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"Evaluating the impact of border and domestic policies on trade: a product-spatial GPS approach to control for spillover effects"

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Preliminary version

Abstract

This work aims at analyzing the causal relationship between border and domestic policy support and trade performance at product level by applying nonparametric matching econometrics that allow us to address potential endogeneity issues, such as selection bias. More specifically, in order to tackle the presence of spillover effects - very common in the context of international trade - we propose an original revision of the spatial propensity score matching by extending it to the case of continuous treatment and weighting the spatial lags according to the products' distances over the so-called Product Space (Hidalgo et al, 2007; Hausmann and Klinger, 2007). Through this strategy, we can control for interference and spillovers caused by policy interventions of main global exporter countries (external spillover) as well as spillovers caused by government interventions over other sectors (internal spillover). We test our model by empirically analyzing the impact of agricultural incentives on exports flows for a set of 78 countries from 1995 to 2011 by matching standard data sets. Preliminary results show that not considering spillover effects generates an underestimation of the treatment assessment that could have relevant policy implications.

Keywords: Agricultural policy, Trade performance, Cross-country analysis, Generalized Propensity Score, Product Space

JEL codes: C21, F14, F60, O50, Q17

1. Background and aim

A significant strand of trade literature is traditionally devoted to assessing the impact of policy measures – both domestic and foreign - on trade performance. The most common techniques to estimate this effect are gravity models, for an ex-post assessment, and computable general equilibrium (CGE) models for an ex-ante assessment. Recently, impact evaluation techniques have been used to address the issue of endogeneity and self-selection in measuring this kind of effects, an issue that is very common in the context of international trade. Most papers that use counterfactual methods for evaluating the impact of a policy on trade (see, for instance, Baier and

Bergstrand, 2009; Montalbano and Nenci, 2014; …) usually assume that "the treatment received by one unit does not affect other units' outcome" (Cox 1958). This non-interference (or interaction) assumption - the stable unit treatment value assumption (SUTVA) in the Rubin Causal Model (Rubin, 1974) – is likely to be violated in the context of international trade flows (Baier and Bergstrand, 2009). An incentive or disincentive applied to a traded product can influence another product – both domestic and foreign - that shares similar characteristics. Furthermore, selection into a policy for a product is often not random.

In this work, we specifically address this issue by proposing a counterfactual method that takes into account the presence of spatial externalities and analyzes simultaneously direct and indirect effects of a continuous treatment. More specifically, we adopt a "product" spatial lagged model, applying the spatial propensity score matching technique (Cerqua and Pellegrini, 2016, 2017; Chagas et al, 2012) to the case of continuous treatment (Hirano and Imbens, 2004; Imai and van Dyk, 2004) and weighting the spatial lags according to the products' distances over the so-called Product Space (Hidalgo et al, 2007; Hausmann and Klinger, 2007). Through this strategy, we can control for the interference and spillovers caused by policy interventions of main global exporter countries (external spillover) as well as spillovers caused by government interventions over other products (internal spillover). We do this by adopting the measure of the minimum of the pair wise conditional probability of being co-exported (a proxy for capabilities similarities shared by pairs of products globally traded) as distance between products. The Product Space's distance between any pair of goods ranges from a minimum of 0 to a maximum of 1. Values close to unity reflect similarities in the capabilities required for realizing two different goods and reflect a sort of substitutability between them: when two products share several production capabilities, the introduction (or the existence) of domestic or foreign (dis)incentives on one of these goods can boost the producers to modify their production choices, both within a country and across countries. To better control for external spillovers we include information on the revealed comparative advantage (RCA) (Balassa, 1965) of other countries: countries that are main exporters of a certain product could potentially influence markets in other countries and, in particular, export performances. In this light, the highest is the RCA index for a country, the highest is the probability to influence foreign markets.

To make our argument as persuasive as possible, we test our model in an empirical application that assesses the impact of agricultural policy support on trade performance at product level for a set of 78 countries from 1995 to 2011 by using standard data sets. More specifically, we match the World

Bank “Distortions to agricultural incentives” database (Anderson and Nelgen, 2012) with trade data from BACI dataset by CEPII.

Most countries in the world adopt trade and domestic market policies that impact their agricultural sector. Such policies affect market structure, productivity, agricultural output composition as well as food security (Magrini et al, 2017). Thanks to the World Bank “Distortions to agricultural incentives” database by Anderson and Nelgen (2012), which collects indicators converting different policy instruments into a common metric (the Nominal Rate of Assistance) for a large set of countries and a long period, it is possible to analyze the extent to which, in recent years, agri-food products are incentivized or disincentivized by governments policies.

The originality of this work comes from its methodological approach that brings the Product Space’s relatedness between goods in the GPS analysis. This analysis has also important policy implications: empirical outcomes can help policy makers decide whether support policies are generating intended effects.

The work is organized as follows: Section 2 presents the methodological approach; Section 3 describes data and variables; Section 4 shows the empirical results and Section 5 concludes.

2. Methodology

The adoption of an impact evaluation method such as the generalized propensity score matching permits us to address the potential endogeneity issue as well as to overcome the need of identifying control groups which is traditionally difficult in non-experimental setting. Similarly to Egger et al. (2012) and Magrini *et al* (2017), we recourse here to the Generalized Propensity Score (GPS) estimator, originally proposed by Hirano and Imbens (2004) and Imai and van Dyk (2004) which is a generalization of the binary treatment propensity score and corrects for selection bias in a setting with a continuous treatment. By exploiting the observable determinants of different treatment intensities by units, this technique allows us to match the most similar units within the treatment group and remove self-selection without the need of resorting to untreated control groups. The main novelty of this paper is the attempt to include in the analysis the spillover effects that might come from the non-compliance of the Stable Unit Treatment Value Assumption.

2.1 The Generalized Propensity Score

To apply the GPS technique, we assume that: for each unit of observation there is a vector of covariates X, a "treatment" received, $\tau \in [\tau_0, \tau_1]$, and a potential outcome, Y=Y(τ).[1] Our aim is to derive an average dose-response function (DRF) across all observations that illustrates the expected value of the outcome variable conditional on continuous treatment as follows:

$$D(\tau) = E[Y(\tau)] \qquad (1)$$

While Hirano and Imbens (2004) define the GPS as $R = r(\tau, X)$, with r being the conditional density of the treatment given the covariates X, in our exercise – similarly to De Castris and Pellegrini (2016) – we expect the following to hold:

$$R = r(\tau, Z) \qquad (2)$$

where Z includes both the covariates X and $g(PSLagPS)$ which is the 'product-spatial' lag of the propensity score computed as in Hirano and Imbens (2004).

The implementation of the classic GPS method requires a three-step approach. In the first step, for each unit, we compute the ex-ante conditional probability of receiving a specific treatment. Specifically, we estimate the GPS via the standard normal model (eq. 3) and check the balance of pre-treatment covariates between treatment groups (*i.e.*, the so-called balancing property)[2]:

$$\widehat{R} = \frac{1}{\sqrt{2\pi\widehat{\sigma}^2}} exp\left[-\frac{1}{2\widehat{\sigma}^2}\left(\tau - \hat{\beta}_0 - \hat{\beta}_1'X\right)^2\right] \qquad (3)$$

In the second step, we estimate the conditional expectation of the outcome as a function of two scalars, the treatment level (τ) and the GPS $\lfloor R = r(\tau, X) \rfloor$. The third and final step is to estimate the average DRF of the outcome averaging the conditional expectation over the GPS at any different level of the treatment, as follows:

[1]Following Hirano and Imbens (2004) we assume as well that: Y, τ and X are defined on a common probability space; τ is continuously distributed with respect to a Lebesgue measure on Γ; Y=Y(τ) is a well-defined random variable. For each observation we postulate the existence of a set of potential outcomes, Y(τ), for $\tau \in \Gamma$ where Γ is the interval $[\tau_0; \tau_1]$, referred to as the unit-level dose-response function.

