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Tariff changes go along with other types of reforms that might also affect trade. Moreover, tariffs might be driven by trade

China's Agricultural Trade Cost Elasticity: Estimates from Using Translog Gravity Model

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The elasticity of trade flows with respect to trade costs involve important implications that quantify welfare gains from trade and predict the effects of trade policy on trade flows. The major purposes of this study are to estimate China's agricultural trade–cost elasticity and to analyze its heterogeneity across different types of trading partners. A micro–founded method based on the translog gravity model developed by Novy (2013) is applied to measure the trade–cost elasticity of China's agricultural products using a panel dataset of its major trading partners. First, the estimation results show that there was an obviously negative relationship between the import share of trading partners with respect to China's agricultural products and its corresponding trade–cost elasticity. Specifically, the higher the import share of trading partners with respect to China's agricultural products, the lower the weighted average trade–cost elasticity. Second, the weighted average trade–cost elasticity of aggregate agriculture experienced a rapid downward trend from 1996 to 2016. The trade–cost elasticity fell from 13.68 in 1996 to 6.54 in 2016. Finally, the trade–cost elasticity measure presents significant heterogeneity across various types of trading partners.

Key words: Agricultural products, China, Trade–cost elasticity, Translog gravity

INTRODUCTION

In recent years, China has pursued export–oriented economic policies and experienced a sharp increase in trade with the rest of the world. China's integration into the global economy is largely due to its participation in bilateral and multilateral trade agreements. A large empirical body of literature has shown that China's average trade costs have experienced substantial declines since its trade policy reforms (Shi, 2008; Fang *et al.*, 2010; Xu and Liang, 2010). However, this evidence applies to the aggregated level rather than to the industry specific level, such as the agricultural sector, where special and differential treatments are accepted by multilateral and bilateral trade agreements. Wang *et al.* (2016) demonstrated that China's agricultural exports experienced a modest downward trend in trade costs from 1995–2011. China's agricultural trade costs continue to exist and are much larger than those in non–agricultural sectors. This observation raises a question. By how much do trade costs impede China's agricultural exports? The trade cost elasticity regarding the link between trade costs and trade flows is a crucial parameter to answer this question. Meanwhile, obtaining a correct measure for the trade cost elasticity is also useful in the prediction of the effects of trade policies on trade flows and welfare. Unfortunately, we have little direct information on China's agricultural trade cost elasticity.

There is considerable interest in the literature for the estimation of trade cost elasticity. Romalis (2007) and Caliendo and Parro (2012) identify trade elasticity from variations in tariffs. Eaton and Kortum (2002) and

Simonovska and Waugh (2012) employ price differences across countries as a proxy for trade costs to obtain an estimate of trade elasticity. The estimators that employ tariff data suffer from endogeneity and omitted variable bias[1]. The approaches used by Eaton and Kortum (2002) and Simonovska and Waugh (2012) are restricted to trade in goods where tariffs and price data are available. Novy (2013) developed a translog gravity model to measure the elasticity of trade flows with respect to trade costs. Due to more flexible substitution patterns across goods, translog gravity breaks the constant trade cost elasticity that is the hallmark of traditional gravity equations. Contrary to the standard gravity equation that implies constant trade cost elasticity, the translog gravity equation generates endogenous trade cost elasticity. Another advantage is that the translog gravity model is parsimonious in its data requirements and relatively simple to empirically implement.

Therefore, this paper uses the translog gravity approach to measure the elasticity of China's agricultural trade flows with respect to trade costs. The rest of the paper is organized as follows. Section 2 briefly explains the estimation approach of trade cost elasticity developed by Novy (2013). Section 3 introduces our data and their sources. In Section 4, we use the translog gravity model to measure the elasticity of China's agricultural trade flows with respect to trade costs. In the last section, we discuss our findings and conclude the paper.

TRANSLOG GRAVITY MODEL

The gravity model, a work–horse of international trade analysis, has been used to refer to a variety of dif-

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ferent specifications of the determinants of bilateral trade. However, leading trade models from the current literature imply a gravity equation that is characterized by a constant elasticity of trade flows with respect to trade costs. This means that, for a given change in trade costs, trade is expected to react by the same percentage for all bilateral trading pairs. Novy (2013) challenges this "one size fits all" feature and derives a gravity equation from homothetic translog preferences in a general equilibrium framework. Translog preferences are more flexible since they allow for richer substitution patterns across the different varieties of exports. This flexibility allows the translog gravity equation to estimate the heterogeneous impacts of trade costs across pairs. Based on Novy (2013), we use the translog gravity model to measure the elasticity of China's agricultural trade flows with respect to trade costs. In addition to its key feature of endogenous trade–cost elasticity, the translog gravity model is appealing because it is parsimonious in its data requirements and relatively simple to empirically implement.

