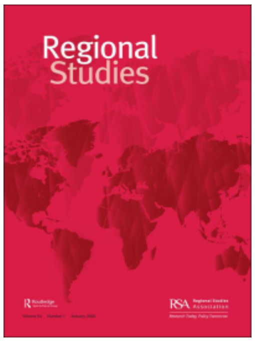

Regional Studies

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/cres20

National and foreign trade elasticities: a spatial econometrics approach

José L. Zofío, Javier Barbero, Jorge Díaz-Lanchas & Damiaan Persyn

To cite this article: José L. Zofío, Javier Barbero, Jorge Díaz-Lanchas & Damiaan Persyn (27 Mar 2025): National and foreign trade elasticities: a spatial econometrics approach, Regional Studies, DOI: 10.1080/00343404.2025.2469608

To link to this article: https://doi.org/10.1080/00343404.2025.2469608

REGIONAL STUDIES
https://doi.org/10.1080/00343404.2025.2469608

Routledge Taylor & Francis Group | Regional Studies Association

OPEN ACCESS | Check for updates

National and foreign trade elasticities: a spatial econometrics approach

José L. Zofío[a,b], Javier Barbero[a], Jorge Díaz-Lanchas[c] and Damiaan Persyn[d,e]

ABSTRACT
The literature estimating trade elasticities at the regional level has overlooked spatial dependence in trade flows, raising concerns about the reliability of results. We address this problem by defining a spatial autoregressive gravity equation that captures spatial spillovers from trade between neighbouring regions. We estimate trade elasticities differentiating between goods imported from regions within the same country (national elasticities) and regions located in third countries (foreign elasticities). The elasticities are identified using a precise measure of iceberg trade costs including economic, engineering and logistic factors. National elasticities are consistently larger than foreign elasticities. We find sizable complementary and competition spatial effects.

KEYWORDS
gravity equation; trade elasticities; spatial econometrics; generalised transport costs

JEL C21, C68, F12, F17, R41
HISTORY Received 31 January 2024; in revised form 24 January 2025

1. INTRODUCTION

The literature extensively calculates trade elasticities through micro-economically grounded gravity equations (Hillberry & Hummels, 2013), revealing the significance of this variable in contemporary spatial economic analysis. Trade elasticities measure the responsiveness of trade flows to changes in economic variables such tariffs, exchange rates or transport costs. Particularly, within the framework of New Trade Theory (NTT) and New Economic Geography (NEG) (Fujita et al., 1999; Krugman, 1995), characterised by constant elasticity of substitution (CES) preferences and imperfect (monopolistic) competition, trade elasticities measuring the sensitivity of consumers' demand to changes in the prices of imported goods' (own-price elasticities) are mathematically equivalent to the elasticity of substitution among imported varieties. The importance of trade elasticity estimates is paramount as their value is crucial for evaluating welfare effects related to trade policy, such as changes in relative tariffs among countries (Bergstrand et al., 2015; Hertel et al., 2007) or changes in transport infrastructure reducing trade costs (Felbermayr & Tarsav, 2022). In the context of regional modelling (e.g., spatial computable general equilibrium models; Bröcker, 2015), pivotal for policy evaluations, the trade elasticity serves as a vital input that shapes market dynamics in response to shocks.

Considerable effort has been directed towards estimating trade elasticities, yet the literature, as surveyed by Head and Mayer (2014) and Bajzik et al. (2020), has not undertaken the simultaneous estimation of both national and foreign elasticities when regional trade flows are available both within countries and between countries. Existing research typically focuses on the international level based on research objectives and data availability. However, when data encompass regional trade at the national and international levels, it becomes possible to differentiate the sensitivity of imports to price changes depending on these two sources of origin. An exception to this gap is found in Zofío et al. (2025), who employ a nested CES utility structure to formulate a gravity equation accounting for both foreign and national trade flows.

CONTACT José L. Zofío jose.zofio@uam.es; jzofio@rsm.nl
[a] Department of Economics, Universidad Autónoma de Madrid, Madrid, Spain
[b] Erasmus Research Institute of Management, Erasmus University, Rotterdam, the Netherlands
[c] Department of Economics, Universidad Pontificia Comillas – ICADE, Madrid, Spain
[d] Thünen Institute of Rural Economics, Braunschweig, Germany
[e] DARE, University of Göttingen, Göttingen, Germany

Supplemental data for this article can be accessed online at https://doi.org/10.1080/00343404.2025.2469608

Additionally, the literature estimating trade elasticities neglects the existence of spatial dependence and the corresponding spillovers among trade flows. This void can be attributed to the limited use of spatial econometrics in specifying and estimating gravity equations. Empirically, spatial dependence in trade flows arises from the spatial structure of the data, reflecting geographical heterogeneity and interrelation leading to spatial externalities. Econometrically, it challenges the independence assumption among trade flows of standard regression models, resulting in correlated residuals, and challenging the reliability of results.

On the one hand, the assumption of independence between import flows of one region from another is unrealistic in our contemporary world of integrated supply chains and logistics networks. Modern manufacturing practices often involve importing intermediates from one region to manufacture final goods that are then exported back to the supplying region. These interconnected trade flows facilitate information exchange among firms in both regions, reinforcing business networks and commercial ties, thereby promoting trade (Rauch, 2001). This feedback loop may also encourage regional governments to establish commercial agreements, intensifying *direct* spatial dependence between the origin and destination regions, and vice versa.

However, on the other hand, this narrowly defined form of spatial dependence, focused on bilateral trade flows, leads to further sources of correlation. While strengthening commercial relationship between two or more regions will bring an increase in trade among partners, this may take place at the expense of third-party regions, which may see how these regions substitute away their exports. This implies that competition effects may rise. An illustrative example of this spatial interdependence is observed in many regions investing in hub-type infrastructure (e.g., ports, warehousing) to enhance business competitiveness, ensuring a strategic advantage in logistical activities such as *en route* storage and transhipping to final destinations (Alamá-Sabater et al., 2013; Bensassi et al., 2015; Díaz-Lanchas et al., 2016; Gallego et al., 2015; Márquez-Ramos, 2016).

According to the principles of spatial economics, targeted infrastructure investments in logistics, warehouses, and wholesale activities, can leverage increasing returns and Marshallian-scale economies that trigger positive reinforcing feedbacks of spatial agglomeration (home-market and price effects). This leads to unequal spatial economic activity distributions that follow 'core–periphery' patterns and leave smaller regions with fewer economic opportunities. However, once a critical threshold or optimal size is reached, agglomerated economies face rising production costs, prompting economic activity to spill over into neighbouring regions. Regional models highlight increased input price gradients as the main driver behind economic activity dispersion towards surrounding regions, fostering commercial interrelationships and associated trade flows (Barbero & Zofío, 2016; Gallego & Zofío, 2018). Despite undeniable competition effects, positive externalities in the form of spatial spillovers may also benefit neighbouring regions.

Porojan (2001), citing Anselin (1998), was among the first authors to estimate a gravity equation using a spatially lagged dependent variable model and a spatial autoregressive (SAR) specification. Analysing trade data for European Union (EU) countries and potential members, he demonstrated that controlling for spatial dependence leads to improved estimations, as indicated by the lowest Akaike information criterion and Schwarz information criterion, resulting in significant changes in the estimates of conventional parameters (e.g., distance, border, etc.). LeSage and Pace (2008), followed by LeSage and Thomas-Agnan (2015), systematically addressed the econometric challenges arising from the issue of spatial dependence. They proposed using weight matrices to capture geographical proximity at the origin, destination and origin–destination levels, incorporating them into a spatially lagged dependent variables model or SAR specification to address associated effects and heteroscedasticity.

Building on LeSage and Pace (2008), several studies have expanded their methodologies. For instance, Behrens et al. (2012) employ an SAR model to address error dependence arising from multilateral resistance in trade flows. These authors formulate a 'spatial' (interaction) matrix based on the relative distribution of population across locations, rather than geographical proximity. Using US–Canada trade data, they demonstrate that adopting SAR methods enhances estimates compared with standard methods neglecting error correlation. LeSage and Llano (2013) extend the gravity model by applying Bayesian methods to estimate an SAR specification. Their model incorporates parameters capturing 'latent' spatial effects (corresponding to unobserved variables) for each region treated as an origin and destination. Using regional trade data from Spanish regions, they find that destination effects exhibit positive and significant spatial dependence. This implies that latent effects are at work at destination to create effects' estimates that are similar to those from regions neighbouring the destinations, aligning with the geographical structure of interregional trade in Spain, where importing regions cluster in specific coastal areas.

This study introduces an analytical framework and estimation methods for jointly estimating foreign and national trade elasticities using spatial econometric techniques. Specifically, we employ an SAR model to estimate a gravity equation with a microeconomic foundation. This model allows us to examine the presence of spatial dependence, encompassing direct and neighbour effects, whose sign (positive or negative) reveals the nature of regional externalities – whether they are complementary or competitive in terms of trade. Our specification extends the traditional gravity equation with proximity matrices that control for neighbour dependence at the origin, destination and origin–destination levels. This comprehensive approach allows to control for the existence of trade externalities that impact the magnitude of the trade elasticities.

Unlike the standard international trade literature, and given the EU's status as a single market, tariffs are not available for identifying trade elasticities. As an alternative price-shifter, we use a precise measure of transport costs. We rely on the generalised transport cost (GTC) approach calculating the minimum cost of shipping freight between any two locations along the least expensive route. Our calculations enhance the approach proposed by Persyn et al. (2022) by identifying the optimal size and type of vehicle depending on several factors: shipping distance, urban layout and the type of commodity transported. These factors collectively contribute to the operating costs of the optimal vehicle, factored into the calculation of the GTC, which in turn is included in the final iceberg formulation of trade costs.

Our results are robust to different econometric specifications and trade aggregation levels and show that national elasticities are systematically larger than foreign elasticities, both reaching averages of 5.371 and 1.986, respectively. We also find complementary and competing spatial effects for neighbouring regions of the origin and destination regions. These findings provide evidence that consumers' preferences for varieties of goods are different when the importing region belongs to the same country or to third countries.

The article is organised as follows. Section 2 introduces the theoretical model underlying the gravity equation specification. Section 3 details the spatial econometric specifications of the gravity equation including the spatial weight matrices. Section 4 outlines the statistical sources, trade data, *ad-valorem* transport costs and ancillary variables used in estimation. Section 5 presents our estimates of trade elasticities and spatial effects. The conclusions in Section 6 emphasise the novelty of our results and underscore the importance of employing spatial methods in trade elasticity estimation.

2. NATIONAL AND FOREIGN TRADE ELASTICITIES

The theoretical model underlying the gravity equation is grounded on the NTT/NEG framework. Household preferences are modelled as a triple-nested utility function. The upper tier utility for the representative consumer located in region $d = 1, \ldots, D$ is:

$$U_d = U(Q_d^1, \ldots, Q_d^c, \ldots, Q_d^C), \tag{1}$$

which aggregates the $c = 1, \ldots, C$ commodities demanded. The quantity Q consumed of each commodity c is a composite of horizontally differentiated varieties of the same good that are produced domestically, QD, or imported either from regions within the same country (*national* trade, QN), or from regions situated in foreign countries (*foreign* trade, QF). Given this structure, the middle tier of the utility function corresponds to the following CES specification:

$$Q_{d^c} = \left[b_{Dd}^c QD_d^c{}^{\frac{\phi^c - 1}{\phi^c}} + b_{Nd}^c QN_d^c{}^{\frac{\phi^c - 1}{\phi^c}} + b_{Fd}^c QF_d^c{}^{\frac{\phi^c - 1}{\phi^c}} \right]^{\frac{\phi^c}{\phi^c - 1}}. \tag{2}$$

The parameters b_{Dd}^c, b_{Nd}^c and b_{Fd}^c represent weights based on idiosyncratic preferences and relatedness specific to each source, that is, domestically consumed, nationally imported and internationally imported.

