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Do regional trade agreements affect agri-food trade? Evidence from a meta-analysis

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Abstract

Regional trade agreements (RTAs) have experienced significant growth worldwide, leading to an increase in studies assessing their impact on bilateral trade flows. With the availability of disaggregated trade data, numerous studies have examined the influence of these agreements specifically on agri-food trade. However, the results of these studies exhibit heterogeneity, posing challenges for policymakers seeking to understand the effects of RTAs on agri-food trade. To address this issue, we conducted a meta-analysis of 61 studies investigating the effects of various RTAs on agri-food trade. Using funnel asymmetric testing, our analysis reveals the presence of publication bias in the existing literature. By accounting for this bias, we found robust evidence that RTAs positively and significantly promote agri-food trade. Notably, the extent of this effect depends on the depth of economic integration within the RTA, distinguishing between customs unions and free trade agreements, as well as the classification of agri-food products as primary or processed. The ex-post effects of RTAs on agri-food trade are less pronounced when we control for both publication bias and heterogeneity, compared to controlling only for publication bias.

KEYWORDS
agri-food trade, gravity model, meta-analysis, RTAs

JEL CLASSIFICATION
F15, F14, Q17, C12

Regional trade agreements (RTAs) remain one of the most important trade policy tools in the global trading system. According to recent statistics from the World Trade Organization (WTO), 354 cumulative number of RTAs were in force in 2022.[1] Interestingly, at the multilateral level, agricultural trade liberalization continues to be one of the most debated issues (Martin, 2018) while also occupying a unique position in global trade policy (Bureau et al., 2019). For agricultural trade, RTAs are critical as trade barriers are higher and protectionist policies are more commonly applied on agri-food products than on manufacturing products. Hoekman and Nicita (2011) indicate that both tariff and nontariff barriers (NTBs) are more restrictive for agricultural compared to nonagricultural products. For instance, the average bound tariff for agricultural products, as of 2013, was 36.5% compared to 11% for industrial products (Bureau & Jean, 2013). Similarly, Grant et al. (2015) identify that sanitary and phytosanitary (SPS) measures within the agricultural sector are more significant and restrictive compared to those in nonagricultural sectors.

Agri-food disputes at the WTO are substantial due to the numerous barriers to agriculture trade (Afesorgbor & Beaulieu, 2021; Santana & Jackson, 2012). RTAs are expected to address these disputes and barriers, and thus, have a greater impact on agricultural than on non-agricultural trade. This was confirmed with empirical evidence by Grant and Lambert (2008) who found that RTAs have a greater impact on agricultural than on nonagricultural trade flows. RTAs are said to be important for agricultural trade, but some studies have argued they are not effective since most RTAs fail to include agri-food products in their product coverage. This is due to classifying most agricultural products as sensitive products. For instance, within the North American Free Trade Agreement (NAFTA), following 5 years of trade liberalization, agricultural trade between the US and Mexico was limited to only nine minor agricultural commodities because of the long phase-out terms for sensitive agricultural products (Hufbauer & Schott, 2005). Indeed, Bureau et al. (2019) state that although the number of RTAs has surged, their role in agricultural trade liberalization has been limited.

Generally, RTAs have been recognized as having widely differing effects on bilateral trade due to their differences in aim, breadth, and scope (Baier et al., 2019). Even within and across RTAs, Baier et al. (2019) indicate that their effects on trade are heterogeneous. There has been an increase in the number of literature on the impact of RTAs on agri-food trade, but the results are highly variable due to increasing heterogeneity in empirical studies. This variation in the literature can be seen from three perspectives: (1) whether the effect of RTAs on agri-food trade are positive or negative, (2) the size (magnitude) of coefficients, and (3) the statistical significance of the estimated coefficients. Figure 1 illustrates the intricacies found within the mixed results in the literature. In terms of signs, although the majority of studies, such as those by Grant and Boys (2012), Grant and Lambert (2008), and Jayasinghe and Sarker (2008) have consistently found positive effects of RTAs on agri-food trade, there are also a number of studies, such as Andersson (2019), Vollrath et al. (2009), and Timsina and Culas (2020) that have found negative effects for certain RTAs. The direction of coefficients holds significance, as it could

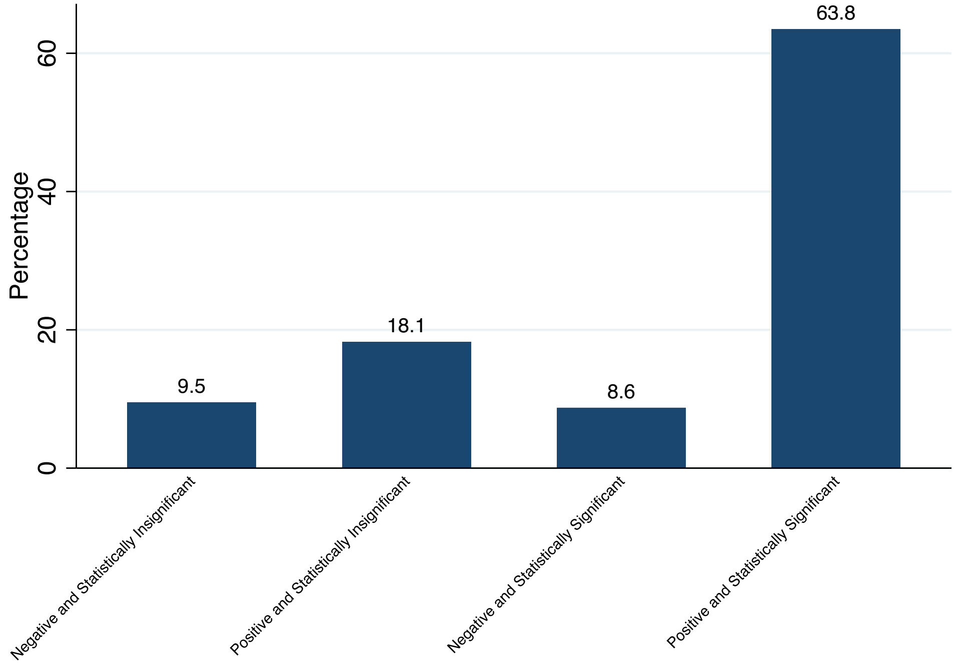

FIGURE 1 Heterogeneity of regional trade agreement effect on agri-food trade.

potentially contribute to publication bias. Researchers might hesitate to report a negative RTA effect on trade due to its theoretical implausibility. Consequently, this could lead to a bias in the distribution of effect sizes toward the positive end.

In econometric or regression analysis, the economic significance of an effect size, as reflected by its magnitude, is just as crucial as its statistical significance. The size of an effect provides the economic meaning to the estimated effect. However, the presence of publication bias can distort the effect sizes and their confidence intervals (Stanley & Doucouliagos, 2012).[2] Table 1 reveals a notable diversity in the magnitude of the effect sizes (δ) of RTAs on agri-food trade. While a considerable portion of the estimates falls within the reasonable range ($0<\delta<1$), there remains a substantial proportion (40%) of effect sizes that are both less than -1 and greater than 1. This highlights that the discussion regarding the impact of RTAs encompasses not only the direction (positive or negative) but also the economic significance of the effect.

