Technological Gap, Demand Lag And Trade

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**Abstract**

The relationship between innovation and trade has been largely seen from the perspective technological gaps and market share advantages for innovative countries. However, this straightforward relationship may not hold in face of certain level of “technology hatred” – as in the case of genetically modified organisms (GMOs). As national regulatory frameworks were built upon unilateral basis, many conflicts emerged opening a room for considering backward effects of technology innovation on trade. Based on firm heterogeneity and evolutionary economics literature the central aim of this paper is to investigate the role of technological gap and demand lag on trade, in the context of certain level of technology “hatred”. The technological gap is the difference or technological distance of techniques employed by late-movers when compared with technology used by leaders. Likewise, the demand lag may be understood as the difference or technological distance of techniques employed by producers in exporting countries and the level of acceptance or compatibility in destination markets. By means of a gravity equation we empirically estimated these effects on bilateral trade flows of soybeans. The results show that both technological gap and demand lag had important impacts on bilateral trade of soybeans from 1995 to 2012.

Keywords: Bilateral Trade, Technology Gap, Demand Lag, Gravity Equation, Firm Heterogeneity

**Resumo**

A relação entre inovação e comércio tem sido amplamente entendida sob o prisma dos hiatos tecnológicos e as vantagens de mercado para os países inovadores. Entretanto, esta relação direta pode não ocorrer quando existe certo nível de rejeição tecnológica – como foi o caso dos organismos geneticamente modificados (OGMs). Como os quadros regulatórios foram elaborados de forma unilateral, muitos conflitos se estabeleceram abrindo espaço para se considerar a existência de efeitos tecnológicos adversos no comércio. Baseado na literatura dos modelos da heterogeneidade da firma e na economia evolucionária, o objetivo central deste artigo é investigar o papel do hiato tecnológico e da rejeição de demanda no comércio. O hiato tecnológico é a diferença ou distância tecnológica entre os países atrasados e os líderes. Analogamente, o hiato/rejeição da demanda é a diferença ou distância entre as preferências tecnológicas dos exportadores e importadores. Por meio de um modelo gravitacional estes efeitos foram estimados empiricamente com bases em dados de comércio da soja em grão. Os resultados confirmam que tanto o hiato tecnológico quanto o hiato da demanda impactaram de maneira significativa os fluxos comercias entre 1995 e 2012.

Keywords: Comércio, Hiato Tecnológico, Rejeição de Mercado, Modelo Gravitacional, Heterogeneidade das firmas

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1. Introduction

It has been commonly accepted that technology innovations have positive impacts on exports since it improves production efficiency of innovative countries. However, when a particular technology is somehow rejected by part of international markets this expected effect can be counterbalanced or even overwhelmed by the negative effect of technology hatred. This is not a completely new idea. Posner (1961) had already pointed to very similar insights in the relation of technology change and trade. But this subject has been largely neglect as technology has been always assumed as a good from the consumer perspective.

In this way, the trade on genetically modified organisms (GMOs) is a good example of how backward technology effects can take place. GMOs have been produced and exported since 1996. The technology became rapidly available to producing countries via trade in technology headed by large multinational seed companies all over the world. But, some important consuming markets have been skeptical about the benefits of the production and consumption of genetically modified food, concerning mainly about high health, environmental and economic potential risks. Mainly because of some market characteristics and data availability the case of genetically modified soybean is a unique experiment to explorer most of the technological impacts we are dealing with.

Together, Brazil, United States and Argentina accounts for 87% of world exports of soybeans, and the EU and China accounts for more than 83% of world imports. While growers in United States and Argentina have been cultivating GM seeds since 1996, it took almost a decade to cultivation be approved in Brazil. Many European countries, however, have been noted contrary to the use of GM seeds in agriculture, encouraging the raising of trade barriers or even banning importation of food or contents deriving from GMOs. On the other hand, in China, although the few limitations to free trade of GM products, no rules preventing the country of being a certain destination for GMOs has passed.

The absence of multilateral bodies powerful enough to enforce a compromise between major players open a room for country-level regulations of approval, coexistence, labeling, and other issues related to GMOs production and trade. As expected, technology turns out to be a new source of trade conflicts lasting until today, as pointed by many applied studies dealing with this puzzle.

The aim of this paper is to evaluate how technical change impacted bilateral trade in the presence of unequal technology adoption and significant levels of technology hatred. Our central hypothesis is that under these circumstances technological innovation leads to a two-fold effect in trade – the technology-gap and the demand-lag. The technology gap can be seen as how advanced or efficient a country technology is in comparison with cutting-edge technologies globally available. The demand lag, instead, is how accepted a country technology is in destination markets in a point of time. These concepts are very insightful to the purposes of this study. They were discussed firstly by Posner (1961), but have been neglected in the new developments of trade theory, partially because of the lack of cases in which these two effects played such clear and opposing roles on trade. As innovation combined with different tastes will increase firm heterogeneity in technological terms, we departed from the general framework by Helpman, Melitz and Rubinstein (2008) – hereinafter referred simply as HMR – to investigate the technology gap and the demand lag.

Noteworthy, the increasingly complexity of new technologies – which not rarely brings cultural and ethical issues into the social approval –, consumers’ increased access to information make this case not a unique of his kind. It is important to note that uncertainty about risks and cultural-based judgments will be always an argument for restrictive unilateral regulations. The growing concern about more social, economic and environmental sustainable production methods is already a reality as one can see through fair trade initiatives, for instance, which establish principles for work contracts and use of particular inputs in agricultural production.

This study contributes to current literature mainly by raising issues about the role of consumer preferences, and the impact of technical progress on trade. We also advance by estimating the effects of demand lag and technology gap simultaneously – as much of the applied works on the field of GMOs consider only the impacts of commercial risks, or demand lag in our jargon. The combination of technology-gap theories and firm heterogeneity models is innovative as far as we know. A better understanding of this matter is needed since changes in technology with backward effects in trade will lead to unequal gains and losses across countries and actors.

This paper is divided into 4 remaining sections besides this introduction. Section 2 brings forward the literature review. Section 3 introduces the methodology. Section 4 brings out the results. Finally, section 5 concludes the paper.

2. Literature Review

Technology has been considered a source of comparative advantage under the Ricardian model of trade in opposition to the Heckscher-Ohlin model, which considers differences in endowment as the major driver of trade. However, Ricardian models of trade usually consider an unchangeable level of technology determining specialization and gains of trade. Perfect competition, absence of trade barriers, homothetic preferences and in some cases geography will create a world with certain degree of specialization and the only way of trading technology is through the trade of goods comprising such technologies. Firms can differ in terms of technology, but perfect competition wipes out effects of any love for variety (Dornbusch, Fischer e Samuelson, 1977; Eaton e Kortum, 2002).

The ideas of technology-gap are mostly related to evolutionary economics as it brings the idea of technical change as the driver of economic change. In general, an innovation in a particular country will result in increased efficiency and gains of market-share. On the other hand, other comparative advantages such as the costs of non-technological factors can counterbalance technological advantages. The speed of the diffusion rate is also central to think impacts of a particular innovation on trade. In some cases the time elapsed between an innovation and its critical adoption point can be delayed by slow market acceptance of a new technology (Dosi, Grazzi e Moschella, 2015; Dosi, Pavitt e Soete, 1990; Dosi e Soete, 1988; Maggi, 1993; Posner, 1961).

Firm heterogeneity models have been raising and discussing a number of interesting questions about trade by going deeper into firms instead of thinking country-level characteristics. Under monopolistic competition, homothetic preferences and love for variety is possible to think trade impacts related to different firms’ efficiencies and product and process innovation as consumers will always see a product of an innovation as a new one. Fixed and variable costs of trade allow the considering of increasing returns to scale in specialization(Helpman, Melitz e Rubestein, 2008; Melitz, 2003).

