estructuraeconòmica
ECONOMÍA APLICADA II

Examining the non-linear relationship between migration and trade

by

Guadalupe Serrano-Domingo
and
Francisco Requena-Silvente

March 2013

Working Papers in Applied Economics

WPAE-2013-10

ECONOMÍA
APLICADA II

VNIVERSITAT DE VALÈNCIA

Departamento de Estructura Económica (Economía Aplicada II), Facultad de Economía, Universitat de València
Avda dels Tarongers, s/n, 46022 – Valencia, Spain
Phone +34 96 382 83 49 / Fax +34 96 382 83 54
http://www.estructuraeconomica.es
e-mail: investigacion.estructura@uv.es

ISSN 2172-3036

EXAMINING THE NON-LINEAR RELATIONSHIP BETWEEN MIGRATION AND TRADE

Guadalupe Serrano-Domingo
Department of Economic Analysis, Faculty of Economics, University of Valencia, Avda dels Tarongers, s/n, Campus dels Tarongers, E-46022, Valencia, Spain
tel. 963828247 fax. 963828249
email: guadalupe.serrano@uv.es

Francisco Requena-Silvente
Department of Applied Economics, Faculty of Economics, University of Valencia, Avda dels Tarongers, s/n, Campus dels Tarongers, E-46022, Valencia, Spain
tel. 963828851 fax. 963828249
email: francisco.requena@uv.es

Abstract: The migration-trade link has been studied extensively since the mid nineties, finding a positive impact through different channels. Based on the generalized propensity score (GPS) methodology, we estimate a dose-response function, depicting a non-linear impact of immigration on exports using regional data for Spain and Italy. For both countries the elasticity of province exports to immigration from a given nationality is always positive. However, it is magnitude varies with the level of immigrants: increasing with less than 100 immigrants; decreasing between 100 and 1500; increasing again with more than 1500. In contrast to previous studies that use country-level data, we find no exhaustion point in the effectiveness of the immigration networks on regional exports.

Keywords: Immigration, exports, generalized propensity score, dose-response function, Spanish provinces, Italian provinces
JEL Classification: C210, F140, F220

1. Introduction and motivation

The migration-trade link has been studied extensively in the economic literature since the mid 1990s. Two main channels have been described in the literature to explain how immigrants can enhance trade: they reduce information/search costs and they increase trust and reduce uncertainty in the international transactions. Migrants act as information providers and trade intermediaries because they have a deep knowledge of their home country's opportunities and potential markets, access to distribution channels, contacts and familiarity to local customs, law and business practices (Gould, 1994; Rauch and Trindade, 2002; Girma and Yu, 2002).

A recent meta-analysis of the impact of immigration on trade by Genc et al (2011) using 48 studies (300 estimates) confirms that an increase in the number of immigrants by 10 percent increases the volume of exports and imports by about 1-2 percent. Moreover, that impact is stronger for goods whose trade is likely to involve informational problems; and, in turn, that impact is stronger for trade with countries that are different from the reference country on a number of dimensions (different level of development, lack of common language and colonial ties); and that impact is stronger when the partner country is characterized by institutional problems.

With a few exceptions previous empirical studies assume that the relationship between migration and trade is linear. Gould (1994) analyses the impact of immigration on trade between the United States and 47 trading partners that were also sources of US immigrants for the period 1970-1986. He finds immigrants increased moderately both imports and exports. More interestingly he attempts to identify the level of immigration associated with the positive effect on trade. To do this, he estimated a specific functional form for the effect of immigrants on transaction costs which is decreasing at a decreasing rate and found that the effect of immigrants on exports is exhausted at a quite small level (around 12,000 immigrants). More recently, Egger et al (2012) find a non-linear relationship between migration stocks in 2000 and bilateral trade flows in 2007 using country-level data. In particular, the response of trade to migration is positive when the number of immigrants living in an OECD country ranges between 200 and 4,000. When the migration stocks exceed the last number, imports to OECD countries from the host countries of immigrants will not increase anymore. Both papers suggest that migrants possess economic, cultural and institutional knowledge about both the home and the host markets, so they are able to mediate economic exchange between those markets. Trade will increase while business networks are set up. But once the "bridge" has been constructed, the need for additional migrants to stimulate trade declines and even could vanish.

If the trade-migration relationship is not always positive, this will suggest that the trade enhancing effect of the immigration networks only works for certain number of immigrants. It could be the case that a certain number of immigrants from the same country living in a province is necessary before an ethnic network becomes effective. It is also possible that the trade-enhancing effect of immigrants may reach its maximum effectiveness for certain number of immigrants. Again, depending on the actual and the optimum number of immigrants, local authorities can be more or less pro-active in order to attract immigrants from specific nationalities in order to boost bilateral exports.

Finally, it is also possible that the stimuli of ethnic networks on bilateral exports trade is subject to decreasing returns as the number of members rises and even become ineffective beyond certain number of immigrants. In this scenario, and depending on the observed level of saturation or exhaustion, the pro-trade effect of immigration at local level would not be a valid argument anymore to compensate other kinds of negative effects associated with an excess of immigrants.

In this paper we investigate whether there is a causal effect of the level of immigrants stock on exports from a host province to the country of origin of the immigrants using data from 50 Spanish and 103 Italian provinces in year 2007. We argue that sub-national data provides greater precision in identifying ethnic networks and in estimating their impact on trade. Herander and Saavedra (2005) disentangle the impact of both the in-state and out-state stocks of immigrants of 36 countries on US state exports between 1993 and 1996. Since the impact of in-state immigrants is greater than that of out-state immigrants, they conclude that network links are about proximity. Using much smaller geographic units (provinces rather than states), Artal et al (2012) find for Spain, Italy and Portugal that the migration-trade link is clearly in-province: exports from a province to a country do not receive any significant stimuli from immigrants from this country living outside of the province. Thus, the trade-promoting effects of immigrant networks are greatest locally and any study about the functional form of the migration-trade link should take into account how immigrants are distributed within a country.[1]

We also argue that the positive impact of immigration on exports may not be constant because the maturity and effectiveness of social networks promoting trade may depend on the size of the community of immigrants of the same nationality living in the region. In fact, the number of immigrants living in one province can vary continuously from one immigrant from certain nationality to thousands of them. Since the number of immigrants from the same nationality living in the provinces is not homogeneous, it can lead to heterogeneous pro-trade effects of immigration.

This assessment of the heterogeneity of immigration effects on exports essentially amounts to estimating a dose-response function as proposed by Hirano and Imbens (2004). In a setting in which doses are not administrated under experimental conditions, estimation a dose-response function is possible by using the generalized propensity score (GPS), methodology that is developed by Hirano and Imbens (2004) and Imai and van Dyk (2004).

Similarly to the binary and multivalued treatment propensity score methods, it is assumed that -conditional on observable characteristics- the level of treatment received can be considered as random ("unconfoundedness"). Hirano and Imbens demonstrated that the GPS has a balancing property that implies that individuals in the same group of GPS should be identical in terms of their observable characteristics, independent of their level of treatment. Under unconfoundedness, the GPS methodology allows incorporating all information necessary for avoiding potential biases in one scalar, allowing the matching on one dimension only, instead of controlling for numerous covariates that may enter in different functional forms, and without imposing strong assumptions about the functional form of the relationship.[2] Furthermore, compared with propensity score methods for multivalued treatments, the GPS has the

[1] Other papers that have taken advantage of the existence of trade and migration data collected at sub-national levels include: Canadian provinces (Wagner et al., 2002); US states (Dunlevy, 2006; Bandyopadhyay et al., 2008); French departments (Briant et al., 2009); Spain provinces (Peri and Requena, 2010); and Italian provinces (Bratti et al, 2011).

[2] Nevertheless, since we will use parametric estimators of the dose-response functions, our conclusions about the form of the migration-trade link may also partially depend on and be sensitive to the model specification.

advantage that we do not have to discretize the continuously distributed stock of immigrants from one nationality living in one region and thus can make use of more comprehensive information.

Additionally, it enables us to identify the entire function of exports over all possible levels of immigration, so we can check if there is a nonlinear relationship between trade and immigration, as suggested by the seminal paper of Gould (1994), and the level of immigration at which exports are maximized or whether the immigration-trade link exhibits turning points or discontinuities.[3]

Our paper is closely related to Egger et al (2012). They also use the GPS methodology and find that the migration-trade links is exhausted once a developed country reaches 4000 immigrants from a particular country. We want to examine if their results hold when we use sub-national data: 4000 immigrants of a particular nationality can be very concentrated or very disperse within a country. We find that after balancing the sample on a rich set of country and province covariates, the estimated dose–response function depicts a non-linear impact of immigration on exports for provinces in Spain and Italy. For both countries the response of province exports (in logs) to immigration from a given nationality is always positive. However, its magnitude varies with the level of immigrants: increasing from 1 to 100 immigrants; decreasing between 101 and 1,500; increasing again with more than 1,500.

We also find evidence of a local maximum impact of immigration on exports: for both countries, the largest value of the potential bilateral exports is reached when the number of immigrants of the same nationality living in the same province reaches 70 for Italy and 100 for Spain. This is a relatively small number of immigrants and it is an argument in favor of local immigration policies promoting ethnic diversity.

Finally, our findings based on the derivative of the dose-response function show that the impact of one additional immigrant on regional exports is always statistically different from zero for any level of immigrants in Spain and Italy. Therefore we do not observe any threshold or exhaustion point as in

[3] Flores (2007), Fryges and Wagner (2008) and Kluve et al (2012) are other examples of estimated U-shape dose-response functions with a continuous treatment in which the estimation of the turning point provides valuable information from a policy perspective.

Egger et al (2012) using country-level data, which implies that there is no reason to impose limits to immigration at local level, at least from the point of view of the migration-trade relationship.

The rest of this paper is structured as follows. Section 2 presents the generalized propensity score methodology. Section 3 presents the data and the results of the GPS. Section 4 presents the main results of the paper, the dose-response function and its derivative. Section 5 concludes.

2. Empirical model

Many questions arise when our objective goes beyond asserting the mere existence of a trade-migration link: Is immigration a truly causal factor of trade? If so, is the trade-migration link linear? Does migration affect trade only after certain stock level or does migration lack of impact on trade after above certain threshold? If it is expected increasing trade above what it would be in the absence of migration, is it also expected that the need for additional migrants decreases once the network is working? Finally, is it possible to find an optimal ethnic network size that maximizes the value of regional exports?

An experimental approach to answer these questions would involve randomly assigning different number of immigrants of the same nationality in host destinations with similar observable characteristics and then analyze their response in terms of their exports performance towards the country of origin of the immigrants. Unfortunately, such an experiment is practically impossible.

In this setting, where treatment doses cannot be administrated under experimental conditions, we assume that the assignment mechanism is unconfounded and estimate the dose-response function, which is required for answering to these questions, by using the generalized propensity score (GPS) methodology. Since it is assumed that, conditional on observable characteristics, the level of immigrants from one nationality living in the region (treatment) can be considered as random, the balancing property of the GPS methodology implies that individuals in the same group of GPS should be identical in terms of their observable characteristics, independent of their level of treatment, and thus, estimate the response –the volume of exports- that corresponds to specific doses of a continuous treatment –the stock of immigrants living in the region.