The heterogeneity in the literature could emanate from different sources. First, a number of studies have employed data at different levels of disaggregation. These studies have tended to find mixed effects of RTA for disaggregated agri-food products. Jayasinghe and Sarker (2008) analyze the effect of NAFTA on trade for six agri-food product categories. Their results show that NAFTA significantly increased the trade flow of meat, vegetables, grains, and sugar within the regional bloc, while there was no significant effect for fruits and oilseeds. This heterogeneous effect of NAFTA on different products was also confirmed in a recent study by Ghazalian (2017). He uses bilateral agricultural trade data disaggregated according to the Standard International Trade Classification (SITC) and groups agri-food trade flow into 10 categories. Ghazalian's results also indicate that there are considerable differences across the effect of NAFTA on different categories of agricultural products. Similarly, Arita et al. (2017) also find

TABLE 1 Categorization of the estimate of the RTA-agri-food effect sizes.

Range of effect sizes	Frequency	Percentage
$-1 < \delta < 0$	397	20.24
$0 < \delta < 1$	1173	59.82
$\delta \geq 1$	391	19.94
Total	1961	100

Note: δ represents an RTA effect on agri-food trade.

that RTAs generally have heterogeneous effects; as they find positive and significant effect for only poultry and corn and a non-significant effect for other products, such as beef, pork, fruits, vegetables, soy, nuts, and wheat.

Second, most studies have evaluated the effect of different types and depths of RTAs on agri-food trade. These RTAs have different arrangements in terms of membership, such as South–South, North–South or North–North. There is a wide range of integration levels and scopes in RTAs, which affects the level of trade liberalization. In some RTAs, such as NAFTA, the Association of Southeast Asian Nations (ASEAN) FTA, the Asia-Pacific Economic Cooperation (APEC), and the Southern Africa Development Community (SADC), which are free trade agreements (FTAs), thus trade liberalization is limited to the removal or reduction of tariffs. While RTAs like the Andean Community, the Southern Common Market (MERCOSUR for its Spanish initials), and the Common Market for Eastern and Southern Africa (COMESA) have FTAs plus common external tariffs, which make them customs unions (CUs), with a greater depth of integration. Ultimately, some RTAs, like the European Union (EU), are at the highest level of integration and are thus expected to have a greater impact on promoting bilateral trade. These different RTA arrangements have different preferences regarding agri-food products, as well as differential impacts on agri-food trade, as was shown by Bureau and Jean (2013).

In addition to variations in integration levels, there is diversity among studies that have explored reciprocal and non-reciprocal trade agreements. Reciprocal agreements involve mutual trade liberalization, where each member reduces trade barriers, whereas non-reciprocal agreements entail one-way trade liberalization. Usually, developed countries unilaterally extend preferential trade agreements (PTAs) to developing countries, exemplified by initiatives like the Generalized System of Preferences (GSP), Everything but Arms (EBA), and the African Growth and Opportunity Act (AGOA).

The diverse range of results can create uncertainty, particularly for policymakers seeking to establish a consensus on the effectiveness of RTAs in promoting agri-food trade. Furthermore, the magnitude of the RTA effect on trade is a point of contention in the literature, with different studies reporting varying effects that can be substantial. The size of this effect is relevant because a substantial effect, exceeding the average estimate of 114% could indicate an upward bias in the estimated effect of an RTA (Baier et al., 2008). Meta-analysis offers two main advantages according to Stanley and Doucouliagos (2012). First, we can derive an underlying effect size after accounting for publication bias. This is important as Stanley and Doucouliagos (2012) indicate that when publication selection bias is present, the average effect of variables can be distorted. As a second approach, meta-regression analysis (MRA) can be used to explain the variation in empirical results in previous literature, as well as to account for the heterogeneity of study designs. Thus, estimates that are not dependent on the study's design can be derived.

Our paper contributes to the literature in different ways. First, it fills an apparent gap, as there exists no meta-analysis study that synthesizes whether there is any underlying effect of RTAs on agri-food trade. Most meta-analyses of the RTA effect on trade have been performed at the level of aggregated trade flow and not specifically focused on agri-food trade. For example, Afesorgbor (2017) focuses specifically on only African RTAs and aggregate bilateral trade flow, and Cipollina and Salvatici (2010) also focus on different RTAs, but trade was measured at the aggregated level. More closely related papers are by Li and Beghin (2012) and Santeramo and Lamonaca (2019), who focused on agri-food trade; however, their meta-analyses were on the effect of nontariff measures (NTMs) and other technical barriers on agri-food trade. Second, we differentiate between the effects of RTAs at different levels of integration to reflect the assertion by Bureau and Jean (2013) that the depth of RTA arrangements matters in trade liberalization. Furthermore, this paper differentiates the RTA effect by categorizing agri-food products as primary, processed, and more specific agri-food groups.

LITERATURE REVIEW

According to Chaney (2008), trade barriers produce more pronounced effects within sectors where the elasticity of substitution is high. Because agricultural products are homogeneous, this is particularly relevant to the sector. Scoppola et al. (2018) argue that the agricultural sector is labeled as a sector with higher elasticity of substitution. Thus, any competitive advantage due to RTAs may affect the market share of trading partners in different markets. Similarly, many studies have also shown that tariffs and NTBs for agricultural products are more restrictive than for nonagricultural goods (see, e.g., Grant et al., 2015; Hoekman & Nicita, 2011). As an example, Hoekman and Nicita (2011) suggest that agricultural sectors in both developing and developed countries are heavily protected where tariffs and NTBs are used to limit agri-food trade.

Assessments of the trade effects of RTAs are usually accompanied by the concepts of trade creation and trade diversion. Trade creation occurs when there is a shift of domestic consumption from high-cost domestic products to low-cost products from a partner country as a result of elimination of trade barriers through an RTA. This results in an improvement in resource allocation and, presumably, positive welfare effects. Conversely, trade diversion refers to a welfare loss which involves a shift of domestic consumption from a low-cost non-member country to a high-cost member country. The majority of prior studies that examined the impact of RTAs primarily concentrated on the trade-creation effect (see, e.g., Ghazalian, 2017; Grant & Lambert, 2008; Jayasinghe & Sarker, 2008).

The principle of non-discrimination in trade is central to the multilateral trade system. However, the General Agreement on Tariffs and Trade (GATT) in Article XXIV allows member states to form free trade areas if they remove substantially all market barriers between them and do not make trade barriers against non-members more restrictive. When trade is non-discriminatory, the home country can export its products provided it has the most efficient producers and then import from low-cost suppliers in a foreign country. This explains, in large part, why bilateral trade flows are heavily influenced by trade agreements; they change this non-discriminatory trade pattern by lowering barriers to trade among member countries (Mujahid & Kalkuhl, 2016).

The agri-food sector remains the most regulated by SPS measures (Santeramo & Lamonaca, 2021). For agricultural trade, SPS measures may constitute a pervasive barrier to international trade if used as protectionist policies. The use of SPS measures has been argued to be a subtle way of erecting protectionist policies using food safety concerns as an excuse (Swinnen & Vandemoortele, 2009). RTAs are critical and expected to facilitate market access for agri-food products among RTA member countries. Santeramo and Lamonaca (2021) argue that RTAs allow regulatory cooperation through the harmonization or mutual recognition of standards that can promote market access for agri-food products. They also provide robust empirical evidence that SPS measures constitute a trade barrier for non-signatories to RTAs.