Novy (2013) derives the following gravity equation for import shares ($\frac{x_{ij}}{y_j}$) based on a translog demand system.

$$\frac{x_{ij}}{y_j} = \frac{y_j}{y^W} - \gamma n_i \, ln(t_{ij}) + \gamma n_i \, ln(T_j)$$

$$+ \gamma n_i \sum_{s=1}^{J} \frac{y_s}{y^W} \, ln\Big(\frac{t_{is}}{T_S}\Big), \tag{1}$$

where x_{ij} denotes the value of exports from exporting country i to importing country j, and y_j denotes the income of country j. y^W is world income, defined as $y^W \equiv \sum_{j=1}^{J} y_j$. n_i is the number of goods for country i. γ denotes translog parameter.

t_{ij} is the bilateral trade costs, which is given as a log–linear function of observable trade cost proxies:

$$ln(t_{ij}) = \rho \, ln(dist_{ij}) + \delta adj_{ij}, \tag{2}$$

where $dist_{ij}$ denotes the distance between the capitals of countries i and j, which can be a proxy variable of t_{ij}. Another proxy variable is the adjacency dummy variable adj_{ij} that takes on the value 1 if country i and country j share a common border or 0 if they do not. ρ is the distance elasticity of trade cost, and δ is the adjacency coefficient.

$ln(T_j)$ is a weighted average of logarithmic trade costs over the trading partners of country j, akin to the inward multilateral resistance in Anderson and van Wincoop (2003). It can be written as

$$ln(T_j) = \frac{1}{N} \sum_{k=1}^{N} ln(t_{kj}) = \sum_{s=1}^{J} \frac{n_s}{N} ln(t_{sj}). \tag{3}$$

We substitute equation (2) into equation (3) to get

$$ln(T_j) = \rho ln(T_j^{dist}) + \delta T_j^{adj}, \tag{4}$$

where $ln(T_j^{dist}) \equiv \sum_{s=1}^{J} \frac{n_s}{N} ln(dist_{sj})$ and $T_j^{adj} \equiv \sum_{s=1}^{J} \frac{n_s}{N} adj_{sj}$.

Since the first and last terms on the right–hand side of equation (1) do not vary over the importing country j, they can be captured by an exporter's fixed effect $S_i \equiv \frac{y_i}{y^W} + \gamma n_i \sum_{s=1}^{J} \frac{y_s}{y^W} \, ln(\frac{t_{is}}{T_S})$. Then, by rewriting equation (1), we have

$$\frac{x_{ij}}{y_j} = -\gamma \rho n_i \, ln(dist_{ij}) + \gamma \rho n_i \, ln(T_j^{dist}) - \gamma \delta n_i \, adj_{ij}$$

$$+ \gamma \delta n_i \, T_j^{adj} + S_i + \varepsilon_{ij}, \tag{5}$$

where ε_{ij} is the mean–zero error term.

The trade cost elasticity follows from equation (1) as[2]

$$\eta_{ij} = \frac{-\gamma n_i}{(x_{ij}/y_j)} . \tag{6}$$

The form of η_{ij} allows trade costs to have a heterogeneous impact across country pairs. Specifically, ceteris paribus, the more that the destination country imports from a particular exporting country, the less sensitive its bilateral imports are to trade costs.

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[2] The trade cost elasticity equation can be obtained as follow

$$\eta_{ij} = \frac{dln(x_{ij}/y_j)}{dln(t_{ij})} = \frac{1}{(x_{ij}/y_j)} \cdot \frac{d(x_{ij}/y_j)}{dln(t_{ij})}$$

Due to the term $\frac{dln(x_{ij}/y_j)}{dln(t_{ij})}$ corresponds to the distance coefficient in equation (1), $-\gamma n_i$, we have

$$\eta_{ij} = \frac{-\gamma n_i}{(x_{ij}/y_j)}$$

[3] Given the standard gravity equation as Anderson and Wincoop (2003) $x_{ij} = \frac{y_i y_j}{y^W} (\frac{t_{ij}}{\Pi_i P_j})^{1-\sigma}$ where t_{ij} is the bilateral trade cost measure, Π_i is the outward multilateral resistance of country i, and P_j is the inward multilateral resistance of country j. $\sigma > 1$ is the elasticity of substitution across goods.

Divide each side of the above equation by y_j, and then take logarithms of both side, we have

$$ln\Big(\frac{x_{ij}}{y_j}\Big) = ln\Big(\frac{y_j}{y^W}\Big) - (\sigma - 1) \, ln(t_{ij}) + (\sigma - 1) \, ln(\Pi_i) + (\sigma - 1) ln(P_j).$$

Use the exporter fixed effect and the importer fixed effect to control for each country's multilateral trade resistance terms, we have

$$ln\Big(\frac{x_{ij}}{y_j}\Big) = -(\sigma - 1) \rho \, ln(dist_{ij}) - (\sigma - 1) \delta \, adj_{ij} + \tilde{S}_i + \tilde{S}_j + \varepsilon_{ij}.$$

To calculate η_{ij}, the value of γ is obtained as follows. First, we estimate the traditional gravity equation[3]

$$ln\left(\frac{x_{ij}}{y_j}\right) = -(\sigma-1)\rho\,ln(dist_{ij}) - (\sigma-1)\delta adj_{ij} + \tilde{S}_i + \tilde{S}_j + \varepsilon_{ij}, \tag{7}$$

where the distance coefficient in equation (7) corresponds to the parameter combination $-(\sigma-1)\rho$. Under the assumption of an elasticity of substitution equal to $\sigma = 8$, the value of ρ can be obtained.

