The Border Effect and the Non-Linear Relationship between Trade and Distance[1]

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Abstract

The border-effect literature confirms that sub-national units tend to trade more with the rest of their country than with foreign markets. However, it is likely that ongoing processes of trade integration will generate a trade-off between internal and external integration for sub-national units within countries. In this paper we estimate the internal and external border effect, using a novel dataset that captures intra- and inter-national shipments between Spanish regions and regions in eight European countries with alternative treatments of the non-linear relationship between distance and trade.

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1. Introduction

Until recent years, international trade literature has been silent on the link between international flows and flows within an exporting country. From the empirical viewpoint, ongoing processes of trade integration such as NAFTA or the EU have inspired new studies on the effect that a country's openness to international markets has on its economic geography (Brülhart et al., 2004; Hanson, 1996, 2001). Some recent papers have also investigated the relationship between international trade performance, firm location choices and the geographical advantages associated with coastlines, trade gateways or certain transport infrastructures (Duranton et al., 2012; Atkin and Donaldson, 2012; Cosar and Fajgelbaum, 2013; Fujita and Mori, 1996). More broadly, the issue has recently been analyzed from a more theoretical viewpoint within the field of Urban Economics and the New Economic Geography (NEG) models (see Brülhard, 2011, for a survey).

From a complementary perspective, the border-effect literature (McCallum, 1995; Helliwell 1996; Anderson and van Wincoop 2003; Chen, 2004; and Okubo, 2004; among others) notes that most countries (or regions within a country) trade more with themselves than with any other country (or regions in the same country) of similar characteristics and size. Both at the regional and national level, *"home bias"* in trade seem to be a stylized fact[2]. However, from the dynamic viewpoint it is not clear if this discontinuity in trade levels will tend to disappear or remain stable after several years of economic interaction. Certain studies have focused on the dynamics of this question, measuring the evolution of internal and external trade over different periods of time. For the U.S., Jackson et al. (2006) have noted that U.S. industries shipped approximately $7 trillion in goods inter-regionally in 1997, with an increase of 18.8% since 1993. However, according to the most recent data in the U.S. Commodity Flow Survey (CFS 2007), in 2007 U.S. establishments shipped $11.6 trillion in goods within the U.S. and $0.87 trillion abroad. In relative terms, the value of U.S. deliveries within the

[2] Although the concepts of "home bias" and "border effect" are different, they are sometimes used synonymously in this literature. Papers using the "home bias" label emphasize the uneven intensity of trade within a region (or a country), whereas those using the "border effect" label tend to remark the negative effect that borders exert on flows delivered to the other regions (or countries). Moreover, because of the number of articles estimating the effect of borders on trade at different spatial scales, other labels are found in the literature. In this paper we adopt the original terminology used by McCallum (1995) and Anderson and van Wincoop (2003), which is standard in the literature.

country was 12 times higher than that of international exports; the factor was 14.1 in 2002 and 13.4 in 2007. More rigorously, for the case of Europe, Head and Mayer (2000) have quantified the evolution of the border effect between the main EU countries between 1978 and 1995, finding a sharp decrease in the first years of integration and a more persistent level after 1986. Poncet (2003) has analyzed the magnitude and evolution of Chinese provinces' engagement in domestic and international trade, finding that from 1987 to 1997 Chinese provinces' greater involvement in international trade went hand in hand with a decrease in domestic trade flow intensity. Even if Chinese provinces still rely more on goods from the rest of China than on international imports, provincial borders within China continue to matter, in the extent that they imply greater discontinuities in the Chinese domestic market.

Given these results, one may wonder if there is a trade-off between the internal and the external integration of a country. Moreover, it is not clear to what extent countries (and each of their sub-national units) that are immersed in regional integration processes such as the EU face a similar trade-off between globalization, increased trade intensity with a reference region (EU), and the maintenance of significant domestic trade (within the countries individually, and within each of their spatial units). Such variations in the trade structure of each country could, of course, have strong effects on internal economic geography (Brülhard, 2011) and, therefore, on the level of internal inequalities and the fulfillment of EU cohesion policy.

Unfortunately, in most cases, a lack of data obscures the answer to these questions. In Europe, for example, knowledge about interregional integration and cross-border economic relationships between countries is very limited, since no information is available on region-to-region flows, whether for trade, capital movements or migration. This gap conflicts with the idea of cross-border regional integration as a key instrument for the EU single-market agenda. Indeed, this objective is supposed to be the driving force behind specific, and expensive, actions by the European

Commission—such as the INTERREG projects[3], the development of cross-border transportation infrastructures and the recognition of several Euroregions[4]—which aim to strengthen economic and institutional relationships in border-regions between at least two contiguous EU countries.

The objective of this paper is twofold. First, it is to shed new light on the existing trade-off between internal and external integration in Europe, measuring the role of different borders as an impediment to trade, both within and between countries. Our approach here is rooted in the literature on the border effect that exists, on the one hand, between and within countries (regional *home bias*)—our unique dataset contains internal and external shipments by road between Spanish regions—and, on the other, between these same regions and those of Spain's main eight European trading partners. Second, our objective is to make a methodological contribution to the literature, specifically in the treatment of the non-linear relationship between trade and distance that occurs (only) when flows are observed at a sufficiently fine spatial level[5].

In this regard, this paper presents a few novelties: (1) It computes the effect of two different types of borders (*Ownregion*, *Owncountry*) simultaneously for inter-regional flows between one country (Spain) and its eight main European partners; it uses region-to-region national and international flows, something that has never been done before in Europe. We obtain robust results for alternative specifications of the gravity model, based on the fixed effect (Anderson and van Wincoop, 2003) approach. (2) Like other papers reporting border effects that shrink along with the size of the exporting unit (Hillberry and Hummels, 2008; Llano-Verduras et al., 2011), we obtain this decrease

[3] INTERREG programs provide funding for interregional cooperation between regions of different EU countries. They have existed since 2002, are implemented under the European Community's territorial cooperation objective and are financed through the European Regional Development Fund. The most recent program, INTERREG IV, ran from 2007 to 2013. It aimed to contribute to the economic modernization and competitiveness of Europe and was linked to the Lisbon and Gothenburg agendas.

[4] The term Euroregion usually refers to a transnational cooperation structure between two (or more) contiguous territories in separate European countries. There are at present several Euroregions, some of which include Spanish regions and their border counterparts in Portugal and France.

[5] This non-linearity can be induced by at least the same factors suggested before for the border effects. It can be also explained by, for example: (i) non-linear relationships between (observable) geographic distance and (usually unobservable) actual trade costs; (ii) different levels of product transportability between each pair of regions; and (iii) different transport-mode mixes for shipments to/from certain locations due to geographical advantage/disadvantage (i.e., remoteness, presence of a coast).

using a lower spatial scale for the importer (foreign regions instead of countries). (3) Finally, it suggests three new alternative strategies for tackling the non-linear relationship between trade and distance that has been discussed by others (Eaton and Kortum, 2002; Henderson and Millimet, 2008; Hillberry and Hummels, 2008). Our paper begins by incorporating a quadratic distance term, so as to capture the fast decrease in trade flows over the shortest distances. It then suggests an alternative strategy, which considers three sub-divisions of the sample by distance travelled. Furthermore, we develop a robust analysis using two innovative approaches—the linear and cubic piecewise regression and a semi-parametric regression—so as to add flexibility without imposing a specific function-form to the non-linear relation between trade and distance. These strategies produce interesting results: (i) a low but persistent *internal border effect*, which reaches a factor of 4, robust to several specifications; (ii) a persistent *external border effect* that is also about 4; (iii) a variation in the elasticity of distance when it is segmented by alternative criteria: especially by the well-known power series known as the *Fibonacci sequence* (to the best of our knowledge, this is the first time that these complementary approaches have been used for this purpose in trade analysis); (iv) finally, a tackling of the endogeneity problem by means of alternative specifications based on Hausman and Taylor (1981), which finds, with respect to our previous estimates based on Anderson and van Wincoop (2003) and Silva and Tenreyro (2006), a small remarkable variation in the estimation of the *external border effect*, with a factor around 5, and the reduction of the internal border effect estimation, with a factor around 2.

The rest of the paper is organized as follows. Section 2 briefly summarizes the literature on border effects at the national and international level. Section 3 describes our method for estimating a region-to-region trade dataset for the Spanish case and offers a descriptive analysis of new trade flows. Section 4 describes the alternative specifications of the gravity equation used in our analysis. Section 5 presents our results, and the final section summarizes our conclusions.

2. The literature on the effect of borders on trade

Some years ago McCallum (1995) found that trade between any two Canadian provinces was (on average) 22 times greater than trade between any Canadian province and any U.S. state. After this seminal contribution, many authors have repeated the exercise with other countries[6] and other spatial units. Some have estimated the relevance of *international frontiers* by comparing the domestic trade volume of one country (region) with its international trade volume (Head and Mayer, 2000; Gil et al., 2005; Minondo, 2007; Chen, 2004), while others have measured the relevance of *internal borders*, estimating how much more trade a region (province) of a given country conducts with itself than with any other region (province) of the same country (Wolf 1997, 2000; Hillberry and Hummels, 2008; Combes et al., 2005; Garmendia et al., 2012).

A number of factors may explain the effect of regional and national borders on the volume of trade. Chen (2004) classified them into two groups, by their exogenous/endogenous nature. The size of the border could be explained exogenously by tariffs, non-tariff barriers, information differences or transaction-cost differences, or endogenously by a low degree of substitutability between local and foreign products (*home bias* in preferences) or optimal location choices on the part of producers. In this respect, trade frictions would affect trade volumes through two channels. A direct effect would occur as frictions changed relative prices, inducing substitution towards proximate products. The indirect effect would occur through co-location. Firms linked closely in the input-output structure would locate nearby so as to minimize trade costs. The geographic location of firms and the importance of intermediate goods could also promote the appearance of core/periphery structures (Fujita et al., 1999), which enhanced internal flows with respect to external ones. Other authors have suggested additional causes for the border effect, such as the heterogeneity of firms (Evans, 2003;

[6] Japan (Okubo, 2004), United States (Wolf, 2000; Hillberry, 2002; Hillberry and Hummels, 2003; 2008; Millimet and Osang, 2007), the European Union (Chen, 2004; Nitsch, 2000, 2002; Evans, 2003), Germany (Shultze and Wolf, 2008), Russia (Djankov and Freund, 2000) and Brazil (Daumal and Zignago, 2008), among others.

Chaney, 2008), multi-stage production (Kei-Mu, 2010) and the misspecification of econometric models used in estimations (Anderson and van Wincoop, 2003; Silva and Tenreyro, 2006).

In this last strand of the literature, some recent papers describe the border effect as an artifact of "spatial aggregation" (Hillberry and Hummels, 2008; Llano-Verduras et al., 2011) or of a mismeasurement of the distance variable (Head and Mayer, 2000, 2002). Hillberry and Hummels (2008) used a micro-dataset on the truck shipments of U.S. firms in 1997, which offered several spatial levels corresponding to states and zip codes. Investigating the non-linear effect of distance on the extensive and intensive margin of U.S. internal shipments, they found no border effect on internal shipments at certain spatial levels (*Ownzip*). The non-linear relationship between trade and distance was controlled for with a quadratic term for the distance variable. Similarly, Llano-Verduras et al. (2011) revised the estimated effect that national boundaries (*Owncountry*) exert on Spanish domestic and international trade (at the country level) by using flow data at two different spatial scales for the exporting unit: namely, the Spanish regions (Nuts 2) and provinces (Nuts 3). They found that the size of the border effect depended largely on the unit of spatial measurement. This paper—although varying the spatial scale for Spanish units: from regions (Nuts 2) to provinces (Nuts 3)—always scaled the foreign partner at the country level. A complementary study, Garmendia et al. (2012), estimated the effect of the regional borders (*Ownregion*) on truck shipments within Spain at the province level (Nuts 3), taking into account social- and business-network effects.

