

**PERSPECTIVES OF THE TRADE CHINA-BRAZIL-U.S.A.:
EVALUATION THROUGH A GRAVITY MODEL APPROACH**

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PERSPECTIVES OF THE TRADE CHINA-BRAZIL-U.S.A.: EVALUATION THROUGH A GRAVITY MODEL APPROACH

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ABSTRACT

Gravity models have been extensively used to study trade patterns among countries. We model the international trade of U.S., Brazil and China during the period of 1995 through 2003. Several models were adjusted to the data set considering the traditional variables used in gravity models, such as, GDP, distance between two countries and relative price index. Moreover, some additional variables were included in the analysis to capture the political and factors that stimulate or restrict trade between pairs of countries. We extend the Dixon and Moon (1993) model incorporating latent variables, in order to model the country-effect and the Business Cycle effect, and also including an Autoregressive - AR(1) - and deterministic trend terms. Hierarchical Bayesian models were applied to the panel data set and the choice of the best model was based on a posterior predictive criterion. The empirical framework used in this article proposes substantial improvements in the statistical methods often applied in the gravity models. These improvements are especially relevant to situations when the availability of data is limited.

Keywords: international trade, gravity model, multivariate regression, Bayesian inference

1 Introduction

The Brazilian foreign trade is basically concentrated in a limited number of countries. In 2004 and 2005, the European Union and the United States were responsible for over 43% of both Brazilian imports and exports. Yet, foreign trade competition, tariff and non-tariff barriers, as well as bilateral and regional agreements limit growth expectations of Brazilian trade with its historical partners (e.g. Japan) (Nukui and Miranda, 2003).

While the Brazilian trade with the traditional countries is stagnated there are an increasing trading movement towards China, countries of the Latin American Integration Association, newcomers of the European Union, members of the Mercosur and of the Asia-Pacific Economic Cooperation (Vizentini, 2003).

China and Brazil have been maintaining informal trade since the creation of the Republic of China, in 1949. In the fifties, the trade flow was inexpressive (around US\$ 8 million) (MDIC, 2002). In the nineties, there has been a boom in the bilateral trade when compared to the previous decade, partially interrupted by the Asian financial crisis in 1997. China, which was ranked fourth in the Brazilian exports destiny, jumped to the third position since 2002, behind the United States and Argentina¹ (Nukui and Miranda, 2004; UN/COMTRADE, 2007).

The total monetary value of Chinese global trade flow increased from US\$ 51.1 billion, in 1984 to US\$ 1.76 trillion, in 2006. Similarly to the exports, Chinese imports steadily grew – an average growth rate of approximately 15% per year between 1993 and 2004 (Figure 1).

¹ Considering the European Union disaggregated by its country members.

This performance of the imports is a consequence of an increasingly trade mainly with the European Union, the United States and with country-members of the Association of Southeast Asian Nations (ASEAN)².

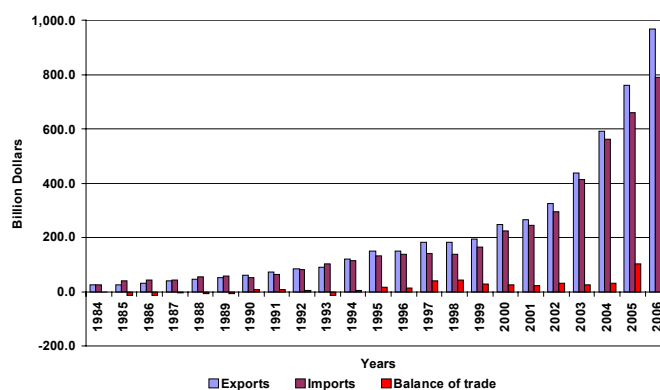


Figure 1. Chinese trade balance. Values in US\$ FOB. Source: UN/COMTRADE (2007)

Between 1984 and 2005, Chinese share in world exports rose from 1.52 to 7.9 % (UN/COMTRADE, 2007). The composition of Chinese exports to the world is presented in Table 1, where it is possible to verify the significant share of the high aggregated value goods. It is also remarkable the concentration of the exports in only two large groups of products, machinery and transport equipment and clothing, which affords for more than 65 % of the total exports.

Table 1. Composition of the Chinese Exports (US\$ million - FOB)

Chinese foreign exports composition in 2005, according to HS 2002	
Machinery and transportation equipment (chapters 81 to 90)	51.07%
Clothing (chapters 61 to 70)	14.63%
Minerals (chapters 71 to 80)	6.61%
Other personal products (chapters 91 to 97)	6.36%
Beverages, tobacco, fuels (chapters 21 to 30)	5.76%
Mineral oil derivatives (chapters 31 to 40)	4.56%
Fibers (chapters 51 to 60)	3.96%
Wood, fur, silk, paper (chapters 41 to 50)	3.90%
Agricultural products (chapters 01 to 10)	1.74%
Processed food (chapters 11 to 20)	1.42%
Total	100%

Source: UN/COMTRADE(2007)

Brazilian global exports, in the period of 1984 through 2005, decreased from 1.65 to 1.2% per cent (UN/COMTRADE, 2007).

² ASEAN is composed by Myanmar (1997), Laos (1997), Thailand (1967) Cambodia (1999) Vietnam (1995) Philippines (1967) Malaysia (1967) Brunei (1984) Singapore (1967) and Indonesia (1967).

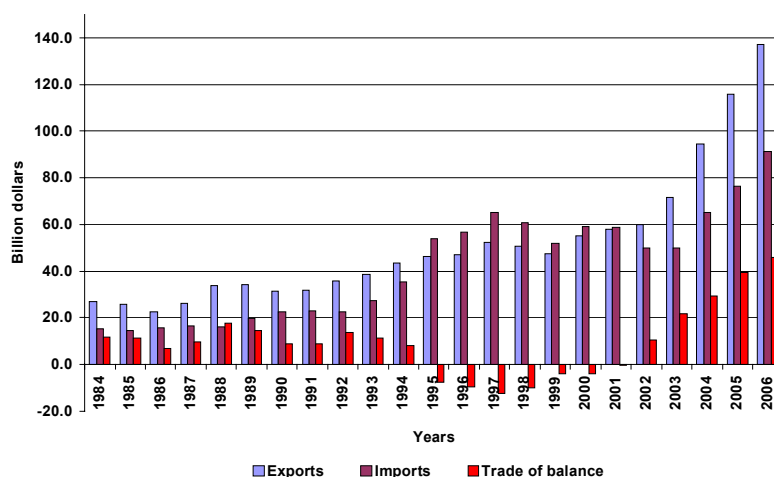


Figure 2 – Brazilian balance of trade (1984-2005).