Thus, GPS method for continuous treatment allows us to determine the causal relationship between exports (the outcome) and immigrants (the treatment) at each value of immigration, without the positive or negative impact of other factors that can affect trade simultaneously with migration, overestimating or underestimating its effect.[4] Once we identify the entire dose-response function of exports over all possible levels of immigration, we can check if there is a nonlinear relationship between trade and immigration, as suggested by the seminal paper of Gould (1994), and thus analyze the level of immigration at the expected outcome is maximized or whether the dose-response function evaluating the immigration-trade link exhibits turning points or discontinuities.

Furthermore, since adjusting by GPS removes the bias in provinces' exports associated with differences in the covariates, we can estimate the varying marginal effects of immigration along the continuous of the stock of immigrants living in the region, by estimating the treatment effect function, which is the derivative of the corresponding dose-response function.

2.1. Generalised propensity score methodology

The approach in this sub-section follows the standard counterfactual approach described by Rubin (1974). We utilize specific techniques described by Imbens (2000) and Hirano and Imbens (2004). For a sample of province-country pairs, indexed by $i=1, \dots, N$ we observe a vector of covariates X_i, the number of immigrants of certain country that the province actually receives (treatment), T_i, and the actual outcome, in terms of the level of bilateral exports, corresponding to the level of treatment received, $Y_i = Y_i(T_i)$.

The description of the GPS method requires some other definitions. For each unit i, let $\{Y_i(t)\}_{t \in \mathcal{T}}$ denote the set of potential outcomes, where $\mathcal{T}$ is a

[4] Nevertheless the validity of the results using GPS methods is strongly based on the unconfoundedness assumption (see Section 3.1). When the unconfoundedness assumption is not plausible, alternative econometric techniques should be considered, such as Instrumental Variable methods.

continuous interval of real numbers [5]. The goal of the analysis is to estimate the average dose–response function (DRF), $\mu(t) = E[Y_i(t)]$ across all province-country pairs. In the remainder of this section the subscript i will be omitted to simplify the notation.

The primary assumption that needs to be made for this approach to work is an unconfoundedness assumption (Rosenbaum and Rubin, 1983), generalized to the continuous treatment case by Hirano and Imbens (2004). Imbens (2000) provides a weak[6] version of unconfoundedness that assumes that the information contained in the covariates X is sufficient to make the potential outcome $Y(t)$ independent of the level of treatment received T: $Y(t) \perp T|X \;\; \forall\, t \in \mathcal{T}$. Under this weak unconfoundedness assumption, there are not systematic treatment assignments based on unobservable characteristics not captured by observable ones. Then, the average DRF could be obtained by estimating average outcomes in subsamples defined by pre-treatment covariates and different levels of treatment. But, as the dimension of the pre-treatment covariates vector increases, increases the difficulty of simultaneously consider all covariates in such vector in the subsample definition. Similarly to the binary treatment study in Rosebaum and Rubin (1983), the problem is solved by adjusting for the generalized propensity score (GPS).

The GPS is defined as follows. Being $r(t,x) = \int_{T|X}(t|X = x)$ the conditional density of the treatment given the pre-treatment covariates, the generalized propensity score (GPS) is defined as $R = r(T,X)$.

The GPS has the property that within strata with the same value of $r(t,x)$, the probability that $T = t$ is independent of the covariates (loosely speaking, $X \perp I\{T = t\}|r(t,X)$), where $I(\cdot)$ is the indicator function. In combination with the *weak unconfoundedness* assumption, this *balancing property* also implies that the assignment to treatment is weakly unconfounded

[5] Following Hirano and Imbens (2004), we assume that $\{Y_i(t)\}_{t\in\mathcal{T}}$, T_i, and X_i are defined on a common probability space, that T_i is continuously distributed with respect to Lebesgue measure on $\mathcal{T}$, and that $Y_i = Y_i(T_i)$ is a well-defined random variable.

[6] Weak unconfoundedness does not require the joint independence of all potential outcomes, but requires conditional independence to hold for each treatment value.

given the GPS (see Hirano and Imbens, 2004). Hence, each and every number of immigrants in a country-province pair would translate into a unique propensity score. This result allows the estimation of the average DRF by using the GPS to remove any bias related to differences in the covariates among groups being assigned to (receiving) different levels of treatment. We first obtain:

(1) $\beta(t,r) = E[Y(t)|r(t,X) = r] = E[\,Y|T = \mathrm{t},\ R = r]$

Where $\beta(t,r)$ is the conditional expectation of the outcome that is estimated as a function of two scalar variables: the treatment level, T, and the GPS, R; or in other words, the conditional mean of the outcome Y given the observed value of the treatment and the GPS. As a second step, we estimate the value of the DRF at each particular level of treatment, t, by averaging the conditional expectation function over the values of the GPS at that particular level of treatment t, ($R^t = r(t,X)$):

(2) $\mu(t) = E\left[\beta\left(t, r(t,X)\right)\right]$

Hirano and Imbens (2004) emphasized that the regression function in (2) does not have a causal interpretation. Nevertheless by averaging over the covariates, $\mu(t)$ corresponds to the value of the dose-response function for treatment value t, which compared with that obtained for another treatment level t', $\mu(t')$, does have a causal interpretation.

2.2. The empirical implementation.

Following Hirano and Imbens (2004), we utilize a flexible parametric specification of the GPS paying special attention to assessing the validity of the assumptions made. First we model the conditional level of the treatment T (immigration stock) given the covariates X using a log-normal distribution:

(3) $lnT|X \approx \mathrm{N}\left(\beta_0 + \beta_1' X, \sigma^2\right)$

After estimating $(\beta_0, \beta_1, \sigma^2)$ by ordinary least squares, the estimated GPS is calculated as:[7]

(4) $\hat{R} = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left(-\frac{1}{2\hat{\sigma}^2}\left(lnT - \widehat{\beta_0} - \widehat{\beta_1}'X\right)^2\right)$

In a second stage we estimate the DRF using the estimated GPS by following two steps. The first step involves estimating the conditional expectation in equation (1), assuming some functional form of the relationship between the three variables. Following Hinaro and Imbens (2004), we implement a partial mean approach by assuming a (flexible) parametric form for the regression function of Y (bilateral exports), on T (the immigration stock), and $\hat{R}$, for each province-country pair:

(5) $\mathrm{E}[Y|T, \hat{R}] = h(T, \hat{R}; \alpha)$

The OLS estimated parameters in (5) are used to estimate the average potential outcome given a treatment level t, averaging over the score function evaluated at the treatment level, $\widehat{R^t}$:

(6) $\mathrm{E}[\widehat{Y(t)}] = \frac{1}{N}\left(\sum h\left(t, \widehat{R^t}; \hat{\alpha}\right)\right)$

In addition, we also compute the first derivative of the DRF, $\mu(t)$, with respect to the argument, i.e. we estimate the treatment effect function, $\theta(\mu) = \mu(t + \delta) - \mu(t)$, which can be defined as the marginal causal effect of a variation of the number of immigrants, $\Delta t = \delta$, on the variation of the bilateral exports. This will allow us to capture the heterogeneity in the magnitude of the impacts on bilateral trade flows (outcome) arising from different dosages of immigration stocks (treatment).

Finally, we use bootstrap methods to obtain standard errors that take into account estimation of the GPS and the α-parameters, i.e. we bootstrap the entire estimation process.

In the empirical implementation of the GPS approach it is also important to assess the weak unconfoundedness assumption, common support condition

[7] As Hirano and Imbens (2004) point out, there are other model specifications that can be used to estimate the GPS. OLS is the best estimator in this case as the dependent variable, while not normally distributed, is continuous, and the properties of OLS are well-known and the estimates easy to replicate.

and balancing of covariates. The procedures are described in more detail in the next section.

3. DATA AND GPS ESTIMATION

To attempt to estimate the impact of migration on exports, we begin by presenting the data and exploring the trade-migration link using conventional regression analysis. Next we report estimates from the GPS estimation and discuss the properties of the estimated GPS, particularly how well the sample balances. In the next section we present the results of the last step, the estimates of the dose–response function. The entire procedure is implemented for each host country (Spain and Italy) separately.

3.1. Data and preliminary exploration of the trade-migration link

We employ three sets of variables in this paper for each host country. First, we choose average bilateral exports from a province to a particular country in 2007 as the outcome of interest.[8] Second, our treatment variable is measured as the bilateral stock of foreigners residing in each province of Spain and Italy at the beginning of 2006. Third, we use a large number of observed pre-treatment "push" and "pull" characteristics of bilateral migration as elements of our set of covariates, X. Most of these variables at province level (population, GDP, unemployment rate, agriculture and non-public services share in value added) steam from ISTAT (Italian National Institute of Statistics) for Italian provinces and from INE (Spanish National Institute of Statistics) for Spanish provinces. For the characteristics of the country of origin of immigrants we resort to the World Bank's WDI database for data on GDP, population, unemployment and income distribution (GINI). We follow Head and Mayer (2000) to construct the geodesic distance variable between each Italian and Spanish province and each foreign country. We calculate a weighted average of the great circle distance (in kilometers) from the capital of each province to the five most important cities of each partner country, in which the weights are the

[8] Trade flows are obtained from Agencia Tributaria - Aduanas (www.agenciatributaria.es) for Spain and from ISTAT (www.coeweb.istat.it) for Italy.

respective populations of the latter.[9] Bilateral culture distance measures based on language, education and industrialization differences are obtained from Dow and Karunaratna (2006).[10] Political freedom index is obtained from Freedom in the World (FIW) and Human right index is obtained from Amnesty International.[11]

Altogether, our study covers 50 Spanish provinces and 103 Italian province of residence as well 87 and 95 countries of origin of immigrants for Spain and Italy, respectively (see Table A.1 in the Appendix for a list). The first columns of Table 1 (SPAIN) and Table 2 (ITALY) provide the mean, standard deviation, minimum and maximum for all variables (outcome, treatment and covariates) we use in our study. Variables in levels refer to year 2000 (except trade flows that refer to 2007 and migration stocks that refer to 2006), while variables in growth rates are calculated for the period 2000-2005.

Before presenting the results for the GPS, we explore first the trade-migration relationship using a standard gravity-type regression analysis. At the risk of abusing of nomenclature, in the gravity equation we refer to observation i as a province-country pair that we called *pc* in order to distinguish clearly monodic and dyadic variables:

$$Y_{pc} = \delta M_{pc} + X'_{pc}\beta + \alpha_p + \gamma_c + \epsilon_{pc}$$

where export flows (in logs) from province p to country c, Y_{pc}, depends on the stock of immigrants, M_{pc}, a vector of dyadic explanatory variables, X_{pc}, containing dyadic trade costs or trade facilitating variables such as distance, common border; and α_p and γ_c are two vectors of monodic province and

[9] The great circle distance between two cities is calculated as follows. First we transform the latitude φ and the longitude λ into radians (x π /360). Second, the formula used to calculate the distance between the pair of cities, one located in the province p (of Spain or Italy) and the other one in country c, is $\Delta_{pc} \equiv \lambda_p - \lambda_c$, $d_{pc} = \arccos[\sin\varphi_p \sin\varphi_c + \cos\varphi_p \cos\varphi_c \cos\Delta_{pc}]z$, with z= 6367 for km. Third, we calculate the population-weighted average distance between the capital of the province p and the cities of the foreign countries "cou" using the formula $D_{p,cou} = \sum_{c\in cou} w_c d_{pc}$, $w_c = pop_c / pop_{cou}$.