In the lower tier of the model, aggregate varieties having a national (QN_d^c) or foreign (QF_d^c) origin enter the utility function (1) as follows:

$$QN_d^c = \left[\sum_{n=1}^{R} b_{nd}^c q_{nd}^c{}^{\frac{\sigma_N^c - 1}{\sigma_N^c}} \right]^{\frac{\sigma_N^c}{\sigma_N^c - 1}}, \tag{3}$$

$$QF_d^c = \left[\sum_{f=1}^{S} b_{fd}^c q_{fd}^c{}^{\frac{\sigma_F^c - 1}{\sigma_F^c}} \right]^{\frac{\sigma_F^c}{\sigma_F - 1}}, \tag{4}$$

where q_{nd}^c and q_{fd}^c are the individual quantities of commodity c consumed in d that are imported from the R regions within the same country, and from the S regions in other countries, respectively. In this level b_{nd}^c and b_{fd}^c are the preference and relatedness parameters for each of the varieties imported from the national or foreign regions – enhanced to capture spatial effects as we show in the next section, and σ_N and σ_F are the common price and substitution elasticities among varieties sourced from each group of regions. As with ϕ_c in (2), we assume that these trade elasticities are equal across regions.

We now determine the demands for the national and foreign imported goods, conditional on the expenditure on each type of commodity depending on its *origin*, E_{od}^c, $o = N, F$, coming from the upper level utility function (1). In this case the optimal sourcing of imports from different regions, n or f, according to (3) and (4), results in the following demand equations:[1]

$$q_{nd}^c = b_{nd}^c{}^{\sigma_N} \frac{p_{nd}^c{}^{-\sigma_N^c}}{P_{Nd}^c{}^{1-\sigma_N^c}} EN_d^c, \text{ and} \tag{5}$$

$$q_{fd}^c = b_{fd}^c{}^{\sigma_F} \frac{p_{fd}^c{}^{-\sigma_F^c}}{P_{Fd}^c{}^{1-\sigma_F^c}} EF_d^c. \tag{6}$$

Assuming that the relevant market structure corresponds to monopolistic competition, destination prices in the numerator correspond to the following specifications:

$$p^c_{nd} = p^c_n(1+\tau^c_{nd}) = \left(\frac{\sigma^c_N}{\sigma^c_N - 1}\right)c^c_n(1+\tau^c_{nd}), \text{ and} \quad (7)$$

$$p^c_{fd} = p^c_f(1+\tau^c_{fd}) = \left(\frac{\sigma^c_F}{\sigma^c_F - 1}\right)c^c_f(1+\tau^c_{fd}), \quad (8)$$

where $p^c_n = \left(\frac{\sigma^c_N}{\sigma^c_N - 1}\right)c^c_n$ and $p^c_f = \left(\frac{\sigma^c_F}{\sigma^c_F - 1}\right)c^c_f$ are mill prices in the region of origin, depending on the marginal cost of production c^c_o, $o = n, f$, and on $\sigma_N/(\sigma_N - 1)$, and $\sigma_F/(\sigma_F - 1)$, which are the mark-ups under monopolistic competition. The consumer prices at the importing region *d*, denoted by p^c_{nd} and p^c_{fd} , include the *ad valorem* (or iceberg) transport costs: τ^c_{nd} and τ^c_{fd}. Finally, the overall price indices in the numerators of (5) and (6) are:

$$P^c_{Nd} = \left(\sum_{n=1}^{N} b^c_{nd}{}^{\sigma_N}(p^c_{nd})^{1-\sigma_N}\right)^{1/1-\sigma_N}, \text{ and}$$

$$P^c_{Fd} = \left(\sum_{f=1}^{F} b^c_{fd}{}^{\sigma_F}(p^c_{fd})^{1-\sigma_F}\right)^{1/1-\sigma_F}.$$

These price indices show that trade flows are dependent on the destination prices of all the varieties produced by all trading partners at the national or foreign level, reflecting the spatial nature of the so-called 'multilateral resistance' (i.e., relative trade costs) to commerce. Controlling for cross-section correlations by resorting to spatial econometrics allows accounting for 'multilateral resistance' and yields improved estimates of the gravity.

3. ECONOMETRIC SPECIFICATION AND ESTIMATION OF TRADE ELASTICITIES

We express the demand equations (5) and (6) in value terms by multiplying both sides by destination prices. Also in a monopolistic competition framework the aggregate import value can be related to each individual firm *h* exports multiplied by the number of symmetric firms *m* operating in the exporting industry, that is, $V^c_{od} = p^c_{od}m^c_o q^c_{hod} = p^c_{od}q^c_{od}$, $o = n, f$.[2] Then, multiplying (5) by (7) and taking natural logs, yields the following gravity equation for (intra-)national trade:[3]

$$\begin{aligned}\ln V^c_{nd} = {} & \sigma^c_N \ln b^c_{nd} + \ln m^c_n + (1-\sigma^c_N)\ln\left(\frac{\sigma^c_N}{\sigma^c_N - 1}\right) \\ & + (1-\sigma^c_N)\ln(c^c_n) + (1-\sigma^c_N)\ln(1+\tau^c_{nd}) \\ & + (\sigma^c_N - 1)\ln P^c_{Nd} + \ln E^c_d. \end{aligned} \quad (9)$$

In the same me vein, multiplying (6) by (8), one obtains the gravity equation for international trade:

$$\begin{aligned}\ln V^c_{fd} = {} & \sigma^c_F \ln b^c_{fd} + \ln m^c_f + (1-\sigma^c_F)\ln\left(\frac{\sigma^c_F}{\sigma^c_F - 1}\right) \\ & + (1-\sigma^c_F)\ln(c^c_f) + (1-\sigma^c_F)\ln(1+\tau^c_{fd}) \\ & + (\sigma^c_F - 1)\ln P^c_{Fd} + \ln E^c_d. \end{aligned} \quad (10)$$

The econometric identification of the trade elasticities relies on the cross-sectional variation of delivered prices induced by trade costs. In our single market setting characterising the EU, delivered prices corresponds to mill prices plus the trade margins, of which *ad valorem* (iceberg) trade costs represent the largest proportion.[4]

3.1. Accounting for direct and spatial (neighbouring) effects in the gravity equation

The above specifications (9) and (10) could be estimated, in principle, separately for each type of trade flow, either national or foreign, and sector *c*. The standard econometric strategy followed by Hummels (2001) and Hertel et al. (2007), for example, exploits the fact that all variables except the bilateral relatedness and transport costs: b^c_{od} , τ^c_{od}, $o = n, f$, are either importer or exporter specific, that is, the importer's price index, P^c_{od}, $o = n, f$, and expenditure EF^c_d, and the exporter's production costs, c^c_o, $= n, f$. We denote by a^c_d and a^c_n the vectors of importer and exporter (within the same country) regional fixed effects.

Considering these variables results in the following specification for the national trade flows:

$$\ln V^c_{nd} = a^c_d + a^c_n + \sigma^c_N \ln b^c_{nd} + (1-\sigma^c_N)\ln(1+\tau^c_{nd}), \quad c = 1, \ldots, C, \quad (11)$$

while the international counterpart, including exporter's fixed effect for foreign countries a^c_f , corresponds to:

$$\ln V^c_{fd} = a^c_d + a^c_f + \sigma^c_F \ln b^c_{fd} + (1-\sigma^c_F)\ln(1+\tau^c_{fd}), \quad c = 1, \ldots, C. \quad (12)$$

Once we have presented the general specification, we introduce spatial dependence through the commodity-specific relatedness variables b^c_{od}, $o = n, f$. Here we differentiate between *direct* and *neighbours'* effects, so these variables can be decomposed as follows: $b^c_{od} = b^{c,\,direct}_{od} \times b^{c,neighbor}_{od}$, $o = n, f$.

First, in the existing literature, the variable $b^{c,direct}_{od}$ refers to idiosyncratic characteristics that *directly* affect trade between the importer region *d* and the exporter region *o*, either within the same country or foreign. How close are the trading partners to each other regarding preferences is usually proxied with the bilateral geographical distance. However, our measure of iceberg trade cost already incorporates this dimension through the GTC. Therefore, we rely on regional adjacency within countries, $Adj.Region_{od}$, $o = n, f$, and between regions belonging to different countries, $Adj.Country_{od}$, $o = n, f$, to capture this relatedness.

Second, we depart from the standard gravity approach and enhance relatedness to account for the spatial dependence of the trade flows by including *neighbouring* effects. Following LeSage and Pace (2008) we consider the spillovers associated with the regions neighbouring the origin and the destination of the bilateral trade flow. Figure 1 shows that these spillover effects arise from the following trade flows: (i) those from the $l = 1, \ldots, L$ neighbours of the exporting region $o = n, f$

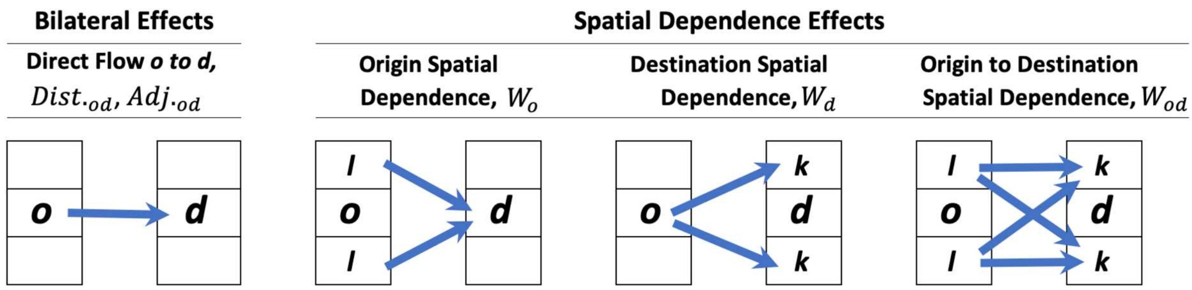

Figure 1. Spatial dependence (neighbouring) effects.

(origin effects) to the destination region d; (ii) those from the origin region $o = n, f$ to the $k = 1, \ldots, K$ neighbours of the importing region d (destination effects); and (iii) those between the L neighbours of $o = n, f$ and the K neighbours of d (origin–destination effects).

The three neighbouring effects are jointly modelled through the following product notation:

$$b_{od}^{c,\, neighbor} = \prod_{l} V_{ld}^{c\, \rho_1 w_{od,ld}} \prod_{k} V_{ok}^{c\, \rho_2 w_{od,ok}} \prod_{l}\prod_{k} V_{lk}^{c\, \rho_3 w_{od,lk}}, \quad o = n, f. \tag{13}$$

The parameters ρ_1, ρ_2 and ρ_3 capture the spillovers associated with the spatial effects, while $w_{od,ld}$, $w_{od,ok}$ and $w_{od,ld}$ are binary variables that are equal to one when the contiguity relationship underlying each type of spatial effect is verified. In the econometric specification the expression of the neighbour effects (13) in logarithms is:

$$\ln b_{od}^{c,\, neighbor} = \sum_{j} \rho_1 w_{od,ld} \ln V_{od}^{c} + \sum_{k} \rho_2 w_{od,ok} \ln V_{ok}^{c} + \sum_{l}\sum_{k} \rho_3 w_{od,lk} \ln V_{lk}^{c}. \tag{14}$$

In the last equality we find the standard representation of the spatial effects through the three matrices weighting the trade flows according to their respective spatial effects: $W_o = I_d \otimes W$, $W_d = W \otimes I_d$, and $W_{od} = W_o W_d$, where W is the row-standardised contiguity matrix of the origin–destination trade flows, I_d is the identity matrix and $\otimes$ denotes the Kronecker product. Expression (14) ensures that all trade flows that do not comply with the neighbouring criteria are excluded when calculating the spillover effects.

3.2. Econometric specification: (intra-)national and foreign (international) trade elasticities

Rather than estimating the sector specific elasticities of trade for national and foreign goods separately, that is, using split subsamples for each type of trade flows according to in (11) and (12), our estimation strategy pools all trade data within each sector. The reason is the intertwined nature of national and international trade flows between EU regions. Since national (interregional) trade cannot be dissociated from international trade in markets as integrated as the EU, the individual estimation of the national and foreign elasticities would face the problem of variables' omission (either international trade flows in equation 11 or national trade flows in equation 12), resulting in biased estimations. In addition, joint estimation of the national and foreign trade elasticity preserves the spatial structure of the regions' connectivity network, which would be lost if the gravity equations were estimated independently.

