Analysis of China's Agri-food Imports In an Extended Gravity Model

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ABSTRACT

Since 2000, China has changed from a net exporter to a net importer of agri-food products to a point such that food security and agricultural trade balance are a major concern to Chinese authorities. This research estimated the effect of the ten explanatory variables that have impacted on China's accelerated food imports from 19 trading partners over 2000-2014. An extended gravity model that include economic, demographic, geographic factors and China's free trade agreements (FTAs) to 5 commodity groups separately, in addition to an aggregated data to allow a deeper understanding about the topic. Results from the research suggest that they all have varying but significant impacts on China's agri-food imports. Agri-food imports to China are predicted to increase. For Chinese authorities to concentrate on own agricultural development and cost-effective trade with other countries including wider FTAs forms an important policy implication from this research.

Keywords: China, Agri-food trade, Gravity model

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1. Introduction

China has become a major importer in the world agricultural market since it emerged from isolation, liberalized its economy, and experienced rising living standards (Chen, 2000; Qiang, Liu, Cheng, Kastner, & Xie, 2013; Shuai, 2010). Ever since China liberalized its economy in the late 1970s, its trade value has increased gradually, especially after China joined the World Trade Organisation (WTO) in 2001. Although China's total exports grew faster than total imports grew faster than total imports leading to huge trade balance surplus, it is quite the opposite when it comes to agri-food trade balance as it switched from a net exporter to a net importer nation. As part of China's WTO accession package, China was committed not to subsidize agricultural exports and to limits its aggregate measure of support (AMS) to agriculture to 10 per cent or less. Import quotas and licenses were phased out and state trading, although retained, has been subject to WTO rules (Ianchovichina and Martin, 2001). Since 2014, China has been the largest importer of agricultural products among 166 members of the WTO. Consequently, China is considered a strategic market by many agri-food-exporting countries. As a result, the factors that influence China's agricultural imports have become a major talking point among China's current and potential business partners.

There has been a vast amount of literature investigating China's agricultural trade growth. A sustained economic growth has been identified as one of the main forces that has driven the growth of agricultural imports into China (Chen & Dong, 2012; Huang, 2014; Shuai, 2010; Wang & Wang, 2012). Many studies focused on the relationship between demographic factors and trade (Nidhiprabha, 2011; Sasaki, 2017; Zhang & Liu, 2015), with population being one of the most important factors that affected China's trade. Distance was identified as a negative factor by most studies and FTAs were mostly considered a positive factor (Huang, 2014; Shuai, 2010; Tang et al., 2015; M. Wang et al., 2014).

Bilateral trade being a mutual relationship, the situation of the partner country can also affect China's imports. Hence the partner country's economic and demographic factors need to be investigated as well. Geographic distance between China and partner countries matters in trade relationships because distance apparently affect transportation cost. Besides, agricultural land is the most important input in agri-food production, which affects the residual agri-food trade. Globally, where land resources are limited in some countries, international trade played an important role in compensating for land scarcity in those countries (Qiang et al., 2013). Obviously, trade openness fundamentally impacts on a country's trade. As a matter of fact, since China joined the WTO in 2001, China has signed more free trade agreements (FTAs) with other countries, which has stimulated trade between China and those partners. This present research also quantifies how FTAs affect agri-food imports into China.

The rest of the paper is constructed as follows. Section 2 reviews some relevant studies on agri-food import globally as well as in China. The research methodology and data descriptions

are presented in Section 3. Sections 4 discusses the findings of our research and Section 5 concludes.

2. Literature review

Hsin Huang, von Lampe, and van Tongeren (2011) suggested that trade in agricultural commodities was ultimately an exchange of services and resources incorporated into the traded goods. This section reviews the related literature about China's trade from two perspectives. The first perspective is based on different factors using the gravity model and other methodologies; the second perspective is based on different commodity groups.

2.1 Factors Perspective

To analyse China's agri-food imports, many studies were based on the gravity model as the gravity model already established itself as a useful trade analysis tool over several decades (Sun & Reed, 2010). Other researchers have applied different regression models to their research to determine how economic, demographic, geographic and FTA factors impacted on China's trade (Huang, 2014; Shuai, 2010; Tang et al., 2015; Wang et al., 2014).

Economic Factors

Wang and Wang (2012), Zhang et al. (2010), Wang et al. (2014), Huang (2014), Shuai (2010) and Zhuang et al. (2007) have identified that economic factors have a very close relationship with China's agricultural trade. Among economic factors, GDP have been most widely investigated. Wang and Wang (2012) pointed out that GDP is the main factor which influences the agricultural trade volume between China and China's main agricultural trading partners. They suggested that per capita income indicates the demand structure of a country: a more similar demand structure means a greater trade potential between the two countries. If two countries had a bigger per capita GDP gap, their demand structure for agricultural products differed more from each other, so that there would be less agricultural products traded between these two countries. Zhuang et al. (2007), M. Wang et al. (2014), H. Huang (2014), Shuai (2010) and Zhang, Xie, and Zheng (2010) all agreed that GDP had a positive impact on agricultural trade. Zhuang et al. (2007) built the gravity model based on the agricultural trade between Guangdong Province (China) and the Association of Southeast Asian Nations (ASEAN). They pointed out that the agricultural export volume of Guangdong Province was significantly influenced by importers' GDP and per capita incomes. Zhuang et al. (2007) realised a broader data base should be introduced to this model and then they put their focus on China's agricultural trade balance rather than agricultural imports only. They found that for every 1% increase in real income per capita of a trading partner, China's agricultural trade balance would increase by 1.3%. In a separate study, Huang (2014) focussed on China and its major trading partners where the partner's economic scale and the distance were the main determinants. Shuai (2010) studied trade between China and the United States, while Zhang,

Xie, and Zheng (2010) built their model on the agricultural trade relationship between China and Africa. Both of these studies found that a GDP increase in the importing country and the exporting country positively influenced agricultural exports and agricultural imports of participating countries.