Regarding the case study, Oliveira *et al.* (2012) [[4]](#footnote-4) point out that competitiveness effect, measured as the amount of variation in exports not explained by increases in destination market absorption or world’s exports increase, brings out some interesting patterns between 1995 and 2012. Brazilian exports increases by competitiveness effect while US decreases when Brazil was considered GM-free and US have achieved high adoption levels – competitiveness can explain up to 60% of Brazilian exports of soybeans in 2000/2002 and -389% of US. However, the competiveness effect will change in favor of U.S. after 2005, when Brazil also adopts the technology – U.S. (31%) and negative to both Brazil (-39%) and Argentina (-47%).

Vigani *et al.* (2012) performed a gravity model to analyze the impact of technology on bilateral trade in 2005, 2006 and 2007. The gravity variable was the gap between the regulatory frameworks of trade partners measured by an index estimated by the authors. Noteworthy, in agriculture, in particular, authors usually consider regulatory differences as non-tariff barriers (NTB) increasing trade costs for most dissimilar partners (Burnquist *et al.*, 2011; Vigani e Olper, 2013; Winchester *et al.*, 2012). The magnitude of the estimated coefficient – in Vigani *et al* (2012) implies that one standard deviation decrease in the GMO dissimilarity index (=0.188) increases exports by 33%, all else remaining equal.

Through a more complete and time-varying restrictiveness index for 2000, 2009 and 2012 it is possible to see that restrictiveness is larger in European countries and South America, and lower for U.S. (Faria e Wieck, 2015). Besides, this study points out to significant impacts of dissimilarity on trade. The index take into account not only biosafety regulatory dissimilarity but also the gap between approved varieties.

Disdie & Fontagné (2010), in turn, studied the impact of the EU *de facto* moratorium and bans of other European countries on the exports of complainants (Canada, Argentina and US) and non-complainants in the WTO dispute from 1995-2005. They conclude that EU measures on GMOs reduced Argentina, Canada and US exports of maize seeds by 89.4% on average[[5]](#footnote-5). Regarding national bans, it appears that only the Austrian ones on maize (seeds and other) and the Italian one on maize seeds do not have a significant impact. All other national safeguard measures affected Argentinean, Canadian and US exports. Noteworthy, recent studies show that policymakers from different member states have kept their positions regarding the technology by voting in a favor or against new approvals in a steady way (Smart, Blum e Wesseler, 2015)[[6]](#footnote-6).

Anderson & Jackson (2004), by using a GTAP model with neoclassical closure, pointed out that since 1998 when the EU implemented the moratorium, GM adopting countries have lost EU market shares to GM free suppliers, particularly Brazil for maize and soybean and Australia and Central Europe for rapeseed. On the other hand, there are evidences that Canada’s rapeseed and US corn sales to the EU were successfully shifted to other markets. This shift to less adverse markets seems to be the case of soybean markets when we consider the replacement of U.S. by Brazilian Exports in the second half of 1990s, along with growing imports of China (see also Smyth, Kerr e Davey, 2006; Stein e Rodriguez-Cerezo, 2009).

In terms of benefits of planting GMOs there are many studies corroborating economic gains ( see Bärwald Bohm et al., 2014; Brookes & Barfoot, 2014; Chavas, Shi, & Lauer, 2014; Qaim & Zilberman, 2003; Sturges et al., 2003). Authors usually point to less expansive and easy control of weed, higher yields and reduction of adoption of tillage systems.

Yield gains are the most questionable benefit being possible to find evidences of negligible or negative effects of technology. However, many studies points to higher yields especially for developing countries in which prior pest controls were poor (Qaim e Zilberman, 2003).

A recent studied estimated that economic gains reached 116.6 billion of USD from 1996 to 2012. For the soybean case, there was a cut down in production costs, mainly through reduced expenditure on weed control (herbicides). In South America, additionally, there were gains associated with the adoption of no tillage production systems, shortening the production cycle, so enabling famers rip benefits of growing a second crop in the interval of two seasons. They estimate that gains for farm incomes amounted 4.8 billions in 2012 (Brookes e Barfoot, 2014).

It is important to note that technology costs vary across countries and so cost savings also differ. In Argentina technology costs vary from 2-4 dollars per hectare, whereas in Brazil it is 11-25 and in US 15-39. Yield gains are more likely to be seen in Brazil and Argentina where insect resistant varieties improved considerably pest control (Bärwald Bohm *et al.*, 2014; Brookes e Barfoot, 2014).

In sum, literature shows that, on the one hand, we have major producing and exporting countries regulating technology in different ways and, so altering the market forces of international technological diffusion. On the other hand, we have major importers taking different regulatory positions towards this same technology. In addition, consumers all over the word will have different views towards the consumption of products deriving from GMOs.

The combination of this initial scenario will become a unique experiment for studying the interactions of technical change and trade. Overall, a set of empirical and theoretical analysis has been pointing to negative effects of regulatory heterogeneity on trade – mainly through asynchronous approval, mandatory labeling and LLP of unauthorized event. However, empirical analyses have often not considered the effects of technological gap on trade, and this effect is important once not all markets developed levels of hatred against the GMOs technology.

It is the same of saying that for each approval of a new variety, countries are facing not only a commercial risk but also an opportunity costs defined as the distance a country is taken from the most innovative markets.

3. Method

In this particular study, we estimate a gravity equation to analyze trade of one-product and breakdown technology change effects into technological gap and demand lag in the presence of heterogeneous firms and asymmetrical approval of the new technology. These objectives created three estimation related challenges.

First, we cannot resort to the convenience of using country fixed effects, as it would hamper the estimation of the technological gap, which is a country-level variable. So we have used country production and country consumption of these commodities to control for size. This procedure is not only recommended but also desired when working with industrial data (Head e Mayer, 2013). The advantage of this procedure is to avoid the problems of aggregation bias, getting more straightforward coefficients in terms of interpretation. By not using country’s fixed effects the control for Multilateral Resistance of Trade (MTR) become central to avoid the so called golden medal mistake of gravity equation (Anderson e Wincoop, 2003; WTO e UNCTAD, 2012). We have used the remoteness index as described by Head e Mayer (2013).

Second, when considering a small continuum of goods the number of non-positive trade flows increase considerably creating difficulties to estimating the log-linear form of the model. Simply cutting out zero-valued flows from the sample is not the best solution since it can potentially create a problem of strong sample selection bias. Yet, zeroes can be meaningful in some situations as when impeditive fixed costs are playing a role in the chance of a country exporting to country – what may occur in our case if levels of “hatred” are big enough to cripple some trade flows. Econometric tests show that censored or truncated regressions and replacement of zeroes with arbitrary numbers are biased and also not preferred to two-stage selection models (Linders e Groot, De, 2006). Thus, we have employed an adapted Heckman (1979) two-stage model to correct for sample bias, as presented by the influential paper by Helpman*,* Melits and Rubinstein (2008), which also controls for firm heterogeneity by assuming monopolistic competition.

Third, technology gap and the demand lag will change over time, and will impact differently on trade for each year . HMR (2008) developed a complete model to assess cross-sectional or pooled data. But the calculation of controls for firm heterogeneity and selection bias are not ready to go with panel data analysis. Several papers attempted to provide a final solution for Heckman type correction in panel-data, but until today there is no optimal solving for this puzzle (Charbonneau, 2014; Gómez-Herrera, 2012; Martínez-zarzoso, Vidovic e Voicu, 2014). Thus, we decided to estimate HMR controls for firm heterogeneity and sample selection bias as in Martínez-zarzoso, Vidovic, & Voicu (2014).

In addition, supported by further statistical tests, we also estimated a Fixed Effect Model on the same panel-data. Our final models can account for the potential problems of sample selection, omitted firm heterogeneity effects and dynamic effects[[7]](#footnote-7) of technology change predicted by Posner (1961). In addition we could also include variables to test for other interesting effects, such as the technology state (Eaton and Kortum 2002) – measured by the countries’ average productivity – and differences in land availability, since factor endowments can be a significant source of trade in agricultural goods.