The pooled approach requires the specification of a single gravity equation where σ_N^c and σ_F^c are simultaneously recovered from the estimated parameters, whose iceberg trade costs, τ_{od}^c, $o = n, f$, are differentiated through a dummy variable that controls for (intra-) national (interregional) trade. The parameter associated with this last interaction captures the additional (marginal) effect on imports if trade is (intra-)national rather than international (the reference category in the specification).

The SAR specification consistent with this strategy, including direct and neighbouring effects, is the following:

$$\begin{aligned} \ln V_{od}^{c} = {} & \alpha_0 + \alpha_o^c + \alpha_d^c + \beta_f^c \ln(1 + \tau_{od}^c) \\ & + \beta_n^c \ln(1 + \tau_{od}^c) \times Intracountry_{od} \\ & + \beta_1^c Adj.Region_{od} + \beta_2^c Adj.Country_{od} \\ & + \beta_3^c Intraregion_{od} + \beta_4^c Intracountry._{od} \\ & + \rho_1 W_o \ln V_{od}^c + \rho_2 W_d \ln V_{od}^c + \rho_3 W_{od} \ln V_{od}^c \\ & + \varepsilon_{od}, \quad o = n, f, \quad c = 1, \ldots, C, \end{aligned} \tag{15}$$

where α_d^c and α_o^c are the importer and exporter region specific fixed effects to account for multilateral resistance terms (Baldwin & Taglioni, 2006; Yotov et al., 2016); $Intraregion_{od}$ and $Intracountry_{od}$ are dummy variables that equal 1 if the trade flow takes place within the same region and country, respectively. As described above, $Adj.Region_{od}$ and $Adj.Country_{od}$ are included as a proxy for direct relatedness effects. Foreign and national elasticities of trade are identified from the parameters associated with the bilateral variation in iceberg costs, that is, $\sigma_F^c = 1 - \beta_f^c$ and $\sigma_N^c = 1 - (\beta_f^c + \beta_n^c)$. From an econometric perspective, the additional advantage of the joint specification (15) over the standard approach based on the individual regressions (11) and (12) is the possibility of testing if the difference between the national and foreign trade elasticities is statistically significant. As for the estimation method, we use the Bayesian Markov chain Monte Carlo

(MCMC) approach, originally developed by LeSage and Pace (2008) and improved by Dargel (2021).

3.3. Measuring trade elasticities at different levels of data aggregation: micro and macro

The model and gravity equation specification from the preceding section are applicable to any number of sectors ($c = 1, \ldots, C$). Our lowest-level estimates, based on available statistical data, involve a two-digit industrial disaggregation of the Statistical Classification of Products by Activity (CPA, ver. 2.1), aligning precisely with the two-digit division classification of the Standard Goods Classification for Transport Statistics (NST 2007, rev. 2). This mapping (detailed in Appendix B in the supplemental data online) results in 14 sectors, reflecting CPA product space trade flows with similar shares in overall trade across sectors.

These results provide sector-specific ‘micro’ elasticity parameters. However, modellers tend to favour the use of common parameters for relatively homogenous sectors; which in turn requires estimates obtained for higher classification levels (i.e., one-digit) (e.g., Duparc-Portier & Figus, 2024). Consequently, we also estimate ‘macro’ trade elasticities for the main three CPA categories of tradable goods: A (Agriculture, forestry and fishing), B (Mining and quarrying) and C (Manufacturing), as well as a single estimate for the foreign and national elasticities for all trade flows.

4. DATA: TRADE FLOWS, GENERALISED TRANSPORT COSTS AND CONTROL VARIABLES

We make use of the latest available year of the EU interregional trade flows database, corresponding to 2013 to perform the estimation of the trade elasticities through equation (15). The set of data required for the estimation includes the following three groups: (1) trade flows (quantity and values); (2) GTCs and associated iceberg values; and (3) ancillary variables capturing the direct and neighbour effects associated to the direct preference parameter.

4.1. Trade flows

Interregional trade flows come from the database jointly elaborated by the Joint Research Center (JRC) of the European Commission and PBL Netherlands. The compilation of the trade flows follows the methodology developed by Thissen et al. (2019), who estimate a trade flows matrix for all 267 (NUTS-2) EU regions that is coherent with national supply and use tables (SUTs) and international trade statistics by EU countries. The first step to obtain this matrix is to estimate probability matrices on re-exporting (and re-importing) flows (e.g., transshipments or intermediate trade associated with logistic supply chains) between EU regions using the European freight transport survey databases, which contain information on freight flows across EU regions differentiated by sectors. Subsequently, the national SUTs are readjusted considering these probabilities and using additional regional information on consumption and production to estimate both intra- and international trade between EU regions. The advantage of the final interregional trade matrix over recent literature aiming at estimating trade flows between EU regions using freight road shipments (Santamaría et al., 2023) is that it offers trade flows by sectors, which allows us to differentiate between national and international elasticities for 14 different sectors. The latest release is based on the 2013 national SUTs published by the EU statistical office, Eurostat, classified according to NACE Rev. 2. Therefore, we stick to a cross-sectional database for 2013. Finally, as these interregional trade flows are denominated in origin, free-on-board (FOB), prices, they must be transformed into cost-insurance-freight (CIF) destination prices as obtained in (15). Details are provided in Appendix C in the supplemental data online.

4.2. Generalised transport costs (GTCs)

The transport costs measure employed in our econometric specification improves existing approaches based on the minimum cost route between an origin and a destination, considering the existing distance and time economic costs from a transport engineering and logistics perspective and the actual road network (Zofío et al., 2014). Persyn et al. (2022) employ this methodology to calculate a dataset of GTCs for the EU regions. However, none of the previous studies allows for the choice of the optimal type of vehicle when calculating the GTCs as they only consider the standard heavy-duty vehicle (HDV). We develop a methodology to identify the optimal vehicle by considering: (1) the shipping distance between the origin i and destination j, $s(d_{ij})$, (2) the degree of urbanisation, u_{ij}; and (3) the type of commodity transported, c. Consequently, vehicle specification, v, is a function of the previous variables: $v(s(d_{ij}),u_{ij},c)$. All these variables restrict the type of vehicle that can be employed for shipping, whose distance and time operating costs are crucial in the calculation of the GTCs, which, in turn, represent the main component of the iceberg trade costs entering the gravity equation. Hence it is paramount that a precise measure of transport cost is developed. We define first the GTC and in subsequent subsections present the methodology to determine the optimal vehicle for each bilateral freight flow.

We denote by GTC_{ij}^{v} the GTC corresponding to the minimum cost itinerary, I_{ij}^{v*}, among the set of possible routes, I_{ij}^{v} of moving the optimal vehicle $v(s(d_{ij}),u_{ij},c)$ between origin i and a destination j. Based on GIS information the optimal itineraries are comprised of arcs a_c, with an associated set of physical and legal attributes (i.e., maximum legal speed), $\mathbf{X}_{a_c}$. The primary physical attributes of an arc are its distance, d_a, road type, r_a, and gradient (steepness), g_a. The arc speed, s_{a_c}, is obtained from these properties, and thereby it is possible to determine the time it takes to cover it, $t_{a_c}^{t} = d_a^{t}/s_{a_c}^{t}$.

The GTC for a given commodity c, GTC_{ij}^{c}, is then the solution to the following problem:

$$\begin{aligned} GTC_{ij}^{c,v} &= f^{c}\,GTC_{ij}^{v} \\ &= f^{c} \min_{I_{ij}\in \mathbf{I}_{ij}} (DistC_{ij}^{v*} + TimeC_{ij}^{v*}) + Taxes_{ij}^{v} \\ &\quad + Vignette_{ij}^{v} + Handling_{ij}^{v}, \end{aligned} \tag{16}$$

where:[5]

$$DistC_{ij}^{v} = \sum\nolimits_{a\in I_{ij}} \left(\sum\nolimits_{k} e_{ak}^{d} f_{ak}^{vd}\right) d_a = \\ = \sum\nolimits_{a\in I_{ij}} (fuel_a^{v} + toll_a^{cv})\, d_a \\ + (tireCS^{v} + maintCS^{v})(fuel_a^{v} d_a), \tag{17}$$

$$TimeC_{ij}^{v} = \sum\nolimits_{a\in I_{ij}} \left(\sum\nolimits_{k} e_{ak}^{v} f_{ak}^{vt}\right) t_a \\ = \sum\nolimits_{a\in I_{ij}} (1 + amortFinCS_a^{v} + insurCS_a^{v} + indCS)(t_a lab_{ij}^{v}). \tag{18}$$

Compared with Persyn et al. (2022), we improve the definition of the GTC in (16) by considering the choice of the optimal type of vehicle, $v(s(d_{ij}),u_{ij},c)$. This qualification is crucial for calculating accurate transport costs for interregional trade taking place in short and medium distances, where the reference 40 tonne articulated truck is not used to freight goods. Thus, the original distance and time costs considered by these authors for that vehicle, e_{ak}^{d} and e_{ak}^{t} (where k denotes cost/km), must be modified by applying the optimal vehicle factors corresponding to distance and time costs in equations (17) and (18): f_{ak}^{vd} and f_{ak}^{vt} (see Appendix D in the supplemental data online), thereby obtaining the new costs at the arc level $e_{ak}^{vd} = f_{ak}^{vd} e_{ak}^{d}$ and $e_{ak}^{vt} = f_{ak}^{vt} e_{ak}^{t}$. Last, once the transport cost for the optimal vehicle is obtained GTC_{ij}^{v}, it is further modified to account for the type of cargo by multiplying by the commodity factors f (see Appendix E online), thereby obtaining $GTC_{ij}^{c,v}$ in (16). In sum, the optimal choice of vehicle for each freight flow is critical for a reliable calculation of the GTCs, which is incorporated through the vehicle factors f_{ak}^{vd} and f_{ak}^{vt}, and the commodity factors f.

4.2.1. *Optimal vehicle size and shipping distance,* $s(d_{ij})$*: 'freight curves'*

The first element of the methodology to determine the optimal vehicle is to establish its size, which depends on the shipping distance. For this purpose, we calculate 'freight curves' reflecting the existence of non-linear (concave) shipping costs that result from economies of distance and size. These functions establish the relationship between the optimal vehicle size depending on the shipping distance between an origin i and destination j, d_{ij} (McCann, 2001). Freight curves identify the vehicle size that minimises the cost per tonne and per unit distance (i.e., €/tonne/km) given the overall distance. Appendix F in the supplemental data online portraits the cost-lines and freight curves for road transportation. We update to 2012 the economic costs for the HDV presented in Zofío et al. (2014, tab. 1) to match the sectoral diversity in trade data and expand the database to include three vehicles and their associated handling times (Burdzik et al., 2014). Table 1 reports the set of distance thresholds that identify the distance at which each vehicle is optimal by minimising the transport cost – last column. The thresholds reported in the last column (f) are calculated as the intersection points between the successive 'cost lines'. Aggregating consecutive thresholds yields the distance at which a given vehicle becomes optimal. Results show that up to a distance of 10 km, the small vehicle is the optimal choice. For the HDV, the cumulated distances show that it is the optimal vehicle choice for shipments greater than 150 km. As commented above, the corresponding factors of proportionality, f_{ak}^{vd} and f_{ak}^{vt}, in the cost of each vehicle with respect to the reference HDV are presented in Appendix D in the supplemental data online.

4.2.2. *Urban configuration and freight transportation,* u_{ij}

The second factor constraining the choice of optional vehicle is the road infrastructure, which we incorporate in the calculation of the GTCs through geographical information systems (GIS), and, more importantly, the existing *urban layout* at origin and destination taken from the Global Human Settlement Layer (GHSL) project of the European Commission. The reason is that the urban grid, along with eventual legislation and city ordinances preventing traffic congestion, air pollution, etc., limit the type of vehicle that can be used when urban legs are part of the optimal itinerary. Table 2 presents the choice of the representative vehicle corresponding to the origin–destination matrix in the range of thresholds between 10 and 150 km.