[10] Physic distances can be downloaded from www.mbs.edu/home/dow/research/public/psydist.html

[11] Data are publicly available in www.freedomhouse.org and www.amnesty.org.

country dummies, respectively, that capture the multilateral resistance terms (Anderson and van Wincoop, 2003, Feenstra, 2002).[12]

Table A.2 in the Appendix displays the results. The OLS estimates show that there is a positive relationship between log of exports and migration, and a negative link between log of exports and the square of migration, suggesting the possibility of a non-linear relationship between log of exports and immigration at province level.[13]

However, regression-type analysis such as OLS has a higher risk of misspecification of the model or of making comparisons between incomparable observations, which could potentially bias the estimates. Propensity score methods can alleviate these potential problems to some extent.

Before presenting the results of the GPS methodology is important to address the possibility of reverse causality between immigration and trade, because this endogeneity problem is a potential case of violating the key assumption of the GPS, weak unconfoundedness (also called assumption of selection on observables).

A positive relationship between immigrants and trade with the migrant-source countries could reflect a situation where the migrants´ location choice is based on patterns in trade activities with migrant source countries, rather than a trade-facilitating impact of migrants. The reason could be that some unobserved characteristics of host provinces or sending countries might affect immigration and in turn the same characteristics might also affect the subsequent exports.

We address reverse causality in our paper using the most common approach, the use of instrumental variables.[14] A valid instrument would have to be known to be linked to immigrants born in specific countries, but being

[12] Notice that, without panel data, the inclusion of a comprehensive set of country and province effects does not allow to include any country-specific or province-specific characteristics.

[13] We also estimated the gravity-type equation using Robinson´s (1988) semi-parametric method. The results (available on request) also support the hypothesis that the relationship between exports and immigration at province level is non-linear.

[14] In our revision of the trade-migration literature, a number of studies have tried to demonstrate that migration spurs trade and not the other way around. In the pioneering paper in this literature, Gould (1994) applied a causality test and found no distinct support for the idea that trade precedes migration. In several studies on the determinants of international migration, bilateral trade is not put forward as an important determinant (Stark, 1984; Hatton and Williamson, 2005).

uncorrelated with province exports to migrant-source countries. We use historical immigrant enclaves (i.e. stock of immigrants in 2002) as instrument.[15]

Table A2 in the Appendix reports both the OLS and the IV estimates. The migration coefficients in the OLS estimates and IV estimates are quite similar, pointing to the consistency of both estimates. The results of the Hausman test, that do not allow the rejection of this null hypothesis, confirm that immigration stock does not suffer strongly from endogeneity in our analysis for Spain and for Italy.

3.2. GPS estimation

In our estimation of the dose-response function, the first step is to estimate the conditional distribution of immigration given the covariates. The GPS model is estimated via standard Ordinary Least Squares. The estimated coefficients of the GPS model and their estimated standard errors are reported in Columns 5 and 6 in Table 1 (SPAIN) and Table 2 (ITALY). The adjusted R-square is 0.66 for Spain and 0.54 for Italy. Notice that we are not interested in the interpretation and statistical significance of the individual effects of the covariates in Table 1 and 2 but in getting an estimate of the GPS that works well in balancing covariates.[16] We obtain this estimation of the GPS according to equation (5) and the previous coefficients' estimations.

The next step is testing whether treatment groups are independent of the covariates. To test this, we first compared the means for every covariate in the analysis for different levels of immigration. The entire sample of country-province pairs are distributed in quartile intervals according to the immigration stocks. Each interval contains 1006 observations in the case of Spain and 2125

[15] Peri and Requena(2010), Briant et al (2010) and Bratti et al (2012) also use lagged immigration stocks as instruments in their analysis of the trade-migration link using regional data in Spain, France and Italy, respectively.

[16] We have explored alternative specifications for Spain and for Italy, separately. We included cubic terms of population and GDP or new variables (e.g. income per capita rather than GDP, a dummy if the province was in the coast). We report the preferred specification for Spain based in the value of R-square and in the assessment of the balancing property. We use the same specification for Italy because alternative specifications allowed us to reach high R-square (up to 0.75) but the assessment of the balancing property did not improve with respect to the one reported in the paper. All the estimations have been implemented using STATA 11.2. We have used a modified version of the STATA package provided by Mattei and Bia (2008). STATA do file are available on request.

observations in the case of Italy. t-statistics for the test of equality of means are reported in the first columns of Table 3 (SPAIN) and Table 4 (ITALY) for each variable in each interval with respect to the other observations outside the interval. As the t-statistics of 7.45 for the *population country* variable in Table 3 (SPAIN) shows, the average population size of the country of origin in country-province pairs with the lowest number of immigrants is much lower than country-province pairs with larger number of immigrants. We repeated this analysis for the four intervals of immigrants for every covariate in the analysis. As Tables 3 (SPAIN) and 4 (ITALY) show, there are large differences in the treatment intervals in terms of the covariates. For the Spanish sample 94 out of 120 (30×4) possible mean differences have t-statistics whose absolute value exceeds 1.96, while in the Italian sample we find 104 out of 120 cases in which the test rejects null of equality of means at the 5% level.

Once the GPS is estimated, the common support condition should be imposed for making treatment groups independent of the covariates. In the treatment literature, it is well known that methods that adjust for pre-treatment observable variables are likely to work poorly if there is not enough overlap in the distribution of covariates by treatment level. In that literature, it is common to gauge the overlap by looking at the distribution of the propensity score across treatment levels, sometimes restricting estimation to the common support region. In the case of continuous treatments it is considerably more difficult to gauge this condition since there is a continuum of treatment levels by definition and consequently multiple parameters of interest, each of them requiring a potentially different support condition. We propose to test the common support condition using histograms to check visually the extent of overlap in the supports of different levels of the treatment (Dehejia and Wahba, 2002). For that purpose, we divide the treatment values (in ascending ordered) into intervals. For each interval, we compute the value of the GPS for each country-province pair at the median level of the treatment for the interval and the value of the GPS at that same median level for all country-province pairs that are not included in the interval in question. Finally, we check the comparability of both the interval of interest and its respective control interval, checking the region of common support between both intervals, by inspecting the overlapping of their propensity score distributions for these two groups (pairs in the interval in question and the rest) by superimposing their histograms. Next we keep only control country-province pairs in other intervals than in the interval of reference if they share a common GPS support with treated pairs in the interval of reference. Since this is done for each of the four intervals, we ensure that each country-province pair within a certain interval lies within the range of observable characteristics of each other interval.

This exercise is repeated for each quartile in turn, resulting in four plots for each of our samples. These plots are shown in Figure 1 for the full Spanish sample and Figure 2 for the full Italian sample. These figures show that the overlap in the support of the estimated GPS across quartiles is very good in general. All observations in black that lie outside the range of grey bars as well as the grey bars that exceed the black ones are dropped. Imposing the common support condition implies the exclusion of 1372 and 1131 country-province pairs for the Spanish sample and the Italian sample, respectively. It ensures comparability of the observations left in each of the samples: we are left with 2653 and 7372 country-province pairs in the Spanish and Italian samples, respectively.

Finally, in the case of a continuous treatment it is crucial to assess the balancing of covariates. This balancing property is evaluated focusing on the common-support restricted samples. If the GPS has been estimated correctly, then the differences in means between these variables at various levels of the treatment variable (immigration stock) will not be statistically significant. In short, after controlling for the propensity to have more immigrants, the various treatment groups should not differ on the basis of other covariates, independent of their level of treatment. We follow Hirano and Imbens´s (2004) approach of "blocking on the score". After we divided our sample according to the levels of the treatment into several intervals (quartile in our case), in each of those treatment interval, we stratify country-province pairs into several groups according to the ascending-ordered values of the GPS evaluated at the median value of the treatment (in our case we choose 6 groups). For each of these GPS groups, we then compare the average covariate values for the observations in that GPS group with those average values for observations that are in the same group but belonging to the rest of treatment intervals. These average differences in covariate values within each of the six GPS groups across treatment levels are then combined into a single figure, weighted by the number of respondents at each level of the GPS. The t-test for differences of means reported in Tables 3 and 4 are based on this difference.

The differences in the treatment levels after balancing on the GPS appear on the right-hand side of Table 3 for the Spanish sample and in Table 4 for the Italian sample. Regarding the balancing property, the last row in Table 3 and 4 shows that both the median and average t-statistic drop drastically for all the intervals.

In the case of Spain, as the Table 3 shows, there are few differences left among treatment intervals after balancing, with only one covariate (a dummy for border) whose t-statistic exceeds 1.96. Thus, the GPS as estimated has the desired property of balancing the Spanish sample. In the case of Italy, as Table 4 shows, the adjustment for the GPS also improves the balance. However, there are some significant differences left among treatment intervals after balancing, all of them corresponding to characteristics of the importing countries. Following the GPS literature (Caliendo and Kopining, 2008; Mattei and Bia, 2008; Flores et al ,2012), if the balancing is rejected we should either re-estimate the GPS equation (1) including new covariates, high-order covariates and interaction terms, or change the number of treatment intervals, or change the number of GPS groups. We tried different specifications, increased the number of intervals (up to 8) and increased the number of groups (up to 10). For presentation purposes, we opted for maintaining the same specification, number of treatment intervals and GPS groups for Spain and Italy because we were not able to achieve the desired property of balancing all the covariates with the Italian sample and, furthermore, at the end, we found that the estimates of the dose-response function and its derivative in the Italian sample did not change significantly after trying alternative assessments of the balancing property.[17]

4. The estimated dose–response function

The final step in our exercise is to estimate the dose-response function. For that purpose we first run a regression with the log of bilateral exports as the dependent variable and the stock of immigrants and the conditional density of immigrants given the covariates on the right hand side (Eq. 5).

We adopt a polynomial parameterization of the immigration stock (either in level or log transformed), the GPS (either in level or log transformed), and its interactive terms. The preferred specification based on the election of the variables in levels or log-form as well as the order of the polynomial terms was based on the Akaike Information Criterion (AIC) for each sample separately. The corresponding results for the preferred dose-response functions are summarized in Table 5. The estimates from these regressions do not have a direct interpretation, but are instead utilized in the calculation of the dose–response functions (Hirano and Imbens, 2004).

The dose–response functions are then estimated for a continuum of levels of immigrants (as described in Eq. 6). This dose-response function relates each value of the dose (i.e. the number of immigrants) to the post-treatment level of province (log) exports to the country of origin of those immigrants.

A plot of the dose-response curves for Spain and Italy is presented in Figure 3.[18] This plot indicates that the association between immigration (dose of

---

[17] As an alternative way to evaluate the balancing of covariates we follow Imai and van Dyk (2004) who proposed regressing each covariate on the treatment variable without and with conditioning on the predicted treatment variable in Eq. 4: $\mathrm{E}[\ln\mathrm{T}|\mathrm{X}]$. Once we condition on $\mathrm{E}[\ln\mathrm{T}|\mathrm{X}]$, it is expected that migration stock is not correlated with the covariate if the adjustment for the GPS works in balancing the observable characteristics. We regress each covariate on the level of immigration stock, because the log of the stock of immigrants and each covariate is necessarily uncorrelated given $\mathrm{E}[\ln\mathrm{T}|\mathrm{X}]$ (see Appendix B in Imai and van Dyk, 2004). The results are reported in Table A.3 in Appendix. For both Spain and Italy, almost all the migration coefficient estimates clearly decrease once we control for $\mathrm{E}[\ln\mathrm{T}|\mathrm{X}]$. Moreover, all but one significant estimate in the case of Spain and a large percentage of significant estimates in the case of Italy become insignificant. The results confirm our previous evaluation, that is, the GPS properly balances the covariates.

