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## A spatial nonparametric analysis of local multipliers

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# A spatial nonparametric analysis of local multipliers

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## Abstract

In this paper we present a spatial nonparametric analysis of local multipliers. Following Moretti (2010), we estimate the effect of an exogenous shock to the employment of the tradable sector on the employment in either the nontradable sector or the rest of the tradable sector using a nonparametric procedure that allows for spatial effects. In addition, due to its nonparametric nature, the adopted procedure is robust not only to possibly nonlinear functional forms but also to endogeneity in the regressors. Our analysis shows that the inclusion of spatial effects reveals the presence of a nonlinear relationship between tradable and nontradable.

**Keywords:** Local Multipliers, Spatial dependence

## 1 Introduction

State and local governments employ large amounts of public funds in economic development policies aimed at attracting and fostering new economic activities or at retaining existing ones. The outcomes of these efforts could be new or more stable jobs, higher income and wealth and an improved tax base. Indeed, it appears that job creation has

actually represented the primary goal sought after by policy makers (Eberts, 2005) possibly because this may also lead to fiscal benefits in the form of an increase of tax revenue net of public expenditure. In fact, due to multiplier effects, the total increase in local jobs can be greater than the increase in jobs in assisted businesses when these businesses produce tradable goods. For this reason, most of local development interventions are actually targeted to the tradable sector.

In the US, a precise account of the total amount of resources involved in these activities is almost an impossible task given the large number of agencies involved and the even larger number of policies being implemented. However, a survey of state-funded programs conducted in 1998 (Poole *et al.*, 1999), calculated that the states allocated approximately \$4.6 billion in tax incentive programs and \$6.3 billion in non-tax incentives. This figure excludes tax and other financial incentives, as well as job training and infrastructure incentives provided by local (substate) governments; it also excludes local development efforts carried out under the leadership of non-governmental organizations. Eberts (2005) reports an overall estimate of \$30 billion a year devoted to local development initiatives through direct and indirect funds which implies more than \$2,000 per targeted job.

In a very recent paper, Moretti (2010a) proposes a simple methodology to assess the effectiveness of local development interventions in creating new jobs. The theoretical framework that underlies the empirical analysis builds on the traditional general equilibrium setting by Rosen (1979) and Roback (1982). The main difference is that here local shocks to local labor markets are not necessarily fully capitalized in the price of land as the local supply of labor is not necessarily infinitely elastic and the local housing supply is not necessarily perfectly inelastic (see also Moretti, 2010b). Inside a city, a positive shock to the labor demand of an industry within the tradable sector, possibly induced by a local development initiative, has positive indirect effects on employment in the nontradable sector as well as in other industries within the tradable sector. There are however offsetting general equilibrium effects that pass through local labor and housing

markets. In particular, if the elasticity of the local supply of labor is not elastic (which, in turn, depends on the degree of geographical mobility of workers and on the elasticity of housing supply), the initial increase in employment crowds out employment in other industries due to a local increase in real wages. Local multipliers are thus the net effect of indirect and general equilibrium effects.

To establish the magnitude of local multipliers, Moretti estimates variants of a very simple model

$$y = \alpha + \beta x + \epsilon \tag{1}$$

in which, when estimating the size of the local multiplier for the nontradable sector,  $y$  and  $x$  are the change in the log number of jobs in the nontradable and tradable sectors respectively; conversely, when focusing on the local multiplier for the tradable sector,  $x$  is the change in the log number of jobs in part of the tradable sector and  $y$  is the corresponding change in the rest of the tradable sector. Estimates of  $\beta$ , can thus be interpreted as elasticities from which it is also possible to derive, for each new job in the tradable sector, the number of additional jobs created either in the nontradable sector or in the rest of the tradable sector. These estimates are obtained either via OLS or, in order to deal with endogeneity concerns, via instrumental variables estimation (IV) where the instrument is the weighted average of nationwide employment growth in manufacturing industries, the weights being defined locally using the employment shares of the industries. According to these IV estimates, approximately 1.6 additional jobs are created in the nontradable sector of a city for each new job in the tradable sector of the same city. In contrast, additional jobs created in parts of the tradable sector appear to have no statistically significant effects on the rest of the tradable sector<sup>1</sup>.

Despite its simplicity, this approach appears to be able to provide rather meaningful estimates. One particularly appealing feature is that the exogenous variation is directly

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<sup>1</sup> De Blasio and Menon (2010) apply this same framework to data on Italian local labour markets but find no significant effects on either nontradable or other tradable industries.

attributed to the tradable sector which is the one that attracts most of the local development initiatives (De Blasio and Menon, 2010). More generally, as emphasized by Moretti, this approach represents a valid alternative to the traditional methodology, local Input-Output analysis, which tends to overlook the employment effect for nontradables as well as the offsetting general equilibrium effects.

There are nonetheless several critical aspects that must be considered when implementing this approach. Firstly, it is essential to be able to deal with the endogeneity concerns which are likely to arise. The most commonly adopted solution is represented by instrumental variable methods, the difficulties of which are well known in the literature (see, for instance, Angrist and Krueger, 2001).