4.2.3. *Economic costs by commodity,* c

The last dimension included in the determination of the optimal vehicle accounts for *the type of commodity (cargo)* being transported. The choice of vehicle depends on the commodity or, more generally, the physical characteristics of the transported cargo in terms of weight and volume. For instance, if the commodity can be transported in batches of euro pallets, then the standard HDV is the appropriate vehicle (Burdzik et al., 2014). However, when liquids, gases or powders (bulk cargo) are transported, a tanker is required. Similarly, in the case of perishable products requiring a temperature-controlled body. Modifications of the above are also necessary in the case of hazardous materials, wide loads, etc. To identify the primary type of vehicle by sector, we use the correspondence matrix aligning the Statistical Classification of Products by Activity in the European Union (CPA 2.1) with the Standard Goods Classification for Transport Statistics, 2007 (NST 2007). For details on these commodity factors f entering the GTCs in (16), see Appendix D in the supplemental data online.

4.3. Iceberg (*ad valorem*) trade costs

Finally, once the GTCs have been determined, it is possible to calculate the bilateral iceberg trade costs used in the SAR gravity equation (15). Matching the trade flows classified according to the CPA 2.1 with their corresponding GTCs, $GTC_{od}^{c,v}$, following the NST 2007 classification (see Appendix B in the supplemental data online), we

Table 1. Distance thresholds for optimal vehicle sizes: handling and hauling costs.

			Handling			
Vehicle	Maximum payload (a) tonnes	Time costs (b) €/h	(c) h	(d) = (c)*(b)/(a) €/tonne	Hauling (e) €/tonne/km	Distance (f) km
HDV (five axles)	25.0	30.4	3.5	4.3	0.050	72.0
Rigid (three axles)	16.0	24.9	2.1	3.3	0.073	25.0
Small (two axles)	6.0	21.0	0.4	1.3	0.206	10.0

Note: HDV, heavy-duty vehicle.
Source: Authors' own calculation based on Burdzik et al. (2014), Zofío et al. (2014) and Ministerio de Fomento (MFOM) (2018).

calculate the iceberg trade cost τ^c_{od} as follows:

$$\tau^c_{od} = \frac{F^c_{od}\sum_{v=1}^{3}\left(\frac{s^v_{od}}{L^v_{od}}\right)GTC^{c,v}_{od}}{V^c_{od}} = \frac{\sum_{v=1}^{3}\left(\frac{s^v_{od}}{L^v_{od}}\right)GTC^{c,v}_{od}}{P^c_o},\ s^v_{od} \geq 0, \quad (19)$$

$$\sum\nolimits_{v=1}^{3} s^v_{od} = 1,$$

where F^c_{od} (tonnes) and V^c_{od} (€) are the quantity and value of the trade flows in origin; $GTC^{c,v}_{od}$ (€/veh.) is the GTC for each vehicle size, calculated in (16); s^v_{od} are the shares of each vehicle in the bilateral shipments between regions; and, finally, L^v_{od} (tonnes/veh.) is the average load of the shipments. This information is obtained from the European Freight Road Transportation (EFRT) survey.

Also, as shown in the second equality, the *ad valorem* aggregated transport cost can be related to the unit price in origin corresponding to each sector P^c_o. We use the information reported in the Community External Trade Statistics (COMEXT) database to calculate unit prices at the national level. For each CPA 2.1 sector and country of origin we obtain unit prices as $P^c_{od} = \sum_D F^c_{od}/\sum_D V^c_{od}$. Table 3 summarises the information on the iceberg trade costs τ^c_{od} by CPA sector, as well as the variables $GTC^{c,v}_{od}$ and P^c_{od}

Table 2. Representative vehicles given distance, city logistics and urban patterns.

		Destination *j*		
		Urban centre	Urban cluster	Rural
10 < d_{ij} ≤ 35 km				
Origin *i*	Urban centre	Small	Small	Small
	Urban cluster	Small	Small	Rigid
	Rural	Small	Rigid	Rigid
35 < d_{ij} ≤ 150 km				
Origin *i*	Urban centre	Rigid	Rigid	Rigid
	Urban cluster	Rigid	Rigid	HDV
	Rural	Rigid	HDV	HDV

Note: Small vehicle: two axles; rigid vehicle: three axles; heavy-duty vehicle (HDV): five axles. It is assumed that the vehicle of choice is the small two-axle truck for distances < 10 km, while the articulated HDV is used for distances > 150 km.

entering its calculation. The information is differentiated in terms of the elasticities of interest: foreign and national. Appendix G in the supplemental data online shows the iceberg, GTCs and units' prices by quintiles of $GTC^{c,v}_{od}$.

5. RESULTS

5.1. Checking the existence of spatial dependence in the standard gravity model

To determine the relevance of the spatial specification over its standard counterpart that ignores spatial dependence, we run the latter model and determine whether spatial autocorrelation is an issue. Table 4 presents the results of the gravity equation (15) as well as those obtained without neighbouring spillover effects.[6] While in the next sections we discuss the relative values of the foreign and national elasticities, the sign and significance of the adjacency and border dummies, and the magnitude and direction of the spatial effects, we start this section showing why accounting for spatial dependence is relevant to obtain unbiased estimates.

Moran's I test for residual spatial autocorrelation or Lagrange multiplier tests (Anselin et al., 1996) are widely used to test for the presence of spatial autocorrelation in the residuals. However, these tests require the calculation of several expressions involving the W matrix. Given that our sample has 63,001 observations, the enormous size of these matrices makes the calculation of these tests impractical. Consequently, we rely on graphical analyses using Moran scatter plots (Anselin, 1996). Figure 2 presents the Moran scatter plots of the non-spatial model, where the standardised residual of this gravity equation estimations is measured on the horizontal axes and the standardised spatial lag of the residual on the vertical axes. The graph displays the Moran scatter plot using the three W matrices: origin, destination and origin–destination. The red straight line is the best fit between the spatial lag of the residuals and the residuals. Its positive and significant slope signals the presence of spatial autocorrelation in the residuals.

As for the estimation strategy of spatial gravity models, LeSage and Pace (2008) suggest starting from the unconstrained spatial Durbin model, where the spatial lags of the origin and destination variables (gross domestic product (GDP), population, etc.) are included as additional regressors. However, as in our regression the importer and exporter characteristics are captured by their corresponding fixed effects, and including spatial lags of these fixed

Table 3. Iceberg, generalised transport costs (GTCs) and unit prices.

CPA	Variables								
	$\bar{\tau}^c_{od}$	$\bar{\tau}^c_{od}$ Foreign	$\bar{\tau}^c_{od}$ National	$\overline{GTC}^{c,v}_{od}$	$\overline{GTC}^{c,v}_{od}$ Foreign	$\overline{GTC}^{c,v}_{od}$ National	$\bar{P}^c_{od}$	$\bar{P}^c_{od}$ Foreign	$\bar{P}^c_{od}$ National
A01	0.343	0.359	0.145	2259	2388	670	427	431	375
A02–A03	0.832	0.874	0.315	2259	2388	670	137	139	121
B	1.236	1.302	0.423	2690	2844	791	26	25	30
C10–C12	0.180	0.189	0.068	2140	2262	636	723	729	652
C13–C15	0.081	0.085	0.029	2015	2130	600	2606	2609	2567
C16–C18	0.131	0.136	0.058	2018	2133	602	1167	1183	959
C19	0.219	0.231	0.071	2489	2632	740	681	683	653
C20–C22	0.477	0.503	0.153	2171	2295	646	343	341	375
C23	0.318	0.335	0.113	2410	2548	712	572	577	512
C24	0.307	0.322	0.126	2113	2234	629	421	421	414
C25	0.016	0.017	0.006	2113	2234	629	8159	8142	8361
C26–C28	0.093	0.097	0.036	2112	2233	630	2245	2246	2235
C29–C30	0.139	0.147	0.046	2063	2180	616	1678	1680	1653
C31–C32	0.730	0.768	0.261	2017	2133	601	249	249	253

Note: Data are averages. CPA, Statistical Classification of Products by Activity.
Source: Authors' own elaboration.

effects would be meaningless, our initial estimation corresponds to the SAR model (15). Figure 3 shows the Moran scatter plots of residuals from the estimation of the spatial gravity equation. The three scatterplots indicate that the spatial gravity model has correctly captured the spatial dependence between trade flows, as the almost zero slopes of the best-fit lines indicate no correlation between the spatial lag of residuals and the residuals.

Comparing the estimated values of the foreign and national elasticities and their underlying coefficients corresponding to the spatial standard gravity equation and its standard counterpart, we see that they are generally lower in the spatial estimation. This signals that not controlling for spatial dependence in the standard gravity equation model would lead to an upward bias in the estimated coefficients and trade elasticities.

5.2. Macro-elasticities of trade for overall trade and main sectors

Now we discuss the estimations of the trade elasticities corresponding to all trade flows, as well as those obtained when estimating equation (15) considering those pertaining to each of the three main sectors: A (Agriculture, forestry and fishing), B (Mining and quarrying) and C (Manufacturing). Table 5 reports the values of the foreign and national elasticities and compares them to those obtained for the aggregate of all trade flows already reported in Table 4. Table 5 includes credible intervals for all these estimations, obtained through MCMC simulations.

The *foreign* macro-elasticities range between $\sigma^A_F = 0.552$ (Agriculture, forestry and fishing) and $\sigma^C_F = 2.475$ (Manufacturing). The lower 2.5% and upper 97.5% thresholds reported in Table 6 confirm that these values are significantly different from zero. This is also the case for the overall foreign elasticity including all sectors, whose estimate is $\sigma_N = 2.038$, also different from zero. Regarding *national* trade elasticities, their values range between $\sigma^B_N = 1.780$ (Mining and quarrying) and $\sigma^C_N = 9.749$ (Manufacturing). Constituting one of the most relevant results of this study we observe that national elasticities are always larger than their foreign counterparts: $\sigma^c_F < \sigma^c_N$. The fact that the credible intervals do not overlap with those of the foreign elasticities shows the robustness of the previous relationship, with national elasticities being significantly different and consistently larger than foreign elasticities. These results show that the sensitivity of trade to price changes within the same country is much larger than that existing for those sourced from third countries. Finally, aggregating all trade flows, the national elasticity also quadruples its foreign counterpart: $\sigma_N = 8.696 > \sigma_F = 2.038$.

Regarding the common set of variables, we see that in all three sectors the dummy capturing trade between adjacent regions within the same country, $Adj.Region_{od}$ is positive and significant. This is not the case for the dummy capturing adjacency between regions belonging to different countries, $Adj.Country_{od}$, which is negative in the primary sectors A and B. This suggests that this dummy is capturing border effects hampering trade except for Manufacturing. As for the dummies capturing internal trade both within the same region, $Intraregion_{od}$, and/or country, $Intracountry_{od}$, they all exhibit positive and significant coefficients, implying increased bilateral trade. Finally, the correlation coefficients lay in the range between 0.676 and 0.749, which are relatively high for SAR specifications.

Now we turn our attention to the sign and magnitude of the spatial dependence effects $b^{c,\,neighbor}_{od}$ defined in equation (14) and incorporated into the SAR gravity

Table 4. Spatial and non-spatial macro-foreign (international) and national elasticities of trade.

