On the spatial effects of transportation on manufacturing employment

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Abstract: This article examines how transport infrastructures influence on employment manufacturing in Spanish regions from 1995 to 2008. We estimate regressions with fixed effects and spatial econometric methods. We find that the density of motorways and the amount of port traffic are relevant determinants of manufacturing employment in the own region, while we do not find clear effects of railways. We also find evidence of negative spillovers both from roads and container port traffic.

Keywords: transportation, roads, ports, manufacturing employment, spatial effects.

JEL Codes: H54, L60, L92, R12, R40, R53

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1. INTRODUCTION

Transport infrastructures are considered a crucial factor for the development of countries, regions and cities. Indeed, better infrastructures imply greater public capital and hence more productivity of private factors, less transport costs for firms and a higher accessibility for territories. Hence, several empirical studies have used production or cost functions to examine the impact of infrastructures on economic growth. Overall, most of these studies focus on aggregate amounts of public capital or as much they distinguish between roads and other infrastructures. The geographical unit of the analysis is quite diverse and it is possible to find studies at the country, regional or local level.

Early examples of studies that use production functions are those of Aschauer (1989), Munell (1990), Garcia-Milà and McGuire (1992) or Holtz-Eakin (1994), while examples of studies that use cost functions are those of Morrison and Schwartz (1996) or Nadiri and Mamuneas (1994).[1] While it is generally (although not unanimously) accepted that public capital may have positive direct effects, the magnitude of the effect is still subject to debate.

Advances in the use of spatial econometric techniques have allowed addressing other research questions as the quantification of spatial spillovers from better infrastructures between nearby regions (Cohen, 2010). Indeed, it is not only relevant to examine whether territories take benefit from their own infrastructures but also from the endowment of neighbors. In this regard, we may find positive and negative spillovers between regions in terms of transport infrastructures.

Overall, we may expect that transport infrastructure improvements have an influence in other regions because of its network nature. This is particularly the case for roads and railways, while it is less clear for airports and ports. Networks in these two latter transportation modes are built by firms producing transport services (ie; airlines, shippers) without making investments associated to sunk costs.

Several studies that focus on the impact of roads and highways on the output of states or counties in US find evidence of non-significant or negative spillovers (Boarnet, 1988; Holtz-Eakin and Schwartz, 1995; Kelejian and Robinson, 1997; Ozbay et al., 2007). Moreno and López-Bazo (2007) also find evidence of negative spillovers when considering investments in transport infrastructures in Spain, while results of Delgado and Álvarez

[1] Melo et al (2013) provides a recent meta-analysis of the impact of transport infrastructure on economic activity.

(2007) and Baños et al. (2013) are inconclusive regarding the direction of the spillovers in analyses also for Spain.

The typical explanation of negative spillovers is related with the migration of mobile production factors (labor and mobile capital). Within the context of competition between regions to be attractive for economic activities, investments in transport infrastructures in one region may have negative effects on other regions as long as better infrastructures imply higher returns for production factors.

On the contrary, Cohen and Morrison Paul (2003, 2004) find evidence of positive spillovers across US states. They estimate cost functions for the manufacturing industry focusing on the role of airports and highways, respectively. Relieve air congestion in one node may benefit to other nodes located in other states, while better highways may allow for travel cost savings for the own and neighboring states given the network characteristics of highways. In more general terms, transport infrastructures may lead to positive spatial spillovers because it may improve the connectivity of geographically linked regions.

In contrast to the vast literature on the link between public capital and output (and to lesser extent costs), few studies have examined the impact of transport infrastructures modes on regional employment. These studies have generally put the attention in one specific transportation mode. Jiwattanakulpaisarn et al. (2009) find that investment in motorways does not have a strong effect on private sector employment in an analysis for the US state of North Carolina, while Bottasso et al. (2013) and Ferrari et al (2010) found that the port throughput has a positive relation with employment in studies that focus on European regions. Brueckner (2003) found a significant causal link between air traffic and employment in service-related industries but not in goods-related industries at US urban areas, while Percoco (2010) obtains evidence of positive spatial spillovers for Italian airports. As far as we know, there are not multivariate empirical studies that evaluate the impact of railways on regional employment.

In this paper, we estimate the determinants of manufacturing employment in Spanish regions using data that goes from 1995 to 2008. Controlling for several attributes of regions, our focus is on the direct and indirect impacts of different transportation modes, including the effects on the areas where the infrastructures are located and also spillovers (positive or negative) to other regions.