Departing from HMR (2008) and taking into account our objectives and estimation strategy we adjusted the model for:

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| --- | --- | --- |
|  |  | (1) |

where, we directly control for country consumption and variables impacting on price index or remoteness , for country outcome ) and production costs variables . The control is defined as in HMR (2008) except for the fact we are controlling firms’ fraction for each period , explicitly assuming that the number of exporting firms can change over time. Note that with this formulation we can compute the technological gap as a country specific-cost affecting the overall production costs. The demand lag, in turn, will be computed as a type of variable cost of trade, making change over the time[[8]](#footnote-8).

As in HMR (2008), our first-stage consists of estimating a Probit model to calculate both the sample selection and the firm heterogeneity controls to be added into the gravity equation at the second-stage. In addition to returning the controls for firm heterogeneity and sample bias, by the means of the Probit model we can breakdown the effects in trade into extensive and intensive margins.

Thus firms’ productivity differs within countries in an interval , in which is the most productive and the least productive firm. Assume that productivities range can be represented by a Pareto distribution . Though, only a share of firms, those with productivity high enough to serve country and breakeven fixed costs of trade, will export. The selection of firms into exporting markets is determined by a cutoff , which is implicitly defined by the zero profit condition[[9]](#footnote-9).

Let be the probability that exports to , conditional on the observed variables[[10]](#footnote-10). Thus we can specify the Probit modelas

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|  |  | (2) |

where is the cdf of the unit-normal distribution. According to HMR (2008) this selection equation has been derived from a firm level decision, and it therefore does not contain the unobserved and endogenous variable that is related to the fraction of exporting firms. Moreover, the Probit can be used to derive consistent estimates of

According to our assumptions, consistent estimation of the log-linear model requires control for both the endogenous number of exporters (via ) and the selection of country pairs into trading partners (which generates a correlation between the unobserved and the dependent variables). Thus, estimates for and are needed.

Additionally, . As has a unit normal distribution, the inverse Mills ratio, as in Heckman (1979) seminal paper, is thus a consistent estimation of . Therefore, is a consistent estimate for and is a consistent estimate for . Thus the model can be estimate using the transformation

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| --- | --- | --- |
|  |  | (3) |

where and is an i.i.d error term satisfying . Note that equation (5) is nonlinear in . However, a linear model can be estimated. Following specifications in HMR(2008) we dropped the Pareto assumption and revert it to the general specification for . Thus, is now an arbitrary and increasing function of . Then, it’s possible to control for using approximated with a polynomial in replacing in the equation at the second-stage. Accordingly, our final estimate equation will be

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| --- | --- | --- |
|  | . | (4) |

As the estimation of the controls for sample selection and firm heterogeneity are not straightforward for panel data, there is a solution proposed by Wooldridge (1995, p.121-130) which makes use of a Chamberlain-Mundlak approach (see works by Egger *et al* (2009); Egger and Pfaffermayr (2011)).

Neither nor coefficients are significant in the pooled data model, meaning that estimate via FE model on panel data is consistent. Our FE model has as individuals the country-pairs and time dimension from 1996 to 2012. Taking country-pairs as ids is very common in the literature (Baltagi, Egger e Pfaffermayr, 2014; Gómez-Herrera, 2012).

An F test for FE model and OLS, with the null hypothesis of non-significant effect of heterogeneity across individuals, returned a p-value < 2.2e-16. A Houseman test with the null hypothesis of non-correlation between unique errors and predictors, we get a p-value =1.914e-13. Thus, the Random Effect model is inconsistent (see Green, 2008, chapter 9). A Lagrange Multiplier Test (Breusch-Pagan), with null hypothesis of no need for fixed time effect, pointed to the need for including time fixed effect in our FE model (p-value< 2.2e-16).

Regarding model fitness, we tested for serial correlation, heteroskedasticity, and multi-collinearity. Breusch-Godfrey/Woodridge test don’t allow us to reject the hypothesis for serial correlation (p-value = 5.117e-08). Also, the Breusch-Pagan test for panel data revealed the problem of heteroskedasticity (p-value < 2.2e-16). We treat both problems with “arellano” correction in R cran according to White method (Arellano, 1987; White, 1980).

All tests and models were run in the Comprehensive R Archive Network (R Cran) making use of *plm*, *glm*, *sandwich*, *lmtest*, *sampleSelection, car* and *tseries*.

* 1. Data

Data on soybean trade comes from BACI database developed by CEPII at a high level of product disaggregation (for detailed information see Guillaume & Zignago, 2010). General gravity data – distance, colonial ties, common language, contiguous or landlocked territories, among others, are from GeoDist database also by CEPII (for detailed information see Mayer & Zignago, 2011). Agricultural related data, such as production, average yield, arable-land and others were collected from the FAOSTAT database.

Data on exchange rates comes from the International Monetary Fund (IMF), and prices data from World Bank Commodity Price Data (The Pink Sheet).

Country-level data on biosafety used to build our technological variables comes from different sources. Data on approval of genetically modified varieties comes mainly from International Service for the Acquisition of Agri-biotech Applications (ISAAA) database. However, when needed – because of missing or incomplete information – data was fulfilled by information from Global Agricultural Information Network (GAINS) report by the Foreign Agricultural Service of the USDA (FAS-USDA) and data from Biosafety-Clearing House (BCH) databases.

The final database used for the estimation of the Probit model contained 39,751 observations for 16 years, 42 variables and 84 countries. From those, only 6,634 observations had positive trade flows. The significant reduction of the database calls for a correct assess of sample selection bias to assure that estimates are consistent. However, as we have seen in 3.1, according to Wooldridge (1995) test, estimating a FE model is consistent without these controls. However, these controls enter the HMR (2008) model via the specification of the theoretical model. The final database for panel estimates has 6,634 observations (id=country-pairs) and 44 variables, containing trade flows of soybean between 1995 and 2012 for 84 countries. In Box 1, in appendix, we briefly introduce the variables actually used in the models.

Technological Variables

General approach to create the variable *Demand lag* consisted of three steps. First, we gathered data on approvals for cultivation, food and feed for all the varieties of soybean available, as reported in ISAAA database. Second, for each and variety we created a dummy variable assuming value 1 when country has approved a variety for cultivation not approved for consumption as food, feed or both in country . Third, we aggregated the values of dummy variables per year to have the total of demand lag for each pair of countries in year .

Further steps were necessary to solve the problem of including countries with “zero” approved varieties into the model. We know that many countries haven’t implemented regulatory frameworks, or have no assessment capacity to carry out tests for identification of imports of unauthorized events. On the other hand, we also know that some countries banned importation of all GMOs. A related problem emerges when a country implements risk assessments measures after 1996 – the first year of commercial release of GMOs.

Therefore, we analyzed all zero approvals case-by-case to determine if the value of total events approved for each year should be ascribed, or zero approval actually means a ban. Underlying information to discriminate between these two types of zero came from GAINS reports, but also from BCH archives and the Africa Centre for Biosafety report (Moola & Munnik, 2007; BCH, 2015; FAS, 2015). As bans to GMOs were usually of public concerns and well disseminated across specialist and media, we created a dummy for bans to correct for false zero approvals . If a ban were reported by one of the data sources for a specific , so the dummy variable was set to 1. Otherwise, if no ban was reported, the dummy is set to 0. By multiplying both we get the adjusted asymmetry between and in terms of approved varieties – i.e. (.

In the case of *Tech. Gap* we took a more pragmatic approach. We simply found the total number of different varieties available and approved for production in at least one country for a given and subtracted the number of approved varieties in particular country to have a “distance” between country varieties and the state of the art of technology. That was possible because major producing countries have taken very clear legal positions towards the technology since the early-1990s. It’s worth noting that we haven’t used logarithm transformation to these variables, as they are derived of dummy variables.

1. Results and Discussion

Results can be seen in Table 1 and 2, in appendix. As tests indicate the consistence of FE models we are setting this model (7) as our benchmark – hereinafter FE (7). But we are also considering results from HMR-I (column 3) along with the Probit results (column 1) – hereinafter HMR-I (3). HMR-I (3) is interesting to discuss the effects on the intensive and extensive margins of trade, as well as the impacts of firm heterogeneity.