Source: UN/COMTRADE (2007)

During 1996 through 1999, Brazil presented a negative total trade balance, as a consequence of the appreciated exchange rates, which was part of the macroeconomic policy program. This trend changed in 2000. Since then balance of trade accumulates surpluses. It is worth to mention that after 1999, a great change in trade balance was caused by the free-floating exchange rate regime.

Table 2 shows the Brazilian trade exports composition relative to the world, in 2005. This is characterized by relatively balanced exports of manufactured, semi-manufactured and non-manufactured products, when compared to China. In the last decade, the share of both manufactured and partially manufactured products has grown, which diverges from previous moments when Brazil was basically a raw material supplier (UN/COMTRADE, 2007).

Table 2 - Composition of the Brazilian exports to the world.

Brazilian foreign exports composition in 2005, according to HS 2002	
Machinery and transportation equipment (chapters 81 to 90)	27.21%
Beverages, tobacco, fuels (chapters 21 to 30)	21.83%
Processed food (chapters 11 to 20)	11.85%
Minerals (chapters 71 to 80)	11.46%
Agricultural products (chapters 01 to 10)	9.94%
Wood, fur, silk, paper (chapters 41 to 50)	6.96%
Crude oil derivatives (chapters 31 to 40)	4.56%
Clothing (chapters 61 to 70)	3.78%
Fibers (chapters 51 to 60)	1.23%
Other personal products (chapters 91 to 97)	1.17%
Total	100.00%

Source: UN/COMTRADE (2007).

In the last decade, Brazil and China increased considerably the bilateral trade flow. This increasing movement was a consequence of the free-floating exchange rate regime adopted in Brazil (Figure 3). There has been a significant expansion of Brazilian exports to China since 2001 and consequently positive bilateral trade flows.

In the period of 1999 through 2003, China was responsible for 15.4% of the whole destination of Brazilian exports. As a result, Brazil has accumulated expressive trade surpluses and three-fold market-share of the Chinese imports, from 0.43%, in 1999 to 1.27%, in 2003 (Funcex, 2004).

By the end of January 2000, Brazil and China formalized an agreement in which China would receive support for a membership position at WTO. In exchange, China accepted to reduce some existing tariffs over 23 products (Lima et al., 2006).

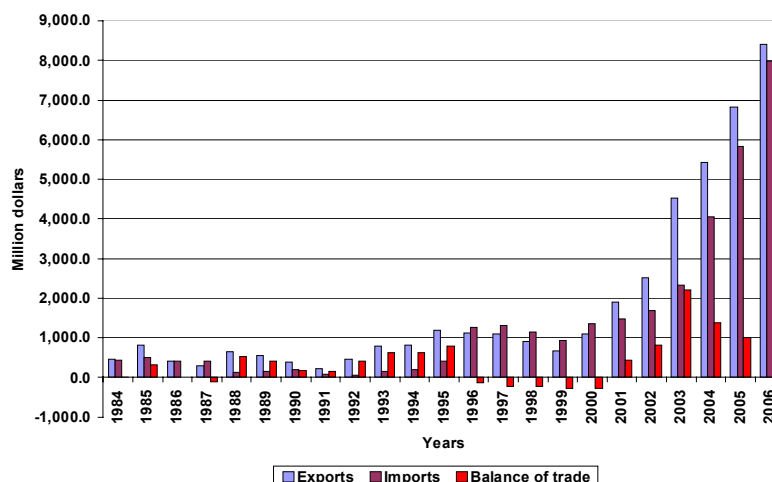


Figure 3. Brazil-China bilateral trade balance – US\$ FOB. Source: ONU/COMTRADE (2007).

The product composition of Chinese exports to Brazil includes a high share of industrialized products, averaged 87% (2002 through 2004); followed by fuels and agricultural products (Lima, Ozaki and Miranda, 2006). On the other hand, Brazilian exports to China are mostly concentrated in non-processed agricultural and mineral products. Figure 4 shows the most representative categories of exported and imported products from China to Brazil during the year of 2006. Two products – soybean and iron – represented 40.5% of the Brazilian sales to China, in 2003; the ten most important products were responsible for 70% of total income. Brazil is a supplier of low aggregate valued products to China (CNI, 2004). This profile differs from the Brazilian foreign commerce with the rest of the World. Global Brazilian exports are basically composed by manufactured products, especially those highly economies of scale demanding.

However, a significant percentage of Brazilian import of Chinese products turned into a series of disputes under the scope of WTO. As a whole, 53 disputes settled in order to protect the Brazilian market, 13 are against China, and other 13 investigations are under appreciation (SECEX, 2004). The particular relationship with Brazil includes another important recent fact, which is strengthen Chinese participation in Latin America, evidenced by its interest to be a shareholder of the Inter-American Development Bank - IDB (Lima et al, 2007).

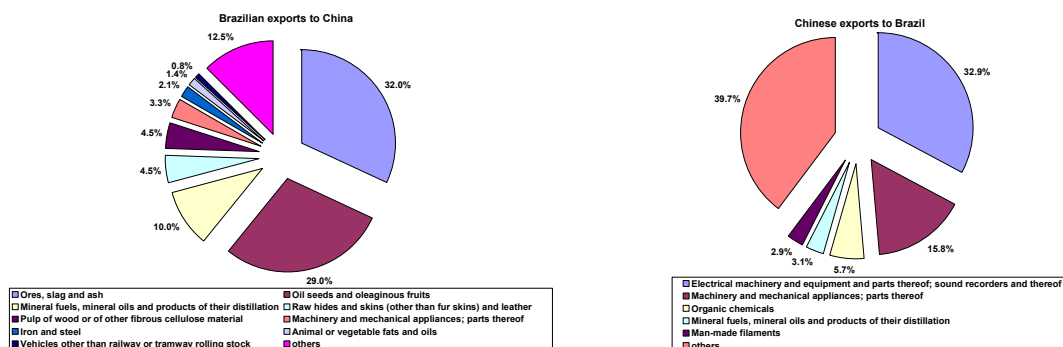


Figure 4. Most relevant categories of products commercialized between Brazil and China, 2006. Source: ONU/COMTRADE (2007)

As the importance of the bilateral trade flow between Brazil and China increases, the higher becomes the demand for high quality and accurate information about the determinants of the bilateral trade. Gravity models emerge as an empirical framework analysis of these determinants. This work intends to identify factors that affect such trade, particularly considering the effects of distance, markets size, as well as political and cultural factors, or others that can even promote or jeopardize commerce based on gravity models.

