Decomposing the impact of GMO regulation on bilateral trade: An application to corn trade

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Abstract:

The stringency of GMO regulation affects trade of agricultural products among countries. On that account, our investigation attempts to shed the light on the complexity of the impact of genetically modified organisms (GMO) regulations among countries on bilateral trade with a focus on GMO approvals. We develop a framework extending Xiong and Beghin (2014) and their decomposition of export supply and imports demand effects. Our approach encompasses the supplemental effect of GMO regulation laxity in production on the exporter's productivity. It decomposes three effects that impact bilateral trade flows between trade partners: productivity in the source country, sorting cost from bilateral dissimilarity in regulations, and stringency impact on import demand. We estimate the model using a panel dataset of corn trade and two econometric approaches (PPML, Heckman sample-selection). We find that GMO laxity in production of exporters has the most prominent and robust effect of enhancing bilateral trade of corn. The effect of GMO laxity in demand appears to be smaller than the export booster effect of GMO adoption. Finally, bilateral dissimilarity in regulations does not appear to matter, once we account for the impact of GMO in production of the exporters and laxity in demand differentiated for importer and exporters. Hence, GMO approval regulations have dominating multilateral effects rather than bilateral ones.

Keywords: Genetically modified organism (GMO), corn, asynchronous regulation, trade

JEL codes: F13, F14, Q17

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Introduction:

During the last three decades, developments in biotechnology and life sciences in general have resulted in the creation of innovative methods that can be applied in agricultural breeding. Genetically modified organism (GMO), as one of the prominent agricultural technologies, consists of inserting DeoxyriboNucleic Acid (DNA), termed recombinant DNA (rDNA) into an organism's genome to make a crop more resistant to pests (insects or plants), increase its ability to uptake nitrogen and or resist drought stress, and many other useful features.

In fact, GMOs have the potential to help farmers prevent crop losses, protect the environment, and fight poverty and hunger (Finger et al. 2011, and Smyth et al. 2015). In 2019, 190.4 million hectares of biotech crops were grown in 29 countries involving nearly 17 million GMO farmers worldwide (ISAAA, 2019). However, the use of GMO aroused much controversy among countries about its alleged impacts on the environment and human health. Therefore, national bodies were established to assess the food-safety, socioeconomic and environmental impacts and spillovers before releasing GMOs into the marketplace. These national regulatory institutions eventually determine, whether to allow uses or cultivation of GMO events, and imports, define specific labelling policy, and establish traceability requirements, all of which vary considerably among countries (Gruère 2006, Davison 2010, Wohlers 2010, Viju et al. 2011, and Vigani and Olper 2013).

Within this context, our investigation attempts to dissect and disentangle the complexity of the impact of GMO regulations among countries on bilateral trade with a focus on the approval of GMO events for corn. We characterize and investigate the stringency of approvals for corn GMO events for various uses and production, and the impact of stringency and asynchronous approvals (AA) across space and time on export supply and import demand using a large panel dataset. AA

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means that the approval of a new GMO event does not occur simultaneously across countries, complicating international trade of major commodities, especially for those in bulk marketing systems with co-mingling of different GMO types. AA has resulted from the growing number of GMO events and their uneven adoption among countries following uncoordinated and heterogeneous approval processes for commercial use such as feed and/or food or for cultivation.

Productivity gains induced by GMO adoption in production shift the exporter supply to the right (expansion). However, the dissimilarity in GMO regulations across countries and regions has limited market integration, with added trade costs (Isaac et al. 2004, and Vigani et al. 2012) to sort out the proper type of commodity to export to various destinations. Trade costs come about as exporters must segregate GMO and non-GMO through separate distribution channels according to the destination and also within GMOs, by excluding events not approved in specific destination markets (Moschini 2008).

On the demand/user side, presumably, the larger the number of approved events for food/feed use in the destination country, the larger the volume of trade, other things being equal. Obviously, countries with stringent GMO regulations have to restrict their imports to fewer GMO types, which could lead to lower volume (demand curve shifting downward). The exact opposite will happen to countries that opted for lax GMO regulations on uses. Their commodity demand is likely to expand as users have more varieties to consume (various GMOs and non-GMOs). That being said, GMO regulations could have a demand-enhancing impact that arise from narrowing information asymmetries and building a strong confidence in imported products. The latter argument may be more important for final products than for primary commodities.

Previous studies have investigated the impact of biotechnology adoption on international trade and the determinants of the GMO regulation restrictiveness. Most of these investigations used a dissimilarity index between importers and exporters based on the different dimensions of the regulation (approvals, labeling, assessment time, traceability, etc.). Vigani et al. (2012) categorized the regulatory dimensions to determine GMO scores, and then, as a second step, GMO regulatory index is used in a gravity model to determine the impact on trade of differences between countries regulatory systems. Another similar work by Winchester et al. (2012) used regulatory dimensions to build a heterogeneity index and in turn incorporated these dimensions in a gravity model as an additional trade cost determinant.

De Faria and Wieck (2016) also derived a heterogeneity index of trade (HIT), which is defined as the difference in standards and regulations between an importer and an exporter. They employed the ISAAA approval database to derive an index that compares GMO uses between partners for each event. However, their method is only considering restrictiveness on the demand side of countries to measure dissimilarity. These studies have a common result, which is that the more dissimilarities between partners is, the less chance they have to trade. Even though these authors have addressed the GMO regulation dissimilarity, we argue that dissimilarity is not sufficiently informative to delineate the effects of GMO policies and provide clear policy implications.

To understand the intricate impact of GMO regulations, there is a need to decompose the GMO regulation and measure its impact on export supply and import demand: productivity in the source nation, cost sorting from regulatory differences across countries, and demand enhancing/reducing effect.

Xiong and Beghin (2014) and Cadot et al. (2018) have adopted an approach decomposing the impact of nontariff measures (NTMs) on export supply and import demand and trade. Biotechnology regulations affecting GMOs can be analyzed as standard-like NTMs to capture their complex impacts on supply and demand, and trade. Accordingly, our analysis develops a framework extending Xiong and Beghin (2014) by encompassing the supplemental effect on the exporter's productivity. It decomposes three effects that impact trade flows between trade partners: productivity in the source country, sorting cost from bilateral dissimilarity in regulations, and demand enhancing/reducing effect. We then provide empirical evidence of the GMO regulation impact on bilateral trade for corn trade.

The impacts on the import demand and the foreign exporter supply of trade partners, are captured using three indices, one related to the import demand as GMO laxity of demand, another related the exporter supply as the GMO (laxity in production approvals) which we call "adoption rate," and the last has to do with the dissimilarity of GMO events between two countries' supply and demand capturing the sorting and segregation costs.

We find that GMO adoption rate of corn exporters has the most prominent and robust effect on enhancing the bilateral trade. The GMO laxity in corn demand is also important but appears to have a much smaller effect than the export booster effect of GMO adoption. However, the bilateral dissimilarity does not appear to systematically matter, given that we account for laxity in cultivation approvals (GMO adoption) and laxity in demand decomposed by importer and exporters countries. Hence, we find strong evidence of multilateral trade effects rather than more specific bilateral ones.