[2]As in Magrini *et* al (2017), to test the balancing property, we organize the data in a group-strata structure. This enables us to compare observations between treatment groups across strata based on the estimated GPS. Specifically, for each treatment group j and each observation i we compute the probability of each trade flow having the median treatment of the group $j(T_M^j)$, i.e. $\widehat{R}_i(T_M^j, X_i)$. We then plot these GPS values in group j against those not in group j and eliminate those observations in groups other than j that lie outside the common GPS support. This means that we keep only those flows which respect the following condition:

$$Min\{\widehat{R}_k(T_M^j, X_k)\} \leq \widehat{R}_l(T_M^j, X_l) \leq Max\,\{\widehat{R}_k(T_M^j, X_k)\}$$

where $k \in$ j and l $\notin$ j.

$$D(\tau) = E\left[\alpha\left(\tau, r(\tau, X)\right)\right] \qquad (4)$$

where α are the parameters to be estimated. It is worth noting that while in the standard panel setting each observation is matched with the average of all the other observations in the same year t regardless of their treatment status (Imai and Kim 2011), in matching techniques, if balancing holds[3], each product-level flow is matched only with those within the same GPS strata (i.e., those that are similar in terms of their observable characteristics).

In our methodological exercise we introduce *new steps*: after obtaining the GPS as specified in step 1, we compute the product-spatial lagged generalized propensity score of each product-country combination by weighting other products' and/or countries' propensity scores according to an *ad hoc* built proximity matrix. The lagged generalized propensity scores are obtained by weighting only contemporaneous values since we are not able to measure over time spillover effects.

The so obtained 'product-spatial' lagged GPS is then included among covariates in order obtain a new GPS as in step 1 (this time with spillover effects) and then moving forward to subsequent step until reaching a new DRF accounting for product-spatial effects.

Apart the SUTVA (Stable Unit Treatment Value Assumption) that we explicitly address and attempt to overcome, the validity of GPS estimates depends crucially on the validity of a set of other assumptions which are standard in impact evaluation literature. The first assumption is the randomness of the treatment, i.e. the "unconfoundedness" or "ignorability of the treatment". This means that, conditional on observable characteristics, the treatment can be considered as random. Imbens (2000) shows that if the treatment assignment is weakly unconfounded given the observed covariates, then it is weakly unconfounded given GPS. Hence this property combined with the balancing property guarantees that the treatment assignment can be considered as random in a non-experimental setting. Another common validity condition is the "overlap assumption", i.e., the need to maintain an adequate balance of observations between treatment and control groups. This is also not an issue here since using GPS we do not rely on control groups but instead work across GPS strata of various "treatment intensities" on a continuous distribution and thus we are able to test alternative group/strata structures for checking the validity of the balancing property.

[3] Note that as long as sufficient covariate balance is achieved, the exact procedure for estimating the GPS is of secondary importance (Kluve et al. 2012).

2.2 Building the product-spatial lags

A crucial aspect of our analysis is reckoning the extent to which exports of product *i* by country A are related to exports of product *j* by country B. In doing so, we need to capture the 'relatedness' between product *i* and product *j* as well as the extent to which foreign country B do influence the domestic market A. After computing a standardized measure of proximity (or distance) that simultaneously takes into consideration these two dimensions we compute two different weighting matrices (differing by the way the two dimensions convey to a unique measure). Obviously, in our analysis we consider also the case in which product i = product j (same product exported by different countries and thus products highly related in terms of substitutability) and when country A = country B (intra-country relatedness and thus with the 'country' relatedness very relevant).

The degree of relatedness between two products is obtained by borrowing the Hidalgo *et al* (2007)'s definition of proximity. In their attempt to picture the over time evolution of the production structure of countries, they built the so-called Product Space which allows to represent the link between each pair of goods by computing the minimum of the pairwise conditional probability of being co-exported with revealed comparative advantage (RCA)[4] higher than unity:

$$\varphi_{ij} = \min\{P(x_i|x_j), P(x_j|x_i)\} \tag{5}$$

where, for each country in the world:

$$x_i = \begin{cases} 1 \; if \; RCA_i \geq 1 \\ 0 \; otherwise \end{cases} \tag{6}$$

The reason why we expect this measure to influence our analysis comes from the idea that the proximity between two products – that ranges between 0 (no relatedness) and 1 (very high relatedness) – reflects the similarities in terms of capabilities required to realize them. Thus, if a product *j* receives an economic incentive, we expect to find spillover effects on the production – and export – of related goods. Both within a country and between country.

This latter aspect – the between country spillover – is taken into consideration by including in the analysis the relative size of all foreign economies as represented by their 'adjusted' Symmetric Balassa Index ($adjSBI$) in the export of product *j* (while the value of the Symmetric Balassa Index

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[4] The Revealed Comparative Advantage (RCA) index developed by Balassa (1965) takes the following form:

$$\mathrm{RCA_{ij}} = \frac{\frac{x_{ij}}{x_{wj}}}{\frac{X_i}{X_w}} \qquad \in [0, \infty]$$

where x_{ij} and x_{wj} are, respectively, the exports of the product (or sector) j from country i and the world exports w of product j, whereas X_i e X_w are, respectively, the total exports of country i and the world total exports.

ranges between -1 and +1, we normalize its value between 0 and 1)[5]. The higher is the comparative advantage of a country in the production of the product *j*, the higher will be its ability to influence the international market of such product and thus – independently from its geographic distance – such country will result in being 'related' the export of *j* in all the other countries. When the spillover effect to be measured is between different products exported by the same country, the value of the Symmetric Balassa Index is set to 1.

For the sake of clarity, let us observe the 'product-country' relatedness between each product-country pair over the two dimensions we have introduced:

$$\varphi_{iA,jB} \; depends \; on \; two \; dimensions \begin{cases} 0 \leq \varphi_{ij} \leq 1 \\ \begin{cases} 0 < adjSBI_{jB} = \frac{1+SBI_{jB}}{2} < 1 \; if \; A \neq B \\ 1 \; if \; A = B \end{cases} \end{cases} \quad (7)$$

The spillover effect between the good *i* exported by country A and good j exported by country B depends, thus, on the proximity between the two goods and the country B's proximity as measured by its size in the good j's international market. When A=B, we assume the 'country' proximity to be equal to 1, meaning the spillover we are considering is within the same country.

We finally compute our product-country proximity measures in two different ways:

$$\varphi^{a}_{iA,jB} = \frac{1}{\sqrt{(1-\varphi_{ij})^2 + (1-adjSBI_{jB})^2}} \quad (8)$$

$$\varphi^{b}_{iA,jB} = \varphi_{ij} * adjSBI_{jB} \quad (9)$$

where $\varphi^{a}_{iA,jB}$ is the inverse of the Euclidean distance (proximities' complement to 1) over product and the country dimensions while $\varphi^{b}_{iA,jB}$ is a multiplicative proximity. The former proximity measure gives higher weights to related country-product pairs with respect to the latter, as represented in

[5] We decided to use the revealed symmetric comparative advantage index by Dalum et al. (1998), which is a widely-used transformation of the Balassa's index, since it allows a more effective comparison between countries. It is defined as:

$$\text{Symmetric BI}_{ij} = \frac{\text{RCA}_{ij} - 1}{\text{RCA}_{ij} + 1} \quad \in [-1, 1]$$

Figures 1 and 2. The φ_{ij} is built on the average proximity levels obtained for time t-1, t and t+1. $adjSBI_{jB}$ are obtained by revealed comparative advantages at time t-1.