EMPIRICAL STRATEGY

Data

To conduct a meta-analysis on the RTA effect on agri-food trade, we follow the Meta-Analysis of Economic Research Network (MEAR-Net) guidelines as in Havránek et al. (2020) and Stanley et al. (2013) in searching, collecting, and coding of the relevant empirical studies. The search for relevant studies was conducted between March 2019 and January 2020. The combination of keywords used in identifying relevant literature with the help of the Boolean connectors are as follows: *trade agreement* (*OR regional trade agreement*, *free trade agreement*, *regionalism*), *agri-food trade* (*OR agricultural trade*, *food trade*) *AND gravity model*. We use the Google Scholar as our main search engine to identify the relevant studies and complement the number of studies using the Web of Science (WoS), AgEcon, and Scopus bibliographic databases. The search produced about approximately 73,000 studies in Google Scholar, indicating a rapid increase in studies and the popularity of the topic within the agricultural and trade literature. Apart from using electronic databases, we also used the forward and backward search approaches by looking at the reference list of the primary studies, as well as recent studies that have cited the primary studies.

Through the screening of the studies, we finally identified 61 studies that met our selection criteria. The first selection criterion was that the papers must be written in English. Second, the papers must be empirical and must use the gravity model as their main econometric tool of analysis. Using only studies that employed the gravity model has the added advantage of making the effect sizes across studies comparable. Cipollina and Salvatici (2010) argue that it is more prudent to restrict the RTA effect to only the gravity model, as using different methodologies could render studies less comparable. In all, the selected studies consisted of 54 number of journal articles and 7 non-journal papers including working papers, conference papers, and reports. The coding and data entry were done by the two authors and the third author double-checked the whole entry to ensure the highest scientific standard. From 61 empirical studies that estimated the gravity model, we derived a total of 1961 effect sizes. Table A1 in the online appendix provides information on the list of individual studies analyzed in detail.

Gravity model

To predict the level of bilateral trade flows induced by an RTA, most of the trade literature employs a (structural) gravity model—which is a basic expenditure equation that indicates how consumers allocate their spending across countries under trade cost constraints. Endogenous to the gravity model is a trade cost term that shows empirically how trade barriers modify predicted frictionless trade. Economists augment this trade cost term with a variable that captures the presence or otherwise of a trade agreement. The term is then used to determine whether bilateral exports have increased, decreased, or stagnated as a result of access to the trade area between each pair of RTA member countries before and after the entry into force of an agreement. Since, an RTA is expected to lower trade costs between countries signatory to the agreement, a priori expected effect on trade flows is positive. The actual effect is, however, an empirical question and may be asymmetric across countries, heterogeneous across sectors, products, or agreement and vary over time. Since trade agreements arise from negotiations between bilateral pairs and are hence unlikely to be randomly distributed across bilateral pairs, endogeneity is a concern, which different authors have addressed using standard instrumental variable approaches (Egger et al., 2011) or fixed effects or first-differencing (Baier & Bergstrand, 2007).

A standard study examining the effect of RTAs on agri-food trade using the gravity equation specifies an extended variant of the econometric model in the form of Equation (1). The specification of the gravity model indicates that trade (X_{ijpt}) of agri-food product p between countries i and j at time t is determined by the market supply potential of i, represented by the GDP (Y_i) of the exporting country, the market demand potential of country j, represented by GDP (Y_j) of the importing country, and the trade cost (T_{ij}) between country i and j. The trade cost is captured by a vector of dyadic variables including distance, tariff, and a set of indicator variables that equal one if i and j share a border, colonial tie, common language, common currency, and GATT/WTO membership. To control for unobserved time-invariant heterogeneity, it is important to include dyadic (α_{ij}), exporter (importer) ($\alpha_{i(j)}$), and product (α_p) fixed effects. Furthermore, to account for external events that are common to all the trading partners, time fixed effects (α_t) are included.

$$X_{ijpt} = exp\left\{\beta_0 + \beta \ln\left[Y_{it}\left(Y_{jt}\right)\right] + \lambda \ln T_{ijt} + \delta RTA_{ijt} + (1-\sigma)\left[P_{it} + \Pi_{jt}\right] + \alpha_{ij} + \alpha_{i(j)} + \alpha_p + \alpha_t\right\} \times \epsilon_{ijpt}. \tag{1}$$

Since RTA is our main variable of interest, we isolate it from the vector of the trade cost variables. The RTA coefficient (δ) measures the effect by which bilateral trade between countries in the same regional bloc is higher than countries not in the same regional bloc. Since the studies estimate the δ in log-linear form, we consider the coefficients as semi-elasticity. For economic interpretation of the δ coefficient, it must be converted using $[(\exp^{\delta} - 1) \times 100\%]$ transformation.

The estimation of the gravity model raises two significant econometric considerations. The first is the presence of the multilateral resistance term (MRT), which includes the inward MRT (P_{it}) and outward MRT (Π_{jt}). MRT signifies that bilateral trade between two countries is influenced not only by bilateral accessibility variables (e.g., distance, borders, common language) but also by the relative geographical positioning of these two countries within the global context. The MRTs are not directly observable to the researcher; however, not properly controlling for this could result in biased results (Baldwin & Taglioni, 2006). Methods used to control for the MRT includes (1) the use of iterative custom nonlinear least squares as proposed by Anderson and van Wincoop (2003), (2) the first order log-linear Taylor expansion by Baier and Bergstrand (2009), and (3) time-varying fixed effects by Feenstra (2016).

The second econometric concern borders on whether studies control for zero flows. Zero flows occur in international trade flow when countries do not trade at all. The use of a log-linearized gravity model excludes zero flows because the log of zero is mathematically undefined and introduces self-selection bias in the gravity model. Properly accounting for zero flows requires using the two-step Heckman selection model by Helpman et al. (2008) or the Poisson pseudo maximum likelihood (PPML) by Santos Silva and Tenreyro (2006). Through the tool of meta-analysis, we examine how controlling for these two major econometric concerns contributes to heterogeneity in the RTA effect on agri-food trade.

In collecting our meta-analysis data, we extract the δ coefficients and their standard errors from the individual studies. To account for the presence of outliers in the collected δ coefficients, we winsorize the coefficients and their standard errors at the 5% level. This approach is used in recent meta-analysis study by Zigraiova et al. (2021), which is an objective way to filter out δ coefficients and their standard errors that are considered as outliers. In addition, we extract additional information on the designs of the studies that account and control for heterogeneity in the studies. Detailed information on all the relevant variables and their descriptive statistics are provided in Table A2 in the online appendix.

Empirical analysis

FAT-PET analysis

Our primary empirical approach employs meta-analysis. Meta-analysis, as defined by Stanley and Doucouliagos (2012), is a systematic review method that involves the statistical analysis of previously published or reported findings related to a specific hypothesis, particularly when there is substantial variation among the empirical results. They indicate that meta-analysis is already a familiar and conventional tool used in medical research to determine the efficacy of drugs used in randomized clinical trials. More recently, we have seen a widespread use of the tool of meta-analysis within the field of economics (see, e.g., Afesorgbor & Demena, 2022; Cipollina & Salvatici, 2010; Demena & Afesorgbor, 2020; Rose & Stanley, 2005). Within the agricultural trade literature, we have seen papers such as Li and Beghin (2012), and Santeramo and Lamonaca (2019) that conducted meta-analyses of the effect of NTMs on agri-food trade. The literature on the effects of RTA on agri-food trade has grown rapidly, with substantial variation and heterogeneity in the results, making meta-analysis an effective tool.