As in other previous studies (Hulten and Schwab, 1991; Cohen and Morrison Paul, 2003, 2004; Morrison and Schwartz, 1996; Moreno and López-Bazo, 2007), we put the attention on manufacturing employment. Cohen and Morrison Paul (2004) argue that the focus on a particular sector results in more plausible and interpretable results than taking a macroeconomic perspective, while Holtz-Eakin and Lovely (1996) shows that the manufacturing activity benefits more than the rest of productive sectors from better transport infrastructures. In any case, it is clear that the manufacturing sector has a strong relevance for regional economies. A high proportion of exports and research and development expenditures have to do with manufacturing activities. Note also that manufacturing establishments can be set in different locations while service industries tend to be located in the central business districts of major urban areas. In this regard, our analysis does not consider transport infrastructures that improve the intra-urban mobility but focus on infrastructures that influence intra-regional and inter-regional mobility.

We add to previous literature by examining the impact of several transportation modes (i.e.; roads, railways and different types of port traffic) on manufacturing employment. Furthermore, we identify the magnitude and sign of spillover effects from transport infrastructures. While previous studies have examined spillovers for network modes (ie; roads), in this paper we also put the attention on the spatial spillovers related with ports.

A priori, it is not clear the effect of a better endowment of transport infrastructures in one region on nearby ones. Indeed, there may be a competition effect related with the agglomeration of activities in the region with better infrastructures and a complementary effect which is associated with the better access to other regions or international markets.

Predictions about the direction of the spatial spillovers are particularly complex in the case of port activities. In particular, we may distinguish between different types of port traffic (container, general non-containerized, bulk). An increasing proportion of port traffic is moved through containers that have the advantage of being easily transferred to surface transportation modes like roads and rails. Hence, ports specialized in container traffic may be channeling goods whose final destination is not the region where the facility is located. Thus, the magnitude of the spatial spillover effects could be higher for container traffic than for other types of port traffic.

The rest of the paper is organized as follows: Section 2 describes the sources of data and a justification of the explanatory variables selected. Section 3 explains the econometric techniques that we use. Section 4 gives details of the empirical model and section 5 presents the main findings. The last section is devoted to summarizing the main findings and discussing the policy implications.

2. DATA AND VARIABLES

In this section we explain the data and variables that we use to estimate the determinants of manufacturing employment across Spanish regions. We consider all Spanish regions with some exceptions. We exclude the Islands (Balearic and Canary) and the two regions in the North of Africa (Ceuta and Melilla) because we would not be able to assess the impact of surface transportation modes in these regions. Data for all variables is available for the period 1995-2008.

The dependent variable in our empirical analysis is the total amount of employees in the manufacturing sector in Spanish provinces (*manufacturing_employment*). The information for this variable was obtained from Spain's Institute of Statistics (INE). These data are available at the province level (NUTS 3). We consider the following explanatory variables:

1) *Motorways_density*: The variable of motorways considers the density of motorways in terms of kilometers per square meters. These data were obtained from the European Database (Eurostat) and are available at the regional level (NUTS 2).

2) *Railways_density*: The variable of railways considers the density of railways infrastructure measured by kilometers of tracks per square meters. These data were also obtained from Eurostat at the NUTS 2 level.

3) *Port_traffic*: The variable of port traffic considers the total amount of traffic of each Port Authority aggregate by province and it is expressed in tones.[2] Given the heterogeneity of traffic that can be found in a port, we not only consider the aggregate amount of port traffic but also the magnitude of different types of port traffic. In particular, we consider the general non-containerized traffic, containers, solid bulk and liquid bulk. Data on port traffic were taken from the historical series provided by the Ministry of Transport.

4) *Potential_market*: We consider the variable of population that is available at the provincial level (NUTS 3) and is provided by the Spain's Institute of Statistics (INE). Using data of population and distance across provinces, we construct the variable of potential market that is measured through the weighted sum of population of all provinces, including

[2]The ports of Almeria and Motril (in Granada province) were managed by a joint port authority until 2002. To assign traffic to each province when they were managed by a joint port authority, we calculate the relative weight of traffic in each port when they have been managed on a separate basis.

the border regions of Portugal and France. [3] Weights are based on the distance from the main city of each province to the main cities of the rest of provinces. The distance data of all capital provinces is collected from Google maps and measured by kilometers.

5) *Education*: The variable of education takes into account the percentage of people with secondary level of education respect to total working age population. Data for this variable were taken from the Instituto Valenciano de InvestigacionesEconómicas (IVIE).