Although the econometric treatment of non-linearities has been widely considered in fields such as labor economics or growth, it has received little attention in the literature of international trade and gravity equations. One of the exceptions, Mukherjee and Pozo (2011) used a gravity model to analyze the impact of exchange-rate volatility on the volume of bilateral international trade through a semi-parametric regression for a panel of 200 countries. This model considers a non-linear relationship between volatility and trade, avoiding the need to superimpose any linearity restriction on the underlying relationship between exchange-rate volatility and trade. Another interesting example is Mundra (2005), who studied the relationship between U.S. bilateral trade and the stock of

immigrants from different countries using a semi-parametric regression, where some variables enter the model linearly and there is no functional form for the proxy of social networks (immigration stock). De Benedictis et al. (2008) investigated the empirical relationship between overall specialization and per capita income using the Balassa Index of Revealed Comparative Advantages and non-parametric regression models. Finally, Ruiz et al. (2009) studied the non-linear relationship between remittances, institutions and growth, and, like Chami et al. (2005), discussed the advantages of semi-parametric approaches over quadratic terms. Moreover, piecewise regression (spline models), another benchmark approach for dealing with non-linearities, has also been neglected in trade analysis. In fact, we have found no remarkable examples in the field of bilateral flows, and just one on the use of spline techniques when modeling time series of product-specific exports (Martín Rodriguez and Cáceres Hernández, 2010).

As noted above, an interesting reference for our approach is Henderson and Millimet (2008), who used different parametric and non-parametric methods to discuss the nonlinear relationship between trade and distance. They specifically questioned two main assumptions of the literature: (i) that the relationship between trade and unobserved trade costs is (log) linear and (ii) that the effects of trade costs on trade flows are constant across country pairs. They then estimated gravity models both in levels and logs using two datasets and different parametric and nonparametric methods. Their paper concluded by suggesting two lines for future research that are worth repeating here: first, their exclusion of zero-trade observations; second, their observation that "while the parametric models outperform their nonparametric counterparts, all of the models perform relatively poorly using cross-country data […]. As a result, there is substantial room for improvement in modeling cross-country trade flows".

A more classical reference is Eaton and Kortum (2002), where a Ricardian model was tested by means of structural equations with bilateral flows for 19 OECD countries in 1990. In some of their specifications, the distance variable is divided into six intervals, as an alternative to the quadratic

form. The length of such intervals is ad-hoc, and its effects over the results are not subject to a robust check against alternative spatial units or division criteria.

At this point, we should specify how our paper differs from the previous literature. With respect to Hillberry and Hummels (2008), our main contribution lies in the discussion of alternative specifications for dealing with the non-linear relationship between trade and distance when the dataset combines domestic and international flows (both at the region-to-region level) any of which may cross up to nine different borders. Whereas Hillberry and Hummels (2008) were able to disentangle the effect of internal borders (*Ownregion* and *Ownzip*) on internal flows within the U.S. at very fine spatial units, they remained silent on the equivalent puzzle for international deliveries. Similarly, Garmendia et al. (2012) focused on the effect of regional and provincial borders (*Ownregion* and *Ownprovince*) and networks on domestic shipments within Spain, but did not consider the effect of national borders on international flows. Conversely, Llano-Verduras et al. (2011) focused strictly on the effect of national borders (*Owncountry*), leaving aside intra-regional flows and own-region borders.

In this paper, all flows and borders are considered simultaneously. Moreover, by using Nuts 2 regions (and not Nuts 3) we are able to obtain shrinking external border effects. Unlike Llano-Verduras et al. (2011), we do this not by changing the "spatial scale of the exporting region" (from Nuts 2 to Nuts 3) but by using regions instead of countries as the importing spatial units.

3. The Data

We should state at the outset that there is no official data on region-to-region international trade flows for any country in the EU. Gallego and Llano (2012), however, have laid out a method for

estimating region-to-region international flows between Spain and eight European countries[7]. It combines region-to-region freight statistics for Spanish trucking with international price indices (deduced from official trade data[8]) for each region-country variety. They then apply a process of homogenization to ensure a match between the dataset and official international trade statistics at the lowest common level of aggregation (year-region-to-country-road)[9]. This novel dataset for region-to-region international trade flows was connected with equivalent data on (intra- and inter-regional) trade flows within Spain, which has been the object of previous analysis (Garmendia et al., 2012). The result is a unique dataset on region-to-region flows for intra-regional, inter-regional and inter-national flows into and out of the regions of Spain (Nuts 2) and the regions of Spain's eight main European partners.

Our distance variable is the *mean actual distance* covered by Spanish trucks between each pair of trading regions, as reported in the survey published by Spain's Ministry of Public Works and Transport (Ministerio de Fomento).[10] This variable has the virtue of capturing the *real distance* travelled by trucks between actual points of departure and destinations. In this sense, it is superior to the variable used by other authors, where intra-national and/or inter-national distance is either an a-priori estimate based on the great circle distance between main cities weighted by population or an

[7] Although for the sake simplicity we use the label EU, our sample of countries does not fall under any specific administrative category. Moreover, we consider certain countries, like Andorra, as single-region countries.

[8] For most of our EU countries, we use two main sources for the inter-national bilateral flows of goods: (1) Trade statistics on intra-EU trade, which register bilateral flows between pairs of countries, both in volume and in monetary units; for certain countries, like Spain, the trade data identify the exporting or the importing region but never both simultaneously. (2) Transport statistics on intra-national and inter-national freight flows, which in some cases (e.g., road freight) provide information on the type of product transported (quantity) as well as on the regional origin and destination of the flows. Our method aims to build up a region-to-region trade dataset by combining these two sources: (1) region-to-region flows in quantities (road-freight statistics) and (2) specific region-to-country trade prices (from the official trade statistics).

[9] Trucks are the main transportation mode for international Spanish exports to the eight EU countries considered in this paper. The survey that provides the basic information on freight flows (volume) covers Spanish trucks only. In order to avoid bias in the estimation of the External Border Effect, region-to-region international flows by road have been re-scaled to the official data on Spanish exports by "road" to each of the eight EU countries. Thus the levels of the Spanish exports for each "Spanish region-country" match the official value of trade split at the "region-to-country by road" level. Therefore, the region-to-region structure is given by the Spanish truck survey, while trade levels are supported by the official trade data broken down at the lowest common level of disaggregation (region-country-year-road).

[10] We obtained the actual distances used in this paper by first screening out outliers: i.e., distances that are too great for a specific dyad. We then computed the actual distance for each regional dyad (aggregate) for each year, starting from the most disaggregated level (micro-data at the municipality level for the Spanish exporting unit). Finally, we obtained intra- and inter-regional distances by averaging the distances observed in all deliveries from 2004 to 2007 for each specific dyad *i-j*.

ad-hoc estimate by mathematical approximation. By using actual distance, we should be able to account for region-to-region inter-country links that are not attributable to the mere allocation of population. There are specific regional endowments or specificities that weighted distance tends to mask. The Ministry's survey also includes the actual distance travelled by trucks for inter- and intra-regional deliveries. Crucially, this allows us to avoid choosing alternative ad-hoc intra-regional distances, which alter results on border effects (Head and Mayer, 2002). Regional GDPs for the EU regions under consideration are published by Eurostat.

3.1. Descriptive Analysis

Before proceeding to the econometric analysis, we will briefly analyze the novel dataset to show the non-linear relation between trade and distance when the spatial grid is sufficiently fine. With this purpose, we offer a first view of the distribution of trade (always region-to-region) as it depends on distance travelled by trucks, for both domestic and international deliveries. Like in (Garmendia et al., 2012; Llano-Verduras et al., 2011; Hillberry and Hummels, 2008), we also use a kernel regression to generate a nonparametric estimate of the relationship between distance and the intensity of Spanish regional export flows[11].

<< Figure 1 about here >>

Figure 1 plots the distribution of domestic and international flows (exports) for each region against those for the rest of Spain's regions and the eight European countries. Note that trade flows are corrected by the GDP of each exporting/importing region. To illustrate the *multi-level dimension of the non-linear relation between trade and distance*, the figure has a separate plot for the kernel regression of each kind of trade flow: i.e., intra-regional flows within Spain, inter-regional flows within Spain and inter-regional exports from Spanish regions to regions in the eight countries. To

[11] We use the Gaussian kernel estimator in STATA, with n = 100 points and the estimator calculating optimal bandwidth.

bring out the great differences in intensity, the graph displays two different scales: one for intra-regional flows (left axis) and one for the remaining flows (right axis). Moreover, to emphasize the similar shape of each kernel distribution, the *international flows* kernel is plotted twice: with its natural scale and re-scaled at a factor of "x4" (in line with the largest *external border effect* reported in this paper). In distinguishing the great differences in the relative intensity of the flows, we can also see the *regularity* of the non-linear relationship between trade and distance over the shortest distance. By mixing together different types of flows, other papers have emphasized the sharp decrease on the intensity of trade over the shortest distances (e.g., 700 km). Our approach shows how length of flow varies by kind of flow.

From this analysis we can conclude that, regardless of flow type, the bulk of trade takes place over short distances and beyond a certain point the negative effect of distance falls off deeply. Hence the relevance of territorial disaggregation, Llano-Verduras et al. (2011) and Garmendia et al. (2012) have shown that, with insufficient territorial disaggregation of trade, the gravity equation may lead to an overestimation of the border effect and an underestimation of the distance effect. As we will see in the next section, this overall effect can arise not just when regions are used instead of provinces, but also when countries are used instead of regions. Because of this non-linearity, moreover, sharp decreases in trade intensity may or may not coincide with the administrative units where the flows are allocated (and where the borders are!). It would thus be interesting to consider econometric procedures flexible enough to control for that.

<< Figure 2 about here >>

Complementarily, **Figure 2** shows the distribution of each type of flow (in logs and without controlling for GDPs) by exporting region. To interpret this, it is critical to take into account that the figure plots the distribution of observations around the corresponding mean rather than aggregate magnitudes. The aim of this graph is threefold: First, to illustrate the variability of trade in each market (intraregional, interregional within Spain and interregional with the rest of Europe), and show

that, although there are some rare small international exports, the intensities for each category are quite stable (structural). Second, as with kernel regressions, to confirm a clear discontinuity in the intensity of trade in the presence of both regional and national borders. Note that in almost all regions, there is little overlap between the intensities of interregional flows within Spain and with Europe, and none at all between intra-regional trade and the other two categories. Third, to demonstrate the remarkable variability in the range of trade intensity by region. For the sake of clarity, the exporting regions are ranked by largest flows (intra-regional). Cataluña has the largest intensities for each category, showing outstanding values for intraregional and international flows. Other cases are also worth mentioning: Galicia and Asturias, for example, show wide ranges of flows, with several outliers in the bottom part of their distribution; conversely, the Madrid region shows a shorter and more compact range (no outliers in the bottom part of the distribution) together with intense flows in all categories.