[18] We calculated the confidence intervals for the DRF and its derivative using bootstrapping. The intervals were very small so we did not report them in the graphs. It is important to point out that the

treatment) and log of exports, when confounding between that dose and the covariates is adjusted for using the GPS approach, is appreciable; the exports response is positive over the entire range of positive treatment doses considered for both countries. The dose-response functions for Spain (left-hand side) and Italy (right-hand side) exhibit very similar patterns. Generally speaking, the estimated dose-response function shows an inverted U-shaped relationship between the number of immigrants and the average potential exports of the provinces between 1 and 1500 immigrants. For the case of Spain, we observe that such a exports response increases rapidly in the range from the dose of 1 immigrant to approximately a treatment of 100 immigrants, then decline in the range of immigrants from 100 to 1,500 and finally increase again. For the case of Italy, the pattern is similar. The rapid response of exports occurs in the range from a dose of 1 immigrant to 70 immigrants, then declines in the range of immigrants from 70 to 1,400 and finally increases again.

The same graph displays the density distribution of immigrants by country-province pairs to illustrate that most provinces have less than 100 immigrants of certain nationality (57.2% in the Spanish sample and 72.1% in the Italian sample), while the percentage of provinces with more than 1500 immigrants of a certain country is small (12.1% in Spain and 4.8% in Italy).

The shape and values of the dose-response function permits to respond to three key questions related to the non-linear relationship between immigration and exports:

(1) Is there a minimum threshold? No. We do not observe that the pro-trade effect of immigrants needs a minimum number of people to become effective; the response of exports is positive from the minimum dose of 1 immigrant.

(2) Is there a saturation point? No. We do not observe that the pro-trade effect of immigrants becomes zero when the number of immigrants of certain nationality reaches certain level.

---

derivative of the DRF was statistically different from zero at confidence level of 1% for any level of immigrants.

(3) Is there an optimal immigration dose? Yes. We do observe that average potential exports reach a maximum when the number of immigrants of certain nationality reaches certain level: 70 in the case of Italy and 100 in the case of Spain. In both cases we should stress the fact that the optimal immigration dose is local.

The resulting dose-response function is depicted in more detail in Figure 4 (SPAIN) and Figure 5 (ITALY) after we split the treatment level below and above the median (361 and 513, respectively, for Spain and Italy). The potential exports of provinces with 1 immigrant reach the level of 665 thousand Euros [=exp(6.5)] in Spain and 1,636 thousand Euros [=exp(7.4)] in Italy. The slope of the dose-response function is very steep within the 1 to 100 interval of immigrants for Spain and 1 to 70 interval for Italy. The maximum value of the potential exports to a certain country is 2,440 thousand Euros [=exp(7.8)] when a Spanish province hosts around 100 immigrants from this country and 6,634 thousand Euros [=exp(8.8)] when an Italian province hosts around 70 immigrants from this country. The estimated (local) optimal dose is relatively small and can be used as a reason to favor the arrival of immigrants of certain nationalities in some provinces whose presence is still insufficient to reach an optimal ethnic network.

Provinces with more than 100 immigrants from a certain nationality will have a potential level of exports below those maxima. The potential minimum performance would be reached when the province is hosting 1,500 immigrants in the case of Spain and 1,400 in the case of Italy. Beyond that number of immigrants of certain nationality the potential exports increase continuously. However we are cautious about inferences when the number of immigrants from the same nationality living in a province is very large (more than 1,500 immigrants according to Figure 3) since the confidence intervals become wider, which is due, to some extent, to the fact that the number of province-country pairs with more than 1,500 immigrants is very small.

The derivatives of the dose-response function (also called treatment-effect function), which are shown at the bottom of Figures 4 and 5, can be interpreted as the increment of the log of exports due to the arrival of one additional immigrant, given the number of immigrants from the same nationality that are living in the province. Notice that the size of these increments change with the size of immigrants' communities living in the province. We compute this treatment effect function by comparing the estimated potential exports of provinces hosting a specific number of immigrants from the same nationality, with respect to the expected exports of provinces with similar characteristics, hosting that specific number of immigrants plus one (since we compute it using a treatment gap, δ, equal to 1).

We compute also the 95% confidence intervals for the derivative functions to test the null hypothesis of the exhaustion of the effect of immigrants on exports. The values of the derivative of the dose-response function are always positive and statistically different from 0. However, the magnitude of the increase in the (log of) exports due to an additional immigrant varies significantly with the level of treatment. For example, if the stock of immigrants of certain nationality living in a Spanish (Italian) province increased from 1 to 2 the log of exports would increase a 0.064 (0.095 for Italy); if the number of immigrants increases from 100 to 101 the log of exports to their home country would increase 0.01 for provinces in both Spain and Italy. Beyond 100 immigrants the effect of immigration on (log) exports is asymptotically close to zero but does not reach this value, remaining statistically positive. This result indicates that receiving an additional immigrant from one nationality, despite the fact that the region already hosts a large number of immigrants from that nationality, will have always a positive effect on exports.

Our results suggest that any increase in the number of immigrants from any nationality living in a particular region would go along with higher levels of bilateral exports. However the impact of immigration on exports is not linear and depends on the size of each ethnic network. In terms of migratory policy at regional level becomes important to know how much an additional immigrant from certain nationality contributes to generate more trade. The absence of an exhaustion point in the increase of exports due to an additional immigrant could be argued against restrictive immigration policies. The fact that the largest impact on exports occurs when the number of people in small ethnic communities rises can be used as an argument in favor of social policies supporting and promoting the diversity of ethnic population in the provinces of Spain and Italy.

5. CONCLUSIONS

In this paper we examine the impact of immigrants on regional exports for Spain and Italy for the year 2007 using a relatively novel approach in this literature: the dose–response function shows the estimated impact of a given level of immigrants on the level of bilateral exports conditional on the generalized propensity score averaged over every country-province pair in the sample. This is in effect a way of answering the counterfactual question of what would have happened to a given province-country pair had they received a different level of immigrants. Diagnostics on the weak unconfoundedness assumption, common support and covariate balance validate the use of this approach.

Our results show that any level of immigrants living in a province stimulates exports from this province to the country of origin of immigrants. Only in the range of immigrants between 100 and 1500 for Spain (70 and 1400 for Italy), there is a decline in the magnitude of impact, although the impact is still positive.

Another interesting finding is the existence of a local optimal dose, which may have important implications from a policy perspective: the volume of exports reaches a maximum when the range of immigrants of certain nationality living in the same province varies between 70 (Italy) and 100 (Spain). The estimated optimal dose is relatively small and can be used as a reason to favor the arrival of immigrants of certain nationalities in some provinces whose presence is still insufficient to reach an optimal ethnic network.

Our conclusions using sub-national data are different from those of Egger et al (2012) using country-level data: there is no need for a critical mass of immigrants to make a trade-enhancing effect "networks" operative within a province in Spain and Italy; there is no evidence of minimum threshold nor exhaustion point in the effectiveness of the immigration networks on regional exports.

ACKNOWLEDGEMENTS: We acknowledge financial support from Spanish Ministry of Science and Innovation (project ECO 2011-27619/ECON) and Generalitat Valenciana (project Prometeo/2009/098).

REFERENCES

Anderson, J. E. and van Wincoop, E. (2003), "Gravity with Gravitas: A solution to the border puzzle," American Economic Review, 93(1), 170-192.

Bandyopadhyay S., Coughlin C.C. and Wall H.J., 2008. Ethnic networks and state exports. Review of International Economics, 16, 1, 199-213.

Bratti, M., De Benedictis, L. and Santoni, G., 2012. On the pro-trade effects of immigrants. mimeo, http://works.bepress.com/luca_de_benedictis/21

Briant A., Combes P.P. and Lafourcade M., 2010. Product complexity, quality of institutions and the pro-trade effect of immigrants. CEPR Discussion Papers 7192.

Caliendo, M. and Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys 22(1), 31-72

Dehejia, Rajeev H. and Wahba, Sadek, 2002. Propensity score-matching methods for nonexperimental causal studies. Review of Economics and Statistics 84(1), 151-161.

Dow, D. and Karunaratna, A. , 2006. Developing a multidimensional instrument to measure psychic distance stimuli. Journal of International Business Studies 37(5), 575-577.

Dunlevy, J., 2006. The influence of corruption and language on the pro-trade effect of immigrants: evidence from the American States. Review of Economics and Statistics 88 (1), 182-186.

Egger, P., Ehlrich, M. and Nelson, D., 2012. Migration and trade. World Economy 35, 216-241.

Feenstra R.C. (2002) "Border effects and the gravity equation: Consistent methods for estimation", Scottish Journal of Political Economy, 49 (5), 491-506.

Flores, C. A., 2007. Estimation of dose-response functions and optimal doses with a continuous treatment. University of Miami, mimeo

Flores, C. A., Flores-Lagunes, A., Gonzalez, A. and Neumann, T.C., 2012. Estimating the effects of length of exposure to a training program: The case of Job Corps. The Review of Economics and Statistics 94 (1), 153-171

Fryges, H. and Wagner, J., 2008. "Exports and productivity growth: First evidence from a continuous treatment approach", Review of World Economy, 144(4), 596-722

Genc, M., Gheasi, M. Nijkam, P. and pot, J., 2011. The Impact of immigration on international trade: A meta-analysis. IZA Discussion Papers 6145

Gould D. M., 1994. Immigrant links to the home country: Empirical implications for United States bilateral trade flows. Review of Economics and Statistics 76(2), 302-316.

Hatton, T., Williamson, J., 2005. What fundamentals drive world migration? In G. Borjas, & J. Crisp (Eds.) Studies in Development Economics and Policy. New York: Palgrave Macmillan

Hirano K. and G. Imbens, 2004. The Propensity score with continuous treatment. In A. Gelman and X.-L. Meng (eds.), Applied Bayesian Modelling and Causal Inference from Missing Data Perspectives, (New York: Wiley), 73-84.

Imai, K., and van Dyk, D.A., 2004. Causal inference with general treatment regimes: generalizing the propensity score. Journal of American Statistical Association, 99, 854-866

Imbens, G., 2000. The role of the propensity score in estimating dose–response functions. Biometrika 87, 706–710.

Kluve, J., Schneider, H., Uhlendorff, A. and Zhao, Z., 2012. Evaluating continuous training programmes by using the generalised propensity score", Journal of the Royal Statistical Society, 175 (2), 587-617

Mattei A., and Bia M., 2008. A STATA package for the estimation of the dose-response function through adjustment for the generalized propensity score. The STATA Journal 8(3), 354-373.

Peri G. and Requena-Silvente F., 2010. The trade creation effect of immigrants: evidence from the remarkable case of Spain. Canadian Journal of Economics 43(4), 1433-1459.

Robinson, P.M., 1988. Root-n consistent semiparametric regression. Econometrica 56 (4), 931–939

Stark, O., 1984. Migration decision making: a review article, Journal of Development Economics, 14, 251–259

Wagner D., Head K. and Ries J., 2002. Immigration and the trade of provinces. Scottish Journal of Political Economy 49 (5), 507-525.

