Policy Effects on Global Palm Oil Trade: A Gravity Model Approach

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Abstract: Oil palm is the major source of edible oil and feedstock consumed in the world. This study examined the determinants of global palm oil trade with attention to the effects of trade policies using a gravity model, PPML estimator, and the data from 1988-2020. Palm oil's dramatic trade growth in recent years can be attributed to the economic growth of large countries, the proximity of partners and policies. Trade agreements increased crude and refined palm oil trade by up to 8 and 4 percent of the global import value, respectively. Further, the effects of policy changes due to Covid-19 and the recent export ban of Indonesia are also quantified.

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1. Introduction

Oil seeds form a critical link in the global supply chain by virtue of their wide use – edible oil for consumers, livestock feed, oleochemicals for industrial use, biofuel for transportation, cosmetics and others (United States Department of Agriculture, USDA, 2022). Among oil seeds, oil palm (*Elaeis guineensis*) is not only the major source of edible oil consumed in the world but also a major ingredient in biofuel production. In addition, its by-product, palm kernel meal, is a major livestock feed, especially in Asian countries. The annual consumption of palm (and kernel) oil is 82.45 million metric tons, which is 39.43 percent of the global oil consumption (USDA, 2022). Palm oil is demanded in more than 150 countries but is commercially supplied by about 13 tropical countries.[1] Not surprisingly, palm oil and related products are extensively traded across countries – according to the USDA (2020a), global oil palm imports (quantity) grew by more than 600 percent between 1988 and 2020. Palm oil trade also carries high economic importance to major producers (Indonesia and Malaysia) and major consumers (China and India). That is, the livelihood of millions of smallholders and landless workers in Indonesia and Malaysia, which together contribute 84 percent of the global production, as well as the composition of Chinese and Indian diets, are interlinked by the palm oil supply chain (Food and Agriculture Organization, FAO, 2019; Mehraban et al., 2021).

Various factors have been cited as reasons for this surge in global palm oil trade: gross domestic product (GDP) growth of large emerging economies hungry for more protein in their diets (China and India) – for example, Organization for Economic Cooperation and Development (OECD)-FAO (2019) found that per capita income growth raises the consumption of edible oil by 2.7 percent per annum between 2008-2017; price competitiveness relative to other edible oils such as soybean or rapeseed or canola oil (figure 1); and contiguity of producing, processing and consuming nations, mostly in Asia (Carter et al., 2007). Likewise, palm oil offers a comparative advantage to producers because unit land of oil palm cultivation can produce more vegetable oil than any other crop (Qaim et al., 2020).

Understanding the pattern of the global palm oil trade is critical, as noted above, for the food security and economic well-being of a large share of the global population. To date, most

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[1] Malaysia, Indonesia, Nigeria, Colombia, Cote d' Ivoire, Papua New Guinea, Thailand, Congo, Kenya, Liberia, Brazil, Guatemala, and Mexico.

studies on the economics of palm oil and its trade have focused on one or a few major producing and/or consuming regions (Robins, 2021; International Council on Clean Transportation 2019; Priyati, 2018; Rifin, 2014). Therefore, the limited focus on understanding palm oil at the global scale obscures the important contribution of more than 100 free trade agreements (FTA) specifying tariff and non-tariff measures (NTM) on palm oil trade. In recent years, these policies and agreements have been buffeted by economic nationalism, sustainability concerns, and the Covid-19 pandemic.

Consider the case of India, a major importer of palm oil primarily for food use. Since 1994, India has adjusted its tariff rate to match global price movements of edible oil, swinging between mostly palm oil and occasionally soybean oil (Carter et al., 2007). While holding the Most-Favored Nation (MFN) rate at 100 percent, India's applied tariffs on five Association of Southeast Asian Nations (ASEAN) countries – Indonesia, Malaysia, the Philippines, Singapore, and Thailand as part of the ASEAN-India FTA – ranged between 37.5 and 74 percent during 2010-2019 (ASEAN-India FTA Schedule, 2011).[2] At the peak of the Covid-19 pandemic in 2020, India reduced its applied rate to 27.5 percent for a few months before reverting to 37.5 percent in early 2021 (USDA, 2020b). The effects of these trade policy changes, as noted before, have implications for international trade flows, and producers' and consumers' welfare, especially in large developing countries like Indonesia and India (Euler et al., 2016; Taheripour et al., 2019). In addition, the design of sustainable policies for the future of the palm oil sector requires that the welfare effects of trade policies are evaluated (Qaim et al., 2020).

This study has two-fold objectives. First, it identifies the determinants of global palm oil trade with particular attention to trade policies. For this purpose, a structural gravity model is estimated using the Poisson-Pseudo Maximum Likelihood estimator at a finer product level – a six-digit Harmonized System (HS) – during 1988-2019. By employing a gravity model of trade flows, commonly used in the international trade literature, this study captures the effect of policies on palm oil trade while controlling for a host of other determinants like population and income growth, and distance between trade partners and any other non-policy association among trading nations. Second, this study identifies varying levels of tariffs (bound, MFN, applied and FTA rates) by country pairs and over time for use in the estimation of the gravity model. The in-

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[2] Most Favored Nation tariff is a nondiscriminatory tariff charged on imports of all World Trade Organization (WTO) members; ASEAN countries: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam.

depth attention to tariff rates allows for an assessment of the effects of recent trade policy changes attributable to Covid-19 (India) and supply chain issues (Indonesia).

Previewing the results, key gravity variables – economic size, distance, cultural proximity – are major drivers of global palm oil trade. While policy barriers generally limit trade, bilateral and regional preferential agreements appeared to have alleviated the negative effects of such barriers on palm oil trade. Specifically, the estimates from the gravity model showed that a major set of trade agreements have been responsible for increasing crude and refined palm oil trade by up to 8 and 4 percent of the global import values, respectively.

The paper proceeds as follows. Section 2 discusses the theoretical gravity model followed by section 3 explaining the data used in the study, model selection, and estimation procedure. Section 4 presents and discusses the results and estimates the actual effects of trade agreements in the context of the global palm oil trade. Section 5 concludes.

2. Method

The traditional gravity equation specifies the monetary value of bilateral trade as a function of exporter- and importer-specific characteristics including their size and proximity (Yotov et al., 2016; Head and Mayer, 2014; World Trade Organization, WTO, 2012;).[3] The multiplicative nature of the above specification allows estimation using natural logarithms of all variables. However, this standard way of estimation will yield biased coefficients because of zero trade flows (those observations will be deleted since the log of zero is undefined). Zero trade flows are critical to assessing trade policy effects, especially for cases of thinner trade relationships that may arise with least developed countries or specific product lines. Specifically, pervasive zero trade values lead to higher conditional variance than the conditional mean (Burger et al., 2009).