The intuition of the modeling approach goes as follows. Import demand is derived assuming that a representative user from country j is a domestic processor of the commodity who is importing intermediate products (corn) from a set of countries i (including her/himself). This user-importer minimizes his inputs cost subject to his capacity of production to produce his final product and meeting regulations. This domestic processor has a constant elasticity of substitution (CES) among all different intermediate products that are imported.

The foreign exporter supply is derived assuming that a representative exporter i sends her/his products to set of destination countries j (including her/his domestic market). The exporter maximizes export revenues subject to her/his capacity of production to be allocated across destinations and facing trade costs to satisfy regulations. This exporter has a constant elasticity of transformation (CET) to adapt the output to specific markets. GMO regulations affect the ease of transformation.

At the trade equilibrium, the sum of import demands for the intermediate product from a specific origin equals the supply for the product from that region. Equilibrium conditions lead to an equilibrium bilateral-trade flow between any exporter and importer providing the foundation of a sectoral gravity model equation (Yotov et al. 2016) and the identification of the three potential supply and demand shifts outlined above. This equation captures and allows to identify the triple effect of GMO regulations.

In the following sections, we formalize the modeling approach and derive the equation to be estimated. Then we present the indices used and the panel dataset used to estimate the three potential impacts. Then we report results of our econometric estimation using the Poisson Pseudo-Maximum Likelihood (PPML) and Heckman's sample selection models. A battery of test attempts to identify a preferred estimation method. Policy implications and prospective expansions are discussed in the final section.

2. The methodological approach

The approach developed here expands on Xiong and Beghin (2014). It disentangles the three separate effects of GMOs and associated regulations on trade. By regulations we mean the type of GMO events approved or not for different uses (cultivation, feed and food uses). The intermediate demand-enhancing/reducing impact of these regulations is associated with the import demand, while the supply-enhancing effect of GMO adoptions is associated with export supply. The latter is presumably driven by the number of events approved for production.

Third, the dissimilarity between importer and exporter's regulations translates into the impact of asynchronous approval (AA) and associated trade cost. The AA trade cost is incorporated in the melting iceberg term (trade cost) along with the traditional trade costs induced by distance, regional trade agreement (RTA) and Tariffs. In the following sub-sections, all products are assumed to be differentiated by country of origin (Armington 1969). This assumption is the foundation of the gravity approach and aligns perfectly with the core of our investigation since every country has its own GMO regulation and produces a common product but with distinct genetic features.

2.1. The Import demand

The import demand for an agricultural commodity like corn is an intermediate demand derived from various industries using and processing it (feed, food, energy, and other processes) (Burgess 1974). The representative domestic processor *j* imports intermediate product *s* that needs to be processed into a final product *k*. The representative processor in country *j* for product *k* purchases these intermediate products across different sources and is characterized by a level of production at year *t*, Q_{kjt}, and a constant elasticity of substitution (CES) technology to aggregating these inputs demands across all sources *i*.

This producer's cost-minimization problem, subject to the prices p_{sijt} of a set of countries Ω and its level of production, is:

$$\underset{\{Q^D_{sijt}\}_{i\in\Omega}}{Min} \sum_s \left[\sum_{i\in\Omega} p_{sijt} Q^D_{sijt} \right],$$

$$s.t\ \textstyle\sum_s \left[\sum_{i\in\Omega} [(\alpha_{sjt} Q^D_{sijt})^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} = Q_{kjt}, (1)$$

with Q^D_{sijt} being the imported quantity demanded of intermediate good *s* at year *t*, sourced in country *i*, subject to reaching aggregate production's level Q_{kjt} of final product *k*. Q_{kjt} can also be interpreted as the aggregate domestic use of product *s*. Q^D_{sijt} is the producer's quantity demanded for intermediate good *s* produced by country *i*, including Q^D_{siit} domestically sourced. Price p_{sijt} is the price of intermediate product *s* produced in country *i* and sold in country *j*. Parameter ϵ is the constant elasticity of substitution (CES) between inputs imported from the set of countries included in *Ω* and it assumed greater than 1, as imports are close substitutes (higher level of ϵ means easier substitution).

Parameter α_{sijt} is an input shifter specific to importer *j* at year *t*, and it reflects the relative contribution of Q^D_{sijt} into the production of Q_{kjt}. Here, we assume that beyond an idiosyncratic component, the usefulness of the intermediate input increases with the number of GMO events and uses approved in country *j*, which we characterized as laxity of GMO regulation in importer *j*. The intuition here is that the more events are approved for more uses in country *j*, the less likely there will be sorting costs by the representative importer in that country. The demand shifter α_{sjt} is characterized as follows:

$$\alpha_{sjt} = \alpha_{j0}\, exp\left(\gamma_1\left(\delta^D_{sjt}\right)\right), (2)$$

$$\text{with } \delta^D_{sjt} = \sum\nolimits_{E_{st}}\left(X^D_{ejt}\right).$$

Parameter δ^D_{sjt} indicates the regulatory laxity of demand and α_{j0} is the idiosyncratic quality of product *s* perceived in absence of regulation in country *j*. According to the International Service for the Acquisition of Agri-biotech Applications (ISAAA), the approval of an event *e* can be for food and/or feed (demand) or none. Variable X^D_{ejt} takes the following parameters accordingly:

$$X^D_{ejt} = \begin{cases} \text{0 if no use is allowed} \\ \text{1/2 if feed or food is allowed} \\ \text{1 if feed and food are allowed.} \end{cases}$$

The demand shifter α_{sjt} is a function of the regulatory laxity of demand δ^D_{sjt} of product *s* in *j* at time *t*. Parameter γ_1 is presumably positive (it is increasing in laxity). In fact, δ^D_{sjt}

incorporates the variable X^D_{ejt}, which indicates whether the use of event *e* is allowed for different uses in country *j* or none, with *e* belonging to set E_{st}, the "global" set of GMO events of product *s* regulated in all countries at time *t*.

Parameter δ^D_{sjt} characterizes the demand shifting effect associated with the degree of demand laxity of country *j*, with high values (close to 1) of δ^D_{sjt} indicating high level of GMO tolerance on demand (low values close to zero indicates high GMO regulatory stringency in demand). Parameter α_{sjt} represents the coefficient of the demand shifter effect for country *j* and it must be positive.

The solution to this minimization problem (1) leads the import demand (3) expressed in volume and (4) expressed in values:

$$Q^D_{sijt} = \frac{{\alpha_{sjt}}^{\epsilon-1} Q_{kjt}}{\Psi_{sjt} {p_{sijt}}^{\epsilon}}, (3)$$

$$V^D_{sijt} \equiv P_{sijt} Q^D_{sijt} = \frac{Q_{kjt} {\alpha_{sjt}}^{\epsilon-1}}{\Psi_{sjt} {p_{sijt}}^{\epsilon-1}}, (4)$$

where $\Psi_{sjt} = [\sum_{i\in\Omega} {\alpha_{sijt}}^{\epsilon-1} {P_{sijt}}^{\epsilon-1}]^{\frac{\epsilon}{\epsilon-1}}$ is the CES price index for aggregate input *s* across all sources *i* for representative importer *j*. Given ϵ is assumed greater than 1, the import demand is positively related to the level of production of product *k*, Q_{kjt}, and the demand shifter α_{sjt}, but negatively related to the price p_{sijt}.