4. The Empirical Model

4.1. Baseline models

As in most of the articles cited previously, the backbone of our investigation is the gravity equation, where the intensity of trade between any two locations (regions or countries) is positively related to their economic size and inversely related to the trade cost (proxy by geographical distance) between them. However, we depart from previous literature by redefining specific border effects to be measured. By *Internal Border Effect (exp|Internal_Border|)* we denote the number of times a Spanish region trades less with any other domestic region in the sample than with itself. By *External Border Effect (exp|External_Border-Internal_Border|)* we denote the number of times a Spanish region trades less with a foreign region elsewhere in Europe than with another Spanish region, controlling for a set of factors.[12]

For the sake of brevity, we define two equations that contain the benchmark models:

[12] Note that with these definitions, the addition of the two border effects (External Border Effect + Internal Border Effect) we denote the number of times a Spanish region trades less with a foreign region elsewhere in Europe than with itself.

$$Ln\frac{T_{ijt}^{eu}}{GDP_{it}xGDP_{jt}} = \beta_0 + \beta_1 Internal_Border + \beta_2 External_Border + \beta_3 Internal_Contig +$$

$$\beta_4 External_Contig + \beta_5 Ln(dist_{ij}) + \mu_{it} + \mu_{jt} + \mu^u + \mu_t + \varepsilon_{ijt} \quad [1]$$

Where $\frac{T_{ijt}^{eu}}{GDP_{it}GDP_{jt}}$ represents bilateral flows originating in Spanish regions and corrected by the GDPs of the trading regions[13]. More specifically, T_{ij}^{eu} is the flow from region *i* in country *e* to region *j* in country *u* in year *t*. Note that: (a) if *e* = *u* = *Spain* and *i* = *j*, Eq. [1] will capture intra-regional trade flows for a Spanish region *i*; (b) if *e* = *u* = *Spain* and $i \neq j$, Eq. [1] will capture inter-regional trade flows for a pair of regions within Spain *ij*; (c) if $e \neq u$, Eq. [1] will capture inter-regional flows between Spain and another European country in the sample. Since this paper focuses on flows originating in Spanish regions, *e* = *Spain*. Because of the characteristics of our road-flow dataset, we exclude flows where the regional partner is a Spanish island (therefore I=15 for Spain). The variables GDP_{it} and GDP_{jt} are the nominal gross domestic product (GDP) of the exporting and importing region, respectively. The variable $Ln\ (dist_{ij})$ is the logarithm of the distance between region *i* and region *j*.

The variable *Internal_Border* controls for flows that cross a domestic frontier, i.e. it takes the value one when the origin and the destination are different regions but both belong to the same country (interregional flows within Spain trade *e*=*u*=*Spain* and $i \neq j$) and zero otherwise. In addition, the variable *External_Border* is a dummy that controls for flows that cross an international boundary, i.e. it takes the value one for inter-national flows (*e*=Spain*; u* =any of the 8 European countries considered) and zero otherwise. The anti-log of the parameter associated with these two variables measures the size of the effect that national and regional borders respectively exert on trade.

To capture the positive effect of adjacency, we introduce two dummy variables: *Internal_Contig* and *External_Contig*. This allows us to consider (simultaneously or independently) the different effects

[13] Note that in the tables of results we refer to this term as T_{ijt}_corr (trade flow corrected for the GDPs' product), instead of $T_{ijt}^{eu}/GDP_{it}GDP_{jt}$, just for saving notation and keeping clear these tables.

that *adjacency* exerts on trade flows between two contiguous regions in Spain or between a Spanish region and a contiguous foreign one. *Internal_Contig* takes the value one when trading regions *i* and *j* are contiguous and both located in Spain and zero otherwise. Similarly, *External_Contig* takes the value one when region *i* is a Spanish region exporting to a foreign contiguous region *j* and zero otherwise. These variables conveniently control for higher inter-regional trade flows between contiguous Spanish regions as well as for the higher concentration of trade between border regions of different countries (Spain-Portugal, Spain-France, Spain-Andorra). It is in line with the results of Lafourcade and Paluzie (2011), who have shown that border regions in countries like France and Spain tend on average to capture larger shares of bilateral trade and FDI flows.

The terms μ_{it} and μ_{jt} correspond to the multilateral-resistance fixed effects for each origin and destination region interacted with time, respectively (Anderson and van Wincoop, 2003; Feenstra, 2002). These fixed effects are meant to control for competitive effects exerted by the non-observable price index of partner regions and by other competitors. They are also meant to capture other particular characteristics of the regions in question. To account for the likely heterogeneity between countries and its effect on the estimate of a single border effect, we have also added for each destination country a fixed-effect term (μ^u). In addition, a time fixed-effect term (μ_t)is included, which controls for cyclical factors that are common to all the European countries (global cycle, developments in the integration process, exposure to external economic shocks, etc).

Eq. [2] describes an alternative specification with certain refinements in the treatment of distance.

$$Ln\frac{T_{ijt}^{eu}}{GDP_{it}GDP_{jt}} = \beta_0 + \beta_1 Internal_Border + \beta_2 External_Border + \beta_3 Internal_Contig +$$

$$\beta_4 External_Contig + \beta_5 dist_{ij} + \beta_6\left(dist_{ij}\right)^2 + \mu_{it} + \mu_{jt} + \mu^u + \mu_t + \varepsilon_{ijt} \qquad [2]$$

It thus includes, apart from the traditional variable $dist_{ij}$, a new variable$\left(dist_{ij}\right)^2$. As in Hillberry and Hummels (2008), Llano-Verduras et al. (2011) and Garmendia et al. (2012), the variable

$(dist_{ij})^2$ is defined as the square of the distance between trading regions and is expected to capture the non-linear relationship between trade and distance that is observed for kernel regressions in Figure 1. Also in line with these papers, we split the interpretation of these two variables (capturing the negative but non-linear effect of distance on trade) into two parts: (i) a negative and direct effect of distance on trade and (ii) a positive effect for the square of the distance, to capture the high concentration of trade over the shortest distance as observed in the kernel regression.

4.2. Alternative specifications

4.2.1. Gravity equation with segmented distance

Next, as an alternative way to deal with the non-linear relationship between trade and distance, we introduce a flexible approach that controls for changes in the slope of our linear estimation for different "segments" of the sample, these segments corresponding to different distances traveled by trucks. Although purely non-parametric techniques such as kernel regression offer certain flexibility, they cannot quantify the border effects under discussion. As we will see in the next section, this new approach generates different results from those of the square of distance. In our view, the variation is due to the differing capacities of the alternative strategies to deal with the non-linear relationship shown in Figure 1, which repeats itself at different levels of aggregation, perhaps as flows cross certain thick borders[14]. For each regression using this approach we proceed as follows[15]: (1) we rank the whole sample by increasing distance; (2) we divide the entire range of distance traveled (max-min distance observed in the sample) into "segments" (stretches). For purposes of rigor, we define the "segments" in three alternative ways:

[14] Two examples of thick borders (i.e., administrative borders coinciding with specific forces that cause considerable agglomeration of trade at a short distance) are: (a) Internal borders defining large metropolitan areas; these may coincide with the space where the forces of economic agglomeration around cities are at work, causing a great volume of intra- and inter-regional flow between contiguous regions. (b) International frontiers, coinciding with disproportionate divisions in terms of legal, cultural, historical and political barriers to trade.

[15] Note that segmentation of the sample by range of distance traveled varies for specifications that estimate *internal border effects* (subsample excluding inter-national flows) or focus on *external border effects* (subsample excluding intra-regional flows).

i. **"Naïve":** The first way simply divides the entire range of actual distance traveled into four stretches of equal length (in kilometers). We call it "naïve" because it ignores the expected higher intensity of flows over the shortest distance.

ii. **"Fibonacci":** The second way follows the *Fibonacci sequence*, a "magical" mathematical relation that appears in several natural phenomena (the reproduction of rabbits, the internal structure of sunflowers, etc.). The sequence has been used in architecture and in certain fields of economics and finance but, to the best of our knowledge, never before in trade. One benefit of the sequence is that it produces "segments" of increasing length. Another is that the sequence, although completely exogenous, fits perfectly with the non-linear intensity of trade at the nearest distance, dividing the entire range of distance as follows: first stretch: 8% of distance; second stretch: 8%; third stretch: 17%; fourth stretch: 25%; fifth stretch: 42% (100% in total).

iii. **"Quartile":** The third way assures an equal distribution of the number of observations per segment. It arranges them into quartiles of observation distribution, ranked by distance traveled.

This novel strategy is formally expressed in Eq. [3]:

$$\frac{T_{ijt}^{eu}}{GDP_{it}xGDP_{jt}} = \beta_0 + \beta_1 Internal_Border + \beta_2 External_Border + \beta_3 Internal_Contig +$$

$$\beta_4 External_Contig + \text{STRETCH}^s * Ln(dist_{ij}) * \theta + \mu_{it} + \mu_{jt} + \mu^u + \mu_t + \varepsilon_{ijt} \qquad [3]$$

$STRETCH^s * Ln(dist_{ij})$ denotes the interaction between the log of the distance and a matrix STRETCH, which contains a set of dummy variables identifying each "segment". By including such interactions, we essentially introduce a set of "semi-dummy" variables, where $Ln(dist_{ij})$ replaces the value one of a normal dummy for the corresponding stretch. θ is a vector containing the coefficients for each distance stretch. Superscript *s* indicates the three alternative ways of splitting the sample (Naïve, Fibonacci, Quartile). The rest of the variables are the same as those used in previous specifications.

4.2.2.A look at the effect of the national border

Before considering alternative treatment for the non-linearities, it is appropriate to analyze the heterogeneity of the external border effect for each destination country. This analysis uses equation [4]. As in equation [3], we still consider the distance variable divided into different stretches. In addition, the *External_Border* effect is split according to the European destination country. Thus, the variable is renamed accordingly, using the label *Border_Country*.

$$\frac{T_{ijt}^{eu}}{GDP_{it}xGDP_{jt}} = \beta_0 + \beta_1 Internal_Border + \beta_2 Border_Country + \text{STRETCH}^s * Ln(dist_{ij}) * \theta + \mu_{it} + \mu_{jt} + \mu_t + \varepsilon_{ijt} \quad [4]$$

Border_Country represents a set of dummies, one for each European country, that take the value 1 when the destination of the flow is a non-Spanish region located in each one of the countries of the sample. Thus, a negative sign is expected for the coefficient of each one of these variables. The absolute value of such coefficient might be over or under the unique *Border_Effect* coefficient estimated in Eq. [3]. The country destination fixed effect, which considered the particular resistance/propensity of each country to import Spanish products is now redundant and drops from the equation.

4.2.3.A Piecewise regression approach

As a robust check, three alternative piecewise regressions—namely, two linear and one restrictive cubic spline models—have been estimated. Piecewise models are also known as spline regressions and are described in the literature as efficient ways to approximate true non-linear relationships in data. Their main advantage is that the shape of the estimated function acquires a larger flexibility and is data driven, since no form is imposed a priori. A piecewise linear function is composed of linear segments—straight lines—separated by a number of *knots*. In some econometric packages (i.e., Stata) the number of knots as well as the specific location of each can be set a priori by the researcher, or be automatically assigned by the procedure to find the best fit for the data. In keeping with our previous models, we consider four segments in every one of them. In our case, the three

spline models can be described by Eq. [5], where element $f(Ln(dist_{ij}))$ corresponds to the three alternative segment definitions:

$$Ln\frac{T_{ijt}^{eu}}{Y_{it}Y_{jt}} = \beta_0 + \beta_1 Internal_Border + \beta_2 External_Border + f(Ln(dist_{ij})) + \mu_{it} + \mu_{jt} + \mu^u + \mu_t + \varepsilon_{ijt} \quad [5]$$

For the first linear spline (M13 in Table 4), three equally spaced knots were set. For the second linear spline (M14 in Table 4) the three knots were assigned in accord with the sample's quartiles. Finally, we estimated a restricted cubic spline to better capture the strong non-linearity observed in the shortest distance (M15 in Table 4), here we also set four segments (knots=3) a priori, although the size of each segment was automatically determined.

4.2.4.A semi-parametric regression approach

We have also applied a semi-parametric approach (Pagan and Ullah 1999; Yatchew, 1998) for the same purpose of achieving some flexibility in modeling the non-linearity as well as in estimating our desired parameters (*internal* and *external border effects*). We have followed Robinson (1988),[16] who described a general model of the type in Eq. [6]:

$$y_{ij} = \beta_0 + x_{ij}\beta + f(dist_{ij}) + \varepsilon_{ijt} \quad [6]$$

Where y_{ij} is the dependent value expressed in dyadic terms ij (bilateral flows divided by the corresponding income levels), and $x_{ij}\beta$ is a matrix with the corresponding explanatory variables whose parameters are to be estimated (*internal* and *external border effects* among others*)*. $dist_{ij}$ is the explanatory variable that enters the equation non-linearly in accord with a non-binding function *f*. This model can be estimated using Robinson's (1988) double residual method, which starts by applying a conditional expectation to both sides of [6]. This leads to:

$$E(y_{ij}|dist_{ij}) = \beta_0 + E(x_{ij}|dist_{ij})\beta + f(dist_{ij}) + \varepsilon_{ijt} \quad [7]$$

[16] Verardi and Nicolas (2012) have described this approach and developed the corresponding Stata routine (*semipar*) for implementing it. We are grateful for this contribution.

