MATCHING FRONTIERS: A RANDOM PARAMETER MODEL APPROACH

José F. Baños*; Ana Rodríguez Álvarez*, Patricia Suárez*

* *Department of Economics, Oviedo Efficiency Group, University of Oviedo*.

Abstract

This paper models the efficiency of labour offices belonging to the Public Employment services (PESs) in Spain using a stochastic matching frontier approach. With this aim in mind, we apply the random parameter model approach (Greene, 2005) in order to control for observed and unobserved heterogeneity. Results indicate that when we analyse the goodness of fit of the estimates we found that it improves by controlling both, observed and unobserved heterogeneity in the inefficiency term. Also, results suggest that counsellors improve the productivity of labour offices and that, the share of unemployed skilled persons, unemployed persons aged 44 or younger, as well as the share of unemployed persons in the construction sector, all affect the technical efficiency of PESs offices.

Key words: labour offices, matching functions, technical efficiency, observed and unobserved heterogeneity, jobseekers.

JEL classification: J24, J45; J64.

1. INTRODUCTION

In all European countries, public employment services (PESs) are the authorities that connect jobseekers with employers. Although the governance of PESs is different in each country, the aim of all PESs is to improve the matching of supply and demand within the labour market through information, placement and the provision of active support services. With regard to the Spanish case, the dramatic growth of unemployment in Spain has resulted in reforms of labour market policies and new labour market programmes. According to Eurostat, in 2013, the expenditure of total labour market programmes, including labour market services amounted to 5.260 billion euros.

The upward trend in registered unemployment in Spain has affected the PESs capacity and the quality of the services offered since the recession of 2008. It is worth emphasizing that the highest priorities of PESs were as expected the long-term unemployed and recipients of unemployment benefits. Consequently, the best candidates to meet the offer's requirement were seldom chosen, whereas unemployed workers not suitable for the offered jobs were often selected for the position. These practices led to the loss of trust in the PESs offices as an intermediary. Thus, when in 1994 the obligation to request workers from the PESs to fill vacancies was terminated, companies stopped using the PESs. Furthermore, employers work with the PESs when their aim is to hire members of groups on a subsidised basis. In this context, evidence suggests that the PESs can act in two ways. On the one hand, PESs can simply manage the hiring of a person who was previously selected by an entrepreneur; on the other hand, they can themselves conduct a real selection of the unemployed worker. Because of this, and regardless of the fact that the process of demand and supply adjustment is not entirely representative, evaluation of the activity of the PESs offices is a key factor for understanding the efficiency of the employment offices.

This paper proposes throwing more light upon the work undertaken by the PESs offices in the process of matching supply and demand in the labour market. In particular, we wish to explore whether all labour offices have or not the same level of efficiency, taking into consideration that they operate under particular circumstances. With this object, we propose to estimate a matching function.

Matching functions represents the flow of new jobs as a function, among others, of the job searchers and the number of vacancies (see for example, Blanchard and Diamond, 1989; Pissarides 1990 or Petrolongo and Pissarides (2001) for a review). This kind of function can be interpreted as a production function where the output is the number of matches (flow of hirings) and the inputs are job seekers and vacancies. Because of this, and given that the idea behind the frontier models is to compare the activity of companies, a natural modelling strategy could be the comparison of several labour offices belonging to PESs in order to build a matching frontier that allows the observed activity of any office to fall short of their maximum potential level. To do this, a composite error term is included which is decomposed into two parts: a two-sided, idiosyncratic error and a non-negative one-side inefficiency component (Ibourk et al. 2004).

Warren (1991) was the first work that applied a frontier approach to matching functions using a US manufacturing sample over the period 1969-1973. However, in this pioneer study, heterogeneity was not taken into account in the one-side error component, that is, it is assumed that the error term has a constant variance. However in many cases the error term may be heteroskedastic, with a variance positively correlated with several characteristics of the observations. While the consequences of heteroskedasticity are not particularly severe in an OLS model (estimators are unbiased and consistent, although they are not efficient), the heteroskedasticity problem is potentially more severe in a stochastic production frontier context. Concretely, heteroskedasticity in the inefficiency term can affect inferences concerning production technology parameters as well as the parameters of either error component (Kumbhakar and Lovell, 2000).

If heterogeneity is more related to inefficiency and thus more likely to be under firms' control, then this should affect directly the one-sided error term. In this sense, heterogeneity is often modelled in the location or scale parameters of the inefficiency distribution which depend on a vector of covariates (see Kumbhakar et al., 1991; Huang and Liu (1994); Battese and Coelli, 1995 or Galán et al., 2014 for a review).