The Poisson-Pseudo-Maximum Likelihood (PPML) estimator is commonly employed for estimation since it retains the multiplicative theoretical structure of gravity models. PPML estimation is robust to alternative patterns of heteroskedasticity and allows the dependent variable to remain in levels (as opposed to logarithms), which permits the inclusion of zero trade flows in the estimation. Following Yotov (2022), the PPML specification takes the generic form:

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[3] Theoretically, the gravity set-up requires intra-national flows, but such data are not available or plagued with significant measurement errors. So, in practice, traditional gravity equation estimates partial direct effects as advocated by Yotov et al. (2016). Moreover, such specifications are appropriate at the six-digit HS product line, as in this study (Head and Mayer, 2014; Baldwin and Taglioni, 2006).

$$Y_{ijt} = \exp\left(X_{ijt}\beta + \delta_{it} + \gamma_{jt} + \theta_{ij}\right) + \epsilon_{ijt} \qquad (1)$$

where,

- i and j denote exporting and importing countries ($i \neq j$), t denotes time in years from 1988 through 2019,
- Y_{ijt} is the dependent variable (the monetary value of bilateral palm oil trade),
- X_{ijt} is the vector of explanatory variables with the corresponding parameter vector β to be estimated,
- ϵ_{ijt} is the error term with mean independence, i.e., E $[\epsilon_{ijt}|X] = 0$, and
- δ_{it}, γ_{jt} and θ_{ij} represents the importer- and exporter-time fixed effects, and pairwise fixed effects, respectively.

Previous research has employed economic size, physical distance, policy barriers, cultural, colonial and linguistic ties, memberships in organizations like WTO, General Agreement on Tariffs and Trade (GATT), special economic zones, and preferential agreements to represent X_{ijt} in equation (1) (McCallum, 1995; Santos Silva and Tenreyro, 2006; Yotov, 2022). Regarding fixed effects, Anderson and van Wincoop (2003) noted that the trade between nations depends on the ease of access to the importer market by exporters given by (a) the direct bilateral resistance and (b) overall resistance to the rest of the world i.e., multilateral resistance. To identify these resistances- observable and unobservable heterogeneities – Feenstra (2004), Beckman and Arita (2016) and others – the empirical literature has considered adding fixed effects (δ_{it}, γ_{jt} and θ_{ij}) to equation (1).

A critical issue in estimating equation (1), particularly with the inclusion of policy variables in X_{ijt}, is the possible endogeneity of regressors. Some studies have acknowledged the difficulty in finding a good instrument set to address the endogeneity problem (Mangelsdorf et al., 2012). However, many studies find that the inclusion of fixed effects such as importer, exporter, time or their interactions can substantially reduce the omitted variables bias (Baier and Bergstrand, 2007; Wang et al., 2022; Mangelsdorf et al., 2012). Studies on the effects of trade policy (tariff and non-tariff) on aggregate or agricultural trade have employed fixed effects to account for both inward and outward sources of multilateral resistances and unobserved and unconstrained heterogeneity across each importer and exporter (Hejazi et al., 2022; Beckman and Arita 2016; Disdier and Maratter 2010; and Disdier et al., 2008).

3. Data, Model Selection and Estimation

3.1. Data

The data assembly begins with the most detailed product classification level – 6th digit Harmonized System (HS) classification – for 194 countries over the period of 1988-2019. Trade data (imports in current US dollars) of refined palm oil, RPO (HS-151190), crude palm oil, CPO (HS-151110), and combined RPO and CPO referred to as PO (HS-1511) are from the United Nations Commodity Trade Database (UN COMTRADE, 2020). With the focus on product lines and the large number of bilateral pairs over a long period of time, missing data issues are unavoidable. Following the general practice of dealing with zero trade values, data for those pairs that do not trade with each other are filled with zero. The descriptive statistics with mean, deviations, and ranges are presented in Table 1.

The dynamic gravity dataset from the United States International Trade Commission (USITC) version 2 is the source for a majority of gravity variables:

- GDPPC: GDP is the total nominal gross value of goods and services added by all the residents of the country along with added taxes minus any subsidies not included in the value. It is divided by population in the respective period to obtain GDP per capita. These data are primarily sourced from Penn World Table and World Bank's World Development Indicators (WDI, 2020).

- Population: Count of all the residents regardless of legal status or citizenship and is a mid-year estimate usually based on the national census.

- Distance: It is measured based on the methodology developed by Mayer and Zignago (2011) (see Gurevich et al., 2018). It uses major cities of economic activity and their population for each pair of countries and averages the distance between the pairs weighted by the population.

- Contiguity: It implies that the destination (importer) and origin (exporter) countries share a common border in a particular year. Countries can be bordering river or a stretch of land to be contiguous to each other.

- Regions: USITC distinguishes countries into the following 14 regions: Africa, Caribbean, Central America, Central Asia, East Asia, Eurasia, Europe, Middle East, North America, Pacific, South America, South Asia, Southeast Asia, and Southern Pole

- Language: Data from the Central Intelligence Agency's World Factbook (2020) are used to find commonly spoken languages. Languages spoken within each country are broken down according to the population percentage speaking that language as their first language and then ordered according to prevalence. When a language is spoken in both countries, this dummy takes value one and zero otherwise.

The missing GDP and population data, about 10 and 4 percent of the total number of observations respectively, are filled from the WDI dataset. Other remaining missing data are filled using the previous years' latest available data from within the dataset. Once the missing values are filled in, there are 1,016,858 observations from combining the gravity and trade data.

Tariff data were not available for all the countries for each year from a single source. A number of sources are used to assemble tariff data. The MFN tariff data are sourced from the World Bank database, which provides a simple average tariff rate for the years 1988 – 2014 (United Nations Conference on Trade and Development, UNCTAD, 2016). To acquire data from the years after 2014, WTO's Regional Trade Agreement (RTA) database was used. The two databases (UNCTAD and WTO) had a few overlapping years for a cross-check of MFN rates.