By subtracting [7] from [6], we obtain Eq. [8]

$$y_{ij} - E\left(y_{ij}\middle|dist_{ij}\right) = \left(x_{ij} - E\left(x_{ij}\middle|dist_{ij}\right)\right)\beta + \varepsilon_{ijt} \quad [8]$$

If the conditional expectations are known, parameter vector β can be estimated by means of OLS. If they are unknown, they can be estimated with a non-parametric kernel estimator, as in Robinson (1988).

4.2.5.A final robust check on endogeneity

Finally, we would like to address an econometric issue that has been analyzed with panel data and gravity equations in previous papers (Egger, 2002; Mitze 2010; Brun et al., 2005; Belke and Spies, 2008; Serlenga and Shin, 2007). The advantage of panel data is that they allow one to control for unobservable bilateral fixed effects, whose existence implies bias in Pooled Ordinary Least Square (POLS) estimates. The Random Effects Model (REM) approach yields consistent estimates only when the regressors are uncorrelated with the unobservable dyadic fixed effect. However, it is likely to find correlation among some exogenous variables and the unobservable pair-individual effects, which is termed as right-hand side endogeneity, in this case the REM approach is not valid. This correlation can be verified with the Hausman Test, whose null hypothesis indicates non-correlation. Although the use of Fixed Effects (FE) estimators is a straightforward way to tackle such a problem and gives unbiased estimates of time-varying variables, when applied to gravity equations it impedes the analysis of important time-invariant variables, such as distance, contiguity and border-effect dummies. As an alternative, several authors have favored the Hausman-Taylor (1981; hereinafter HT) approach, which provides estimates of both time-varying and time-fixed regressors. Departing from some of the following references (Egger, 2002; Mitze 2010; Belke and Spies, 2008), the HT approach can be expressed as a model of the form described in Eq. [9]:

$$\mathrm{Y}_{ijt} = \delta_0 + \delta_1 X1_{ijt} + \delta_2 X2_{ijt} + \gamma_1 Z1_{ij} + \gamma_2 Z2_{ij} + \mu_{ij} + \varepsilon_{ijt} \quad [9]$$

Where Y_{ijt} is the dependent variable; μ_{ij} corresponds to the unobservable bilateral fixed term, iid N(0,σ_μ); ε_{ij} is the residual of the model, iid N(0,σ_ε); $X1_{ijt}$ and $X2_{ijt}$ represent vectors of time-varying variables; and $Z1_{ij}$ and $Z2_{ij}$ contain vectors of time-invariant variables. $X1_{ijt}$ and $Z1_{ij}$ are doubly exogenous variables[17]. $X2_{ijt}$ and $Z2_{ij}$ denote vectors of endogenous variables, which produce a bias under the REM approach. It is worth mentioning that one advantage of the HT estimator is its hybrid nature[18], which allows for endogenous and exogenous regressors.

The HT strategy is a two-step estimation procedure based on the Instrumental Variable (IV) technique, where the second step considers the GLS transformation of the variables. The instruments come from the own specification of the model, exploiting the double dimension of regressors in a panel (time and individual).

More specifically, the instruments for time-varying variables are their *within-group* transformation. In this way the estimator achieves consistent estimates of parameters δ_1 and δ_2. The choice of instruments for the time-fixed regressors depends on their exogenous status. The exogenous regressors, $Z1_{ij}$, serve as a valid instrument of themselves, whereas the endogenous, $Z2_{ij}$, need the *between* information of the exogenous time-varying variables ($\bar{X}1_{ij}$) as instruments. Accordingly, the number of time-fixed endogenous variables should be lower or equal to exogenous time-varying regressors.

To re-estimate Eqs. [1] and [3] under this last constraint, we follow Carrère (2006) passing the variable of GDP's product to the right-hand side, which will be considered as endogenous variable for the HT procedure. *Internal_Border*, *External_Border*, *Internal_Contig*, *External_Contig* and *Distance (Ln(dist$_{ij}$)* are classified as dyadic time-fixed variables, *Ln(GDP$_{it}$*GDP$_{jt}$)* as the only dyadic

[17] In the context of panel data, some authors employ the terminology of doubly exogenous regressors, when they refer to regressors non-correlated neither with the error term nor with the unobservable dyadic fixed effect term, and employ the term of singly exogenous regressors, when they refer to regressors correlated with the unobserved heterogeneity term. Here we employ interchangeably the terms of: exogenous regressors and doubly exogenous; and endogenous and singly exogenous regressors.

[18] In the opposite side, the FEM assumes the correlation of all the variables with the unobservable term, and the REM assumes a non-correlation between regressors and the unobservable term.

time-varying variable, and the multilateral resistant terms (μ_{it}, μ_{jt}) and destination country (μ^{u}) and year (μ_{t}) fixed effects are considered as exogenous monadic variables.

Empirically, the main problem for the HT approach is deciding whether a variable should be considered a-priori as correlated or uncorrelated with the individual effects. We consider different options depending on the economic meaning of the assumption: (i) as a starting point, we consider the non-existence of heterogeneity in the model, and apply a POLS estimator; (ii) we assume the existence of unobservable heterogeneity but with zero correlation with the rest of the regressors, and use the REM estimator; and, finally, (iii) after refusing the null hypothesis of Hausman's test, we follow Carrère (2006) in considering GDP as a significant source of endogeneity.

5. Results

In this section we analyze the main results for the twenty-four models estimated in this paper with our novel region-to-region dataset. The first specifications to be considered use *corrected trade* flows $\frac{T_{ijt}^{eu}}{GDP_{it}GDP_{jt}}$ as the endogenous variable as well as all the fixed-effects approaches described above. However, each uses a different treatment of the distance variable. In contrast to previous papers, the effects of external (*External_Border*) and internal (*Internal_Border*) borders are estimated simultaneously in all specifications: that is, with the whole sample considered at the same time. We are thus able to determine whether the two border effects are at work: that is, when certain (international) flows are crossing two borders (one internal, the other external) or more[19]. Note that such results would not be fully comparable with those previously reported, since with just two dummies we would have to control for three types of flows (intra-regional, inter-regional within Spain and inter-regional with other EU countries). However, this approach is close to computing the *internal border effect* (*Internal_Border*) within a single country (*Euroland*) with two nested

[19] Note that in some cases (e.g., exports from Spain to Germany) a Spanish truck may cross three or four different national borders. As described in the introduction, this could induce additional "jump" in the intensity of trade.

administrative borders, as Hillberry and Hummels (2008) did for the U.S. Our analysis and interpretation of the results will therefore be close to theirs.

The results generated by Eqs. [1] to [3] are reported in Table 1. Ordinary Least Square (OLS) estimators are used when the gravity equation is applied to a dataset with no zero-values, in this case we are modeling only the intensity of flows between regions, not the drivers behind the existence or non-existence of said flows. When zeros are included[20], we use instead the pseudo-maximum likelihood technique (PPML). It was Santos Silva and Tenreyro (2006) who proposed using the PPML approach, which also sorts out Jensen's inequality (note that the endogenous variable is in levels) and produces unbiased estimates of the coefficients by solving the heteroskedasticity problem.

<< Table 1 about here >>

Table 1 reports the results for the first six models. M1 includes the endogenous variable and the distance in logs (OLS without zero flows). M2 include zero flows and use the PPML estimator. Thus the endogenous variable is expressed in levels and distance in logs. In M3 *distance* and the *square of distance* are included in levels. Next, to shed more light on the non-linear relationship between trade and distance, M4–M6 report the corresponding results for three alternative models based on our alternative strategy (Eq. [3]), which segments the sample in three ways by trucking distance. This procedure estimates the elasticity of distance in each interval. Note that in these models the distance variables for each "stretch" are also expressed in logs.

The first three models (M1-M3) generate significant coefficients with the expected signs for all variables except *External_Contig*. This result suggests that the difference in the intensity of trade between a Spanish region and a foreign border region, on the one hand, and between non-adjacent

[20] The zero values considered in our dataset correspond to region dyads that had non-zero values at least in one year in the period 2004–2007. Zeros corresponding to regions that did not receive any exports from a Spanish region during that period are not considered in our sample.

Spanish regions, on the other, is non-significant. However, the coefficient for the *Internal_Contig* variable is positive and significant. In the three models the coefficient for the distance variable is negative and significant, with elasticities that are within normal range. Moreover, the results for distance variables that control for the non-linear relationship between trade and distance in M3 suggest that distance acts as a clear impediment to trade (negative coefficient for $dist_{ij}$), but an impediment that tapers off as distance increases (positive coefficient for $dist_{ij}^2$).

Regarding the *External Border Effect*, model M1 reaches a value of 2 (exp|2.055-1.373|) while the other two (M2–M3) reach a factor of 3. Note that the latter two stand up robustly to alternative specifications (M4-M6), subsamples, estimation procedures and treatments for the non-linear relationship between trade and distance. This persistent value between 3 and 4 for *External Border Effect* is very close to the one obtained by Llano-Verduras et al. (2011) with region-to-country [3.3 = exp(1.2)] and province-to-country [4.9 = exp(1.6)] data. Note that these papers use different datasets and definitions of the border dummy, but similar specifications for distance and the same estimation procedures as in M2 and M3 (PPML). By contrast, the results for the *Inrernal Border Effect* are more puzzling, showing a larger variation with respect to the econometric method used to control for the non-linearity. On the one hand, the factor obtained for *Internal Border Effect* for M1, M4, M5 and M6 is exactly the same (4) and in almost all cases is very close to *External Border Effect*. On the other, *Internal Border Effect* slightly rises for M2 (factor of 8) and skyrockets to a factor of 34 in M3. Note that this jump just occurs when the PPML is used with the whole sample (zero flows included) and the quadratic term. Similar results have not been reported in articles where *Internal Border Effect* was estimated alone (Garmendia et al., 2012): that is, with the external border effect and international flows excluded.

Table 1 reports promising results for models M4 to M6, which employ our new controls for non-linearity. The coefficients for *STRETCH*Ln(dist$_{ij}$)* in each of the segments are negative and highly significant for these three alternative models. More interestingly, in M4 (Naïve) and M6 (Quartile)

the negative elasticity for each stretch decreases, which is consistent with a segmentation where the distance variable is shorted in increasing order. In M5 (Fibonacci), however, the negative elasticity of distance increases in the first two segments (from –1.104 to –1.151) and decreases thereafter (from –1.151 to –1.002). The last part of Table 1 shows the results for the Wald test applied to the Null-hypothesis of equal elasticity between consecutive stretches of distance. The results show that the differences between the stretches are statistically significant, with the exception of the first three consecutive segments in the Fibonacci division. For *External Border Effect*, the three alternative procedures for segmenting the sample reach significant factors that in absolute terms vary across 3 and 4, close to the obtained in M2 and M3. Moreover, the results for *Internal Border Effect*, also point out to a factor around 4, which is significant in all cases. Therefore, we can conclude that *Internal Border Effect* increases when zero flows are included and the PPML is used (M2–M3) but this effect is controlled for when segmented distance is used (M4–M6). Finally, it is interesting to note that the coefficients for *Internal_Contig* and *External_Contig* become non-significant. This suggests that when the non-linear relationship is controlled for by segmentation of the sample into stretches, the alternative control for the higher intensity of trade over the shortest distance (contiguity) becomes redundant.