Figure 1: Product-Country proximity as a function of product proximity and country proximity. Inverse of distance measured as in (8).

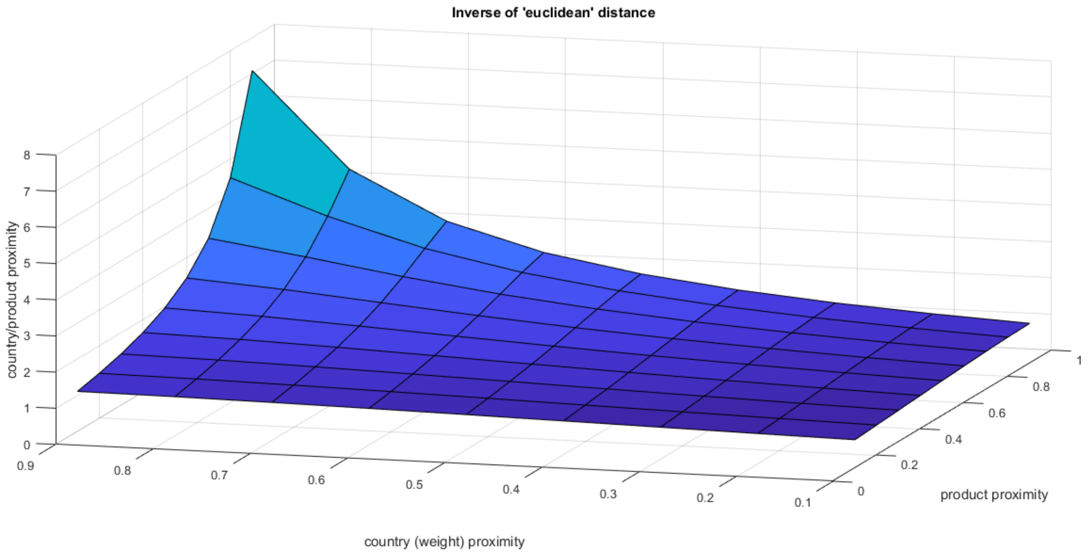
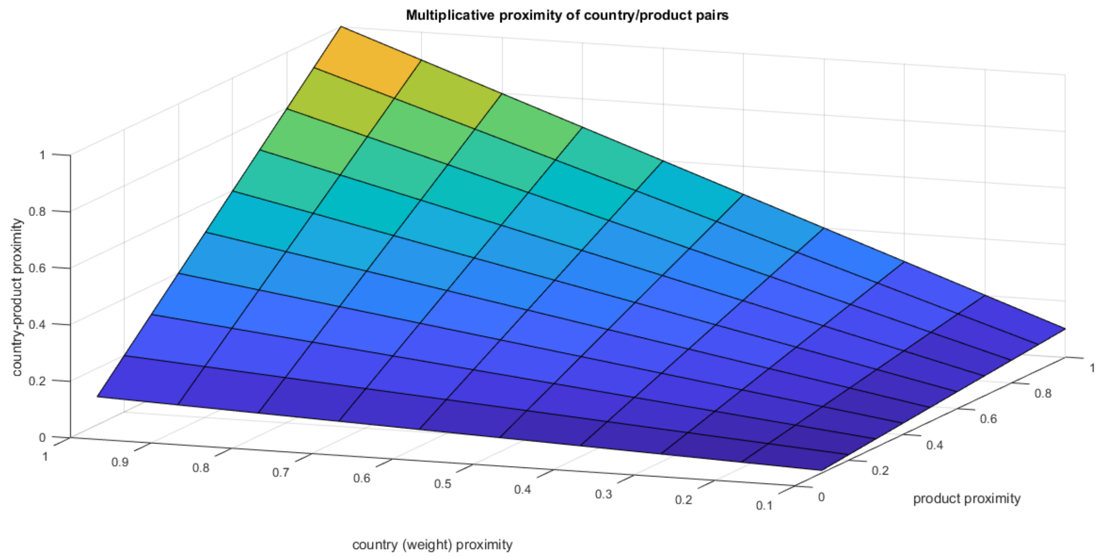


Figure 2: Product-Country proximity as a function of product proximity and country proximity. Inverse of distance measured as in (9).



3. Data and Variables

In order to test our model, we carry out the empirical analysis referring to well-known data sets. Specifically, we use the World Bank “Distortions to agricultural incentives” database developed by Anderson and Nelgen (2012) to proxy the treatment variable and the BACI -CEPII trade data to proxy the outcome variable.

3.1 The Nominal Rate of Assistance

Anderson and Nelgen's (2012b) World Bank database provides annual values for a set of standardized measures of policy-related distortions, for a total of 82 countries (which together account for over 90% of global agricultural output) and 70 products, over the period 1955-2011[6]. It contains aggregate and by product Nominal Rate of Assistance (NRA) measures defined as the percentage by which government policies directly raise (or lower) the gross return to producers from a product above the world price:

$$NRA = [E.P\,(1+d) - E.P\,]/E.P \qquad (10)$$

where E is the exchange rate, d is a distortion due to government interventions and P is the foreign price of an identical product in the international market (Anderson, 2006). Positive values of NRA denote a rise in domestic producers' gross return (the observed price is higher because of the presence of an output subsidy and/or a consumption tax), while negative values denote a lower gross return for domestic producers (the producers receive less than the price for the same product in the absence of government interventions)[7].

Similarly to Anderson and Nelgen (2012a, 2012b) and Magrini *et al* (2017) to avoid negative values we convert NRA into the nominal assistance coefficient (NAC) by the formula:

$$NAC = [\mathrm{NRA} + 1] \qquad (11)$$

Governments can influence agricultural incentives directly through a broad set of policy instruments. They include interventions in both input and output markets (e.g. subsidies, controls over land use, producer and consumer price supports, taxes, food reserves releases) and border measures that have an impact on a country's external balance and terms of trade. Trade policies such as export and import taxes, subsidies and quantitative restrictions are among the most frequently used instruments and account for 60 percent of agricultural NRAs at the global level. In contrast, domestic agricultural policies which provide direct subsidies or tax inputs and outputs contribute only minimally to price incentives (Anderson et al., 2013b).

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[6] After data cleaning, countries in our sample are 78.

[7] The border price, used as a benchmark for producer prices when calculating the NRA, is adjusted to take account of all the additional costs generated by the value chain activities and not imputable to the policy interventions (Anderson and Valenzuela, 2008).

3.2 Covariates and outcome

The issue of the covariates able to explain the probability of reaching a specific level of policy incentive is a controversial one. In this work, the selection of the covariates used in the first step of our GPS matching procedure follows both the political economy of agricultural and food policies literature (Anderson 2013; Anderson, Rausser, and Swinnen 2013; Swinnen 2010) and trade policy literature. Specifically, we use the following variables: the GDP per capita (in log, as well as its squared and cubic power) to control for the level of development of the economy and its non-linearities (Dehejia and Wahba, 1999 and Dehejia, 2005); the population (in ln, and its squared power) to control for the country size; the per capita arable land (in ln) to control for the relative agricultural comparative advantage; the agricultural total factor productivity growth rate to control for the productivity of the agricultural sector; the sectoral imports (in ln) to control for the country dependence from foreign markets as well as the anti-trade pattern (Swinnen, 2010). All covariates refer to time t-1.