Besides the gravity model, other econometric methods have been used to study the relationship between economic factors and trade. Lubna et al. (2016) introduced a panel data approach to conclude that a GDP increase would lead to direct increases in both imports and exports. Chen and Dong (2012) investigated the relationship between GDP and trade through an opposite perspective; their study showing that exports and imports had significant positive impacts on GDP based on nonparametric local linear kernel estimation. Lehmijoki and Palokangas (2010) also suggested that China's exports contributed extraordinarily to its economic growth.

None of the studies cited above investigated the sub-category of China's agricultural trade. Instead, they used overall agricultural trade volume or value as their data base. We believe that different agri-food may correspond differently to GDP increase; thus this research investigated into China's agri-food trade in five important sub-categories.

Demographic Factors

Population was found to positively correlate with import trade based on a gravity model introduced by Wang and Wang (2012). Specifically, they found that every 1% increase in China's population would result in a 1.5% enhancement in agricultural imports, since a larger population meant a larger food demand. In contrast, Huang (2014), also using a gravity model, could not establish the significance of the population variable in their research on China's 50 largest trading partners. Huang (2014) based their conclusion only on a 2004 data base.

Tian et al. (2013) built their gravity model on a data base of 176 countries from 1970 to 2006. Their study revealed that the employment ratio influenced international trade. More specifically, a high level of employment in the exporting country would enhance production so that exports would soar, and a high employment ratio in the importing country would lead to a larger income so that imports improved. Thus, they concluded that every 1% rise in employment in the exporting country would create at least 3% export enhancement, and every 1% increase in employment in the importing country would create more than a 2% increase in imports.

Some scholars investigated the impact of demographic factors on China's trade based on different methodologies other than the gravity model. Nidhiprabha (2011) noticed that with China's population base and the one-child policy, its working age ratio would not decline by more than 2 years at least until 2030. High working age ratio was identified as one of the main forces that assured China's continuous trade and economic growth. Zhang and Liu (2015) concluded that trade had significantly contributed to urbanization in China. Hu et al. (2009)

showed that the urban population influenced non-agricultural employment- meaning that imports and exports affected non-agricultural employment.

Geographic factors

One of the key functions of a gravity model is to predict and explain bilateral trade flows in terms of the distance between trading partners (Brakman & Bergeijk, 2010). Although distance can be interpreted on many levels, the most fundamental level is geographic distance. H. Huang (2014); Sheng, Tang, and Xu (2014); Rahman (2003); R. R. Huang (2007); Shuai (2010); L. Wang and Wang (2012); H. Zhang et al. (2010); Zhuang et al. (2007); Sun and Reed (2010) and M. Wang et al. (2014) all found geographical distance negatively influenced bilateral trade, which meant the greater the geographical distance between two countries, the less the trade volume between them.

Other studies looked into the relationship between agricultural land and agricultural trade. Furumo and Aide (2017) revealed that land for oil palms in Latin America and Caribbean (LAC) kept expanding by converting from other land, so that the oil palm trade of both exports and imports in the region increased and the oil palm sector developed more sustainably. Henders et al. (2015) suggested that cropland expansion in the tropical region contributed radically to agricultural supply and exports, so that global demand for agricultural commodities has become an increasingly important driver of land-use change. Qiang et al. (2013) identified other land-use demands due to rapid economic development, urbanization, and population growth would lead to more agricultural trade, especially when trade was directed from a relatively more efficient country to a less efficient country. Accordingly, Qiang et al. (2013) focused more on the productive areas hidden in imported or exported agricultural goods.

However, the extent to which the scale of agricultural land as associated with agri-food imports into China has been less studied, and there were even fewer studies based on the gravity model.

Trade agreement factor

There are many studies that considered the effect of free trade agreements (FTAs) on bilateral trade based on the gravity model. Almost all of these studies found a positive impact of FTAs on agri-food trade. Although East Asia is considered to be a latecomer in respect to FTAs, East Asian nations benefited significantly from FTAs (Mölders & Volz, 2011). Yang and Martinez-Zarzoso (2014), Sun and Reed (2010), Roberts (2004), L. Wang and Wang (2012) and Sheng et al. (2014) all held the view that the ASEAN–China Free Trade Agreement (ACFTA) led to a substantial and significant trade creation between ASEAN and China. Paladini and Cheng (2015) tried to evaluate whether there was any evidence that the ACFTA has been responsible for the growing trade imbalance between China and Indonesia, but they found no conclusive results about the negative effects on the ACFTA for Indonesia by using the gravity model. Zhuang et al. (2007) identified that ASEAN brought a rapid increase of agri-food imports into

Guangdong Province of China, but a slow increase in agri-food exports to ASEAN. Tsang and Au (2008) found that the textile and clothing trade within the North American Free Trade Agreement (NAFTA) has been increased between 1990 and 2001, but decreasing after 2005 due to agreements on the textile and clothing trade within South East Asian developing countries. In addition, trade liberalization has not only accelerated the volume of traded agricultural products, but also raised the relative price of exports and generated gains from trade (Lehmijoki & Palokangas, 2010; Qiang et al., 2013).

2.2 Commodity Perspective

Among all of China's agricultural imports recorded in the UN Comtrade Database, commodity code HS 12 (oil seed, oleagic fruits, grain, seed, and fruits), HS 15 (animal or vegetable fats and oils), HS 44 (wood and articles of wood), HS 47 (pulp of wood, fibrous cellulosic material) and HS 52 (cotton) were the commodity groups with largest trade values in 2014. Those agri-food accounted for a total value of US$108 billion, which is 63% of the value of China's total agricultural imports in 2014. Consequently, several studies have focused on specific commodities within agri-food trade.