<< Table 2 about here >>

To bring home the previous results, Table 2 summarizes the main features of the three alternative segmentations and provides measures of overall fitness for each segment. Several points are worth mentioning: (i) The three sequences have been defined not by volume or nature of trade but, instead, by distance range and number of observations (zero flows included). Thus the *Fibonacci* and *Quartile* sequences consider segments of different length. (ii) The percentage of zero values for each stretch and each criterion is different. Zero values are highly concentrated in the longest trips (mainly international flows). (iii) For a complementary view, we show the close fit obtained with the models

run separately for each segment of the sample[21]. Table 2 reports the R^2 for regressions that use ($Ln(dist_{ij})$) or ($dist_{ij}$, $dist_{ij}^2$): i.e., for the counterparts to the specifications used in M2 and M3. Note that, although the three alternative segmentation criteria generate the same R^2 ($Ln(dist_{ij})$) and R^2($dist_{ij}$, $dist_{ij}^2$) for the whole sample (TOTAL column), the quality of the fit is different for each segment and sequence. Throughout the sample (TOTAL), R^2 is always higher with $Ln(dist_{ij})$ (90.5%) than with $dist_{ij}$ or $dist_{ij}^2$ in levels (88.2%). The *Fibonacci* sequence (followed by *Quartile*) shows the best fits when the model is regressed for the last subsamples (largest distances) and generates the highest R^2 ($Ln(dist_{ij})$) and R^2($dist_{ij}$, $dist_{ij}^2$). Conversely, although the *Naïve* sequence performs well for the first two stretches, it fails for the last two.

<< Figure 3 about here >>

To complement the previous table, Figure 3 shows the distribution of the dependent variable (in logs) in regards to distance. It uses three different colors for identifying the main categories of trade flows (intra-regional; inter-regional within Spain; inter-regional exports to the eight EU countries). It also includes full-vertical lines in red for identifying the five stretches of the Fibonacci sequence, and short-vertical-lines in blue for the Quartile. The plot shows a clear "jump" in the intensity of intra-national (red-crosses and blue-bullets) and inter-national (green hollow circles) flows. The non-linear relationship is also clear.

5.1. Specifications for a country-specific analysis

We would now like to discuss the national border effect in greater detail, taking each country separately. As described in section 4.2.2, this analysis is based on Eq. [4]. Table 3 reports our results with three alternative specifications according to the three alternative segmented-distance variables proposed (Naïve, Fibonacci, and Quarterly) to treat the non-linearity in distance. The *External Border Effect* is now broken-down into each destination country. Observe though that here the

[21] Note that the results in Table 2 consider the sample subdivided according to the Naïve, Fibonacci and Quartile criteria and use the strategy for Eq. [1] and [2].

interpretation of the external border effect keeps being the same as so far, e.g., how much less a Spanish region exports to a non-adjacent foreign region than to a non-adjacent Spanish region, ceteris paribus. Taking into account the non-significant results obtained for the contiguity variables in models M4–M6, henceforth we exclude these variables when the distance variable displays a more flexible role.

<< Table 3 about here >>

The results are ranked by increasing order of *Country_border* coefficients in M8 (the ranking is pretty homogeneous for the two last specifications, Fibonacci and Quartile criteria). The lowest effects for *border* with M8 used as a benchmark are obtained for Portugal (3.9), Andorra (4.3), and Germany (4.5), followed by UK (4.7), Belgium (4.7), Netherlands (4.8), Italy (4.8) and France (5.3).

If we consider *border* as a measure of integration between Spanish regions and the regions of the eight European partners—with size and bilateral distance previously controlled for—it is remarkable to find the highest levels of integration not always with the regions of the nearest countries but sometimes with the regions in Belgium and Germany. In fact, it is remarkable the high border effect obtained for France, which is the country with the most intense trade relation with Spain. This result just can be explained by the fact that, although the actual trade is large, it is far from what the model will expect taking into account the huge trade potential of this country with regards to the Spanish regions (large GDP and high accessibility by road). This fact is empowered by the circumstance that two important Spanish regions in terms of interregional exports to the rest of Spain (Cataluña and País Vasco) are indeed neighboring regions to France. Thus, since the model is expecting a much larger trade than the observed one, the border effect of France will be larger than the one of Portugal (with a high accessibility, but a lower GDP) or further destinations such as Germany or Belgium. Segmented distance performs similarly here, where in some cases the first segments show a lower negative elasticity than the next.

<< Figure 4 about here >>

Digging deeper into this analysis, Figure 4 plots the spatial concentration of exports delivered from two key Spanish regions, Cataluña and Madrid, divided by their corresponding intra-regional flows. In the four maps, the *palette* corresponds to the number of flows, with seven color intensities automatically determined by the ArcGis's "natural break" option. We use this so that the data can speak for themselves. The first two are for Madrid, the others for Cataluña. We then use different frames to identify the regions included in the corresponding *Fibonacci* and *Quartile* stretches. It is worth mentioning that the color intensity shows a clear discontinuity in the relevance of trade flows between Spanish and European markets, even for a highly open border region such as Cataluña. It is also interesting to note which regions are included in each stretch for the two cases considered here: in the case of Madrid, the first stretch of the *Fibonacci* division (completely exogenous to our dataset) perfectly matches the two contiguous regions (Castilla y León and Castilla–La Mancha), while the second stretch captures the rest of the Spanish regions with the sole exceptions of Cataluña and Galicia. By contrast, the first stretch of the *Quartile* division is now broader, including all the Spanish regions as well the Portuguese and the nearest French ones. However, if we consider the regions classified in every stretch for Cataluña, we see that the stretches for national and international markets do not exactly correspond. We should thus emphasize that the composition of each stretch will naturally depend on the specific location of each Spanish exporting region.

5.2. Robust checks with alternative procedures

Before we conclude, we analyze in this section the results obtained for a last set of specifications based on the last two alternative econometric methods described in section 4.2: namely, the spline and semi-parametric regressions. It is now worth considering that these flexible procedures play a competing role against the contiguity dummies, which also tend to control for "jumps" in the relationship between trade and distance. Taking our cue from their non-significant results in certain cases of the previous section, we therefore now exclude adjacency dummies.

<< Table 4 about here >>

Table 4 reports alternative results for *Internal_Border* and *External_Border effects* when they are computed by the methods described in Eqs. [3] and [5-6]. The first three models—M10, M11 and M12—correspond to the PPML estimates applied to the whole dataset (with zeros) once the sample has been controlled by the three sets of semi-dummies containing the segmented distance (Naïve, Fibonacci and Quarterly, respectively). The results vary slightly from those reported in Tables 1. *Internal Border Effect* remains significant but decreases to a factor of 3, while *External Border Effect* reaches a factor of 4. The next models (M13, M14, and M15) correspond to three alternative procedures for estimating the spline regression. In M13 the knots of the spline regression are equally spaced over the range of the distance variable, in M14 they are placed at the quartiles of the distance variable, and in M15 the "natural spline" (i.e., where spline regression creates variables containing a restricted cubic spline) is applied.

Although the spline models (M13–M15) resemble our previous approach (M10–M12), there are several differences worth mentioning: (i) the three spline models are based on the OLS estimator and are applied to our restricted sample with no zero flows; (ii) conversely, our previous approach used the PPML estimator and the complete sample. The consequences are twofold. First, the number of observations considered for the PPML-STRETCH approach is 6,376, whereas that for the SPLINE-OLS is 3,688; segment length in each is therefore different under the quartile criterion. Second, the PPML gives more consideration to the largest-value observations: that is, the ones taking place within Spain. That said, the two approaches rely on similar assumptions and reach coherent results: in both cases the *Internal* and *External Border Effect* are low and significant, with a factor that ranges from 3 to 2 for *Internal Border* and from 4 to 2 for *External Border*. Moreover, negative elasticity for the distance variable also varies by stretch: in contrast to our finding when the semi-dummy variables were used for segmenting the distance (M10–M12), the negative elasticities for the first and subsequent stretches of distance in models M13–M15 do not show a clear decreasing pattern (in absolute terms); now, for example, the largest negative elasticity corresponds to the third

segment in all cases; besides, in some of them the coefficient becomes non-significant or even positive (stretch 2, 3 and 4 in M15-Cubic spline).

The last two columns correspond to the results obtained with the semi-parametric regression. In M16 the model is estimated with country fixed effects and time fixed effects, while in M17 time-origin region and time-destination region fixed effects are also added. The idea here, as in Benedictis et al. (2008), is to test extent to which our results are affected by the inclusion of a large number of fixed effects. Note that elasticity for distance is excluded, since its effect is captured by the corresponding kernel distribution, and extracted from both sides of the function as expressed in Eqs. [7] and [8]. Now, when this highly flexible approach is applied, *Internal Border Effect* becomes significant and positive again with a factor around 4 and 5, while *External Border Effect* decreases to a factor of 2.

Finally, to illustrate the performance of these three highly flexible approaches for dealing with the non-linear relationship between trade and distance, we report two informative plots. Figure 5 shows the scatterplot of the dependent variable (in logs) with respect to distance (levels), along with the trade predicted with the cubic spline regression and the model using the *quadratic* term (D_{ij}^2). Similarly, Figure 6 shows the scatterplot of the dependent variable against the prediction based on the semi-parametric approach (M17).

<< Figure 5 about here >>

<< Figure 6 about here >>

Figure 5 tries to shed some light on the alternative performance of the spline model versus the quadratic form and, more specifically, on the atypical high internal border effect obtained in M3 versus that in any other specification. The blue vertical lines indicate segments automatically set by the cubic spline (C1, C2, C3). A vertical black line indicates the distance 2,280 km, which is the distance at which the quadratic term of the distance variable is reverted: the turning point where the

parabola's slope becomes positive[22]. Several results are worth mentioning. First, although the scale of the graph does not show this clearly, the spline-model prediction is a better fit than the quadratic-model prediction for the largest flows over the shortest distance (intra- and inter-regional within Spain over the shortest distance). Second, the shape of the predictions based on spline and square-of-distance models for international flows (in green) is very similar. Moreover, if we consider that our sample is of eight EU countries and of relatively short distances (< 3,000 km), the number of flows going beyond the parabola's turning point (2,280 km) is not especially high for non-zero values. However, this could point to a stronger limitation in Table 2, where PPML and zero flows are included, since the turning point occurs at 1,873 km.

At this point, it is worthwhile to sum up our results, which might have something to do with the nature of the two border effects considered here. On the one hand, *Internal Border*, far from being explained by external barriers to trade (division or fragmentation), seems most closely related to the economics of agglomeration around metropolitan areas (Diaz-Lanchas, et al., 2013), as well as to the spatial spillover of the strongest regions and their neighbors. It thus seems sensitive mostly to mismeasurement, spatial-unit use (modifiable area unit problem, MAUP) and aggregation bias. *External Border*, on the other hand, seems to harder to budge (Wei, 1996). First, region-to-region international flows lead to lower external borders than do region-to-country datasets. However, even when we include zero flows (which tend to increase the external border, since most zero flows correspond to international flows) and control for the non-linear relationship of trade, we obtain a positive and significant factor of 4. Finally, according to our results, we find no strong variations in border effects when using alternative treatments for non-linearity (log-log; quadratic terms; and more flexible approaches based on segmented distance and non-parametric approaches) with the exception

[22] Although widely used for dealing with non-linear functions, the quadratic model suffers from a potential limitation: the reversal of the effect's direction. Normally, the quadratic model is used under the assumption that the turning point lies outside the sample (Gould, 1993). In order to compute the point at which the effect changes direction, we use the following expression: $-\beta_5/(2\beta_6)$, where β_5 and β_6 are, respectively, the coefficients for the distance and the square for distance in our Eq. [2]. The 2,280km [–(–2.98523)/(2*0,654596)], corresponds to the estimate plotted in the graph, which was based on OLS and the sub-sample with non-zero flows (equivalent to the spline estimates plotted in the same graph). If the analysis were repeated with a specification equivalent to that in model M3 (Table 2)—i.e., with the PPML and zero flows—then, the turning point would be 1,873 km [–(–2.012/(2*0.537))= 1,873].

of M3 for *Internal Border*. Nevertheless, our results show larger variations in the elasticity of distance (by segment) and in the role played by (external and internal) contiguity than in the *border effects* themselves.

5.3. Endogeneity

In this section we focus on the additional robust check on endogeneity, which is based on the HT procedure. The results are reported in Table 5.