Then, we estimate equation (5) to obtain the distance coefficient $\gamma\rho$. Therefore, we can obtain the value of γ using the above two steps.

DATA

Equation (6) is applied to calculate the trade–cost elasticity of China's agricultural exports to its 33 trading partners[4] over a longer period (1996–2016). The major trading partners included in our analysis account for 80.25 percent of China's total agricultural exports during the sample period. We adopt HS classification and define agricultural products as all products from chapters (01) to (24) and from chapters (50) to (53) in the HS classification standards. The necessary data is primarily the exported agricultural trade data for China, sourced from the UN COMTRADE database and denominated in US dollars. We compiled a total of 684 observations over the years 1996–2016[5]. The income data of trading partners are taken from the World Bank Development Indicators Annual Database (WDI), which is denominated in US dollars.

To obtain the value of γ, we need to regress the traditional gravity equation (7) and the translog estimating equation (5). In this analysis, the bilateral distance between capital cities and adjacency information between two countries were taken from the CEPII Database.

Before the regression, we need to calculate the multilateral resistance terms $(ln(T_j^{dist}) \equiv \sum_{s=1}^{J}\frac{n_s}{N}\,ln(dist_{sj})$ and $T_j^{adj} \equiv \sum_{s=1}^{J}\frac{n_s}{N}\,adj_{sj})$. To conduct this calculation, we required data on $n_{s(s\neq CHN)}$, which is the number of goods that originate from country s. n_s is not directly available, but by following the approach of Hummels and Klenow (2005), it can be expressed as the extensive margin of country s relative to the rest of the world. The extensive margin is measured by weighting categories of goods by their overall importance in exports. We

directly obtain the value of n_s from Hummels and Klenow (2005). The value of N is the sum of the extensive margin of 124 exporting countries[6].

Regression results on the panel data are presented in Table 1. The regression coefficients of the explanatory variables are similar to the theoretical expectations. Combined with the traditional gravity equation, the coefficient on the variable $ln(dist_{ij})$ corresponds to $-(\sigma-1)\rho$. We can obtain $-(\sigma-1)\rho = -1.120$ from columns 1 and 2. The elasticity of substitution is equal to $\sigma = 8$, and we obtain the value of ρ as 0.160. As the translog estimating equation (5) shows, the coefficient on the variable $ln(dist_{ij})$ corresponds to $-\gamma\rho n_i$. We take -0.001 from columns 3 and 4 of Table 1, since $\gamma\rho n_i = 0.001$. We have already obtained $n_i = n_{CHN} = 0.704$. Then, we get $\rho n_i = 0.113$. Then, the value of the translog parameter follows as $\gamma = 0.009$. The trade–cost elasticity can be calculated across different import shares of trading partners with respect to China's agricultural products.

Table 1. Regression of translog estimating equation and traditional gravity estimating equation

	$ln\left(\frac{x_{ij}}{y_j}\right)$	$\frac{x_{ij}}{y_j}$
$ln(dist_{ij})$	–1.120***	–0.001**
	(–25.350)	(–3.100)
adj_{ij}	0.786***	0.000
	(6.330)	(0.110)
$ln(T_j^{dist})$		0.000
		(0.210)
T_j^{adj}		–
$\_cons$	1.493***	0.008
	(4.060)	(1.000)
N	684	684
R^2	0.944	0.658

Notes: t–statistics (in parentheses) computed with White's heteroscedasticity–consistent standard errors. *, ** and *** indicates significance at the 10, 5 and 1 percent levels, respectively.

MEASUREMENT RESULTS

We estimate bilateral trade–cost elasticity for China's agricultural products with its 33 trading partners over the sample period 1996–2016 (see Table 2). The main

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[4] The 33 trading partners include China, Hong Kong(HKG),Japan(JPN), United States of America(USA), Republic of Korea(KOR),Thailand(THA), Malaysia(MYS), Bangladesh(BGD), Philippines(PHL), Indonesia(IDN), Russian Federation(RUS), Germany(DEU), Netherlands(NLD), Italy(ITA), United Kingdom(GBR), Canada(CAN), India(IND), Australia(AUS), Singapore(SGP), Spain(ESP), Mexico(MEX), Pakistan(PAK), Brazil(BRA), Benin(BEN), Nigeria(NGA), France(FRA), Myanmar(MMR), Togo(TGO), Belgium(BEL), Sri Lanka(LKA), Turkey(TUR), Egypt(EGY),Iran(IRN), South Africa(ZAF).