Oilseeds and oilseed products are vital commodities in international trade. Production of this category has rapidly expanded in recent years because of yield growth and demand characteristics linked to more income-elastic products (Ying, Houston, Escalante, & Epperson, 2012). Ying et al. (2012) also suggested that the distance between two countries and border trade barriers had significant and substantive impacts on the trade value of oilseeds and oilseed products.

In regard to HS 44 (wood and articles of wood), Buongiorno (2016) found that their export was inelastic with respect to the exporter's gross domestic product (GDP) and elastic with the importer's GDP. However, both the GDP of the exporter and the importer affected wood exports positively. In addition, the export of HS 47 (pulp of wood, fibrous cellulosic material) was positively elastic with respect to the exporters' GDP and importers' GDP in the same study. Tang et al. (2015) indicated that China's economic growth and exporters' economic growth had positive impacts on wood pulp exports to China, and distance had a significant negative impact on China's wood pulp and recovered paper imports.

Cotton is an essential product to China as its remarkable GDP growth started from the labour-intensive industry like textiles, and cotton is the primary raw material for that industry (T. Zhang, 2011). China is the largest textile exporter and cotton consumer in the world. With China's production output at a deficit to its consumption; China's cotton stocks were worked down at a rapid rate, and China was expected to import more cotton (Robinson, 2016). There has been few research on the cotton trade with the gravity model, but there are more studies investigating China's textile trade. Lau and Bilgin (2010) suggested that GDP per capita influenced the textile trade between China and the USA positively. Tsang and Au (2008)

studied the correlation between FTAs and textile trade, and identified a significant impact of FTA on clothing trade.

3. Research Method and Data

3.1 Theoretical Foundations of the Gravity Model

The gravity model originated from the notion of Isaac Newton's Law of Universal Gravitation describing the gravitational attraction between bodies with mass: that is, force is directly proportional to the product of the two masses and inversely proportional to the square of the distance between them.

$$\mathrm{F} = \mathrm{g}\frac{M_1 \times M_2}{D^2} \tag{1}$$

In equation (1), F stands for the force between objects 1 and 2; M_1 and M_2 represent the weight of object 1 and object 2 respectively; and D measures the distance between two objects. Tinbergen (1962) and Pöyhönen (1963) extended the application of the gravity model into world trade volumes and the equation was specified as:

$$T_{ij} = \alpha\frac{GDP_i \times GDP_j}{D_{ij}^2} \tag{2}$$

where T_{ij} indicates the export volume from the exporting country i to the importing country j; and GDP_i and GDP_j are country i and j's respective economic sizes, measured by gross domestic product. D_{ij} represents the bilateral distance between the two countries and α is a constant of proportionality. This gravity model indicates the relationship between GDP, distance, and trade volume in bilateral trade. The larger the two trading partners, the larger the trade flow; and the further the distance between the two countries, the smaller the bilateral trade (Brakman & Bergeijk, 2010).

Taking the logarithm of the equation (2), we get the following linear form of the model:

$$\ln T_{ij} = \beta_0 + \beta_1 \ln GDP_i + \beta_2 \ln GDP_j + \beta_3 \ln D_{ij} \tag{3}$$

where β_0, β_1, β_2, and β_3 are the coefficients to be estimated. Equation (3) is the baseline model where bilateral trade flows are expected to be a positive function of GDP and a negative function of distance (Zhang et al., 2010). When estimated using least squares (OLS) method, this baseline model gives relatively good results. However, there are other factors that can influence trade levels as well leading to extended gravity models.

3.2 Extended Gravity Model

In this research, we use an extended gravity model to include economic, demographic and geographic factors as they affect trade. We follow that approach of Sun and Reed (2010).

$$\ln T_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln P_{it} + \beta_4 \ln P_{jt} + \beta_5 \ln E_{it} + \beta_6 \ln E_{jt} + \beta_7 \ln A_{it} + \beta_8 \ln A_{jt} + \beta_9 FTA_{dummy} + \beta_{10} \ln D_{ij} + \varepsilon \quad (4)$$

where T_{ijt} stands for the trade value from the exporting country i to the importing country j at time t. Independent variables of equation (4) are defined in Table 1 below.

Table 1: Independent Variables and Expected Signs

Independent Variables	Description	Expected Sign
$\boldsymbol{GDP_{it}}$	Gross domestic product of the exporting country i at time t	+
$\boldsymbol{GDP_{jt}}$	Gross domestic product of the import country j at time t	+
$\boldsymbol{P_{it}}$	Population of exporting country i at time t	-
$\boldsymbol{P_{jt}}$	Population of importing country j at time t	-
$\boldsymbol{E_{it}}$	Proportion of employment in agriculture of exporting country i at time t (% of total employment)	-/+
$\boldsymbol{E_{jt}}$	Proportion of employment in agriculture of importing country j at time t (% of total employment)	+
$\boldsymbol{A_{it}}$	Agricultural land area of exporting country i at time t	+
$\boldsymbol{A_{it}}$	Agricultural land area of importing country j at time t	-
$\boldsymbol{FTA_{dummy}}$	Dummy variable =1 if country i and j have free trade agreement or belong to the same free trade region at time t	+
$\boldsymbol{D_{ij}}$	Distance between country i and j	-

Notice that the log-linear of equation (4) assumes a linear relationship between independent and dependent variables and that T_{ijt} is required to be positive (i.e. $T_{ijt} > 0$). Consequently, there is a potential bias in the log-linear model caused by zero trade and heteroscedasticity. Burger, Oort, and Linders (2009) suggested the use of a Poisson Quasi Maximum Likelihood (PQML) model instead of the normal OLS as below:

$$T_{ijt} = \exp(\beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln P_{it} + \beta_4 \ln P_{jt} + \beta_5 \ln E_{it} + \beta_6 \ln E_{jt} + \beta_7 \ln A_{it} + \beta_8 \ln A_{jt} + \beta_9 FTA_{dummy} + \beta_{10} \ln D_{ij} + \varepsilon) \quad (5)$$

