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Industry employment and import competition: a generalised propensity score approach

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ABSTRACT

In this paper we assess the impact of import penetration of developed countries and developing countries in 2004 on manufacturing employment across 21 OECD countries and 114 industries in 2008 using generalised propensity score estimation procedures for the case of bivariate continuous treatments. This novel approach considers the different levels of import penetration from developed and developing countries as endogenous continuous treatments. We find evidence of a negative impact of imports on OECD industrial employment. Such negative impact is increasing in the intensity of import penetration and the strength of the impact rises faster as imports increase from developed countries rather than from developing countries.

1. Introduction

In this paper we investigate whether there is a causal effect of the level of import penetration on industrial employment, considering separately imports from industrialized economies and imports from developing and emerging economies. Much of the empirical work has been focused on the impact of either aggregated imports or imports from a particular country (being the most popular case, China). Nevertheless, imports from various source trade partners and its interactions may affect differently the magnitude and direction of the impact of import penetration on industrial employment.

Under these circumstances we use the Generalized Propensity Score (GPS) methodology to deal with continuous endogenous treatments, originally proposed by Hirano and Imbens (2004) and Imai and van Dyk (2004). Specifically, we base on Egger and Ehrlich (2013) demonstration of the suitability of this methodology for multiple continuous treatment variables, to analyze the possible differences between the impact of imports depending on the country of origin, that is, we consider the case of more than one continuous treatments (in our case two doses) on domestic employment (one outcome or response).

Under unconfoundedness[1], the GPS methodology allows incorporating all information necessary in order to avoid 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, without imposing strong assumptions about the functional form of the relationship and allowing us to identify the entire range of employment outcomes over all possible levels of import penetration rates.[2] Furthermore the GPS has the advantage that we do not have to discretize the continuously distributed imports penetration variable from each trade partners group and thus can make use of more comprehensive information.

Our analysis goes deeper beyond asserting the mere existence of a (negative) relationship between import penetration and employment. We further investigate whether there are differences of the impact of imports penetration depending on the level of development of the trade partners who sell the products to the industry in the domestic economy, the possibility of a level of imports penetration at which the effects on the shares of industrial employment are maximized and the possibility of turning points or discontinuities in the industrial employment shares-imports penetration relationship.[3]

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[1] The *unconfoundedness assumption* implies that the potential outcome, conditional on observable characteristics, is independent of the level of treatment(s) received that can be considered as random.

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

[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.

We exploit the UNIDO Demand Supply Balance database (DSBD) to construct our dataset: for a sample of industries (114 manufacturing sectors) and and 21 OECD countries we obtain the employment shares in 2008 and the imports penetration rates in 2004, separating trading partners by the level of development into developed ones and developing and emerging ones. Next we construct a vector of technological, factor endowments and institutional comparative advantage covariates to implement the GPS methodology. We find that after balancing the sample on a rich set of destination country and dyadic covariates, the estimated dose–response (D-R) function reveals that the impact of imports penetration on sector employment rates is negative but non-linear. The graphical representation of the D-R function (and the marginal effects) for the entire sample (and for the restricted sample of 14 EU economies) that the negative impact of imports is increasing in the intensity of import penetration. However, the negative impact becomes stronger as imports increase from developed countries rather but not from developing countries. In fact, when imports comes mainly from developed countries, additional imports from developing countries have zero-impact on industry employment.

The rest of this paper is structured as follows. Section 2 presents the literature review and Section 3 describes the generalized propensity score methodology. Section 4 presents the data and the results of the GPS. Section 5 shows the main results of the paper, the dose-response function and its derivative. Section 6 concludes.

2. Literature review

For decades, several stylized facts have characterized international trade: first, most trade in manufactures took place among high-income economies; second, as a consequence, intra-industry trade represented a dominant share of international exchanges and comparative advantage was not as a dominant force as expected according to the factor endowments theory. In this framework, imports from low-wage countries were small in relation to total trade and, in most cases, concentrated in natural resources and/or primary products. However, this scenery has changed in the last twenty years. On the one hand, offshoring processes have been spreading out intensely; as an implication of this trend, there has been a continuous increase of exports of manufactured goods originated in low-income towards high-income countries, the rise of China as a major player in world trade being the primary example. These processes have taken place at the same time than a continuous decline in wages and employment in the manufacturing sector in most of OECD countries, which is the main reason why an expanding body of research has been looking for the way imports of manufactures have affected the main labor indicators in the importing economies.

Early papers on this topic, such as Grossman (1987), measured import competition as the relative price of imports in terms of the domestic price aggregate. This author reported a weak link between import competition and domestic wages, whereas employment seemed more sensible, although the variance of response across sectors was important. Afterwards, other papers using larger datasets were more successful in documenting the existence of a negative effect of import competition, either measuring it by import share (Freeman and Katz, 1991) or import prices (Revenga, 1992), on both manufacturing employment and wages.[4]

Perhaps the seminal paper which has set the pattern for most of the subsequent research is Bernard et al. (2006). These authors use plant-level data to study the different responses of US firms to international competition exposure. One of the aims of the research is to observe whether changes across industries reinforce US comparative advantages, so the authors distinguish between imports from low-income and high-income countries, pioneering this empirical. Using plant death and employment growth (for the surviving plants) as dependent variables, it is found that plants in industries with higher exposure to imports are less likely to survive; the result holds for imports originated in low-income countries and other origins, but the former effects is more than three times the latter. The same outcome is achieved for the employment growth of the surviving plants.

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[4] There has been a debate in the literature about the proper way of measuring import penetration. Federico (2012) summarizes the disadvantages of the import prices option in front of the import quantities (values or volumes of imports, normally scaled on domestic consumption or output).

A number of articles have appeared since Bernard et al. (2006) deepening the study of the US case, such as Harrison and McMillan (2011), Ebenstein et al. (2012), Autor et al. (2013), but also focused on the performance of European or Latin American economies: Biscourp and Kramarz (2007) for France, Onaran (2008) for Austria, Federico (2012) for the Italian case, Mion and Zhu (2013) for Belgium or Ashournia et al. (2014) for Denmark, Álvarez and Claro (2008) for Chile or Iacovone et al. (2013) for Mexico, among others. Leaving aside the fact that these broad areas imply very different labor markets, a common result in most of them is that higher import penetration originated in low-income countries tends to affect negatively manufacturing employment in the domestic country.

However, this general result is not unanimously achieved. Thus, Harrison and McMillan (2011) show that import competition is an important determinant of the decrease in US manufacturing employment, but the fact that imports come from low-income countries is not significant in the analysis. From a different perspective, Ebenstein et al. (2012) focus on the impact of foreign employment of affiliate firms and import penetration on domestic wages. Thus, the effect of higher employment abroad as a consequence of the offshoring decision depends on the country where the affiliate firm is located being low or high-income type. However, the impact of import penetration is unambiguously negative when significant. An interesting outcome is that import penetration have a significant impact only if the exposure of domestic workers to offshoring and import competition is taken into account at the occupation level (considering all sectors); however, nor affiliate employment in low-income countries nor import penetration show a significant impact if the exposure is analyzed at the industry level (and, therefore, the sample only takes into account manufacturing wages).