After assembling the MFN tariff data, the next step involved getting applied tariff data that came in different forms: Free trade agreements (FTA), preferential trade agreements (PTA), Regional Trade Agreements, Duty-Free Tariff (DFT) for Least Developed Countries (LDCs) tariffs, and others. Common tariffs applied by or on the same region such as the case of the EU and ASEAN were accounted for by countries' year of entry into such agreements. Apart from the readily available data from WTO's RTA portal, individual country documents were accessed for additional data and verification purposes. Some of the tariff finders that aided the process, especially in the context of trade agreements are Canada Tariff Finder, the FTA tariff tool provided by the United States International Trade Administration (USITA, 2020), ASEAN Tariff Finder, Indian Trade Portal, New Zealand Foreign Affairs and Trade Tariff Finder, and Australian FTA Portal. Table 2 gives an example of the Indian CPO tariff schedule from the ASEAN5 – India trade agreement.[4]

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[4] Association of Southeast Asian Nations-5: Indonesia, Malaysia, Philippines, Singapore and Thailand.

3.2. Model Selection and Estimation

The final specification of the gravity model was arrived at after extensive tests on several dimensions detailed below. Two alternative representations of the trade policy variable, the main focus of this study, yield equations (2.1) and (2.2) in the spirit of Yotov (2022), and Yang and Hillberry (2022):

Model A $$Trade_{ijt} = \exp\big[\beta_0 + \alpha_1 lnTariff_{ijt} + \beta_1 lnGDPPC_{ijt} + \beta_2 lnDistance_{ijt} + \beta_3 Contiguity_{ijt} +$$
$$\beta_4 SameRegion_{ijt} + \beta_5 Same\ Language_{ijt} + \delta_{it} + \gamma_{jt}\big] + \epsilon_{ijt} \qquad (2.1)$$

Model B $$Trade_{ijt} = \exp\big[\beta_0 + \alpha_2 FTA_{ijt} + \beta_1 lnGDPPC_{ijt} + \beta_2 lnDistance_{ijt} + \beta_3 Contiguity_{ijt} +$$
$$\beta_4 SameRegion_{ijt} + \beta_5 Same\ Language_{ijt} + \delta_{it} + \gamma_{jt}\big] + \epsilon_{ijt} \qquad (2.2)$$

where,

- i and j denote exporting and importing countries ($i \neq j$), t denotes time in years from 1988 through 2019,
- *lnGDPPC*: logarithm of the GDP per capita represents the size of participating economies; it is the ratio of the sum of GDPs of importing and exporting countries and the sum of their population,
- *lnDistance*: logarithm of the distance between the exporter and importer,
- *lnTariff*: logarithm of tariff rate applied by importing country on the exporter,
- *FTA*: Free Trade Agreement which takes the value 1 when a trading pair signed a preferential agreement (within the sample period) and thereafter; otherwise it takes the value 0,
- *Contiguity*: dummy variable which takes a value of 1 if the two countries are contiguous and zero otherwise,
- *Same region*: dummy variable that takes the value of 1 if the two countries are in the same region; zero otherwise,
- *Same language*: dummy variable that takes the value of 1 if some of the residents of exporter and importer countries speak the same language, and zero otherwise,
- α's are estimated effect of trade policy (tariffs) on palm oil trade, which are the parameters of interest, and β's are the coefficient estimates of the remaining variables, and
- δ_{it}, γ_{jt} and θ_{ij} represents the importer- and exporter-time fixed effects, and pairwise fixed effects.

First, several other trade facilitation variables – WTO or GATT membership dummy, type of polity, political stability, environmental stringency, and others – were considered. Data for these other variables were taken from the USITC dynamic gravity dataset as well as other sources such as the World Bank. Many of these variables were highly collinear, especially with the fixed effects included in equation (1)'s estimation. Second, alternative functional forms (log, levels, reciprocal, polynomial) were tested using likelihood ratio (LR) tests and Akaike and Bayesian Information Criteria (AIC-BIC). LR tests along with theoretical consistency of gravity effects aided in the final selection of the linear-log model as shown in equations (2.1) and (2.2). Continuous independent variables (distance, GDPPC and tariff) have been transformed into natural logarithms while categorical ones are retained in levels. The FTA dummy variable in equation (2.2) is created to capture the broader impacts of trade liberalization measures of the agreements, not just the tariff cuts (Baier and Bergstrand, 2007). Third, the dependent variable (import) was specified in levels, i.e., nominal value. Yang and Hillberry (2022) report that the statistical inference from the LR test of the PPML estimator is sensitive to data scaling of the dependent variable affecting the test of the significance of the model as well as any restrictions placed on its coefficients. The LR test that all coefficients are equal to zero is conducted using two different scales of a dependent variable (in the standard dollar and in million dollars), but the hypothesis was rejected in both instances.

Fourth, as noted at the end of section 2, the identification of tariff effect on palm oil trade requires the inclusion of fixed effects (Yotov, 2022; Baier and Bergstrand, 2007). Many studies on agricultural trade also control for the endogeneity by including importer- and exporter-time fixed effects, and/or pairwise fixed effects.[5] After extensive specification tests using all three pair-wise fixed effects, equations (2.1) and (2.2) include time-varying directional (importer-year and exporter-year) fixed effects. That is, they account for time-varying sources of multilateral resistances and unobserved and unconstrained heterogeneity across each importer and exporter (Anderson and van Wincoop, 2003). Unfortunately, some variables that vary by exporter but are constant across importers and time or that vary by the importer but constant across exporters and

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[5] Disdier and Maretter (2010) include importer, exporter and time fixed effects (FE) separately to measure the impacts of nontariff measures (sanitary and phytosanitary plus technical barriers) on agricultural trade. Hejazi et al. (2022) include importer, exporter and product FEs separately to estimate the impact of phytosanitary policy on fruits and vegetables trade. Wang et al. (2022) include country-year and country-product FEs while studying the effect of certification policy on imports. Beckman and Arita (2016) include importer and exporter FEs separately to examine the effect of non-tariff measures and tariff-rate-quota on agricultural trade. Similarly, upon including country-sector, country-year, sector-year FEs, the exogeneity was assured in Harding and Javorcik (2011) while studying the effect of investment promotion strategies on foreign direct investment (FDI) inflows.

time showed collinearity with the pair-wise fixed effects. Such collinearity led to exclusion of one set of fixed effects, importer-exporter pair-wise fixed effects, as well as the combining of GDP per capita of importing and exporting pairs to arrive at GDP per capita (*lnGDPPC*).