Sample Selection and Firm Heterogeneity Biases

As expected, the controls for firm heterogeneity and selection bias play a role only in the HMR-I (3). Firm heterogeneity is related to prohibitive fixed costs leading to the lack of trade between country pairs. This latter effect is important since we are assuming that the adoption of GM technology by Argentina and the US along with non-adoption by Brazil from 1996-2005 may have caused changes in the extensive and intensive margin of trade.

A comparison between models in columns (2) and (3) in table 2 provides a picture about the general impact the proposed controls have on the coefficients. The absence of controls will make some coefficients have an upward bias. Overall, variables controlling for sizes, country remoteness and bilateral trade costs returned upward biased coefficients, whereas country ’s remoteness is downward. Interestingly, coefficients with higher importance for extensive margin of trade not only return downward biases but also became significant after the controls introduction (see coefficients for Language, Same Country, and RTA in columns (1) to (3) in table 2).

Results are consistent with HMR (2008), where the firm heterogeneity overcomes the effects of selection bias. Also, the coefficients are positive, meaning that countries with higher proportion of exporting firms and unobserved characteristic of countries determining positive trade flows will also positively impact on trade volumes.

Note that none of the controls are significant in FE (7). Comparing model HMR-I (3) with FE (7) we can see that some coefficients will return greater and others smaller coefficients. However, remoteness and exchange rate of exporters and common language will be statistically insignificant in (7) but significant in (3).

Impacts of country-level variables

From the supply side, based on theory and studies on aggregated data, we can expect that soybean trade will increase along with higher outcomes of soybean and average yields of exports. Conversely, trade volumes tend to be decreased by higher exchange rates, lack of maritime exits and remoteness.

Production and yield returned the expected impact on trade flows as we can see in columns (3) and (7) in 2. Given the production elasticity of trade reported in FE (3), for each increase of say, 10%, in production, trade will increase by 3.8%. Trade elasticity of production is not higher because of internal consumption of soybean in major producing countries (e.g. China) and some of the larger exporters produce small quantities of soybean (eg. the Netherlands). Note that production also impacts the probability of exporting, but the relevant impact will be at the intensive margin of trade. Exporter with higher average yields, which can be seen as a result of technologies available at the country level, also increases the volume of trade significantly. An increase in average productivity level of 10 % makes exports increase by 11.4%. The parameter in in Eaton and Kortum (2002) model, representing the general level of technology in a country can be a theoretical explanation for the high yield elasticity of exports.

Paradoxically, landlocked exporters tend to export considerably higher volumes when compared to countries with maritime access[[11]](#footnote-14). However, this effect has a negative impact on the extensive margin of trade, indicating that landlocked country has on average less trade connections than others. A closer look at the data shows that this seeming odd result is valid only for the soybean case, given intra-bloc trade in European Union and significant shares of world exports of landlocked countries like Paraguay, Switzerland, Bolivia, Zambia, Austria and Hungary.

Remoteness and variations of the exchange rate in exporting countries aren’t significant in FE (7), and have very small values in HMR-I (3) models. This result is explained by the concentrated international supply of soybeans – primarily in the Americas. Variations in exchange rate in exporting countries are expected to impact trade in two different ways. On the one hand it makes soybean export prices in countries with devaluated currency cheaper. On the other hand, it makes the inputs used in production more expensive. Some studies show that currency devaluations in South America displace exports of the US in international markets (Andino e Koo, 2005). However, our results show that impacts on the likelihood of exports are possibly very low and positive (0.08%), meaning that currency valuation in country increases the likelihood of positive trade flows, marginally. Regarding the intensive margin of trade, HMR-I (3) returned an elasticity of 0.082 for this variable. It can be a result of the predominance of increases of imported inputs relative prices as well as an indication of the weakness of this variable to explain bilateral trade of soybeans as the international prices are always given in USD dollars regardless variation of international currencies.

From the demand side, theory predicts that bilateral trade tends to increase along with higher demand levels, valuated exchange rates, absence or high imperfectness of substitute goods, easy access to the sea and low levels of remoteness.

Results show that one increase of 10% in consumption, will lead to an increase of 3% of imports. This number isn’t higher because larger consuming markets also produce certain amounts of soybean, with the obvious exception of the EU. The effect of substitutes goods (Other Goods *i*) shows that soybean has not a close substitute for meal production in international markets[[12]](#footnote-15). For each increase of 10% in imports of other meals feedstock, such as meat and bone meals, fishmeal, among others, imports of soybean increase by 2.12% on average. HMR-I (3) returns coefficients with the same sign and significance but with smaller values.

Importing countries with high degrees of remoteness, devaluated currencies and landlocked will actually import less volumes of soybean. Landlocked countries import on average 60% less when compared to countries with maritime access. Currency devaluations and increases in the remoteness index have smaller impacts, but considering the magnitude of small percentages applied on huge amounts of soybean traded, the economic significance can be considerable in some cases. HMR-I (3) shows similar impacts in terms of sign, magnitude and significance of coefficients. Noteworthy, landlocked country tends to have more positive trade inflows when compared to others, accordingly to results of model (1).

In sum, we can say size and state of technology in producing countries are the key drivers of exports volume. On the demand side, size, remoteness, valuated currencies and access to maritime routes are the most important drivers of trade inflows. In addition, the lack of international close substitutes for soybean will also play a role in determining demand.

Impact of trade-level variables

First, it is important to note that common language is not significant according to our benchmark model FE (7). On the other hand, this variable is highly significant in the HMR-I (3) model. Thinking of Brazil, Argentina and United States, it is difficult to think about a determined effect as the number of countries speaking Portuguese will be reduced – as well as their economic importance. This and other qualifications peculiar to our case, such as the importance of China as a consumer market, and absence of a larger producer speaking Chinese, will make the analysis of language effect ambiguous.

Countries having colonial ties trade approx. 158% more when compared to others. On the other hand, countries sharing a same colonist for long periods will trade reduced volumes of soybean (46.5% approx.). It can be a result of agricultural specialization of colonies, making the trade of agricultural products smaller between two agricultural-based countries, but intense between industrialized and agricultural countries. Impact on extensive margins, however, will be positive (see column (1) in table 2). As expected, RTAs will have the very same type of impact on trade.

Distance, as a proxy for variable costs of trade based on the Samuelson’s “iceberg costs” is expected to decrease trade volumes. According to our estimates, a 10% increase in distance will lead to 28.9% decrease in the volume trade (see column (7) in table 2). That is a consistent result, as international freights tend to be a significant component of trade costs. The access to the Pacific Ocean by the U.S. will make “iceberg costs” of exporting to China smaller when compared to costs of Brazilian exports to the same market. Additionally, results of HMR-I (3) suggest that distance has a negative impact on the probability of trade, but a positive effect in volumes. This can be a result of gains of scale. Related to distance effects, the estimates show that countries sharing a land border will trade significantly more than others.

Finally, we can expect that endowment of land will be important to partially explain the formation and direction of soybean trade flows. This variable can be somehow interpreted as the effects of differences in input costs and that will lead to industry specialization, *ceteris paribus*. It is a source of trade mostly considered in HO models, but also treatable in the framework developed by Eaton and Kortum (2002), if we assume that relative endowments of land will impact the costs of production of agricultural goods. The difference in land endowment will impact mostly on the extensive margin of trade. If this difference increases by 10%, trade will increase by approximately 1.87%. Note that the values of the coefficients are very similar in HMR-I (3) model.

In sum, the trade between countries located geographically closer, sharing a border, with colonial ties and different factors endowment (land) is comparatively more frequent and higher in volume. Remarkably, countries under regional trade agreements and considered as the same countries trade more often but in lower volumes.