Some authors have argued that not all low-income countries are equivalent in terms of their exports of manufactures. An increasing number of papers have specifically put the spotlight on China, given the dominance it has achieved in international trade in a relatively short period of time. The key point is whether China's exports affect more deeply the manufacturing sectors of the importing countries just because of its size or there exist some qualitative differences in its pattern of exports.[5]

Import penetration of Chinese products usually has a negative impact on employment growth, as in Alvarez and Claro (2008) or Mion and Zhu (2013). However, when aggregated imports from other low-income countries are considered, the evidence is mixed: the effect is also negative in the former paper but not significant in the latter (the same as imports from other OECD countries, which are also considered).[6] Federico (2012) also identifies a negative impact of import penetration on employment which is stronger if imports come from low-income countries and not significant for high-income countries. Adopting a different empirical approach, Autor et al. (2013) confirm the negative impact of import penetration on manufacturing labor markets but zero impact on non-manufacturing sectors. In this case, the authors search for specific effects from Chinese exports to the U.S. out of other low-income exporters. They found that imports from other low-income countries have a similar effect as Chinese imports. Biscourp and Kramarz (2007) do not consider China but low-wage, European Community (EC) countries and non-EC OECD countries. In all cases, the impact of import competition displays a negative effect on employment growth, although the highest negative impact for imports from non-EC OECD countries. In Onaran (2008), offshoring has positive or negative effects on employment depending on the goods imported being final or intermediate and coming from high-income countries, East (of Europe) countries or rest of the world.

The above differences in the impact on employment growth depending not only on the exporting countries being high or low-income, but also between low-income countries (China versus other countries) could be a symptom of important dimensions in the analysis which should also be taken into account. One obvious candidate is the type of goods being imported. This issue deals

[5] Its export patterns differ from that of countries with similar characteristics: Chinese products have lower export prices than those from countries with similar income per capita and display higher quality than expected according to China's income level.

[6] In the case of the impact on firm survival, Álvarez and Claro (2006) obtain a negative effect for the case of China but positive for the other low-income countries, whereas it is not significant regardless of the type of exporting country in Mion and Zhu (2013).

with the reason behind the offshoring decision, which in fact determines the types of goods which the importing country will buy from the affiliate firms (Harrison and McMillan, 2011). Thus, we should observe a negative effect if the affiliate firm abroad produces the same type of goods that domestic firms import compete with domestic production. However, no significant effect or even a positive one could appear in the case in which imports mostly consist of final goods not produced domestically or intermediate goods which might reduce the costs of local firms.[7]

In fact, the evidence observed in Federico (2012), Iavocone et al. (2013) and Mion and Zhu (2013) suggest that some firms can benefit from cheaper inputs and therefore increase employment. Biscourp and Kramarz (2007), however, obtain a negative effect for both imports of final and intermediate goods.

Most of the papers reviewed above have found that increasing imports from low-income exporting countries have a negative impact on domestic employment. However, the likely interactions between imports originated in different types of countries have been mostly ignored in the empirical research. Focusing on manufacturing employment in the U.S., White (2008) finds that the usual negative effect on employment is aggravated if the observed imports have shifted from being originated in high to low-income countries. To the best of our knowledge, this paper remains the only one where this issue is taken into account, up to the present research.

3. Methodology

We use the GPS methodology for causal inference considering two continuous treatment variables based on Egger and Ehrlich (2013), that shows the applicability of the Hirano and Imbens (2004) approach to the case of multiple continuous treatments, whereof the bivariate continuous treatment model is a special case (see Egger et al., 2012). We first describe the GPS methodology and next we explain how to implement it.

3.1. Generalised propensity score methodology

[7] See Baldwin and Lileeva (2008) or Goldberg *et al.* (2010).

We consider a sample of cross-section industry-country observations, indexed by i=1, … ,N and the sector employment share in each country (the outcome), EMP_i. We investigate the impact of import penetration on the outcome variable, considering two different treatments or groups of countries of origin of imports: developing [or low income countries] (*L=LOWIMP*) and developed [or high-income] countries (*H=HIGHIMP*). Both import penetration rates are continuous variables. Furthermore, we assume that both variables are potentially endogenous treatments.

We denote the potential levels of both import penetration from developing countries and import penetration from developed countries as L, H. The potential levels of treatments are associated with sets of potential treatment levels of L $\in [l_0, l_1]$ and $H \in [h_1, h_2]$, respectively.[8] The rate of import penetration from developing countries and import penetration from developed countries for one industry in the domestic economy actually observed is H_i, L_i, and the actual outcome, in terms of the observed levels of treatment, $EMP_i = EMP_i(L_i, H_i)$.

The description of the GPS method requires some other definitions. For each unit *i*, let $\{Y_i(l,h)\}$for $l \in \mathrm{L}$, $h \in H$ denote the set of potential outcomes The goal of the analysis is to estimate the average dose–response function (DRF), $\mu(l,h) = E[EMP_i(l,h)]$ for each sector in the domestic economy i.

We assume that each treatment is a function of a vector of observed covariates X_{Li}, X_{Ui} that determine the observed treatment values according to a structural model: $L_i = f(X_{Li}, \delta_L) + \varepsilon_{Li}$; $H_i = f(X_{Hi}, \delta_H) + \varepsilon_{Hi}$, where f (.) are flexible functions, δ_L, δ_H are unknown parameters, and $\varepsilon_{Li}, \varepsilon_{Hi}$ are the error terms. We can define Z_i as the joint set of exogenous regressors or independent columns in $[X_{Li,} X_{Hi}]$, and its potential value by z. The previous model in its reduced form could be written as: $L_i = f(Z_i, \gamma_L) + v_{Li}$; $H_i =$

[8] See Egger and von Ehrlich(2013) for the general case of multiple continuous endogenous treatment variables.

$f(Z_i, \gamma_H) + v_{Hi}$, where γ_L, γ_H are unknown parameters, and v_{Li}, v_{Hi} are the corresponding error terms. [9]

The primary assumption that needs to be made for this approach to work is an confoundedness assumption generalized to the multiple continuous treatments by Egger and von Ehrlich (2013): $EMP_i(l, h) \perp L_i, H_i | Z_i \; \forall \; l \in L \, , h \in H$. This assumption means that, conditional on the vector of covariates, Z_i, the potential outcomes Y_i are independent of the treatments status in the two treatment dimensions L_i, H_i. That is, 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 both treatments. 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. The problem is solved by adjusting for the generalized propensity score (GPS).

The GPS is defined as follows. Being $r(l, h, z) = \int_{L_i, H_i | \, Z_i}(l, h|\mathrm{z})$ the bivariate conditional joint density of l, h given z, the generalized propensity score (GPS) is defined as $R_i, = \mathrm{r}(L_i, H_i, Z_i)$.

The GPS has the property that within strata with the same value of $r(l, h, z)$, the probability that $L_i = l \text{ and } H_i = h$ is independent of the covariates (loosely speaking, $Z_i \perp 1\{L_i = l, \; H_i = h\} | r(l, h, Z_i)$. In combination with the *weak unconfoundedness* assumption, this *balancing property* also implies that the assignment to treatments is weakly unconfounded *given the GPS* (see Hirano and Imbens, 2004). Hence, each import penetration rate in a country-industry 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

[9] Following Hirano and Imbens (2004), we assume that $\{EMP_i(l, h)\}_{\text{for } l \in \mathcal{L}, \, h \in \mathcal{H}}$, L_i, H_i and Z_i are defined on a common probability space. L_i, H_i are continuously distributed with respect to Lebesgue measure on $\mathcal{L}$ and $\mathcal{H}$, respectively, and that $\mathrm{EMP_i} = \mathrm{EMP_i}(L_i, H_i)$ is a well-defined random variable.

to differences in the covariates among groups being assigned to (receiving) different levels of treatments.