3.3 Data Description

Our sample consists of 19 countries that exported agricultural products to China. These are Australia, Belgium, Brazil, Canada, France, Germany, Indonesia, Italy, Japan, Malaysia, the Netherlands, New Zealand, the Philippines, South Korea, Spain, Sweden, Thailand, United Kingdom and the USA. 14 of our selected countries are categories as developed while other 5 are developing countries. These countries were chosen because they had a continuous trade history with China from 2000 to 2014 in five of the most valuable agri-food trading groups in 2014 as per UN Comtrade database. Data used in this research ranged from 2000 to 2014 (15 years).

The definition of an agricultural product for this research came from the UN Comtrade, which had the following commodity codes: HS 12 (oil seed, oleagic fruits, grain, seed, fruit), HS 15 (animal or vegetable fats and oils), HS 44 (wood and articles of wood), HS 47 (pulp of wood, fibrous cellulosic material) and HS 52 (cotton). These five commodity groups accounted for 63% of the value of China's total agricultural imports in 2014 (see Figure 1). Except for two missing observation of HS 47 for Malaysia in 2000 and 2001, each commodity has a total of 285 observations for the whole period 2000-2014. In total, there are 1,423 observations in our sample.

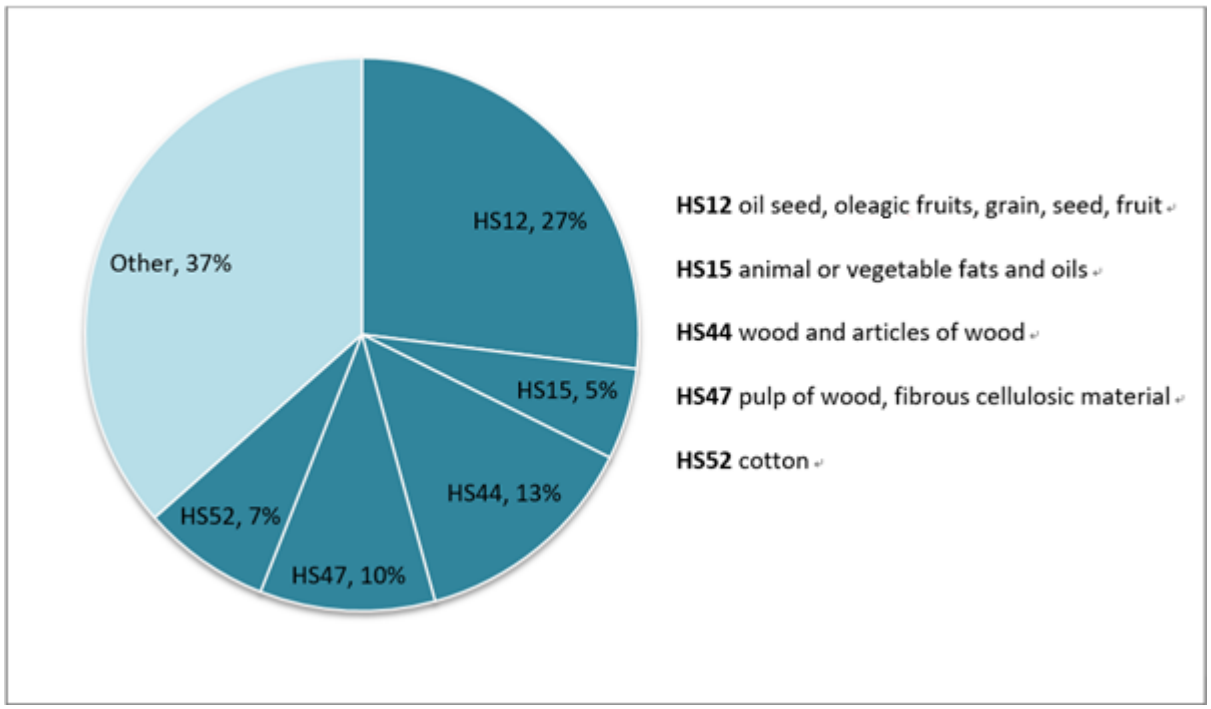

Figure 1. Proportion of Agricultural Products Imported into China in 2014

Source: World Trade Organisation and the UN Comtrade.

The data used in this research was obtained from multiple sources. Bilateral trade flow data came from the UN Comtrade Database (http://comtrade. un. org); we applied nominal trade values. Data on gross domestic product (GDP), population, proportion of agricultural employment and agricultural land area came from the World Bank Development Indicators database. Data on distance came from the Centre d'Etudes Prospectives et d'Informations Internationales (http://www.cepii.fr/anglaisgraph/bdd/distances.htm). The great circle formula is used to calculate the geographic distance between countries, referenced by latitudes and longitudes of the largest urban agglomerations in terms of population. The WTO Regional Trade Agreements (RTA) database was the main source for FTAs. For time intervals, we selected annual data.

4. Results and Discussions

4.1 Gravity Model Results for Five Commodity Groups Separately

Our first set of gravity models are applied to five commodity groups separately. These are HS 12 (oil seed, oleagic fruits, grain, seed, and fruit), HS 15 (animal or vegetable fats and oils), HS 44 (wood and articles of wood), HS 47 (pulp of wood, fibrous cellulosic material) and HS 52 (cotton). In a second exercise, we apply the gravity model collectively to all these commodity groups. Table 2 illustrates the results of the first set relating to five commodity groups. The table demonstrates statistically significant coefficients as the modulus of each variable passed the significance level of 1%.