Table 1.SPAIN.

Summary Statistics of Covariates and Their Coefficients in the GPS Model.

		50 SPANISH PROVINCES				50 SPANISH PROVINCES		
		Summary descriptives				GPS model		
		(1)	(2)	(3)	(4)	(5)		(6)
		Mean	Std. Dev.	Min	Max	GPS coeff		s.e.
Outcome	ln(exports prov-cou). N=3778	7,43	2,99	0	15,78			
Treatment	number immigrants prov-cou. N=4025	1077	5653	1	148906			
Covariates	ln(population cou)	9,80	1,48	6,46	14,09	1,575	***	0,202
	ln(population cou)2	98,14	30,24	41,80	198,57	0,002		0,011
	ln(GDP cou)	11,68	1,91	7,42	16,44	-0,947	***	0,137
	ln(GDP cou)2	139,97	44,99	55,01	270,14	-0,004		0,007
	growth population cou	1,00	1,03	-1,54	3,54	-0,283	***	0,034
	growth GDP cou	14,86	5,50	2,23	35,36	0,105	***	0,006
	ln(physical distance cou)	8,26	0,80	5,41	9,90	-1,319	***	0,045
	distance language cou	-0,56	1,62	-3,87	0,53	-0,690	***	0,030
	education distance cou	1,39	0,69	0,10	2,79	-0,268	***	0,084
	industrialisation distance cou	0,42	0,68	-1,26	1,45	-1,326	***	0,112
	political freedom index cou	2,80	1,70	1,00	7,00	-0,057	**	0,025
	human right index cou	2,42	0,95	1,00	4,92	-0,030		0,048
	Gini cou	39,27	9,54	24,70	60,00	0,027	***	0,006
	unemployment rate cou	9,98	6,60	0,70	36,10	0,010	**	0,004
	border cou	0,04	0,19	0,00	1,00	1,390	***	0,178
	member EUEFTA cou	0,27	0,44	0,00	1,00	0,593	***	0,072
	dummy =1 if imports 1995 > 0 prov-cou	0,71	0,45	0,00	1,00	0,361	***	0,069
	ln(1+number of emigrants in cou)	2,29	2,33	0,00	10,57	0,221	***	0,017
	ln(population prov)	6,44	0,84	4,52	8,71	-5,876	***	1,365
	ln(population prov)2	42,17	11,16	20,46	75,83	0,490	***	0,106
	ln(GDP prov)	9,53	0,89	7,63	12,14	7,418	***	1,758
	ln(GDP prov)2	91,59	17,35	58,22	147,29	-0,368	***	0,092
	growth population prov	1,25	1,11	-0,46	3,71	0,381	***	0,029
	growth GDP prov	7,30	0,82	4,98	9,16	-0,078	**	0,035
	unemployment rate prov	7,77	2,73	2,16	13,67	-0,011		0,015
	unemployment rate change prov	-5,09	3,49	-14,56	1,15	0,045	***	0,010
	share agriculture in value added prov	5,41	3,92	0,17	17,98	-0,001		0,010
	share services in value added prov	64,25	6,89	53,60	83,24	0,036	***	0,005
	growth in agriculture value added prov	0,04	0,14	-0,23	0,56	0,028		0,199
	growth in services value added prov	0,30	0,21	-0,05	1,01	0,250	*	0,133
	Constant					-13,300	**	4,589
	R-squared (GPS model)						0,661	
	Observations (full sample)						4025	

Note: All the covariates expressed in levels refer to year 2000 and those expressed in growth rates refer to period 2000-2005. "cou" stands for country and "prov" stands for province. In the GPS estimation, the dependent variable is ln(number immigrants prov-cou) at the beginning of 2006. Symbols ***, **, * stand for significance level at the 1%, 5% and 10%, respectively.

Table 2.ITALY.

Summary Statistics of Covariates and Their Coefficients in the GPS Model.

		103 ITALIAN PROVINCES				103 ITALIAN PROVINCES		
		Summary descriptives				GPS model		
		(1)	(2)	(3)	(4)	(5)		(6)
		Mean	Std. Dev.	Min	Max	GPS coeff		s.e.
Outcome	ln(exports prov-cou). N=8004	7,92	2,77	0	15,39			
Treatment	number immigrants prov-cou. N=8503	319	1559	1	62020			
Covariates	ln(population cou)	9,89	1,43	7,20	14,09	1,266	***	0,133
	ln(population cou)2	99,94	29,52	51,86	198,57	-0,024	***	0,007
	ln(GDP cou)	11,66	1,85	7,42	16,44	-0,267	**	0,105
	ln(GDP cou)2	139,44	43,88	55,01	270,14	0,003		0,005
	growth population cou	1,02	1,03	-1,54	3,54	-0,852	***	0,024
	growth GDP cou	14,66	4,94	2,23	28,97	0,030	***	0,004
	ln(physical distance cou)	8,07	1,01	4,31	9,85	-0,622	***	0,027
	distance language cou	0,14	0,34	-0,74	0,53	-0,147	**	0,068
	education distance cou	1,06	0,75	-0,42	2,53	0,667	***	0,055
	industrialisation distance cou	0,72	0,67	-0,96	1,75	0,296	***	0,083
	political freedom index cou	2,83	1,64	1,00	7,00	0,008		0,018
	human right index cou	2,47	0,96	1,00	4,92	0,086	***	0,036
	Gini cou	38,76	9,06	24,70	58,65	-0,010	***	0,004
	unemployment rate cou	9,85	6,53	0,70	36,10	0,011	***	0,004
	border cou	0,08	0,28	0,00	1,00	0,851	***	0,067
	member EUEFTA cou	0,24	0,45	0,00	1,00	0,001		0,044
	dummy =1 if imports 1995 > 0 prov-cou	0,92	0,26	0,00	1,00	0,406	***	0,067
	ln(1+number of emigrants in cou)	2,52	2,44	0,00	13,35	0,196	***	0,009
	ln(population prov)	6,09	0,72	4,49	8,30	0,858		0,674
	ln(population prov)2	37,59	9,20	20,15	68,85	-0,087	*	0,052
	ln(GDP prov)	9,30	0,78	7,45	11,90	-1,462	*	0,794
	ln(GDP prov)2	87,08	14,96	55,54	141,71	0,137	***	0,040
	growth population prov	0,58	1,17	-9,83	1,95	0,138	***	0,017
	growth GDP prov	3,63	0,95	1,50	7,23	-0,046	*	0,028
	unemployment rate prov	9,63	7,58	1,71	30,53	-0,058	***	0,010
	unemployment rate change prov	-3,06	4,30	-17,83	1,49	-0,054	***	0,012
	share agriculture in value added prov	3,62	2,26	0,27	11,10	-0,013		0,009
	share services in value added prov	68,17	7,56	52,70	86,75	0,014	***	0,003
	growth in agriculture value added prov	-0,02	0,03	-0,11	0,08	0,333		0,620
	growth in services value added prov	0,20	0,11	0,01	0,69	0,393	***	0,145
	Constant					-2,150	**	2,314
	R-squared (GPS model)					0,540		
	Observations (full sample)					8503		

Note: See Table 1.

Table 3. SPAIN.

Differences in the treatment levels before and after balancing on the GPS: t-stats for equality of means

	Prior to balancing on the GPS				After balancing on the GPS			
Covariates	Interval Q1	Interval Q2	Interval Q3	Interval Q4	Interval Q1	Interval Q2	Interval Q3	Interval Q4
ln(population cou)	**7,45**	**6,80**	**-3,01**	**-11,33**	1,45	-1,67	-0,23	0,77
ln(population cou)2	**7,37**	**6,44**	**-3,20**	**-10,68**	1,35	-1,69	-0,11	0,71
ln(GDP cou)	**7,99**	**4,84**	**-4,05**	**-8,79**	-0,01	-0,18	0,82	-0,68
ln(GDP cou)2	**8,32**	**4,80**	**-4,61**	**-8,52**	-0,13	-0,17	0,98	-0,78
growth population cou	**-7,03**	-1,61	**4,11**	**4,50**	0,42	-0,14	-0,65	0,30
growth GDP cou	**2,54**	**4,11**	-1,72	**-4,93**	0,52	-1,40	0,15	1,10
ln(physical distance cou)	**-6,76**	-1,20	1,79	**6,15**	1,50	-1,21	-0,74	0,82
distance language cou	**-12,62**	**-3,28**	**5,39**	**10,41**	0,69	-0,35	-0,14	-0,51
education distance cou	**-3,24**	-0,18	**3,01**	0,41	1,41	-0,97	-1,49	1,51
industrialisation distance cou	**-3,58**	0,68	**3,03**	-0,13	1,65	-1,65	-1,45	1,02
political freedom index cou	**-4,05**	0,56	**2,35**	1,13	0,96	-0,96	-0,82	1,10
human right index cou	0,63	**4,28**	1,60	**-6,52**	1,60	-1,41	-1,31	1,72
Gini cou	**7,29**	**5,55**	**-2,32**	**-10,59**	1,35	-1,31	-0,81	1,53
unemployment rate cou	1,49	1,88	-1,45	-1,92	-0,08	-0,76	0,81	0,05
border cou	**7,25**	**7,25**	0,86	**-15,73**	-0,94	-1,52	-1,43	**2,60**
member EUEFTA cou	**6,64**	0,67	-1,38	**-5,91**	-0,45	0,50	0,10	0,06
dummy =1 if imports 1995 > 0 prov-cou	**16,58**	**1,98**	**-3,90**	**-14,49**	-0,16	1,53	-0,61	-0,96
ln(number of emigrants prov-cou)	**20,87**	**8,90**	**-7,76**	**-22,17**	-1,88	0,54	1,75	-0,45
ln(population prov)	**20,29**	**3,04**	**-2,17**	**-21,31**	-0,15	1,68	-0,22	-1,51
ln(population prov)2	**19,99**	**3,73**	**-2,10**	**-21,87**	-0,20	1,63	-0,15	-1,49
ln(GDP prov)	**21,06**	**3,10**	**-1,96**	**-22,39**	-0,02	1,80	-0,49	-1,42
ln(GDP prov)2	**20,70**	**3,61**	-1,89	**-22,72**	-0,07	1,77	-0,44	-1,41
growth population prov	**13,85**	**3,30**	**-2,97**	**-14,19**	0,84	0,39	-0,54	-0,78
growth GDP prov	**5,77**	0,19	-1,17	**-4,78**	0,38	0,32	-0,33	-0,23
unemployment rate prov	**2,39**	-0,85	-1,40	-0,14	-0,20	0,04	0,46	-0,55
unemployment rate change prov	**5,72**	**2,41**	0,68	**-7,85**	0,31	0,59	-0,77	-0,10
share agriculture in value added prov	**-17,61**	0,07	1,39	**16,00**	-0,07	-1,81	0,71	1,18
share services in value added prov	**13,61**	**3,25**	**-2,75**	**-14,12**	-0,70	0,78	0,40	-1,00
growth in agriculture value added prov	**-8,90**	0,37	1,84	**6,64**	0,41	-0,79	-0,16	0,86
growth in services value added prov	0,90	-1,67	0,10	0,67	-0,09	-0,03	0,12	0,32
Observations	1006	1006	1006	1007	568	830	736	519
Median abs(t-value)	**7,27**	**3,19**	**2,24**	**8,65**	0,48	1,09	0,63	0,80
Mean abs(t-value)	**9,29**	**3,28**	**2,69**	**9,98**	0,72	1,01	0,68	0,93

Note: "cou" stands for country and "prov" stands for province. t-values reported in bold face indicate significance at the 5% level. The four intervals of approximately the same size are generated according to the distribution of migration stocks. Observations which do not satisfy the common support condition are excluded from the respective intervals. In order to account for the GPS values we split up the GPS values evaluated at the median treatment intensity of the respective interval into six groups of approximately same size according to the GPS distribution.