We first define:

(1) $\beta(l,h,r) = E[EMP_i(l,h\,)|r(h,h,Z_i) = r] = E[\,EMP_i|L_i = l\,, H_i = h,\; R_i = r]$

where $\beta(l,h,r)$ is the conditional expectation of the outcome that is estimated as a function of both treatments level, $L_i,\; H_i$ and the GPS, *R*; or in other words, the conditional mean of the outcome EMP given the observed value of the treatments and the GPS. As a second step, we estimate the value of the DRF at each particular combination of treatments *(l, h)* by averaging the conditional expectation function over the values of the GPS at those particular levels of both treatments ($R^{l,h} = r(d,u,Z_i)$):

(2) $\mu(l,h) = E[\beta(l,h,r(l,h,Z_i))]$

Hirano and Imbens (2004) emphasized that the regression function in (1) does not have a causal interpretation. Nevertheless by averaging over the covariates, $\mu(l,h)$ corresponds to the value of the dose-response function for a combination of treatment values (l*, h*) which compared with that obtained for another combination of treatments, *l′, h′* : $\mu(l',h')$, does have a causal interpretation.

3.2. The empirical implementation.

First we estimate the reduced form equations for both treatments: the import penetration from developing countries rate: $L_i = f(Z_i, \gamma_L) + v_{Li}$; and import penetration from developed countries rate: $H_i = f(Z_i, \gamma_H) + v_{Hi}$, by ordinary least squares, obtaining the predicted conditional averages $\hat{L}_i = f(Z_i, \hat{\gamma}_L)$and $\hat{H}_i = f(Z_i, \hat{\gamma}_L)$. Following Egger and Von Ehrlich (2013) and Egger, Nelson and Von Ehrlich (2012), we assume a bivariate normal distribution of the disturbances of the two reduced-form regressions, $v_{Li}\,, v_{Hi}$, to compute the GPS as:[10]

(3) $\hat{R} = \frac{1}{2\pi\hat{\sigma}_L\hat{\sigma}_H\sqrt{1-\hat{\rho}^2}} exp\left(-\frac{1}{2(1-\hat{\rho}^2)}\left[\left(\frac{L_i-\hat{L}_i}{\hat{\sigma}_L}\right)^2 + \left(\frac{H_i-\hat{H}_i}{\hat{\sigma}_H}\right)^2 - \left(2\hat{\rho}\,\frac{(L_i-\hat{L}_i)(H_i-\hat{H}_i}{\hat{\sigma}_L\hat{\sigma}_H}\right)\;\right]\right)$

[10] 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.

where $\hat{\sigma}_L, \hat{\sigma}_H$ are the standard errors corresponding to disturbances v_{Li}, v_{Hi} respectively, and $\hat{\rho}$ is the estimated correlation between those disturbances (see Greene, 2011)

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 output variable, the two treatments and the GPS variables. Following Hinaro and Imbens (2004), we implement a partial mean approach by assuming a (flexible) parametric form for the regression function of Y (sector employment share), on both treatments, L, H (import penetration from developing countries and import penetration from developed countries), and $\hat{R}$, for each industry-country pair (we omit subscript i to simplify the notation):

(5) $\mathrm{E}\left[EMP|L,H,\hat{R}\right] = h(L,H,\hat{R};\alpha)$

The OLS estimated parameters in (5) are used to estimate the average potential outcome given a level t of one of the treatments, while anchoring the value of the other treatment which is assumed constant, $\overline{t'}$, averaging over the score function evaluated at that treatment level, t, that is $\widehat{R^t}$:

(6) $\mathrm{E}\left[\widehat{EMP(t)}\right] = \frac{1}{N}\left(\sum h\left(t,\widehat{R^t};\hat{\alpha},\overline{t'}\right)\right)$

In addition, we also compute the first derivative of the DRF, μ(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 in the level of import penetration, $\Delta t = \delta$, on the variation of the sector employment share. This will allow us to capture the heterogeneity in the magnitude of the impacts on the sector employment share in an OECD country (outcome) arising from different exposure to imports from developing (developed) countries given the level of exposure to imports from developed (developing) countries.

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

4. Data and bivariate GPS results.

Our dependent variable (outcome) is the level of sector employment normalized by total manufacturing employment (EMP) in 2008 for a sample of 21 OECD countries and 114 (4 digit ISIC rev 3) manufacturing sectors. Our two treatment variables are the sector imports from developing and emerging industrial economies (L=LOWIMP) and the sector imports from industrialized economies (H=HIGHIMP) in 2004, normalized by apparent consumption (total production plus total imports minus total exports) in the country of destination.

The outcome and the two dose variables are obtained directly from UNIDO Industrial Statistics Databases 2012 and UNIDO Industrial Demand-Supply Balance Database 2012, respectively.[11] Table A.1 displays the countries and 4 digit ISIC sectors included in the sample.

The first three rows of Table 2 display some descriptive statistics of the outcome and treatment variables. On average employment in each sector accounts for less than 1 percent of total manufacturing employment in each country (which is proportional to the number of sectors in the data), with some sectors accounting for more than 10 percent of total manufacturing employment (i.e. leather products in Portugal in 2008). Imports penetration exhibit a substantial difference in value depending on the country of origin: for the group of developing countries, average imports penetration in 2004 was about 4 percent, much lower than the average one from developed countries (30 percent).

Before we start implementing the GPS methodology we run a simple regression of EMP in 2008 on LowIMP and HighIMP as explanatory variables rolling the year of reference backwards from 2007 to 2002. The regression

[11] Employment data for Japan is from 2007. Apparent consumption is equal to domestic production minus exports plus imports.

includes country and industry fixed effects. Results in Table 1 confirm that the negative impact of both LowIMP and HighIMP on EMP is statistically different from zero for any year of reference. In our GPS analysis we choose the year 2004 based on the value of the R-squared.

To obtain the GPS, we estimate separately by OLS each of the dose variables (LowIMP and HighIMP) on a vector of covariates. The set of explanatory variables of the treatment variables (LowIMP and HighIMP) in the GPS equations includes country and industry characteristics that have been obtained from multiple sources. We did a revision of the empirical literature on import demand and import supply factors in order to select the covariates in the GPS equations. Together with standard gravity factors (income size and distance), a set of Ricardian, Hechscher-Ohlin and institutional comparative advantage variables is included based on the recent contributions by Nunn (2007), Chor (2010), Cunat and Melitz (2012) and Minondo and Requena (2013) to explain the determinants of import flows.[12] These variables are obtained from the combination of country characteristics and industry characteristics such that the combination is industry-country specific. Finally, we include another set of variables defined at industry-country level such as level of trade openness, intensity of intra-industry trade, average applied tariff protection and relative wages in the industry. The period of reference for the variables is 1999-2004, always before the year selected for the dose variables (2004). Table A.2 in the Appendix provides the description and sources of the explanatory variables used in the GPS equation. Our final dataset contains 1976 observations after deleting industry-country pairs without complete information.