Finally, the study considered inward measures only, i.e., barriers applied by the importing country to the exporting nations, only. Data on export policies are not consistently available, and those effects are likely included in the exporter-time fixed effects. The PPML method of estimation was chosen over traditional approaches, e.g., ordinary least squares, and the inbuilt robust standard errors are used throughout. As mentioned earlier, the PPML estimator can capture the information in the zero trade flows, accounts for heteroskedasticity and allows the estimation of the model with a large set of fixed effects considered (Yotov et al., 2016).[6] While PPML estimation of equations (2.1), Model A, directly yields elasticities to calculate the tariff effect on palm oil trade patterns, and the elasticity of FTA dummy will be computed for equation (2.2), Model B (Anderson, Larch and Yotov, 2015; Larch and Yotov, 2016; Yotov et al., 2016).

4. Results and Discussion

Recall that the study aims to identify the determinants of global palm oil trade with particular attention to trade policies. This section, first, describes a host of determinants from the gravity model. Then, the impacts of tariffs and FTAs are discussed.

4.1. Gravity Model

The results of the fitted version of the PPML-estimated gravity model are presented in Table 3. The econometric specification of equations (2.1) and (2.2), after the series of validation and sensitivity analysis noted in the previous section, allowed for a variety of characteristics to affect bilateral trade between the countries. Columns 1, 2, and 3 of Table 3 present the results of equation (2.1), i.e., Model A, which uses the actual tariff rate for CPO, RPO, and PO employing 54,139, 98,190, and 9,271 observations, respectively. Likewise, columns 4, 5, and 6 present the result of equation (2.2), i.e., Model B, which uses the FTA dummy employing 1,016,849 observations in each column. All columns control for the importer-time and exporter-time fixed effects and presents robust standard errors. Most estimates of the gravity model for all three products yielded statistically significant coefficients with signs consistent with the predictions of

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[6] The Poisson distribution is the discrete probability distribution, appropriate for the large proportion of zero in the trade data.

the underlying economic theory. Recall that the coefficients of the (continuous) explanatory variables are elasticities. The elasticities for categorical variables are computed and they are kept beside each coefficient.

The result from Models A and B are consistent throughout with few exceptions. The following description focused primarily on Model A's results, but relates them to those of Model B wherever appropriate. The coefficient estimate of the logarithm of (combined) GDP per capita is positive and statistically significant for all three products: CPO, RPO, and PO. That is, all else constant, an increase in the combined GDP per capita by 1 percent increases trade by 0.76, 0.94 and 1.24 percent, respectively for CPO, RPO and PO (Table 3, Columns 1, 2 and 3). The seminal article on PPML estimation – Santos Silva and Tenreyro (2006) – affirmed the positive effect of importers' and exporters' GDP on trade. Wang (2016) also found a positive effect of GDP on the palm, rapeseed, sunflower, and soybean oil trade. Likewise, the distance variable has a negative coefficient, which is statistically significant in all three cases. An increase in distance by 1 percent decreases trade by 1.06, 1.13 and 0.73 percent, respectively. Many studies have found that geographical distance discourages trade between countries (Yotov et al., 2016; Filippini and Molini, 2003). In addition to distance, tariffs negatively affect trade flows across countries for all three products. The highest response to a 1 percent increase in the tariff rate, according to Model A in columns 1, 2, and 3, is observed in the CPO case (0.75 percent), followed by those of PO (0.66 percent) and RPO (0.45 percent). Alternatively, FTA effects, according to Model B in columns 4, 5 and 6, are higher for PO (3.276 percent), followed by RPO (1.370 percent) and CPO (0.853 percent). Section 4.3 below employs the tariff effects estimated here to quantify the actual impact of trade agreements with further detail. [7]

In Table 3 under Model A, countries that are contiguous trade more of CPO (0.74 percent) and RPO (0.545 percent), but the effect appears muted at the aggregated PO level in column 3. It may arise with the simultaneous export of CPO and re-import of RPO by several South-East Asian economies. However, under Model B, with the higher observations, sharing a national border dictates the increment in the aggregated PO trade by 0.895 percent (column 6), which is also statistically significant. Similarly, countries that share a common language also trade more – by 1.563 for CPO and 1.061 for RPO (columns 1 and 2, respectively) – with each

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[7] Another version of Model B using only the sample of Model A, observations with actual tariff rates available (restricted sample size), is shown in Appendix 1. The results are consistent except for FTA effects on CPO trade.

other, given the concentration of production in South-East Asia. Fidrmuc and Fidrmuc (2016) and Wang (2016) also suggest that if a common language is spoken by even a small share of the two countries' population, more trade can arise with easy communication of contract terms.

Finally, the same region dummy has a negative but insignificant effect on CPO trade under model A (column 1), but is negative and highly significant under model B (column 4). Consistent and significant under both models, countries in the same region increase RPO trade by up to 4.20 percent (column 2). Part of the explanation may lie in the trade pattern shown in figure 2, i.e., globally, all regions import CPO mostly from Asia (1988-2019). Moreover, some of the intra-regional trade is likely picked up by the relatively larger contiguity-effect for CPO.

The above results are well aligned with prior literature as well as the real-world context. The positive GDP coefficient corroborates that the demand of major palm oil players – which are some of the world's largest and fastest-growing economies – has increased trade. India, China, and the EU together accounted for more than 78 percent of the total global imports of palm oil in 2019 (UN COMTRADE, 2020). As Frankel, Stein and Wei (1995) noted, GDP captures the purchasing power, which led to an increase in the protein-based diet in developing countries like India and China in recent years. In the EU case, the launch of RED in 2009 increased the usage of palm oil in biofuels to meet sustainability goals. On the other hand, Indonesia and Malaysia are large exporters likely driven by comparative advantage and economies of scale (Kumar and Ahmed, 2015).

While distance has a negative effect on trade in all three products, contiguity appears to play a distinct role. Contiguous countries that extensively trade palm oil are Indonesia and Papua New Guinea, Guatemala and Mexico, Thailand and Malaysia, Singapore and Malaysia, Peru and Colombia, and Honduras and Guatemala. Moreover, significant vertical trade between Singapore (RPO) and Indonesia (CPO) affirms the importance of contiguity in the palm oil trade. While the topographical requirement of oil palm (mostly concentrated in the tropical region) has enabled inter-regional crude palm trade, refineries for RPO are located throughout the world. For example, refining, bleaching and deodorizing CPO are mainly done by companies like Unilever and Nestle, which have processing plants located across the world (Pacheco et al., 2017).

As noted in the introduction, trade policies appear to change more frequently in many countries depending on internal and external events. While India is a case in point, others such as Nigeria and Fuji have also directly altered tariff rates to adjust to domestic market conditions,

and the EU trade in palm oil, initially driven by RED, has taken on a revised target, i.e., zero by 2030, on the use of palm oil in biofuel production (Carter et al., 2007; Gourichon, 2019; USDA, 2019).[8] Section 4.3 below takes a closer look at the effect of trade agreements. Prior to that, an attempt is made below to validate the tariff effects estimated in the gravity models using the recent Covid-19 pandemic experience in the Indian context. Also, the sensitivity of palm oil trade to policies is demonstrated using the impact of Indonesia's recent export ban.