Yet, considering the United States an important trade partner for both countries, and that is also a country with continental dimension, similarly to China and Brazil, the U.S. was included in the analysis.

This work models the trade flow among Brazil, China and U.S. through gravity equations in a situation of limited number of observations. To deal with this problem, the panel data set was empirically modeled through Bayesian inference. Particularly, hierarchical Bayesian models in a multivariate regression context.

This article is arranged according to the following outline. In the next section, we briefly review the gravity model literature. Section 3 shows in details the econometric model. Section 4 shows the data used in this work. In Section 5 we present the empirical application and discussion of the results and in Section 6 we conclude the paper.

2 The Gravity Model

The gravity models typically specify that the trade flow of country i for country j can be explained by the supply conditions in country i , demand in country j , and by variables that favor or limit the transactions (Bergstrand, 1985; Fink and Braga, 1999).

At the beginning, gravity models were developed intuitively, without concerns on economical foundations (Leamer and Stern, 1970). During the years, several economists have been successfully using gravity models. Although its intuitive appealing, some theoretical questions could not be solved until then. Several trials have been done to clarify the microeconomic basis of the gravity model (Linneman, 1966, apud Bergstrand, 1985; Anderson, 1979). It is interesting to note that gravity models work like the Heckscher-Ohlin model for inter-industry trade and Helpman-Krugman-Markusen model for intra-industry trade (Bergstrand, 1985).

Recently, beyond the innumerable incursions clarifying the economical basis of the gravitational equation, several economists applied the gravitational equation and its variants

to study several subjects in international trade. Some considered different explanatory variables for explaining the bilateral flows, such as, the importer and exporter size, e.g. the Gross Domestic Product (GDP), the distance between their economic center and by whatever other variable that may encourage or make the commerce more difficult for both partners (resistance factors) (Bergstrand, 1985). Others included the population as a proxy of the size of the importer and exporter countries (Linnemann, 1966, apud Pollins, 1989; Aitkin, 1973, apud Feenstra, 2004, Harris and Matyás, 1998).

When pairs of commercial partners are distant from each other, its trade is unfavorable due to the increase in the costs of transportation and also the reduced business knowledge. Tariffs and cultural differences (e.g. language) will also have relative influence. Similarly, economical and political alliances, such as free trade agreements, can reduce the physical resistances to the trade (Leamer and Stern, 1970).

Intuitively, countries tend to strengthen the trade with other similar countries, considering their relative size. Distance, plays an important role, influencing trade flows and according to literature it shows negative elasticity below 1. Resistance variables can be included in the analysis, such as dummy variables for neighbour countries (with a common physical border) and for preferential agreements (Tinbergen, 1962).

In most of the empirical works, gravity models assume perfect substitution among goods from different countries. However, if goods are differentiated by origin, the typical gravity equation becomes misspecified and the estimation biased (Bergstrand, 1985).

Feenstra (2004) presents a simple version of the gravity equation, under the assumption of free trade, in which all countries have identical prices. This assumption is omitted allowing different prices in the existence of trade barriers among countries.

In this simple model, Feenstra (2004) concludes that countries market shares in the international trade are balanced by their share in the world production, meaning that a bilateral exports from country i to country j are proportional to their GDP. Some of these questions and others related to the model specification are extensively discussed in recent works (Helpman, 1987 and Debaere, 2002, apud Feenstra, 2004; Ewebett and Keller, 1998, 2002, apud Sheldon, 2005).

Recent developments in the gravity models also stressed the role of price effects (Anderson, 1979; Feenstra, 2004) According to Feenstra (2004), in the literature there are basically three different price approaches in order to address prices indexes measurement: i) prices indexes applied to measure prices effects in the gravity equation (Bergstrand, 1985, 1989; Baier and Bergstrand, 2001); ii) estimate the border effects as a way to quantify price relevance (Anderson and Van Wincoop, 2003); and, iii) using the fixed effects in order to consider price effects (Redding and Venables, 2000; Rose and van Wincoop, 2001).

Whenever there are border effects (costs of transports and tariffs, for instance), prices are not balanced among countries and the trade model is more complex than in the gravity equation. In this case, it is necessary to assume a specific utility function as the CES (Constant Elasticity Substitution).

When modeling the resistance and facilitation effects, it is important to consider other variables than distance and relative price. Dixon and Moon (1993) and Pollins (1989), incorporated political and social factors affecting the trade partners choices. In this sense, Dixon and Moon (1993) proposed two different variables in the gravity model: i) similarities in the domestic government arrangements and practices; ii) similarities in the external policy orientation (such as, the exchange regime and foreign aid).

In this work we follow the basic notation of Dixon and Moon (1993). The structural form of the gravity equation is presented in equation (1):

$$X_{ijt} = A Y_{it}^{\beta_1} Y_{jt}^{\beta_2} G_{ij}^{\beta_3} R_{it}^{\beta_4} \exp(\beta_5 D_{jt} + \beta_6 F_{jt}) \varepsilon_{ijt} \quad (1)$$

In which:

X_{ijt} = Exports from nation i to importer j at time t ;

Y = Economic size of exporter i and importer j ;

G = Geographical distance between two nations;

R = Relative price index;

D = Factors that stimulate or restrict trade between pairs of countries; and

F = Political variable.

Taking logarithmic on both sides of equation (1) and including the autoregressive term, the deterministic trend and the latent variables, in order to capture the country-effect ζ_i - allowing different propensities of countries to export - and the Business Cycle effect ξ_t as follows:

$$x_{ijt} = a + \beta_1 y_{it} + \beta_2 y_{jt} + \beta_3 g_{ij} + \beta_4 r_{it} + \beta_5 d_{jt} + \beta_6 f_{jt} + \beta_7 x_{ij(t-1)} + \xi_t + \zeta_i + u_{ijt} \quad (2)$$

In which $x_{ijt} = \ln X_{ijt}$, $a = \ln A$, $y_{it} = \ln Y_{it}$, $y_{jt} = \ln Y_{jt}$, $g_{ij} = \ln G_{ij}$, $r_{it} = \ln R_{it}$, $d_{jt} = \ln D_{jt}$, $f_{jt} = \ln F_{jt}$ and $u_{ijt} = \ln \varepsilon_{ijt}$.