Table 2 displays the descriptive statistics in the first four columns. The last two columns show the estimated OLS coefficients of the explanatory variables (and its squared terms) in the two equations of the reduced form for each treatment variable. At this stage our main concern is to get a high R-squared so we are confident that our exogenous variables help to explain the variability in our two treatment variables. The R-squared coefficients for

[12] Kowalski, P. (2011) offers a comprehensive review of all the "comparative advantage" variables used in the recent empirical literature.

LowIMP and HighIMP are 0.365 and 0.451, respectively. We think that the goodness-of-fit is good enough since the treatment variables are defined as the ratio of imports to apparent consumption in an industry-country pair in year 2004 (cross section data) and we did not include country and industry fixed effects. Notice that we are not interested in the interpretation and statistical significance of the individual effects of the covariates in Table 2 but in getting an estimate of the GPS that works well in balancing covariates.

We obtain the estimation of the GPS according to equation (3) and the previous coefficients' estimations in Table 2, by assuming bivariate normality of the disturbances and after computing the predicted conditional averages of the treatments, the standard deviation of the disturbances in each equation and the correlation between those disturbances.

The concern with an unconditional regression of EMP (outcome) on both LowIMP and HighIMP (treatments) is that the impact of each treatment on the outcome might be confounded by the omission of relevant variables as listed in Table 2. This risk would be particularly pertinent if LowIMP and HighIMP varied strongly with those variables. However, under the weak unconfoundedness assumption, there are not systematic treatment assignments based on unobservable characteristics not captured by observable ones, thus, it is assumed that -conditional on observable characteristics- the level of each treatment received can be considered as random. Then, the GPS in (3) would incorporate all information necessary for avoiding potential biases in one scalar (a balancing score), allowing the matching in the data in the LowIMP-HighIMP domain. As a consequence, the potential outcome EMP would be independent of the level (combination) of treatments, LowIMP-HighIMP, received.

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 order) into groups, splitting the sample along two dimensions, the LowIMP-space and the HighIMP-space. For each group, we compute the value of the GPS for each industry-country pair at the median level of the two treatments for the group and the value of the GPS at those same median levels for all industry-country pairs that are not included in the group in question. Finally, we check the comparability of both the group of interest and its respective control group, checking the region of common support between both groups, by inspecting the overlapping of their propensity score distributions for these two groups by superimposing their histograms. Next we keep only control industry-country pairs in other groups than in the group of reference if they share a common GPS support with treated pairs in the group of reference. Since this is done for each of the four groups, we ensure that each industry-country pair within a certain group lies within the range of observable characteristics of each other group.

This exercise is repeated for each group in turn, resulting in four plots for each of our samples. These plots are shown in Graph 1. These plots show that the overlap in the support of the estimated GPS across groups 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 63 industry-country pairs so our final sample contains 1913 industry-country pairs.

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 variables (LowIMP and HighIMP) will not be statistically significant. In short, after controlling for the propensity to have more LowIMP and/or more HighIMP, the various treatment groups should not differ on the basis of other covariates, independent of their level of treatment. We follow Hirano and Imbens (2004) approach of "blocking on the score". After we divided our sample according to the levels of the treatment into several groups, in each of those treatments groups, we stratify industry-country pairs into several blocs according to the ascending-order values of the GPS evaluated at the median value of the treatments (in our case we choose 6 blocs). For each of these GPS blocks, we then compare the average covariate values for the observations in that GPS block-with those average values for observations that are in the same block but belonging to the rest of treatment groups. These average differences in covariate values within each of the six GPS blocks 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 Panel B of Table 3 are based on this difference. Regarding the balancing property, the last row in Table 3 shows that both the median and average t-statistic drop drastically for all the groups and only 6 covariates out of 120 have a t-statistic that exceeds (in absolute value) 1.64. This illustrates that conditioning on the GPS is extremely powerful in the data. Hence, we hypothesize that there is little chance that the observable variables included in the empirical model explaining LowIMP and HighIMP confound the impact of LowIMP and HighIMP on sector employment rates, EPM.

Estimating the multivariate dose-response and treatment effect functions

The final step in our exercise is to estimate the dose–response function. For that purpose we first run a regression with EMP as the dependent variable and LowIMP and HighIMP and the conditional joint density of LowIMP and HighIMP given the covariates on the right hand side (Eq. (3)). We adopt a polynomial parameterization of the two treatments, the GPS and its interactive terms. The preferred specification based on the election of the variables as well as the order of the polynomial terms was based on the Akaike Information Criterion

(AIC). The corresponding results for the preferred dose–response functions are summarized in Table 4. 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 in the (LowIMP-HighIMP) space. (as described in Eq. (6)). This dose–response function relates each pair of values of the two doses (one for LowIMP and another for HighIMP) to the post-treatment level of industry employment rate in a particular country.

A plot of the dose–response curves for the full sample of 21 OECD countries is presented in Graph 2 (3-dimension) and Graph 3 (cross-sections for different moments of the distribution of LowIMP and HighIMP). This plot indicates that the association between levels of imports penetration from developing countries and developed countries immigration (dose of treatments) and the level of industrial employment rate in OECD countries (outcome), when confounding between that doses and the covariates is adjusted for using the GPS approach, is appreciable; the employment rate response is negative over the almost entire range of positive doses of both treatments. Generally speaking, the estimated dose–response function shows a strong decline in the sector employment rates as imports from both developing and developed countries increase up to 20 percent of domestic consumption. Once imports penetration reaches that level, additional imports still exhibit a negative impact on industrial employment but become much more attenuated.

Below 20 percent threshold in the value of imports penetration rate there is a notorious asymmetry between imports by country of origin: the negative impact of foreign competition on employment is much more pronounced for imports coming from developed countries than those coming from developing countries. This finding seems to corroborates recent evidence using alternative econometric methods that suggest that imports from developing countries rather than imports from developing countries (and particularly, from China or from the BRIC group) have a larger detrimental impact on industrial employment in OECD countries.

When imports from developed countries reach 20 percent of domestic consumption in certain sector, imports from developing countries seem to have an almost zero impact on employment rates in this sector. However, the negative impact of imports from developed countries on sector employment persists when imports from developing countries are above 20 percent of domestic consumption.

Conclusions

This paper assesses the role of imports from developed and developing countries on sector employment rates in a large data-set of industry-country pairs. Using the GPS methodology for multiple endogenous continuous treatments - through a generalization of existing estimation procedures for an assessment of causal effects of univariate continuous treatments on outcome and obtaining the corresponding Dose-Response function - the impact of different levels of imports from developed countries and from developing countries on sector employment rates is assessed in a quasi-experimental design.

We find a negative impact of imports penetration on industrial employment in the OECD countries in 2008. However, the findings suggest that imports from developed countries tend to have a larger negative impact on sector employment rates than imports from developing countries. In fact, when imports from developed countries are large compared to imports from developing countries, the negative impact of imports from developing countries on industrial employment tends to be negligible and even to disappear. Our findings corroborate recent studies showing that the source of imports is important and imports from developed countries tend to exhibit higher negative impact on employment in OECD countries than imports from developing countries.

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Table A.1. Countries and sectors in the sample.