$$\delta_{ks} = \beta_0 + \beta_1 SE_{ks} + \epsilon_{ks}. \tag{2}$$

To perform the meta-analysis, we use the funnel asymmetric test (FAT) and the precision effect test (PET) as in Equation (2) to determine whether there is an underlying effect beyond publication bias. δ_{ks} is the kth estimated RTA effect on agri-food trade reported by the sth individual study, and SE_{ks} is the standard error of the estimated δ_{ks}, and ϵ_{ks} is the error term. According to Stanley and Doucouliagos (2012), the FAT is used to test the presence or absence of publication bias in the literature. The FAT is represented by β_1, meaning that the estimated coefficients should be unaffected by the standard errors when there is no publication bias; otherwise, publication bias exists in the literature. Similarly, the PET is captured by the β_0, which indicates the underlying effect from the empirical studies after accounting for publication bias.

$$t_{ks} = \beta_0 \frac{1}{SE_{ks}} + \beta_1. \tag{3}$$

In estimating Equation (2), the error term is not expected to be independent and identically distributed as the variance of the effect and the error term would vary from one study to another (Stanley & Doucouliagos, 2012). Thus, it is obvious that estimating the equation using ordinary least square (OLS) would produce an inefficient estimator because of hetero-skedasticity. To solve this econometric problem, we used the weighted least squares (WLS) approach suggested by Stanley (2005). This approach transforms Equation (2) by dividing both left- and right- hand sides by the SE_{ks}, and thus producing Equation (3). We weighted all estimations by using the inverse of the standard errors. This transformation converts our dependent variable from the effect sizes (δ_{ks}) into t-values ($t_{ks} = \frac{\delta_{ks}}{SE_{ks}}$).

As highlighted by Stanley and Doucouliagos (2012), when estimating the aforementioned models, there is a valid concern regarding potential dependence among reported estimates, which can lead to autocorrelation among error terms. They indicate that two main types of dependence are within and between dependence. Within dependence arises when the estimates reported in a given study share common attributes due to researchers' idiosyncratic choices about data, methods, and variables (Stanley & Doucouliagos, 2012). Addressing within-dependence requires the use of a fixed effect (FE) estimator in which the reported estimates are clustered within the same study and thus help to produce cluster-robust standard errors.[3] Between-dependence arises when multiple studies are conducted by the same author. Since the authors are unlikely to contradict their previous results, there is also the likelihood of potential dependence across studies that are related to the same researchers. To minimize these forms of dependence, it is important to use the multi-level mixed (MLM) model as suggested by Bateman and Jones (2003) and Stanley and Doucouliagos (2012). The MLM approach attempts to model both the within- and between-study dependence.[4]

Multivariate meta-analysis

Apart from publication bias, which can be solved using our FAT-PET analysis, heterogeneity among and within primary studies also matters (Havranek & Irsova, 2017). To account for the heterogeneity in the empirical studies, we also conducted the moderator analysis to explain the variation in the literature. Econometrically, we account for heterogeneity by using Equation (4). This equation includes many moderator variables (Z_{hks}) that account for the variation in the design and characteristics of the primary studies.

$$\delta_{ks} = \beta_0 + \beta_1 SE_{ks} + + \beta_k \sum_{h=1}^{n} Z_{hks} + \epsilon_{ks}, \tag{4}$$

where h is the number of the moderator variables and Z_{hks} is the specific moderator variable, as listed in Table A2 in the online appendix. It is important to control for heterogeneity because, although many of the studies used the gravity model and thus have comparable effect sizes, there is still extreme variation in many dimensions. First, in the choice of the dependent variable, the studies measured trade using either export, import, or aggregated (sum of both export and import). Second, the studies also measured the trade-creating effects for different RTAs at different depth of integration (such as FTA, PTA, or CU). Third, although we focus on agri-food trade, there are also different product classifications, where some studies estimated the gravity model using total agri-food trade, processed, or primary agri-food products. More specifically, the studies also used trade flow at different levels of disaggregation (HS—harmonized system of classification), thus estimating gravity models for more specific products. In our data, we identify six main groups into which we classify the products, namely, (1) animal products, (2) cash crops, (3) grains and oilseeds, (4) fruits and vegetables, (5) prepared foodstuffs, and (6) aggregated products. Product classifications are important, especially as Santeramo and Lamonaca (2019) found that the effect of trade policy variables could be sector- or product-specific. For example, they found that NTMs have trade-distorting effects on seafood products, meat, fruits and vegetables, cereals, and oil seeds, but no adverse effect on fats and oils.

Apart from these, most of the studies differed in terms of the set of standard control variables. A vector of standard control variables includes GDP, distance, tariff, and a set of indicator variables that show whether the trading partners share a border, common language, common currency, and membership in the WTO. The omission of any relevant control variables can bias the RTA effect on agri-food trade. Thus, in accounting for heterogeneity in the design of the studies, we examine whether the inclusion or exclusion of any of these important variables has any systematic influence on the estimated RTA coefficient.

We also account for other dimensions that are not directly related to the gravity model but that can also be potential sources of heterogeneity, such as the data, estimation techniques, and publication characteristics. For data, the studies employed different types of data, such as panel and cross-sectional data, the number of countries (both exporters and importers), and span of years for the data. For estimation characteristics, different studies used varying types of fixed effects, such as dyadic, country, time, and product fixed effects. The inclusion of different fixed effects is important, as they can be used to minimize endogeneity concerns in the estimation of the gravity model (Baier et al., 2008). For instance, dyadic fixed effects can control for unobserved or non-measurable regulations between the trading partners. The RTA coefficient could be biased without the use of dyadic fixed effects if an unobserved variable is correlated with the RTA variable. For publication characteristics, we also control for different dimensions that relate to whether a study has been peer-reviewed, the number of citations, and the impact factor of the publication outlet of the study.

Our moderator analysis considers 39 potential explanatory variables. The inclusion of all these variables in a single regression could lead to over-specification bias and a multicollinearity problem (Cazachevici et al., 2020; Stanley & Doucouliagos, 2012). To circumvent these problems, we use more recent approaches including Bayesian model averaging (BMA) and frequentist model averaging (FMA) (see, e.g., Cazachevici et al., 2020; Zigraiova et al., 2021). BMA involves running many regressions using different subsets of the moderator variables (Zigraiova et al., 2021). According to Zigraiova et al., this approach uses a Markov chain Monte Carlo algorithm that approximates the model space and uses the subset of the model space that has the highest posterior model probabilities (PMPs). BMA also reports the posterior mean and posterior standard deviation of the coefficient based on the weighted average of the coefficients from all the estimated models where PMP is used as weight (Zigraiova et al., 2021). Additionally, BMA reports the posterior inclusion probability (PIP), which sums all the PMPs of the models in which the specific variable was included. Based on the values of PIP, Zigraiova et al. (2021) indicate to classify a moderator variable as decisive ($PIP > 0.99$), strong ($0.95 < PIP < 0.99$), positive ($0.75 < PIP < 0.95$), weak ($0.5 < PIP < 0.75$), or irrelevant ($PIP < 0.5$).

Because BMA results only provide information on the relevance of the moderator variables in explaining the heterogeneity, we as well resort to the estimation of FMA as an additional robustness check. FMA results provide point estimates that can be used to quantify the effect of different moderator variables on the RTA effect sizes. As noted by Zigraiova et al. (2021), FMA utilizes Mallow's criteria as weights due to their greater asymptotic optimality.