3 Empirical Model

In the last decade, a diversity of econometric methods has been used in order to estimate gravity models. Dixon and Moon (1993) used GLS-ARMA method, proposed by Stimson (1985), in a database composed by 76 importer countries from the U.S. between 1966 and 1983. Frankel and Romer (1999) detected the sensitivity of the gravity model in a bilateral trade context when inserting instrumental variables related to geographical distance and estimated the model using ordinary least squares (OLS) methods.

Mátyás (1997) and Harris and Mátyás (1998) proposed the use of fixed and random effects panel data estimation to identify temporary Business Cycles and some particular characteristics of import and export countries. Eaton and Tamura (1994) adopted a Threshold Tobit method in order to assign meaningful probabilities to the event of nontrade.. Ranjan and Tobias (2007), following Koop and Poirier (2004), and Chib and Jeliazkov (2004) developments, included specific country effects and modeling data through non-parametric Bayesian inference.

The choice of the econometric method depends on the data set available. In this work, particular covariates are used to each one of the selected countries varying in time. The panel data framework offers a more detailed analysis of the effects in the unities (countries or regions) and the estimation of the parameters that could not be estimated in the case of only cross-section or time-series database.

The Bayesian approach for traditional panel data considers that the generating process for the observations $\mathbf{y}_i = (\mathbf{y}_{i1}, \mathbf{y}_{i2}, \dots, \mathbf{y}_{it})'$ is made by the following multivariate regression model:

$$\mathbf{y}_i = \mathbf{X}_i \mathbf{B}_i + \boldsymbol{\varepsilon}_i \quad (i = 1, 2, \dots, m) \quad (3)$$

The \mathbf{y} observations are allocated in a $t \times m$ matrix with m variables and t observations. Matrix \mathbf{X}_i is composed of covariates $t \times k$, $\mathbf{B}_i = (\beta_1, \beta_2, \dots, \beta_m)$ is a $k \times m$ matrix of the regression parameters, and $\boldsymbol{\varepsilon}_i$ is a $t \times m$ matrix of non-observed random errors. Furthermore, it is assumed that the lines of the matrix $\boldsymbol{\varepsilon}_i$ are independent and normally distributed with zero mean and covariance matrix $\boldsymbol{\Sigma}$ positive definite of dimension $m \times m$ (Tiao and Zellner, 1964; Zellner, 1975).

Under these suppositions, the distribution of \mathbf{y} , given \mathbf{X} , \mathbf{B} and $\boldsymbol{\Sigma}$ is:

$$p(\mathbf{y} \mid \mathbf{X}, \mathbf{B}, \boldsymbol{\Sigma}) \propto \mid \boldsymbol{\Sigma} \mid^{-t/2} \exp \left[-1/2 \operatorname{tr} (\boldsymbol{\varepsilon})' \boldsymbol{\Sigma}^{-1} (\boldsymbol{\varepsilon}) \right] \quad (4)$$

in which “tr” denotes the trace operator.

The likelihood function for both \mathbf{B} and $\boldsymbol{\Sigma}$ is given by:

$$l(\mathbf{B}, \boldsymbol{\Sigma} \mid \mathbf{y}, \mathbf{X}) \propto \mid \boldsymbol{\Sigma} \mid^{-t/2} \exp \left\{ -1/2 \left[\operatorname{tr} (\mathbf{S}) \boldsymbol{\Sigma}^{-1} - \operatorname{tr} (\mathbf{W}) \boldsymbol{\Sigma}^{-1} \right] \right\} \quad (5)$$

in which $\mathbf{S} = (\mathbf{y} - \mathbf{X}\hat{\mathbf{B}})'(\mathbf{y} - \mathbf{X}\hat{\mathbf{B}})$, $\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ and $\mathbf{W} = (\mathbf{B} - \hat{\mathbf{B}})' \mathbf{X}'\mathbf{X} (\mathbf{B} - \hat{\mathbf{B}}) \boldsymbol{\Sigma}^{-1}$

Before going further into the analysis, it is important to note two aspects: first, each vector i was modeled separately. Unlike the traditional panel data methods of estimation, which uses one vector of mean and a matrix of covariance, here we adopted a univariate formulation for each i . In other words, instead of $\mathbf{y}_i \sim N_i(\mathbf{X}_i \mathbf{B}_i, \boldsymbol{\Sigma})$, $\boldsymbol{\varepsilon}_i \sim N_i(\mathbf{0}, \boldsymbol{\Sigma})$, it is considered $\mathbf{y}_i \sim N(\mu_i, \tau)$, in which τ is the precision parameter. The prior distributions of \mathbf{B} were modeled in a multivariate framework in order to capture the correlation structure among parameters. Secondly, we are modeling the mean structure, leaving precision constant throughout the analysis. In other words, we considered $\mu_i \equiv E(\mathbf{y}_i)$. Basically, the idea is evaluate the effects of the response variable by using μ_i .

The empirical works modeled the response variable by using the existing covariates structure. In this work, the dependence structure is modeled using hierarchical models.

In such models, the dependence structure between the parameters can be represented by the joint probability distribution. Consequently, we can define a prior distribution for these parameters, assuming that they can be considered as a sample from a common population distribution.

Modeling the structure underlying the mean yield realization by adopting hierarchical models is intuitive and facilitates the visualization of each component in the analysis instead of

modeling such structure directly through the y_i^3 . However, one limitation of the building correlation structure by hierarchical models is that all of the pairwise correlations would be positive.

In many applications, the observed variable is modeled conditional on a given number of parameters that receive a prior probability distribution, which in turn receive other parameters, called hyper-parameters. One can assign probability distributions to these parameters (hyper-prior distributions). Priors can then be chosen to reflect prior knowledge of these hyper-parameters. In situations where relatively little is known about the hyper-parameters, diffuse prior distributions can be adopted. However, we must be careful to recognize that improper priors may yield improper posterior distributions⁴. The point is that although results may seem reasonable, the problem might not be well diagnosed; in other words, inferences are made to an inexistent posteriori distribution (Hobert and Casella, 1996).