Previous studies about spatial spillovers from transport infrastructures use generally monetary values of the stock of capital, while here we use physical indicators (number of kilometers of highways and railways, and port traffic measured by tones of goods). Another difference with previous studies is that the dependent variable refers to the employment in a particular sector, while other studies focus on gross domestic product or costs. Hence, our more disaggregated approach may complement results from previous empirical literature about spatial spillovers from transport infrastructures. Note that the use of physical measures may capture more appropriately the services provided by the infrastructures as long as the stock of capital is essentially an indicator of construction costs. It is also worth mentioning that we examine spatial spillovers from network modes (ie; trains and roads) but also from punctual modes (ie; ports). In this sense, container traffic is characterized by a smooth transfer from the port to surface transportation modes. Hence, we will provide new insights about spatial spillovers for transport services that rely on good intermodal connections.

Table 1 shows the descriptive statistics of the variables used in the empirical analysis, while figure 1 depicts the regional allocation of employment in the manufacturing industry.[4]

INSERT TABLE 1

Concerning the geographical distribution of employment on the manufacturing sector, the difference between coastal areas and interior areas is high. On the one hand, there are twelve regions (nine situated in the coast and three located in the interior) that present the highest values of the total employment in manufacturing industry, so in these regions we found more than a half of total employment in manufacture sector. We can group these regions in three different areas: Mediterranean Coast, Ebro Valley and Madrid. On the

[3]We take into account the border regions in Spain. We consider the interior regions of Portugal: Minho-Lima; Cávado; Douro; Alto Trasos Montes; Beira Interior Norte; Beira Interior Sul; Alto Alentejo; Alentejo Central; BaixoAlentejo; Algarve. In the case of France, we consider: Pyrénées Atlantiques; Hautes-Pyrénées; Haute-Garonne; Ariège; Pyrénées-Orientales.

[4]The Stata software provide us the map of the distribution of employment manufacturing industry by quantile measure and grouped in four different intervals of values.

other hand, the regions that present smaller values are located in the interior of the country, with the exception of Madrid.

INSERT FIGURE 1

Concerning the infrastructure variables, the geographical distribution of network modes (ie; railways and motorways) is quite similar. In this regard, one of the main objectives of transport policies in Spain has been to improve the connections between the capital and periphery regions (Albalate at al., 2012). Hence, the region of Madrid enjoys the highest density of motorways and railways in Spain. In contrast, the main ports are generally located in the Mediterranean Coast.

3. THE EMPIRICAL STRATEGY

In this section we explain the different econometric techniques that we use to estimate the determinants of employment in the manufacturing sector. We use two different econometric approaches in our empirical analysis. First, we make regressions with standard panel data techniques that do not consider the spatial interaction between provinces but take into account the heterogeneity across regions not captured by the explanatory variables. Given that the spatial spillovers between provinces may be especially relevant in the context of our research, we also estimate a spatial panel data model with spatial fixed effects and spatially lagged dependent variable.[5]

Hence, we first estimate a Fixed Effects model with two different specifications. In the first one, we consider that all explanatory variables are exogenous. In the second, we apply an instrumental variables procedure that take into account the potential endogeneity of the port traffic variable. Then, we estimate a Spatial Durbin Model with two different specifications as well. We use a binary contiguity weight matrix and an inverse distance weight matrix. In the case of the spatial estimation, we consider different variables for the port traffic variable; the total amount of port traffic and different types of port traffic.

[5]We have also made dynamic regressions with the GMM estimator. The results are disappointing because the only significant variable is the lag of the endogenous variable and the variable of motorways. One possible explanation is that the sample does not have enough time variability to identify relevant effects of the growth rates. Note also that a disadvantage of GMM is that it does not capture the heterogeneity between regions and, more importantly, it does not allow identifying the spatial effects that is one of the main objectives of our analysis.

The estimates can present heteroscedasticity, non-stationarity and temporal autocorrelation problems in the error term. We have applied different tests in order to use the appropriate error terms. The Augmented Dickey-Fuller test indicates that the dependent variable does not contain a unit root and hence we confirm that there is no long-term co-integration relationship. The Wooldridge test for autocorrelation in panel data claims that we may have a problem of serial autocorrelation that must be treated so that we apply clusters in the error term to deal with serial autocorrelation. Note also that we make our estimations with standard errors that are robust to heterocedasticity. Finally, we include year dummies in all the regressions.

- **Model 1: No spatial effects**

In the fixed effects regressions, the equation to estimate for the corresponding province *i* in year *t* is as follow:

$$Manufacturing\_Employment_{it} = \beta_0 + \beta_1 Motorways\_density_{it} + \beta_2 Railways\_density_{it} + \beta_3 Port\_Traffic_{it} + \beta_4 Market\_Potential_{it} + \beta_5 education_{it} + \mu'_t + \varepsilon_{it} \quad (1)$$

Overall, we expect a positive sign in the coefficient associated to all explanatory variables. A better endowment of network infrastructures (ie. motorways and railways) in a province may imply a reduction in transportation costs for firms and an increased accessibility for territories. Both factors may allow attracting new manufacturing firms and promoting the expansion of activities of those firms already established in the province. The port traffic variable has to do with international accessibility so that both exports and imports may be cheaper for local firms.