Impacts of technological variables

Precisely, differences in mandatory labeling regimes are more a proxy for regulation asymmetry than for technological change, impacting mostly on the extensive margin of trade. This assumption is based on several studies, which points out that mandatory labeling is one of the most detrimental factors impacting trade of GMOs(Carter e Gruère, 2006; Foster, 2010; Regimes e Giannakas, 2013). There are evidences that countries with mandatory labeling imported soybeans primary from Brazil, at least until the end of 2012 (Oliveira *et al.*, 2013). Authors estimated that when mandatory labeling regimes are increased by one year, imports from Brazil increase by 4.5%. The existence of a mandatory labeling regime in destination and absence in sourcing countries decreases the probability of trade almost by 3%. Beforehand, we can see that the coefficients of our technological variables behavior steadily in all models.

The Demand Lag variable, in turn, was defined based on the general idea of imitation lag developed by Posner (1961). In this study we consider that the lag will enlarge market shares of countries producing the old good in markets averse to the technology. The duration and the proportion of the lag will determine the backward effects of technology.

We assume that technology-gap is also key to determine trade volumes. The rationale behind this is that international competition and innovation rate will create an international technology frontier, which is constantly moving forward given the pace and nature of innovation in the economic system. As technology will impact on the overall production costs and not all the countries developed technology “hatred”, there will be gains of adoption that should be considered. From that, trade should increase as countries adopted newer and better technologies of production, in those markets without high levels of technology hatred. That is because in “common” markets, “common” technological effects are expected to stand out – i.e. the positive impact of technology on overall production costs will be a source of comparative advantage.

Our estimates from the FE (7) in 2 show that the technological gap is statistically and economically significant. For each variety that a producing country doesn’t grant approval for any reason, trade will decrease by 16.4% on average. Looking at the coefficients of HMR-I (3) we can say that impacts can be even larger – 3.4% in the extensive margin and 22.2% in the intensive margin. Interestingly, the demand lag will have a very similar impact. A difference in approved varieties between exporting and importing countries will decrease trade by 16%. HMR-I (3) also returns greater coefficients - 2.1% decreases in the extensive and 24.9% in the intensive margins.

The similarity of the impacts of both variables may be an indication of the existence of certain market rationality in approving new varieties, which balances opportunity costs of not approving new and better varieties, and the commercial risks involved in adopting too many varieties in the context of certain level of technology “hatred”.

Notwithstanding, the technological advance and development of new and better varieties considerably increased the opportunity costs of non-adoption. From a more evolutionary perspective, very high opportunity costs can make an advantage of an innovator irreversible. In other words, in the absence of non-technological advantages if a proved better technology is available and adopted by other producing countries, the late-mover can fail to catch-up, loosing significant shares of the market or even leaving the marketplace.

In sum, at the same time countries with more similar pace of approvals – smaller demand-lags – tend to trade more (extensively and intensively), there are opportunity costs of not approving better varieties that can decrease trade at the same time. In other others, we are saying that countries faced a kind of technological trade-off in deciding about adoption under technology rejection.

1. Conclusions

The central aim of this paper was to study the relationship of technological gap and demand lag on bilateral trade under high levels of “hatred” toward the “new” product. The case of GM-soybean is a suitable experiment, since both the adoption rate in producing countries and the acceptance of the “new” product in international markets were asymmetric and asynchronous across time and countries. Moreover, the production and consumption of soybeans are concentrated at country level, mitigating problems related to the lack of disaggregated data of trade on conventional and GM grains.

In the international arena, Brazil, United States, Argentina at the supply side, and China and the EU countries at the demand side, are the protagonists of the history of trade in soybeans. Brazil adopted the technology ten years after growers in U.S. and Argentina planted their first genetically modified seeds. On the other hand the EU members, the second largest destination of soybeans, developed high levels of technology hatred. Yet, China hasn’t raised significant bans against the consumption of GMOs, being an important player to mitigate commercial risks.

Considering the underlying idea of technology differences creating comparative advantages, the theory of firm heterogeneity and the central concepts of demand lag and technological gap, we structured a model in which bilateral trade is a function of sizes, variable and fixed costs of trade and technological variables. The inclusion of the technology-gap is our major contribution in the matter of correct specification of empirical models. Without this control, the analysis is partial, since technology hatred is not verified in everywhere.

We found that both the technological gap and the demand lag had significant impacts on trade. Impacts can be seen in the extensive and intensive margins.

We believe results can contribute to better designs of technological and trade policies, since they provide a broader perspective of technological effects on trade. We also believe that other similar cases marked by technological frictions can emerge at anytime, as the “preference for technology” seems to be a structural change in consumption patterns.

The increased concern about the production means and their relation with ethical, environmental, social and economic factors will likely increase trade conflicts if multilateral bodies have reduced coordination power – as seen in the case of modern biotechnology and trade. Clearly, agriculture is the sector to which impacts tend to be more noteworthy, given the especial features faced by this sector, as intense competition in international markets and increased concern of consumers about food safety.

Lastly, future research on the relationship of technological change and trade is needed to advance in theoretical developments, especially to relax some of the strong assumptions on consumer behavior. Empirical studies of other products and industries is also required to investigate if this effect is particular to agricultural goods subjected to commercialization approval, or the technological effects can be thought from a more general perspective.

Appendix I

Box 1– Model’s Variables Description

|  |  |  |
| --- | --- | --- |
| **Variable Name** | **Description** | **Source** |
| Bilateral Trade | Natural logarithm of annual exports of soybean (HS6-120100) from country to country , calculated from the original variable “v”. | BACI-CEPII |
| Production | Natural logarithm of annual outcome of soybean, calculated from the original variable “Production Quantity” given in metric tons. It includes declared and estimated data. | FAOSTAT |
| Consumption | Natural logarithm of annual domestic supply (imports-exports+stocks) of soybeans, including uses as food, feed, seed, processing, waste and others given in metric tons. | FAOSTAT |
| Distance | Natural logarithm of geodesic distances between most populated cities in and . Distance (or dist in original database) was calculated following the great circle formula. | GeoDist -CEPII |
| Land Border | Dummy variable assuming value 1 if and are contiguous, 0 otherwise. | GeoDist -CEPII |
| Language | Dummy variable assuming value 1 if and share a common language spoken for at least by 20% of the population, 0 otherwise. | GeoDist -CEPII |
| Colony | Dummy variable assuming value 1 if and had/have a colonial tie, 0 otherwise. | GeoDist -CEPII |
| Same Country | Dummy variable assuming value 1 if and is considered the same country. Value 1 is settled when countries were/are considered the same state or the same administrative entity for a long period (25-50 years in the twentieth century, 75 year in the ninetieth and 100 years before). | GeoDist -CEPII |
| Exch. Rate | Natural logarithm of the inverse official annual exchange rate given in value of local currencies in terms of 1 US dollar (1/ex\_rate). | FMI database |
| Landlocked | Dummy variables assuming value 1 if a country is landlocked. | GeoDist -CEPII |
| Yield *j* | Natural logarithm of country average yield per unit of harvested area for crop products. In most of the cases yield data are not recorded but obtained by dividing the production data by the data on area harvested. | FAOSTAT |
| Land | Natural logarithm of differences between and in terms of land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years). Variable named as arable-land in the original database. | FAOSTAT |
| RTA | Dummy variable assuming value 1 if countries and make part of Regional Trade Agreement (RTA), and 0 otherwise. | International Economics Data and Programs - (Sousa, 2012) |
| Other Goods | Natural logarithm of an index built by aggregating annual imports of major substitutes goods for soybean meal by , such as meat meal (HS6-230110), fishmeal (HS6-230120), cottonseed meal (HS6-230610), linseed meal (HS6-230620) and groundnut meal (HS6-230500). Value given in tones. | BACI-CEPII |
| Mand. Label | Dummy variable assuming value 1 if country has implemented mandatory labeling rules and country hasn’t, and 0 otherwise. | GAINS Report - USDA |
| Price | Natural logarithm of average annual prices of soybean in global markets given in nominal USD. | World Bank Commodity Price Data ( The Pink Sheet) |
| Remoteness | Natural logarithm of remoteness index as proposed by Head (2003) – i.e. . Annual nominal GDP data comes from IMF databases and distance from GeoDist. | IMF Data  GeoDist -CEPII |
| Tech. Gap | Variable calculated as the difference between numbers of approved varieties for production in country and the total varieties of GM-soybean adopted by other Raw data includes approval of GM-variety in producing countries. | ISAAA approval database |
| Demand Lag | Variable calculated as the difference between number of approved varieties for production in country and the total varieties approved for consumption in country . Original data includes approval of GM-variety in producing and importing countries. | ISAAA approval database |

Source: Prepared by the author.