RESULTS AND DISCUSSIONS

FAT-PET results

To determine whether there is any underlying RTA effect on agri-food trade, we first use a naive approach by computing the weighted and unweighted average of the effect sizes. These results are presented in Table 2, which shows that an average effect of 0.440 (weighted) and 0.498 (unweighted), thus, indicating that, on average, an RTA has a positive effect on agri-food trade. The positive influence of RTAs on agri-food trade is consistent with the outcomes of meta-analysis studies conducted by Cipollina and Salvatici (2010) and Head and Mayer (2014), which explored the impact of RTAs on overall trade. It is worth noting that the magnitude of

TABLE 2 Simple and weighted means of the RTA effect sizes.

Method	(1) Effect size	(2) S.E	(3) 95% confidence interval	(4)
Simple average effect[a]	0.498 [64.5%]	0.015	0.468	0.529
Weighted average effect[b]	0.440 [55.2%]	0.013	0.415	0.466

Note: The numbers in the [ ] are coefficients converted using $[(\exp^{\delta} - 1) \times 100\%]$ transformation.
[a]The arithmetic mean of the estimate of the RTA coefficient.
[b]Uses inverse variance as weight.

TABLE 3 Bivariate FAT-PET analysis.

VARIABLES	(1) OLS	(2) FE	(3) MLM
PET (underlying effect)	0.355*** [42.6%]	0.275*** [31.6%]	0.284*** [32.8%]
	(0.0961)	(0.0971)	(0.0209)
FAT (publication bias)	0.769	1.494*	1.327***
	(0.621)	(0.874)	(0.452)
Observations	1961	1961	1961
Number of studies	61	61	61
R^2	0.166	0.077	

Note: The dependent variables are *t*-values of the associated reported effect sizes. Robust standard errors clustered at the level of studies in parentheses. The numbers in the [ ] are coefficients converted using $[(\exp^{\delta} - 1) \times 100\%]$ transformation. MLM does not produce an R^2.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

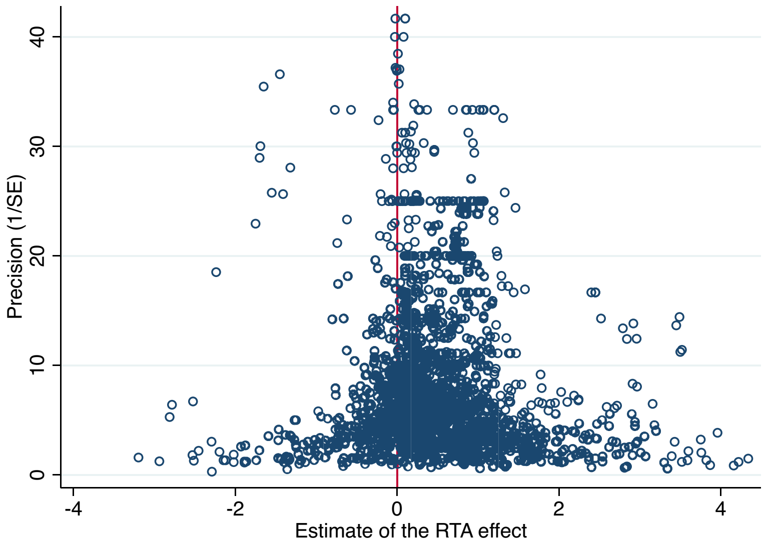

FIGURE 2 Funnel plot.

their RTA effects are comparable with our study. Specifically, Cipollina and Salvatici (2010) documented an average effect of 0.59, while Head and Mayer (2014) identified an average effect of 0.5.[5] However, the presence of publication bias and heterogeneity does not make inferences based on (un)weighted plausible.

We follow the econometric approach by using FAT-PET analysis. To show the robustness of our results, we employ OLS, FE, and MLM to estimate the FAT-PET equation; however, our preferred model is the MLM. The results for the FAT-PET analysis are presented in Table 3. The underlying effect, as captured by PET, shows an RTA effect of 0.284, indicating RTAs across studies, on average, increase agri-food trade by 32.8% $[(\epsilon^{0.284}-1)\times 100\%]$ between RTA members compared to non-members.

Our first step in assessing publication bias was to use the funnel plot, as shown in Figure 2. The funnel plot is a scatter plot which shows the relationship between effect sizes (δ_{ks}) and their precisions ($\frac{1}{SE(\delta_{ks})}$). The presence of publication bias is graphically confirmed by the funnel plot in Figure 2. Based on Rose and Stanley (2005), if the pictorial view of the funnel plot is not symmetric, then it is a signal that there is publication bias. Empirically, our FAT coefficient also shows a positive and significant effect, indicating the presence of publication bias in the literature. As RTA effects on trade should typically be positive, publication bias in the empirical literature is not surprising. Therefore, researchers finding results contrary to a positive significant RTA effect may have difficulty publishing their work.

The FAT-PET analysis in Table 3 utilizes a linear approach. However, recent studies have introduced more advanced robustness checks using nonlinear approaches. This is crucial considering that the functional form of meta-average regressions may be non-linear (Gechert et al., 2022). These nonlinear approaches are presented in Table 4. First, Ioannidis et al. (2017) develop the weighted average of adequately powered (WAAP) method to demonstrate how statistical power above 80% can correct for publication bias. Second, Andrews and Kasy (2019) propose a selection method that corrects for selective publication bias using the probability of publication as a function of study results. Third, Bom and Rachinger (2019) introduce the

TABLE 4 Nonlinear bivariate FAT-PET analysis.

	(1) WAAP	(2) Selection model	(3) Kinked model	(4) Stem method	(5) p-uniform
Effects beyond bias	0.399*** [49%]	0.301*** [35.1%]	0.355*** [42.6%]	1.075*** [192%]	0.432** [54%]
	(0.071)	(0.033)	(0.018)	(0.424)	(0.248)
Obs.	1961	1961	1961	1961	1961
Studies	61	61	61	61	61

Note: WAAP is the weighted average of adequately powered. The numbers in the [ ] are coefficients converted using $[(\exp^{\delta}-1)\times 100\%]$ transformation.
***$p<0.01$; **$p<0.05$; *$p<0.1$.

kinked model, which incorporates an endogenously determined cut-off expressed as a function of the first-stage estimate of the underlying effect to correct publication bias. Fourth, Furukawa (2019) develops the stem-based method, which calculates the PET by exploiting potential trade-offs between bias and variance. This method is robust to the publication selection process. Fifth, van Aert and van Assen (2021) introduce the p-uniform method, which utilizes the distribution of *p*-values to identify an underlying effect where the distribution is uniform.

The results for these nonlinear approaches robustly confirm the linear results in Table 3, and they indicate that there is an effect beyond publication bias. Therefore, compelling evidence is presented indicating that the impact of RTAs on bilateral agri-food trade remains positive and statistically significant, even when utilizing nonlinear methods.

Different levels of disaggregation are used to gain a deeper understanding of the impact of RTAs on different groups of agri-food products. First, we classify based on whether an agri-food product is a primary or processed. Scoppola et al. (2018) argue that because of product differentiation and the different levels of substitutability for primary and processed agri-food products, trade policy variables are likely to have a differential effect on them. Hence, we estimate the FAT-PET model for primary products, processed products, and mixed products (when a study estimates the gravity model for primary and processed products) in Table 5. The results show that the RTA effect is positive and significant for both primary and processed products separately, but the effect is more pronounced for processed products. Specifically, the effect of RTAs on primary products is 31.8% $[(e^{0.276}-1)\times 100\%]$ compared to 67% for processed products. Primary products, according to Scoppola et al. (2018), have higher elasticity of substitution; thus, the effects of trade-promoting policies such as signing trade agreements are expected to have a lower effect compared to processed products that have lower elasticity of substitution. They explained that this is primarily due to the differential effect of lower trade costs on the extensive and intensive margins of trade. For primary or homogeneous products, the reduction in trade cost allows an increase in trade at the intensive margins, while the extensive margins effects are weak.