Employment in manufacturing activities should also be higher in provinces with higher market potential as long as the exploitation of scale economies may be easier and transportation costs lower. As the analysis is done at the province level we do not expect to find a centrifugal effect related with congestion because this effect could be just relevant when analyzing the location of manufacturing firms within the province. Furthermore, the availability of skilled workers can also affect positively the amount of manufacturing employment in a province.

There are various techniques and estimation models available for estimating equations with panel data. An advantage of the fixed effects model is that it allows controlling for any omitted variable which is correlated with the variables of interest and does not change over time. However, the fixed effects model only considers the within variation of data. The advantage of the random effects model is that it considers the within and between variation of data so it is more efficient than the fixed effects model. The disadvantage of this latter technique is that the random effects could be correlated with the explanatory variables so that the estimation could not be consistent. The Hausman test shows that systematic differences between the random and fixed effects are found and thus the fixed effects model should be preferred to the random effects model

We also take into account the possibility that some endogenous explanatory variables might bias the estimations. This may be particularly the case of transport infrastructures. The endogeneity problem should not be a concern in the case of network modes because they have a strong inertia as data it is included in terms of number of kilometers per square meter. Note also that investments in network modes in Spain have focused the attention on passengers rather than on freight (Albalate et al., 2012, 2013) and more generally it is sensible to argue that the manufacturing sector activity is unlikely to driven policy decisions across regions (Cohen and Morrison, 2003).

However, a potential simultaneous determination may be taken place between port traffic and employment in the industry sector. In order to deal with this possible endogeneity issue, we estimate the fixed effects model with an instrumental variables procedure in which the instruments of the variable of port traffic are one, two and three lags of this variable.

- **Model II: Spatial effects**

In the Spatial Durbin regressions, the equation to estimate for the corresponding province *i* in year *t* is as follow:

$$\text{Manufacturing\_Employment}_{it} = \alpha_0 + \alpha_1 W{*}\text{Manufacturing\_Employment}_{it} + \\ + \alpha_2\text{Motorways\_density}_{it} + \alpha_3\text{Railways\_density}_{it} + \alpha_4\text{Port\_Traffic}_{it} + \alpha_5\text{Potential\_Market}_{it} + \\ \alpha_6\text{education}_{it} + \alpha_7 W{*}\text{Motorways\_density}_{it} + \alpha_8 W{*}\text{Railways\_density}_{it} + \alpha_9 W{*}\text{Port\_Traffic}_{it} + \\ \alpha_{10} W{*}\text{Potential\_Market}_{it} + \alpha_{11} W{*}\text{education}_{it} + \mu'_t + \varepsilon_{it} \qquad (2)$$

The difference between equation (1) and equation (2) is that the latter includes the spatial lag of the dependent variable (W*Y) and the spatial lag of explanatory variables (W*X) where W (N x N) is a spatial weight matrix which defines dependence across N regions.[6] The Spatial Durbin Model takes into account how the variation in the explanatory

[6] According to Hughes (2011), when the number of time period is high (T≥10), it is reasonable estimate a model with a spatially lagged dependent variable. In our case, the number of time periods is 14.

variable for a single region can affect the dependent variable in all other regions, through the introduction of these additional spatial variables.

To calculate the spatial interaction effects, we estimate a spatial panel data model with the Maximum Likelihood method.[7] Firstly, we estimate a spatial and time period fixed effects in order to test the hypothesis if the Spatial Durbin model can be simplified to the spatial error model or to the spatial lag model. For doing that, we consider the results from Wald and LR tests. Secondly, we estimate a spatial and time-period fixed effects with bias-corrected and a Random spatial effect in order to calculate the Hausman's specification test to analyze the random effects model against the fixed effects model. Results of all these tests confirm that the most suitable model is the Spatial Durbin Model with spatial and time period fixed effects. (Elhorst, 2012a, 2012b)

A key aspect of spatial econometric models is to specify the spatial weight matrix (W). The W is a positive (N x N) matrix that describes the structure of dependence between units in the sample and where the weight (w_{ij}) reflects the link between two units (i and j) (Elhorst and Halleck-Vega, forthcoming). Anselin (1988) considers that the elements of the weight matrix are non-stochastic and exogenous to the model. Thus, an advantage of specifying the matrix W based on location is that the elements are exogenous (Elhorst and Vega, forthcoming).[8]

In our analysis we consider two different weight matrices. On the one hand, we consider a binary contiguity matrix (W_1) with elements w_{ij}=1 whether two units share a common border and w_{ij}=0 otherwise. On the other hand, we construct an inverse distance matrix of capital Spanish provinces in kilometers. In our analysis, and in order to estimate a spatial panel data model, we assume that spatial weight matrices (W) are constant over time; and also that our panel is balanced (Elhorst, 2010).