[5] The maximum number of observations is 33*21=693, but 9 observations are missing.

[6] Hummels and Klenow (2005) measured the extensive margin of 126 exporting countries/regions, but in this paper we drop Congon and Taiwan.

[7] Measurement results show that the span of trade–cost elasticity is very large, which minimum value is 0.04 and maximum value is 1608.

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Table 2. Index of agricultural bilateral trade–cost elasticity between China and major trading partners

	AUS	BEL	BEN	BGD	BRA	CAN	DEU	EGY	ESP	FRA	GBR	HKG	IDN	IND	IRN	ITA
1996	37.180	–	1.046	3.080	131.162	48.122	46.688	17.110	78.149	85.826	52.406	0.290	12.207	32.831	1607.041	41.654
1997	36.028	–	0.853	2.699	128.588	52.936	41.648	22.838	49.520	83.504	66.102	0.294	7.481	35.943	309.816	33.159
1998	32.320	–	0.518	2.615	149.967	48.100	34.276	18.910	38.170	79.478	69.531	0.342	1.832	25.126	33.816	37.843
1999	25.125	25.061	0.450	2.118	130.813	51.528	40.028	8.711	38.511	98.977	64.857	0.376	2.832	13.723	92.467	30.113
2000	30.119	21.813	0.421	1.790	220.731	40.809	32.792	12.172	30.309	82.859	59.427	0.378	3.084	16.880	57.434	20.780
2001	25.349	24.335	0.276	1.957	169.834	35.749	30.139	12.180	31.619	77.805	54.313	0.377	3.900	17.364	189.980	22.840
2002	22.307	32.006	1.437	2.466	104.978	33.722	33.925	16.181	59.688	109.783	60.698	0.350	2.994	16.425	66.775	26.099
2003	18.725	20.075	0.237	1.335	121.749	31.603	32.380	8.653	56.466	105.469	53.686	0.261	3.126	14.336	7.057	25.836
2004	20.281	18.413	0.199	1.256	105.763	27.194	32.406	4.601	39.779	107.474	57.635	0.244	3.747	11.434	52.288	26.242
2005	21.477	11.047	0.134	0.998	77.757	25.442	24.273	7.505	24.844	83.472	48.925	0.263	3.843	10.751	12.075	19.883
2006	17.565	10.486	0.103	0.809	61.679	24.558	20.989	6.954	22.698	65.097	42.250	0.263	3.398	11.968	43.616	17.440
2007	15.777	10.478	0.079	0.794	76.547	22.040	19.708	7.593	21.487	61.891	42.939	0.276	2.904	13.682	35.443	17.407
2008	15.498	9.381	0.061	0.725	31.646	20.195	18.522	5.724	22.254	51.603	33.891	0.277	3.538	13.851	46.228	16.278
2009	14.131	10.061	0.074	0.803	49.334	18.042	19.067	6.743	22.140	54.923	30.055	0.293	3.327	13.599	33.477	19.002
2010	14.488	8.022	0.070	0.622	24.838	17.412	15.836	6.937	15.535	49.361	24.606	0.259	2.825	13.779	26.291	13.004
2011	13.403	7.830	0.077	0.531	22.928	16.925	14.554	5.209	13.259	42.113	22.098	0.251	2.775	15.488	25.706	11.020
2012	14.909	7.532	0.113	0.545	24.535	15.552	14.544	5.971	15.127	42.468	23.283	0.245	3.232	15.277	30.720	13.736
2013	13.758	7.835	0.082	0.526	20.850	16.516	14.988	6.328	13.676	42.408	21.134	0.216	3.379	14.452	31.571	12.618
2014	12.571	8.390	0.089	0.599	26.407	15.377	14.786	6.585	13.470	43.211	23.149	0.224	3.082	16.956	17.422	13.035
2015	12.370	7.698	0.103	0.640	23.623	13.808	–	6.368	11.940	38.469	22.947	0.243	3.308	18.883	9.132	12.394
2016	10.909	8.159	0.160	0.704	22.443	12.493	15.397	7.471	11.207	39.546	21.362	0.240	3.236	20.295	–	12.756