Table 1 – Descriptive Statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Statistic** | **N** | **Mean** | **St. Dev.** | **Min** | **Max** |
|  | | | | | |
| *t* | 6,634 | 2,003.9 | 5.0 | 1,995 | 2,012 |
| *Bilateral Trade* | 6,634 | 5.6 | 3.6 | 0.0 | 16.5 |
| *Production* | 6,634 | 13.7 | 3.5 | 3.4 | 18.3 |
| *Distance* | 6,634 | 8.3 | 1.2 | 4.1 | 9.9 |
| *Land Border* | 6,634 | 0.2 | 0.4 | 0 | 1 |
| *Language* | 6,634 | 0.2 | 0.4 | 0 | 1 |
| *Colony* | 6,634 | 0.1 | 0.2 | 0 | 1 |
| *Same Country* | 6,634 | 0.05 | 0.2 | 0 | 1 |
| *Price* | 6,634 | 5.8 | 0.3 | 5.3 | 6.4 |
| *Land* | 6,634 | 1.3 | 2.3 | -6.1 | 16.6 |
| *Yield* | 6,634 | 10.0 | 0.3 | 8.1 | 10.6 |
| *Tech. Gap* | 6,634 | 7.4 | 3.9 | 0 | 15 |
| *Mand. Label* | 6,634 | 0.3 | 0.4 | 0 | 1 |
| *Demand Lag* | 6,634 | 1.5 | 2.9 | 0 | 15 |
| *RTA* | 6,634 | 0.3 | 0.5 | 0 | 1 |
| *Exch. Rate* | 6,634 | -1.8 | 2.5 | -9.9 | 3.1 |
| *Exch. Rate* | 6,634 | -1.9 | 2.5 | -9.9 | 3.1 |
| *Consumption* | 6,634 | 5.6 | 2.9 | -2.3 | 11.2 |
| *Other Goods* | 6,634 | 10.8 | 2.0 | -3.9 | 14.3 |
| *Landlocked* | 6,634 | 0.2 | 0.4 | 0 | 1 |
| *Landlocked* | 6,634 | 0.1 | 0.3 | 0 | 1 |
| *Remoteness* | 6,634 | 18.0 | 1.0 | 16.5 | 22.3 |
| *Remoteness* | 6,634 | 17.8 | 0.9 | 15.7 | 24.3 |
|  | 6,634 | 1.0 | 0.6 | 0.0 | 3.5 |
|  | 6,634 | 0.9 | 0.5 | 0.3 | 6.3 |
|  | 6,634 | 1.0 | 1.7 | 0.1 | 39.3 |
|  | 6,634 | 1.5 | 7.3 | 0.02 | 246.2 |
|  | | | | | |

Source: prepared by the authors.

Table 2 – Estimates Results

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | *Dependent variable: Bilateral Trade* | | | | | | |
|  | | Probit | OLS-HMR | OLS-HMR I | FE | FE-I | FE-II | FE-III |
|  | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Production *j* | | 0.027\*\*\* | 0.408\*\*\* | 0.302\*\*\* | 0.395\*\*\* | 0.382\*\*\* | 0.381\*\*\* | 0.381\*\*\* |
|  | | (0.001) | (0.016) | (0.025) | (0.030) | (0.032) | (0.026) | (0.032) |
| Remoteness | | 0.003\* | -0.073\* | -0.120\*\*\* | -0.045 | -0.049 | -0.043 | -0.043 |
|  | | (0.002) | (0.039) | (0.039) | (0.097) | (0.096) | (0.071) | (0.096) |
| Exch. Rate | | 0.008\*\*\* | 0.122\*\*\* | 0.082\*\*\* | 0.041 | 0.043 | 0.045\* | 0.045 |
|  | | (0.001) | (0.017) | (0.018) | (0.034) | (0.034) | (0.027) | (0.034) |
| Landlocked *j* | | -0.029\*\*\* | 1.455\*\*\* | 1.678\*\*\* | 1.141\*\*\* | 1.165\*\*\* | 1.169\*\*\* | 1.169\*\*\* |
|  | | (0.004) | (0.116) | (0.117) | (0.244) | (0.243) | (0.183) | (0.243) |
| Yield *j* | | 0.054\*\*\* | 1.226\*\*\* | 1.001\*\*\* | 1.138\*\*\* | 1.141\*\*\* | 1.143\*\*\* | 1.143\*\*\* |
|  | | (0.005) | (0.127) | (0.130) | (0.270) | (0.270) | (0.196) | (0.270) |
| Consumption *i* | | 0.009\*\*\* | 0.317\*\*\* | 0.267\*\*\* | 0.302\*\*\* | 0.300\*\*\* | 0.301\*\*\* | 0.301\*\*\* |
|  | | (0.001) | (0.017) | (0.018) | (0.020) | (0.020) | (0.017) | (0.020) |
| Remoteness | | -0.003\*\* | -0.110\*\*\* | -0.086\*\* | -0.102\*\* | -0.101\*\* | -0.105\*\*\* | -0.105\*\*\* |
|  | | (0.010) | (0.038) | (0.037) | (0.040) | (0.040) | (0.038) | (0.040) |
| Exch. Rate | | 0.008\*\*\* | -0.075\*\*\* | -0.111\*\*\* | -0.066\*\*\* | -0.071\*\*\* | -0.072\*\*\* | -0.072\*\*\* |
|  | | (0.001) | (0.014) | (0.015) | (0.014) | (0.014) | (0.014) | (0.014) |
| Landlocked *i* | | 0.010\* | -0.623\*\*\* | -0.573\*\*\* | -0.589\*\*\* | -0.604\*\*\* | -0.607\*\*\* | -0.607\*\*\* |
|  | | (0.006) | (0.116) | (0.116) | (0.117) | (0.117) | (0.118) | (0.117) |
| Other Goods | | 0.028\*\*\* | 0.162\*\*\* | 0.060\*\* | 0.217\*\*\* | 0.213\*\*\* | 0.212\*\*\* | 0.212\*\*\* |
|  | | (0.001) | (0.023) | (0.030) | (0.027) | (0.027) | (0.024) | (0.027) |
| Distance | | -0.063\*\*\* | 0.058 | 0.370\*\*\* | -0.303\*\*\* | -0.287\*\*\* | -0.289\*\*\* | -0.289\*\*\* |
|  | | (0.002) | (0.061) | (0.075) | (0.067) | (0.067) | (0.069) | (0.067) |
| Land Border | | 0.193\*\*\* | 1.916\*\*\* | 0.884\*\*\* | 1.543\*\*\* | 1.533\*\*\* | 1.534\*\*\* | 1.534\*\*\* |
|  | | (0.014) | (0.128) | (0.165) | (0.141) | (0.141) | (0.132) | (0.141) |
| Language | | 0.059\*\*\* | 0.019 | -0.344\*\*\* | -0.014 | -0.019 | -0.015 | -0.015 |
|  | | (0.006) | (0.092) | (0.099) | (0.105) | (0.105) | (0.097) | (0.105) |
| Colony | | 0.006 | 1.022\*\*\* | 0.917\*\*\* | 0.950\*\*\* | 0.953\*\*\* | 0.949\*\*\* | 0.949\*\*\* |
|  | | (0.010) | (0.160) | (0.159) | (0.143) | (0.142) | (0.164) | (0.142) |
| Same Country | | 0.032\*\* | -0.210 | -0.360\* | -0.389\* | -0.381\* | -0.382\* | -0.382\* |
|  | | (0.015) | (0.201) | (0.201) | (0.213) | (0.213) | (0.208) | (0.213) |
| Land | | 0.008\*\*\* | 0.211\*\*\* | 0.179\*\*\* | 0.182\*\*\* | 0.186\*\*\* | 0.187\*\*\* | 0.187\*\*\* |
|  | | (0.001) | (0.022) | (0.023) | (0.027) | (0.027) | (0.024) | (0.027) |
| RTA | | 0.033\*\*\* | -0.210\* | -0.327\*\*\* | -0.401\*\*\* | -0.379\*\*\* | -0.390\*\*\* | -0.390\*\*\* |
|  | | (0.005) | (0.127) | (0.126) | (0.143) | (0.142) | (0.131) | (0.142) |
| Price | |  |  |  | 5.223\*\* | 5.229\*\* | 5.246\*\* | 5.246\*\* |
|  | |  |  |  | (2.273) | (2.313) | (2.518) | (2.317) |
| Mand. Label | | -0.029\*\*\* |  |  |  |  |  |  |
|  | | (0.023) |  |  |  |  |  |  |
| Tech. Gap | | -0.034\*\*\* | -0.376\*\*\* | -0.222\*\*\* |  | -0.163\*\* | -0.164\*\*\* | -0.164\*\* |
|  | | (0.003) | (0.046) | (0.050) |  | (0.065) | (0.060) | (0.065) |
| Demand Lag | | -0.021\*\*\* | -0.316\*\*\* | -0.249\*\*\* |  | -0.159\*\*\* | -0.160\*\*\* | -0.160\*\*\* |
|  | | (0.003) | (0.046) | (0.049) |  | (0.061) | (0.057) | (0.061) |
|  | |  |  |  |  |  |  |  |
|  | |  |  | 1.164\*\*\* |  |  | -0.022 | -0.022 |
|  | |  |  | (0.261) |  |  | (0.433) | (0.438) |
|  | |  |  | 7.995\*\*\* |  |  | -0.512 | -0.512 |
|  | |  |  | (1.069) |  |  | (1.737) | (1.576) |
|  | |  |  | -2.249\*\*\* |  |  | 0.082 | 0.082 |
|  | |  |  | (0.439) |  |  | (0.673) | (0.599) |
|  | |  |  | 0.209\*\*\* |  |  | -0.018 | -0.018 |
|  | |  |  | (0.052) |  |  | (0.073) | (0.063) |
|  | |  |  |  |  |  |  |  |
| Constant | | -4.689\*\*\* | -13.107\*\*\* | -16.403\*\*\* |  |  |  |  |
|  | | (0.384) | (1.611) | (1.857) |  |  |  |  |
| Observations | | 39,751 | 6,634 | 6,634 | 6,634 | 6,634 | 6,634 | 6,634 |
| R2 | |  | 0.425 | 0.438 | 0.253 | 0.254 | 0.255 | 0.255 |
| Akaike Inf. Crit. | | 24,191.690 |  |  |  |  |  |  |
| F Statistic | |  | |  |  | | --- | --- | | 135.398\*\*\* (df = 36; 6597) |  | | 128.565\*\*\* (df = 40; 6593) | |  |  | | --- | --- | | 47.974\*\*\* (df = 39; 5522) |  | |  | |  |  | | --- | --- | | 53.285\*\*\* (df = 35; 5526) |  | |  |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | | | | |
| With the exception of Model (5) all models have robust stand errors (*arellano*). Dummies for year fixed effects were used to all models and are omitted. | | | | | | | | |