Our outcome variable is the logarithm of the value of the product export flows. Product trade data come from the BACI -CEPII database. We use Harmonized System (HS) classification at the maximum disaggregation available (six digits) and select agricultural, food and fishery products listed under Chapters 1 to 24, 40 and 51 to 53 of the HS codes.

See Table A.1 in the Appendix for additional details and sources on data and variables.

The complete data-set on which we estimate the GPS from 1995 to 2011 includes about 31,600 observations[8]. The descriptive statistics are reported in Table 1.

Table 1: Descriptive statistics

Variable	**N**	**Mean**	**SD**	**Min**	**Max**
NAC	31589	1.22	0.33	0.16	2.08
GDP per capita	31589	21917.19	18983.23	186.66	91617.28
Population	31589	7.10E+07	1.87E+08	2.69E+05	1.34E+09
Product imports	31589	45423.19	2.55E+05	0	2.26E+07
Arable land (hpp)	31589	0.38	0.46	0	2.57
Agricultural TFP growth rate	29087	0.02	0.06	-0.39	0.38

Source: Authors' elaboration

[8] After eliminating outliers and checking the matching between FAOstat nomenclature and HS nomenclature.

4. Empirical analysis

Our empirical exercise aims at evaluating the impact of agricultural policy support on agricultural export performance of 78 countries between 1995 and 2011. In this analysis, we assign to each of the product observations matched merging BACI dataset with the WB database the corresponding level of treatment.

We first regress the NAC, our measure of (dis)incentive, on the set of pre-treatment characteristics by adopting Ordinary Least Squares (OLS) for the first stage of the GPS exercise[9].

The results of the first stage estimates are reported in Table 2. They show that: the higher is the economic development and size of a country, the lower is its use of agricultural incentives.

Table 2: First stage estimates for classical GPS and with spill-over effects over the (transformed) treatment variable.

	Initial Stage	First stage with PSLag A	First stage with PSLag A
GDP percapita at t-1 (in ln)	-0.265*	-0.310***	-0.364***
	(0.138)	(0.138)	(0.138)
GDP percapita at t-1 (in ln) ^2	0.044***	0.050***	0.057***
	(0.016)	(0.016)	(0.016)
GDP percapita at t-1 (in ln) ^3	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Population at t-1 (in ln)	-0.168***	-0.171***	-0.175***
	(0.015)	(0.015)	(0.015)
Population at t-1 (in ln) ^2	-0.168***	-0.171***	-0.175***
	(0.000)	(0.000)	(0.000)
Imports at t-1 (in ln)	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)
Arable land at t-1 (hpp, in ln)	-0.039***	-0.039***	-0.038***
	(0.002)	(0.002)	(0.002)
Agricultural TFP growth at t-1	-0.025	-0.002	-0.013
	(0.028)	(0.028)	(0.028)
PSLgpscore (A)		-0.564***	
		(0.030)	
PSLgpscore (B)			-0.587***
			(0.028)
Constant	1.796***	2.528***	2.722***
	(0.418)	(0.421)	(0.418)

[9]Following Magrini *et al* (2017) and Serrano-Domingo and Requena-Silvente (2013), we prefer using OLS estimators rather than other available estimators, although the Jarque-Bera normality test on the distribution of the residuals of our first stage is not always perfectly respected (probably because a very high number of observations have the same treatment level corresponding to NRA=0) even after transforming our treatment variable in *ln* and dropping outliers. As stated by Serrano-Domingo and Requena-Silvente (2013) "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".

Adjusted R2	0.09	0.11	0.11
N	28,954	28,954	28,954

*The number of asterisks indicates that the coefficients are statistically significant: * 10 %. ** 5 %, *** 1 %*

Furthermore, the higher is the arable land available, the lower is the average rate of incentive while the coefficient associated to the inward trade flow confirm that sectors with higher imports at time t-1 tend to raise the level of agri-food incentives. The coefficients of the two spatially lagged GPScore reflect the existence of a statistically significant link between units treated and 'product-country' neighbors.

After having estimated the first stage, before obtaining the Dose Response Functions of the GPS we need to test the "balancing property" for all our estimates. We first compare the covariates across the four groups we divided our treatment into with and without the GPS correction. Then we performed a series of two-sided t-test across groups, for each covariate. The correction is performed through the imposition of the common support condition (eliminating those control observations outside GPS support of the treated groups). Table 3 reports the t-stats value of the differences in the covariates by treatment levels before and after balancing on the GPS, both for classical methodology and product-spatially lagged models.

Table 3: T-tests for the respect of the balancing property

Differences in the covariates by Treatment Levels before and after Balancing on the GPS for classical methodology and for product-spatially lagged models (T-stats for Equality of Means)

	Prior to balancing on the GPS				After balancing on the GPS			
Covariates	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
GDP percapita at t-1 (in ln)	**30.718**	**-5.171**	**-5.292**	**-22.852**	0.810	-0.793	0.643	0.123
GDP percapita at t-1 (in ln) ^2	**29.220**	**-4.358**	**-4.645**	**-22.516**	0.564	-0.723	0.675	0.291
GDP percapita at t-1 (in ln) ^3	**27.722**	**-3.556**	**-4.032**	**-22.138**	0.326	-0.645	0.704	0.450
Population at t-1 (in ln)	**-4.507**	**-8.906**	0.162	**11.181**	1.002	**-2.089**	-0.162	0.048
Population at t-1 (in ln) ^2	**-4.071**	**-9.136**	-0.164	**11.170**	1.007	**-2.089**	-0.176	0.085
Imports at t-1 (in ln)	**22.052**	**-12.428**	**-6.336**	**-7.862**	-0.050	**-3.040**	-0.570	1.601
Arable land at t-1 (hpp, in ln)	**-25.365**	-1.885	**7.916**	**20.773**	-1.552	-0.049	1.340	1.759
Agricultural TFP growth at t-1	**4.773**	-1.556	**-6.212**	1.300	1.055	-0.409	-1.417	0.300
No. of observations	10246	4239	4973	9496	10234	4237	4973	9488
Mean t-value	13.083				0.775			

	Prior to balancing on the GPS				After balancing on the GPS			
Covariates	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
GDP percapita at t-1 (in ln)	**30.718**	**-5.171**	**-5.292**	**-22.852**	0.961	-1.464	0.218	1.942
GDP percapita at t-1 (in ln) ^2	**29.220**	**-4.358**	**-4.645**	**-22.516**	0.630	-1.381	0.304	**2.121**
GDP percapita at t-1 (in ln) ^3	**27.722**	**-3.556**	**-4.032**	**-22.138**	0.310	-1.272	0.388	**2.276**