Table 2. Continued

	JPN	KOR	LKA	MEX	MMR	MYS	NGA	NLD	PAK	PHL	RUS	SGP	TGO	THA	TUR	USA	ZAF
1996	7.886	4.186	5.282	627.550	–	4.554	55.127	9.480	11.857	2.250	7.305	1.305	0.481	15.785	75.443	80.679	28.976
1997	7.584	3.066	3.636	330.222	–	2.084	42.037	10.652	8.762	2.420	9.123	1.731	0.623	11.726	36.005	77.040	26.128
1998	7.623	3.167	3.303	170.573	–	2.124	47.899	12.092	27.627	1.393	7.108	2.692	0.956	12.131	99.132	81.520	23.221
1999	7.964	2.995	2.805	162.529	–	1.938	26.148	12.531	20.204	3.321	9.224	3.082	0.970	8.064	82.783	80.042	23.219
2000	7.460	2.391	2.406	112.003	1.359	1.775	14.568	9.809	8.724	3.205	12.578	3.421	0.701	5.361	46.544	68.687	20.105
2001	6.279	2.305	1.828	91.459	0.662	2.111	12.272	9.902	18.921	3.461	10.525	3.066	0.428	6.658	41.536	69.880	18.692
2002	6.109	2.295	2.369	67.216	0.602	1.524	35.051	13.973	10.257	2.966	6.684	2.922	1.804	6.101	45.716	57.990	11.856
2003	6.097	2.009	1.396	31.220	0.879	1.404	7.365	14.195	11.943	2.057	6.423	2.577	0.344	4.394	22.675	46.392	9.425
2004	5.429	2.557	1.383	18.573	0.886	1.913	12.665	14.298	10.266	2.147	8.482	2.714	0.169	4.241	24.497	44.013	16.212
2005	5.037	2.299	1.457	24.063	1.071	1.713	14.623	11.320	4.278	2.150	9.181	2.766	0.147	3.929	17.742	37.703	15.929
2006	4.612	2.476	1.524	20.809	0.959	1.646	17.744	8.547	5.505	1.908	9.082	3.040	0.117	3.713	18.464	30.360	12.375
2007	4.573	2.310	1.386	22.909	1.258	1.547	18.805	7.690	5.993	1.996	9.070	3.803	0.100	3.352	16.888	27.399	11.260
2008	5.544	2.345	1.610	19.443	2.074	1.589	9.881	8.485	6.466	2.332	10.282	3.229	0.093	2.726	18.762	24.328	10.198
2009	5.853	2.322	1.846	16.573	2.230	1.276	6.480	8.287	4.370	1.745	9.216	3.160	0.088	2.384	19.149	26.157	9.341
2010	5.328	2.183	1.814	14.802	2.263	1.227	12.537	6.756	3.244	1.869	8.629	3.427	0.059	2.039	11.544	21.879	10.587
2011	4.746	2.065	1.679	11.537	2.073	1.144	7.869	6.199	3.467	1.616	8.891	3.512	0.047	1.633	10.876	19.611	9.442
2012	4.435	2.238	1.720	13.326	1.688	1.146	7.467	6.023	3.482	1.318	9.407	3.522	0.042	1.505	15.009	19.206	8.588
2013	3.942	2.261	1.679	13.156	1.243	0.981	8.042	5.943	3.855	1.092	8.990	2.946	0.057	1.317	13.850	19.552	8.495
2014	3.759	2.239	1.633	13.017	0.974	0.987	9.356	5.642	3.218	1.333	7.679	2.671	0.054	1.184	14.565	20.158	8.323
2015	3.705	2.401	1.341	11.517	1.076	0.908	5.192	4.960	2.721	1.047	6.673	2.664	0.072	0.889	17.384	20.887	8.348
2016	4.257	2.376	1.390	10.032	1.034	0.947	8.612	4.920	3.342	0.785	5.736	2.844	0.090	0.968	20.854	21.817	7.454

results illustrate that bilateral trade cost elasticity varies across trading partners[7], depending on how intensely the exporting destination trades with China. In addition, trade–cost elasticity heterogeneity in bilateral trade is significantly revealed by the measurement results, as we compare the weighted average trade–cost elasticity in China's agricultural products exported to different trading partners.