Secondly, there might be concerns about the functional form since the linear one is not necessarily the most appropriate to represent the underlying relation between exogenous and induced variations in local employment. The literature on urban dynamics offers several indications pointing in this direction. For example, due to agglomeration economies, urban size and density affect productivity in a multiplicity of ways (Combes et al., 2010; Duranton and Puga, 2004) and, therefore, the overall effect derived from an additional job in the tradable sector might not be uniform. At the same time, agglomeration diseconomies due to higher crimes, taxes, land prices, traffic congestion and environmental pollution (see, for instance, Glaeser, 1998) may overcome benefits when city size surpasses some specific threshold, and economic activity may be induced to locate elsewhere. Finally, from a rather static viewpoint, as the city gets larger additional demand derived from the initial shock is more likely to be satisfied by local nontradable and tradable industries (Bartik, 2003).

Finally, within the theoretical framework outlined above space clearly plays a key role through trade and factor flows. This role, however, is completely neglected in the empirical implementation and this suggests that the local multipliers might not be appropriately estimated. Two types of concerns arise here. From an econometric point of view,

neglecting space might lead to omit spatially structured covariates thus running the risk of obtaining biased estimates. Under these circumstances, identifying valid instrumental variables could be extremely difficult as the omitted factors are often unobservable. From a more interpretative point of view, ignoring space in the empirical model means overlooking that the exogenous variation that benefits one city does not necessarily come exclusively from the tradable sector of the same city. Consider, for example, a city in which there has been no local exogenous variation in the tradable sector. Implicit in model (1), no changes in nontradable (or rest of tradable) sector employment should be observed. However, such changes could be induced by exogenous variations in the tradable sectors of other cities, with an intensity that is possibly negatively correlated with relative distance. To the extent in which this happens, the local multiplier estimated through model (1) might be biased. In particular, a positive (negative) effect on nontradable (or rest of tradable) sector employment from additional tradable jobs in neighboring cities leads to overestimate (underestimate) the local multiplier.

As already mentioned, Moretti explicitly recognizes the importance of the first type of concerns and adopts an IV estimator. In the present paper, we actually confront with all three issues and we do this by resorting to a nonparametric framework.

## 2 Modelling spatial dependence

In the analysis of cross-section data quite often researchers have to face problems of misspecifications caused by dependence across spatially organized observational units. Indeed, explanatory variables are often unable to capture unobservable spatial factors and problems related to omitted variables can easily arise. In such instances, usual methods, like IV estimation, fall short from representing a viable solution because spatial dependence is due to latent, although relevant, influences.

The spatial econometric literature offers a number of models (Le Sage and Pace, 2006).

Instances are the Spatial Error Model

$$\begin{aligned}\mathbf{Y} &= \beta\mathbf{X} + \mathbf{u} \\ \mathbf{u} &= \lambda W\mathbf{u} + \epsilon\end{aligned}\tag{2}$$

the Spatial Lag Model

$$\mathbf{Y} = \rho W\mathbf{Y} + \beta\mathbf{X} + \epsilon\tag{3}$$

and the Spatial Durbin Model

$$\mathbf{Y} = \rho W\mathbf{Y} + \beta\mathbf{X} - \lambda W\mathbf{X}\beta + \epsilon\tag{4}$$

where  $\mathbf{Y}$  is an  $n \times 1$  vector,  $\mathbf{X}$  is an  $n \times p$  matrix<sup>2</sup>,  $\epsilon \sim N(0, \sigma^2 I_n)$  is a  $n \times 1$  vector of innovations,  $-1 < \rho < 1$ ,  $-1 < \lambda < 1$ ,  $\beta$  is a  $p \times 1$  vector of parameters and  $W$  is a  $n \times n$  spatial weights matrix whose  $w_{ij}$  elements are non negative when  $i \neq j$  and zero otherwise.

The logic underpinning these models originates from an econometric approach that aims at obtaining estimates possessing standard statistical properties. In other words, within this approach a specific role is played by  $W$ , a term that tries to provide a synoptic representation of spatial relations with the fundamental aim of obtaining unbiased estimates.

Some authors, for example Corrado and Fingleton (2011) and Fingleton and Lopez-Bazo (2006) argue that the econometric approach follows a somewhat mechanical procedure, i.e. it chooses one of the possible spatial specifications on the basis of the statistical significance of the spatial term's coefficient and on its contribution to the achievement of more satisfactory residuals diagnostics. As a result, however, it runs the risk of losing sight of the substantive meaning of the model. In addition, there might be a problem of indeterminacy with respect to the model to choose: when more than one model is acceptable in terms of its statistical properties, the econometric approach does not seem

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<sup>2</sup> For simplicity's sake we assume  $p = 1$ . All that follows can be generalized to the multivariate case  $p \geq 2$ .

to dwell on the issue of the correct specification in order to provide an explanation to the economic phenomenon at hand.

This point, however, is a crucial one since different spacial model provide different or even conflicting views on the nature of the relationship among the included variables. More precisely, the implications derived from a Spatial Error Model, where the spatial dependence has a nuisance nature leading to nonspherical residuals, tend to differ widely from the implications arising from a Spatial Lag Model or a Spatial Durbin one, where the spatial dependence is included as an explanatory variable in its own right and is justified by the existence of spatial spillovers.

So, on the one hand stands the econometric approach characterized by a tendency to comply with the theoretical requirements of the estimates which might lead to a sort of indeterminacy about the economic interpretation of the phenomenon. On the other hand stands an antithetic approach that considers this indeterminacy as a serious flaw. In its more extreme examples it somehow avoids confronting with the spatial dependence issue from a technical viewpoint and adopts *ad hoc* solutions without checking that the resulting model possesses sound statistical properties.

In our view, therefore, there is scope for a method that focuses on a substantive explanation of the economic phenomenon but, at the same time, allows for spatial dependence in order to reach statistically sound estimates.