2.2 *The exporters' supply*

The foreign exporters' supply comes from a representative producer of the intermediate good *s* in country *i* who exports to country *j*, belonging to the set of countries *Ω* including his/her domestic market. This representative producer is characterized by a capacity of production Q_{sit} at year *t* and a constant elasticity of transformation (CET) technology. The transformation technology allows the producer to adapt her/his intermediate good to each's destination's regulations affecting

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GMOs. The producer problem is:

$$\underset{\{Q_{sijt}^{S}\}_{j\in\Omega}}{Max} \sum_{s}\left[\sum_{j\in\Omega} p_{sijt}Q_{sijt}^{S}\right],$$

$$s.t \sum_{s} (A_{sit})^{-1}\left[\sum_{j\in\Omega}(\tau_{sijt}Q_{sijt}^{S})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} = Q_{sit}, (5)$$

where Q_{sijt}^{S} is the quantity supplied from country *i* going to country *j* at year *t*. The exporter maximizes profit shipping to various destinations and taking into account the cost of transformation τ_{sijt} to meet regulations and trade costs in country *j* at time *t*.

Products are differentiated by destination, given each country level of regulatory stringency/laxity. All exporters need to comply with these destination-specific requirements. The elasticity of transformation η is assumed to be negative. A higher absolute value of η in absolute value means that transformation is easier (Powell and Gruen 1968).

As an extension of the Xiong and Beghin (2014) and Cadot et al. (2018) investigations on standard-like NTMs, we incorporate the productivity gains associated with the adoption of GMOs in the production of intermediate product s. An additional shifter is introduced via parameter A_{sit} in (5). It shifts the production possibility frontier (PPF) outward with increasing levels of GMO adoption. The intuition here is that by adopting new GMO events in the production of intermediate good *s*, the exporter *i* gains productivity leading to a rightward shift of the export supply. The global shifter A_{si} is defined as follows:

$$A_{sit} = exp\left(\gamma_2\left(\frac{N_{it}}{N_t^T}\right)\right), (6)$$

with N_{it} being the number of approved events for cultivation in country *i* at time *t* and Nt_T being the worldwide number of approved events for cultivation at *t* (events improved at least in one country at time *t*). Shifter A_{sit} takes high values indicating high rate of GMO adoption, and vice versa for low values. The implicit assumption is that a large number of events approved for

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cultivation indeed translates into a wider adoption of these events in cultivation.

Transformation shifter τ_{sijt} includes the various trade costs faced by *i* while trading with *j* at time *t* (tariff, distance, RTAs, GMO dissimilarity between *i* and *j*). It is expressed as:

$$\tau_{sijt} = \left(1 + Tar_{sijt}\right)\left(1 + Dist_{ij}\right)^{b_d} \exp\left(-b_r Rta_{ijt}\right) \exp\left(\gamma_3 \delta_{sijt}^{Diss}\right), (7)$$

where Tar_{sijt} represents the bilateral tariff imposed by *j* on product *s* sourced in *i* at time *t*. Dichotomous variable Rta_{ijt} indicates if a regional trade agreement exists between countries *i* and *j* at time *t*. Variable $Dist_{ij}$ is the distance between partners and it is time-invariant. Variable δ_{sijt}^{Diss} indicates the bilateral dissimilarity index between the exporter's (supply) and the importer's (demand) GMO regulatory laxities relative to the average dissimilarities across all destinations. If the exporter's supply has a lax GMO regulation regime compared to the importer's regime, then there will be an additional cost of sorting and segregation. The relative bilateral dissimilarity index is formulated as follows:

$$\delta_{ijst}^{Diss} = \frac{Dissimilarity\ between\ i\ and\ j\ at\ t\ for\ product\ s\ for\ each\ event}{average\ dissimilarity\ among\ all\ ij\ pairs\ at\ t} = \frac{\sum_{t} \max\left(0, X_{eit}^{S} - X_{ejt}^{D}\right)}{\frac{\sum_{jt} \sum_{E_{st}} \max\left(0, X_{eit}^{S} - X_{ejt}^{D}\right)}{Number\ of\ pairs}}, (8)$$

where X_{eit}^{S} indicates whether the supply of product *s* based on the single event *e* is allowed in country *j* or not at time *t*, and with $e \in E_{st}$ being the set of approved GMO events of product *s* in the world at time *t*. X_{eit}^{S} takes on the following values:

$$X_{eit}^{S} = \begin{cases} 0 \text{ if cultivation of product s using event } ns \text{ is NOT allowed} \\ 1 \text{ if the cultivation of product } s \text{ is allowed at time } t \end{cases}$$

As the index increases, the exporter will face higher cost. Now if the exporter's GMO regime is more stringent then the importer's demand, we assume that there will be negligible to no cost for the exporter to segregate and sort between non-GMO and various GMO types since most of the latter will be prohibited.

The formulation of the dissimilarity index in (8) is reminiscent of the Anderson and van

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Wincoop (2003) exporter's multilateral resistance term. The index is measured with respect to the average dissimilarity across all destinations for a given exporter, expressing relative dissimilarity. Note that we account for GMO adoption of exporter *i* (through shifter A_{sit}) and GMO regulatory laxity (α_{sjt}) of importer *j*. These two measures characterize the exporter's and the importer's regulatory multilateral regimes in aggregate, but not their dissimilarity on a particular bilateral basis nor by comparing their regulations for each specific event. Having similar events approved by both an exporter and an importer, reduces bilateral trade frictions linked to GMO regulations, other things being equal. This is what the bilateral dissimilarity index is meant to capture, beyond the aggregate multilateral characterization of adoption by the exporter and overall laxity of regulation in demand of the importer.

The solution to the maximization problem of equation (5) leads to the foreign export supply (9) in volume and the foreign export supply in value (10):

$$Q_{sijt}^{S} = \frac{Q_{sit}(\tau_{sijt})^{\eta-1}}{\Pi_{sit}(A_{sit})^{\eta-1}p_{sijt}{}^{\eta}}, (9)$$

$$V_{sijt}^{S} \equiv P_{sijt}Q_{sijt}^{S} = \frac{Q_{sit}(\tau_{sijt})^{\eta-1}}{\Pi_{sit}(A_{sit})^{\eta-1}p_{sijt}{}^{\eta-1}}, (10)$$

where $\Pi_{sit} = (A_{sit})^{-\eta}[\sum_{j\in\Omega}\tau_{sijt}{}^{\eta-1}P_{sijt}{}^{1-\eta}]^{\frac{\eta}{\eta-1}}$ is the CET price index for product *s* across all destinations *j* for a representative exporter *i*, expressing the aggregate cost to export to all destinations. Given η is negative, the export supply is positively related to the level of production of product *s* in *i* at time *t*, Q_{sit}, the global shifterA_{sit}, and the price p_{sijt} but negatively related to the transformation shifter τ_{sijt} .