The estimated signs for coefficients of GDP_{it} (GDP of exporting country) of HS 12, HS 47 and HS 52 were consistent with their expectations, which meant that a GDP increase in exporting countries would enhance the exports of HS 12, HS 47 and HS 52 to China from the 19 countries. A larger GDP represents more products that can be exported (Shuai, 2010). However, the estimated signs for coefficients of GDP_{it} of HS 15 and HS 44 were negative that need some rationalizing. For HS 15, Malaysia and Indonesia claimed over 77% of total exports to China among the 19 countries. Hence their GDP affected the model results more than the other countries. Malaysia and Indonesia both had a relatively small GDP in the 19 countries during 2000 -2014. In such a situation, the GDP of the exporter had an adverse impact on exports of HS 15 to China. For HS 44, the "hot money" theory of Sarno and Taylor (1999) could explain this inconsistency. According to Sarno and Taylor (1999), money will flow from a low return product to a high return product. Since wood is a raw material with low added value, it is a low return product. In a country with growing GDP, it is likely that more money will be invested in high return products, such as high value-added products. In such a situation, wood is not product that hot money would flow to, hence less wood would be produced for export.

Table 2: Poisson Gravity Model Results for Five Commodities Separately

Variable	Oil seed (HS 12)	Animal fat (HS 15)	Wood (HS 44)	Wood pulp (HS 47)	Cotton (HS 52)
GDP_{it} (β_1)	0.77*** (0.00003)	-0.70*** (0.000007)	-0.25*** (0.00002)	0.14*** (0.00001)	1.87*** (0.00003)
GDP_{jt} (β_2)	3.99*** (0.00011)	6.18*** (0.00017)	-1.04*** (0.00017)	5.02*** (0.00014)	-0.90*** (0.0002)
P_{it} (β_3)	0.11*** (0.00003)	1.80*** (0.00001)	0.16*** (0.00001)	0.35*** (0.00001)	-0.99*** (0.00002)
P_{jt} (β_4)	-14.13*** (0.00252)	-33.47*** (0.00386)	26.06*** (0.00377)	-51.76*** (0.00314)	98.80*** (0.00426)
E_{it} (β_5)	-0.01*** (0.00002)	0.67*** (0.000006)	-0.27*** (0.00001)	-0.19*** (0.000009)	0.89*** (0.00002)
E_{jt} (β_6)	2.80*** (0.00014)	7.82*** (0.00022)	-1.96*** (0.00023)	2.44*** (0.00019)	7.63*** (0.00026)
A_{it} (β_7)	0.60***	-1.19***	0.46***	0.27***	1.14***

	(0.000006)	(0.000008)	(0.000004)	(0.000003)	(0.000008)
A_{jt} (β_8)	25.28*** (0.00219)	-44.02*** (0.00314)	34.50*** (0.00382)	-21.39*** (0.00277)	25.80*** (0.00369)
FTA_t (β_9)	1.76*** (0.00005)	0.38*** (0.00001)	1.12*** (0.00002)	-0.22*** (0.00001)	-0.20*** (0.00003)
D_{ij} (β_{10})	3.47*** (0.00003)	2.08*** (0.00001)	0.01*** (0.00001)	0.09*** (0.000008)	-2.43*** (0.00002)

Notes: *** indicate significance of the t-statistic at 1%. All of the independent variables were found to be significant at this level. Standard errors are in brackets. HS 12 = oil seed, oleagic fruits, grain, seed, fruit. HS 15 = animal or vegetable fats and oils. HS 44 = wood and articles of wood. HS 47 = pulp of wood, fibrous cellulosic material. HS 52 = cotton. Data period: 2000 to 2014.

The estimated signs for coefficients of GDP_{jt} (GDP of importing country) of HS 12, HS 15 and HS 47 were consistent with their expectations, which meant that a GDP increase in China would enhance the import of these products to China from the 19 countries. A larger GDP represents more money that can be spent on buying from others (Shuai, 2010). However, the estimated signs for coefficients of GDP_{jt} of HS 52 and HS 44 were negative, which did not agree with expectations. As mentioned before, wood is a low return product, thus according to the "hot money" theory of Sarno and Taylor (1999), China is most likely to import more high return products than wood. Additionally, according to C. Zhu, Taylor, and Feng (2004), the increased rates of consumption for wood in China were lagging behind much higher growth rates for GDP, due primarily to stagnation in the volume of wood used in the construction sector. This also contributed to the negative coefficient for GDP_{jt}. The inconsistency for HS 52 was mainly because the fashion trends favoured products made from man-made fibres rather than cotton in recent years (Robinson, 2016). China is the largest consumer of cotton and the largest supplier of textile products to the world (Robinson, 2016). The change in fashion trends affected the demand for cotton-made products, which further affected the cotton demand in China. A closer inspection of data on cotton imports and GDP of China during 2000 to 2014 (not reported in this paper), revealed that though the GDP of China was accelerating, demand for cotton could not match the speed of the GDP growth. Hence GDP_{jt} had a small negative effect on the import of cotton to China.