Concerning the interpretation of the coefficients, the direct effects are the coefficient estimates of the non-spatial variables and the spillover effects are those associated with the

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[7] In general in the literature of spatial econometrics, we can distinguish three different types of interaction effects: The endogenous interaction effects among the dependent variable, the exogenous interaction effects among the explanatory variables, and the interaction effects among the error terms. The Spatial Durbin Model includes a spatially lagged dependent variable and spatially lagged explanatory variables; i.e. endogenous and exogenous interaction effects. Elhorst (2010) and LeSage and Pace (2009) consider that the Spatial Durbin Model is generally the most suitable specification to take into account the spatial effects.

[8] There exist different specifications. The most common are spatial weight matrix based on physical contiguity, i.e. when the regions share borders, and spatial weight matrix based on geographic distance between regions. There are others spatial weight matrixes based on similar economic characteristics between regions (for example, income levels) or spatial weight matrixes based on trade relationships between regions.

spatially lagged explanatory variables. A change in a single observation (region) associated with any given explanatory variable will affect the region itself (a direct impact) and potentially affect all other regions indirectly (an indirect impact).

The expected results for the direct effects are the same as those that we should obtain in the model without spatial effects. This being said, the value of the coefficients could be different as it is suggested by Cohen (2010).

The expected sign of the coefficient associated to the spatially lagged dependent variable is, a priori, unclear. A high level of employment in the manufacturing sector in one region may have positive effects on nearby regions because the closest locations will take benefit from an easier access to suppliers and specialized employees. However, regions with high levels of employment in the manufacturing industry may take benefit from the exploitation of agglomeration economies so that they draw employees from the less productive regions.

It is not clear a priori either the expected direction of the indirect effect of network modes. On the one hand, we may find a positive indirect effect because the increased connectivity of improved highways and rails goes beyond the region where they are located. However, we may also find a negative indirect effect because the region with better infrastructures may attract employees from other regions. Similarly, regions close to "port regions" may take advantage of an easier access to goods produced in distant markets but those "port regions" may also draw employees from regions with no port activities. The magnitude of the spatial spillover effects could be higher for container traffic due to the greater opportunities of type of traffic for multi-modal combinations. Finally, the indirect effect for the variable of potential market is expected to be positive due to the benefits related to the proximity to dense markets in terms of transport costs.

4. RESULTS

Table 2 shows the results of the regressions. The first column shows results of Fixed effect estimation (FE) and the second column shows the results of Fixed effect estimation with Instrumental Variables. Furthermore, the last two columns shows the result of the Spatial Durbin Model, where the third column present the results considering contiguity relationship between regions and the last column shows the results when we consider the distance between regions.[9] Respect to these last two columns, the first five rows describes

[9] As we observe in the spatial lag and spatial error model, when we take the Likelihood Ratio (LR(test and the Wald Test we reject both test and in consequence, the Spatial Durbin Model is considered the one that best describes the data (Elhorst, 2012).

the direct effect of the variable inside the region. And, from sixth row to eleventh row we observe the spatial interaction, i.e. how the neighbors affect in other territory. The explanatory capacity of the estimated models is quite satisfactory with a high R^2.

INSERT TABLE 2

The following conclusions can be drawn from our findings. First, we find evidence that motorways influence positively on industrial employment. Indeed, the coefficient associated to this variable is positive and statistically significant at the 1% level in all the regressions. Note that the value of the coefficient is much higher when we take into account the spatial effects. The elasticities obtained from the estimates are about 7% or higher.

In contrast, we do not find clear evidence that railways influence positively on regional employment in the manufacturing sector. The coefficient associated to this variable is positive but not statistically significant in any of the regressions made. Again, the value of the coefficient is much higher when we take into account the spatial effects. The elasticities obtained from the estimates are about 2% or higher.

A possible interpretation of results for the railways variable has to do with the transport policies applied in Spain since the nineties. Investments in rails have focused on the development of the high-speed rail network which in Spain has been designed in a way that it is hardly compatible with freight. Hence, Spain's freight rail transport presents one of the lowest shares in Europe (Albalate et al., 2013).