Population at t-1 (in ln)	**-4.507**	**-8.906**	0.162	**11.181**	1.114	-1.578	-0.207	-0.187
Population at t-1 (in ln) ^2	**-4.071**	**-9.136**	-0.164	**11.170**	1.081	-1.618	-0.259	-0.109
Imports at t-1 (in ln)	**22.052**	**-12.428**	**-6.336**	**-7.862**	1.477	**-3.474**	-0.752	1.121
Arable land at t-1 (hpp, in ln)	**-25.365**	-1.885	**7.916**	**20.773**	**-2.198**	0.589	1.533	1.104
Agricultural TFP growth at t-1	**4.773**	-1.556	**-6.212**	1.300	1.190	-0.219	-1.403	-0.038
PSLgpscore (A)	**-5.144**	**-10.926**	**-12.619**	**23.786**	0.904	-1.851	**-2.569**	**2.542**
No. of observations	10246	4239	4973	9496	10232	4238	4971	9481
Mean t-value	13.117				1.169			

	Prior to balancing on the GPS				After balancing on the GPS			
Covariates	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
GDP percapita at t-1 (in ln)	**30.718**	**-5.171**	**-5.292**	**-22.852**	1.243	-1.789	-0.464	**2.695**
GDP percapita at t-1 (in ln) ^2	**29.220**	**-4.358**	**-4.645**	**-22.516**	0.966	-1.667	-0.372	**2.798**
GDP percapita at t-1 (in ln) ^3	**27.722**	**-3.556**	**-4.032**	**-22.138**	0.694	-1.519	-0.283	**2.882**
Population at t-1 (in ln)	**-4.507**	**-8.906**	0.162	**11.181**	0.601	-1.499	-0.099	-0.407
Population at t-1 (in ln) ^2	**-4.071**	**-9.136**	-0.164	**11.170**	0.600	-1.549	-0.158	-0.306
Imports at t-1 (in ln)	**22.052**	**-12.428**	**-6.336**	**-7.862**	1.618	**-3.408**	-0.956	1.088
Arable land at t-1 (hpp, in ln)	**-25.365**	-1.885	**7.916**	**20.773**	**-3.128**	0.501	1.605	1.515
Agricultural TFP growth at t-1	**4.773**	-1.556	**-6.212**	1.300	1.185	-0.239	-1.399	0.007
PSLgpscore (B)	**3.845**	**-13.431**	**-25.593**	**26.826**	1.835	**-2.528**	**-5.574**	**4.174**
No. of observations	10246	4239	4973	9496	10226	4239	4969	9476
Mean t-value	13.465				1.492			

Before controlling for GPS, there are significant differences across the treatment groups with respect to the covariates (bold numbers refer to t-statistic value that reject the null hypothesis of equality of means). After the correction, the average t-statistic value passes from 8.15 to a value of 1.18 (lower than the 95 percent confidence interval threshold of 1.96). Figures in the Appendix report the GPS distributions before and after the common support imposition, with right panel distributions that have a better fit than left ones.

The second stage estimates are reported in Table 4 while the corresponding Dose-Response Functions (DRF) and Treatment Effect Functions (TEF) are presented in Figures 3 and 4.

The estimates in Table 4 come from a polynomial parameterization of the conditional expectation of the outcome (exports) as a function of the observed treatment (NAC) and the estimated GPS, calculated for the classical and the modified (with spillover effects) GPS. All NAC, GPS, and interaction terms coefficients are always statistically significant. These results: i) show the existence of a causal link between NAC and exports; ii) confirm both our initial hypothesis about the existence of self-selection into different agricultural incentive intensities and the goodness of the GPS technique adoption to control for this selection bias. The inclusion of product-spatial lagged generalized propensity scores (columns “PSGPS A” and “PSGPS B”) does not change the significance levels and the signs of coefficients but increases the value associated to each NAC coefficient. This reflects the fact that the average effects estimated with the classical GPS technique are underestimated.

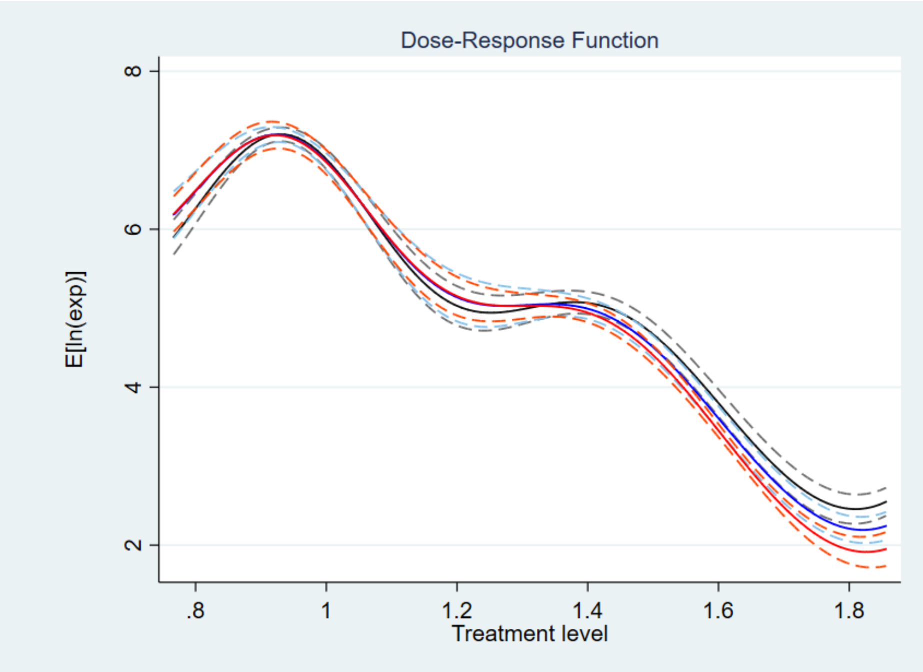
Table 4: Second stage estimates. The dependent variable is the ln of exports

variables	GPS	PSGPS A	PSGPS B
NAC	36.525***	40.031***	41.086***
	(4.554)	(4.511)	(4.470)
NAC2	-44.688***	-45.908***	-47.607***
	(3.892)	(3.792)	(3.753)
NAC3	13.944***	13.784***	14.324***
	(1.010)	(0.966)	(0.955)
NAC*gpscore	4.986***	4.876***	5.384***
	(0.569)	(0.523)	(0.522)
gpscore	-7.002***	-7.345***	-7.389***
	(1.912)	(1.855)	(1.858)
gpscore^2	17.195***	15.942***	15.763***
	(2.111)	(2.022)	(2.042)
gpscore^3	-9.949***	-9.094***	-9.103***
	(0.807)	(0.769)	(0.778)
constant	-3.443**	-4.676***	-4.839***
	(1.360)	(1.366)	(1.357)
Adjusted R2	0.06	0.06	0.07
N	28,932	28,922	28,910