References

ANDERSON, J. E.; WINCOOP, E. VAN. Gravity with Gravitas : A Solution to the Border Puzzle. **The American Economic Review**, v. 93, n. 1, p. 170–192, 2003.

ANDERSON, K.; JACKSON, L. A. **Standards , trade and protection : the case of GMOs**. Adelaide: [s.n.].

ANDINO, J.; KOO, W. W. The Impact of Brazil and Argentina ’ s Currency Devaluation on U . S . Soybean Trade. **Agribusiness & Applied Economics**, n. 574, p. 18, 2005.

ARELLANO, M. **Computing robust standard errors for within group estimatorsOxford Bulletin of Economics and Statistics**, 1987.

BALTAGI, B. H.; EGGER, P.; PFAFFERMAYR, M. **Panel Data Gravity Models of International TradeWorking Papers CESifo**: Category 8: Trade Policy. Munich: [s.n.].

BÄRWALD BOHM, G. M. *et al.* Glyphosate effects on yield, nitrogen fixation, and seed quality in glyphosate-resistant soybean. **Crop Science**, v. 54, n. 4, p. 1737–1743, 2014.

BROOKES, G.; BARFOOT, P. The global income and production effects 1996 – 2012 Economic impact of GM crops. **GM Crops**, v. 5698, n. March, p. http://dx.doi.org/10.4161/gmcr.28098, 2014.

BURNQUIST, H. L. *et al.* **Heterogeneity Index of Trade and Actual Heterogeneity Index – the case of maximum residue levels ( MRLs ) for pesticides**Agricultural & Applied Economics Association’s 2011 AAEA & NAREA Joint Annual Meeting. **Anais**...Pittsburgh: 2011

CARTER, C.; GRUÈRE, G. International approval and labeling regulations of genetically modified food in major trading countries. *In*: JUST, R. E. ( U. OF M.; ALSTON, JULIIAN M. (UNIVERSITY OF CALIFORNIA, D.; ZILBERMAN, DAVID (UNIVERSITY OF CALIFORNIA, B. (Eds.). . **Regulating agricultural biotechnology: economics and policy**. New York, NY: Springer New York, 2006. p. 459–480.

CARVALHO, F. **O comportamento das exportações brasileiras ea dinâmica do complexo agroindustrial. 1995**. [s.l.] São Paulo University, 1995.

CHARBONNEAU, K. B. **Multiple Fixed Effects in Binary Response Panel Data Models**. Ottawa: [s.n.].

CHAVAS, J. P.; SHI, G.; LAUER, J. The effects of GM Technology on maize yield. **Crop Science**, v. 54, n. 4, p. 1331–1335, 2014.

DISDIE, A.-C.; FONTAGNÉ, L. Trade Impact of European Measures on GMOs Condemned by the WTO Panel. **Review of World Eocnomics**, v. 146, n. 3, p. 495–514, 2009.

DISDIER, A.-C.; FONTAGNÉ, L. Trade impact of European measures on GMOs condemned by the WTO panel. **Review of World Economics**, v. 146, n. 3, p. 495–514, 23 maio 2010.

DORNBUSCH, R.; FISCHER, S.; SAMUELSON, P. A. Comparative Advantage, Trade, and Payments in a Ricardian Model with a Continuum of Goods. **The American Economic Review**, v. 67, n. 5, p. 823–839, 1977.

DOSI, G.; GRAZZI, M.; MOSCHELLA, D. Technology and costs in international competitiveness: From countries and sectors to firms. **Research Policy**, v. 44, n. 10, p. 1795–1814, 2015.

DOSI, G.; PAVITT, K.; SOETE, L. Technology gaps, cost-based adjustments and international trade. *In*: **The Economics of Technical Change and International Trade**. [s.l: s.n.]. .

DOSI, G.; SOETE, L. Technical change and international trade. *In*: SOETE, L. (Ed.). . **The Economics of Technical Change and International Trade**. [s.l: s.n.]. p. 401–431.

EATON, J.; KORTUM, S. Technology, Geography, and Trade. **Econometrica**, v. 70, n. 5, p. 1741–1779, 2002.

FARIA, R. N. DE; WIECK, C. Empirical evidence on the trade impact of asynchronous regulatory approval of new GMO events. **Food Policy**, v. 53, p. 22–32, 2015.

FOSTER, M. **Evidence of price premiums for non-GM grains in world marketsAustralian Agricultural and Resource Economics Society**ABARE, Australia, , 2010.