4.2. Covid-19, Indonesia's Export Ban, and Palm Oil Trade

Palm oil trade appears sensitive to trade policy changes on the exporter as well as the importer side. To cope with the Covid-19-related price increase of agricultural products, India reduced its palm oil tariff by 10 percentage points in 2020, from the pre-pandemic rate of 37.5 percent on imports from ASEAN-5 countries. The lower tariff came into effect in November 2020. Using the CPO tariff coefficient (elasticity) of -0.75 percent in table 2, this study estimated that India's import value should have increased by 20.13 percent.[9] Given the 2019 value of imports from Malaysia and Indonesia ($3.28 billion), the lower tariff translated into a $660 million increase in import value. An article from a major Indian newspaper reported that the CPO import jumped by 24 percent in the first quarter of 2020-21 (*The Hindu Business Line,* 2021).

Another recent event affecting global palm oil trade is the export ban of Indonesia (April 28, 2022). With Indonesia accounting for 45 (70) percent of CPO (RPO) imports, India again, faced major disruptions. In November 2021, India reduced the tariff on RPO from 32.5 to 17.5 percent owing to supply chain issues and food price inflation (*The Hindu Business Line,* 2022; Christina and Nangoy, 2022).[10] Using the RPO tariff coefficient (elasticity) of -0.45 percent from table 3, this study estimated that India's import value should have increased by 20.67 percent. Given the 2020 value of RPO imports from Indonesia ($82.64 million), the lower tariff translated

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[8] In Fiji where the oil is mostly used in food, imports increased by ten-folds between 2000 to 2009. To control unexpected increases in obesity (i.e., high saturated fat content of CPO), the tariff rate was increased from 15 to 32 percent in 2012 (Coriakula et al., 2018).

[9] Out of India's total edible oil imports, CPO contributes 57 percent in 2020-21 which is 12.8 percent higher than in 2019-20 (*The Hindu Business Line*, 2022). Note that the change in tariffs from 37.5 to 27.5 percent equals a -26.60 percent change. Multiplying that with the CPO tariff elasticity gives 20.13 percent.

[10] The change in tariffs from 32.5 to 17.5 percent equals a -46.15 percent change. Multiplying that with the RPO tariff elasticity gives 20.67 percent.

into an increase in import value of more than $17 million. However, the bilateral trade was suspended for a few weeks until the ban was lifted after three weeks.[11]

4.3. Trade Agreements and Global Palm Oil Trade

Under the original GATT and now WTO, countries impose MFN tariffs on each other but are also allowed exceptions as part of a separate agreement (regional or preferential) with other countries. To interact preferentially, countries form 'blocs' of economic partnership based on geographical proximity, policy alignment and other factors. By signing such agreements countries aim for better market access including trade facilitation, harmonization of sanitary and phytosanitary measures and technical barriers, and protection of intellectual property rights (Balu and Ismail, 2011). Many studies have shown that such preferential trading systems increase trade flows (Rose, 2004).

Trade agreements have been one of the key focus areas of major palm oil trading countries. Between 2005 and 2020, major exporters – Indonesia, Malaysia, Thailand, Colombia, Papua New Guinea – have signed FTAs or PTAs with some of the major importers – India, China, European Union Countries, United States – to reduce tariffs and increase trade flows. Few studies have evaluated the effects of such trade agreements collectively or individually in the context of palm oil. Consistently, Table 3 (columns 4, 5 and 6) shows that having FTA can significantly increase the palm oil trade.[12] The positive impact is highest at the aggregated scale, and in RPO followed by CPO. An exception being Wang (2016), who found FTA partners traded 77 percent more palm oil than those who did not have such agreements. This study, by focusing on product-lines and directly estimating the tariff elasticity can identify the important role of each of the trade agreements on the palm oil trade. Tables 4 and 5 show the effects of major PTAs and FTAs on CPO and RPO, respectively.

ASEAN-India FTA (AIFTA) came into effect on January 1, 2010. Table 4 shows that the average MFN tariff on CPO imposed by India on ASEAN countries and ASEAN on India before the trade agreement came into effect is 60.37 percent, while the AIFTA tariff is 39.89 percent. The difference between these two tariffs (-33.92 percent) multiplied by the tariff elasticity (-

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[11]Starting January 1, 2023, Indonesia is tightening PO exports by allowing fewer shipments overseas – exporters are allowed to ship six times their domestic supply volume which is two times less than that allowed until 2022 (The Economic Times, 2022).
[12]Harada and Nishitateno (2021) report that the import tariff reduction through FTA has increased the wine trade volume in East Asia.

0.75) and further multiplied by the prior year (2009) trade value ($2751.35 million) quantifies the effect of AIFTA on CPO trade. Table 4 shows that AIFTA is responsible for more than $699.94 millions of trade increase in 2010 between ASEAN and India, which is about 3.93 percent of the global CPO trade value. Similarly, ASEAN Trade in Goods Agreement (ATIGA) which was implemented in 2010 was responsible for an increase of more than $583.09 million of palm oil trade within ASEAN countries (3.28 percent of global CPO trade).

South Asian Free Trade Agreement (SAFTA) that came into force in 2004 was signed by seven South Asian countries – India, Pakistan, Bangladesh, Sri Lanka, Nepal, Bhutan and Maldives – and later joined by Afghanistan. Table 4 shows that the MFN tariff among these countries averaged to 59.51 percent, while the SAFTA rate was lower at 25.16 percent. Thus, SAFTA was responsible for an increase of trade value by 0.44 percent among South Asian countries, but it only yielded a smaller 0.03 percent boost to global palm oil trade compared to AIFTA or ATIGA. Likewise, Colombia which is one of the major CPO exporters signed an FTA with the United States in 2012. Before the FTA, the average MFN tariff between these two nations was 10 percent, which was completely removed in 2012. However, the U.S.-Colombia pact was responsible for only a 0.01 percent increase in global CPO trade.