Table 4. ITALY.

Differences in the treatment levels before and after balancing on the GPS: t-stats for equality of means

	Prior to balancing on the GPS				After balancing on the GPS			
Covariates	Interval Q1	Interval Q2	Interval Q3	Interval Q4	Interval Q1	Interval Q2	Interval Q3	Interval Q4
ln(population cou)	**21,02**	**9,21**	**-7,62**	**-22,72**	-1,23	-1,62	0,95	**2,34**
ln(population cou)2	**20,69**	**9,37**	**-6,94**	**-23,29**	-1,16	-1,55	0,81	**2,29**
ln(GDP cou)	**25,52**	1,21	**-14,73**	**-11,34**	**-4,07**	**2,09**	**4,03**	-1,43
ln(GDP cou)2	**25,07**	1,76	**-14,41**	**-11,80**	**-3,98**	1,94	**3,95**	-1,32
growth population cou	**-18,46**	-0,86	**4,68**	**14,45**	1,25	-1,82	-0,61	-0,77
growth GDP cou	**6,70**	**2,66**	**2,34**	**-11,78**	0,65	0,39	-2,17	1,63
ln(physical distance cou)	**-24,17**	**-3,92**	**9,80**	**17,87**	**3,07**	-1,17	**-2,66**	1,82
distance language cou	-1,84	1,32	**6,56**	**-6,04**	1,05	0,22	**-1,26**	0,77
education distance cou	**-10,00**	**8,16**	**10,22**	**-8,38**	**5,54**	**-3,32**	**-5,07**	**2,32**
industrialisation distance cou	**-8,94**	**7,00**	**10,75**	**-8,80**	**4,63**	**-3,08**	**-4,17**	**3,21**
political freedom index cou	**-2,14**	**7,45**	**5,88**	**-11,23**	**3,37**	**-2,47**	**-2,80**	**2,20**
human right index cou	**5,71**	**11,05**	-0,19	**-16,74**	**2,20**	**-3,55**	-1,71	**2,82**
Gini cou	**-14,69**	**4,83**	**5,74**	**3,96**	**3,02**	**-3,36**	-1,50	**2,09**
unemployment rate cou	**5,09**	**8,73**	0,93	**-14,88**	**2,32**	-1,94	-1,21	1,06
border cou	**9,54**	**3,80**	**-2,72**	**-10,63**	-0,40	0,55	0,96	-1,18
member EUEFTA cou	**10,58**	**-4,00**	**-9,06**	**2,50**	**-4,24**	**2,23**	**4,01**	**-2,24**
dummy =1 if imports 1995 > 0 prov-cou	**19,89**	1,38	**-8,35**	**-12,63**	-1,94	0,32	1,48	0,70
ln(number of emigrants prov-cou)	**18,07**	1,05	**-13,79**	**-5,14**	**-4,17**	1,29	**4,96**	**-2,45**
ln(population prov)	**15,51**	**7,51**	-1,83	**-21,50**	-0,52	-0,06	0,82	-0,92
ln(population prov)2	**15,34**	**7,69**	-1,56	**-21,81**	-0,52	-0,08	0,84	-0,89
ln(GDP prov)	**18,49**	**9,22**	**-2,71**	**-25,51**	-0,66	-0,22	1,09	-1,02
ln(GDP prov)2	**18,32**	**9,36**	**-2,41**	**-25,81**	-0,67	-0,22	1,10	-0,98
growth population prov	**10,13**	**3,27**	**-3,05**	**-10,35**	-0,28	-0,10	0,51	0,10
growth GDP prov	-1,60	-0,78	-0,02	**2,39**	0,00	-0,18	-0,11	0,38
unemployment rate prov	**-9,00**	**-5,39**	**3,20**	**11,22**	0,03	0,58	-0,48	0,02
unemployment rate change prov	**6,47**	**4,63**	**-2,28**	**-8,84**	0,20	-0,58	0,32	0,07
share agriculture in value added prov	**-11,80**	**-6,29**	**3,39**	**14,78**	0,30	0,44	-0,97	0,72
share services in value added prov	**-3,41**	-1,41	**1,97**	**2,84**	-0,38	0,28	-0,08	-0,05
growth in agriculture value added prov	**-5,54**	**-2,93**	1,94	**6,53**	-0,02	0,22	-0,39	0,41
growth in services value added prov	-1,48	**-2,09**	0,44	**3,12**	-0,30	0,31	-0,28	0,26
Observations	2125	2125	2125	2128	1914	2013	1962	1483
Median abs(t-value)	**12,64**	**4,73**	**5,21**	**11,56**	1,24	1,23	1,24	1,25
Mean abs(t-value)	**13,19**	**5,22**	**5,84**	**13,14**	1,97	1,34	1,91	1,42

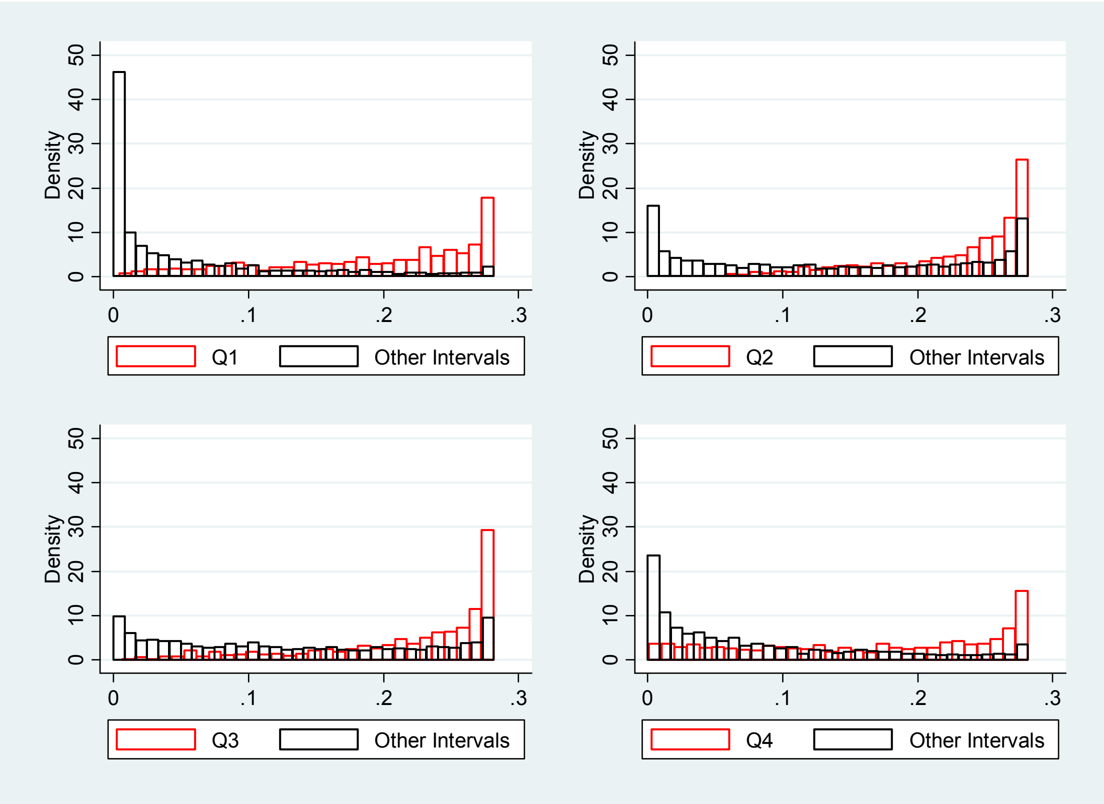
Note: See Table 3

Table 5. SPAIN & ITALY.
Estimated Parameters of the Conditional Distribution of log of exports given log of Immigration Stocks and the GPS.

	SPAIN	ITALY
ln(migr)	0.928***	1.027***
	[0.366]	[0.109]
ln(migr)^2	-0.399***	-0.581***
	[0.109]	[0.0369]
ln(migr)^3	0.0355***	0.0552***
	[0.0085]	[0.00333]
R	-8.227***	-29.82***
	[2.627]	[1.979]
R^2		24.68***
		[5.826]
R x ln(migr)	3.396***	8.252***
	[0.584]	[0.234]
Constant	6.297***	7.907***
	[0.329]	[0.172]
Observations	2516	7730
R-squared	0.033	0.281
AIC	10811.32	37940.61

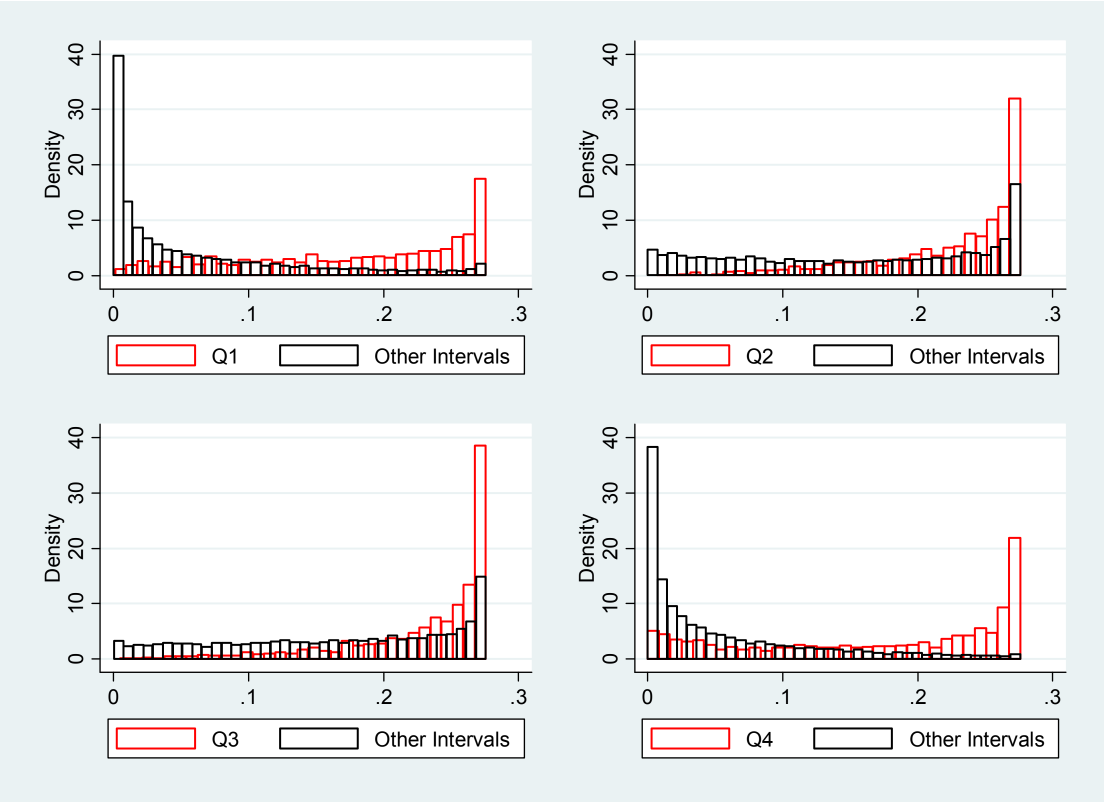
Note: ***, ** and * for significance levels at 1, 5, and 10%, respectively. $\ln(\text{migr})$ refers to logarithm of stock of immigrants in exporter province from importing country. R refers to generalized propensity score calculated according to equation (2) using the coefficients from the first stage regression in Table 1 for Spain and Table 2 for Italy. We estimate the standard errors of the dose-response function by bootstrapping with 1000 iterations that take into account that the second-stage estimates involve imprecision from first-stage estimates. We did not include country-province pairs with zero export flows.