For P_{it} (population of exporting country), only the estimated sign of HS 52 was consistent with expectations, which shows a negative relationship between the exporter's GDP and the export of cotton to China from the 19 countries. The estimated signs for the coefficients of P_{it} for HS 12, HS 15, HS 44 and HS 47 were positive, which, apparently, were not consistent with expectations. This situation led to the thinking that an incorrect hypothesis might have been made. The research expected the population to have a negative impact because with the same level of GDP a larger population gives the country a smaller GDP per capita. However, during the 15 years, the population of the target countries varied as well as their GDP. A larger population did not represent a smaller GDP per capita. Inversely a larger population gave the exporting country more input to produce agri-food. Therefore, the exporter's population had

a positive impact on HS 12, HS 15, HS 44 and HS 47. For HS 12, the USA and Brazil have long been the two leading producers of oilseeds (Ying et al., 2012), as well as the largest exporters to China. The USA and Brazil claimed over 90% of total exports for HS 12 to China among the 19 countries. Meanwhile, for HS 47, the USA, Brazil and Canada were the largest exporters to China, which claimed over 60% of total exports to China among the 19 countries. Hence their population affected the model results more than the other countries. USA and Brazil both had a growing population during 2000 -2014, as they ranked first and third respectively among the 19 countries in terms of their population growth. In such a situation, the exporter's population had a positive impact on exports of HS 12 and HS 47 to China.

P_{jt} (population of importing country) had a negative coefficient with HS 12, HS 15 and HS 47 that corresponded to their expectations. As China has been the largest oilseeds consumer and the third largest producer in the world (Ying et al., 2012), a growing population would enable China to produce more oilseeds by themselves instead of importing from other countries. Hence, the population of China influenced the import of HS 12 negatively. For HS 47, although China has been the largest paper consumer in the world in 2009, the production and consumption of paper products have overlapped since 2006 (Tang et al., 2015). This overlap illustrated that a growing population enabled China to produce more pulp wood by themselves to meet their demand instead of importing from others. Hence China's population influenced the import of HS 47 adversely. Because of food security concerns, a country with a larger population will try to produce more agri-food by itself rather than import from other countries. However, HS 52 and HS 44 being cash crops, such security concerns do not apply. Already the second largest market for industrial timber, China is facing a shortage in wood (Zhu et al., 2004); the increasing population would only expand the demand for wood as the real estate industry in China has been growing at full speed. Hence China's population influenced wood exports to China positively. It should be noted that the absolute value for the coefficient for P_{jt} was many times larger compared to its counterpart of P_{it} (26.06 and 0.16 respectively). Consequently, the change in China's population would affect wood imports more significantly than a change in the exporter's population. For HS 52, being the world's largest cotton consumer and textile products supplier, China needed people not only to produce the cotton but also make the textiles. Since cotton is a labour-intensive plantation and textile is a labour-intensive industry (Robinson, 2016), a growing population would enable the country to have more labour to engage in this industry. In addition, an expanding population represents an increasing demand. Therefore, the population of China had a positive effect on cotton imports.

The estimated coefficients for E_{it} (proportion of agricultural employment for exporter) were negative for HS 12, HS 44 and HS 47, which meant the proportion of agricultural employment compared to the total employment for the 19 exporting countries adversely influenced the export of HS 12, HS 44 and HS47 to China. For HS 44, as wood has a low return on investment, the resources would be distributed to higher return investment to provide more benefit. Thus,

if there were more people engaged in the agriculture sector, they would come to high value-added products. Meanwhile, within the same area of land, wood needed more years since a tree needs longer years to grow compared to most vegetables and fruits; hence if there were more people coming into the agriculture sector, they would be more likely to produce fast-grown and short-term agricultural products. In other words, the higher proportion of employment in agriculture would neither increase the production of wood nor the export of wood. For HS 47, the USA, Brazil and Canada were the largest exporters to China, which claimed over 60% of total exports among the 19 countries. Because the USA, Brazil and Canada all had a small proportion of agricultural employment and their proportions were declining over the 15 years, it could contribute to the negative coefficient for E_{it}. As the percentage of employment in agriculture among exporters declined, the export of HS 12, HS 44 and HS 47 to China would rise. To the contrary, the estimated coefficients for E_{it} were positive for HS 15 and HS52, which meant the proportion of agricultural employment in total employment for the 19 exporting countries positively influenced their export to China. For HS 15 it is more complicated: Malaysia and Indonesia claimed over 77% of total exports among the 19 countries, with Malaysia 47% and Indonesia 31%. However, Malaysia was quite developed in the agriculture sector with the agricultural employment proportion below 10%, while Indonesia on the other hand, had around 40% of agricultural employment. Taking the rest of the 17 countries into consideration, the result suggested that the proportion of agricultural employment among exporters affected the export of HS 15 to China positively with a coefficient valued at 0.67. For HS 52, the largest exporters of cotton were the USA, Australia and Japan, which claimed over 80% of total exports among the 19 exporters during 2000-2014. These three exporters were all well-developed countries with a low proportion of agricultural employment, thus a larger E_{it} represented more labour and stronger productive forces in the agriculture sector. It allowed exporters to produce more agri-food, and furthermore enabled more agri-food exports. Therefore, the agricultural employment of the exporters impacted positively on the cotton exports to China.

The estimated coefficients for E_{jt} (proportion of agricultural employment for importing country) for HS 12, HS 15, HS 47 and HS 52 were all consistent with their expectations. As China was a developing country, a lower proportion of agricultural employment meant more self-sufficiency (or less import-dependent). Thus E_{jt} was positive. However, the estimated coefficient for E_{jt} of HS 44 was negative, apparently inconsistent with its expectation. Although the percentage of employment in agriculture was decreasing, the total forested land in China was limited, which affected employment and production in the forests. But China had a rapidly increasing population that were asking for more wood than China could produce, and the gap between demand and supply was continuously expanding (Tang et al., 2015; C. Zhu et al., 2004). Therefore, the import of wood was increasing despite a decline in the proportion of agricultural employment.

The estimated signs for coefficients of A_{it} (agricultural land area of exporting countries) of HS 12, HS 44, HS 47 and HS 52 were consistent with expectations, which meant that an increase in agricultural land area in exporting countries would enhance the export of these products to China from the 19 countries. The reason for this is the larger areas of agricultural land enabled the exporting country to produce and export more. However, the estimated coefficient for A_{it} of HS 15 was negative, which, apparently, was not consistent with expectations. As Malaysia's agricultural land area was the second smallest agricultural land area among the 19 exporters and given that Malaysia accounted for 47% of the total exports of HS 15 to China, the results of the model suggested that the agricultural land area impacted adversely on the export of HS 15 to China.