### **3 Nonparametric regression with spatially dependent data**

In this Section we describe a new procedure, hereafter SNP, for nonparametric regression with spatially dependent data. The SNP procedure, whose details are in Gerolimetto and Magrini (2009), is a two-step nonparametric regression that aims at incorporating the information on spatial dependence by means of a nonparametric estimate of the spatial covariance matrix.



### 3.1 Nonparametric regression basics

Nonparametric regression has become quite a standard statistical tool when the functional form is possibly neither linear nor nonlinear of a specific type. Indeed, given a model such as

$$y = m(x) + \epsilon$$

where  $\epsilon$  is the i.i.d. error term and  $m(x)$  is a smooth function, linearity of  $m(x)$  is not always straightforward. Under this circumstance, the parametric literature typically offers Non Linear Least Squares Estimates that require the specification of a functional form with respect to which the minimization problem can be solved. When making assumptions on the functional form of  $m$  is not possible or not recommended, the nonparametric methods represent a preferable option.

In general, the estimate of a nonparametric regression can be obtained in correspondence of some fixed points by means of some smoothing methods. Among the most commonly adopted estimation techniques is the local constant estimator (LCE, hereafter), also known as Nadaraya-Watson estimator (Nadaraya, 1964; Watson, 1964):

$$\hat{m}(x) = \frac{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)Y_j}{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)} \quad (5)$$

where  $h$  is the bandwidth, the parameter that controls the degree of smoothness. The local linear estimator (LLE) is also rather well-known and it is often preferred to LCE for its better mean bias properties:

$$\hat{m}(x) = \frac{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)Y_j}{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)} + (x - \bar{X}_w) \frac{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)(X_j - \bar{X}_w)Y_j}{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)(X_j - \bar{X}_w)^2} \quad (6)$$

where

$$\bar{X}_w = \frac{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)X_j}{\sum_{j=1}^n K\left(\frac{x-X_j}{h}\right)}$$

Recently Phillips and Su (2009) claim that nonparametric regression has more robustness advantages beyond robustness to specific functional form, for which it is commonly

appreciated. The authors demonstrate that nonparametric regression can also display a robustness to endogeneity since it concentrates on local information thus attenuating the weight of tail information possibly suffering more heavily from endogeneity effects. In addition, they provide Monte Carlo simulations showing that, in the presence of endogenous variables, nonparametric kernel regression outperforms the parametric estimate even when the functional form is known.

This further form of robustness is a particularly appealing feature. Even in situations in which the functional form is known (e.g., even in the linear case) nonparametric regression represents an appropriate alternative to instrumental variables estimation in order to tackle endogeneity concerns with the additional advantage of simplicity as it does not require the identification of the instruments.

### **3.2 The SNP procedure**

As highlighted by Martins-Filho and Yao (2009), most asymptotic results for the LCE estimator in case of dependent errors are unfortunately contingent on the assumptions made on the covariance structure and it is not possible to generalize their application to different parametric structures. Stimulated by this lack of generality, attention within the nonparametric literature has focused on estimators that, by incorporating the information contained in the error covariance structure, outperform, both asymptotically and in finite samples, traditional nonparametric ones. Here, we specifically draw on the work by Martins-Filho and Yao (2009) who establish a set of sufficient conditions for the asymptotic normality of the local linear estimator (LLE) when the error correlation structure is as general as possible.

In short, SNP, whose details are in Gerolimetto and Magrini (2009), is a two-step procedure for nonparametric regression with spatially dependent data that does not require *a priori* parametric assumptions on spatial dependence; information on its structure is actually drawn from a nonparametric estimate of the errors spatial covariance matrix.

The SNP procedure moves from a pilot estimate of the nonparametric regression with the local linear estimator and consists of two steps: firstly, the covariance matrix is estimated nonparametrically through a spline correlogram (Bjørnstad and Falk, 2001); secondly, a modified regression is run exploiting the information on spatial dependence just obtained.

The procedure consists of the following steps:

0. *Pilot fit*: estimate  $m(X)$  with a local polynomial smoother with fixed bandwidth<sup>3</sup>. As for the degree of the polynomial,  $p = 1$  is usually considered (local linear estimator). The output is  $\hat{u} = Y - \hat{m}(X)$ .
1. *Nonparametric covariance matrix estimation*: obtain  $\hat{V}$ , the estimated spatial covariance matrix of  $\hat{u}$ , using the spline correlogram, a continuous nonparametric positive semidefinite estimator of the covariance function developed by Bjørnstad and Falk (2001).
2. *Final fit*: feed the procedure with the information obtained from the estimate of the spatial covariance matrix  $\hat{V}$  by running a modified regression where  $Y$  is replaced by  $Z = \hat{m}(X) + L^{-1}\hat{u}$  and  $L$  is obtained by taking the Cholevsky decomposition of  $\hat{V}$ . The nonparametric estimate  $\check{m}$  resulting from this second fit is done by choosing the bandwidth parameter with a modified version of the Residual Spatial Autocorrelation criterion suggested by Ellner and Seifu (2002).