Table 5 shows the four major trade agreements in the RPO context. ATIGA is responsible for about 1.44 percent of global RPO trade. EU has trade agreements with several pacific States, which supply palm oil and palm kernel oil. Papua New Guinea, one of the top exporters to the EU among pacific states, maintains a duty-free agreement with EU for major agricultural products including palm oil (Papua New Guinea Trade Policy Framework, 2006). EU-Pacific States FTA between Papua New Guinea and EU implemented in 2009 increased RPO trade by more than $140 million, accounting for 1.01 percent of global RPO trade. AIFTA is also responsible for a significant increase in total RPO trade (0.70 percent). Although the EU-Colombia pair had a 36.22 percent difference between MFN and FTA tariff, trade created by their agreement accounted for about 0.01 percent only of global RPO trade.

Overall, it suggests that having a preferential trade agreement, FTA in this case, for a specific commodity can increase trade on all three products, significantly. Nonetheless, the net increment in palm oil trade under such trade agreements depends on the magnitude of tariff reduction for specific product lines. With trade policies changing more frequently depending on internal and external events, they potentially cause a steep decline in the global trade of oil palm.

These trade-inhibiting measures will likely increase the cost of producers, lower market prices, and hence, negatively affect welfare large number of workers engaged in palm and palm oil production, processing and distribution.

5. Conclusion

Despite concentrated production, worldwide consumption via international trade has made palm oil an indispensable link in the global supply chain. This study examined the determinants of global palm oil trade with particular attention to the effect of trade policies, while controlling for a host of other determinants like population and income growth, and distance between trade partners and any non-policy association among trading nations.

Among the key determinants, GDP per capita positively affected palm oil trade in the aggregate as well as its constituents: crude and refined palm oil (CPO and RPO). Distance between countries – often a proxy for transportation costs and implications for infrastructure policies – has negative effects on the import of both CPO and RPO. Likewise, having a common language or being contiguous to a trade partner increased palm oil trade. As expected, the tariff of the importing country has a significant negative effect on CPO, RPO and aggregated palm oil trade.

To reduce barriers to trade, countries have established bilateral or regional preferential agreements. The effect of having free trade agreements results in significantly higher palm oil trade than that in the absence of such agreements. The estimates from the gravity model allowed for an evaluation of the effects of a selected set of trade agreements. This study found that some of the major trade agreements have been responsible for increasing crude and refined palm oil trade by up to 8 and 4 percent of the global import values, respectively, over the past two decades. Also, the estimated gravity model allowed a simulation of recent policy changes either expanding or limiting trade. For example, recent liberalization by India, due to the Covid-19 pandemic, is found to have increased palm oil trade by up to 20 percent of India's import value. Frequent trade-limiting policy changes will have large negative effects on the global palm oil trade with implications for consumer welfare in India and China, major importers, and the jobs and income of millions in Indonesia and Malaysia, the major exporters.

Figures
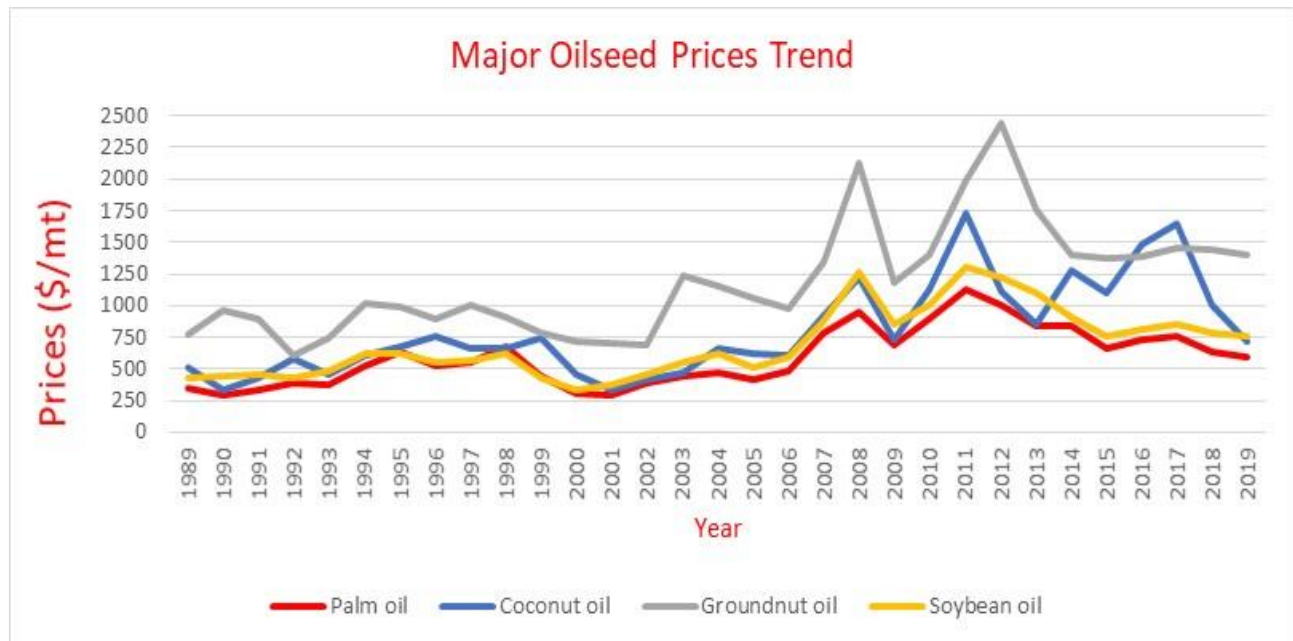
Figure 1: Major oilseeds prices trend (1989 – 2019)