Furthermore, our analysis shows that the employment in the manufacturing sector is higher in regions with larger ports. The coefficient associated with the port traffic variable is positive and statistically significant in all the regressions, although the statistical significance in the fixed effects regressions with no instrumental variables is just at the 10% level. The elasticities obtained from the estimates are about 3%, which in relative terms are higher than those obtained for railways and motorways because it is easier to increase port traffic than kilometers of roads or railways. Interestingly, the value of the coefficient is slightly lower when we take into account the spatial effects in contrast of what we have found in the network modes variables.

Note that the value of the coefficient of the port traffic variable is almost identical in both fixed effects regressions regardless an instrumental variable procedure is applied or not. Hence, the potential endogeneity between employment in the manufacturing sector and port traffic do not seem to be troublesome from a statistical point of view. Thus, the regressions with spatial effects assume that the port traffic variable is exogenous.

As expected, the coefficient associated to the variable of potential market is positive and statistically significant in all the regressions. On the contrary, the effect of the variable of education is also positive but not statistically significant. A possible interpretation of the result for this variable is that differences in the education levels across regions within the same country could not be enough high to report statistical significant effects. This does not mean that the availability of skilled employees is not having an influence on the amount of employment but it could have a modest effect on the distribution of such employment across regions.

Recall that the spatial lagged variables show the indirect effects of the explanatory variables in the sense that changes in the value of those explanatory variables will have an effect on other regions and this effect will be higher the closer geographically these regions are.

The coefficient associated to the spatially lagged dependent variable is negative although it is only statistically significant at the 10% level when we use the spatial weight matrix with distances. This result could be interpreted as evidence of concentration of industrial activities in some regions due to the exploitation of agglomeration economies. Indeed, agglomeration economies may have some effect in the location of industrial employment across nearby regions. However, it should be recognized that the geographical level of the analysis should be more disaggregated in order to capture in a more precise way the effect of such economies on industrial employment.

Importantly, the coefficient associated to the spatially lagged motorways variable is negative and statistically significant at the 1% level regardless the spatial weight matrix that we use. Hence, a good endowment of motorways in one region has a negative effect on the employment in the manufacturing sector in other nearby regions. In comparison to the direct effect, the magnitude of the indirect effect is very high although it seems to be more plausible in the regression that uses the binary contiguity matrix. Thus, we find evidence that the negative effect related with the migration of employees to more productive regions is stronger than the positive effect related with the improved connectivity of the less productive regions. This result is in line of that obtained by Holl (2004) who analyzes the impact of road transport infrastructure on the location of manufacturing establishments using micro-level data. She finds that the benefits from road improvements are concentrated near the new infrastructure.

Similarly, the coefficient associated to the spatially lagged port traffic variable is negative and statistically significant although in the regression that use the distance weight matrix the statistical significance is just at the 10% level. The magnitude of the indirect effect is also very high when we make the comparison with the direct effect. From our results, it seems that the positive externalities of port activities tend to be concentrated in the region where the port is located.

We also find that the coefficient associated to the spatially lagged railways variable is positive and it is statistically significant at the 10% level in the regression that uses the weight matrix with distances. This is in contrast with the non-statistical significance of the direct effect of the railways variable. Overall, we do not find a clear effect of railways on industrial employment even taking into account the positive indirect effect in the regression that use the spatial weight matrix with distances.

As expected, we find that the coefficient associated to the spatially lagged potential market variable is positive and statistically significant at the 5% regardless the weight matrix used. A region seems to take advantage of being located close to other populated regions so that it may gain cheap access to large markets. It is also not surprising not finding statistically significant spatial effects of the education variable.

Table 3 shows the results of the estimation when we make the distinction between different types of port traffic. In these regressions, we only report results of the spatial regressions for the port traffic variables. The first two columns show the Spatial Durbin Model with a weight matrix for contiguity regions. And the third and fourth column shows the Spatial Durbin Model with a weight matrix for distance between regions. In both tables we take into account the influence on total traffic on employment industry (first row), the general traffic (second row) and container traffic (third row). Finally, the last two rows show the results with solid bulk (fourth row) and liquid bulk (fifth row).

Results for the direct effects are similar regardless of the spatial weight matrix used. The impact of the general (non-containerized) traffic is much higher than that obtained when we focus on the total amount of traffic, while the impact of the container traffic is quite similar as in the regression that focus on the total amount of traffic. In this regard, note that a high and increasing proportion of total goods moved in a port use containers. In contrast, we do not find a positive direct effect of bulk traffic in line of the results obtained by Botasso (2013).