### 3.3 Estimating spatial models with SNP

To see how the SNP procedure can be utilized to estimate models like (2),(3) and (4) consider their nonparametric counterparts moving from the following very general setting:

$$\begin{aligned} \mathbf{Y} &= M(\mathbf{X}) + \mathbf{u} \\ \mathbf{u} &= \theta W \mathbf{u} + \epsilon \end{aligned} \tag{7}$$

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<sup>3</sup> As usual in two-step nonparametric regressions, undersmoothing in this first stage is required to avoid bias piling up.

where

- $M(\mathbf{X}) = m(\mathbf{X})$  and  $\theta = \lambda$  for a nonparametric Spatial Error Model
- $M(\mathbf{X}) = (I - \rho W)^{-1}m(\mathbf{X})$  and  $\theta = \rho$  for a nonparametric Spatial Lag Model
- $M(\mathbf{X}) = (I - \rho W)^{-1}(I - \lambda W)m(\mathbf{X})$  and  $\theta = \rho$  for a nonparametric Spatial Durbin Model

In the function  $M(\mathbf{X})$  in (7) actually has two components: the first is a general function of the covariate matrix  $m(\mathbf{X})$  while the second is a spatial factor whose form depends on the spatial data generating process<sup>4</sup>. Obviously, when  $m(\mathbf{X}) = \mathbf{X}\beta$ , these models simply revert to (2),(3) and (4).

We must stress that the advantage of estimating function  $M$  via SNP is that no assumption is required on its functional form and, consequently, neither on  $m(\mathbf{X})$  nor on the spatial factor that combine into  $M(\mathbf{X})$ .

Moreover, by estimating spatial models via SNP, spatial dependence is not filtered out as if it was a nuisance element. On the contrary, SNP's rationale is to include spatial dependence as a substantive element with the objective of obtaining estimates that are unbiased but, at the same time, retain a transparent interpretation from an economic viewpoint.

## 4 Empirical analysis

In the empirical analysis we use data from the Bureau of Economic Analysis on employment by NAICS 2-digit industry for 363 US metropolitan areas between 2001 and 2008. Differently from Moretti's analysis, therefore, the territorial unit is the metropolitan area which can be argued to be appropriate than cities for this type of analysis because better suited to capture the true boundaries of the local labor markets. Another element of

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<sup>4</sup> Clearly, in case of Spatial Error Model, the spatial factor is simply the identity matrix.

departure from Moretti’s work is in the definition of tradable and nontradable sectors. In particular, we have adopted the classification of internationally tradable and nontradable activities derived by Jensen and Kletzer (2005, Table 4). It must be observed that, in effect, these authors define tradable activities as those activities which are traded domestically and identify them on the basis of their geographic concentration within the US. In other words, the definition of tradable activities obtained by Jensen and Kletzer corresponds exactly to what is needed for the present analysis. On the other hand, the common practice that restricts the tradable sector to manufacturing is likely to introduce a bias by excluding industries which should clearly be considered as tradable within an intra-national context.

We estimate the following regression models:

$$\Delta N^{NT} = m(\Delta N^T) + \epsilon \quad (8)$$

$$\Delta N^{T1} = m(\Delta N^{T2}) + \zeta \quad (9)$$

where  $\Delta N^{NT}$  and  $\Delta N^T$  are, respectively, the change in the log number of jobs in the nontradable and tradable sectors while  $\Delta N^{T1}$  and  $\Delta N^{T2}$  are, respectively, the change in the log number of jobs in part of the tradable sector and the corresponding change in the rest of the tradable sector.

We use three different estimation methods. First, among the conventional parametric methods, we run an OLS regression; then, among nonparametric methods, we employ the local linear estimator (NP) as well as the spatial nonparametric regression estimator (SNP) described in the previous session. Bandwidths for nonparametric estimates have been selected using the (leave-one-out) cross validation method. The distance matrix for the SNP procedure is obtained from Euclidean distances across metropolitan areas centroids.

We start the analysis by considering the effect of tradable on nontradable. The OLS elasticities are reported in Table 1. In particular, the elasticity that describes the effect

is 0.53, a value which is in line with what reported by Moretti. However, since in our data there are approximately 1.6 nontradable jobs for each tradable job, we obtain that an additional job in the tradable sector of a city only leads to 0.84 jobs in the nontradable sector of the same city. It is worth noting, however, that the null hypothesis of spatial independence in the residuals is strongly rejected by the Moran's I test (based on an inverse of distance weight matrix and 9999 permutations).

These results can be compared with those from the nonparametric methods in Figure 1 displaying the three estimated regression lines. In order to better appreciate the differences among the estimates, in the next two figures we confront the OLS elasticity, represented by a dotted line, with the elasticities estimated via the traditional nonparametric procedure (Figure 2) and the spatial nonparametric counterpart (Figure 3). In addition, 5% confidence bands around the elasticities derived from the nonparametric estimates are reported in order to understand whether these are significantly different from those derived from OLS. As we can see from Figure 2, the confidence bands always include the horizontal line corresponding to the OLS estimate thus suggesting the absence of any significant difference with respect to the elasticity obtained through the local linear estimator. In addition, this seems to suggest that the linear specification might not be inappropriate. A totally different picture however emerges when we move to Figure 3. Here, the 5% confidence intervals suggest that the elasticity obtained by SNP is significantly different from that derived from OLS over a large part of the domain. More in detail, we observe an inverted U-shaped elasticity: it starts from a significantly lower value than the OLS counterparts; it then overtakes it, although for a rather limited range of values; it finally declines although this feature does not appear to be significant since the confidence bands now get wider due to boundary variability. Thus, the use of an estimator that allows for spatial effects alters the results in quite a striking way. The radical change in implications can be fully appreciated from Figure 4. Here, in analogy with the interpretation of the elasticities offered by Moretti which considers the initial

level of employment as given, we show the number of additional jobs in the nontradable sector for each new job in the tradable sector at different tradable employment levels. The additional effect is extremely small (less than 0.2) for low employment levels and reaches approximately the value of one for an employment size of about 350,000. As noted previously, the subsequent decline cannot be considered a significant feature.