Source: *Global Economic Prospects*, 1989-2019
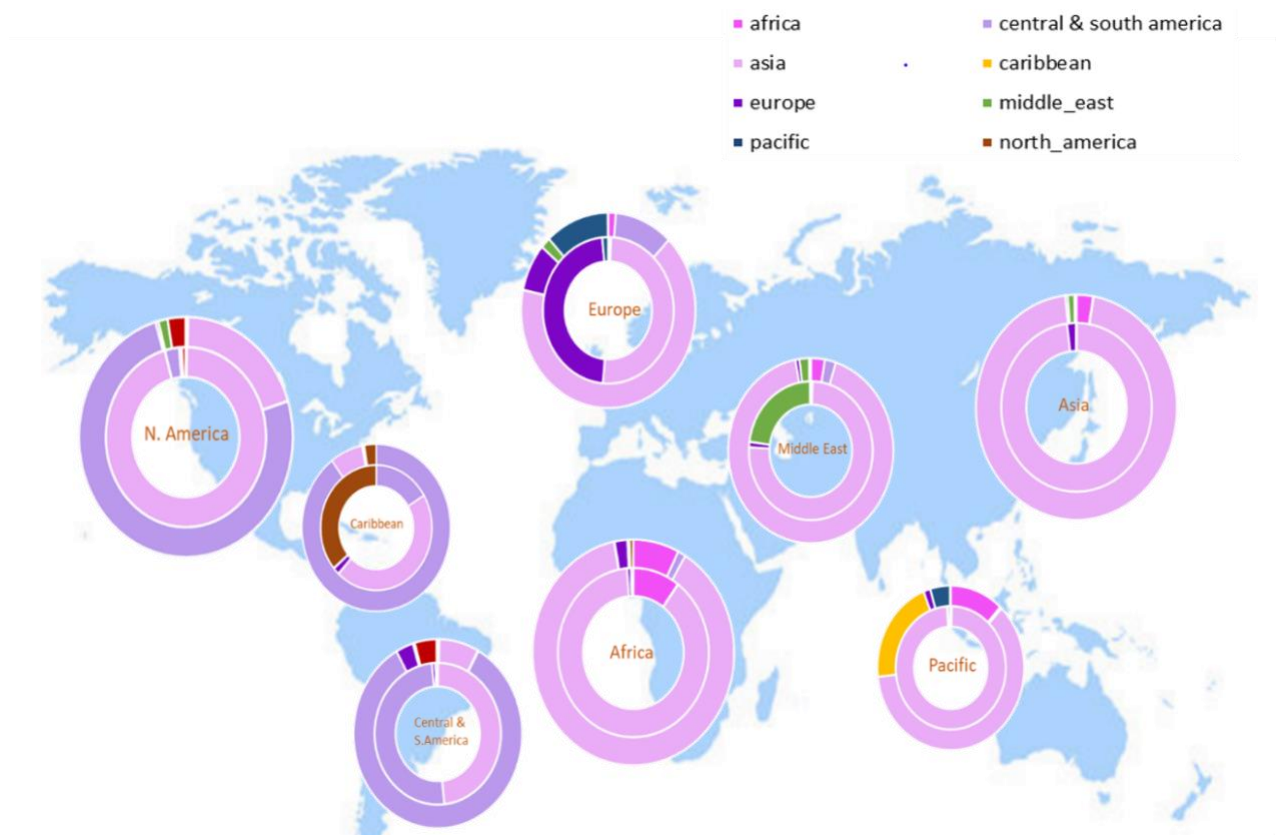
Figure 2: Total Palm oil trade flow from 1988 to 2019 between regions.

Note: Outer ring *is Crude Palm Oil, and the inner ring is Refined Palm Oil.*

Source: World map - iStock by Getty Images; Data - United Nations (2020)

Tables

Table 1: Descriptive Statistics of the variables used (1988-2019)

Variables	N	Mean	SD	Min	Max
Trade Value HS-151110	1,016,858	222965.70	16600000	0	4280000000
Trade Value HS-151190	1,016,858	233044.80	9794019	0	2500000000
Trade Value HS-1511	1,016,858	377358.80	20100000	0	5200000000
GDP per capita Importer	1,016,858	10418.49	18277.47	65.93	198418.30
GDP per capita Exporter	1,016,858	10418.53	18277.47	65.93	198418.30
Distance	1,016,858	7948.71	4522.32	75.82	19734.64
Tariff HS-151110	54,139	12.53	18.52	0	204.42
Tariff HS-151190	98,190	8.37	13.75	0	204.42
Tariff HS-1511	9,271	16.28	25.01	0	204.42
FTA HS-151110=1	1,016,858	0.004	0.06	0	1
FTA HS-151190=1	1,016,858	0.05	0.21	0	1
FTA HS-1511=1	1,016,858	0.001	0.03	0	1
Contiguity=1	1,016,858	0.02	0.13	0	1
Common Language=1	1,016,858	0.36	0.48	0	1
Same Region=1	1,016,858	0.16	0.36	0	1

Note: HS-151110 and HS-151190 is the harmonized system code for crude palm oil (CPO) and refined palm oil (RPO) at the 6-digit level, and HS-1511 is the harmonized system code at the 4-digit level for CPO and RPO combined. Tariff HS-151110, Tariff HS-151190 and Tariff HS-1511 are the variables used in equation (2.1), and FTA HS-151110=1, FTA HS-151190=1 and FTA HS-1511=1 are the variables used in equation (2.2). Note that there are 190 exporters involved in the CPO trade and 194 importers (full sample) involved in the RPO trade.

Table 2: ASEAN-5 – India Bound, Most Favored Nation and Preferential Tariff Rate Schedule

Bound rate	Base MFN	Preferential rate imposed by India on ASEAN -5 (Indonesia, Malaysia, the Philippines, Singapore, and Thailand)								
		2010	2011	2012	2013	2014	2015	2016	2018	2019
300	100	76	72	68	64	60	56	52	44	37.5

Source: Association of Southeast Asian Nations–India Free Trade Area (AIFTA) Schedule - India to Association of Southeast Asian Nations 5 CLMV, Annex 1 C.F.R. (2011).

Table 3: Gravity Model Estimates for Crude (CPO), Refined (RPO) and Overall Palm Oil (PO) Trade, 1988-2019