Regarding the indirect effect, we focus the attention on the two categories of port traffic that have a relevant positive direct effect. In this regard, the indirect effect of the general (non-containerized) traffic do not seem to be relevant while the indirect effect of the container traffic is negative and statistically significant at the 5% level in the regression that uses the binary contiguity spatial matrix. Note that one important characteristic of container traffic is that it can be easily moved by trucks and trains. Given the good intermodal transportation options that containers provide to shippers, this type of traffic does not necessarily have the region where the port is located as final destination. In contrast, the general (non-containerized) traffic has more frequently the region where the port is located as the final destination. This may explain that the indirect effect is negative and statistically significant (at least in the regression with the binary contiguity spatial matrix) for the container traffic but it is not relevant for the general (non-containerized traffic).

Overall, we find that the employment in the manufacturing sector in a region is positively affected by the availability of good infrastructures (motorways, ports) and the proximity to large markets. Results of our analysis are in line of those obtained by Bottasso et al. (2013) and Ferrari et al (2010) concerning ports, while we find stronger positive effects for motorways than those obtained by Jiwattanakulpaisarn et al. (2009). In any case, the geographical unit of observation and the econometric techniques may condition the results of estimates. In contrast to previous studies on employment equations, our focus is on the spatial effects of infrastructures across nearby regions.

Concerning the spatial spillover effects, results of our analysis suggest that the negative indirect effect related with the agglomeration of activities in the region with better infrastructures is stronger than the positive effect related with the improved connectivity between nearby regions. These results are in line of those obtained in previous studies that consider spatial spillovers by examining the relationship between output and investments (Boarnet, 1988; Holtz-Eakin and Schwartz, 1995; Kelejian and Robinson, 1997; Moreno and López-Bazo, 2007).

An important difference with these previous works is that we not only consider network infrastructures like roads but also single facilities like ports. In this regard, we find similar results for roads and port traffic (particularly container traffic). A plausible explanation of finding similar results for roads and container traffic is that containers are moved through multi-modal combinations including maritime and surface transportation modes.

INSERT TABLE 3

5. CONCLUSIONS

In this paper, we have found that the endowment of transport infrastructures has a relevant influence on the employment in the manufacturing sector. The density of motorways and the amount of port traffic (particularly general and containerized traffic) have a positive and statistically significant impact, while we do not find a clear effect of the density of railways. The proximity to large markets (measured by population) is also a major determinant of the employment in the manufacturing sector.

Furthermore, we have found evidence of negative spillovers from transport infrastructures. Indeed, better infrastructures in a region do not seem to imply an advantage for neighboring locations. Hence, results of our analysis suggest that industrial activities tend to be concentrated in those regions that are more attractive for manufacturing firms. These regions are characterized by being close to large cities, close to waterways and with a high-density of motorways.

Results of our analysis also suggest that the econometric technique employed have a relevant influence on the estimated impact of transport infrastructures. In our case, it seems that the use of spatial econometric techniques increase the magnitude of the coefficients for network facilities (ie. motorways, railways), while it reduces the magnitude of the coefficient for single facilities (i.e; ports).

Note also that the geographical unit of observation may also have an influence on the results. The use of more or less aggregated geographical units is usually conditioned by the availability of data. In our case, one limitation of our analysis is that the dependent variable is at the Nuts-III, while the network modes variables are at the Nuts-II. This being said, the use of different spatial weight matrixes may help to identify any potential distortion of the different geographical level of analysis of the dependent and some explanatory variables.

To conclude, a priority of transport policies in Spain and many other countries has been reducing the differences in the income levels across regions. Promoting the regional convergence is also one of the main objectives of policies implemented by the European Union. From our analysis, these policies must take into account the negative spatial spillovers from transport infrastructures as long as these spillovers may create difficulties in achieving such regional convergence.

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TABLES AND FIGURES

Table 1. Descriptive statistics of variables

Variable	Obs	Mean	Std.Dev.	Min	Max
Employment Industry	658	60.63	95.69	4.8	626.7
Motorways	727	0.023	0.015	0	0.09
Railways	727	0.028	0.012	0.02	0.09
Port Traffic	797	0.60	1.194	0	7.6
Potential Market	731	0.91	1.001	0	6.3
Education	727	4.16	1.992	0	11.5

Figure 1. Distribution of manufacturing employment (NUTS-3)