2.3. Equilibrium

At the equilibrium, the importer producer's demand of product s matches the exporter producer supply $V_{sijt}^{D} = V_{sijt}^{S}$. The solution to this equality leads to the equilibrium trade value V_{sijt}, which represents the bilateral trade of product *s* between country *i* and country *j*. The price p_{sij} is also determined by solving the equilibrium equality:

$$p_{sijt} = \left(\frac{Q_{kjt}}{\Psi_{sjt}}\right)^{\frac{1}{\epsilon-\eta}} \left(\frac{\Pi_{sit}}{Q_{sit}}\right)^{\frac{1}{\epsilon-\eta}} \left(\frac{\tau_{sijt}}{A_{sit}}\right)^{\frac{1-\eta}{\epsilon-\eta}} \alpha_{sjt}{}^{\frac{\epsilon-1}{\epsilon-\eta}}, (11)$$

Therefore, the equilibrium trade value V_{sij} is generated as follows:

$$V_{sijt} = \left(\frac{Q_{kjt}}{\Psi_{sjt}}\right)^{\varphi} \left(\frac{Q_{sit}}{\Pi_{sit}}\right)^{1-\varphi} \left(\frac{\alpha_{sjt}A_{sit}}{\tau_{sijt}}\right)^{\theta}, (12)$$

where $\varphi = \frac{1-\eta}{\epsilon-\eta} > 0$, and $\theta = \frac{(\epsilon-1)(1-\eta)}{(\epsilon-\eta)} > 0$.

Equation (12) shows that equilibrium bilateral trade value increases in the importing country ability to process Q_{kjt} and exporting country's capacity of production Q_{sit}. It also presumably increases with the demand shifter (GMO tolerance index on demand), and the GMO adoption factor A_{sit}, but decreases in the bilateral trade cost τ_{sijt}. Now by substituting (2), (6) and (7) into (12) and taking it to the logarithmic transformation, we get the following representation of the equilibrium trade value:

$$\ln(V_{sijt}) = \theta \ln(\alpha_{j0}) + \varphi q_{kjt} + (1-\varphi)q_{sit} - \varphi\psi_{sjt} - (1-\varphi)\pi_{sit} - \theta ln(1 + Tar_{sijt}) -$$
$$\theta b_d ln(1 + Dist_{ij}) + \theta b_r Rta_{ijt} + \theta\gamma_1(\delta^D_{sjt}) + \theta\,\gamma_2\, A_{sit} - \theta\gamma_3\delta^{Diss}_{sijt}, (13)$$

Where $q_{kjt} = lnQ_{kjt}, q_{sit} = lnQ_{sit}, \psi_{sjt} = ln\Psi_{sjt}, and\ \pi_{sit} = ln\Pi_{sit}$.

Equation (13) constitutes an extended gravity equation model. Along with the traditional gravity variables (production capacities, distance, tariff, and RTAs), the model captures the demand laxity of importer *j*, the GMO adoption rate of exporter *i*, and the regulatory dissimilarity between *i* and *j*. By decomposing the triple effect of approvals on bilateral trade, our model introduces a tractable approach to study the policy implications of GMO regulations based on microeconomics fundamentals for supply, demand and trade. Explicitly, our conceptual approach allows us to see separately the impact of GMO regulations on the importer and the exporter, and in turn it provides a better understanding of forces at work.

3. Empirical specifications

By using the theoretical model, we will be able to capture the different impact of GMO regulation on bilateral trade. To implement (13) in the econometric investigation we make the following modifications given that some variables are not easily observable.

In the first place, multilateral trade resistance terms ψ_{sjt} and π_{sit} are unobservable effects as spelled out by Anderson and van Wincoop (2003). They summarize the multilateral resistance terms faced by the importer and exporter across all trade partners. To cover these price terms, we use exporter and importer fixed effects as they vary together in the in the same dimension. Considering that our model includes unilateral parameters (A_{sit} and α_{sjt}) which are time variant and specific to exporter and importer, we deploy country-specific fixed effects which are fixed over time. The reason being that these parameters would be perfectly collinear to the time-varying fixed effects. We also use bilateral country-pair fixed effects to control for country-pair heterogeneity. Note that in case of using the latter fixed effects, all time invariant bilateral variables like distance are omitted because of perfect collinearity.

Another common issue with gravity models is zero trade flows. To solve the issue, we use two main methods, which are widely accepted (Yotov et al. 2016, and Martin and Pham 2020): the Poisson Pseudo Maximum Likelihood PPML (Santos Silva and Tenreyro 2006) and the Heckman Sample selection (Heckman 1979). The first method PPML provides consistent estimators of the model. It also deals with the heteroskedasticity, which makes the PPML a robust approach. The potential drawback of PPML is that it does not address the potential censoring occurring with zeros (Martin and Pham 2020). In accordance with equation (13), our PPML estimation is as follows:

$$V_{ijt} = \exp\,(a_0 + Fi + Fj + Fij + a_1\, q_{kjt} + a_2\, q_{sit} + a_3\, ln\big(1 + Tar_{sijt}\big) + a_4\, Rta_{ijt} + a_5\big(\delta^D_{sjt}\big) + a_6\,(A_{sit}) + a_7\delta^{Diss}_{sijt}) + \mu, \quad (14)$$

where Fi, Fj, and Fij are the exporter, importer, and the country-pair time-invariant individual fixed effects. Therefore, we are assuming that the multilateral-resistance terms are time-invariant during the years of the study.

The second empirical strategy is the Heckman sample selection. This method accommodates for the zero trade flows by justifying the absence of trade and having an explicit extensive margin of trade and takes into account the non-random selection into trading. The exporter determines the destination of its exports based on explanatory variables that explains the selection of the destination. Another feature of the Heckman model is to investigate the impact of GMO regulation through the intensive margin (volume of existing trade) and the extensive margin as trade propensity (0,1). The empirical specification of the Heckman model is as follows:

$$\ln\big(T_{sijt}\big) = a_0 + Fi + Fj + Fij + a_1\, q_{kjt} + a_2\, q_{sit} + a_3\, ln\big(1 + Tar_{sijt}\big) + a_4\, Rta_{ijt} + a_5\big(\delta^D_{sjt}\big) + a_6\,(A_{sit}) + a_7\delta^{Diss}_{sijt} + \omega \quad (15)$$

$$D_{sijt}{}^* = a_0{}^* + Fi^* + Fj^* + Fij^* + a_1{}^*\, q_{kjt} + a_2{}^*\, q_{sit} + a_3{}^*\, ln\big(1 + Tar_{sijt}\big) + a_4{}^*\, Rta_{ijt} + a_5{}^*\big(\delta^D_{sjt}\big) + a_6{}^*(A_{sit}) + a_7{}^*\delta^{Diss}_{sijt} + a_8{}^*\ln\,(pop_{it}) \;+\omega^* \quad (15)$$

$$\ln\big(T_{sijt}\big) = \begin{cases} \ln\big(V_{sijt}\big)\; if\; D_{sijt}{}^* > 0 \\ n.a\; if D_{sijt}{}^* \le 0 \end{cases}, \quad (16)$$

with T_{sijt} being the value traded of product *s* between countries *i* and *j*, when observed, and $D_{sijt}{}^*$ being the binary unobserved variable that determines whether to trade or not. Equation (14) is an outcome equation that explains the connection between existing trade flows and a set of explanatory variables. Equation (15) is the selection equation, which describes the relationship between the probability of trade and a set of explanatory variables, including corresponding fixed effects Fi^*, Fj^*, and Fij^*.