Breaking down our results for specific products, we observe that the impact of RTAs on the trade of these agri-food products is consistent in terms of direction (positive) and statistical significance, except for cash crops. However, there are variations in the magnitude of the effects among different product groups. In particular, we find that the effects of an RTA on grains and oilseed have a greater positive and significant impact of 154.5% $[(e^{0.934}-1)\times 100\%]$ compared to other products, such as animal (28.8%), fruits and vegetables (45.4%), and prepared foodstuffs (11.5%).

TABLE 5 Bivariate FAT-PET for different products (MLM estimations).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Products categories			Specific products					
Variables	**Primary**	**Processed**	**Mixed**	**Aggregate**	**Animal**	**Cash crops**	**Fruits & Vegetables**	**Grains & oilseeds**	**Prepared foodstuffs**
PET (underlying effect)	0.276*** [31.8%] (0.0286)	0.511*** [66.7%] (0.0506)	0.191*** [21%] (0.0344)	0.306*** [35.8%] (0.0290)	0.253*** [28.8%] (0.0385)	−0.0247 (0.0458)	0.374*** [45.4%] (0.0736)	0.934*** [154.5%] (0.106)	0.109** [11.5%] (0.0552)
FAT (publication bias)	1.578*** (0.565)	−0.948 (1.374)	1.617*** (0.549)	0.792 (0.740)	1.548*** (0.562)	3.130** (1.298)	0.607 (1.019)	−1.300 (1.055)	1.262 (0.771)
Observations	843	373	745	1071	366	62	205	68	189
Number of studies	39	17	29	34	24	8	20	11	13

Note: The dependent variables are t-values of the associated reported effect sizes. Mixed is when the study mixes both primary and processed products while aggregate is when studies measure agri-food trade at an aggregated level. The numbers in the [ ] are coefficients converted using $[(\exp^{\delta} - 1) \times 100\%]$ transformation. Robust standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE 6 Bivariate FAT-PET for the depth of RTA (MLM estimations).

VARIABLES	(1) PTA	(2) FTA	(3) CU	(4) Others
PET (underlying effect)	−0.0126	0.204*** [22.6%]	1.567*** [379.2%]	0.324*** [38.3%]
	(0.0562)	(0.0262)	(0.0936)	(0.0453)
FAT (Publication bias)	3.473**	1.652***	−7.295***	1.197
	(1.506)	(0.464)	(1.882)	(1.043)
Observations	171	1261	116	413
Number of studies	10	36	12	26

Note: The dependent variables are t-values of the associated reported effect sizes. Others is when the study mixes different types of RTAs without explicitly indicating the specific type. The numbers in the [ ] are coefficients converted using $[(\exp^{\delta}-1)\times 100\%]$ transformation. Robust standard errors clustered at the level of studies in parentheses.
$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.

In the bivariate analysis, we also assess whether the RTA effects differed based on the depth or type of RTA. Table 6 presents the effect on agri-food trade for different types of RTAs. Quantitatively, we find that CUs have a greater impact compared to FTAs. In terms of the size of the effect, CUs promote agri-food trade by, on average, about 379% $[(e^{1.567}-1)\times 100\%]$ compared to 22.6% for FTAs. CUs signify a deeper form of integration as they involve having FTAs plus common external tariff. This is consistent with the studies by Ghosh and Yamarik (2004) and Baier et al. (2014) which indicate that the level of integration increases the amount of trade creation. Similarly, for studies that did not differentiate whether an RTA is either an FTA or a CU (others), on average, also find positive and significant effects. For PTAs, which are non-reciprocal trade agreements, our result shows a negative and insignificant effect. Admassu (2020) emphasizes the ineffectiveness of PTAs, especially when they cause developing countries to channel resources to preference-receiving sectors at the expense of other sectors. This is likely to weaken other sectors not receiving those preferences, and therefore decrease overall trade flows (Admassu, 2020).

Explaining the heterogeneity

In determining which moderator variables can significantly explain the heterogeneity in the RTA effect on agri-food trade, we first present a graphical illustration of BMA results in Figure 3. The figure shows all the explanatory variables on the vertical axis, while the horizontal axis shows the individual models and their PMPs. According to Zigraiova et al. (2021), the best models in terms of data fit relative to parsimony are on the left. The blue and red colors differentiate a whether an explanatory variable in the model has a positive or negative effect on the RTA effect on agri-food trade. The blue color indicates that the variable is included in the model and has a positive effect, while the red color delineates that the variable has a negative effect. A blank cell indicates that the variable is not included in the model and that it has no significant effect on the RTA effect on agri-food trade. Based on the BMA graphical results, we can identify that 8 variables among the vector of moderator variables have significant effects on the RTA effect of agri-food trade.

To determine the strengths and weaknesses of the variables in explaining the variation, the use of PIP is necessary. The quantitative results regarding the relevance of the variables, as

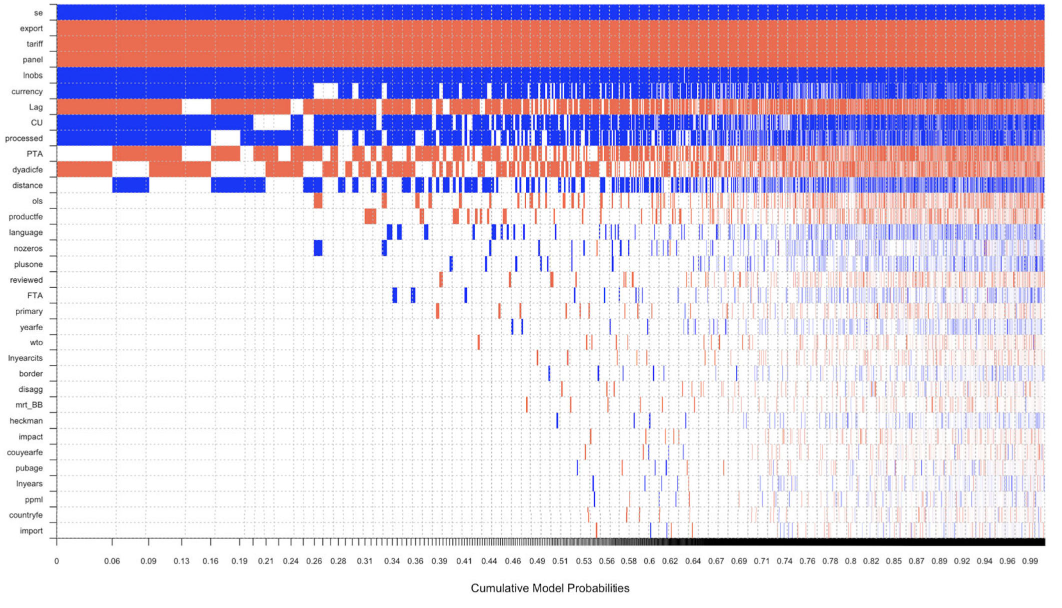

FIGURE 3 Model inclusion in Bayesian model averaging.

generated by BMA, are reported in columns (1)–(3) of Table 7. Following the PIP rule of thumb, our results classify three variables as highly relevant determinants of variation, as their PIPs are greater than 0.99. These variables are panel data, export, and tariff. The variable (number of observations) has a strong effect, with its PIP falling between 0.95 and 0.99. Additionally, four variables, namely processed products, custom union, common currency, and lag RTA, have a positive effect, as their PIPs fall between 0.75 and 0.95. The remaining variables either have a weak effect ($0.5 < PIP < 0.75$) or are considered irrelevant ($PIP < 0.5$). Overall, these findings provide insights into the varying strengths and effects of the variables in explaining the observed variation.