Figure 1. SPAIN. GPS Support Condition



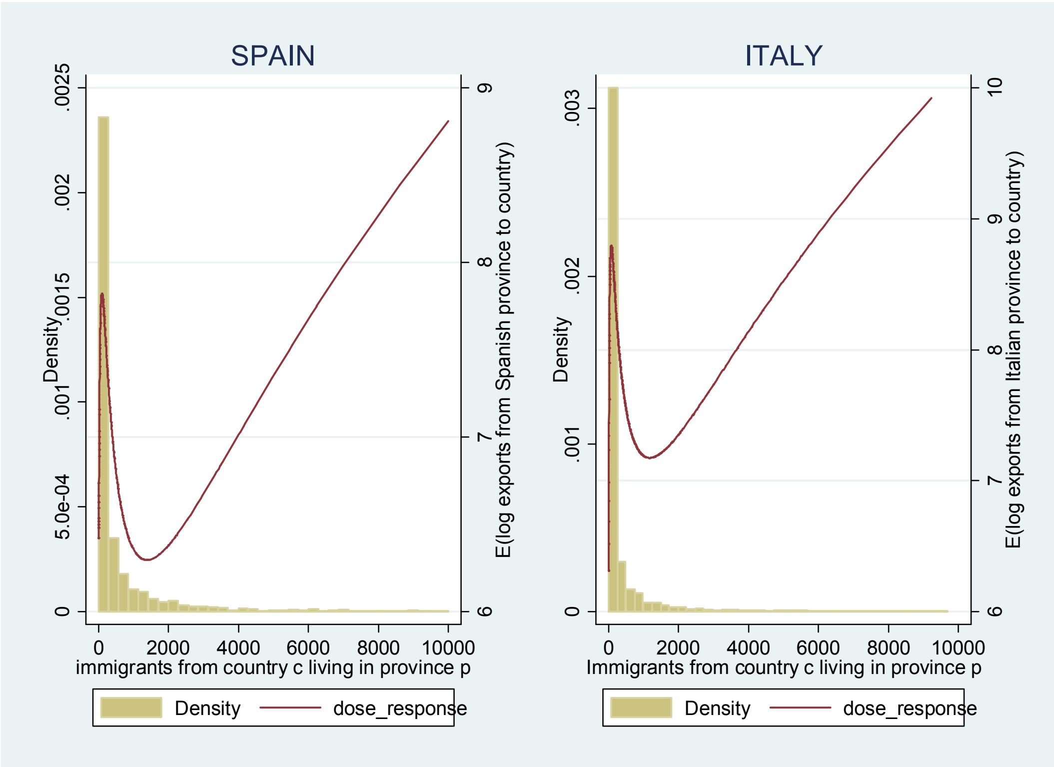
Notes: There are four intervals of equal size, each of them having 25% of the distribution of migration stocks (in ascending order). Province-country pairs with relatively low migration belong to interval Q1 whereas pairs with high migration belong to interval Q4. In each histogram, the generalized propensity scores are evaluated at the median migration level of the respective interval, for both the observations within that particular interval as well as for the respective control observations belonging to all other intervals.

Figure 2. ITALY. GPS Support Condition



Notes: See Figure 1

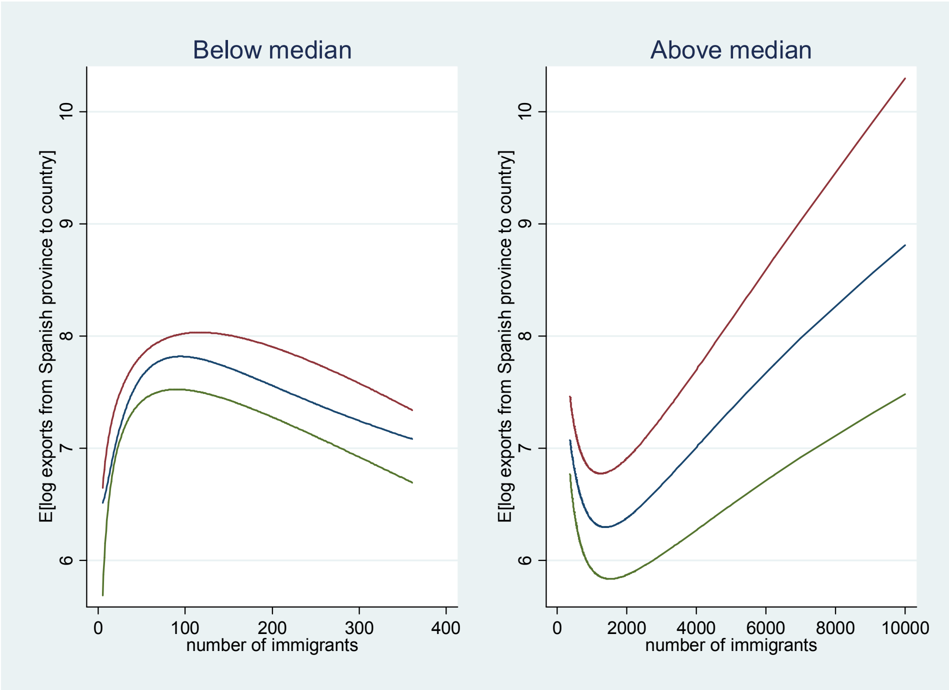
Figure 3. Distribution of immigrants stocks (density) and dose-response function



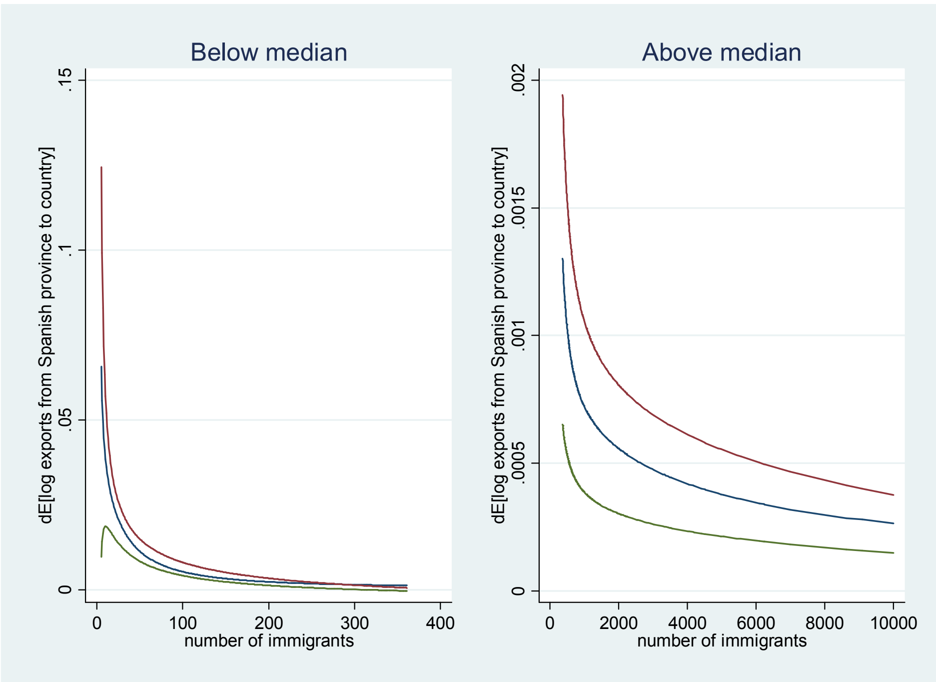
Note: The density distribution of immigration is based on the total number of province-country pairs in the sample. Density for values of immigration above 10,000 have been trimmed for presentation purpose.

Figure 4. SPAIN. Dose-response function and Derivative function of dose-response function

DOSE-RESPONSE FUNCTION (SPAIN)



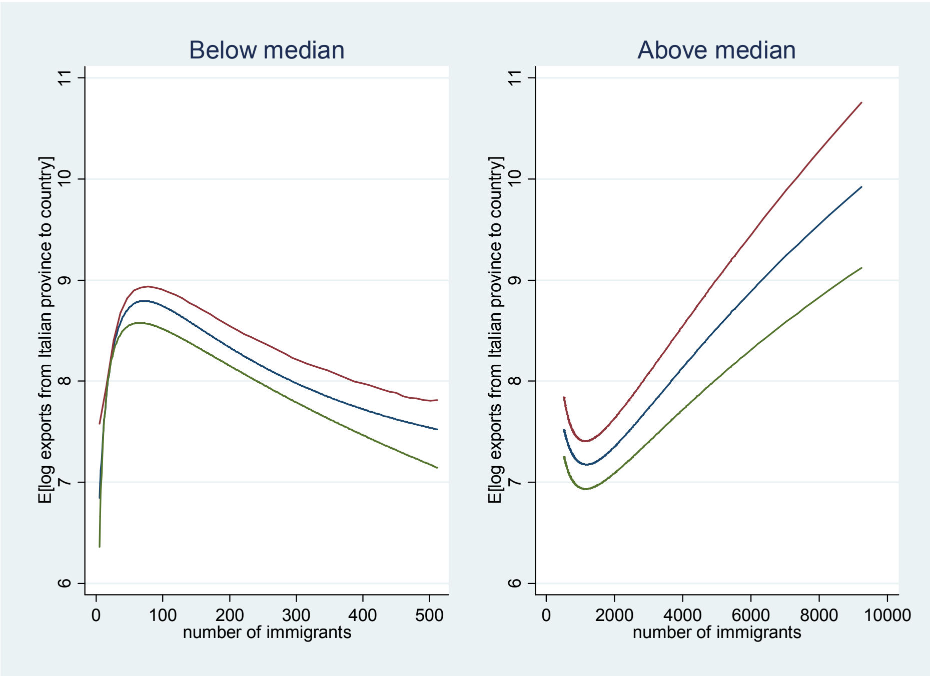
DERIVATE OF DOSE-RESPONSE FUNCTION (SPAIN)