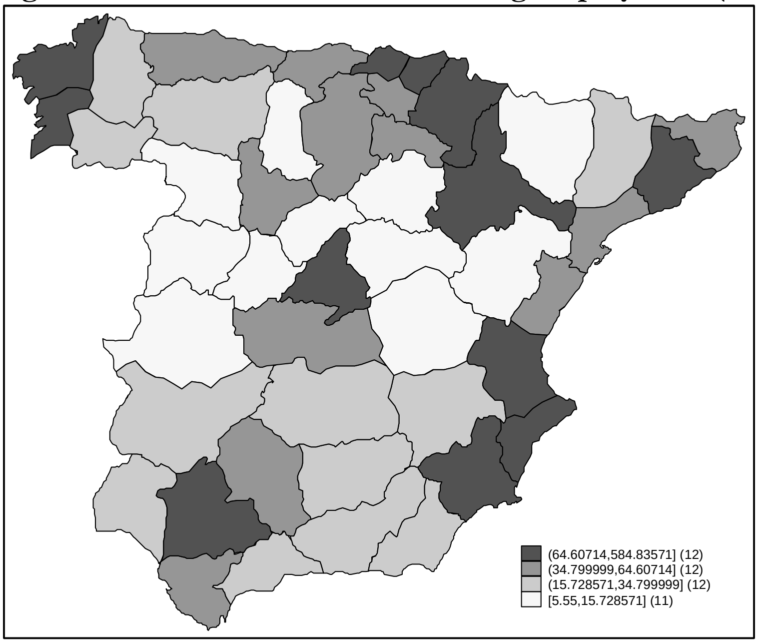

Table 2. Results of estimates of the employment equation

	DEPENDENT VARIABLE: Manufacturing_Employment			
EXPLANATORY VARIABLES	Fixed Effects	Fixed Effects-IV	Spatial Durbin Model (W -Contiguity)	Spatial Durbin Model (W-Distance)
Motorways_density	232.8*** (4.25)	232.7*** (3.84)	879.461*** (8.479)	829.363*** (8.761)
Railways_density	67.87 (1.33)	68.08 (1.19)	127.446 (1.347)	99.717 (1.189)
Port_Traffic	4.077* (1.83)	4.079*** (4.66)	3.084*** (3.462)	3.092*** (3.415)
Potential_ Market	17.56*** (2.85)	17.64*** (4.65)	11.419** (2.464)	11.945*** (2.681)
Education	0.199 (1.27)	0.203 (1.09)	0.271 (1.393)	0.275 (1.407)
Constant	28.73*** (4.18)	28.72*** (7.95)	-	-
W* Manufacturing_Employment	-		-0.018 (-0.327)	-0.273* (-1.604)
W*Motorways	-		-688.098*** (-4.147)	-2098.638*** (-3.739)
W*Railways	-		104.907 (0.668)	795.605* (1.772)
W*Port_Traffic	-		-6.453*** (-3.326)	-15.489* (-1.877)
W*Potential Market	-		24.245** (2.456)	72.708** (2.545)
W*Education	-		-0.030 (-0.074)	-0.702 (-0.433)
Time specific effects Spatial specific effects	Yes No	Yes No	Yes Yes	Yes Yes
Wald Test Spatial Lag	-		37.45 (p=0.000)	33.14 (p=0.000)
LR test spatial Lag	-		37.42 (p=0.000)	32.36 (p=0.000)
Wald Test Spatial Error	-		38.79 (p=0.000)	34.40 (p=0.000)
LR test spatial Error	-		37.81 (p=0.000)	34.20 (p=0.000)
p-hausman			0.0001	0.0112
Observations R-squared Test joint significance	658 0.778 11.15	656 0.778 55566.01	658 0.995	658 0.995

Note 1: t-statistics in brackets “robust to heteroscedasticity and cluster by province”

Note 2: Statistical significance at 1%(***), 5%(**), 10% (*).

Table 3. Results of estimates of the employment equations (with different categories of port traffic)

	Spatial Durbin Model (Contiguity)		Spatial Durbin Model (Distance)	
Explanatory variables (port traffic)	**Direct Effect**	**Indirect Effect**	**Direct Effect**	**Indirect Effect**
Total	3.085*** (3.462)	-6.453*** (-3.326)	3.093*** (3.415)	-15.489* (-1.877)
General	52.564*** (7.755)	-16.974 (-1.172)	51.613*** (7.629)	9.175 (0.184)
Container	3.337*** (2.578)	-7.122** (2.379)	3.409** (2.524)	-11.804 (-0.857)
Solid Bulk	-7.161* (-1.76)	7.662 (0.819)	-7.306* (-1.789)	58.926 (1.451)
Liquid Bulk	3.056 (1.308)	-24.085*** (-5.151)	-0.128 (-0.051)	-109.252*** (-4.664)

Note 1: t-statistics in brackets.
Note 2: Statistical significance at 1 %(***), 5 %(**), 10% (*)