In such a case, inferences are being made on a non-existent posterior distribution. In a practical sense, as shown in Gelfand and Smith (1990), this problem can be prevented by considering proper prior distributions that assure that the Markov Chain Monte Carlo (MCMC) estimation process will be well-behaved, where ignorance can be represented as values for the precision parameter close to zero.

The next step is to assign prior distributions for both \mathbf{B} and τ . The prior distributions are, respectively:

$$\mathbf{B} \sim N_m(\boldsymbol{\mu}_0, \boldsymbol{\Lambda}_0), p(\mathbf{B}) \propto |\boldsymbol{\Lambda}_0|^{m/2} \exp[-1/2 (\mathbf{B} - \boldsymbol{\mu}_0)' \boldsymbol{\Lambda}_0^{-1} (\mathbf{B} - \boldsymbol{\mu}_0)] \quad (6)$$

$$\tau \sim G(v, \kappa), p(\tau) = (e^{-\kappa\tau} \kappa^v \tau^{v-1})/\Gamma(v) \quad (7)$$

in which $v = 10^{-3}$, $\kappa = 10^{-3}$. To the hiper-parameters of the prior distribution \mathbf{B} were associated the following hiper-priors:

$$\boldsymbol{\mu}_0 \sim N_m(\boldsymbol{\mu}_1, \boldsymbol{\Lambda}_1), p(\boldsymbol{\mu}_0) \propto |\boldsymbol{\Lambda}_1|^{m/2} \exp[-1/2 (\boldsymbol{\mu}_0 - \boldsymbol{\mu}_1)' \boldsymbol{\Lambda}_1^{-1} (\boldsymbol{\mu}_0 - \boldsymbol{\mu}_1)] \quad (8)$$

$$\boldsymbol{\Lambda}_0 \sim W_m(\boldsymbol{\Theta}, \psi), p(\boldsymbol{\Lambda}_0) = |\boldsymbol{\Theta}|^{\psi/2} |\boldsymbol{\Lambda}_0|^{-(\psi+1)/2} \exp[-1/2(\text{tr}(\boldsymbol{\Theta} \boldsymbol{\Lambda}_0))] \quad (9)$$

³ For this alternative version, Anselin (1988) shows several models, such as, SUR (seemingly unrelated regression), where the Beta coefficients are allowed to vary in one of the two dimensions and the error term is correlated in the other dimension. In those models the dependence structure is modeled through the error term ε_{it} , where $y_{it} = x_{it}\beta_{it} + \varepsilon_{it}$.

⁴ In this context, Hobert and Casella (1996) estimated the parameters of a hierarchical linear mixed model using the Gibbs sampler and warned about using a non-informative prior distribution that can lead us to an improper posterior distribution.

In which $\mu_1 = [0.1]_{m \times 1}$, $\Lambda_1 = [1.0E-6]_{m \times m}$, $\Theta = [1]_{m \times m}$, is a diagonal, symmetrical and positively defined matrix, $\psi = m$, and $\psi \geq p$, known as the Wishart distribution (Spiegelhalter et al., 2003).

The previous model was extended, in order to capture the effect of countries i and the Business Cycles through latent variables denoted by \mathbf{z} . Consequently, \mathbf{z}_i is the latent variable designed to capture effects of the cross-section heterogeneity and \mathbf{z}_t the latent variable assigned to the Business Cycles effect. Both \mathbf{z}_t and \mathbf{z}_i are independent and normally distributed. The conditional density is given by: $p(\mathbf{z} | \mathbf{y}, \mathbf{X}, \theta)$, in which θ represents the vector of all parameters. The posterior density is given by:

$$p(\theta | \mathbf{y}) = \int p(\theta | \mathbf{y}, \mathbf{z}) p(\mathbf{z} | \mathbf{y}) \quad (10)$$

The criteria used to choose the best model are based on Laud and Ibrahim (1995). These criteria are easy to interpret, since they are not based on asymptotic results and they allow for the incorporation of prior distributions. Working in the predictive space, the penalty appears without the necessity of asymptotic definitions. Intuitively, good models must predict close to what is observed in identical experiments.

The criteria, from now on “squared predictive error criteria” (SPE), were formalized by Gelfand and Ghosh (1998) using a specific loss function. The objective is to minimize the posterior predictive loss. The posterior predictive distribution is given by:

$$p(\mathbf{y}_{new} | \mathbf{y}_{obs}) = \int p(\mathbf{y}_{new} | M) p(M | \mathbf{y}_{obs}) dM \quad (11)$$

in which M represents the group of all parameters of a specific model and \mathbf{y}_{new} is the replicate of the vector of observed data \mathbf{y}_{obs} .

The model selection criteria is based on a discrepancy function $d(\mathbf{y}_{new}, \mathbf{y}_{obs})$, and the objective is to choose the model that minimizes the expectation of the discrepancy function, conditional on \mathbf{y}_{obs} and M_n , where the subscripts n represent all parameters in a specific model n . If we consider Gaussian models, the discrepancy function is given by $d(\mathbf{y}_{new}, \mathbf{y}_{obs}) = (\mathbf{y}_{new} - \mathbf{y}_{obs})'(\mathbf{y}_{new} - \mathbf{y}_{obs})$ and D_{Mn} by:

$$D_{Mn} = E[(\mathbf{y}_{new} - \mathbf{y}_{obs})'(\mathbf{y}_{new} - \mathbf{y}_{obs}) | \mathbf{y}_{obs}, M_n] \quad (12)$$

$$D_{Mn} = E \sum_t [(y_{t,new} - y_{t,obs})^2 | \mathbf{y}_{obs}, M_n] \quad (13)$$

The authors demonstrate that D_{Mn} can be factored into two additive terms G_{Mn} and P_{Mn} . The first, $G_{Mn} = \sum_t [y_{t,obs} - E(y_{t,new} | \mathbf{y}_{obs})]^2$, represents the sum of squared errors, in other words, a

measure of goodness-of-fit, and the second, $P_{Mn} = \sum_t \text{var}(y_{t,new} | \mathbf{y}_{obs})$, a penalty term. In models that are over- or under-fit, the predicted variance tends to be large and thus P_{Mn} is large. Thus, the penalty is considered in the analysis regardless the model dimension.