<< Table 5 about here >>

The firsts three models (M18–M20) are based on Eq. [1], and the next four (M21–M24) on Eq. [3], but both equations have the GDP product on the right-hand side. No zero values are included. M18 and M24 report the results for the POLS estimator, which assumes the non-existence of unobservable bilateral fixed effects. The latter uses a segmented distance variable, in keeping with the Fibonacci criterion, and excludes contiguity variables. Both estimates bring out the expected signs on the parameters, which are highly statistically significant, except for the external contiguity in M18. In M24, the negative effect of the distance variable decreases along the stretches and reveals a drop in the *Internal Border Effect*, from 5 to 3. The *External Border Effect*, on the other hand, keeps constant around 4.

M19 assumes zero correlation between the unobservable dyadic heterogeneity and the regressors (REM approach). The results show some differences with the POLS estimates. The main significant changes occur in *the Internal Border Effect*, which takes the value 4 (5 in POLS). The end of the M19 column reports results for the Hausman test, whose null hypothesis of non-correlation among regressors and unobservable bilateral effect is rejected.

M20 corresponds to a Hausman and Taylor (1981) approach, which considers GDP products as endogenous regressors. In relation with the RE approach (M19), M20 shows the same *External*

Border (4), but a significant smaller coefficient for the *Internal Border* estimate, which passes from 4 in M19 to 3 in the HT approach. Following Carrère (2006), we report at the end of the M20 column our results for the Hausman test between the HT estimates and the RE (GLS) estimates. The rejection of the null hypothesis suggests that the HT approach improves the estimate: in other words, the instrumented variable is actually an endogenous component in the regression.

Models M21, M22 and M23 record the results of the HT approach when the distance variable is segmented under different criteria (Naïve, Fibonacci and Quarterly, respectively). For our benchmarks, we take estimation M20 for the three models M21, M22 and M23 and the last column M24 (POLS, with the distance variable split in accordance with Fibonacci criterion) for the second, M22. Of the three models, only the one operating under the Fibonacci criterion displays a "monotonous" decrease of the negative effect of distance along the stretches. In comparison with M20, the M22 (Fibonacci) estimates show the greatest reduction in the *Internal Border* estimation: from 3 in M20 to a statistically non-significant 1. In the *External Border* estimates, the three segmented specifications (Naïve, Fibonacci and Quarterly) pass smoothly from a value of 4 in M20 to 5.

Comparing M22 with the POLS estimation where the distance variable is also divided (M24), we find that once it is tackled the endogeneity problem, the new border estimations yield a bit more dispersed values: the Internal Border in M22 leaves to be significant, while for the POLS estimator gets a significant factor of 3; instead the External Border Effect leads to a somewhat higher estimate in M22 (5) against the POLS (M24) factor (4).

In general, the results reveal a big variability in the *Internal Border* parameter (from 3 to 5 under POLS approaches, and from 1 to 4 under HT approaches). Meanwhile, the other parameters lie on a narrow range along the different specifications. More research, beyond the scope of this paper, is no doubt needed in this field, but our testing of a vast range of specifications can perhaps serve as a benchmark.

6. Conclusions

In this article we aim to shed new light on the *non-linear relationship between trade and distance* and its effect on the regional and national border effects of a country. With this purpose, we have made use of a novel dataset for inter-regional trade flows by Spanish trucking, including intra-national and inter-national flows between Spanish regions (NUTS 2) and the regions of Spain's eight main European partners and considering actual distance for the shipments.

In line with previous papers, we have considered three classic ways for dealing with non-linearity (log-log OLS; log-PPML; quadratic terms and PPML). In addition, we have developed a new strategy to deal with this *non-linearity*. Namely, we segment the sample, considering alternative stretches of the distance variable. Moreover, we have applied two additional estimation methods (piecewise regression and semi-parametric approaches) to estimate the desired parameters while managing the non-linearity in the most flexible way. The results obtained with these alternative strategies are quite robust: the internal border effect seems to be a robust factor around 4, reaching lower significant values (2) for some specifications. The effect of the national border reaches a significant factor that oscillates between 3 and 5. We consider that these results support the call of Henderson and Millimet (2008) for further research on the appropriate gravity equation functional form, using parametric and non-parametric procedures. We have made the attempt here by using inter-national and inter-regional flows simultaneously.

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TABLES

Table 1. Alternative Estimates for *External Border Effects*.
M1–M2 are based on Eq. [1], M3 on Eq. [2], M4–M6 on Eq. [3].

	M1	M2	M3	M4-Naïve	M5-Fibonacci	M6-Quartile
	OLS	PPML	PPML	PPML	PPML	PPML
VARIABLES	$Ln(T_{ijt_corr})$	T_{ijt_corr}	T_{ijt_corr}	T_{ijt_corr}	T_{ijt_corr}	T_{ijt_corr}
$Ln(dist_{ij})$	-1.035***	-0.908***				
	(0.0769)	(0.104)				
$dist_{ij}$			-2.025***			
			(0.284)			
$dist_{ij}^2$			0.541***			
			(0.0787)			
$Ln(dist_{ij}$ stretch1)				-1.179***	-1.104***	-1.195***
				(0.158)	(0.215)	(0.146)
$Ln(dist_{ij}$ stretch2)				-1.129***	-1.151***	-1.116***
				(0.145)	(0.193)	(0.136)
$Ln(dist_{ij}$ stretch3)				-1.082***	-1.128***	-1.082***
				(0.140)	(0.177)	(0.132)
$Ln(dist_{ij}$ stretch4)				-1.044***	-1.048***	-1.046***
				(0.136)	(0.166)	(0.129)
$Ln(dist_{ij}$ stretch5)					-1.002***	
					(0.159)	
Internal_Border	-1.373***	-2.031***	-3.513***	-1.380***	-1.339***	-1.289***
	(0.231)	(0.385)	(0.302)	(0.482)	(0.488)	(0.471)
External_Border	-2.055***	-3.155***	-4.541***	-2.566***	-2.600***	-2.498***
	(0.352)	(0.456)	(0.391)	(0.534)	(0.534)	(0.523)
Internal_Contig	0.396***	0.570***	0.997***	0.312	0.199	0.243
	(0.0922)	(0.193)	(0.181)	(0.218)	(0.238)	(0.221)
External_Contig	0.249	-0.186	0.270	-0.398	-0.471	-0.493
	(0.157)	(0.325)	(0.318)	(0.339)	(0.345)	(0.344)
Constant	-20.60***	-21.25***	-24.50***	-20.26***	-20.53***	-20.20***
	(0.313)	(0.466)	(0.258)	(0.646)	(0.845)	(0.605)
Internal Border Effect	4	8	34	4	4	4
External Border Effect	2	3	3	3	4	3
Null hypothesis†	$Ln(dist_{ij}$ stretch1)-$Ln(dist_{ij}$ stretch2)=0, $\chi2$			5.5**	1.09	15.57***
	$Ln(dist_{ij}$ stretch2)-$Ln(dist_{ij}$ stretch3)=0, $\chi2$			16.52***	0.67	9.05***
	Ln(distij stretch3)-$Ln(dist_{ij}$ stretch4)=0 $\chi2$			7.57***	15.22***	10.94***
	$Ln(dist_{ij}$ stretch4)-$Ln(dist_{ij}$ stretch5)=0, $\chi2$				16.23***	
Observations	3,688	6,376	6,376	6,376	6,376	6,364
R-squared	0.812	0.905	0.882	0.906	0.906	0.905

Note: Standard robust errors (origin and destination regional partners clustered) in parentheses with ***, ** and * respectively denoting significance at 1%, 5% and 10%. Fixed effects of origin-region by year (μ_{it}), destination-region by year (μ_{jt}), destination-country (μ^u) and year (μ_t) included. Wald test was calculated to evaluate significant differences between the coefficients associated to the stretches of distance in models M4, M5 and M6. Tijt_corr = Tijt/GDPixGDPj

Table 2. Characterization for three Alternative Segmentations.

Naive	Km. (thousands)	0.0229 - 0.7921	0.7946 - 1.5606	1.5618 - 2.3285	2.3318 - 3.1		TOTAL
	Range	25%	25%	25%	25%		100%
	obs. (%)	18%	31%	42%	9%		100%
	zeros (%)	1%	12%	24%	5%		44%
	R2 ($Ln(dist_{ij})$)	**90%**	**68%**	**16%**	**23%**		0.905
	R2 ($dist_{ij}$, $dist_{ij}^2$)	**88%**	**68%**	**18%**	**23%**		0.882
Fibonacci	Km. (thousands)	0.0229 - 0.2791	0.2802 - 0.5357	0.5366 - 1.048	1.0488 - 1.8153	1.819333 - 3.1	TOTAL
	Range	8%	8%	17%	25%	42%	100%
	obs. (%)	5%	6%	15%	42%	33%	100%
	zeros (%)	0%	0%	2%	22%	18%	44%
	R2 ($Ln(dist_{ij})$)	**89%**	**75%**	**62%**	**34%**	**18%**	0.905
	R2 ($dist_{ij}$, $dist_{ij}^2$)	**90%**	**75%**	**62%**	**34%**	**18%**	0.882
Quartiles	Km. (thousands)	0.0229 - 1.0187	1.0231 - 1.5823	1.5825 - 1.961	1.9648 - 3.1		TOTAL
	Range	32%	18%	12%	37%		100%
	obs. (%)	25%	25%	25%	25%		100%
	zeros (%)	2%	12%	15%	14%		44%
	R2 ($Ln(dist_{ij})$)	**90%**	**48%**	**34%**	**0.24%**		0.905
	R2 ($dist_{ij}$, $dist_{ij}^2$)	**88%**	**47%**	**33%**	**0.24%**		0.882

Note: Fixed effects of origin-region by year (μ_{it}), destination-region by year (μ_{jt}), destination-country (μ^u) and year (μ_t) included. The endogenous variable is Tijt_corr = Tijt/GDPixGDPj.

Table 3. External Border Effects by Country. PPML Procedure. Region-to-Region Spanish exports 2004–2007. M7–M9 are based on Eq. [4]

	M7	M8	M9
VARIABLES	Tijt_corr	Tijt_corr	Tijt_corr
Ln($dist_{ij}$ stretch1)	-1.318***	-1.132***	-1.303***
	(0.110)	(0.210)	(0.0961)
Ln($dist_{ij}$ stretch2)	-1.255***	-1.191***	-1.215***
	(0.0988)	(0.184)	(0.0895)
Ln($dist_{ij}$ stretch3)	-1.204***	-1.166***	-1.181***
	(0.0954)	(0.166)	(0.0870)
Ln($dist_{ij}$ stretch4)	-1.162***	-1.080***	-1.145***
	(0.0930)	(0.156)	(0.0844)
Ln($dist_{ij}$ stretch5)		-1.033***	
		(0.150)	
Internal Border	-0.943***	-1.143***	-0.960***
	(0.362)	(0.417)	(0.349)
Border_AD	-2.361***	-2.606***	-2.380***
	(0.447)	(0.486)	(0.435)
Border_BE	-2.224***	-2.701***	-2.434***
	(0.423)	(0.477)	(0.411)
Border_DE	-2.169***	-2.657***	-2.384***
	(0.418)	(0.475)	(0.403)
Border_FR	-2.495***	-2.817***	-2.553***
	(0.395)	(0.445)	(0.385)
Border_IT	-2.259***	-2.716***	-2.466***
	(0.416)	(0.474)	(0.402)
Border_PT	-2.357***	-2.497***	-2.268***
	(0.390)	(0.441)	(0.384)
Border_NL	-2.213***	-2.711***	-2.435***
	(0.427)	(0.482)	(0.413)
Border_UK	-2.228***	-2.687***	-2.430***
	(0.417)	(0.475)	(0.402)
Constant	-19.75***	-20.43***	-19.80***
	(0.485)	(0.828)	(0.443)
Internal Border	3	3	3
Portugal	4.1	3.9	3.7
Andorra	4.1	4.3	4.1
Germany	3.4	4.5	4.2
United Kingdom	3.6	4.7	4.3
Belgium	3.6	4.7	4.4
Netherlands	3.6	4.8	4.4
Italy	3.7	4.8	4.5
France	4.7	5.3	4.9
Observations	6,376	6,376	6,364
R-squared	0.903	0.904	0.895

Note: Standard robust errors (origin and destination regional partners clustered) in parentheses with ***, ** and * respectively denoting significance at 1%, 5% and 10%. Fixed effects of origin-region by year (μ_{it}), destination-region by year (μ_{jt}) and year (μ_t) included. Tijt_corr = Tijt/GDPixGDPj.