The estimation of the Heckman model is two-step procedure where we estimate equations (14) and (15) jointly (OLS and Probit, respectively) accounting for the covariance of the error terms in the two equations. The Heckman procedure leads to include the inverse Mills ratio (the ratio of the standard normal density divided by the standard normal cumulative) into the outcome equation to account for this covariance of the error terms and the sample selection present in the data. Note that we exclude one explanatory variable from the outcome equation to avoid any potential effect on the fixed cost of trade. The variable included in the selection equation is the population of country i at time t, pop_{it} and it affects presumably the fixed cost to trade or not, but no impact on the variable trade cost of country i.

4. Data

The database consists of data on approvals of various GMO events for different uses, bilateral trade data, and data for other covariates explaining bilateral trade. We describe these next.

The GMO events approval across countries are provided in the ISAAA GM approval database, which is one of the best global sources of information on GM crop approvals. It includes GM crop approvals for a series of crops per country along with their commercial traits, developer, and the type of approvals and a time stamp. In this investigation, we focus on maize as one of the major crops traded across countries. It also has the most approved events since the first commercialization of GMOs. For each event listed in the ISAAA database, there are three types of approval: cultivation, food, or/ and feed use. To allow variation over time, we collect data on maize GMO approval from 1996 to 2018. We add countries that were not included in the ISAAA list of countries and which are trading maize. We set a cutoff level as the lowest level observed in the trade flows among the ISAAA countries to remove marginal importer and exporter: for exports, Nigeria with $61,288 trade value and for imports, Zambia with $2,503,755 trade value. We finally

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cover 127 countries in total, with ISAAA list included. [1]

We retrieve data on bilateral trade from BACI, a detailed international trade database from the French research center CEPII (Centre d'Etudes Prospectives d'Informations Internationales) considered the golden standard on bilateral trade flows with a sophisticate treatment of zero trade flows. The flows are estimated via COMTRADE and then adjusted using a mirroring process to obtain more reliable data (Gaulier and Zignago 2010). The bilateral trade data are in physical (metric tons) and value form (US dollars).

BACI also has additional information how to distinguish zeros from missing flows. In fact, the absent bilateral flows could be zero or just not reported. To make sure the missing values are zeros, we check whether the trading partners have traded any product for every year between 1996 and 2018. If there is trade other than maize, we assume that the missing maize flows in BACI primary database are just zeros flows. Otherwise, the bilateral trade of maize between the two partners is not reported. This dataset breaks down trade flows at the 6-digit HS code level; we retrieve data on products of HS-100510 (maize seed) and HS-100590 (other than seed) and then aggregate them to obtain trade flows of maize with HS-1005 code system in volume (quantities).

Data on corn/maize production, Q_{sit} and Q_{kjt}, are collected mainly from FAOSTAT and supplemented by USDA's PS&D database for a few countries (Burundi, Libya, Norway, and Singapore). For the aggregate processed good production's level Q_{kjt} of country j, the total domestic use of maize is used as a proxy. The population of country i is also acquired from FAOSTAT. For the RTAs, we deploy Larch's Regional Trade Agreements Database based on WTO notifications of preferential trade agreements.[2] The variable Rta_{ijt} takes the value of 1 if a

[1] We assume countries that were not mentioned in ISAAA during the period covered, have not approved any events for any use during 1996-2018.
[2] https://www.ewf.uni-bayreuth.de/en/research/RTA-data/

regional trade agreement between *i* and *j* exists at time *t*. If not, it takes the value of 0. Data on MFN applied tariffs are obtained from WTO data (TRAINS data). Although MFN applied tariffs are multilateral, we derive some bilateral variation in the ad valorem tariff by considering regional trade agreements between partners. The formula is as follows:

$$Tar_{sijt} = (MFN_{sj})(1 - Rta_{ijt}). \ (147)$$

Equation (17) suggests that the applied MFN tariff MFN_{sj} of an importer is not applied when the bilateral partners sign a regional trade agreement. Most RTA eliminate tariffs on most products. On that account, the variable Tar_{sijt} becomes partially bilateral. At last, bilateral distance, $Dist_{ij}$, comes from the CEPII GeoDist database. The latter variable proxies for transportation cost.

Table 1 provides a summary statistic of the three GMO indices. We assume that the effect of GMO demand laxity on net importers differs from the net exporters. Therefore, we generate two different demand indices: one covers the net importers and the other covers the net exporters.[3]

Table 1: Summary Statistics of the three indices with equation number

Variables	Mean	Standard Deviation	Min	Max
GMO Adoption (6)	0.03	0.10	0	3815
GMO Dissimilarity (8)	0.69	16.99	0	1
GMO demand Laxity of net Importer (2)	5.65	13.09	0	88
GMO demand laxity of net Exporter (2)	2.92	9.45	0	48

[3] We tested an aggregated formulation of demand laxity where we do not differentiate between net importer and net exporter. Table A2 in the Annex indicates that dissimilarity matters but the effect is small, however, demand laxity in the PPML approach is not statistically significant. Hence, we disaggregated net importer and net exporter assuming that the laxity affects countries differently.

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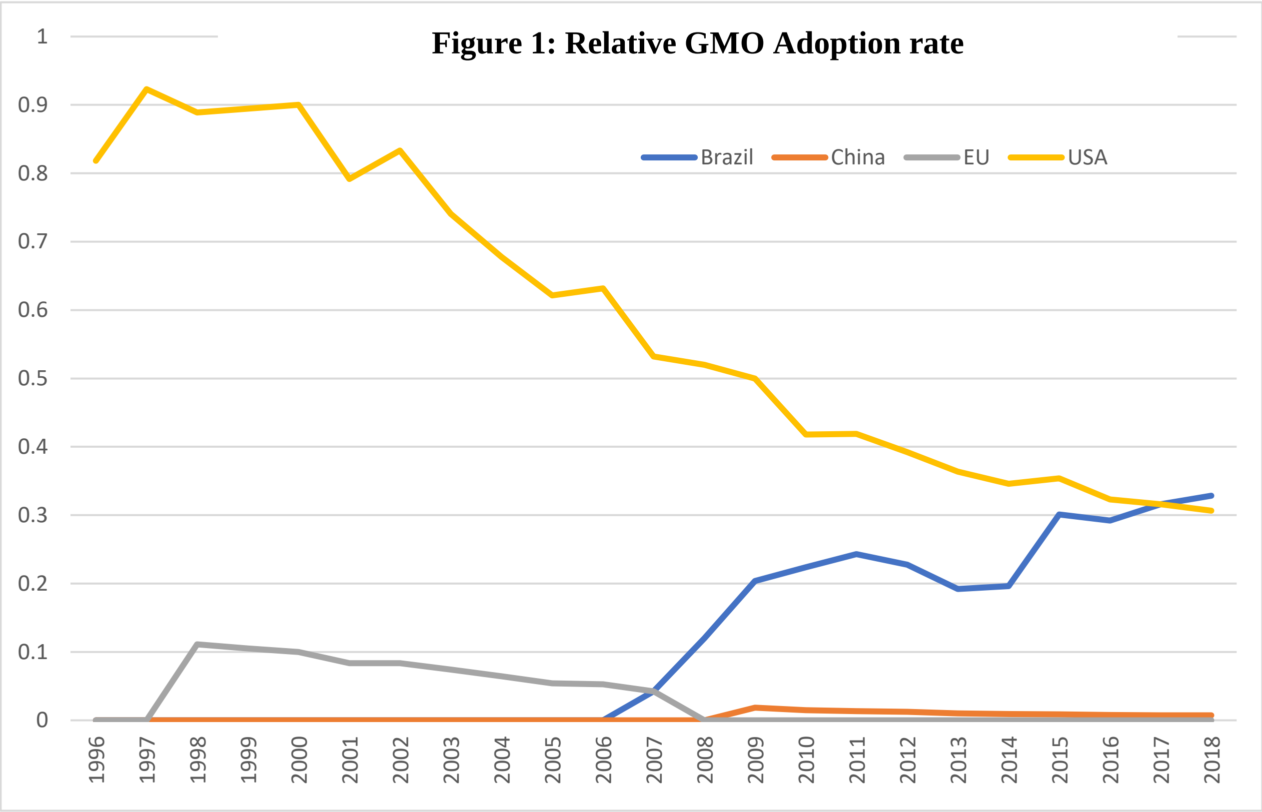
To illustrate the indices, Figure 1 displays the GMO adoption rate over time in Brazil, China, and the USA. As we explained before, this index is relative to the total approved events at



