of furniture; other manufacturing

Source: World Input-Output Database.

Table A2. List of Countries of the World Input-Output Tables

Abbr.	Country	Abbr.	Country
AUS	Australia	ITA	Italy
AUT	Austria	JPN	Japan
BEL	Belgium	KOR	South Korea
BGR	Bulgaria	LTU	Lithuania
BRA	Brazil	LUX	Luxembourg
CAN	Canada	LVA	Latvia
CHN	China	MEX	Mexico
CYP	Cyprus	MLT	Malta
CZE	Czech Rep.	NLD	Netherlands
DEU	Germany	POL	Poland
DNK	Denmark	PRT	Portugal
ESP	Spain	ROU	Romania
EST	Estonia	RUS	Russia
FIN	Finland	SVK	Slovak Rep.
FRA	France	SVN	Slovenia
GBR	United Kindom	SWE	Sweden
GRC	Greece	TUR	Turkey
HUN	Hungary	TWN	Taiwan
IDN	Indonesia	USA	United States
IND	India	ROW	Rest of the World
IRL	Ireland		

Source: World Input-Output Database.