In addition, we present the FMA results in columns (4)–(6) of Table 7. The FMA results display coefficients that reflect how a moderator variable impacts the effect sizes, along with their associated standard errors. Under data characteristics, we find that using panel data is significant, in that, using a panel data in estimating the RTA effect on agri-good trade can lead to a lesser effect by 0.268 compared to studies the used cross-sectional data. This means that using cross-sectional data could lead to a upward bias in the RTA effect on agri-food trade. Baier and Bergstrand (2007) provide a nuance about how the use of cross-sectional data can lead to serious over or under estimated RTA effect on trade. They explained that since RTAs are likely to be endogenous, and the use of cross-sectional data in estimating the gravity model could limit the use of fixed effects to minimize any endogeneity concern. Similarly, the number of observations has a strong effect on the effect size, as a 1 percentage increase in observations is associated with 0.055 increase in the effect size. The number of years and whether a trade data is disaggregated are irrelevant, as their PIPs are less than 0.5.

For the type of product, only processed product has a positive and significant effect while primary product is irrelevant. Based on the FMA coefficient, using processed trade data leads to a higher RTA coefficient by 0.015. The difference in how primary and processed products

TABLE 7 Bayesian and Frequentist model averaging regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Bayesian model averaging			**Frequentist model averaging**		
	Post mean	**Post std. dev.**	**PIP**	**Coefficient**	**Std. error**	***p*-Value**
Standard error	0.566	0.087	1.000	0.534	0.101	0.000
Panel	−0.315	0.066	0.999	−0.268	0.104	0.010
ln (observations)	0.044	0.011	0.994	0.055	0.015	0.000
ln (years)	0.000	0.004	0.017	−0.015	0.026	0.563
Disaggregated trade	−0.001	0.008	0.020	0.015	0.063	0.812
Primary product	−0.002	0.013	0.044	−0.018	0.040	0.649
Processed product	0.086	0.061	0.735	0.088	0.049	0.073
OLS	−0.014	0.041	0.144	−0.110	0.053	0.037
Dyadic FE	−0.127	0.122	0.565	−0.086	0.079	0.275
Country FE	0.000	0.005	0.017	−0.036	0.051	0.487
Product FE	−0.012	0.036	0.120	−0.116	0.064	0.070
Year FE	0.001	0.010	0.035	0.065	0.053	0.222
MRT-BB	−0.001	0.018	0.020	−0.050	0.128	0.695
Country year FE	0.000	0.006	0.018	0.016	0.052	0.751
Plus one	0.013	0.066	0.054	0.377	0.176	0.033
PPML	0.000	0.006	0.017	0.053	0.061	0.380
Heckman selection	0.001	0.011	0.019	0.145	0.081	0.075
Nozeros	0.006	0.027	0.064	0.133	0.074	0.074
CU	0.169	0.105	0.796	0.173	0.082	0.034
FTA	0.003	0.015	0.047	0.005	0.045	0.918
PTA	−0.101	0.095	0.592	−0.173	0.073	0.017
Lag RTA	−0.237	0.141	0.809	−0.231	0.101	0.023
Currency	0.154	0.088	0.824	0.104	0.070	0.140
Distance	0.082	0.097	0.455	0.118	0.083	0.154
Language	0.009	0.031	0.102	0.081	0.060	0.178
Border	0.001	0.009	0.022	−0.053	0.060	0.374
Export	−0.380	0.039	1.000	−0.338	0.068	0.000
Import	0.000	0.006	0.016	−0.005	0.048	0.910
Tariff	−0.333	0.054	1.000	−0.292	0.077	0.000
WTO	−0.001	0.011	0.028	0.000	0.016	1.000
Publication age	0.000	0.001	0.019	0.000	0.004	1.000
Reviewed	−0.005	0.027	0.053	0.000	0.030	1.000
Impact factor	−0.001	0.022	0.019	0.000	0.066	1.000

(Continues)

TABLE 7 (Continued)

	(1) Bayesian model averaging	(2)	(3)	(4) Frequentist model averaging	(5)	(6)
	Post mean	Post std. dev.	PIP	Coefficient	Std. error	*p*-Value
Study citation	0.000	0.004	0.024	0.000	0.011	1.000
Intercept	0.396		1.000	0.169	0.213	0.427

Note: The dependent variables are the effect sizes. PIP > 0.99 → decisive, 0.95 < PIP < 0.99 → strong, 0.75 < PIP < 0.95 → positive, 0.5 < PIP < 0.75 → weak, and PIP < 0.5 → irrelevant.

responds to RTA has been confirmed in Scoppola et al. (2018). They argue that trade policy variables such as RTA respond differently to primary and processed products because of the varying level of protection and substitutability. For estimation characteristics, our results indicate the use of fixed effects (country, product, and year) does not significantly affect the RTA effect on trade. Our results indicate that the number of years of data and whether a study used disaggregated trade flows do not contribute significantly to heterogeneity in the RTA effect on agri-food trade. In terms of estimation characteristics, the inclusion of dyadic fixed effects is crucial, as the remaining variables are deemed irrelevant based on their PIPs (Posterior Inclusion Probabilities). Dyadic fixed effects within the gravity model serve to capture unobserved bilateral heterogeneity, including factors such as unmeasurable domestic regulations and the relationship between pairs of countries. Baier and Bergstrand (2007) indicate that adjusting for unobserved time-invariant heterogeneity using dyadic effects has a significant impact on the RTA effect of trade.

We find that the controlling for MRT did not affect the variation in the effect sizes of the gravity model, which was one of the major econometric concerns. This non-significance could be due to the fact that the most studies did not correctly control for MRT by using standard approaches as in Anderson and van Wincoop (2003), Baier and Bergstrand (2009) or Feenstra (2016).[6] Similarly, we do not find that approaches used to control for zero flows contribute significantly to heterogeneity in the previous studies. Specifically, all variables that are considered as treatments for zero flows have their PIPs less than 0.5.

For the choice of dependent, we see that studies that used export as their dependent variable compared to import are more likely to report less pronounced effect. The direction of trade (i.e., export or import) used in the estimation of the gravity model greatly contributes to explaining heterogeneity. Exports have a negative effect, which means that studies that used exports as their dependent variable would report a lower effect of RTAs on trade. This effect is plausible as exports tend to be under-reported by most countries; imports are more accurate, as countries monitor imports more keenly (Feenstra et al., 1999).

For depth of the economic integration, we find that different forms of trade agreements have a significant effect in explaining the variation in the RTA effect on agri-food trade in tandem with the results in Table 6. Studies that focused on trade agreements that are CUs report a greater positive impact compared to studies that employed trade agreements that are at a lower level of integration. Studies that used PTAs also tend to report lower RTA effects, while an FTA becomes not an important variable in explaining the heterogeneity. These results are intuitive, as FTAs and PTAs have lower depth of integration compared to CUs. This result is consistent with Baier et al. (2014), which indicated that deeper trade agreements, such as CUs have larger

TABLE 8 Meta-effect based on best practices.