4 Data

The data set consists on two different periods. The first one comprised data in the period of 1962 through 2003 in which the basic gravity model was estimated using traditional variables (exporter and importer GDP, and distance). The second group of models was estimated using all other variables: relative price index, tariffs and political variables, in the period of 1995 through 2003.

Gross domestic product and consumer price index data were all obtained from the World Development Indicators 2005 for the three selected countries. Relative prices series were calculated by the consumer price index ratio for each pair of countries. Those were obtained in order to test difference in price effects on exports. The aggregated value, in dollars, of exports and imports from Brazil, U.S.A and China (1987-2003) are from the United Nations Commodity Trade Statistics Database – COMTRADE (United Nations, 2007).

In the case of distance variable, it was considered the maritime miles between relevant ports of exportation/importation chosen for each country: Santos (Brazil) – Los Angeles (US) (5,708 maritime Miles), Santos – Shanghai (China) (11,056 maritime miles) and Los Angeles – Shanghai (7,384 maritime miles) (Dataloy, 2007):

Tariffs for Brazil, China and the United States were obtained from the World Integrated Trade Solution (WITS)⁵. In the database there are two types of tariffs: i) bound rates (BND); and, ii) effectively applied rates (AHS). The former is the upper bound rate and the latter is the effective rate. In our case, we chose the AHS rate which is consistent with our purposes and presented better results in the early runs of the models. Both are weighted averages. Most of data source is the United Nations Commodity Trade – COMTRADE. Due to the lack of some observations, some information was also obtained from the Integrated Database (IDB) of the World Trade Organization (WTO).

The political indicators were obtained from the non-governmental organization Transparency International: the corruption perception index (CPI) which measures the perception of entrepreneurs, academics, business people, and risk analysts in terms of corruption perception for a diversity of countries. It is an index scaled between zero (higher level of corruption perception) and 10 (lower level of corruption perception) (Transparency International, 2007). The CPI was first released in 1995.

The second source comes from the Heritage Foundation. Two indexes were used in the analysis: index of trade freedom and freedom from corruption. Both indexes are scaled from zero to one hundred. The higher the score, the more freedom is supposed for each of the countries (Heritage Foundation, 2007). Both indexes started in 1995.

Finally, the third group of data was those of trade agreements established among Brazil, China and the United States, obtained since 1966. The source of this information was the U.S. Department of Commerce (United States of America, 2007) and the Brazilian Ministry of External Relations (Brazil, 2007).

⁵ Software available at wits.worldbank.org/witsweb, a conjoint effort from both the World Bank and the United Nations Conference on Trade and Development (UNCTAD). The WITS software centralizes information from a diversity of sources.

5 Empirical Application

5.1 Brazil - Bilateral Trade

The gravity model was analyzed, considering first Brazil as exporter country and U.S. and China as importer; and, second, U.S. as exporter and Brazil and China as importer. We run three chains to check the mixing of the Markov sequence and also check for all the parameters the graphical diagnostics of convergence. Results showed that all parameters achieved good convergence and mixing.

A first estimation was applied for the period 1962 through 2003 in accordance to the basic gravity model, though such analysis restrict and may exclude other potentially relevant explanatory variables. Afterwards, a more complete cross-section database was chosen, though it restricted analysis for years between 1995 and 2003. Those models are showed in Tables 4a and 4b, respectively.

The first panel data included Brazilian bilateral exports to China and to the United States as the dependent multivariate variable. Afterwards, U.S. bilateral trade flows to China and Brazil were analyzed (Tables 5a and 5b). In the first column, the explanatory variables are shown. In the remaining columns, estimated parameters of the gravity equations and its respective estimate standard deviation are presented in parentheses.

In Table 4a, coefficients obtained for the Brazilian trade flow confirm expectations in terms of magnitude and sign for the variables related to market size, GDP_i and GDP_j . However, the sign for Distance is positive, different from the results founded in the literature, especially when the Weighted Applied Tariffs were not included. The inclusion of both - Freedom of Corruption Index and Trade Agreement variables - worsened the results for models 5 and 6.

Table 4a. Comparison of different gravity models - Brazil bilateral exports to China and US. Panel (cross-section/ time series). 1962-2003

Variables	Model 1 (1962-2003)	Model 2 (1995-2003)	Model 3 (1988-2003)	Model 4 (1992-2003)	Model 5 (1995-2003)	Model 6 (1995-2003)
Constant	-98.31 (11.07)	-80.02 (45.76)	-73.98 (24.20)	-8.24 (21.66)	-37.08 (37.27)	-36.74 (24.79)
GDP_i	1.93 (0.41)	1.24 (3.30)	1.95 (1.19)	2.47 (1.39)	1.73 (2.84)	1.93 (2.51)
GDP_j	1.72 (0.26)	1.65 (1.10)	1.23 (0.36)	-0.09 (0.69)	0.62 (1.08)	0.43 (1.03)
Distance	2.12 (1.27)	2.35 (3.69)	0.93 (1.35)	-3.79 (2.70)	-0.38 (3.20)	-0.54 (3.33)
Relative Prices			-0.03 (0.02)			
Weighted Applied Tariffs				-0.04 (0.13)	-0.38 (0.12)	-0.38 (0.12)
Freedom from Corruption					-0.31 (1.17)	
Agreements						-0.01 (0.03)
SPE	5.35	0.44	0.36	0.16	0.29	0.29

The introduction of the Weighted Average Applied tariffs in the model changed the sign of the coefficients, becoming the result for the GDP_j worse. The results for the tariffs are similar and negative for all the models presented, indicating that the tariffs reduction in the nineties caused a positive effect on the bilateral trade flows (Model 4 to 6). Model 4 is the best model according to the SPE criteria. In other words, this is the best model to predict the data set. In this model the Relative price is excluded. Model 9 include most of the variables and has the sign compared to the parameters of the model 4.

Models 5 and 6 evaluate the relation between the Freedom of Corruption Index and the number of Brazilian Agreements, respectively, which increases in time. The coefficients did not show the expected signs.

The two last columns in Table 4a show the Brazilian bilateral trade results when the political and commercial variables are considered. The new explanatory variables introduced in the model were the Freedom Corruption Index for the importer and the intensity of agreements between the countries, both for the importers. Other variables also examined were an Autoregressive AR (1) variable, a deterministic trend and two latent variables, one referring to the importer Country-effect specification and the other one to the Business Cycles (Table 4b). These last two variables were tested to check for misspecifications issues.