The relationship between Trade– cost elasticity and import shares

Figure 1 plots the trade–cost elasticity of China's agricultural products in 2016[8] against the corresponding import shares of trading partners[9]. The negative correlation between the two indexes indicates that the effect of trade costs varies depending on how intensely two countries trade with each other. Specifically, the higher the import share of trading partners with respect to China's agricultural products, the lower the weighted average trade–cost elasticity. For example, the first observation on the right corresponds to the Philippines, which provide 1.1 percent of its total imports, and its trade–cost elasticity is quite low at 0.79. The second observation from the left corner corresponds to Japan's import share of 0.2 percent, and its trade–cost elasticity is 4.25. The third observation from the left–hand side corresponds to Turkey's import share of 0.04 percent, and its trade–cost elasticity is quite high at 20.85. Figure 1 also shows the 'one size fits all' trade–cost elasticity from the traditional gravity model by the horizontal line with the value of 7. The differential effect of trade costs for China's agricultural exports is the evidence that the common 'one size fits all' trade–cost sensitivity is not reasonable. It cannot respond to changes in the competitive trade environment.
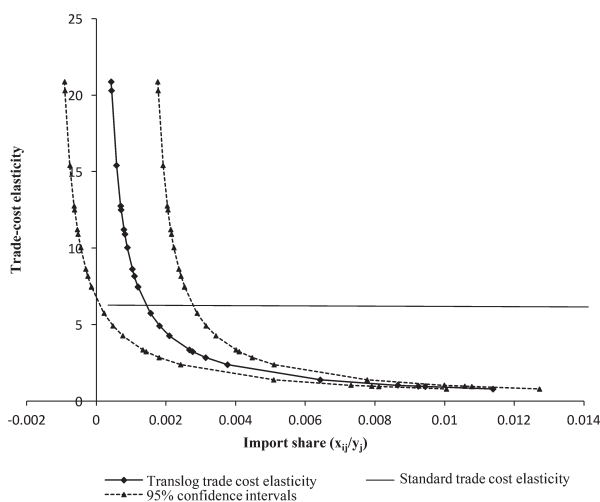
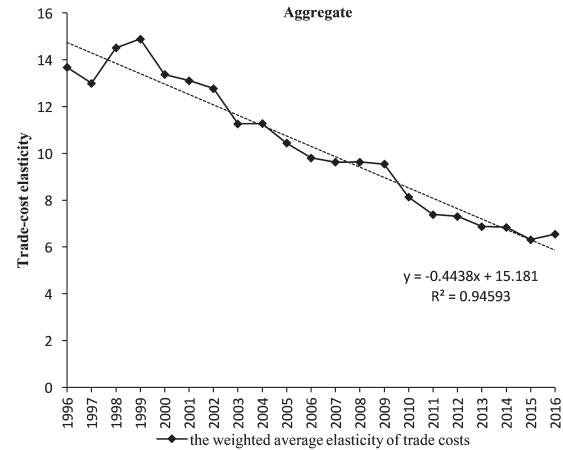**Fig. 1.** Trade-cost elasticity of China's agricultural products in 2016.

Fig. 2. Weighted average trade-cost elasticity as measured for China's agricultural products.

Aggregate agriculture

Figure 2 illustrates the weighted average elasticity of trade flows with respect to trade costs for China's aggregate agriculture trade with 33 trading partners over the sample period of 1996–2016. The measure is expressed as the trade–weighted average trade–cost elasticity, which is an average of its exporting trade–cost elasticity weighted by the value of trade with each trading partner. China's export of agricultural products experienced an obvious downward trend in trade–cost elasticity. More specifically, the trade–cost elasticity of China's agricultural products was 13.68 in 1996 and fell to 6.54 in 2016, with a reduction of 52.13 percent. In addition, China's addition to the WTO facilitated its integration into the global economy. Before joining the WTO, the weighted average trade–cost elasticity of China's agricultural products strongly fluctuated. Since joining the WTO, the trend of China's agricultural export trade–cost elasticity to trading partners has been steadily dropping. Integration into the world economy has proven a powerful means for China to build closer economic relationships with trading partners. Trade liberalization and trade facilitation promote China's agricultural exports by breaking tariff and non–tariff trade barriers. However, the weighted average trade–cost elasticity was 6.57 in 2016, which is still high. This means that if trade costs fall by 1 percent, then trade is expected to go up by 6.57 percent. Reducing trade costs will continue to have a huge impact on China's agricultural exports.

Different continents' countries

Figure 3 illustrates the differential trade–cost elasticity across continental trading partners. The overall trend of the weighted average trade–cost elasticity in several intercontinental countries is heterogeneous. China's agricultural products face the highest trade–cost

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[8] The similar results hold for other years as well as the whole sample period.

[9] We plot Fig1 using the data within 95% confidence intervals of the import share $\left(\frac{x_{ij}}{y_j} \right)$.

elasticity when entering North and South American markets, followed by European, Oceanic, African countries, and Asian countries, respectively. Specifically, the weighted average trade–cost elasticity for American countries was quite high at 19.8, followed by an elasticity of 12.8 for European countries and 10.9 for Oceanic countries in 2016. African countries' trade–cost elasticity was 6.9, which was higher than the 2.2 for Asian countries in 2016. Taking into account that geographical distance is still the main factor affecting import shares, Asian countries were China's major trading partners for a long time. They were also important export markets for China's agricultural products. However, American countries are geographically far from China. Sino–US bilateral trade is more sensitive to trade costs. However, the trade–cost elasticity facing China's agricultural exports to American trading partners experienced a rapidly downward trend. It declined from 82.7 in 1996 to 19.8 in 2016, a reduction of 76 percent. The trade–cost elasticity for European, Oceanic, and African countries present a relatively modest trend. The weighted average trade–cost elasticity with respect to Asian trading partners in the sample period only ranges from 2 to 5. Figure 3 shows that China's agricultural exports to several intercontinental countries experience an obviously convergent trend in weighted average trade–cost elasticity from 2008. The gap between America and Asia narrows from 78.2 in 1996 to 17.6 in 2016. Specifically, the weighted average trade–cost elasticity in China's agricultural exports to American countries declined by a staggering 70.9 percent between 1996 and 2008, but Asian countries' trade–cost elasticity went down by 28.79 percent. After 2008, the trade–cost elasticity of American countries experienced a relatively modest downward trend. The elasticity for American countries was 24.1 in 2008 and 19.8 in 2016, a reduction of 17.7 percent. For Asian countries, the value changes from 3.2 in 2008 to 2.2 in 2016, corresponding to a 30.4 percent decrease. Bilateral trade grows faster when the initial trade relationship was thin. When they already engaged in a lot of trade, country pairs hardly benefit. It also reveals that the overall decline in trade–cost elasticity is largely caused by the American trading partners.