Countries & Number of industries i		Sectors ISIC 4 digit & Number of countries in each sector											
AUT	82	**1511**	21	**1723**	20	**2222**	20	**2710**	18	**2930**	19	**3520**	15
BEL	70	**1512**	18	**1729**	18	**2411**	14	**2720**	16	**3000**	14	**3530**	18
CAN	91	**1513**	21	**1730**	15	**2412**	14	**2811**	21	**3110**	18	**3591**	11
DEU	105	**1514**	17	**1810**	18	**2413**	14	**2812**	20	**3120**	18	**3592**	11
DNK	72	**1520**	20	**1820**	13	**2421**	15	**2813**	18	**3130**	19	**3599**	13
ESP	113	**1531**	17	**1911**	15	**2422**	21	**2893**	20	**3140**	18	**3610**	21
FIN	87	**1532**	15	**1912**	13	**2423**	20	**2899**	19	**3150**	21	**3691**	18
FRA	114	**1533**	21	**1920**	14	**2424**	21	**2911**	17	**3190**	18	**3692**	19
GBR	106	**1541**	21	**2010**	20	**2429**	15	**2912**	17	**3210**	19	**3693**	17
HUN	97	**1542**	10	**2021**	20	**2430**	14	**2913**	14	**3220**	19	**3694**	13
IRL	58	**1543**	18	**2022**	21	**2511**	18	**2914**	18	**3230**	13	**3699**	19
ITA	111	**1544**	13	**2023**	21	**2519**	18	**2915**	20	**3311**	19		
JPN	109	**1549**	17	**2029**	21	**2520**	21	**2919**	20	**3312**	17		
KOR	106	**1551**	12	**2101**	19	**2610**	20	**2921**	21	**3313**	17		
NLD	67	**1552**	8	**2102**	21	**2691**	12	**2922**	17	**3320**	14		
NOR	88	**1553**	13	**2109**	21	**2692**	17	**2923**	15	**3330**	8		
POL	108	**1554**	20	**2211**	14	**2693**	13	**2924**	17	**3410**	15		
PRT	111	**1600**	12	**2212**	15	**2694**	15	**2925**	18	**3420**	19		
SVN	83	**1711**	16	**2213**	7	**2695**	21	**2926**	13	**3430**	17		
SWE	93	**1721**	19	**2219**	13	**2696**	20	**2927**	16	**3511**	20		
USA	105	**1722**	19	**2221**	20	**2699**	20	**2929**	18	**3512**	16		

Note: See http://www.unido.org/index.php?id=1002111 for the ISIC rev 3 classification.

Table A.2. Definition and sources of the covariates in the first stage estimation of GPS.

Variable name	Definition & Sources
Economic size (log) GDP_c	Real Gross Domestic Product in 2002, US $ from Penn World Tables (PWT 8.0)
Income per capita (log) $GDPPC_c$	Real GDP divided by population in 2002, US $ from Penn World Tables (PWT 8.0)
Distance (log) $DIST_c$	Distance in kms to the closest BRIC country (China, Russia, India, Brazil) (distance between capitals). Own elaboration using cepii database http://www.cepii.fr/anglaisgraph/bdd/distances.htm
Capital intensity * capital abundance $k_i * k_c$	Sector capital intensity is the physical capital stock per worker in 2002 using US data. Own elaboration using NBER-CES Manufacturing Industry Data http://www.nber.org/nberces/) and correspondence tables between SIC 4-digit classification (459 manufacturing sectors) and ISIC 4-digits rev 3 (130 manufacturing sectors). Country capital abundance is the physical capital stock per worker in 2002 and comes from Penn World Tables (PWT 8.0).
Skill intensity * skill abundance $h_i * h_c$	Sector human skill intensity is the ratio of non-production workers to total employment in 2002 using US data. Own elaboration using NBER-CES Manufacturing Industry Data and correspondence tables SIC 5-digit classification and ISIC 4-digits rev 3 (see above). Country skill abundance is calculated as the average years of schooling in the total population in 2000 from Barro and Lee (2010) www.barrolee.com .
R&D intensity * R&D abundance $R\&D_i * R\&D_c$	Sector R&D intensity is the share of firms' R&D expenditure on total output in 2002 using US data. Own elaboration using Nunn and Trefler (2013) (http://scholar.harvard.edu/nunn/home) and correspondence tables between USA-IO 6-digit classification (381 manufacturing sectors) and ISIC 4-digits rev 3 (130 manufacturing sectors). Country R&D expenditure (% GDP) in 2002 comes from WDI On-line.
Contract Intensity * legal strength $CONTRACT_i * LEGAL_c$	Own elaboration using relationship-specific investments (contract intensity) from Nunn (2007) (http://scholar.harvard.edu/nunn/home) and correspondence tables between USA-IO 6-digit classification (381 manufacturing sectors) and ISIC 4-digits rev 3 (130 manufacturing sectors) and Economic Freedom Dataset (Gwartney, Hall, and Lawson 2010) (http://www.freetheworld.com/datasets_efw.html) for country data
Volatility * Labour market flexibility $VOL_i * FLEX_c$	Volatility is measured as the standard deviation of the annual growth rate of firm sales and comes from Cunat and Melitz (2007) and correspondence tables between USA-SIC 2, 3 & 4-digit classification and ISIC 4-digits rev 3. Labour market flexibility is proxied by the Employment Law Index, which ranges between 0 and 100 where higher values indicate increasing levels of rigidity. It comes from Botero et al (2004) and refers to the period 1999-2002. [*Labor dataset_qje_dataforweb_2005.xls*].
Complexity * skill abundance $COMPLEX_i * h_c$	Own elaboration using Minondo-Requena (2013) measure of complexity (number of tasks required to produce a final unit of output in the industry) and correspondence tables between NAICS 4-digit classification (85 manufacturing sectors) and ISIC 4-digits rev 3 (130 manufacturing sectors). Country skill abundance is calculated as the average years of schooling in the total population in 2000 from Barro and Lee (2010) www.barrolee.com .
$TFP_i * GDPPC_c$	Following Nunn (2007) we include the interaction between product of sector's Total Factor Productivity in 2002 and country GDP per capita in 2002 using NBER-CES Manufacturing Industry Data and PTW 8.0.

$\frac{VA}{OUT_i} * GDPPC_c$	Following Nunn (2007) we include the interaction between sector's ratio of value added to gross output in 2002 and country GDP per capita in 2002 using NBER-CES Manufacturing Industry Data and PTW 8.0, respectively.
$WAGE_{i,c}$	Ratio of wages in sector-country pair, normalized by the total wage in manufactures in the country (average 2002-2002) and is obtained directly from UNIDO Industrial Statistics database
$IIT_{i,c}$	The Grubel-Lloyd index of intra-industry trade is used to measure the importance of product differentiation and scale economies across sectors and countries in 2002. Own elaboration using COMTRADE database.
$TARIFF_{i,c}$	Average Applied Tariff at the HS 6 digit level using MAcMapHS6v2 for 2004 and correspondence tables between HS and ISIC rev3 using as a weights the HS export values.
$OPENNESS_{i,c}$	It is measured as the ratio of trade (imports and exports) to total output (average 2002-2002) and is obtained directly from UNIDO-IDSB database.

Note: See Table 3 for descriptive statistics of the covariates in the first stage estimation of GPS.