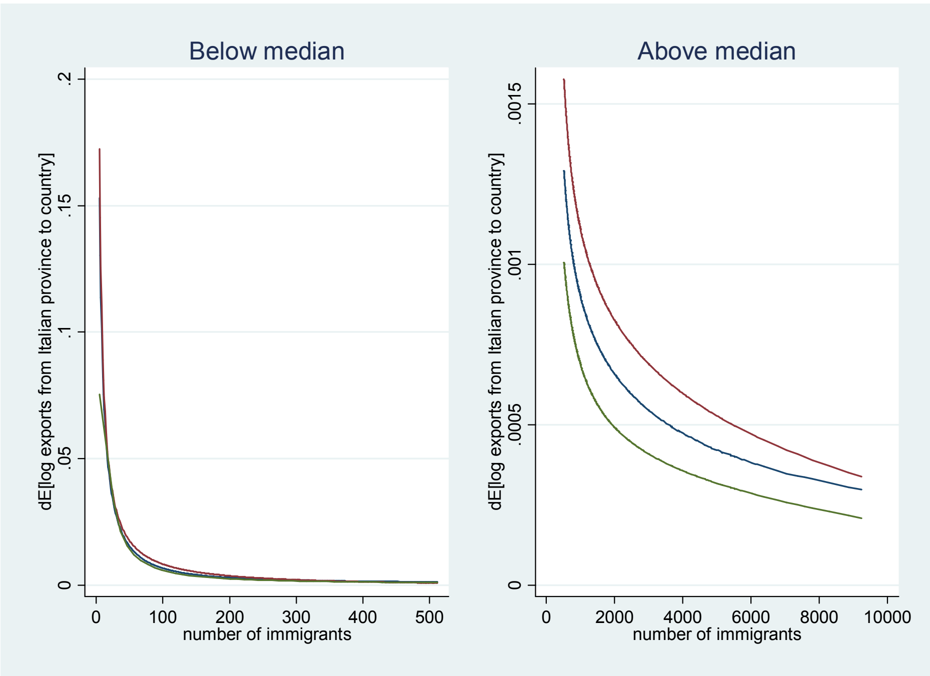
Note: The median value of the treatment is 361 based on the range of treatment values. Observations with treatment level above 10,000 immigrants are trimmed for presentation purpose. Confidence intervals constructed by bootstrapping (100 iterations)

Figure 5. ITALY. Dose-response function and Derivative function of dose-response function

DOSE-RESPONSE FUNCTION (ITALY)



DERIVATE OF DOSE-RESPONSE FUNCTION (ITALY)



Note: The median value of the treatment is 513 based on the range of treatment values. Observations with treatment level above 10,000 immigrants are trimmed for presentation purpose. Confidence intervals constructed by bootstrapping (100 iterations)

Appendix A1. List of countries of origin of immigrants (ISO3 codes)

ALB, ARG, ARM, AUS, AUT, BEL, BEN, BGD, BGR, BLR, BOL, BRA, CAN, CHE, CHL, CHN, COL, CRI, CZE, DEU, DNK, DZA, ECU, EGY, ESP*, EST, ETH*, FIN, FRA, GBR, GEO, GHA, **GNQ**, GRC, GTM, HND, HRV, HUN, IDN, IND, IRL, IRN, ISR, **ITA**, JAM*, JOR, JPN, KAZ, KEN, KOR, LKA, LTU, LVA, MAR, MDA, MDG*, MEX, MKD, MLI, MRT, MYS*, NGA, NIC, NLD, NOR, NPL, NZL, PAK, PAN, PER, PHL, POL, PRT, PRY, ROM, RUS, **SAU,** SEN, SGP*, SLE, SLV, SVK, SVN, SWE, SYR, THA, TUN, TUR, TZA*, UGA*, UKR, URY, USA, VEN, VNM, YEM, ZAF, ZMB*

There are 87 countries in Spanish sample and 95 countries in Italian sample with complete information to perform the GPS regression analysis. In bold, countries included only in Spanish sample. With asterisk countries included only in Italian sample)

Table A.2. Estimates of the trade-migration link using a gravity equation.

PANEL A: SPAIN	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
M*pc*	0.0052	0.0194	0.027	0.0061	0.0119	0.0268
	(1.77)	(3.29)	(2.55)	(2.64)	(1,98)	(2.28)
Square of M*pc*		-0.0001	-0.0004		-0.0001	-0.0004
		(2.82)	(1.72)		(1.18)	(2.08)
Cubic of M*pc*			0.0000001			0.0000001
			(1.24)			(2.11)
ln distance	-1.287	-1.291	-1.229	-1.288	-1.292	-1.293
	(6.08)	(6.12)	(6.12)	(6.09)	(6.12)	(6.12)
border dummy	4.818	4.712	4.709	4.813	4.761	4.705
	(15.76)	(9.12)	(6.12)	(9.32)	(11.11)	(9.01)
Hausman test:				0.065	4.454	1.695
[p-value]				[1.000]	[1.000]	[1.000]
Adjusted R2	0.789	0.789	0.789	0.789	0.789	0.789
N	3778	3778	3778	3778	3778	3778
PANEL B. ITALY	OLS	OLS	OLS	IV	IV	IV
	(7)	(8)	(9)	(10)	(11)	(12)
M*pc*	0.0078	0.0405	0.068	0.0036	0.0395	0.072
	(1.28)	(3.01)	(2.82)	(0.93)	(2.31)	(2.60)
Square of M*pc*		-0.0010	-0.0033		-0.0012	-0.0045
		(3.92)	(2.21)		(3.10)	(2.14)
Cubic of M*pc*			0.00003			0.00005
			(1.72)			(1.64)
ln distance	-0.661	-0.666	-0.667	-0.659	-0.667	-0.671
	(6.25)	(7.49)	(7.51)	(7.38)	(7.56)	(7.58)
border dummy	2.256	2.145	2.089	2.278	2.147	2.078
	(13.68)	(5.89)	(5.70)	(13.69)	(5.90)	(5.68)
Hausman				0.861	3.865	2.999
[p-value]				[1.000]	[1.000]	[1.000]
Adjusted R2	0.835	0.835	0.835	0.835	0.835	0.835
N	8004	8004	8004	8004	8004	8004

Note: Dependent variable is (log) of exports from province *p* to country *c* in 2007. M*pc* are foreign-born people from country *c* living in province *p* at the beginning of 2006 (expressed in thousands). Additional control variables in all columns include province dummies (50 for Spain and 103 for Italy) and country dummies (87 for Spain and 95 for Italy). The instrumental variable is the stock of immigrants at the beginning of 2002 (expressed in thousands). The Hausman tests refer to the differences of IV estimates and OLS estimates. Standard errors in parenthesis.

Table A.3. Covariate balance with and without adjustment

	SPAIN				ITALY			
	Unconditional effect of T		Effect of T conditional on E(log(T)/X)		Unconditional effect of T		Effect of T conditional on E (log(T)/X)	
	coefficient	std error	coefficient	std error	coefficient	std error	coefficient	std error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
population cou	0.0055	(0.0041)	-0.0018	(0.0042)	**0.0080**	(0.0026)	**-0.0057**	(0.0025)
(population cou)2	0.0862	(0.0835)	-0.0675	(0.0857)	**0.1788**	(0.0524)	**-0.1087**	(0.0501)
GDP cou	0.0019	(0.0050)	-0.0071	(0.0052)	**-0.0164**	(0.0034)	**-0.0435**	(0.0033)
(GDP cou)2	0.0110	(0.1166)	-0.0239	(0.1207)	**-0.3924**	(0.0799)	**-1.0240**	(0.0783)
growth population cou	**-0.0058**	(0.0028)	-0.0019	(0.0029)	**-0.0085**	(0.0029)	0.0043	(0.0029)
growth GDP cou	**0.0351**	(0.0150)	0.0251	(0.0156)	**0.0577**	(0.0096)	0.0137	(0.0096)
physical distance cou	-0.0007	(0.0019)	-0.0001	(0.0020)	**-0.0161**	(0.0018)	-0.0008	(0.0018)
distance language cou	**-0.0131**	(0.0042)	-0.0013	(0.0044)	**0.0040**	(0.0006)	**0.0037**	(0.0007)
education distance cou	0.0010	(0.0018)	0.0019	(0.0019)	**0.0136**	(0.0014)	**0.0102**	(0.0014)
industrialisation distance cou	0.0025	(0.0018)	0.0038	(0.0019)	**0.0122**	(0.0012)	**0.0110**	(0.0013)
political freedom index cou	-0.0032	(0.0046)	0.0011	(0.0048)	**0.0255**	(0.0030)	**0.0215**	(0.0031)
human right index cou	**0.0050**	(0.0025)	0.0024	(0.0026)	**0.0115**	(0.0018)	0.0031	(0.0018)
Gini cou	**0.0783**	(0.0256)	0.0314	(0.0266)	**-0.0752**	(0.0171)	-0.0106	(0.0175)
unemployment rate cou	-0.0098	(0.0185)	-0.0175	(0.0193)	**0.1333**	(0.0118)	**0.0793**	(0.0120)
border cou	**0.0017**	(0.0002)	**0.0011**	(0.0002)	**0.0054**	(0.0005)	**0.0026**	(0.0005)
member EUEFTA cou	**0.0029**	(0.0012)	0.0017	(0.0012)	**-0.0039**	(0.0006)	**-0.0042**	(0.0007)
dummy =1 if imports 1995 > 0 prov-cou	0.0016	(0.0012)	0.0009	(0.0013)	**0.0030**	(0.0005)	-0.0008	(0.0005)
ln(number of emigrants prov-cou)	**0.0110**	(0.0052)	0.0068	(0.0051)	**-0.0247**	(0.0061)	**-0.0562**	(0.0062)
population prov	0.0003	(0.0019)	-0.0030	(0.0020)	**0.0064**	(0.0012)	0.0001	(0.0012)
(population prov)2	0.0050	(0.0241)	-0.0041	(0.0250)	**0.0778**	(0.0152)	-0.0006	(0.0154)
GDP prov	0.0006	(0.0019)	-0.0029	(0.0020)	**0.0094**	(0.0013)	0.0010	(0.0013)
(GDP prov)2	0.0118	(0.0366)	-0.0576	(0.0380)	**0.1752**	(0.0242)	0.0175	(0.0242)
growth population prov	**0.0058**	(0.0029)	0.0020	(0.0030)	**0.0113**	(0.0022)	0.0032	(0.0022)
growth GDP prov	**0.0049**	(0.0022)	0.0017	(0.0023)	-0.0012	(0.0018)	-0.0006	(0.0018)
unemployment rate prov	-0.0028	(0.0076)	-0.0037	(0.0079)	**-0.0836**	(0.0142)	-0.0103	(0.0146)
unemployment rate change prov	**0.0137**	(0.0075)	0.0098	(0.0079)	**0.0372**	(0.0081)	0.0158	(0.0084)
share agriculture in value added prov	0.0082	(0.0099)	0.0083	(0.0104)	**-0.0188**	(0.0042)	-0.0015	(0.0043)
share services in value added prov	0.0059	(0.0177)	0.0040	(0.0177)	**-0.0729**	(0.0137)	-0.0207	(0.0141)
growth in agriculture value added prov	-0.0001	(0.0004)	-0.0001	(0.0004)	**-0.0002**	(0.0001)	-0.0001	(0.0001)
growth in services value added prov	-0.0004	(0.0006)	-0.0002	(0.0006)	-0.0002	(0.0002)	-0.0001	(0.0002)

Note: T is the immigration stock. Columns 1, 3, 5 and 7 contain the results of regressing the corresponding observable covariates on T. Columns 2, 4, 6 and 8 contain the same results conditional on the predicted ln(migr), E[lnT|Xi]. We use the level of immigration (T), because ln(migr) and each covariate is necessarily uncorrelated given (see Imai and van Dyk, 2004). Bold numbers indicate significance at 5%.