VARIABLES↓	With Actual Tariff						With FTA Dummy (Full Sample)					
	(1) CPO (HS-151110)		(2) RPO (HS-151190)		(3) PO (HS-1511)		(4) CPO (HS-151110)		(5) RPO (HS-151190)		(6) PO (HS-1511)	
	Coefficient	Elasticity	Coefficient	Elasticity	Coefficient	Elasticity	Coefficient	Elasticity	Coefficient	Elasticity	Coefficient	Elasticity
Ln GDPPC	0.755*** (0.115)	**0.755**	0.936*** (0.0854)	**0.936**	1.244*** (0.0911)	**1.244**	0.473*** (0.0984)	**0.473**	0.684*** (0.0570)	**0.684**	0.626*** (0.0762)	**0.626**
Ln Distance	-1.056*** (0.118)	**-1.056**	-1.133*** (0.0967)	**-1.133**	-0.733*** (0.110)	**-0.733**	-1.446*** (0.0635)	**-1.446**	-1.184*** (0.0521)	**-1.184**	-1.104*** (0.0528)	**-1.104**
Ln Tariff HS-151110	-0.755*** (0.226)	**-0.755**										
Ln Tariff HS-151190			-0.448*** (0.0645)	**-0.448**								
Ln Tariff HS-1511					-0.660*** (0.102)	**-0.660**						
FTA HS-151110=1							0.617** (0.293)	**0.853**				
FTA HS-151190=1									0.863*** (0.0947)	**1.370**		
FTA HS-1511=1											1.453*** (0.183)	**3.276**
Contiguity=1	0.554* (0.319)	**0.740**	0.435*** (0.151)	**0.545**	0.0989 (0.138)	0.104	1.211*** (0.362)	**2.357**	0.553*** (0.0962)	**0.738**	0.639*** (0.154)	**0.895**
Common Language=1	0.941*** (0.112)	**1.563**	0.723*** (0.0854)	**1.061**	1.068*** (0.0782)	**1.910**	0.528*** (0.0940)	**0.696**	0.918*** (0.0600)	**1.504**	0.838*** (0.0578)	**1.312**
Same Region=1	-0.369 (0.726)	-0.309	1.648*** (0.183)	**4.197**	0.541*** (0.183)	**0.718**	-2.452*** (0.521)	-0.914	1.716*** (0.108)	**4.562**	-0.155 (0.231)	-0.144
Constant	24.12*** (1.502)		20.86*** (1.053)		16.99*** (1.260)		27.31*** (1.007)		21.24*** (0.691)		22.31*** (0.757)	
Importer-Time FE	Yes		Yes		Yes		Yes		Yes		Yes	
Exporter-Time FE	Yes		Yes		Yes		Yes		Yes		Yes	
Pseudo-R-squared	0.971		0.958		0.963		0.940		0.947		0.932	
Log Likelihood	-2.67×10^10		-2.76×10^10		-2.75×10^10		-1.02×10^11		-8.16×10^10		-1.75×10^11	
N	54,139		98,190		9,271		1,016,849		1,016,849		1,016,849	

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

Note: The table presents results from the Poisson-Pseudo-Maximum Likelihood (PPML) Estimator. Actual Tariff Rate of CPO, RPO and PO is the parameter of interest for Columns 1, 2 and 3; FTA dummies (taking 1 if a particular transaction is under FTA) for CPO, RPO and PO is the parameter of interest for remaining columns. All the equations control for the importer-time and exporter-time fixed effects and standard errors are obtained from the inbuilt robust procedure. Columns 4, 5 and 6 use full samples, and columns 7, 8 and 9 in Appendix 1 using only samples that have the actual tariff rates available (restricted sample size). Tariff HS-151110, Tariff HS-151190 and Tariff HS-1511 are the variables used in equation (2.1), and FTA HS-151110=1, FTA HS-151190=1 and FTA HS-1511=1 are the variables used in equation (2.2). Elasticity for the categorical variables is obtained as ($e^{coefficient} - 1$).

Table 4: Crude Palm Oil (CPO): Effects of Preferential Agreements on Trade

Preferential Agreement	Year	MFN Tariff	FTA Tariff	Percent Difference between FTA and MFN Tariffs	Elasticity	Elasticity × Percent Change	Prior Year Trade Value ($ million)	Trade Increase Attributable to FTA ($ million)	Global trade in the year of FTA was implemented ($ million)	FTA induced trade, percent
ASEAN-India Free Trade Agreement (AIFTA)	2010	60.37	39.89	-33.92	-0.75	25.44	2751.35	699.94	17789.00	3.93
ASEAN Trade in Goods and Agreement (ATIGA)	2010	21.50	1.07	-95.02	-0.75	71.27	818.17	583. 09	17789.00	3.28
South Asian Free Trade Agreement (SAFTA)	2004	59.51	25.16	-57.72	-0.75	43.29	2.23	0.97	3632.75	0.03
US-Colombia	2012	10.00	0.00	-100.00	-0.75	75.00	4.20	3.17	23652.26	0.01

Note: The estimated elasticities are obtained from Table 3 using equation (2.1).

Table 5: Refined Palm Oil (RPO): Effects of Preferential Agreements on Trade

Preferential Agreement	Year	MFN Tariff	FTA Tariff	Percent Difference between FTA and MFN Tariffs	Elasticity	Elasticity × Percent Change	Prior Year Trade Value ($ million)	Trade Increase Attributable to FTA ($ million)	Global trade in the year of FTA was implemented ($ million)	FTA induced trade, percent
ASEAN Trade in Goods and Agreement (ATIGA)	2010	14.80	3.39	-77.09	-0.45	34.69	488.48	169.05	11776.43	1.44
EU- Pacific States FTA (PNG)	2009	12.80	1.98	-84.53	-0.45	38.04	369.86	140.39	13879.26	1.01
ASEAN-India Free Trade Agreement (AIFTA)	2010	55.86	42.23	-24.40	-0.45	10.98	748.26	82.01	11776.43	0.70
EU-Colombia	2012	16.4	10.46	-36.22	-0.45	16.30	8.16	1.33	17193.95	0.01

Note: The estimated elasticities are obtained from Table 3 using equation (2.1).

Appendices

Appendix 1: Gravity Model Estimates for CPO, RPO and PO Trade, 1988-2019

| | With FTA Dummy (Model B) with Restricted Sample Size | | | | | |
| | (8) CPO (HS-151110) | | (9) RPO (HS-151190) | | (10) PO (HS-1511) | |
VARIABLES↓	Coefficient	Elasticity	Coefficient	Elasticity	Coefficient	Elasticity
Ln GDPPC	0.763***	**0.763**	0.940***	**0.940**	1.186***	**1.186**
	(0.116)		(0.0861)		(0.0902)	
Ln Distance	-1.057***	**-1.057**	-1.109***	**-1.109**	-0.644***	**-0.644**
	(0.128)		(0.0947)		(0.113)	
FTA HS-151110=1	0.233	0.262				
	(0.489)					
FTA HS-151190=1			0.790***	**1.203**		
			(0.172)			
FTA HS-1511=1					0.536**	**0.709**
					(0.246)	
Contiguity=1	0.595*	**0.813**	0.488***	**0.629**	0.181	0.198
	(0.332)		(0.155)		(0.136)	
Common Language=1	0.946***	**1.575**	0.732***	**1.079**	1.066***	**1.904**
	(0.111)		(0.0859)		(0.0792)	
Same Region=1	-0.332	-0.283	1.652***	**4.217**	0.592***	**0.808**
	(0.767)		(0.181)		(0.189)	
Constant	22.01***		19.35***		14.88***	
	(1.466)		(1.066)		(1.267)	
Importer-Time FE	Yes		Yes		Yes	
Exporter-Time FE	Yes		Yes		Yes	
Pseudo-R-squared	0.970		0.958		0.963	
Log Likelihood	-2.70×10^{10}		-2.77×10^{10}		-2.81×10^{10}	
N	54,139		98,190		9,271	

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

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