Table 1. Descriptive statistics of outcome and treatments

	Mean	Std. Dev.	Min	Max
EMP (Outcome)	0.009	0.012	0.001	0.131
LowIMP (Treatment 1)	0.083	0.097	0.001	0.604
HighIMP (Treatment 2)	0.301	0.204	0.067	0.945
Number countries =	21			
Number of industries =	114			
Number observations =	1976			

Table 2. Dependent variable: Sector employment share in 2008 *(EMP)*

Year	2007	2006	2005	2004	2003	2002	2004	2004
LOWIMP *in year t*	-0.0267***	-0.0268***	-0.0270***	-0.0271***	-0.0258***	-0.0224***	-0.0338***	
	[0.00543]	[0.00567]	[0.00568]	[0.00584]	[0.00604]	[0.00610]	[0.00613]	
HIGHIMP *in year t*	-0.0202***	-0.0203***	-0.0202***	-0.0206***	-0.0202***	-0.0192***		-0.0222***
	[0.00173]	[0.00172]	[0.00169]	[0.00173]	[0.00168]	[0.00173]		[0.00183]
Constant	0.0148***	0.0149***	0.0147***	0.0147***	0.0139***	0.0133***	0.0131***	0.0117***
	[0.000894]	[0.000927]	[0.000889]	[0.000883]	[0.000823]	[0.000765]	[0.000862]	[0.000543]
Observations	2,015	2,000	1,994	1,987	1,983	1,971	1,988	1,988
R-squared	0.618	0.617	0.618	0.619	0.617	0.614	0.577	0.606

Note: The regression includes country-specific and industry-specific dummies (not reported). Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Descriptive statistics of covariates and first stage of GPS estimation.

	Summary descriptives				GPS model			
					Treatment 1: LowIMP		Treatment 2: HighIMP	
	Mean	Std. Dev.	Min	Max	GPS coeff	s.e.	GPS coeff	s.e.
GDP_cou	13.06	1.44	10.05	16.18	-0.021	0.02	0.135 ***	0.04
GDPPC_cou	3.01	0.54	1.65	3.74	-0.057	0.06	-0.307 ***	0.10
DISTANCE	8.85	0.55	7.06	9.32	-0.639 ***	0.19	-0.300	0.25
K_i*K_c	15.62	0.82	13.35	18.53	-0.279 ***	0.08	0.502 ***	0.13
H_i*H_c	0.98	0.40	-0.14	2.16	0.006	0.03	0.113 ***	0.04
R&D_i*R&D_c	0.02	0.09	0.00	1.59	-0.222 ***	0.05	-0.269 **	0.14
CONTRACT_i*LEGAL_c	0.41	0.17	0.02	0.85	0.071	0.06	-0.110	0.11
VOL_i*LABMFLEX_c	0.20	0.08	0.01	0.47	0.174	0.13	-0.544 **	0.24
COMPLEX_i*H_c	4.73	1.51	0.91	8.83	-0.097 ***	0.01	-0.007	0.01
VA/OUTPUT_i*GDPPC_c	1.56	0.45	0.45	3.07	0.068 *	0.04	0.134 **	0.07
TFP_i*GDPPC_c	3.08	0.77	1.07	7.45	-0.020	0.03	-0.114 ***	0.03
WAGE_ic	1.05	0.85	0.18	11.45	-0.039 ***	0.01	-0.079 ***	0.01
IIT_ic	0.53	0.27	0.01	1.00	-0.169 ***	0.04	-0.040	0.06
TARIFF_ic	1.60	0.74	0.00	5.86	0.049 ***	0.01	0.069 ***	0.02
OPENNESS_ic	0.63	1.14	0.00	16.62	2.109 ***	0.40	6.118 ***	0.92
GDP_cou ^2	172.60	38.01	100.93	261.87	0.001 ***	0.00	-0.007 ***	0.00
GDPPC_cou ^2	9.33	2.95	2.71	14.02	0.014	0.01	0.059 ***	0.02
DISTANCE ^2	78.72	9.08	49.89	86.90	0.039 ***	0.01	0.023	0.02
K_i*K_c ^2	244.65	25.71	178.10	343.23	0.009 ***	0.00	-0.014 ***	0.00
H_i*H_c ^2	1.11	0.82	0.00	4.65	-0.008	0.01	-0.047 **	0.02
R&D_i*R&D_c ^2	0.01	0.10	0.00	2.54	0.109 **	0.05	0.286 **	0.14
CONTRACT_i*LEGAL_c ^2	0.19	0.14	0.00	0.71	-0.027	0.07	0.227 *	0.14
VOL_i*LABMFLEX_c ^2	0.05	0.04	0.00	0.22	-0.371	0.27	1.138 **	0.49
COMPLEX_i*H_c ^2	24.62	15.18	0.82	78.03	0.009 ***	0.00	0.002	0.00
VA/OUTPUT_i*GDPPC_c ^2	2.62	1.43	0.20	9.43	-0.022 **	0.01	-0.054 ***	0.02
TFP_i*GDPPC_c ^2	10.07	5.15	1.14	55.50	0.005	0.00	0.014 ***	0.00
WAGE_ic ^2	1.82	6.36	0.03	130.99	0.003 ***	0.00	0.007 ***	0.00
IIT_ic ^2	0.35	0.29	0.00	1.00	0.115 ***	0.03	0.024	0.06
TARIFF_ic ^2	3.13	2.96	0.00	34.35	-0.007 ***	0.00	-0.022 ***	0.00
OPENNESS_ic ^2	1.31	2.34	0.00	276.22	-19.751 ***	4.92	-44.264 ***	13.48
Constant					5.253 ***	1.0684	-3.322 **	1.54
R-squared (GPS model)					0.365		0.451	
					RHO treat 1 - treat 2 = 0.147			

Note: "c" stands for country, "i" stands for industry and "^2" stands for squared term. In the last column RHO stands for the correlation of residuals of the OLS regressions. See Table A.2. for a definition of the covariates. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Differences in the treatment levels before and after balancing on the GPS: t-stats for equality of means.