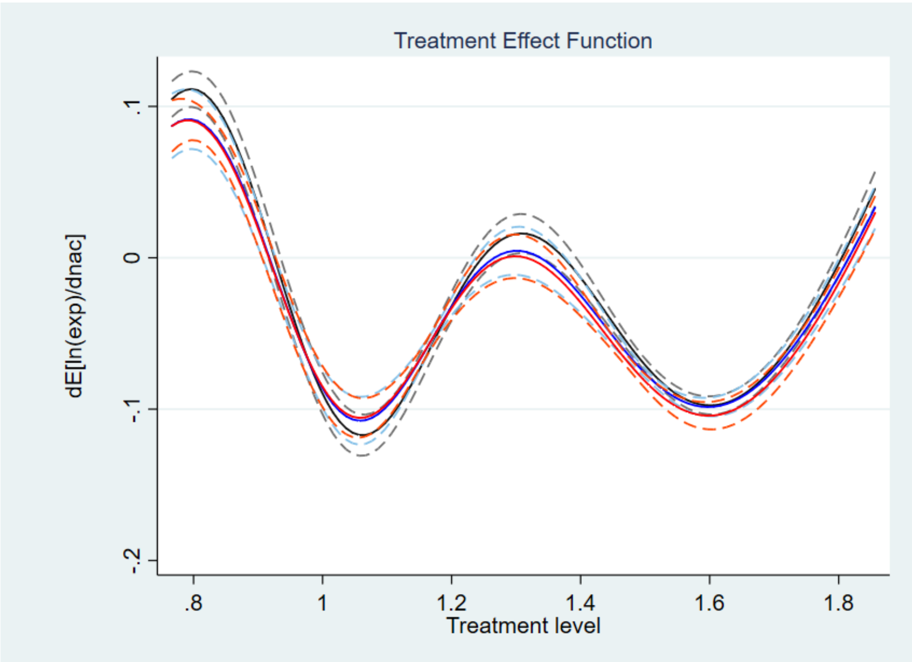
*The number of asterisks indicates that the coefficients are statistically significant: * 10 %. ** 5 %, *** 1 %*

Figure 3: The impact of agricultural (dis)incentives on exports.

a. DRFs for classical GPS (black lines) and GPS with spillover effects (blue line for PSLGPS A and red line for PSLGPS B)



b. TEF for classical GPS (black lines) and GPS with spillover effects (blue line for PSLGPS A and red line for PSLGPS B)



In order to have a graphical representation of the relationship between agricultural incentives and exports, we can observe the results represented in the DRF and the TEF in Figure 3[10]. The upper panel (a) reports the DRF, which provides a picture of the average effect; the lower panel (b) depicts the TEF, that is, the first derivative of the respective DRF. The corresponding standard errors and 90% confidence intervals of both functions are also reported (dotted lines in the figures). According to the estimated DRF, on average, the higher is the level of agri-food incentive, the lower is the incentive to export (relative prices are higher domestically). The highest level of exports is registered when NAC assumes values ranging from 0.8 to 1 (corresponding to negative values of NRA). We find also that the highest marginal benefit—on average—is obtained with NAC values around 0.8. Adopting agricultural support measures in the form of trade policies (import duties, quotas, non-tariff barriers, export prohibition or subsidies, export restriction, etc.) and/or domestic policies (introduction, removal or reduction of VAT or corporate tax; social policies, production support policies; *etc.*) seems being to the advantage of domestic production and at the expenses of trade.

Including spill-over effects increases the magnitude of public (dis)incentives on export flows, above all for value of NAC higher than 1.3 (the DRF with spillover effects lies under that obtained with the classical methodology).

5. Conclusions

In this work we applied nonparametric matching econometrics to analyze the causal relationship between border and domestic policy support and trade performance at product level. In order to tackle the presence of spillover effects we proposed an original revision of the spatial propensity score matching by extending it to the case of continuous treatment and weighting the spatial lags according to the products' distances over the so-called Product Space. Through this strategy, we can control for external as well as internal spillovers. To test our model, we empirically studied the impact of agricultural policy measures – from the World Bank "Distortions to agricultural incentives" database (Anderson and Nelgen, 2013) – on agricultural exports flows – from BACI-CEPII product trade data - for a set of 78 countries over the period 1995-2011.

First results show that increasing agricultural incentives negatively affect the level of exports. The inclusion of spillover effects, which is the main novelty of the present work, increases – even though

[10] Following Egger, von Ehrlich, and Nelson (2012), we test our DRF for different orders of the polynomial terms, dropping those that proved insignificant.

slightly – the negative effect of NAC on outward trade flows. This shows that the average effects estimated with the classical GPS technique are underestimated. These results confirm both our initial hypothesis about the existence of self-selection into different agricultural incentive intensities and the goodness of the GPS technique adoption to control for this selection bias.

These findings raise important issues for policy-making. The first message for policy-makers is that raising the level of incentives in agricultural products is not the solution to foster trade flows and, on the contrary, exports are more incentivized when the level of domestic protection is low. Hence, policy-makers should put emphasis on complementary factors other than policy incentives to foster trade flows.

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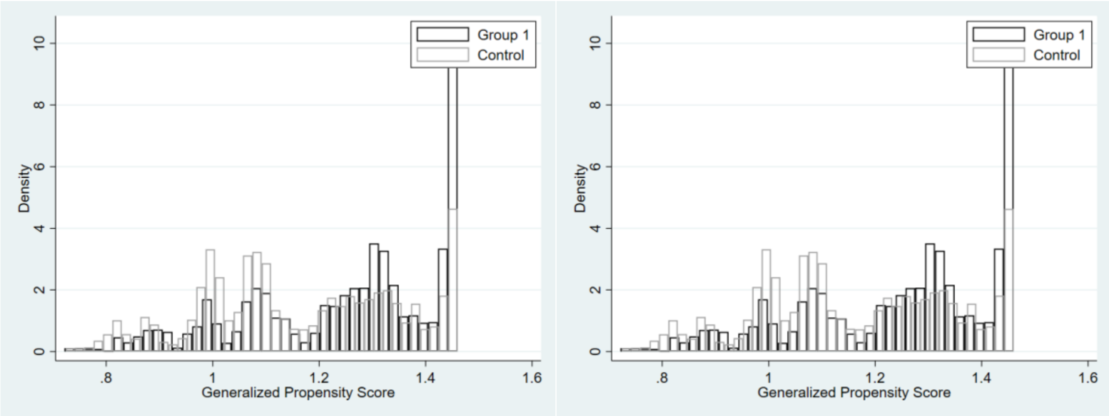
Appendix

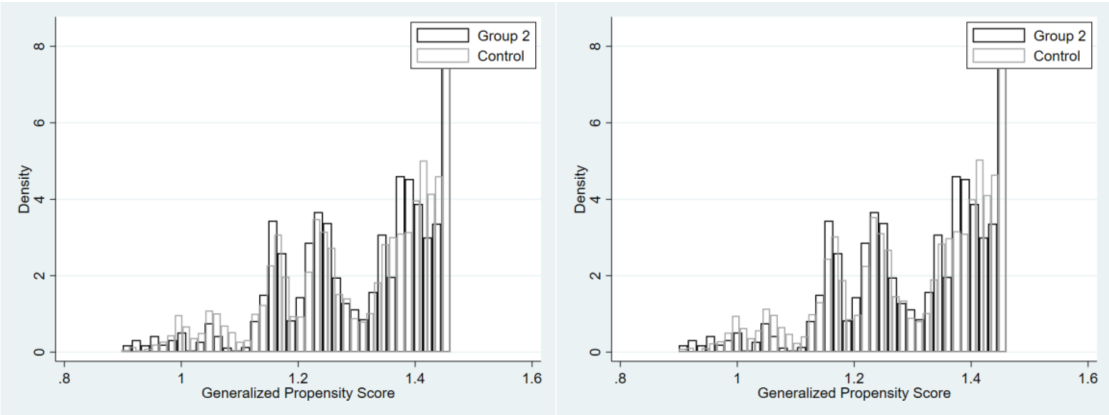
Table A.1. - Variables and Data

Type	Variable	Source
Agricultural incentives (treatment)	Nominal Rates of Assistance (NRA): sum of the rate of assistance to output (equal to the sum of the nominal rate of assistance to farm output conferred by border price support and the domestic price support) and the rate of assistance to farm inputs, accounting for domestic trading costs, processor and wholesaler costs, international trading costs and product quality and variety differences for determining the urban consumer price P_c>P_fg (farm gate)	World Bank dataset (Anderson and Nelgen, 2012,“Updated National and Global Estimates of Distortions to Agricultural Incentives, 1955 to 2010”)
Observable characteristics (covariates)	Per capita GDP (constant 2010 USD) Population (in thousands) Per capita arable land (hectares per person)	World Bank - World Development Indicators
	Agricultural Total Factor Productivity (TFP) growth index (base year 1961=100)	Economic Research Service of the United States Department of Agriculture
	Agri-food sectoral imports (current USDD)	BACI - CEPII database
Exports flows (Outcome)	Exports of agricultural, food and fishery products listed under Chapters 1–24, 40 and 51-53 of the HS codes	BACI -CEPII database