	(1) Meta-effect	(2) Lower 95% CI	(3) Higher 95% CI
Meta-effect based on BMA variables (PIP > 0.75)	0.192 [21.2%]	−0.380	0.764
Meta-effect based on BMA variables (PIP > 0.5)	0.163 [17.7%]	−0.396	0.721
Meta-effect for BMA (PIP > 0.5) and other variables	0.276 [31.8%]	−0.269	0.821

Note: The other variables include distance, country-year FE (controlling for MRT) and PPML (zero flows).

effects on trade than FTAs and PTAs. For studies that lagged the RTA variables, we also see this led to a smaller effect size.

For the inclusion of control variables, only common currency and tariff are relevant in explaining the heterogeneity in the RTA effect on trade. Studies that controlled for common currency tends to report greater effects of RTA on agri-food trade. In addition, we find that the inclusion of tariff as additional variable in the gravity model also leads to lower RTA effect. This is also intuitive as tariff reduction accompanies the formation of most RTAs, so including tariff as a control will reduce the magnitude of the RTA effect on trade. Other control variables such as distance, border, and WTO membership, do not significantly affect the RTA effect. In terms of publication characteristics, all the variables such as publication age, whether a study is published in a peer-reviewed journal, number of citations and impact factor are not relevant in explaining the heterogeneity in the effect sizes.

Utilizing the insights from BMA results, we employ an OLS regression to estimate the best practice effect of RTAs on agri-food trade, considering the 8 identified variables that significantly contribute to heterogeneity with PIP > 0.75.[7] Table 8 showcases the outcomes for these 8 moderator variables. To enhance robustness, we incorporate moderator variables with PIPs exceeding 0.5, along with additional relevant moderator variables for estimating the gravity model. The outcomes derived from the best practice approach reveal that, when factoring in publication bias and heterogeneity, the RTA effects on agri-food trade fall within the range of 18% to 32%. This effect is less pronounced compared to considering only publication bias, as observed in the FAT-PET analysis.

CONCLUSION AND POLICY IMPLICATIONS

This study provides the first meta-analysis of the effects of RTAs on agri-food trade. In recent years, RTAs have increased exponentially, and we have seen more studies evaluating RTA effects on agri-food trade; thus, a meta-analysis of RTA effects on agri-food trade has become necessary. Furthermore, RTAs and agri-food trade remain prominently on the radars of both developing and developed countries. Because of the heterogeneity across studies, understanding whether RTAs really promote agri-food trade remains a policy-relevant question.

This study conducts a meta-analysis of the existing literature: 61 empirical studies that generated 1961 effect sizes. We first find that RTAs generally have a positive and significant effect on agri-food trade. The ex-post effect of an RTA, after accounting for only publication bias (as determined by the FAT-PET analysis), averages between 32% and 43%. This means that an

RTA increases trade by about these percentages. It is important to note, however, that the effects of RTAs on agri-food trade depend on the depth to which economic integration has been achieved, as CUs tend to have more pronounced effects than RTAs with lower levels of economic integration, such as PTAs and FTAs. Disaggregating the effect between primary and processed agri-food products, we find a greater effect for processed products compared to primary products. Further disaggregating of the RTA effects on specific agri-food products reveals heterogeneous effects. Specifically, we find that the RTA effect on the agri-food trade is most pronounced for grains and oilseeds, followed by fruits and vegetables, animal products, and prepared foodstuffs. Additionally, our findings provide evidence of the presence of publication bias in the empirical literature. This could be due to the presence of conventional views that RTAs are mostly trade-creating.

To explain the heterogeneity in the literature, our study employs two main econometric approaches, BMA for relevance and FMA for the effect of various variables on the RTA effect on agri-food trade. Based on these two methods, our findings show that heterogeneity in the design of previous studies can explain the variation in the literature. We find 8 variables to be key moderator variables in explaining the variation in the results. For data characteristics, we find that the type of data and number of observations are the only significant determinant of effect sizes. In addition, the lagging of RTA, processed agri-food trade product, and the inclusion of control variables such as tariff and common currency, using exports as the outcome variable, are all significant in explaining the heterogeneity. In accounting for heterogeneity and publication bias, our results still show that the effect of RTAs on agri-food trade remains positive and significant. The ex-post effect of an RTA after accounting for publication bias and heterogeneity (based on the best practice approach) averages between 18% and 32%.

Our study offers policy implications for the agri-food sector, as the results demonstrate the effective utilization of RTAs in promoting agri-food trade. RTAs can reduce the endemic trade barriers faced by agri-food products in the global market. Therefore, countries should make adequate provisions for the agri-food sector when negotiating trade agreements, that is, the scope and coverage of these trade agreements must be extended to cover agri-food products. A smaller RTA effect for primary products than processed products has implications for developing countries that export primary products primarily. Thus, developing countries must endeavor to add value to their primary agricultural products that are exported to developed countries. Furthermore, there is a necessity to broaden the range of products encompassed by PTAs and GSPs extended by developed countries to developing nations. Finally, our findings underscore the advantage of deeper economic integration for agri-food trade. Consequently, nations should prioritize the enhancement of their economic integration initiatives. This is particularly crucial since many RTAs are currently in the initial stages of economic integration, such as FTAs. There is an increasing necessity for more RTAs to evolve into CUs with common external tariffs, especially to eradicate the lingering rules-of-origin barriers within FTAs.

Considering that our analysis predominantly draws upon empirical studies that emphasize trade creation over trade diversion, we suggest that future meta-analyses should encompass the welfare effects of RTAs by examining both trade creation and trade diversion. Furthermore, we acknowledge the limitation of not being able to directly compare the RTA effect on agricultural trade with manufacturing trade. Therefore, future analyses should also consider incorporating trade in nonagricultural sectors to determine which sector is more significantly impacted by RTAs.

ENDNOTES

[1] http://rtais.wto.org/UI/PublicMaintainRTAHome.aspx, accessed August 15, 2022.

[2] Publication bias is the preference of accepting research papers or choosing results for their statistical significance (Stanley & Doucouliagos, 2012).

[3] A FE operates under the assumption that the disparities among studies can be attributed solely to within-study variation resulting from sampling fluctuations. In the context of the FE, the effect size from each study is posited to consist of two components. Specifically, $\delta_s = \theta + \epsilon$, where θ represents the single population effect size, and ϵ signifies the deviation of the effect size from the true population parameter. Although the true population effect size remains unknown, it is estimated through a weighted average across the individual studies.

[4] This type of data interdependence in an MLM can be accommodated through a two-level model, $t_{ks} = \beta_0 \frac{1}{SE_{ks}} + \beta_1 + \tau_s + \epsilon_{ks}$ Here, the subscript k signifies the regression specification or estimate from study k. Meanwhile, τ_s represents the study-level random effect (random intercept). In this modeling framework, the estimates at level 1 are clustered and nested within studies at level 2 (Demena & van Bergeijk, 2017).

[5] The studies by Cipollina and Salvatici (2010) and Head and Mayer (2014) did not conduct a FAT-PET analysis, so we are can only compare the means.

[6] In Table A2, we see less than 30% of the studies control for MRT.

[7] The best practice approach is when in the of context of multivariate regressions, neither publication bias nor underlying effect can be pinpointed to a single moderator variable, but rather a combination of variables. The selection of the variables is contingent on the personal judgment of the researcher (Stanley & Doucouliagos, 2012).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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