Table 4. Alternative Estimates for the *External* and *Internal Border Effect*. M10–M12 are based on Eq. [3], M13–M15 on Eq. [5] and M16–M17 on Eq. [6].

	M10 Naïve PPML	M11 Fibonacci PPML	M12 Quartile PPML	M13 Naïve SPLINE-OLS	M14 Quartile SPLINE-OLS	M15 Cubic SPLINE-OLS	M16 SEMI-PAR	M17 SEMI-PAR
VARIABLES	Tijt_corr			Ln(Tijt_corr)				
Ln($dist_{ij}$ stretch1)	-1.318***	-1.132***	-1.303***	-0.891	-1.287***	-1.36***		
	(0.110)	(0.210)	(0.0961)	(0.647)	(0.0591)	(0.0842)		
Ln($dist_{ij}$ stretch2)	-1.255***	-1.191***	-1.215***	-1.25***	-0.850***	0.467*		
	(0.0988)	(0.184)	(0.0895)	(0.135)	(0.203)	(0.252)		
Ln($dist_{ij}$ stretch3)	-1.204***	-1.166***	-1.181***	-1.233***	-1.509***	-3.966		
	(0.0954)	(0.166)	(0.0870)	(0.0912)	(0.379)	(3.008)		
Ln($dist_{ij}$ stretch4)	-1.162***	-1.080***	-1.145***	-1.089***	-1.315***	8.703		
	(0.0930)	(0.156)	(0.0844)	(0.190)	(0.454)	(16.84)		
Ln($dist_{ij}$ stretch5)		-1.033***						
		(0.150)						
Internal_Border	-0.943***	-1.143***	-0.960***	-0.997**	-0.692***	-0.576**	-1.45***	-1.66***
	(0.362)	(0.417)	(0.349)	(0.403)	(0.225)	(0.238)	(0.354)	-0.3367
External_Border	-2.361***	-2.606***	-2.380***	-1.797***	-1.508***	-1.396***	-2.27***	-2.29***
	(0.447)	(0.486)	(0.435)	(0.485)	(0.365)	(0.367)	(0.419)	-0.497
Constant	-19.75***	-20.43***	-19.80***	-21.14***	-19.66***	-19.37***		
	(0.485)	(0.828)	(0.443)	(2.501)	(0.306)	(0.393)		
Internal Border Effect	3	3	3	3	2	2	4	5
External Border Effect	4	4	4	2	2	2	2	2
Observations	6,376	6,376	6,364	3,688	3,688	3,688	3,688	3,688
R-squared	0.904	0.906	0.896	0.811	0.812	0.811	0.322	0.501
FE origin-region x time	YES	YES	YES	YES	YES	YES	NO	YES
FE destination-region x time	YES	YES	YES	YES	YES	YES	NO	YES

Note: Standard robust errors (origin and destination regional partners clustered) in parentheses with ***, ** and * respectively denoting significance at 1%, 5% and 10%. Fixed effects of destination-country (μ^u) and year (μ_t) included. Models M16 and M17 use the distance variable in levels (kilometers). Tijt_corr = Tijt/GDPixGDPj.

Table 5. Border Effect Estimates by the Hausman-Taylor (1981) Procedure. Region-to-Region Spanish Exports 2004–2007. M18–M20 are based on Eq. [1] and M21–M24 on Eq. [3].

	M18	M19	M20	M21	M22	M23	M24
	POLS	REM (GLS)	HT(†)	HT	HT	HT	POLS
VARIABLES				Naïve	Fibonacci	Quarterly	Fibonacci
Ln(GDPi x GDPj)	0.646***	0.622***	0.637***	0.635***	0.635***	0.633***	0.641***
	(0.0372)	(0.0303)	(0.0415)	(0.0414)	(0.0414)	(0.0416)	(0.0375)
$Ln(dist_{ij})$	-0.981***	-1.034***	-1.088***				
	(0.0955)	(0.0955)	(0.145)				
$Ln(dist_{ij}$ stretch1)				-1.224***	-1.504***	-1.196***	-1.312***
				(0.151)	(0.304)	(0.167)	(0.148)
$Ln(dist_{ij}$ stretch2)				-1.198***	-1.482***	-1.188***	-1.267***
				(0.135)	(0.266)	(0.148)	(0.135)
$Ln(dist_{ij}$ stretch3)				-1.221***	-1.443***	-1.186***	-1.244***
				(0.130)	(0.240)	(0.142)	(0.127)
$Ln(dist_{ij}$ stretch4)				-1.237***	-1.391***	-1.209***	-1.195***
				(0.128)	(0.224)	(0.138)	(0.120)
$Ln(dist_{ij}$ stretch5)					-1.404***		-1.199***
					(0.215)		(0.117)
Internal Border	-1.513***	-1.377***	-1.239**	-0.847*	-0.391	-0.897*	-1.020***
	(0.307)	(0.332)	(0.536)	(0.497)	(0.589)	(0.515)	(0.345)
External Border	-2.902***	-2.865***	-2.722***	-2.419***	-2.046***	-2.470***	-2.478***
	(0.421)	(0.538)	(0.756)	(0.738)	(0.792)	(0.753)	(0.439)
Internal Contig	0.438***	0.400**	0.365				
	(0.116)	(0.161)	(0.262)				
External Contig	0.319	0.298	0.237				
	(0.216)	(0.267)	(0.448)				
Constant	-3.623**	-2.298	-2.780	-2.197	-1.125	-2.194	-2.142
	(1.781)	(1.501)	(2.070)	(2.089)	(2.328)	(2.077)	(1.851)
Internal Border Effect	5	4	3	2	1	2	3
External Border Effect	4	4	4	5	5	5	4
Hausman test(i)		822.39***					
Hausman test between HT and RE estimates(ii)			658.4***				
Observations	3,688	3,688	3,688	3,688	3,688	3,676	3,688
R-squared(iii)	0.777	0.770	0.742	0.742	0.743	0.742	0.779

Note: Standard robust errors in parentheses with ***, ** and * respectively denoting significance at 1%, 5% and 10%. Fixed effects of origin-region by year (μ_{it}), destination-region by year (μ_{jt}), destination-country (μ^{u}) and year (μ_t) included. The dependent variable is the log-transformation of regional trade flows (Ln(Tijt)). In Hausman and Taylor estimates the dyadic exogenous variable valid to be an instrument is distance, while the likely endogenous variable is the product of GDP's.

(i) Hausman test between the FE and RE estimations.

(ii) Hausman test between HT and RE(GLS) estimates.

(iii) In the calculation of R^2 for Hausman & Taylor estimation, we follow to Carrere (2006) which corresponds to 1-[Sum of Square Residuals]/[Total Sum of Square].

FIGURES

Figure 1: Kernel Regression: Intra- & Inter-National Trade Relative to GDP (NUTS-2 Region-to-Region) on Distance. Zero Flows Excluded. (€). 2004–2007.

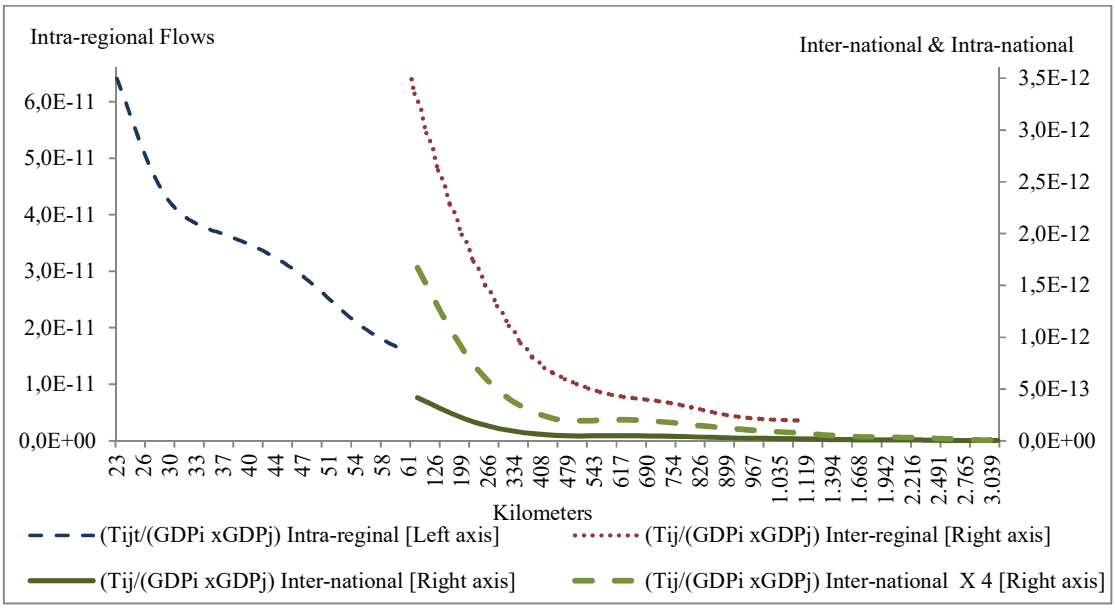
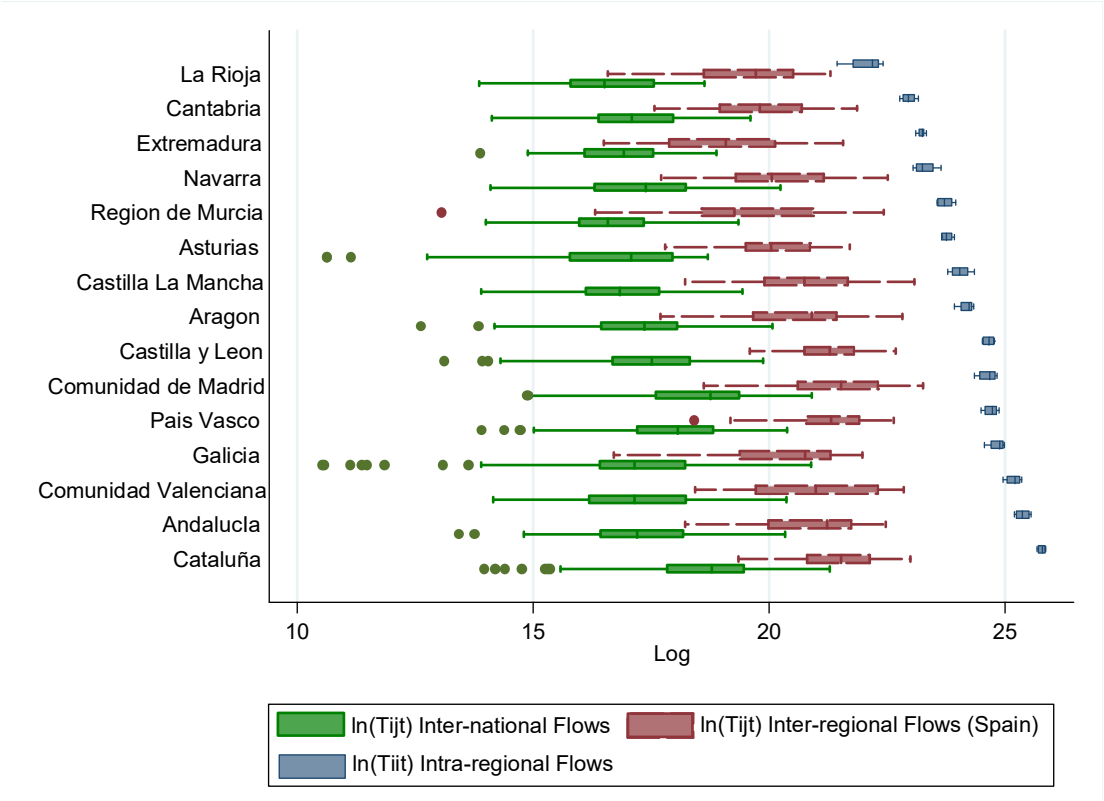


Figure 2: Distribution of trade flows by nature and exporting region. 2004–2007.