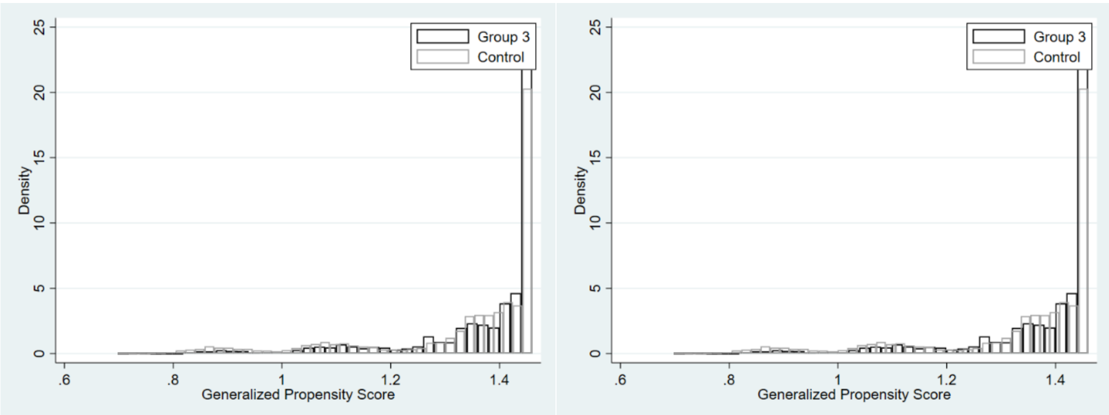
Common support before and after GPS: classical GPS – Group 1



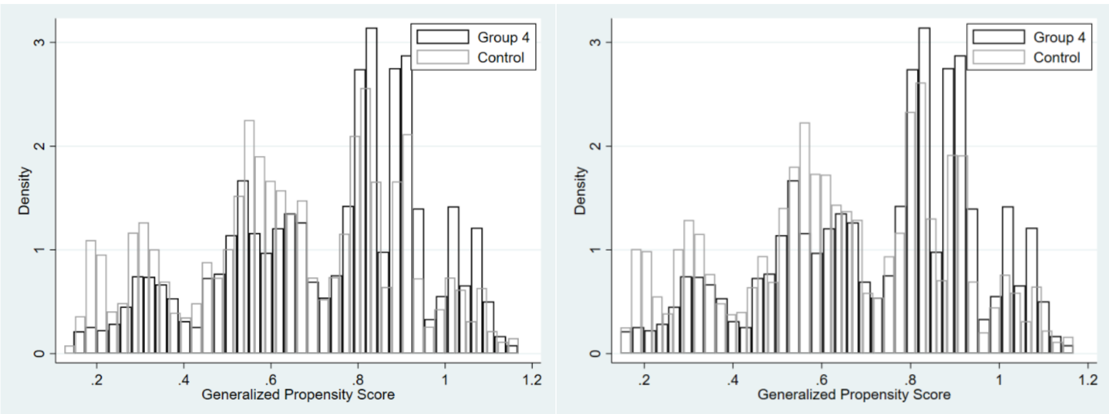
Common support before and after GPS: classical GPS – Group 2



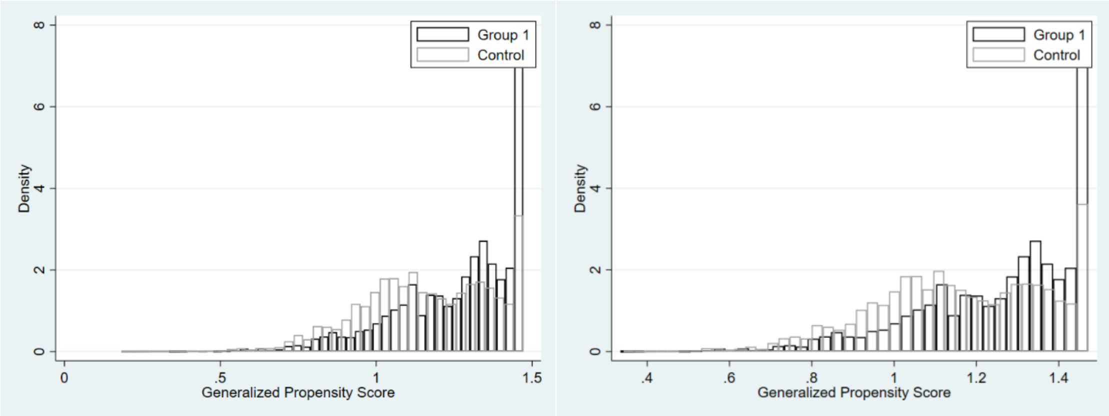
Common support before and after GPS: classical GPS – Group 3



Common support before and after GPS: classical GPS – Group 4



Common support before and after GPS: PSLGPS A – Group 1



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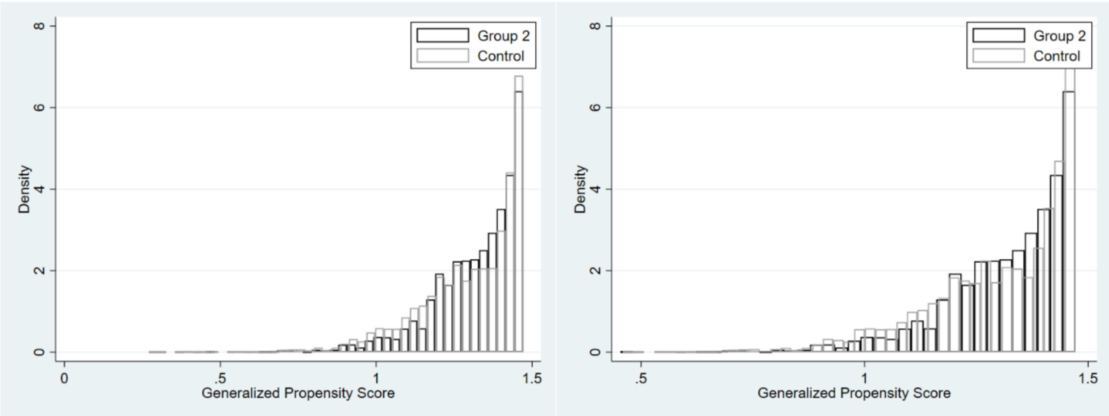