We can now turn to the estimation of the effect of tradable on other parts of tradable. The analysis we carry out here differs once more from the one by Moretti. Given that we have data on employment by NAICS 2-digit industry, we cannot randomly distinguish groups of manufacturing industries. However, in our case, the tradable sector is not confined exclusively to the manufacturing industry so we focus on the 6 industries which are predominantly attributable to the tradable sector (in the sense that the weight reported by Jensen and Kletzer exceeds 0.6). Next, we consider all combinations of these industries that lead to different groupings and repeat the analysis for each of them. Table 2 presents the estimation results obtained with OLS and SNP. In particular, the first two columns reports the OLS elasticities and the corresponding standard errors. The remaining columns report some summary statistics of the distribution of the elasticity values obtained for each of the possible regressions. As we can see, OLS elasticities are strongly significant and quite close to one; similarly, the distributions of SNP elasticities are quite peaked around the same value. A typical example of this behavior is reported in the last column of Table 1, as far as OLS is concerned, and in Figures 6 and 7 for the nonparametric counterparts. Here, we note that the OLS elasticity is very close to the value of one. In addition, contrary to what noted in Figures 2 and 3, now both the NP and SNP estimated elasticities do not differ significantly from the OLS over the very large majority of the domain. In sum, an additional job in part of the tradable sector generates a response in the other part of the tradable sector that does not alter the ratio between the number of jobs in the two parts.

## 5 Conclusions

In this paper we estimated local multipliers and of the corresponding effect, in terms of additional jobs in the rest of a local economy, deriving from an extra job in the tradable sector. Specifically, we employed three different estimators: the OLS, the nonparametric local linear estimator and a spatial nonparametric estimator (based on a local linear smoother). Our results suggest that allowing for spatial dependence modifies the picture arising from more conventional estimators. In particular, using SNP we find that the relationship between the change in tradable jobs and the change in nontradable jobs is nonlinear. In addition, tradable on nontradable has an inverted U-shaped effect that starts from values which are significantly lower than those obtained from the other two estimators. This confirms the supposition that space clearly plays a key role through trade and factor flows.