Developed countries vs Developing countries

We categorize trading partners as developed[10] or developing[11] countries according to the International Monetary Fund's development classification. We compare the weighted average trade–cost elasticity of China's agricultural export patterns with developed and developing trading partners. Figure 4 shows that the trade–cost elasticity of developed countries with respect to China's agricultural products is higher than that for developing countries. However, the gap narrows from 16.83 in 1996 to 8.18 in 2016. The trade–cost elasticity facing China's agricultural exports to developed trading partners experienced an obvious decline. Specifically, the trade–cost elasticity declined from 21.1 in 1996 to 10.9 in 2016, an average annual reduction rate of 2.3 percent. However, the trade–cost elasticity of developing countries experienced a less significant decline. The weighted average trade–cost elasticity with respect to developing partners in sample period only ranges from 2 to 5. It was only 4.25 in 1996 and dropped to 2.72 in 2016, an average annual reduction rate of 1.7 percent. There was a willingness by developed countries to maintain protectionist trade policies in their agricultural sectors. Therefore, the resistance of developed countries to import China's agricultural products is greater than that
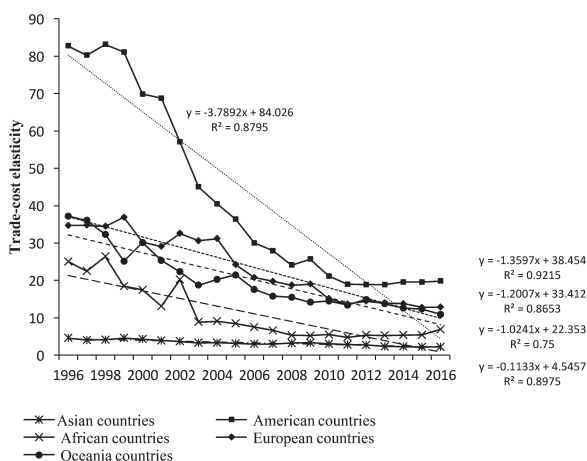

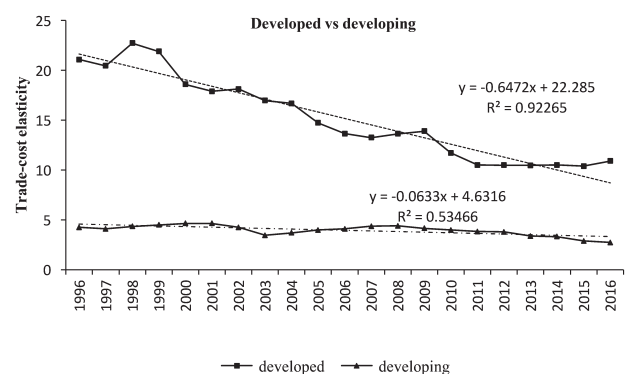**Fig. 3.** Weighted average trade-cost elasticity of China's agricultural products across continents.

Fig. 4. Weighted average trade-cost elasticity of China's agricultural products across developmental partner groups.

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[10] The 12 developed countries/regions include Australia(AUS), Belgium(BEL), Canada(CAN), Germany(DEU), Spain(ESP), France(FRA), United Kingdom(GBR), Japan(JPN), Italy(ITA), Republic of Korea(KOR), Netherlands(NLD), United States of America(USA).

[11] The 21 developing countries/regions include China, Hong Kong(HKG), Thailand(THA), Malaysia(MYS), Bangladesh(BGD), Philippines(PHL), Indonesia(IDN), Russian Federation(RUS), India(IND), Singapore(SGP), Pakistan(PAK), Brazil(BRA), Benin(BEN), Nigeria(NGA), Myanmar(MMR), Togo(TGO), Sri Lanka(LKA), Egypt(EGY), Iran(IRN), South Africa(ZAF), Turkey(TUR), Mexico(MEX).

of developing countries. The import value of developed countries with respect to China's agricultural products is lower. Additionally, the income level of developed countries is higher than that of developing countries. The import share of developed countries is smaller than that of developing countries. Developed countries are more sensitive to trade costs.