time *t*. We assume that GMO technology expands the production frontier of a country, but the expansion depends on what other countries allow for production. Therefore, the relative GMO adoption rate captures the relative competitiveness gain of countries disproportionally adopting GMOs for cultivation relative to other producers. According to the graph, The United States exhibit the highest adoption rate until 2017.

Because other countries are progressively adopting more GMO events that the United States has not approved yet, the GMO adoption index of the United States has been declining over years (from 0.8 in 1996 to 0.3 in 2018). Brazil is one of these countries that recently have been adopting GMO events quicker that the United States has been. As shown in the graph, Brazil has

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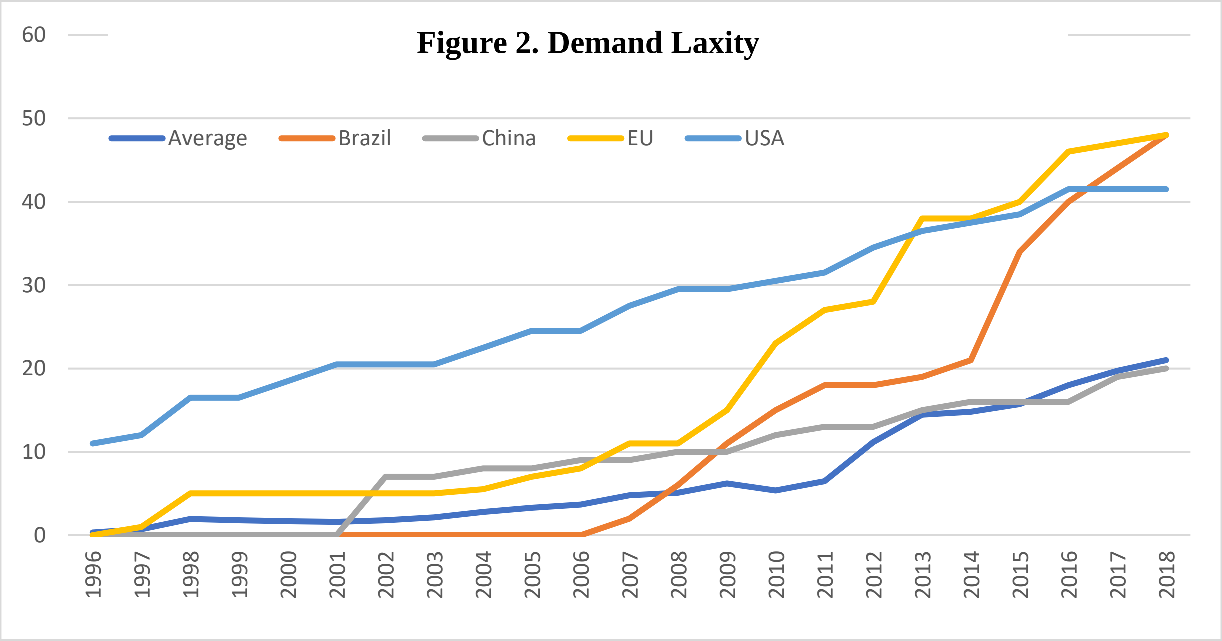
started adopting GMO events since 2007 and it has exceeded the U.S. GMO adoption in 2018.

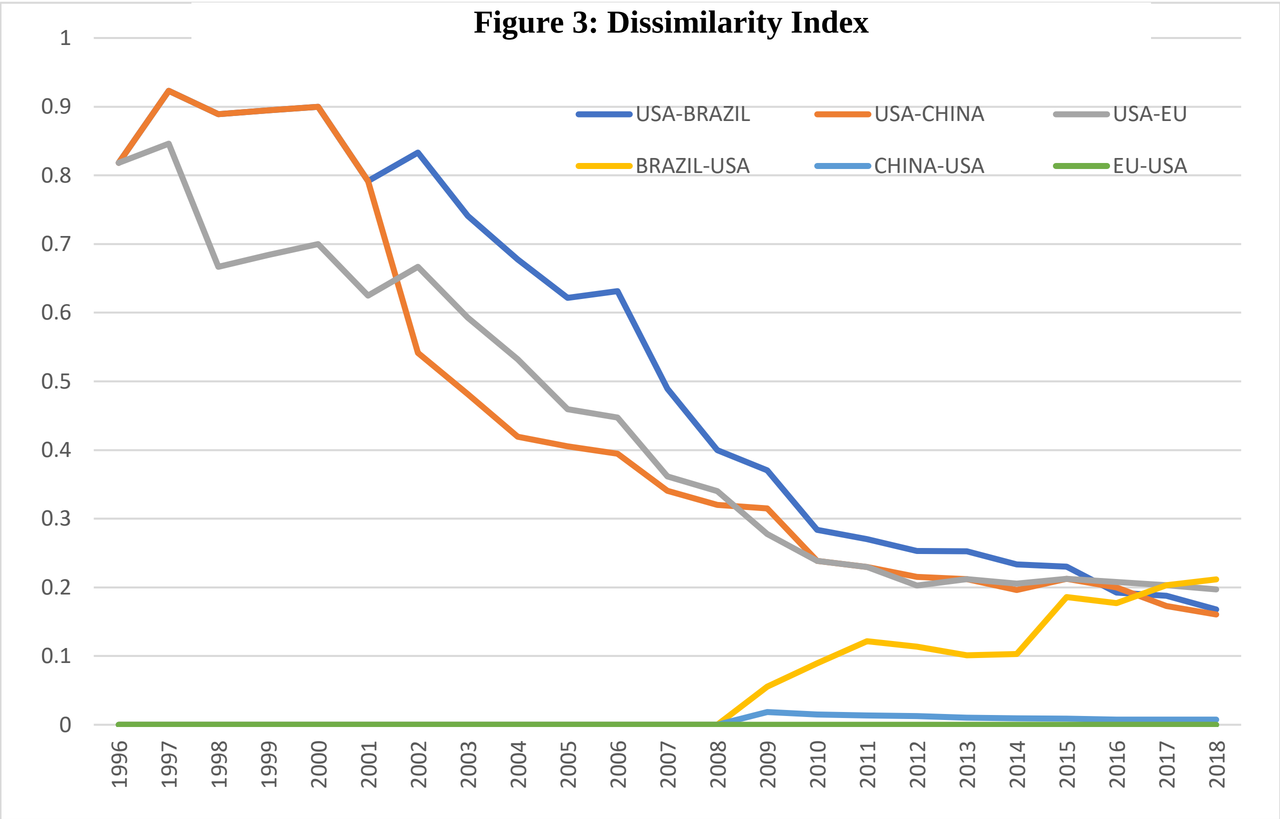
The European Union have adopted some maize GMO events between 1998 and 2007, then most of these events have been expired and the European regulator did not renew them due to the strong opposition to GMOs. In 2015, the European Commission enacted a regulation allowing EU nations to opt out of producing GMO foods, despite the fact that several countries already had a de facto ban in place at their national level. China has the lowest adoption rate among all (close to zero), although it is the world's largest grower of corn by area (FAOSTAT, 2020)