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## Figures and Tables

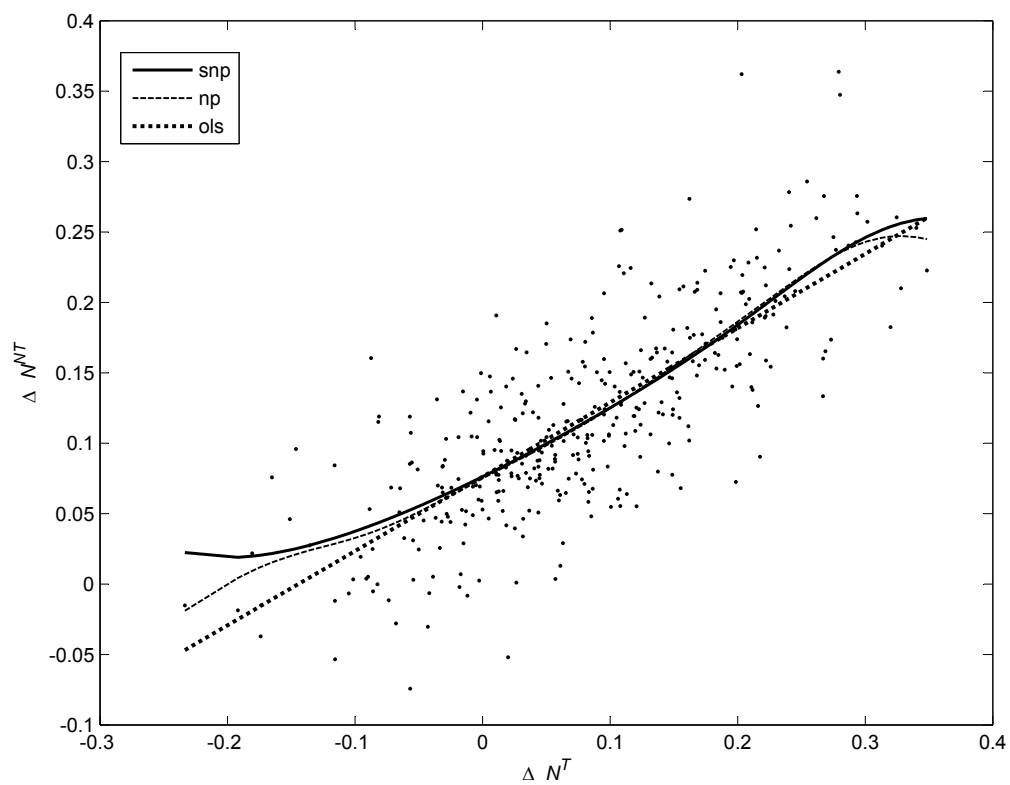


Figure 1: Tradable - Nontradable: fit

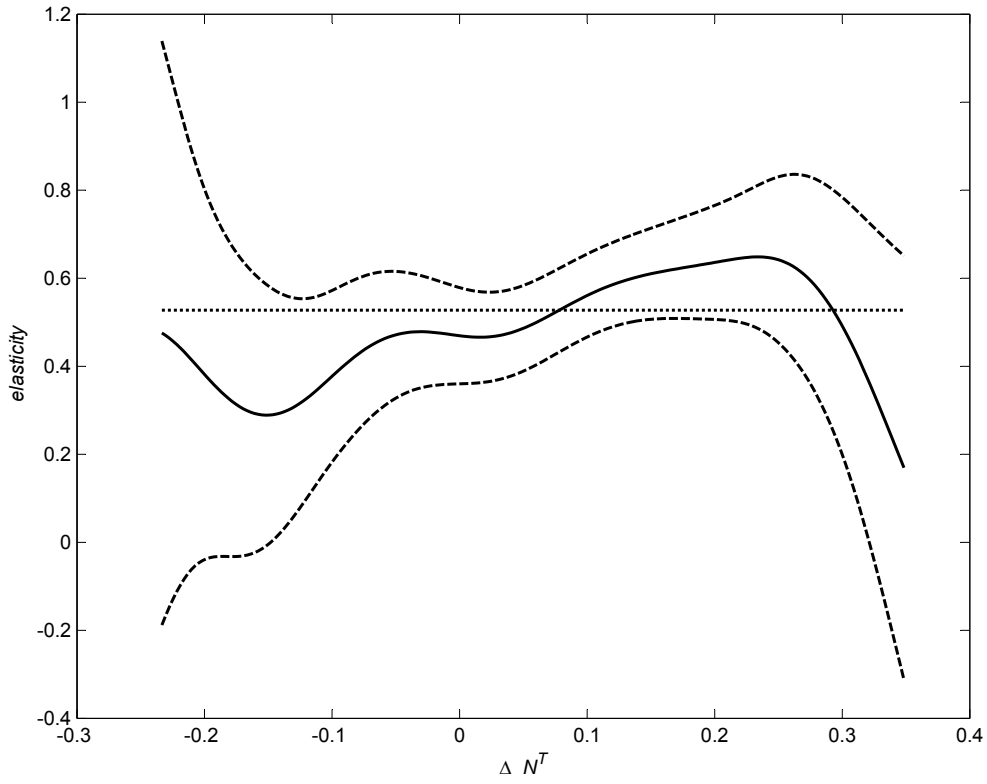


Figure 2: Tradable - Nontradable: elasticity (NP)

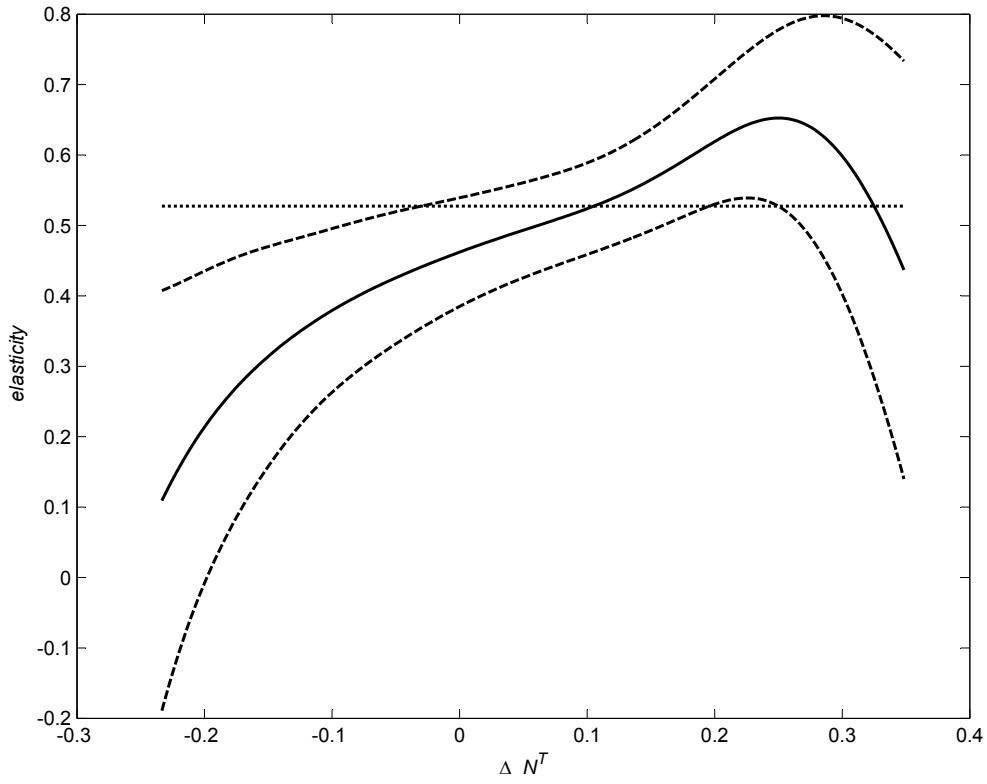


Figure 3: Tradable - Nontradable: elasticity (SNP)