Table 4b shows results for the complete model. The Autoregressive term AR(1), included in the model, is not shown in the table. In general, this variable does not perform well in this model for the Brazilian bilateral trade flows.

Table 4b. Comparison of different gravity models - Brazil bilateral exports to China and US. Panel (cross-section/ time series). 1995-2003

Variables	Model 7 (1995-2003)	Model 8 (1995-2003)	Model 9 (1995-2003)
Constant	-10.33 (27.30)	14.75 (26.55)	-100.40 (35.53)
GDP_i	3.27 (3.03)	5.23 (4.22)	3.83 (3.76)
GDP_j	-1.18 (1.64)	-0.27 (1.36)	-0.54 (3.58)
Distance	-3.26 (3.82)	-19.02 (9.63)	-1.36 (4.17)
Relative Prices			-0.31 (6.48)
Weighted Applied Tariffs	-0.31 (0.13)	-0.35 (0.12)	-0.23 (0.52)
Freedom from Corruption Agreements	1.83 (1.87)	0.93 (1.49)	2.05 (4.46)
Linear trend	0.10 (0.06)		
Latent variable for the U.S.		35.39 (2.20)	
Latent variable for China		46.99 (4.86)	
Latent economic cycles (t)*			44.80 (2.11)
SPE	0.27	0.27	0.17

* average value.

We run several models including the latent variable in order to catch other importing Countries-effects. When doing this, the negative sign of the constant turns into positive and increases its value. Moreover, the inclusion of a Latent Variable for Business Cycles seems to be correlated to the Relative Prices. Excluding the Relative Price in the model, the Business Cycles coefficients change in sign and magnitude. Another interaction was noticed, related to the importer GDP sign. The Freedom of Corruption Index, in this case, was positive, indicating that as the corruption perception in the importers countries is getting better, the bilateral trade increases.

One should note that the more parsimonious the model, the better the expected results of the gravity model. For instance, the inclusion of explanatory variables changes signs of the parameters, according to the expected results. Probably the reduced number of cross-sectional data is affecting the estimates for the countries variables, such as Distance, Latent for countries and agreements. This statement is plausible because the U.S. and China are both great markets for Brazil. Changes in these selected variables may influence the results in the gravity model.

5.2 U.S. - Bilateral Trade

Results for the United States bilateral trade flows with Brazil and China were also analyzed in order to provide opportunities to compare their determinants with those verified for Brazil.

Table 5a presents the results of this trade. In the second column, considering the traditional explanatory variables in the period of 1962 through 2003, results show the expected signal. The third column shows the same model in the period of 1995 through 2003. There is a significant change in the GDP_i and Distance estimation, possibly because of the small number of observations.

In general, estimates for Relative Prices and for the Political Indexes showed better results for the gravity equation in the case of the US bilateral trade compared to the Brazilian case. However, tariffs get worsen. When trying to exclude Relative Prices, the sign and magnitude of the Weighted Applied Tariffs were not stable. This fact deserves a more detailed study, because the Chinese process of applying for a WTO membership may have caused this unexpected outcome.

It is worth to comment that the SPE criteria indicate that the models specification were better for the U.S. case than for the Brazilian's as exporters.

Still comparing results for Brazil and U.S. bilateral trade models, one could affirm that the Relative Prices (given by the ratio between the exporter consumer price index and the importer consumer price index) did not perform well in the model. On the other hand, the Weighted Applied Tariffs show expected signal results.

The Trade Freedom Index and the bilateral Agreements variables between the U.S. and both importers governments (Brazil and China) showed relevant results. Comparing models 3 and 4, one can note that coefficients change little. The importer and exporters GDP are different, alternating their relevance in explaining the bilateral trade considering different years, but the Relative Prices and the Weighted Applied Tariffs showed very equivalent results, in signs and magnitudes.

Considering the Index Perception of Corruption, it seems to influence the sign of the importer GDP, turning its coefficient into negative. All the models including the Perception of Corruption Index showed the same pattern. There was a cross effect on the importers GDP measures.

Table 5a. Comparison of different gravity models with a basic specification for the United States bilateral exports to China and US. Panel (cross-section/time series). 1962-2003

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(1962-2003)	(1995-2003)	(1992-2003)	(1995-2003)	(1995-2003)	(1995-2003)
Constant	-42.31 (8.30)	29.58 (12.28)	-60.91 (17.99)	-78.23 (45.31)	-56.60 (18.46)	-20.78 (17.95)
GDP _i	1.28 (0.45)	-0.91 (0.48)	0.11 (0.72)	0.97 (1.32)	2.59 (0.59)	0.78 (1.83)
GDP _j	1.22 (0.22)	1.75 (0.33)	1.14 (0.39)	0.54 (0.61)	-0.85 (0.44)	0.89 (0.47)
Distance	-0.64 (0.53)	-3.05 (0.74)	5.55 (2.24)	6.40 (6.05)	2.77 (1.66)	-0.91 (4.80)
Relative prices			-0.10 (0.03)	-0.10 (0.06)		-0.07 (0.04)
Weighted Applied Tariffs			-0.02 (0.14)	-0.01 (0.18)	-0.07 (0.16)	0.59 (0.41)
Freedom from Corruption						-1.53 (1.36)
Corruption Perception					1.28 (0.35)	
AR(1)						0.34 (0.24)
SPE	1.07	0.07	0.10	0.08	0.07	0.02

The last model in Table 5a added the Autoregressive component to the gravity equation. The impact of this lagged variables were positive and significant for the U.S. for all the models with this variable. On the opposite side, in the Brazilian bilateral trade flows case this fact was not relevant.

In this model, some coefficients behave as expected (Relative Prices, Distance and GDPs) while others showed different results (Freedom of Corruption and Trade Policy variables).

Comparing results from Table 4a and 5a, it is worth mentioning that the standard deviations of the U.S. coefficients for importer size seem to be slightly better in relation to the Brazilian case.

In both cases, distance is still a problem. The fact is that the cross-section data is considerably small to have a significant impact on results. As we have already stressed, including the Relative Prices, the coefficients were more reasonable and stable for the U.S. than for the Brazilian case. However, better results were found in the case of Applied Tariffs, as a resistance measure for the Brazilian bilateral trade equations.

In both cases, the Political Variables did not perform well. This result suggests that might be the case of increase the cross-sectional data set in order to improve the results.