The estimated signs for coefficients of A_{jt} (agricultural land area of importing country) for HS 15 and HS 47 meant that an increase of agricultural land area in China would reduce the import of these products to China. China could produce more of these products by themselves if it had more agricultural land. On the contrary, HS 12, HS 44 and HS 52 had positive estimated signs for coefficients of A_{jt}. China's agricultural land area did not change much from 2000 to 2014, with an average rate of change of 0.19% annually. When compared to other factors like GDP, population and agricultural employment, the change in the agricultural land area of China was unnoticeable. For HS 44, since the demand for wood in China was increasing drastically, the recovered forest land could not make up for the growing demand (Tang et al., 2015; C. Zhu et al., 2004). China's import of HS 44 was rising while supply agricultural land was increasing. For HS 52, the cotton acreage in China did not change much although total agricultural land increased, requiring more imports.

The estimated coefficients for FTAs of HS 12, HS 15 and HS 44 were positive, which agreed with their expectations. Free trade agreements or being in a free trade region would lower the trading costs between partner countries. Particularly for HS 15, Malaysia and Indonesia claiming over 77% of total exports, have both been members of the Association of Southeast Asian Nations (ASEAN) since 2010. For HS 44 (wood), according to the General Administration of Customs of the People's Republic of China, tariffs range from 8% to 70% for non-FTA countries, but 0% for its FTA members. Thus, the FTA impact of the export of HS 44 to China was significantly positive. However, the estimated coefficients for FTAs of HS 52 and HS 47 were negative, which were inconsistent with expectations. For HS 47, the three largest exporters (the USA, Brazil and Canada which claimed over 60% of China's total imports of HS 47) did not have any FTA with China nor did they belong to any free trade region with China. The tariff for HS 47 is 8% according to the General Administration of Customs of the People's Republic of China. As China imported most of its wood pulp from countries rich in forest resources like USA, Brazil and Canada, the low prices in these countries outweighed the 8% tariff reduction that comes with an FTA. Hence FTA did not show a positive effect on trade of HS 47. A similar argument applies regarding HS 52 (cotton). USA, Australia and Japan claiming over 80% of China's total imports of cotton, did not have any FTA with China nor did they

belong to any free trade region with China during 2000 to 2014. United States and Australia having the best cultivating and harvesting machines are the dominant cotton producers in the world where absence of FTA did not negatively impact on their cotton exports to China (The China–Australia Free Trade Agreement entered into force in December 2015, after our data period).

Unexpectedly, the estimated signs for coefficients of distance of HS 12, HS 15, HS 44 and HS 47 were positive, which did not agree with expectations of a gravity model. Only HS 52 had a negative coefficient for distance. As modern container shipping and cheap fuel reduced transportation costs remarkably, the results indicated that distance was less of a deterrent in current times. For HS 12, the distance between China and its largest exporters, the USA and Brazil (claiming over 90% of China's import), were too far, 11000 km and 17600 km respectively. For HS 15, Malaysia and Indonesia ranked in the middle among the 19 exporters according to distance from China but claimed over 77% of the total exports of HS 15 to China among the 19 countries. For HS 52, the USA, Canada and Brazil claimed over 60% of the total exports of HS 47, and their distance from China ranked among the furthest four among all 19 exporters. For HS 44, tariff reduced from 70% to 0% due to FTA balancing the difference in transportation costs due to distance. This helped explain why distance was no longer a serious impediment to countries trading with each other.

4.2 Poisson Gravity Model Results for Chinese Aggregated Agri-food Imports

To eliminate the influence of conditions that only applied to a particular commodity group, an aggregated variable consisting of all five commodity groups (HS 12, HS 15, HS 44, HS 47 and HS 52) was generated. This aggregated data contains 1423 observations of exports from the 19 selected countries to China. Table 3 illustrates the result of the analysis, which again demonstrated statistically significant coefficients as the modulus of each variable passed the significance level of 1%. In particular, the estimated signs for GDP_{it} (GDP of exporting country), GDP_{jt} (importing country), P_{jt} (population of importing country), E_{it} (proportion of agricultural employment for exporting), E_{jt} (proportion of agricultural employment for importing country, A_{it} (agricultural land area of exporting country) and FTA_t were all consistent with expectations. Sign of only one of the estimated coefficients for P_{jt} was somewhat inconsistent with its expectation.

As expected, the estimated coefficients for GDP_{it} and GDP_{jt} were both positive, with absolute values of 0.60 and 3.51 respectively. The results suggest that the aggregated exports of five commodity groups to China would rise 0.60% and 3.51% respectively for every 1% increase in GDP of exporter or importer country. It is reasonable to expect that the GDP of China would have a much stronger impact on its agri-food imports compared to the GDP of its trading partner. China's GDP grew rapidly during the examined period and an expected continuation of growth signals to a growing import of agri-food.

Table 3: Poisson Gravity Model Results for the Export of Five Commodity Groups to China by All Export Values

Variable	GDP_{it} (β_1)	GDP_{jt} (β_2)	P_{it} (β_3)	P_{jt} (β_4)	E_{it} (β_5)	E_{jt} (β_6)	A_{it} (β_7)	A_{jt} (β_8)	FTA_t (β_9)	D_{ij} (β_{10})
Coefficient	0.60***	3.51***	0.79***	-13.12***	0.04***	3.12***	-0.25***	12.83***	2.36***	1.93***
	(0.00003)	(0.00011)	(0.00003)	(0.00252)	(0.00002)	(0.00014)	(0.000006)	(0.00219)	(0.00005)	(0.00003)
R-squared	0.30									

Note: *** indicate the significance of the t-statistic at 1%. All of the independent variables were found to be significant at this level. Standard errors are in brackets. 1423 observations.