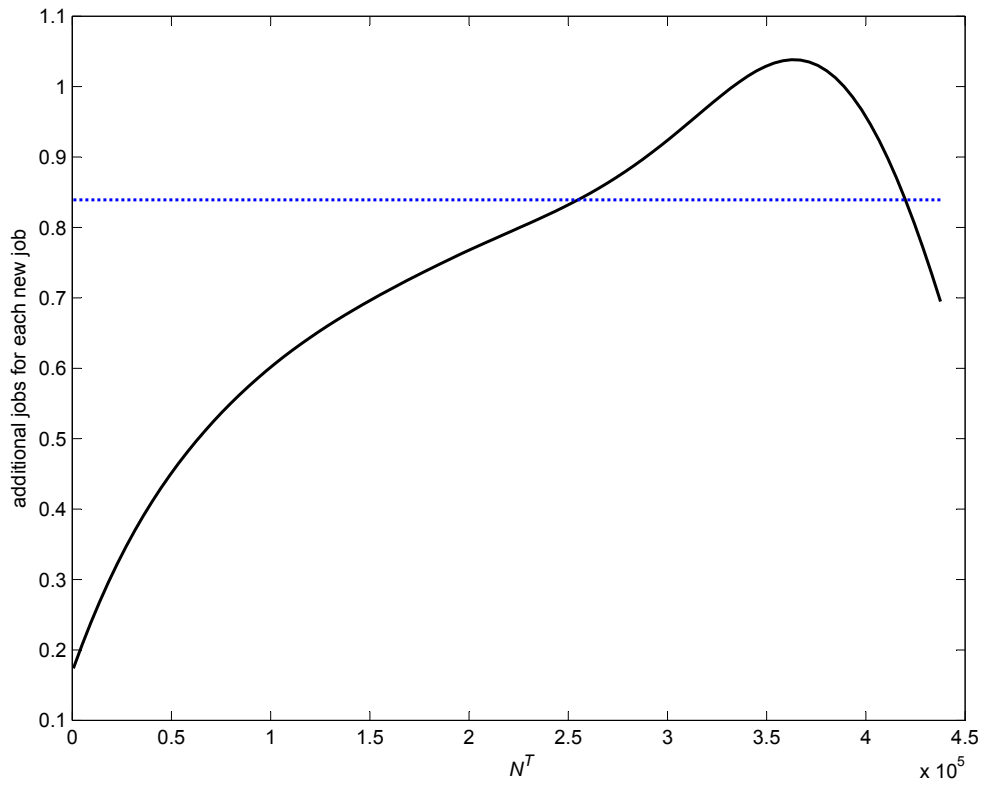


Figure 4: Tradable - Nontradable: additional jobs (SNP)