Note: The box records the second and the third quartiles of the variable, being the line that divides the box between these two quartiles the average. The first and the second whiskers correspond to the first and the fourth quartiles, respectively. The dot values are usually interpreted as outliers, but in this case we consider them as extreme values.

Figure 3: Trade flows by nature and distance stretches. 2004–2007.

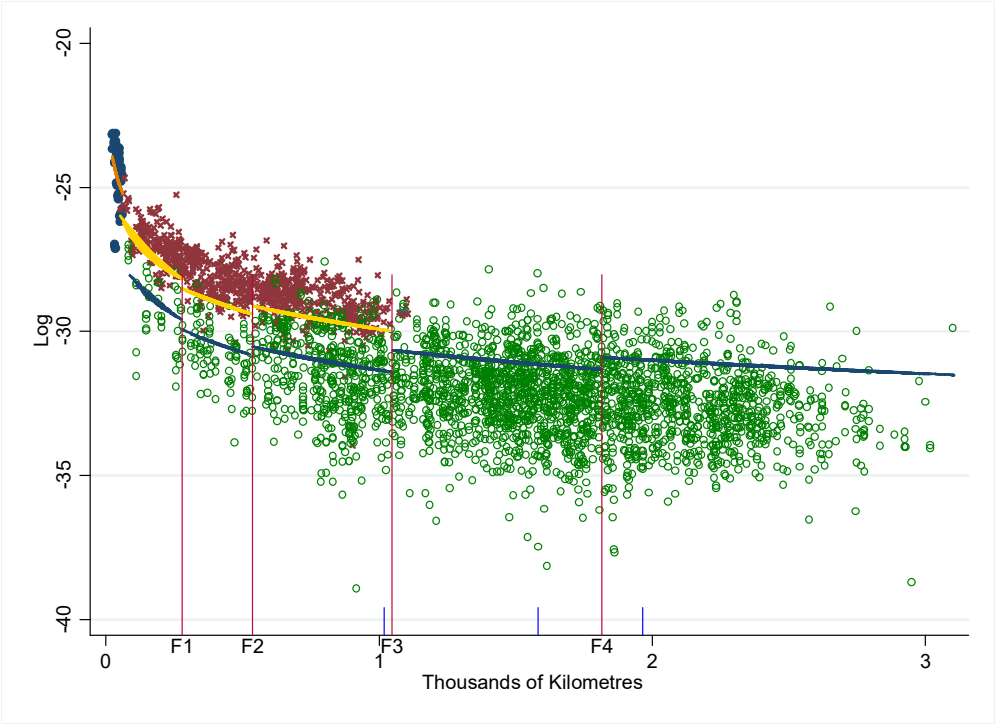
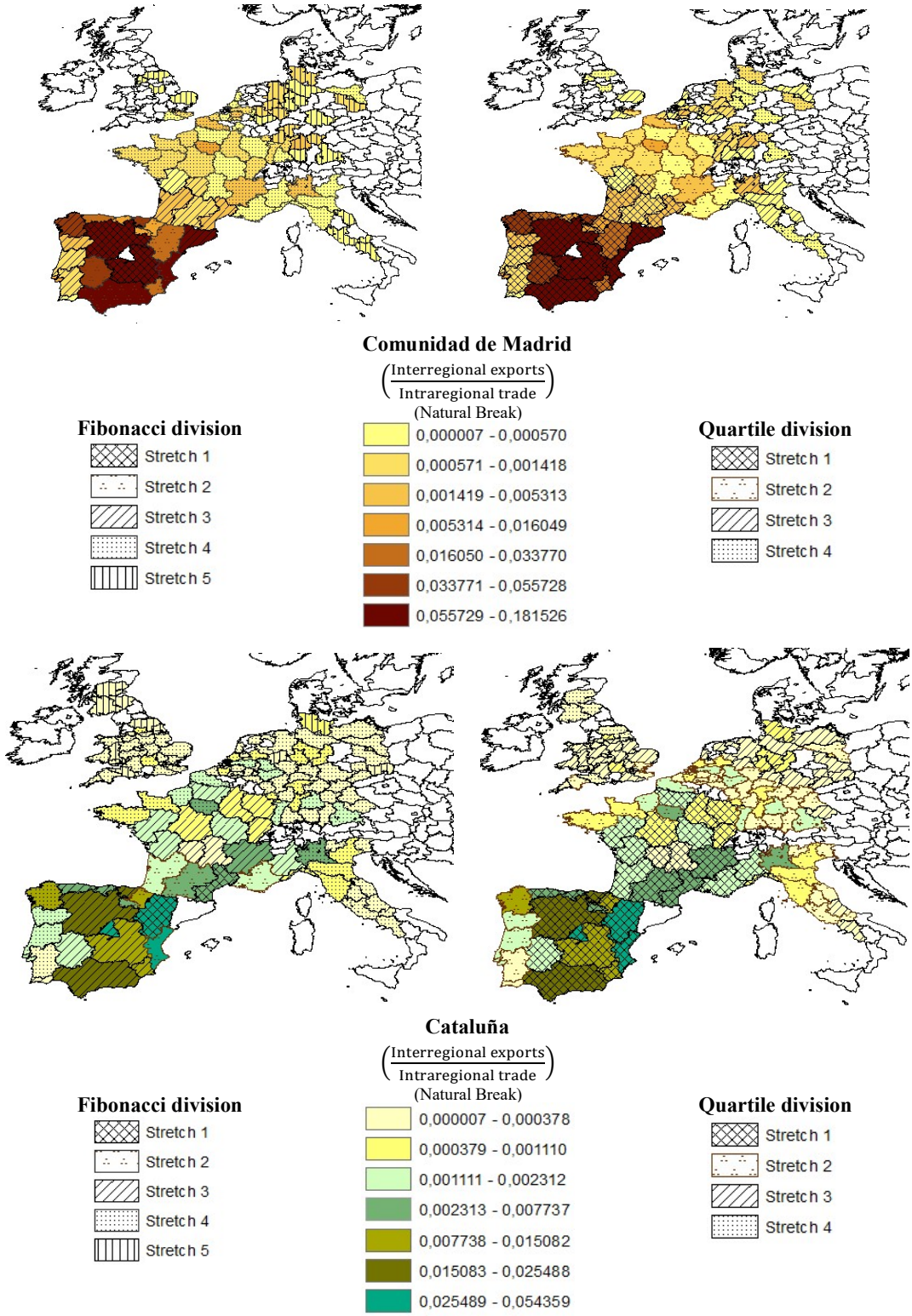


Figure 4. Interregional exports (divided by the intra-regional trade) and main distance stretches. Madrid versus Cataluña. Average Flows for 2004–2007.



(*) The variable represented in these graphs consider the average across the whole period of the interregional export divided by the intraregional flows $\sum_t \frac{\overline{T}_{ijt}}{T_{ii,t}}$.

Figure 5. Spline regression scatterplot. 2004–2007.

In this regression the zero values and contiguity dummies are not included

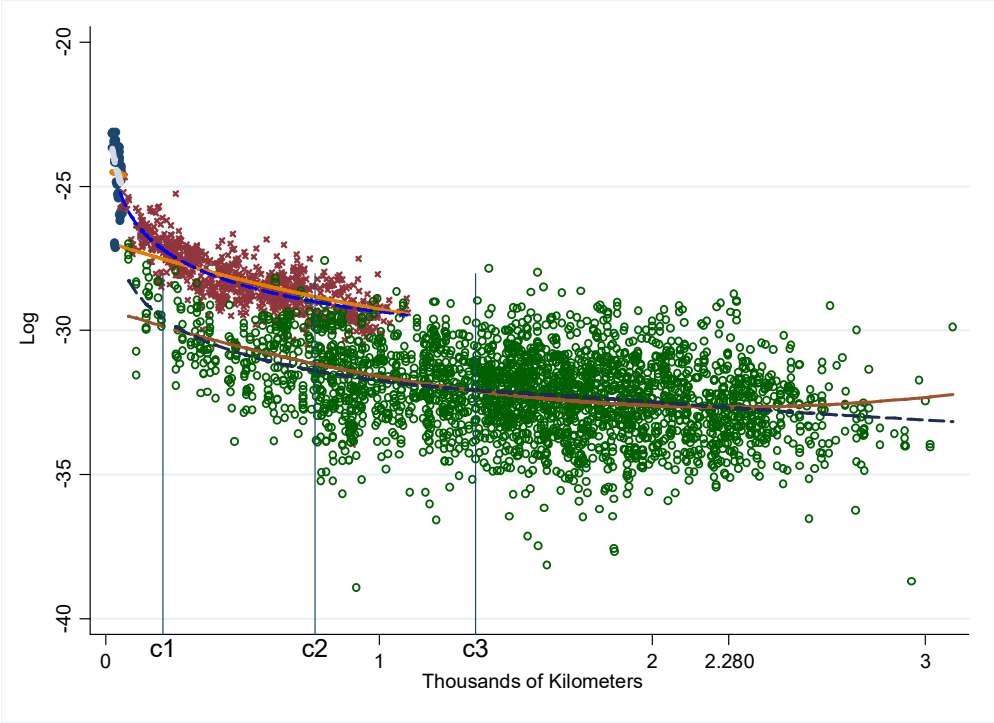
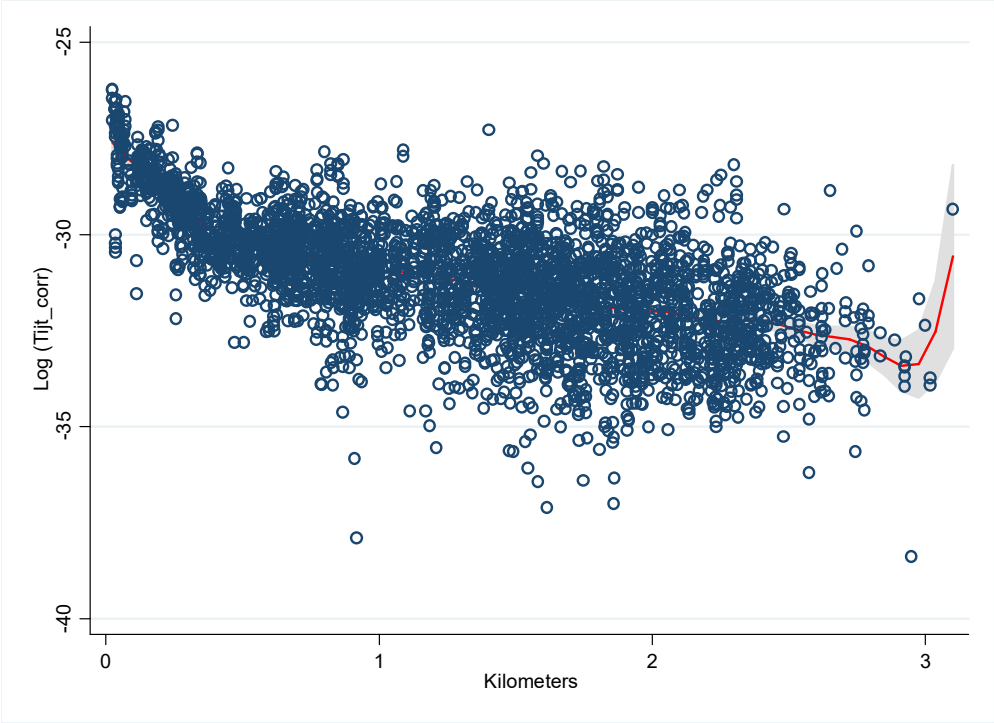



Figure 6: Semi-parametric regression scatterplot. 2004–2007.