RTA countries vs non–RTA countries

Trade–cost elasticity heterogeneity in bilateral trade is clearly revealed in Figure 5. In Figure 5 we compare the weighted average trade–cost elasticity of China's agricultural exports to RTA[12] countries with those of non–RTA[13] countries from 1996 to 2016. The trade–cost elasticity of non–RTA countries in the sample period ranges from 14 to 52, which is significantly higher than those for RTA countries (2 to 5). However, the gap narrows from 45.18 in 1996 to 12.59 in 2016. Specifically, the trade–cost elasticity of China's agricultural exports fell very rapidly, as is evidenced by a reduction of approximately 69.9 percent when entering non–RTA markets. However, the trade–cost elasticity facing China's agricultural exports to RTA trading partner experienced a relatively gentle decline, with an average annual reduction rate of 2.3 percent. This means that it was necessary to reduce trade costs with respect to non–RTA countries. However, individual RTA trading partners still have trading potential. For example, the trade–cost elasticity for India was 20.29 in 2016. It was higher than other non–RTA trading partners' trade–cost elasticity, such as with an elasticity of 5.7 for Russia. In recent years, China engaged in multilateral or bilateral negotiations to sign free trade agreements (FTAs). As of 2016, China had 14 FTAs in operation, with another 8 under negotiation and another 6 under preliminary consultation. FTAs will eliminate certain tariffs and non–tariffs barriers and facilitate economic and trade cooperation.
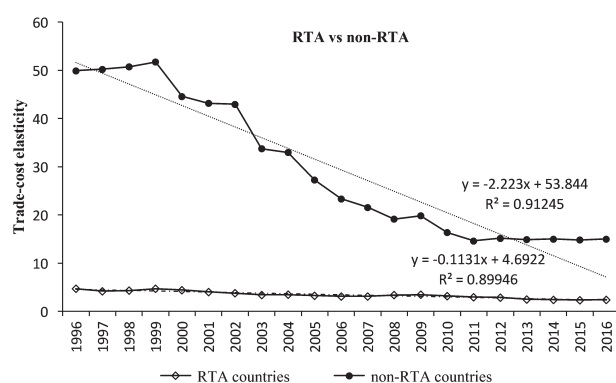

Fig. 5. Weighted average trade-cost elasticity of China's agricultural products across RTA partner groups

CONCLUSIONS

This paper applies a trade–cost elasticity equation based on the translog gravity model developed by Novy (2013) to measure the trade–cost elasticity of China's agricultural exports. It applies a panel dataset for its major trading partners. In contrast to the traditional gravity equation based on CES, the translog gravity generates a variable, endogenous trade–cost elasticity. With respect to the realistic competitive trade environment, the flexible trade–cost elasticity is more reasonable and representative. Moreover, this method is parsimonious in its data requirements and easy to empirically implement.

The empirical results presented in this paper confirmed that trade–cost elasticity varies based on the intensely of the trade between two countries. We found there is a negative correlation between the import share of trading partners and trade–cost elasticity. Bilateral trade is more sensitive to trade costs when China provides a relatively smaller import share of agricultural products to its trading partners. Moreover, China's trade cost elasticity experienced an obviously downward trend during the period of 1996–2016. China has pursued export–oriented economic policies in recent years. The rapid increase of exports was followed by a reduction in trade–cost elasticity. However, the trade–weighted average trade–cost elasticity was 6.54 in 2016, which suggests that China still has agricultural exporting potential. The significant heterogeneity and substantial differences have been revealed in the measurement results, as we compare the weighted average trade–cost elasticity in China's agricultural products exported to different trading partners. On average, the trade–cost elasticity for American countries is the highest among several continents, and China's agricultural exports face a lower trade–cost elasticity when entering other Asian markets. The trade–cost elasticity of developed trading partners with respect to China's agricultural products is higher than that for developing trading partners. Moreover, China's agricultural products face a higher trade–cost elasticity when exporting to the non–RTA countries than RTA countries.

This paper offers direct information on the estimate of China's agricultural trade–cost elasticity. It provides an accurate and convenient measure for trade cost elasticity, which is useful in the prediction of the effects of trade policy on trade flows. Furthermore, a variable trade–cost elasticity is more reasonable in order to quantify welfare gains from trade. Therefore, the trade–cost elasticity measured by this method can answer the question of how much trade costs reductions would promote China's agricultural exports.

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[12] The 14 RTA countries/regions include Australia(AUS), Bangladesh(BGD), China, Hong Kong(HKG), India(IND), Indonesia(IDN), Japan(JPN), Republic of Korea(KOR), Sri Lanka(LKA), Myanmar(MMR), Malaysia(MYS), Pakistan(PAK), Philippines(PHL), Singapore(SGP), Thailand(THA).

[13] The 19 non–RTA countries/regions include Germany(DEU), Netherlands(NLD), Italy(ITA), United Kingdom(GBR), Canada(CAN), Spain(ESP), Mexico(MEX), Brazil(BRA), Benin(BEN), Nigeria(NGA), France(FRA), Togo(TGO), Belgium(BEL), Turkey(TUR), Egypt(EGY),Iran(IRN), South Africa(ZAF), Russian Federation(RUS), United States of America(USA).

AUTHOR CONTRIBUTIONS

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