	Sectors	
Variables	All sectors, spatial	All sectors, standard non-spatial
$\sigma_F^c = 1 - \beta_f^c$	2.038	3.432
$\sigma_N^c = 1 - (\beta_f^c + \beta_n^c)$	8.696	14.246
$\sigma_F^c >=< \sigma_N^c$	<	<
$\beta_f^c(\ln(1+\tau_{of}^c))$	−1.038**	−2.432***
	(0.060)	(0.062)
$\beta_n^c(\ln(1+\tau_{on}^c))$	−6.658**	−10.814***
	(0.408)	(0.439)
Adj.Region	0.527**	0.913***
	(0.037)	(0.040)
Adj.Country	0.016	0.215***
	(0.014)	(0.016)
Intraregion	4.627*	2.964***
	(1.011)	(1.150)
Intracountry	2.081***	3.719***
	(0.063)	(0.059)
$W_o \ln V_{od}^c$	0.271**	
	(0.009)	
$W_d \ln V_{od}^c$	0.374***	
	(0.007)	
$W_{od} \ln V_{od}^c$	−0.094*	
	(0.015)	
Intercept	3.251**	7.377***
	(0.120)	(0.104)
R^2	0.743	0.670
Observations	63,001	63,001

Note: Importer and exporter fixed effects. Significances: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

specification (15). The parameter ρ_1 associated with the origin effects $W_o \ln V_{od}^c$ is positive and statistically significant for all sectors. It ranges between 0.257 for Manufacturing and 0.370 for Mining and quarrying. Destination effects $W_d \ln V_{od}^c$, whose associated parameter is ρ_2, are also positive and significant, and exhibit similar values. Once again, the smallest value, 0.369, is observed for Manufacturing and the biggest value, 0.569, for Mining and quarrying. This confirms that trade flows are not only affected by direct bilateral effects concerning the two trading regions, but they are also positively affected by the existing trade between neighbouring regions at origin and destination, whose effect should not be overlooked.

However, from the perspective of origin–destination spillovers, ρ_3, trade seems to be also negatively affected by competition effects. The existence of these competition effects, whose rationale was discussed in the introduction, has been already reported in the international trade literature (e.g., Barbero & Rodríguez-Crespo, 2018). Both the results for overall trade and the three main sectors exhibit negative effects, with negative values ranging between −0.029 for Agriculture, forestry and fishing and −0.186 for Mining and quarrying. Given that the negative values of the origin–destination parameters ρ_3 are smaller than those of origin, ρ_1, and destination, ρ_2, a net positive spillover effect prevails. The main takeaway is that given the statistical significance of spatial dependence revealed by the SAR model, neglecting its inclusion in the specification would produce biased estimates of the trade elasticities parameters.

These findings provide credible sector-specific values for foreign and national trade elasticities. These values can be adopted by regional spatial modellers when simulating the effects of public policies within single markets like the EU and calculating the associated welfare effects, as it would add precision and confidence in the attained results. As these values critically depend on the iceberg trade costs – from which foreign and national elasticities are recovered, Appendix H in the supplemental data online presents a robustness exercise showing their relevance when capturing a wide array of trade frictions. There we estimate the same model (15) but including the geodesic distance, $Dist_{\cdot od}$, as the usual proxy for direct relatedness effects. As expected, the distance parameters are significant at the expense of those of the iceberg trade costs, τ_{od}^c, given the correlation between the two variables, which in turn results in trade elasticities losing statistical significance. That is, the parameters β_f^c and β_n^c are not significant when the geodesic distance is included in the specification. The reason is that the GTCs entering the iceberg specification are already dependent on distance through the choice of optimal vehicle and its associated distance costs (see equation 17). The collinearity between the geodesic distance and the GTC prevents the simultaneous inclusion of both variables in the gravity specification (15). This result illustrates how the iceberg trade costs already include any information on transport frictions that the geodesic distance could bring eventually into the model. We conclude then that the iceberg cost is a more suitable variable to identify the effect of price variations on trade flows, as it incorporates more comprehensive information regarding economic, engineering and logistics costs, beyond the customary distance variable.

5.3. Micro-elasticities of trade for individual sectors

Focusing on lower level product categories, we report in Tables 7 and 8 our estimation results for the 'micro' foreign and national trade elasticities corresponding to the 14 sectors whose data belong to the two-digit CPA 2.1 classification (see Appendix B in the supplemental data online). The elasticities are reported in the first two rows, while their credible intervals are presented in Table 9.

As in the case of the macro-elasticities, we notice first that the estimated foreign and national estimated elasticities are positive in all sectors and different from zero. The only exception is sector C26–C28 (including Computer electronic and optical products, C26; Electrical

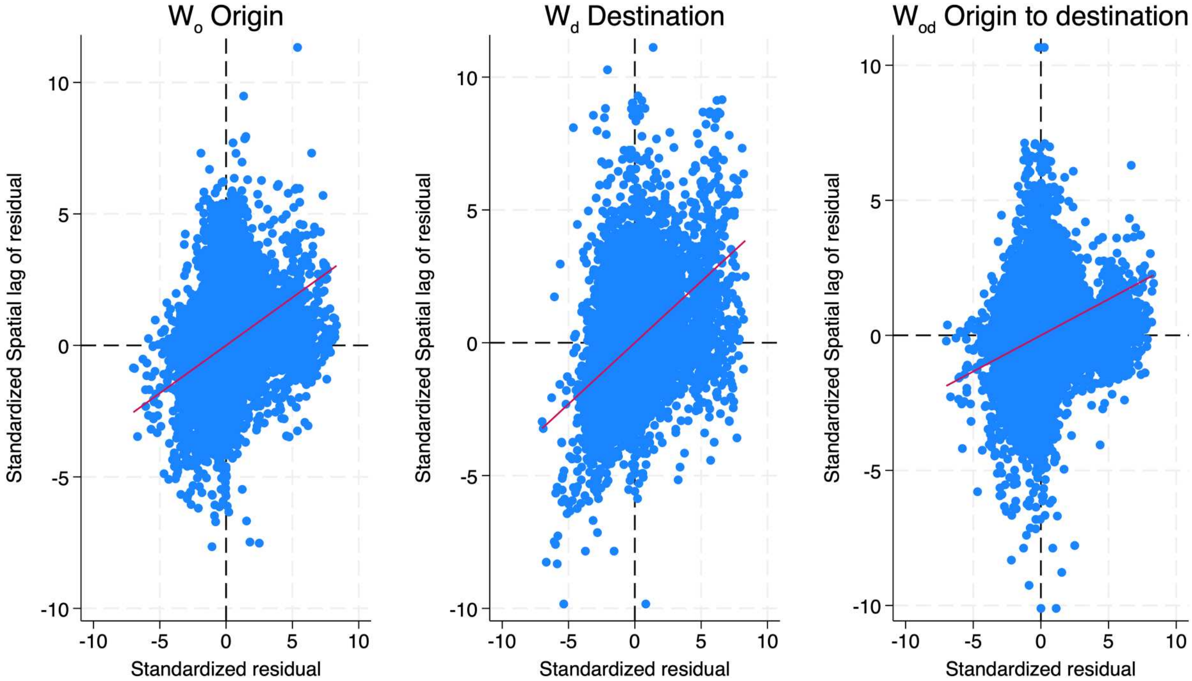

Figure 2. Moran scatterplots of the residuals in the standard (non-spatial) gravity equation.

equipment, C27; and Machinery and equipment, C28) that presents negative values in the interval of the national elasticity. Comparing the credible intervals in Table 8, we confirm that national elasticities are always larger than their foreign counterparts, that is, $\sigma_F^c < \sigma_N^c$. The median of foreign elasticities stands at 1.259, while that of national elasticities is 5.666. The third rows in Tables 7 and 8 summarise if foreign and national elasticities differ from each other based on the intervals. Comparing the upper value of the 97.5% threshold for foreign elasticities and the 2.5% lower threshold for the national elasticities, we require these values do not overlap. With this criterion in mind, all foreign elasticities are smaller than the national elasticities except, once again, in sector C26–C28. As expected, these results confirm that (intra-)national trade flows are more sensitive to price changes than their international counterparts, being one of the reasons the easiness of consumers to substitute between products sourced from regions within their own country, which they know better than foreign goods.

As for the common set variables, their value and significance is the same as those obtained for the macro-level regressions. The dummy capturing trade between adjacent regions within the same country, $Adj.Region_{od}$, is again positive and significant, while adjacency between regions belonging to different countries, $Adj.Country_{od}$, is negative in the primary sectors A and B, and all manufacturing sectors up to C19. Since the overall effect for Manufacturing is positive (see the aggregate regression in Table 5), we see that its positive effect on trade in heavy industries predominates, driving the results of the whole sector. Concerning the dummies capturing internal trade both within the same region, $Intraregion_{od}$, and/or country, $Intracountry_{od}$, the results concur with those of the macro-regressions, exhibiting positive and significant coefficients and implying increased bilateral trade. Before commenting in depth the values of the foreign and national elasticities, as well as those of the spatial effects, we see that the correlation coefficients are gain satisfactory for SAR specification, laying in the range between 0.425 and 0.749, and a mean of 0.656.

5.3.1. Foreign (international) elasticities of trade

Foreign trade elasticities differing statistically from one range between the smallest value observed in sector A01 (Agriculture), $\sigma_F^{A01} = 0.468$, and the largest value in sector C25 (Fabricated metal products), $\sigma_F^{C25} = 9.75$. With the exception of this last value, foreign elasticities corresponding to trade between regions belonging to different EU countries are similar to those reported in the literature on *international* trade flows, that is, $\sigma_F^c < 4$. A first set of results outside the EU correspond to those surveyed in Table 1 by Hillberry and Hummels (2013, vol. 1, p. 221) for multi-country (e.g., the Global Trade Analysis Project (GTAP) model) and single-country models (world data). Foreign elasticities range between [0.9, 34.4] – although the upper value, corresponding to the Gas sector, can be also regarded as an outlier in the distribution. Since the level of sectoral aggregation is like ours, we confirm that our estimates of comparable (i.e., foreign) trade elasticities are in accordance with those reported in previous studies.

There are also a few studies reporting trade elasticities between EU *countries* using different econometric approaches and for specific sectors. Németh et al. (2011) rely on a panel data analysis econometric framework that uses dynamic adjustments and obtain estimates in the range [0.6; 1.7]. These values are remarkably similar to ours, since all foreign elasticities reported in Tables 7 and 8 lay within that range except four sectors, which

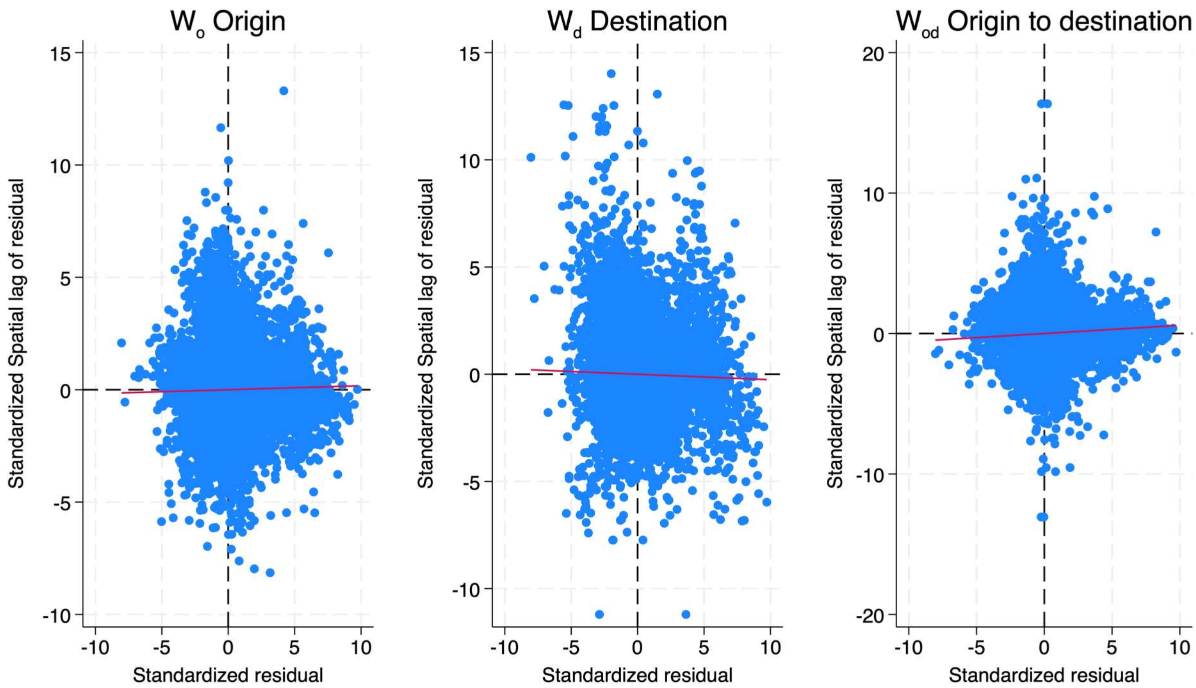

Figure 3. Moran scatterplots of the residuals in the spatial gravity equation.