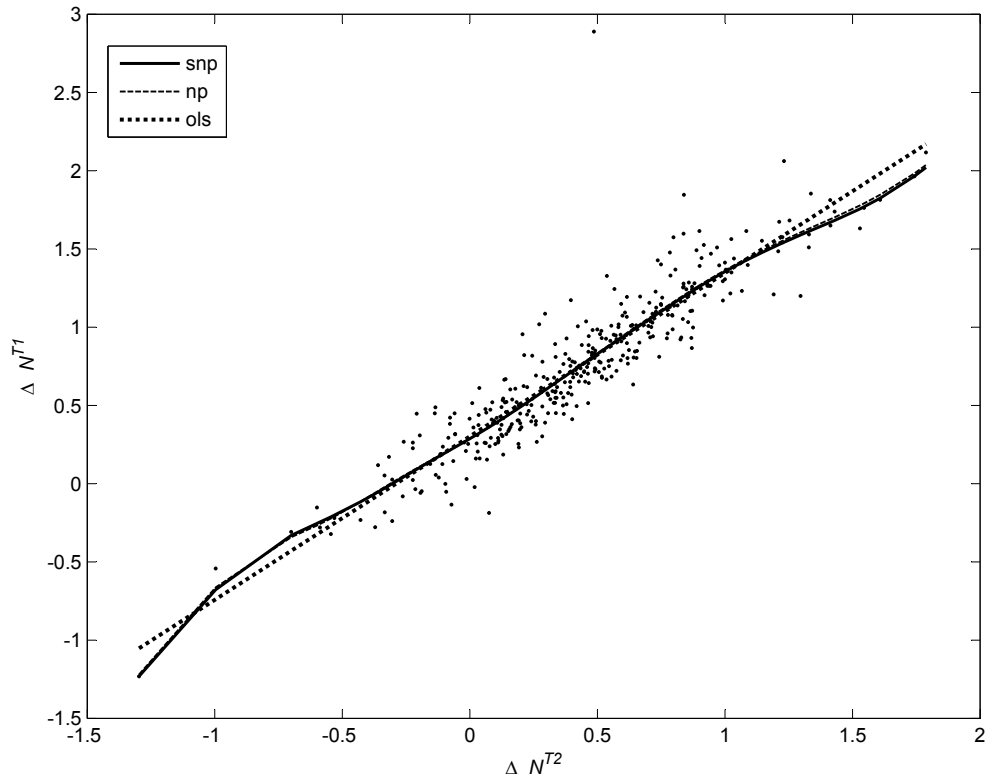


Figure 5: Tradable1 - Tradable2: fit

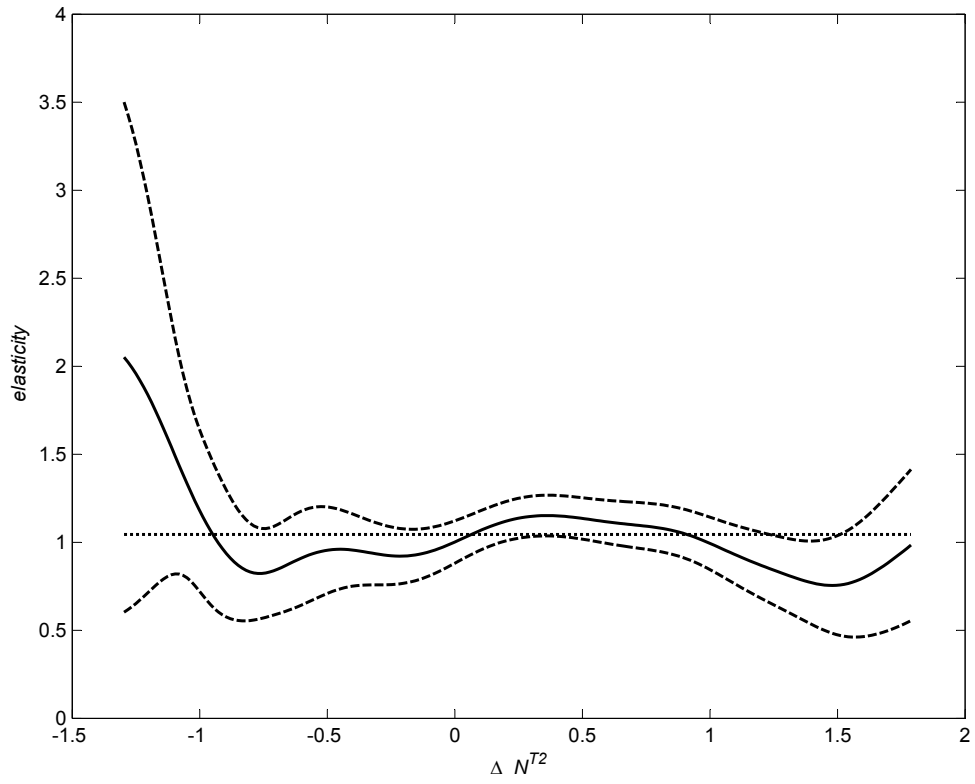


Figure 6: Tradable1 - Tradable2: elasticity (NP)



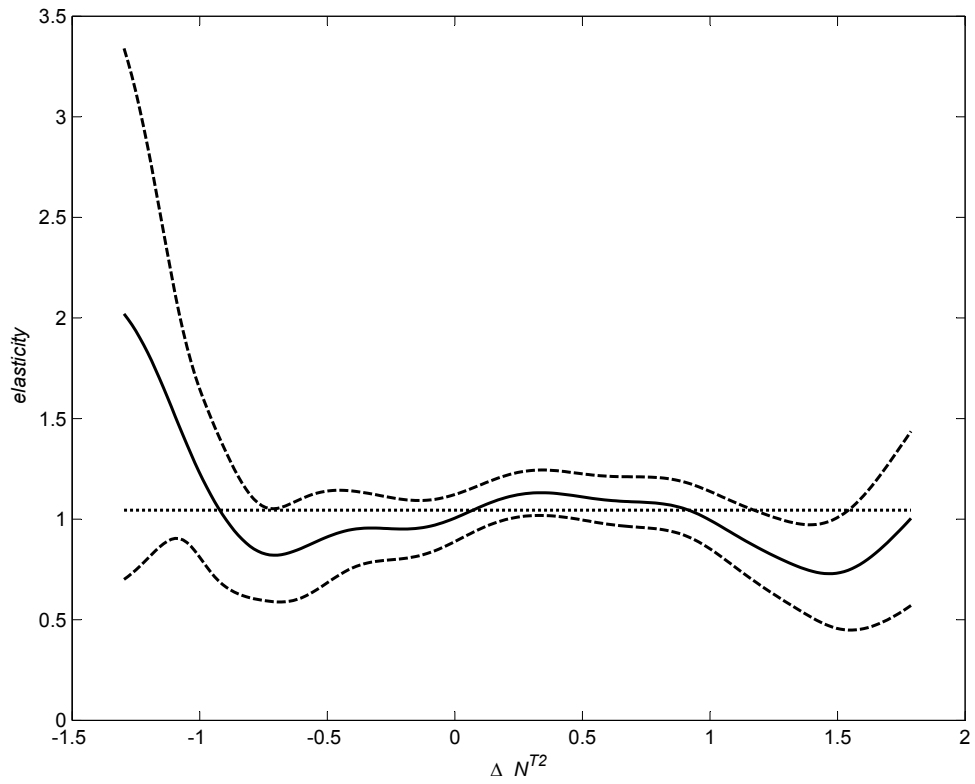


Figure 7: Tradable1 - Tradable2: elasticity (SNP)

	Effect of tradable on	
	nontradable	tradable
constant	0.076222	0.302038
s.e.	0.002965	0.014701
p-level	0	0
elasticity	0.527438	1.044434
s.e.	0.022292	0.024066
p-level	0	0
implied additional jobs	0.8392	0.980349
$R^2$	0.6079	0.8392
Moran's I	10.3592	5.3381
p-level	0	0

Table 1: OLS local multipliers

	OLS		SNP				
	b	s.e.	D10	median	D90	mean	s.e.
1	1.030218	0.018521	0.993362	1.037917	1.056904	1.034586	0.025945
2	1.046561	0.016461	1.016919	1.020367	1.036264	1.023869	0.007398
3	1.012747	0.0164	0.928523	1.045951	1.087402	1.023292	0.059529
4	1.049241	0.027855	1.000415	1.036434	1.054849	1.031804	0.020162
5	0.992998	0.014725	0.957929	0.985592	1.044046	0.993718	0.030815
6	1.068252	0.019093	1.012124	1.033642	1.130195	1.052855	0.043048
7	1.032465	0.025409	1.025131	1.028909	1.030585	1.028349	0.002058
8	1.044434	0.024066	1.012324	1.088044	1.128423	1.080475	0.042494
9	1.064682	0.021718	1.045275	1.066208	1.077721	1.063769	0.012018
10	0.95054	0.014213	0.939965	0.941793	0.945162	0.942324	0.002006

Table 2: Trade-Trade local multipliers