Figure 2 presents the GMO demand laxity between 1996 and 2018 in Brazil, China, EU, USA. It shows that demand laxity across these countries have been increasing since the 90s. Unlike GMO adoption rate, the demand laxity index is not relative, and it is calculated as the number of approved events for use in every country at time *t*. Therefore, we assume that approving GMO events for use will shift the demand curve upward without considering what other countries have approved. Even though Brazil has started to approve maize GMO events for use (feed or/and food) only in 2007, its demand laxity index has rapidly increased to be one of the laxest regulations in



2018. EU countries have been approving maize GMO events for use since 1998 and the number of approved events reaches 48 in 2018.

Figure 3 represents the dissimilarity index between source *i* and destination *j* between 1996 and 2018 for the USA and its main partners: Brazil, China, and EU. The index here is shown before we normalize its value by the average dissimilarity of the exporters as it is described in the methodology section. The USA-Brazil dissimilarity, with the USA as the source and Brazil as the destination, has been reduced due to the increasing adoption rate and demand laxity. On the other hand, when we consider the USA as the destination, Figure 3 shows that the dissimilarity is very small for all partners between 1996 and 2018, except for Brazil. Since 2007, Brazil started to approve maize events for cultivation and some of these events are not approved for use in the USA yet. This explains why the dissimilarity between Brazil and the USA is increasing lately.



5. Estimation Results

We use PPML and Heckman sample selection approach to estimate equations (13)-(16). Recall we rely on a series of fixed effects to add robustness to the model and overcome potential omitted variable issues. We then test the specifications to select a preferred model. We first use the Ramsey Regression Equation Specification Error Test (RESET), which tests if higher order terms, or a nonlinear model are needed to explain the data. Results are shown in Table 2.

The RESET test shows that basic PPML and PPML with only country fixed effects are suffering from misspecification. Adding country-pair fixed effects to the model fixes the misspecification; the *p*-value for the Chi-square statistics leads to accept the hypothesis that the PPML model is well specified.

Concerning the Heckman approach, we also check the normality and homoskedasticity of the model by running a simple RESET test on the outcome and the selection equations. The result presented in Table 2 indicates that the model fails the test, which is not surprising since the normality and the homoskedasticity of errors are strong assumptions for trade data (Santos Silva and Tenreyro 2006). On the other hand, the Inverse Mill's ratio is highly significant, suggesting that nations are self-selecting into trading and in turn, this is justifying the correction from the Heckman procedure's usage. When departing from homoscedastic normal errors, correcting for sample selection is not easily done. Some solutions have been proposed for heteroskedastic error but not have not been widely adopted (Donald 1995, Xiong and Chen 2014).

To compare and discriminate between PPML and Heckman selection specifications, we perform the HPC test suggested by Santos Silva et al. (2015) to test competing models with non-negative data with many zeros. The outcome of the HPC test, shown in Table 2, allow us to accept both specifications as their validities are statistically significant. Hence, in summary, the RESET test indicates departure from Heckman's assumptions and the HPC test does not differentiate

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between the two approaches. For the latter reason, we elect to present both specifications with the RESET test caveat in mind and given the importance of the extensive margin to explain trade.

Table 2: Specification test of PPML and the Heckman methods

Model / TEST	PPML	PPML with Country FEs	PPML with country & country-pair FE	Heckman With country FEs	
				Outcome Eq	*Selection Eq*
RESET test	Chi² = 8.09 Prob>Chi² = 0.00	Chi² = 9.44 Prob>Chi²=0.00	Chi² = 2.56 Prob> Chi²=0.10	Chi² = 2268.74 Prob>F = 0.00	Chi²= 248.34 Prob>F = 0.00
HPC test	-	-	t = -0.737 Prob>t = 0.769	t = 0.818 Prob>t = 0.207	
Inverse Mills (Ratio)	-	-	-	0.781**[4] (0.0691)	

Table 3 displays the estimated coefficients using PPML effects and the Heckman selection, with country and country-pair fixed effects. Both methods show that the GMO adoption rate has a significant enhancing impact on bilateral trade via the exporter supply in both models. Regarding the demand laxity, the results indicate that it has a negative impact on the imports of net exporters, but no significant effect is systematically captured for net importers in the PPML and very small in absolute value for the Heckman approach. This result likely reflects that net exporters' ample domestic supplies can satisfy domestic demand when the latter is flexible in terms of GMO events, and reduce the reliance on imports. Note that the export boosting effect of GMO adoption seems to be much greater than demand laxity in absolute values, by several orders of magnitude. The bilateral relative GMO dissimilarity between the exporter and importer does not seem to matter statistically, given that we account for GMO adoption and laxity on importer and exporters.

As to the rest of estimated coefficients, PPML and the Heckman selection have similar qualitative and expected results with respect to the production capacities of exporter and the intermediate demand of importer proxying the processed product transformation. The production's

[4] ** indicates $p<0.05$ and the standard errors are in parentheses.

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level of exporter is a crucial factor for the bilateral trade, and it has a positive effect. The magnitude is slightly more elevated for PPML.

Table 3: Estimated Coefficients using PPML and Heckman models with fixed effects

VARIABLES	PPML with FEs	Heckman with FEs	
		Outcome Eq	Selection Eq
Production of *i*	1.953*** (0.131)	1.161*** (0.110)	0.529*** (0.026)
Domestic consumption in *j*	1.700*** (0.198)	0.438** (0.144)	0.411*** (0.037)
Tariff	0.007 (0.010)	0.510*** (0.050)	-0.096*** (0.013)
RTA	-0.057 (0.170)	1.675*** (0.053)	0.183*** (0.015)
Distance	N/A (omitted)	-4.729*** (0.074)	-2.419*** (0.017)
Dissimilarity	-0.000 (0.0003)	0.000 (0.001)	-0.000 (0.0003)
GMO Adoption	0.343** (0.165)	2.153*** (0.265)	0.076 (0.094)
Net Importer Laxity	-0.000 (0.001)	-0.007*** (0.002)	0.004*** (0.000)
Net Exporter Laxity	-0.018*** (0.003)	-0.010*** (0.002)	0.004*** (0.000)
Population *i*	-	-	3.31e-06*** (2.91e-07)
Constant	-2.100** (0.714)	10.153*** (0.582)	4.427*** (0.156)
(Fi, Fj)	-	X	X
(Fi, Fj, Fij)	X	-	-
Observations	217,063	36,222	180,836
R-squared	0.926	-	-

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; (Fi, Fj) are country fixed Effects; Fij is the country-pair fixed effects. Inversed Mills ratio not shown here –see Table 2.