The estimated coefficient for P_{it} was positive with an absolute value of 0.79, which indicated that an increase in the population of the exporter would lead to an increase in exports of the aggregated commodity to China. On the contrary, the estimated coefficient for P_{jt} was negative for China. Although the population of China is growing, the growth rate is declined due to the one-child policy in China during our observation period.

The estimated coefficients for both E_{it} and E_{jt} were positive, with absolute values of 0.04 and 3.12 respectively. The results suggested that the exports of the aggregated five groups of agri-food could expect a boost when the proportion of agricultural employment in the exporter or importer rises. The estimated coefficients for A_{it} is negative, suggesting that more agricultural land in China can lead to more domestic productions and thus reduce agri-food imports. Meanwhile, the positive sign of A_{jt} suggested that expansion of the agricultural land area in the exporting countries would lead to an increase of their exports of agri-food to China.

Agreeing with the expectation, the estimated coefficient for FTA was positive with an absolute value of 2.36, which demonstrated that the exports of agri-food to China would increase if more exporters signed FTAs with China or belonged to the same free trade region. Meanwhile, since four out of five commodities show positive signs for D_{ij} (see Table 2 above), the result for the aggregated variable also show a positive association. We continue to hold on the argument that geographic distance is not an obstacle for international trade anymore, and agri-food imports to China from countries from further distances such as the USA or Brazil has in fact increased rather than decreased.

5. Conclusions

China has become one of the world's largest agricultural importers. This research estimated the effect of ten explanatory factors in China and its trading partners (GDP, population, proportion of agricultural employment, agricultural land area, FTAs and geographical distance) on Chinese agri-food imports for five commodity groups as well as their aggregated import

during the 2000-2014 period using an extended gravity model. These five commodity groups are HS 12 (oil seed, oleagic fruits, grain, seed, fruit), HS 15 (animal or vegetable fats and oils), HS 44 (wood and articles of wood), HS 47 (pulp of wood, fibrous cellulosic material) and HS 52 (cotton). Important trading partners of Chinese agri-food import included Australia, Belgium, Brazil, Canada, France, Germany, Indonesia, Italy, Japan, Malaysia, the Netherlands, New Zealand, the Philippines, South Korea, Spain, Sweden, Thailand, United Kingdom and the USA.

Results from our research suggest that all of the stated factors have had significant impacts on China's agri-food imports. Specifically, the level of GDP of the exporting countries had a positive effect on the exports to China except for exports of HS 15 and HS 44. China's GDP indicated a positive impact on China's imports apart from HS 44 and HS 52. The exporter's population affected agri-food exports to China positively except for cotton. On the contrary, China's population adversely affected imports to China apart from wood and cotton. The proportion of agricultural employment of the exporter had a positive relationship with exports of HS 15, HS 52 and total exports of the five agri-food groups and a negative relationship with the others. China's proportion of agricultural employment demonstrated a positive influence on China's agri-food imports except for imports of wood. Both the agricultural land area of the exporter and the importer indicated a positive effect on China's imports except for imports of HS 15. China's agricultural land area impacted negatively on imports of HS 47. FTAs influenced agri-food imports to China positively apart from imports of HS 47 and HS 52. Unexpectedly, distance influenced agricultural imports to China positively except for imports of cotton.

Our findings also suggest that China's agri-food imports are expected to increase, and the main driving force is the growing Chinese demand. As China's GDP keeps growing, the need for more and better quality agri-food products directly cause this change this demand. Hence, for China's government and decision makers, it is important to put more effort into China's own agricultural development and agri-food trade with diverse countries to alleviate its food security concerns.

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Results and Discussions

	Oil Seed (HS12)	Animal fat (HS15)	Wood (HS44)	Wood pulp (HS47)	Cotton (HS52)	All5 (Aggregate)
Intercept	61.498**	43.841	63.134*	99.944***	15.665	45.854***
	(36.047)	(34.024)	(33.269)	(34.143)	(35.225)	(0.055)
GDP_{China}	0.059	0.253**	0.200	0.038	0.079	0.269***
	(0.142)	(0.136)	(0.132)	(0.132)	(0.139)	(0.000)
$Population_{China}$	3.138*	2.378	3.393*	4.911***	0.827	1.897***
	(1.905)	(1.800)	(1.760)	(1.801)	(1.863)	(0.003)
$Employment_{Exporter}$	0.071***	0.071***	0.022	0.034**	0.052***	0.108***
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.000)
$LAND_{Exporter}$	0.006	0.082***	0.058**	0.075***	0.124***	0.238***
	(0.025)	(0.024)	(0.023)	(0.023)	(0.026)	(0.000)
Distance	0.053	0.158***	0.047	0.087***	0.252***	0.073***
	(0.032)	(0.031)	(0.030)	(0.030)	(0.030)	(0.000)
$REGION*GDP_{China}$	0.050	0.042	0.097***	0.058*	0.011	1.087***
	(0.036)	(0.034)	(0.034)	(0.034)	(0.036)	(0.000)
$REGION*Population_{China}$	0.060	0.059	0.134***	0.082*	0.023	1.424***
	(0.049)	(0.047)	(0.047)	(0.046)	(0.050)	(0.000)
FTAdummy	0.061	0.073	0.155***	0.174***	0.113*	2.287***
	(0.066)	(0.061)	(0.059)	(0.061)	(0.064)	(0.000)

Note: Standard errors are inside the brackets; *, ** and *** denotes 10%, 5% and 1% significance levels, respectively.