Table 5. Spatial macro-foreign (international) and national elasticities of trade.

	Sectors			
Variables	A Agriculture, forestry and fishing	B Mining and quarrying	C Manufacturing	All sectors
$\sigma_F^c = 1 - \beta_f^c$	0.552	0.917	2.475	2.038
$\sigma_N^c = 1 - (\beta_f^c + \beta_n^c)$	5.439	1.780	9.749	8.696
$\sigma_F^c >=< \sigma_N^c$	$<$	$<$	$<$	$<$
$\beta_f^c(\ln(1 + \tau_{of}^c))$	0.448*	0.083	−1.475**	−1.038**
	(0.071)	(0.034)	(0.086)	(0.060)
$\beta_n^c(\ln(1 + \tau_{on}^c))$	−4.887**	−0.863*	−7.273**	−6.658**
	(0.425)	(0.244)	(0.543)	(0.408)
Adj.Region	0.783**	0.908**	0.557**	0.527**
	(0.068)	(0.049)	(0.040)	(0.037)
Adj.Country	−0.353**	−0.390**	0.101**	0.016
	(0.027)	(0.022)	(0.015)	(0.014)
Intraregion	6.371*	7.700*	4.568*	4.627*
	(1.934)	(1.462)	(1.085)	(1.011)
Intracountry	2.774**	1.860**	1.864***	2.081***
	(0.107)	(0.099)	(0.058)	(0.063)
$W_o \ln V_{od}^c$	0.360***	0.370***	0.257**	0.271**
	(0.007)	(0.008)	(0.008)	(0.009)
$W_d \ln V_{od}^c$	0.379***	0.593***	0.369***	0.374***
	(0.007)	(0.012)	(0.007)	(0.007)
$W_{od} \ln V_{od}^c$	−0.029	−0.186**	−0.073*	−0.094*
	(0.013)	(0.016)	(0.015)	(0.015)
Intercept	1.783**	−0.051	2.994**	3.251**
	(0.180)	(0.134)	(0.122)	(0.120)
R^2	0.676	0.749	0.728	0.743
Observations	63,001	63,001	63,001	63,001

Note: Importer and exporter fixed effects; Significances: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 6. Credible intervals for spatial macro-foreign (international) and national elasticities of trade.

Sector	Estimate	Lower 2.5%	Upper 97.5%
Foreign (international) elasticities of trade			
Agriculture, forestry and fishing	0.552	0.412	0.690
Mining and quarrying	0.917	0.850	0.982
Manufacturing	2.475	2.312	2.633
All sectors	2.038	1.924	2.147
National elasticities of trade			
Agriculture, forestry and fishing	5.439	4.621	6.254
Mining and quarrying	1.780	1.293	2.261
Manufacturing	9.749	8.650	10.817
All sectors	8.696	7.875	9.502

nevertheless do not exceed the upper threshold by much (with the exception of the previously mentioned sector C25), that is, $\sigma_F^{C24} = 2.158$ (Basic metals),- $\sigma_F^{C26-28} = 2.678$ (including Computer electronic and optical products, C26; Electrical equipment, C27; and Machinery and equipment, C28), and $\sigma_F^{C29-30} = 2.577$ (Motor vehicles trailers and semi-trailers, C29; and Other transport equipment, C30). On their part, Olekseyuka and Schürenberg-Frosch (2016), considering single-sector co-integration time series analysis, obtain elasticities for selected manufacturing sectors in the range [0.300; 3.670]. As for their panel data results, their pooled fixed effects estimations yield trade elasticities in the range [0.320; 2.430]. These results are also equivalent to ours, offering reassurance about the calculated national elasticities.

5.3.2. (Intra-)national elasticities of trade

As for the second level of trade flows, (intra-)national (or interregional) elasticities, our results indicate considerable variability across sectors. These elasticities range between the minimum value observed in sector B (Mining and quarrying): $\sigma_N^B = 1.780$, and, once again, sector C25 (Fabricated metal products): $\sigma_N^{C25} = 143.432$. The reason for this high sensitivity of trade flows to the iceberg trade cost is twofold. First, the large physical concentration of trade in very short distances in what is known as the 'extensive margin' of trade in the literature (Hillberry & Hummels, 2008; Díaz-Lanchas et al., 2022). The latter authors show that the elasticity of trade flows to transport costs is larger for intraregional trade due to the acute reduction of trade flows that is observed for low transport costs (or, equivalently, at short distances given the positive correlation between distance and iceberg trade costs through the inclusion of distance costs in the GTCs entering the latter; see equation 19). This fall in trade flows over a short range of the iceberg trade costs is particularly extreme for this sector, which results in the large value of the estimated national and foreign price elasticities. Second, as shown in Table 3 and Appendix G in the supplemental data online, the average iceberg trade cost for C25 (0.016) is very small due the large unit prices reported in the COMEXT database of Eurostat (€8159/tonne transported). Since iceberg trade costs are expressed in terms of the value of the commodities transported (again, see equation 19), dividing the GTCs by such large units further reduces the variability of the iceberg trade costs, this time regarding the intensive margin (i.e., in terms of the value of the commodities transported), which also results in a sharp decline in trade flows for relatively low transport costs or, equivalently, their associated short distances. The combination of these two features, a sharp decline in the density of trade flows over low trade costs (short distances) in both the extensive and intensive margins (particularly the second one) ultimately explains the large value of the elasticities. Similar reasons can be recalled for the minority of manufacturing sectors whose national elasticity exceeds a value of 10 (three out of 13 sectors, excluding sectors C26–C27 whose elasticity is not different from 1), although their values cannot be deemed outliers.

Considering all sectors, as already reported, the median national trade elasticity is 5.666. Contrary to the case of foreign elasticities, both small and large elasticities can be found in the primary sectors: Agriculture, $\sigma_N^{A01} = 6.800$; Products of forestry and fishing, $\sigma_N^{A02-03} = 5.371$; and Mining and quarrying $\sigma_N^B = 1.780$, and across all manufacturing sectors, where the lowest value corresponds to sector C26–C28: $\sigma_N^{C26-28} = 2.185$. Despite the difference in absolute values between foreign and national trade elasticities, both series highly correlate: $\rho(\sigma_F^c, \ \sigma_N^c) = 0.953$.

5.3.3. Accounting for spatial effects

As for the spatial dependence effects $b_{od}^{c,\ neighbor}$, represented by the origin, destination, and origin–destination regressors, we observe once again at the micro-level that the parameter ρ_1 corresponding to $W_o \ln V_{od}^c$ is positive and statistically significant in all sectors. It ranges between 0.090 for sector C20–C22 (including Chemicals products, C20; Pharmaceutical products, C21; and Rubber and plastics products, C22), and 0.513 for sectors C13–C15 (Textiles, C15; Wearing apparel, C16; and Leather products, C17). On its part, the parameter ρ_2 associated with destination effects $W_d \ln V_{od}^c$, is also positive and significant in all sectors, with similar range between 0.150 for sectors C16–C18 (Wood, C16; Paper, C17; and Printing products, C18), and 0.614 for C29–C30 (Motor vehicles, C29; and Other transport equipment, C30). In this way we confirm that the results obtained for the macro-sectors hold at the micro-level, that is, trade flows are influenced not only by direct bilateral effects between the two trading partners, but also by the existing trade between neighbouring regions at origin and destination, which plays a significant role and should not be ignored.

Table 7. Spatial micro-foreign (international) and national elasticities of trade.

	Sectors						
Variables	**A01**	**A02–A03**	**B**	**C10–C12**	**C13–C15**	**C16–C18**	**C19**
$\sigma_F^c = 1 - \beta_f^c$	0.532	0.867	0.917	0.963	1.518	1.764	1.061
$\sigma_N^c = 1 - (\beta_f^c + \beta_n^c)$	6.800	5.371	1.780	10.653	5.635	5.697	12.540
$\sigma_F^c > = < \sigma_N^c$	$<$	$<$	$<$	$<$	$<$	$<$	$<$
$\beta_f^c(\ln(1 + \tau_{of}^c))$	0.468*	0.133*	0.083	0.037	−0.518	−0.764*	−0.061
	(0.103)	(0.038)	(0.034)	(0.180)	(0.210)	(0.231)	(0.147)
$\beta_n^c(\ln(1 + \tau_{on}^c))$	−6.268**	−4.504**	−0.863*	−9.690**	−4.118	−3.933*	−11.479**
	(0.445)	(0.231)	(0.244)	(1.065)	(1.351)	(1.010)	(0.897)
Adj.Region	0.891**	0.289**	0.908**	1.111**	0.068	0.556**	0.645**
	(0.069)	(0.046)	(0.049)	(0.074)	(0.046)	(0.069)	(0.065)
Adj.Country	−0.379**	−0.272**	−0.390**	−0.576**	−0.544**	−0.252**	−0.526**
	(0.028)	(0.019)	(0.022)	(0.030)	(0.021)	(0.027)	(0.027)
Intraregion	6.626*	4.201*	7.700*	4.858	7.680*	5.694	6.098*
	(1.990)	(1.310)	(1.462)	(2.085)	(1.359)	(1.997)	(1.851)
Intracountry	2.202**	3.531***	1.860**	2.320**	2.436***	3.192***	2.434**
	(0.081)	(0.085)	(0.099)	(0.091)	(0.074)	(0.086)	(0.080)
$W_o \ln V_{od}^c$	0.371***	0.249***	0.370***	0.256***	0.513***	0.125**	0.304***
	(0.008)	(0.004)	(0.008)	(0.005)	(0.015)	(0.006)	(0.006)
$W_d \ln V_{od}^c$	0.390***	0.257***	0.593***	0.483***	0.614***	0.150**	0.497***
	(0.007)	(0.006)	(0.012)	(0.012)	(0.013)	(0.006)	(0.012)
$W_{od} \ln V_{od}^c$	−0.049*	0.038*	−0.186**	−0.041	−0.314**	0.169**	−0.118**
	(0.014)	(0.010)	(0.016)	(0.014)	(0.023)	(0.009)	(0.017)
Intercept	1.726**	0.739*	−0.051	2.813**	0.107	0.350	1.245**
	(0.183)	(0.123)	(0.134)	(0.193)	(0.123)	(0.184)	(0.169)
R^2	0.665	0.586	0.749	0.668	0.851	0.447	0.716
Observations	63,001	63,001	63,001	63,001	63,001	63,001	63,001

Note: Importer and exporter fixed effects. Significances: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8. Spatial micro-foreign (international) and national elasticities of trade (cont.).