GÓMEZ-HERRERA, E. Comparing alternative methods to estimate gravity models of bilateral trade. **Empirical Economics**, v. 44, n. 3, p. 1087–1111, 28 mar. 2012.

GUILLAUME, G.; ZIGNAGO, S. **BACI: International Trade Database at the Product-Level. The 1994-2007 Version**. Paris: [s.n.]. Disponível em: <http://www.cepii.fr/CEPII/fr/publications/wp/abstract.asp?NoDoc=2726>.

HEAD, K.; MAYER, T. Gravity Equations: Workhorse, Toolkit, and Cookbook. **Handbook of International Economics**, p. 63, 2013.

HECKMAN, J. Sample selection bias as a specification error. **Econometrica: Journal of the econometric society**, v. 47, n. 1, p. 153–161, 1979.

HELPMAN, E.; MELITZ, M.; RUBESTEIN, Y. Estimating trade flows: Trading partners and trading volumes. **The Quarterly Journal of Economics**, v. CXXIII, n. May, p. 441–487, 2008.

HIGHQUEST; SOYTECH. **How the Global Oilseed and Grain Trade WorksU.S. Soybean Export Council**. Danvers MA: [s.n.].

LINDERS, G.-J. M.; GROOT, H. L. F. DE. **Estimation of the Gravity Equation in the Presence of Zero FlowsTinbergen Institute Discussion Paper**. Amsterdam: [s.n.]. Disponível em: <http://www.econstor.eu/handle/10419/86589>. Acesso em: 12 set. 2014.

MAGGI, G. Technology gap and international trade: an evolutionary model. **Journal of Evolutionary Economics**, p. 109–126, 1993.

MARTÍNEZ-ZARZOSO, I.; VIDOVIC, M.; VOICU, A. M. **EU-Accession Effects on Sectoral Trade : A Helpman-Melitz-Rubinstein Approach with Panel DataCategory 8: Trade Policy**. Munich: [s.n.].

MAYER, T.; ZIGNAGO, S. **Notes on CEPII’s distance measures: the GeoDist databaseCEPII Working Paper**. Paris: [s.n.]. Disponível em: <http://mpra.ub.uni-muenchen.de/36347/2/MPRA\_paper\_36347.pdf>.

MELITZ, M. J. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. **Econometrica**, v. 71, n. 6, p. 1695–1725, 2003.

MOOLA, S.; MUNNIK, V. **GMOs in Africa : food and agriculture Status report 2007Africa**. Johannesburg: [s.n.].

OLIVEIRA, P. R. S. *et al.* **Adoption Of Technologies With Market Rejection And Return On Exports: Brazil, United States, Argentina And The Case Of Gm-Soybeans**17th ICABR Conference: “INNOVATION AND POLICY FOR THE BIOECONOMY”. **Anais**...Ravello - Italy: 2013

POSNER, M. International trade and technical change. **Oxford economic papers**, v. 13, n. 3, p. 323–341, 1961.

QAIM, M.; ZILBERMAN, D. Yield effects of genetically modified crops in developing countries. **Science (New York, N.Y.)**, v. 299, n. 5608, p. 900–902, 2003.

REGIMES, R.; GIANNAKAS, K. Inserting Gm Products Into The Food Chain: The Market And Welfare Effects Of Different Labeling And Regulatory. **American Journal of Agricultural Economics**, v. 86, n. 1, p. 42–60, 2013.

SMART, R. D.; BLUM, M.; WESSELER, J. EU Member States’ Voting for Authorizing Genetically Engineered Crops: a Regulatory Gridlock. **German Journal of Agricultural Economics**, v. 64, n. 4, p. 244–262, 2015.

SMYTH, S.; KERR, W. A.; DAVEY, K. A. Closing markets to biotechnology: does it pose an economic risk if markets are globalised? *In*: **International Journal of Technology and Globalisation**. [s.l: s.n.]. v. 2p. 377.

SOUSA, J. DE. The currency union effect on trade is decreasing over time. **Economics Letters**, v. 117, n. 3, p. 917–920, 2012.

STEIN, A. J.; RODRIGUEZ-CEREZO, E. **The global pipeline of new GM crops Implications of asynchronous approval**. Luxembourg: [s.n.].

STURGES, W. *et al.* Insect-Resistant GM Rice in Farmers ’ Fields : Assessing Productivity and Health Effects in China. 2003.

TOMICH, F. A.; LEITE, C. A. M. **Competitividade das exportações brasileiras de frutas selecionadas**. [s.l.] Universidade Federal de Viçosa., 1999.

VIGANI, M.; OLPER, A. GMO standards, endogenous policy and the market for information. **Food Policy**, v. 43, p. 32–43, 2013.

VIGANI, M.; RAIMONDI, V.; OLPER, A. International trade and endogenous standards: the case of GMO regulations. **World Trade Review**, v. 11, n. 03, p. 415–437, 6 jul. 2012.

WHITE, H. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. **Econometrica**, v. 48, n. 4, p. 817–838, 1980.

WINCHESTER, N. *et al.* The Impact of Regulatory Heterogeneity on Agri-food Trade. **World Economy**, v. 35, n. 8, p. 973–993, 2012.

WOOLDRIDGE, J. M. Selection corrections for panel data models under conditional mean independence assumptions. **Journal of Econometrics**, v. 68, p. 115–132, 1995.

WTO; UNCTAD. Analyzing bilateral trade using gravity equation. *In*: **A Pratical Guide to Trade Policy Analysis**. [s.l: s.n.]. p. 101–136.

1. Professor at the Pontifical Catholic University of Campinas and Associate Researcher at University of Campinas (Unicamp) [↑](#footnote-ref-1)
2. Professor at the University of Campinas (Unicamp) [↑](#footnote-ref-2)
3. Professor at the University of Illinois at Urbana-Champaign [↑](#footnote-ref-3)
4. Authors employed a Constant Market Share (CMS) technique, which assumes that a country keeps constant it market shares being any change in the trade-flows a result of three basic effects: growth of world trade, destination market and competitiveness. Competitiveness is a residual effect and can have a number of explanations such as reduced production or trade costs or, in the case studied, certain level of hate against GMOs, see (Carvalho, 1995; Tomich e Leite, 1999). [↑](#footnote-ref-4)
5. However Disdier & Fontagné (2010) did not analyzed soybean trade because they focused on potential regulatory effects, and soybean was the only crop that was approved before the de facto moratorium initiated in 1998. Our study goes to another direction, showing that impacts beyond the differences in regulatory positions can give out many interesting stylized effects of technology adoption under certain levels of hatred. [↑](#footnote-ref-5)
6. The EU pressured by national interest groups did not approve any new event between 1998 and 2003. This period was defined by literature as the de facto moratorium. The controversies and conflicts that arose from this period were discussed at the DSB (Dispute Settlement Body) under WTO. [↑](#footnote-ref-6)
7. By dynamic we mean an effect changing over time. [↑](#footnote-ref-7)
8. For clarity, we are not saying that geographical distance changes over the time, but we are saying that some variable costs, such as “demand lag” can vary across the ’s. [↑](#footnote-ref-8)
9. Remember we are assuming a Pareto distribution for firm heterogeneity with productivities varying from to . Zero profit condition was defined as

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   where are fixed costs of trade and is the minimum productivity necessary to make any export from country to country profitable. [↑](#footnote-ref-9)
10. As in HMR (2008) we divided equation 4 by the standard deviation before specifying the Probit equation to avoid imposing conjunct normality . However we omitted the star as a superscript to indicate it. Empirical estimations, as suggested by WTO & UNCTAD (2012), usually ignores this step. We run models with and without this procedure and we have found no meaningful differences in the model coefficients. [↑](#footnote-ref-10)
11. Landlocked countries tend to trade less (extensive and intensive margins) due to their remoteness leading to increased trade costs – including transaction and transportation costs. According to World Bank they trade on average 60% less when compared to countries with maritime boundaries. [↑](#footnote-ref-14)
12. Soybean meal represents around 80% of soybeans use (HighQuest e Soytech, 2011). [↑](#footnote-ref-15)