	Panel A: Prior to balancing on the GPS				Panel B: After balancing on the GPS			
Covariates	Group Q1	Group Q2	Group Q3	Group Q4	Group Q1	Group Q2	Group Q3	Group Q4
GDP_cou	**-5.85**	**10.70**	**-12.30**	**7.35**	-1.02	-0.84	1.62	0.10
GDPPC_cou	0.09	**2.02**	**-2.13**	0.02	-0.56	-0.38	0.70	0.31
DISTANCE	**3.85**	**-6.66**	**8.66**	**-5.80**	0.14	0.83	**-2.76**	0.59
K_i*K_c	0.23	**-5.09**	**3.60**	1.24	-0.39	0.52	0.29	-1.03
H_i*H_c	-1.23	**-5.88**	**5.24**	**2.86**	0.63	1.22	-1.04	-1.54
R&D_i*R&D_c	**-5.73**	0.74	1.56	**3.39**	1.63	-0.23	-0.15	-1.16
CONTRACT_i*LEGAL_c	**1.98**	-1.20	**1.73**	**-2.38**	0.57	0.34	-0.31	0.38
VOL_i*LABMFLEX_c	0.55	**8.28**	**-6.36**	**-2.41**	-0.35	-1.31	1.23	**2.10**
COMPLEX_i*H_c	0.36	**-5.55**	**7.04**	**-1.81**	-0.11	0.96	-1.57	-0.75
VA/OUTPUT_i*GDPPC_c	**-2.77**	**2.32**	0.54	-0.09	0.30	-0.91	0.05	0.14
TFP_i*GDPPC_c	0.28	**5.01**	**-4.01**	-1.28	-0.88	-0.91	0.68	1.06
WAGE_ic	**-5.42**	**-3.86**	**4.73**	**4.55**	0.86	1.13	-1.31	-1.59
IIT_ic	**-2.20**	**-6.55**	**8.17**	0.64	-0.21	0.68	**-2.41**	-1.00
TARIFF_ic	0.21	0.37	-1.61	1.04	0.13	0.84	0.06	-0.04
OPENNESS_ic	**8.47**	**-7.83**	**3.39**	**-4.00**	**-2.84**	**2.74**	1.03	0.51
GDP_cou ^2	**-5.79**	**10.89**	**-12.71**	**7.50**	-1.05	-0.86	**2.19**	0.13
GDPPC_cou ^2	0.12	**1.90**	**-2.05**	0.03	-0.49	-0.35	0.74	0.29
DISTANCE ^2	**3.85**	**-6.53**	**8.40**	**-5.68**	0.11	0.82	**-2.69**	0.57
K_i*K_c ^2	0.23	**-5.06**	**3.46**	1.34	-0.41	0.53	0.33	-1.05
H_i*H_c ^2	-0.35	**-6.33**	**4.85**	**1.80**	0.42	1.51	-0.96	-1.54
R&D_i*R&D_c ^2	**-4.16**	0.60	**1.66**	**1.89**	1.53	-0.27	-0.21	-0.88
CONTRACT_i*LEGAL_c ^2	**2.35**	**-2.13**	**2.16**	**-2.39**	0.44	0.56	-0.32	0.34
VOL_i*LABMFLEX_c ^2	-0.13	**7.62**	**-6.44**	-1.01	-0.33	-1.57	1.24	1.74
COMPLEX_i*H_c ^2	0.74	**-4.47**	**5.86**	**-2.11**	0.13	0.89	-1.16	-0.42
VA/OUTPUT_i*GDPPC_c ^2	**-3.28**	**2.11**	0.69	0.48	0.42	-0.80	0.09	-0.01
TFP_i*GDPPC_c ^2	0.73	**4.78**	**-3.82**	**-1.68**	-0.86	-0.84	0.72	1.18
WAGE_ic ^2	**-3.88**	**-1.96**	**2.67**	**2.77**	0.71	0.82	-1.05	-0.95
IIT_ic ^2	**-2.03**	**-5.66**	**7.32**	0.42	-0.11	0.65	**-2.25**	-0.75
TARIFF_ic ^2	**-2.52**	0.63	-0.74	**2.64**	0.46	0.61	0.04	-0.48
OPENNESS_ic ^2	**3.04**	**-4.88**	**1.92**	-0.10	-1.52	1.61	1.00	-0.31
Median absolute t-statistic	**2.12**	**4.95**	**3.71**	**1.85**	0.45	0.83	0.98	0.67
Mean absolute t-statistic	**2.42**	**4.59**	**4.53**	**2.36**	0.65	0.88	1.01	0.76
Observations	494	494	494	494	485	481	468	479

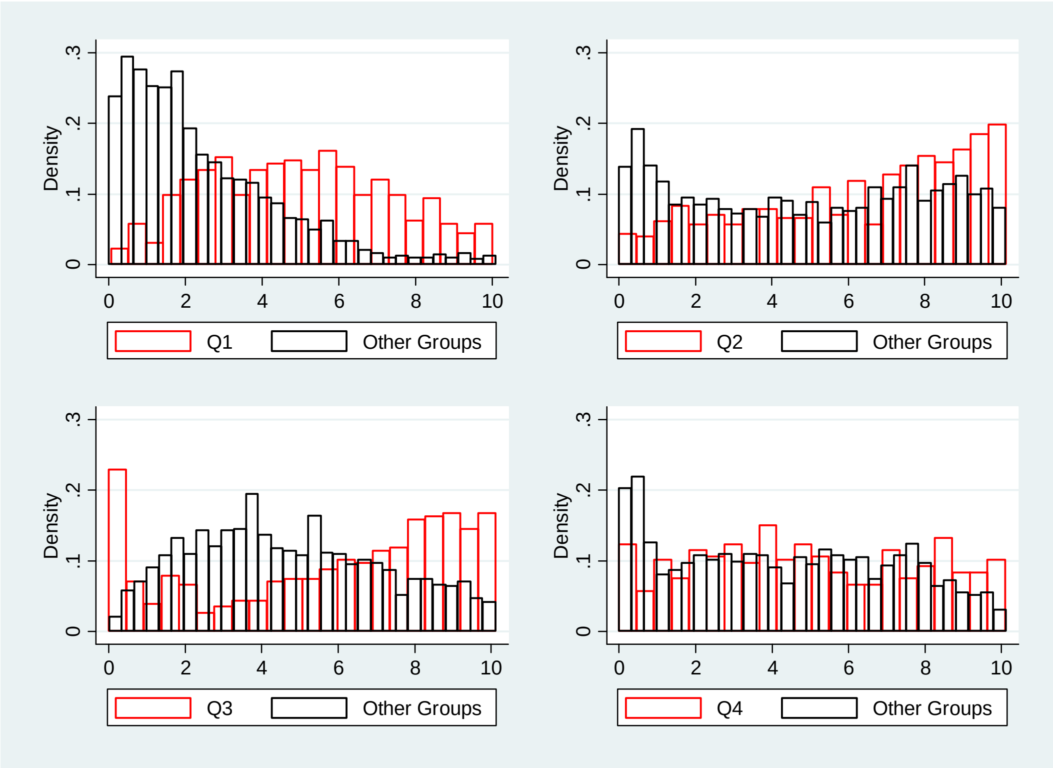
Note: "c" stands for country, "i" stands for industry and "^2" stands for squared term. t-values reported in bold face indicate significance at the 5% level. The four groups of approximately the same size are generated according to the distribution of LowIMP-HighIMP space. Observations which do not satisfy the common support condition are excluded from the respective groups. In order to account for the GPS values we split up the GPS values evaluated at the median treatment intensities of LowIMP and HighIMP of the respective groups into six blocks of approximately same size according to the GPS distribution.

Table 5. Estimation of the dose-response function.