	Sectors						
Variables	**C20–C22**	**C23**	**C24**	**C25**	**C26–C28**	**C29–C30**	**C31–C32**
$\sigma_F^c = 1 - \beta_f^c$	1.129	1.173	2.158	9.575	2.678	2.577	1.344
$\sigma_N^c = 1 - (\beta_f^c + \beta_n^c)$	4.365	4.990	7.562	143.432	2.185	8.588	4.782
$\sigma_F^c > = < \sigma_N^c$	<	<	<	<	=	<	<
$\beta_f^c(\ln(1 + \tau_{of}^c))$	−0.129	−0.173	−1.158**	−8.574*	−1.678*	−1.577**	−0.344*
	(0.102)	(0.098)	(0.090)	(1.604)	(0.353)	(0.236)	(0.059)
$\beta_n^c(\ln(1 + \tau_{on}^c))$	−3.235*	−3.817**	−5.403**	−133.859**	0.493	−6.011*	−3.438**
	(0.585)	(0.469)	(0.407)	(10.950)	(1.462)	(1.166)	(0.402)
Adj.Region	0.671**	1.616**	0.323**	0.941**	1.080**	1.067**	0.620**
	(0.091)	(0.069)	(0.050)	(0.068)	(0.078)	(0.079)	(0.071)
Adj.Country	0.289**	0.683**	0.339**	0.058	0.327**	0.437**	0.442**
	(0.038)	(0.029)	(0.021)	(0.028)	(0.031)	(0.032)	(0.029)
Intraregion	1.167	6.387*	5.142*	5.937*	3.451	5.327	3.328
	(2.665)	(1.901)	(1.427)	(1.908)	(2.264)	(2.317)	(2.003)
Intracountry	3.704***	1.285**	1.508**	3.451***	1.323**	1.468**	2.236**
	(0.116)	(0.066)	(0.060)	(0.097)	(0.069)	(0.071)	(0.105)
$W_o \ln V_{od}^c$	0.090**	0.233***	0.280**	0.242**	0.093**	0.105**	0.199**
	(0.007)	(0.007)	(0.010)	(0.008)	(0.006)	(0.006)	(0.008)
$W_d \ln V_{od}^c$	0.177***	0.367***	0.525***	0.379***	0.141**	0.258***	0.453***
	(0.005)	(0.007)	(0.010)	(0.007)	(0.006)	(0.005)	(0.008)
$W_{od} \ln V_{od}^c$	0.088**	−0.063*	−0.178**	−0.118**	0.110**	0.093**	−0.050*
	(0.011)	(0.014)	(0.019)	(0.016)	(0.011)	(0.011)	(0.014)
Intercept	2.262**	1.173**	1.063**	0.931*	2.486**	1.366**	2.504**
	(0.251)	(0.176)	(0.138)	(0.179)	(0.214)	(0.215)	(0.188)
R^2	0.403	0.599	0.717	0.663	0.425	0.501	0.649
Observations	63,001	63,001	63,001	63,001	63,001	63,001	63,001

Note: Importer and exporter fixed effects. Significances: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 9. Credible intervals of spatial micro-foreign (international) and (intra-)national elasticities of trade.

Sector	Estimate	Lower 2.5%	Upper 97.5%
Foreign (international) elasticities of trade			
A01	0.532	0.326	0.732
A02-A03	0.867	0.792	0.939
B	0.917	0.850	0.982
C10-C12	0.963	0.605	1.316
C13-C15	1.518	1.103	1.938
C16-C18	1.764	1.309	2.206
C19	1.061	0.771	1.336
C20-C22	1.129	0.933	1.332
C23	1.173	0.987	1.362
C24	2.158	1.990	2.321
C25	9.575	6.410	12.633
C26-C28	2.678	2.008	3.348
C29-C30	2.577	2.117	3.012
C31-C32	1.344	1.229	1.462
National elasticities of trade			
A01	6.800	5.916	7.681
A02-A03	5.371	4.931	5.806
B	1.780	1.293	2.261
C10-C12	10.653	8.497	12.771
C13-C15	5.635	3.034	8.252
C16-C18	5.697	3.556	7.740
C19	12.540	10.715	14.311
C20-C22	4.365	3.171	5.493
C23	4.990	4.047	5.888
C24	7.562	6.738	8.345
C25	143.432	121.568	164.739
C26-C28	2.185	−0.886	5.168
C29-C30	8.588	6.167	10.975
C31-C32	4.782	3.968	5.594

Finally, from the perspective of origin–destination spillovers, ρ_3, we find that this parameter is statically significant for all sectors. However, the results are heterogenous with most sectors exhibiting a negative value, associated with competition effects, while the remaining sectors present a positive sign, which show trade reinforcing effects (e.g., through supply chain complementarities as discussed in the introduction). As many as eight sectors present negative effects (only one sector with negative value is not statistically significant), while the remaining five sectors exhibit positive effects. Negative values range between −0.049 for A01 and −0.314 for C13–C15, while positive values range between 0.038 for A02–A03 and 0.169 for C16–C18. Once again, as observed in the macro-level results, the negative values of the origin–destination parameters ρ_3 are in general one order of magnitude smaller than those of origin, ρ_1, and destination, ρ_2. Therefore, a net positive spillover effect promoting trade predominates. The key point is that, due to the statistical significance of spatial dependence shown by the SAR model, omitting it from the specification would lead to biased estimates, particularly the trade elasticity parameters of interest.

6. CONCLUSIONS

This study contributes to regional literature in two significant ways. Using trade data between EU regions, we propose the differentiation and joint estimation of two distinct trade elasticities driving imports from foreign regions located in other countries (foreign elasticities) and those sourced from regions within the same country (national elasticities). We argue and formalise that consumers' preferences for varieties of goods should be different when the importing region belongs to the same country or to third countries. Second, the existence of spatial dependence has been neglected when calculating trade elasticities, compromising the reliability of existing estimates. To address this gap, we incorporate the presence of spatial spillovers into an SAR gravity equation, derived from a three-tier CES utility function, establishing a microeconomic foundation for both elasticities.

Building on LeSage and Pace (2008), we integrate three regional contiguity matrices capturing neighbour spillovers from the origin, destination, and origin–destination perspectives. To identify the trade elasticities, we compute a precise measure of iceberg trade cost that improves the methodology developed by Persyn et al. (2022) and that feeds the SAR gravity equation at different levels of sectorial disaggregation of trade flows. This measure is based on least cost freight transportation routes between EU regions (GTCs), which incorporate the economic costs associated with an optimal choice of vehicle, the urban layout, and the nature of the transported goods.

Before discussing our results regarding the foreign and national elasticities, as well as the spatial effects, we first show that spatial dependence is present in our trade data. Resorting to Moran's scatter plot we confirm that the residuals of the standard (non-spatial) model exhibit spatial autocorrelation, and that the SAR model can deal with it effectively, thereby obtaining unbiased estimates. In this regard we conclude that our estimates of the foreign and national trade elasticities are satisfactory given their magnitude and statistical significance. The foreign elasticities lay in the range of previous estimates for international trade with an average of 1.986. National elasticities are always larger than their foreign counterparts with their average standing at 5.371. These results are robust at the macro-level when using all trade flows and also for the regressions considering data grouped by each of the three main sectors. At the micro-level for individual sectors, the reported foreign elasticities have values around those normally reported in the international trade literature and are statistically significant (i.e., the credible intervals exclude zero). As for national elasticities, these are substantially greater than foreign ones and are also statistically different (i.e., credible intervals do not overlap).

This confirms the hypothesis that national trade is more sensitive to price variations than international trade. The higher elasticity of national goods to trade costs may be a consequence of the fact that intranational trade faces fewer non-price related trade restrictions than international trade, even within single market areas such as the EU. In other words, varieties of goods produced in regions belonging to the same country are better known by consumers and may exhibit higher homogeneity. Therefore, consumers find it easier to substitute goods sourced from nearby regions within the same country, as they are better informed about the price and characteristics of relatively similar products, than if they are imported from abroad for which close substitutes are difficult to find. These findings are also in line with previous studies showing that trade flows respond differently and in a non-linear way to changes in trade costs, leading to uneven densities of trade flows across regions and eventually shaping differences in the home-bias trade effect between national and foreign trade flows. For instance, Hillberry and Hummels (2008) and Díaz-Lanchas et al. (2022) show that the price elasticity of trade flows (shipments) to low transport cots (i.e., at short distances within the same municipality) is three times larger than those for larger transport costs (or farther distances), which would correspond to international trade between regions belonging to different countries. Our results present similar differences in magnitude, representing a plausible outcome.

As for the spatial spillovers, their positive magnitude and significance evidence that spatial dependence at the origin and at destination exhibit complementary effects, and therefore reinforce bilateral trade flows – their magnitudes being on average 0.244 and 0.377, respectively. On the contrary, for most sectors, competition effects emerge for the origin–destination dependence, with an average negative value of − 0.134. Therefore, the net effect of all three sources of spatial dependence is positive. From the perspective of the social planner, these results confirm that investing in making one's region more attractive from the perspective of transport and regional infrastructure policies pays off in the form of higher levels of trade, not only through the usual channels of reducing transport costs, but also through spillover effects. On the contrary, losing ground with other regions, that is, considering only increments in the trade flows of neighbouring regions to each origin–destination pair, does not benefit these latter regions because the spillovers are competitive (Barbero & Zofío, 2016).

Understanding consumers' sensitivity to price changes in national and foreign imports is crucial for trade and regional modelling literature. A more refined analysis of these elasticities for the European regions introduces significant complexities into the dynamics of the European single market integration. National elasticities capture the responsiveness of trade flows within member states, while international elasticities reflect the response to cross-border trade variations within the EU. This distinction is critical for enhancing trade models and their capacity to capture the true nature of market integration. For example, traditional gravity models, such as those refined by Anderson and van Wincoop (2003), typically rely on a single trade elasticity, which can mask the differential impacts of domestic versus international trade frictions. By recognising and incorporating these differences, policymakers can design more effective strategies to address persistent trade barriers and optimise the functioning of the single market. Additionally, accounting for spatial dependence – where the trade flows of one region influence its neighbouring regions – underscores the importance of regional cooperation and integrated infrastructure policies, both at the national and supranational levels.

Moreover, the welfare gains from trade, as studied by Hertel et al. (2007), depend on reliable estimates of trade elasticities, particularly in relation to changes in allocative efficiency or the variety of goods available to consumers. Our results demonstrate that ignoring the reallocation of trade flows within countries when markets open, whether due to tariff changes or transport cost reductions, can distort estimates of welfare effects, especially when spatial spillover effects between regions are considered. A region's attractiveness in terms of transport infrastructure is not only related to relatively low transport costs, but also to the positive externalities that it may generate for neighbouring areas (Gallego & Zofío, 2018; Gallego et al., 2022). However, these spillovers can be competitive rather than complementary, meaning regions that fall behind in terms of infrastructure investment might not share the benefits, emphasising the need for coordinated regional development strategies.

Finally, distinguishing between national and international elasticities, along with accounting for spatial dependence, greatly enhances the accuracy of spatial general equilibrium models used to simulate policy impacts. These spatial models often rely on elasticities within frameworks that include CES utility functions, monopolistic competition, and increasing returns to scale, making differentiation crucial for realistic policy simulation. Homogenising trade elasticities – while ignoring spatial dependencies – risks undermining the accuracy of these models. Differentiating elasticities allows for a more precise description of consumer behaviour and spatial spillovers, leading to more reliable evaluations of infrastructure investments, transport cost reductions, and other regional policy interventions. These improvements not only enhance trade within the single market but also ensure that the spillover effects benefit a broader spectrum of regions, supporting the goal of balanced regional development across the EU.

ACKNOWLEDGEMENTS

The authors thank the associate editor and three anonymous referees for their helpful comments and suggestions, which significantly improved the paper. They are grateful to Giovanni Mandras for providing the trade flow data used in this research.

DATA AVAILABILITY STATEMENT

The data are available from the sources identified in the paper.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

FUNDING

José L. Zofío and Javier Barbero are thankful for grant PID2022-138212NA-I00 funded by MICIU/AEI/10.13039/501100011033 and by the European Regional Development Fund (ERDF) of the European Union. We gratefully acknowledge financial support from the Communidad de Madrid/ESF (PHS-2024/PH-HUM-530), and the Government of the Principality of Asturias and the European Regional Development Fund (IDE/2024/000712).