The results in Table 5b incorporate the Linear Trend and the Latent Variables (for Country-effects and Business Cycles). In fact, when including the Linear Trend all the results change in sign and magnitude.

Table 5b. Comparison of different gravity models with a basic specification for the United States bilateral exports to China and US. Panel (cross-section/ time series). 1995-2003

Independent variables	Model 7 (1995-2003)	Model 8 (1995-2003)	Model 9 (1995-2003)
Constant	10.89 (39.06)	20.12 (31.64)	-98.40 (47.48)
GDP _i	1.26 (1.35)	1.89 (1.27)	2.19 (4.10)
GDP _j	0.24 (0.64)	0.06 (0.72)	-0.25 (1.48)
Distance	-10.76 (5.55)	-13.23 (3.91)	5.27 (9.09)
Relative prices	-0.13 (0.06)	-0.10 (0.03)	-0.07 (0.15)
Weighted Applied Tariffs	-0.22 (0.32)	-0.12 (0.28)	-0.03 (0.43)
Freedom from Corruption	0.45 (0.62)		
Trade Freedom		0.24 (0.38)	0.22 (1.25)
Latent variable for Brazil	57.53 (1.30)	57.07 (1.33)	
Latent variable for China	62.85 (1.32)	62.42 (1.27)	
Latent economic cycles (t)*			15.36 (1.05)
SPE	0.04	0.04	0.04

* average value

Unlikely, modeling using the Latent Variables provided really reliable results (columns 2, 3 and 4). The best-fitted models also included both Relative Prices and the Applied Weighted Average Tariffs. However, differently from the previous results (Table 5a), when including the Business Cycles there is some interference in the Relative Prices effects, in such a way that when running with both variables, the Business Cycle effects are positive and significant large. If the Relative Prices are removed from the model, the Business Cycle effects become negative and significantly lower.

Another general comment is related to the Autoregressive variable and running the model concomitantly with the Latent Variables. The model adjustment gets worse significantly.

Models 7 to 9 showed favorable coefficients for the importer/exporter GDPs, for the Relative Prices and also for the Applied Tariffs. In the case of model 7, the Index that measures Freedom from Corruption was positive, following the expectation as the higher the Perception of Corruption, the more transparent are the trade transactions. This term was expected to be positive.

Making some slight changes in the variables to measure resistance/incentives to trade, one can notice that the signs and magnitudes of the variables are consistent and almost the same for the models presented in Table 5b. In column 3, the model 8 shows the substitution of the Freedom from Corruption Index by the Trade Freedom index, and both presented positive effects on bilateral trade flows for the US exports. Thus, these results indicate that reducing corruption and/or reducing trade barriers, tariffs and non-tariff barriers, favors commerce.

An additional comment is worth. The barriers are being modeled in two ways. First, through the Applied Average Weighted Tariffs and secondly through the Trade Freedom Index. The latter includes tariffs and non-tariffs barriers to trade. An increase in the values of this variable represents a reduction in trade barriers (expected to have positive sign).

In Model 9, when including the Latent Variable for the Business Cycles an important change is noticed in the importer GDP, suggesting that this Latent affects the time series variable.

Comparing results presented in Tables 4b and 5b, respectively, for Brazilian and North-American bilateral exports, it is evident that coefficients for the U.S. are more consistent with the literature when considering their magnitudes.

The Relative Price variable was not significant for the gravity model adjustment in the case of Brazil. But, it was for the U.S.. The Applied Tariff coefficient performed well for both cases, but it is systematically higher for the Brazilian exports.

Political indexes did not perform well for the Brazilian models but in the case of the U.S. exports, this variable presented some level of consistence. The Latent Variable for countries showed some interesting results and particularly stronger effect for China than for the U.S. or Brazil (Table 4b and 5b, in sequence).

Differently from the results of table 4a and 4b, tables 5a and 5b shows that the inclusion of variables reduce the SPE criteria. In terms of prediction the last 4 models for modeling the US bilateral trade with the selected countries are better than the previous models. In other words, these models fit better the data set.

6 Conclusion

This paper proposes to identify relevant factors affecting trade between Brazil and China, analyzing also the U.S. participation, because of its importance as a partner for both countries. In fact, considering the distance among these countries and their large territories and consumer market, it was adopted a gravity model structure. Moreover, cultural and political aspects are supposed to have an important role, as language, political structure and the presence of government controls on trade. These are factors that, intuitively, becomes China a differentiated partner from others traditional Western ones. In order to model our panel data set we use a Hierarchical Bayesian model. We added to the traditional determinants, latent variables to check for country-effects and Business Cycle effects, as well as an Autoregressive component and a deterministic trend.

Even modeling the data through the Bayesian Inference approach, it seems that the small number of cross-sectional and temporal observations did not provide enough information to have a good analysis. Particularly, the distance variable and the political effects had a poor performance. On the other hand, the temporal variables showed consistent results.

For instance, the GDP coefficients presented the expected sign and proper magnitudes. The trade barriers, more specifically the Applied Weighted Average Tariffs of the importers, presented statistically significant and negative effects on the bilateral countries trade, particularly for Brazilian exports. But also for the North American flows.

It is worth mentioning that the Relative Prices showed interesting results for the U.S. gravity model but not for Brazil. One possibility to explain this behavior it is the kind of products these countries commercialize and also the complex protectionism structure that countries adopt to restrict trade (trade barriers).

About the Latent Variables included in the modeling, it was noticed that they had better effects in the U.S. case. The Business Cycle variable presented significant effects but its incorporation seems to cause unexpected changes in other variables. The cross-sectional Latent Variables also showed large and significant coefficients. Systematically, the effects were higher for China, than for the other countries.

In spite of the fact we are using an index for the Relative Prices, this index should receive special attention, getting a data set that represents better the relative exporting prices between trade partners.

It is important to consider that the Relative Prices are supposed to be more sensitive whenever transactions involve more differentiated products than homogeneous, based on the literature. So, there is opportunity to go further with this research to discriminate the exports/imports composition and incorporate this feature in the models, disaggregating the sales according to suitable classification systems.

A next step would be enlarging the number of countries for the cross-section analysis. For Brazil, it is very important to verify the trade pattern with the Eastern countries as traditionally too little attention has been given to the Asian partners in applied econometric studies, because of the relevance that the European Union and the United States for Brazilian imports/exports has always had..

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