The intermediate demand for maize represented by the domestic consumption of maize is also an important element of trade. Distance is omitted in the PPML estimation since it is time invariant, and it is perfectly collinear with the country-pair fixed effects. However, it is negatively related to bilateral trade in the Heckman estimation as shown in Table 3 for both the selection and

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intensive margin equations. Elasticities are in the high end of the range of distance responses in the literature (Disdier and Head 2008).

Regarding the trade policy-based trade cost coefficients, tariff and RTAs appear to have different results in both approaches and it is not consistent with previous research, probably due to the way we derived the two variables. The PPML approach shows non-significant coefficients of Tariff and RTAs, however, in the Heckman approach, the coefficients are significant. For that reason, we rely on the Baldwin-Taglioni (2006) approach to account for potential bias from omitted variables, using time-varying fixed country effects and cross-section bilateral fixed effects to test the significance of time-variant bilateral variables.

The intuition in Baldwin-Taglioni is to capture all variation except the time-varying bilateral variation embodied in the dissimilarity index and other time-varying bilateral variables such as RTA and Tariff. We estimate all bilateral time-variant coefficients for Tariff, RTA, and GMO dissimilarity. The results of the approach are presented in Table A1 in the appendix. Table A1 shows that RTAs and tariff are not significant when considering time-variant fixed effects for exporters and importers and time-invariant bilateral effects. Thus, this explains the inconsistency of the estimated effects of tariffs and RTAs in between PPML and Heckman models. In addition, this extended fixed-effect treatment confirms the evidence in Table 3 on the statistical insignificance of the GMO dissimilarity index.

Further dissecting the Heckman approach results, the marginal effects of covariates along the extensive margin are defined as the effects on the percentage change in the probability to see new trade take place. In Table 4, the marginal effects of covariates along the intensive margin are defined as the effects on existing trade volume in terms of elasticities inclusive of their effects via the Inverse Mills Ratio (IMR).

We find that lax demand entails less trade between partners quantitatively, but it might

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influence the chance of forming a trading partnership. To put the findings in an economic context, countries with lax GMO regulation can import maize from a large set of countries as they have been approving more events. For that reason, the selection equation suggests that the likelihood of trade partnership is higher as countries tend to have less stringent demand towards GMO maize. Therefore, the flexibility of sourcing from different countries induces lower bilateral trade since imports scattered among a larger set of partners. The net effect of the two marginal effects in net-importing countries is near zero (-0.006) and 50% bigger but still moderate for net-exporting countries (-0.009).

Table 4: Intensive and extensive margins including via the IMR

	Intensive Margins	Extensive Margins
Dissimilarity	0.000 (0.001)	0.000 (0.000)
GMO Adoption	2.153*** (0.265)	0.009 (0.011)
Net Importer Laxity	-0.007*** (0.002)	0.001*** (0.000)
Net Exporter Laxity	-0.010*** (0.003)	0.001*** (0.000)

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

The GMO adoption and the demand laxity rates are positively correlated with 0.767 value. Net-exporter countries with less stringent demand tend to have less stringent supply regulations. Therefore, the demand triggered by the approval of GMO events for use is more likely to be satisfied domestically.

The GMO adoption has a strong positive intensive margin with elasticity equal to 2.153. The difference in magnitudes with the corresponding PPML elasticity (0.343) in Table 3 remains perplexing. However, the marginal effect of the GMO adoption rate is statistically insignificant. Finally, margins of the dissimilarity index are insignificant, as expected since the coefficients in Table 3 had low significance.

6. Conclusion

In this paper, we decompose the effect of GMO regulation on bilateral trade based on a framework extending Xiong and Beghin (2014) by including the additional impact on exporters' productivity and competitiveness. We decompose three factors that potentially can influence trade flows between trading partners: productivity in production in the source nation, cost sorting from regulatory differences across countries, and demand enhancing/reducing effect through laxity of regulation regarding uses. We apply the framework to bilateral trade of corn and GMO events approvals for cultivation and food and feed uses.

Our empirical results indicate that GMO adoption rate in the corn market has the most dominant and positive impact on bilateral trade but affecting trade through a multilateral fashion rather than a bilateral one. The demand laxity in demand for countries that are net exporters seems to have a reducing effect on trade, also in a multilateral fashion (affecting all sources), but for demand emanating from countries that are net importers, this impact is not significant. Regarding the extensive margin of trade, the likelihood of forming new trade partners is highly correlated with laxer demand GMO regulation. The explanation behind this finding is that by approving more events for use the importer will eventually have the ability to import from a larger set of countries.

Lastly, our results suggest that the GMO bilateral dissimilarity index capturing the bilateral cost of segregation does not have any impact on the bilateral trade given that we already accounted for multilateral regulatory characterization via the exporter's GMO adoption and the destination's GMO laxity in demand.

Our results shed a new light on the trade effects of GMO regulation, here with a focus on approval of GMO events. We identify multilateral effects, which rationalize how stringency in regulation can reduce trade as previous papers, but our results point to stringency in cultivation approvals with exporters rather than through bilateral asymmetries. Rather than focusing on asymmetries, our policy implication is to focus on the pro-trade effects of having many events approved in cultivation, allowing for relative competitiveness as an exporter, offering different type of the same commodity. As this paper addresses only one commodity (corn/maize), our implications are tentative and further applications of the proposed framework will hopefully confirm our findings with a panel of commodities.

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Appendix:

Table A1: Baldwin-Taglioni treatment with PPML

Variables	Coefficient	Standard Error	*p*-value
Tariff	0.070	0.078	0.370
RTA	0.178	0.171	0.298
Distance	Omitted	-	-
Dissimilarity	0.000	0.000	0.414
Number of observations= 217,063 **Pseudo R-squared**= 0.972			

Table A2. PPML and Heckman regression results with aggregate demand laxity

VARIABLES	PPML with FEs	Heckman with FEs	
		Outcome Eq	**Selection Eq**
Production of *i*	1.896*** (0.133)	1.162*** (0.11)	0.553*** (0.027)
Domestic consumption in *j*	1.669*** (0.193)	0.334** (0.145)	0.541*** (0.037)
Tariff	0.005 (0.095)	0.54*** (0.05)	-0.11*** (0.013)
RTA	-0.072 (0.165)	1.71*** (0.054)	0.189*** (0.015)
Distance	0 (omitted)	-4.74*** (0.073)	-2.413*** (0.017)
Dissimilarity	-0.000 (0.000)	-0.0078** (0.003)	-0.007 (0.0009)
GMO Adoption	0.321** (0.156)	2.27*** (0.266)	0.223** (0.097)
Demand laxity	-0.123 (0.171)	-0.0031** (0.0013)	0.003*** (0.0003)
Population *i*	-	-	3.45e-06*** (2.94e-07)
Constant	-1.699** (0.716)	10.48*** (0.578)	3.923*** (0.154)
(Fi, Fj)	-	X	X
(Fi, Fj, Fij)	X	-	-
Observations	217,063	180,836	36,222
R-squared **Inverse Mills (Ratio)**	0.926 -	- 0.783** (0.069)	- -