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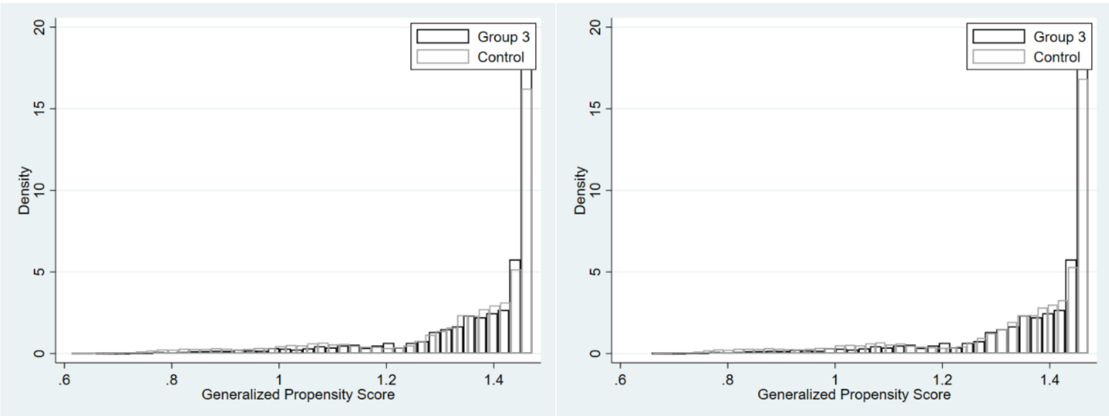
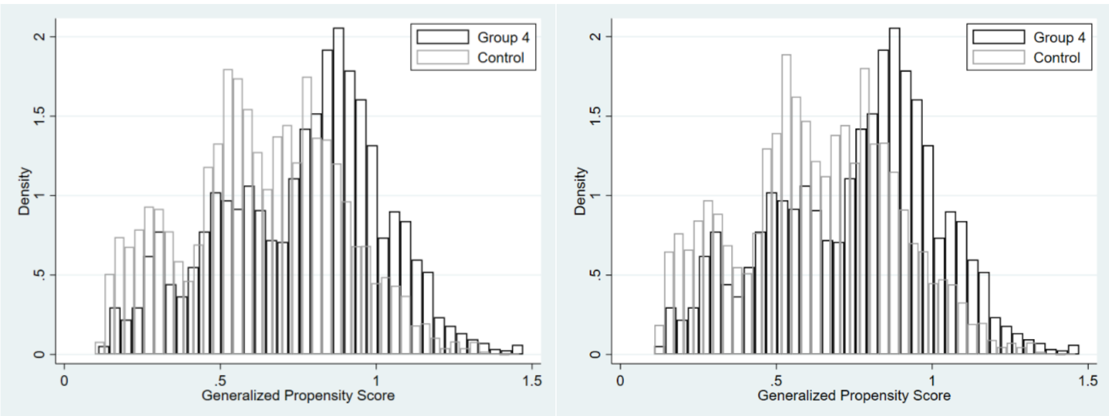
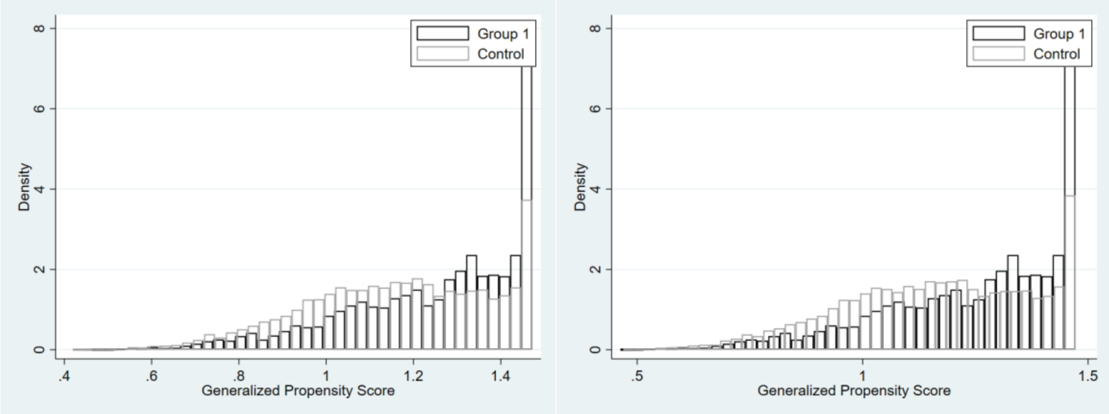


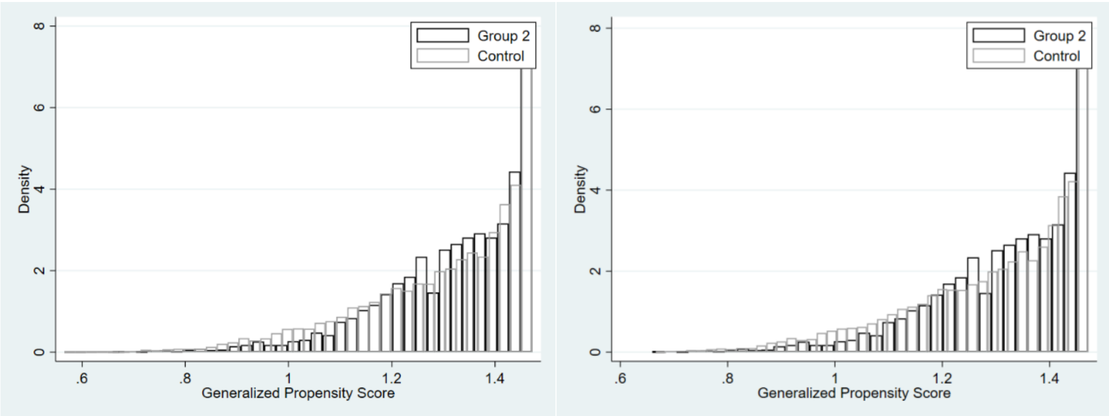
Common support before and after GPS: PSLGPS A – Group 4



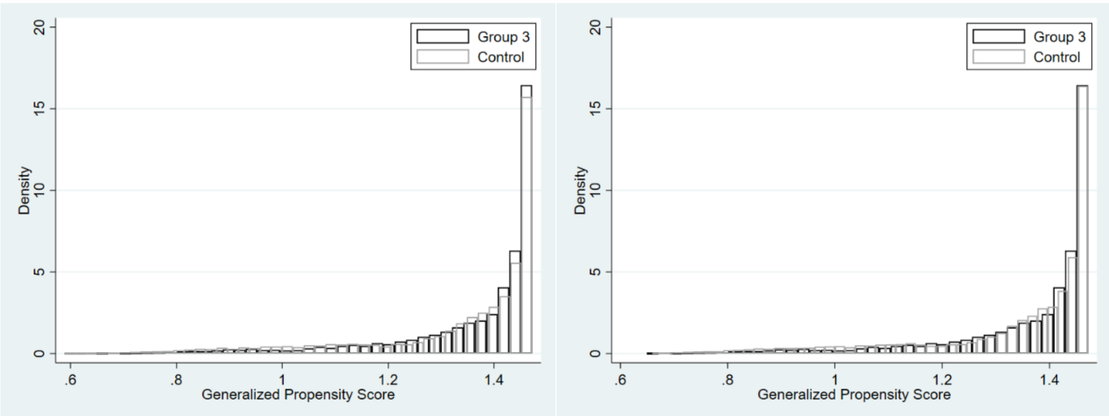
Common support before and after GPS: PSLGPS B – Group 1



Common support before and after GPS: PSLGPS B – Group 2



Common support before and after GPS: PSLGPS B – Group 3



Common support before and after GPS: PSLGPS B – Group 4