	Coeff.		t-stat
LowIMP	-0.358	***	(2.94)
HighIMP	-1.155	***	(8.59)
LowIMP^2	-0.059	***	(2.92)
HighIMP^2	-0.133	***	(4.71)
LowIMP*HighIMP	0.054	*	(1.70)
R	0.061	*	(1.84)
R^2	0.005		(1.20)
R*LowIMP	-0.095	***	(4.20)
R*HighIMP	0.188	***	(7.41)
(R*LowIMP)^2	-0.002	***	(4.98)
(R*HighIMP)^2	0.003	***	(4.88)
R*LowIMP*HighIMP	0.007		(1.31)
Constant	-7.684	***	(31.44)
N	1903		
R-squared	0.148		

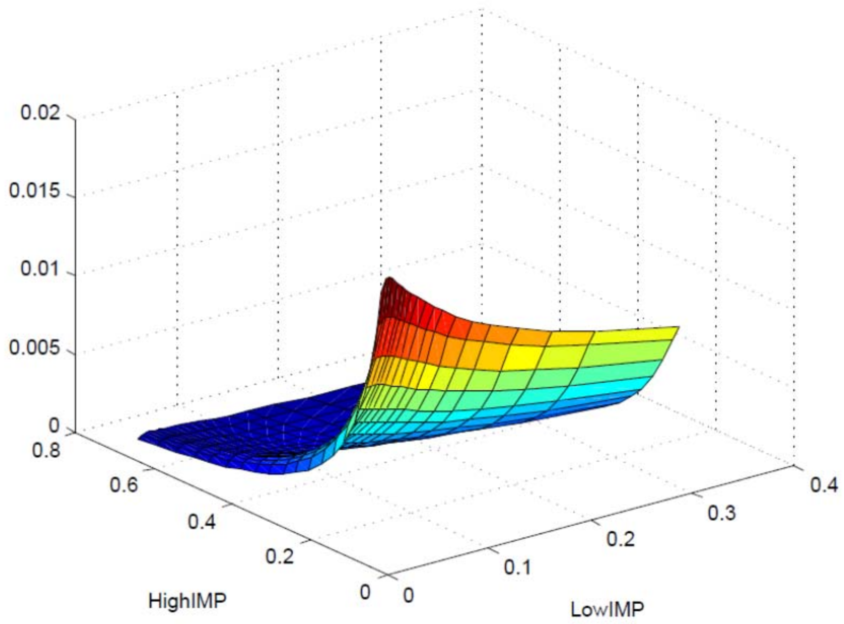
Note: ***, ** and * for significance levels at 1, 5, and 10%, respectively. Dependent variable is EMP. The treatment variables are LowIMP and HighIMP. R refers to generalized propensity score calculated according to Eq. (1) using the coefficients from the first stage regression in Table 3. We estimate 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.

Graph 1. GPS support condition (four groups and 6 blocks).

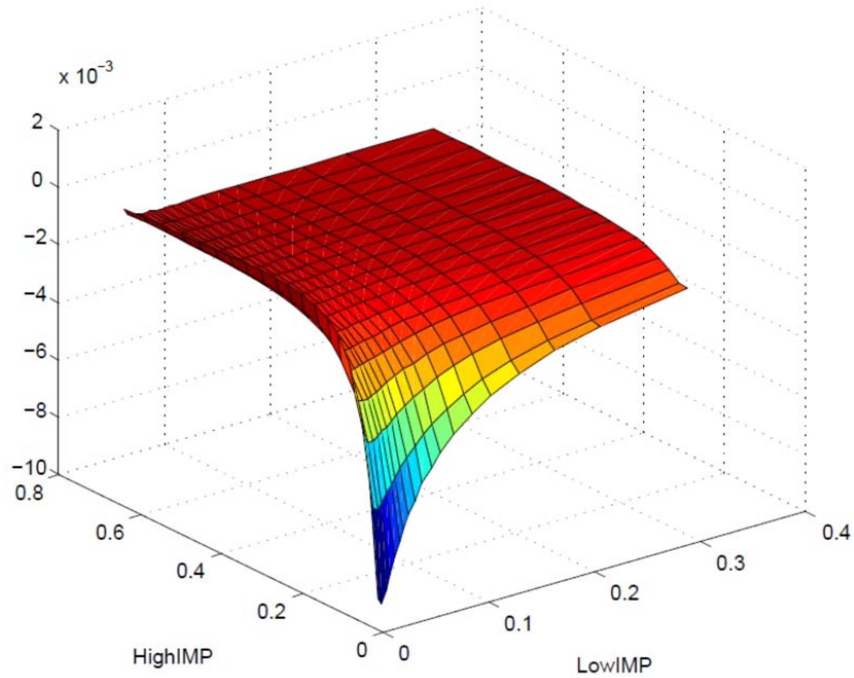


Notes: There are four groups of equal size, each of them having 25% of the distribution of LowIMP-HighIMP space after sorting the data in ascending order and splitting LowIMP space and HighIMP space into two parts each. Industry-country pairs with relatively low LowIMP and HighIMP belong to group Q1 whereas pairs with high low LowIMP and HighIMP belong to group Q4. In each histogram, the generalized propensity scores are evaluated at the median LowIMP and HighIMP levels of the respective group, for both the observations within that particular group as well as for the respective control observations belonging to all other groups.

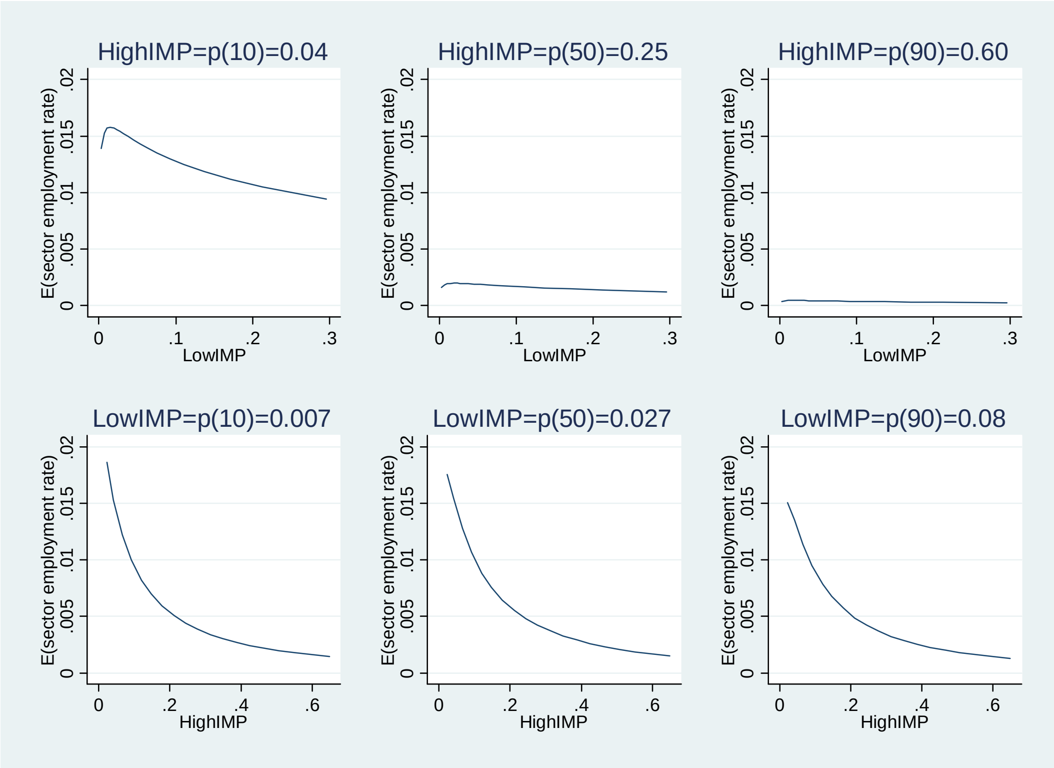
Graph 2.A Dose-response function. 3D representation.



Graph 2.B Marginal effects. 3D representation.



Graph 3.A Dose-Response function. One-dimensional analysis.



Graph 3.B Marginal effects. One-dimensional analysis.