NOTES

1. Appendix A in the supplemental data online presents the mathematical derivations of the demand equations, the optimal prices and the gravity equations.
2. We assume that all firms within a given region operate with the same technology and face the same input costs. Consequently, for simplicity, we drop the firm-specific subscript h in the following expressions.
3. In the final econometric specifications of the gravity equations shown below, the number of firms or varieties, along with the preference parameters, and any origin-specific determinants are eventually swept out by the fixed effects capturing export-only characteristics. Correspondingly, the importer region's price index, expenditure and any other destination-specific determinants are also swept out by the importers' fixed effects.
4. The difference between (export) FOB and (import) CIF definitions of trade flows is discussed in section 4.1.
5. See Persyn et al. (2022) for an in-depth analysis of each component of the distance and time economic costs e^d_{ak} and e^v_{ak} (€/km). The primary component of distance cost is fuel cost ($fuel_a$), calculated by multiplying the fuel price at the origin (€/litre) by the fuel consumption of the reference vehicle along the optimal route. For international shipments, we account for country-specific prices based on the length of each segment within different countries. Toll costs ($toll_a$) vary by region and route due to differences in national tolling policies (e.g., vignettes or country-wide electronic tolls) and different rates per road segment. The main time cost is the driver's labour (t_a-lab_{ij}), determined by multiplying the hourly wage cost (lab_{ij}) taken from Eurostat by the time (h) required to complete the optimal route, minimising costs. Labour costs also reflect the average wages at both the origin and destination. The remaining costs are proportional to the cost shares (CS) of these primary components, based on the cost structures provided by the Spanish Observatory of Freight Road Transportations in 2018 (Ministerio de Fomento (MFOM), 2018).
6. The model is estimated for a sample of 251 EU NUTS-2 regions. For the SAR model we follow customary practice in spatial econometrics and exclude islands as they are not physically contiguous to other regions and, therefore, do not have spatial interaction in our model given the W matrix.

ORCID

José L. Zofío http://orcid.org/0000-0003-1170-9501
Javier Barbero http://orcid.org/0000-0002-2155-3996
Jorge Díaz-Lanchas http://orcid.org/0000-0002-3031-9683
Damiaan Persyn http://orcid.org/0000-0003-2742-6522

REFERENCES

Alamá-Sabater, L., Márquez-Ramos, L., & Suárez-Burguet, C. (2013). Trade and transport connectivity: A spatial approach. *Applied Economics*, *45*(18), 2563–2566. https://doi.org/10.1080/00036846.2012.669466

Anderson, J. E., & Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, *93*(1), 170–192. https://doi.org/10.1257/000282803321455214

Anselin, L. (1996). The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In M. Fischer, H. Scholten, & D. Unwin (Eds.), *Spatial analytical perspectives on GIS in environmental and socio-economic sciences* (pp. 111–125). Taylor & Francis.

Anselin, L. (1998). Lagrange multiplier tests for spatial dependence and spatial heterogeneity. *Geographical Analysis*, *20*(1), 1–17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*(1), 77–104. https://doi.org/10.1016/0166-0462(95)02111-6

Bajzik, J., Havranek, T., Irsova, Z., & Schwarz, J. (2020). Estimating the Armington elasticity: The importance of study design and publication bias. *Journal of International Economics*, *127*, 103383. https://doi.org/10.1016/j.jinteco.2020.103383

Baldwin, R., & Taglioni, D. (2006). *Gravity for dummies and dummies for gravity equations* (Working Paper Series 12516). National Bureau of Economic Research (NBER). https://doi.org/10.3386/w12516

Barbero, J., & Rodríguez-Crespo, E. (2018). The effect of broadband on European Union trade: A regional spatial approach. *The World Economy*, *41*(11), 2895–2913. https://doi.org/10.1111/twec.12723

Barbero, J., & Zofío, J. L. (2016). The multiregional core–periphery model: The role of the spatial topology. *Networks and Spatial Economics*, *16*(2), 469–496. https://doi.org/10.1007/s11067-015-9285-7

Behrens, K., Ertur, C., & Koch, W. (2012). 'Dual' gravity: Using spatial econometrics to control for multilateral resistance. *Journal of Applied Econometrics*, *27*(5), 773–794. https://doi.org/10.1002/jae.1231

Bensassi, S., Márquez-Ramos, L., Martínez-Zarzoso, I., & Suárez-Burguet, C. (2015). Relationship between logistics infrastructure and trade: Evidence from Spanish regional exports. *Transportation Research Part A: Policy and Practice*, *72*, 47–61. https://doi.org/10.1016/j.tra.2014.11.007
Bergstrand, J. H., Larch, M., & Yotov, Y. V. (2015). Economic integration agreements, border effects, and distance elasticities in the gravity equation. *European Economic Review*, *78*(C), 307–327. https://doi.org/10.1016/j.euroecorev.2015.06.003
Bröcker, J. (2015). Spatial computable general equilibrium analysis. In C. Carlsson, M. Andersson & T. Norman (Eds.), *Handbook of research methods and applications in economic geography* (pp. 41–66). Edward Elgar.
Burdzik, R., Ciesla, M., & Sladkowski, A. (2014). Cargo loading and unloading efficiency analysis in multimodal transport. *Promet – Traffic & Transportation*, *26*(4), 323–331. https://doi.org/10.7307/ptt.v26i4.1356
Dargel, L. (2021). Revisiting estimation methods for spatial econometrics. *Journal of Spatial Econometrics*, *2*(10), 1–41. https://doi.org/10.1007/s43071-021-00016-1
Díaz-Lanchas, J., Gallego, N., Llano, C., & De la Mata, T. (2016). Testing transport mode cooperation and competition within a country: A spatial econometrics approach. In R. Patuelli, & G. Arbia (Eds.), *Spatial econometric interaction modelling, advances in spatial science* (pp. 317–364). Springer. https://doi.org/10.1007/978-3-319-30196-9_14
Díaz-Lanchas, J., Zofío, J. L., & Llano, C. (2022). A trade hierarchy of cities based on transport cost thresholds. *Regional Studies*, *56*(8), 1359–1376. https://doi.org/10.1080/00343404.2021.1967922
Duparc-Portier, G., & Figus, G. (2024). How should governments respond to energy price crises? A horse-race between fiscal policies. *Energy Economics*, *130*, 107284. https://doi.org/10.1016/j.eneco.2023.107284
Felbermayr, G. J., & Tarsav, A. (2022). Trade and the spatial distribution of transport infrastructure. *Journal of Urban Economics*, *130*, 103473. https://doi.org/10.1016/j.jue.2022.103473
Fujita, M., Krugman, P., & Venables, A. (1999). *The spatial economy: Cities, regions, and international trade*. MIT Press. https://doi.org/10.7551/mitpress/6389.001.0001.
Gallego, N., Llano, C., De La Mata, T., & Díaz-Lanchas, J. (2015). Intranational home bias in the presence of wholesalers, hub-spoke structures and multimodal transport deliveries. *Spatial Economic Analysis*, *10*(3), 369–399. https://doi.org/10.1080/17421772.2015.1062126
Gallego, N., Llano, C., & Zofío, J. L. (2022). Transportation gateways and trade: How accessibility to the border shapes the spatial concentration of commerce. *Regional Studies*, *57*(3), 537–559. https://doi.org/10.1080/00343404.2022.2094907
Gallego, N., & Zofío, J. L. (2018). Trade openness, transport networks and the spatial location of economic activity. *Networks and Spatial Economics*, *18*(1), 205–236. https://doi.org/10.1007/s11067-018-9394-1
Head, K., & Mayer, T. (2014). Gravity equations: Workhorse, toolkit and cookbook. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics* (Vol. 4, pp. 131–195). North-Holland. https://doi.org/10.1016/B978-0-444-54314-1.00003-3
Hertel, T., Hummels, D., Ivanic, M., & Keeney, R. (2007). How confident can we be of CGE-based assessments of free trade agreements? *Economic Modelling*, *24*(4), 611–635. https://doi.org/10.1016/j.econmod.2006.12.002
Hillberry, R., & Hummels, D. (2008). Trade responses to geographic frictions: A decomposition using micro-data. *European Economic Review*, *52*(3), 527–550. https://doi.org/10.1016/j.euroecorev.2007.03.003
Hillberry, R., & Hummels, D. (2013). Trade elasticity parameters for a computable general equilibrium model. In P. Dixon, & D. Jorgenson (Eds.), *Handbook of computable general equilibrium modeling* (Vol. 1, pp. 1213–1269). Elsevier. https://doi.org/10.1016/B978-0-444-59568-3.00018-3
Hummels, D. (2001). *Toward a geography of trade costs*. Purdue University.
Krugman, P. (1995). Increasing returns, imperfect competition and the positive theory of international trade. In G. M. Grossman, & K. Rogoff (Eds.), *Handbook of international economics* (Vol. 3, pp. 1243–1277). North-Holland. https://doi.org/10.1016/S1573-4404(05)80004-8
LeSage, J. P., & Llano, C. (2013). A spatial interaction model with spatially structured origin and destination effects. *Journal of Geographic Systems*, *15*(3), 265–289. https://doi.org/10.1007/s10109-013-0181-8
LeSage, J. P., & Pace, R. K. (2008). Spatial econometric modeling of origin–destination flows. *Journal of Regional Science*, *48*(5), 941–967. https://doi.org/10.1111/j.1467-9787.2008.00573.x
LeSage, J. P., & Thomas-Agnan, C. (2015). Interpreting spatial econometric origin-destination flow models. *Journal of Regional Science*, *55*(2), 188–208. https://doi.org/10.1111/jors.12114
Márquez-Ramos, L. (2016). Port facilities, regional spillovers and exports: Empirical evidence from Spain. *Papers in Regional Science*, *95*(2), 329–351. https://doi.org/10.1111/pirs.12127
McCann, P. (2001). A proof of the relationship between optimal vehicle size, haulage length, and the structure of transport-distance costs. *Transportation Research Part A: Policy and Practice*, *35*(8), 671–693. https://doi.org/10.1016/S0965-8564(00)00011-2
Ministerio de Fomento (MFOM). (2018). *Observatorio del Transporte de Mercancías por Carretera 2018, Secretaría General de Transportes*. MFOM.
Németh, G., Szabõ, L., & Ciscar, J. C. (2011). Estimation of Armington elasticities in a CGE economy–energy–environment model for Europe. *Economic Modelling*, *28*(4), 1993–1999. https://doi.org/10.1016/j.econmod.2011.03.032
Olekseyuka, Z., & Schürenberg-Frosch, H. (2016). Are Armington elasticities different across countries and sectors? A European study. *Economic Modelling*, *55*(2), 328–342. https://doi.org/10.1016/j.econmod.2016.02.018
Persyn, D., Díaz-Lanchas, J., & Barbero, J. (2022). Estimating road transport costs between and within European union regions. *Transportation Policy*, *124*, 33–42. https://doi.org/10.1016/j.tranpol.2020.04.006
Porojan, A. (2001). Trade flows and spatial effects: The gravity model revisited. *Open Economies Review*, *12*(3), 265–280. https://doi.org/10.1023/A:1011129422190
Rauch, J. E. (2001). Business and social networks in international trade. *Journal of Economic Literature*, *39*(4), 1177–1203. https://doi.org/10.1257/jel.39.4.1177
Santamaría, M., Ventura, J., & Yeşilbayraktar, U. (2023). Exploring European regional trade. *Journal of International Economics*, *146*, 103747. https://doi.org/10.1016/j.jinteco.2023.103747
Thissen, M., Husby, T., Ivanova, O., & Mandras, G. (2019). *European NUTS 2 regions: Construction of interregional trade-linked supply and use tables with consistent transport flows* (JRC Working Papers on Territorial Modelling and Analysis No. 01/2019). Publications Office of the European Union.
Yotov, Y. V., Piermartini, R., & Larch, M. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. WTO iLibrary.
Zofío, J. L., Condeço-Melhorado, A. M., Maroto-Sánchez, A., & Gutiérrez, J. (2014). Generalized transport costs and index numbers: A geographical analysis of economic and infrastructure fundamentals. *Transportation Research Part A: Policy and Practice*, *67*, 141–157. https://doi.org/10.1016/j.tra.2014.06.009
Zofío, J. L., Díaz-Lanchas, J., Persyn, D., & Barbero, J. (2025). Estimating national and foreign trade elasticities using generalized transport costs. *Journal of Regional Science*, *65*(2), 471–496. https://doi.org/10.1111/jors.12746