In this line, and using the Battese and Coelli (1995) model, Bodman (1999) explain labour market inefficiency for Australia during the period 1978-1997. This model was also applied in several research papers which estimated parametric matching functions: Ibourk and Perelman (2001) in order to analyse the activity of the Employment Information and Orientation Centres in Morocco for the period 1995-1997; Fahr and Sunde (2002) using data for Western Germany in the period 1980-1995; Ilmakunnas and Pesola (2003) who estimate a matching frontier using regional panel data for Finland from 1988 to 1997 ; Ibourk et al. (2004) for French data from 1990-1995 or Fahr and Sunde (2006) for Western Germany data in the period 1980-1997 who analyse, as a novelty, the spatial autocorrelation in hiring.

On the other hand, Hynninen and Lahtonen (2007) use a fixed effects model to analyse the matching of job seekers and vacant jobs using Finland data for the period 1995-2004. With the same data, Hynninen (2009) employs a true fixed-effects model in order to separate cross-sectional heterogeneity from inefficiency, and the inefficiency terms are modelled following also the Battesse and Coelli (1995) model. Finally, Němec

(2015) analyses Czech reginal labour markets for the period 1999-2014 using a fixed effect panel stochastic model.[1]

This paper continues and extends the empirical literature on matching functions in several ways. First, we follow Greene (2005) in order to present a model that explores both the observed and unobserved heterogeneity in the inefficiency component of the distribution. In this way, the model nests the previous specifications in the matching literature analysed above that capture only observed heterogeneity.

As Galán et al. (2014) point out, the literature on modelling unobserved firm characteristics in inefficiency is still scarce. Although heterogeneity in stochastic frontier models has also been studied in the Bayesian context (see Galán et al., 2014 for a review), we do not know any empirical example using a parametric approach. In this sense, this paper contributes to the empirical literature by modelling unobserved firm characteristics in the variance of the inefficiency term. Concretely, here we apply this model to explore empirically the technical efficiency of labour offices in Asturias (a province in northern Spain). As far as we know, it is the first paper that estimates a matching frontier for the Spanish case, this constituting the second contribution of our paper.

The structure of the paper is as follows. In Section 2 we contextualize and explain our proposed model. In Section 3 we present our database sourced from a Spanish sample comprising monthly panel data from 25 local labour offices in Spain during the year 2013. In Section 4 we present the empirical results. The last part is a conclusion presenting a summary of the main findings.

2. METHODOLOGY

This paper designs a matching function as a frontier. With this aim, we use an inequality formula in order to permit the differentiation of observed output in a labour office with its maximum (potential) in the following manner:

[1] It is possible to apply DEA techniques to estimate a matching frontier. See for example, Sheldon (2003) that assess the efficiency of job placement services in Switzerland in the period 1997-98 or Althin and Behrenz (2005) that analyse Swedish employment offices for the period 1992-1995.

$$M_{it} \leq Af(U_{it}, V_{it}, C_{it}, E_{it}, \beta) \tag{1}$$

Where M is the output and represents the placements or jobs filled by a worker registered in the PESs offices using as the source of this information the contracts presented by businesses to employment; A is a constant; U are the demands for employment or workers registered in the labour offices on the last working day of the current month; V is the supply or registered job vacancies registered in the labour offices by businesses the current month; β are parameters to be estimated; t is time and i are employment offices.

Moreover, in line with Sheldon (2003) or Suárez et al. (2014), it is important to understand that the work of the PESs goes beyond simple intermediation. For example, the aim of the PESs is also to offer assistance and orientation services for the unemployed. For this reason, it is important to take into account one more input called "job counsellors per unemployed". In particular, we use the number of counsellors per job seeker in each office (C_{it}).

In addition, we include in the matching frontier an environmental variable (E) in order to encompass the existence of several circumstances which are beyond the PESs offices.

In Eq. (1), M_{it} is the *observed* output and $Af(.)$ is the deterministic matching function frontier that represents the *optimal or potential output* level. By formally expressing inequality inside the model, we allow the observations to deviate from their optimal (potential) values. In order to contrast the model, we transform the inequality above into an equality (Aigner et al., 1977 and Meeusen and van den Broeck, 1977):

$$M_{it} = A\ f(.)\exp(v_{it} - u_{it}) \tag{2}$$

Where in (2) the error term has been divided into two parts: the term v_{it} is a random disturbance term included to capture the effects of statistical noise, and u_{it} allows the observed output of any office to fall short of the maximum potential output level (the negative sign meaning that all offices have to be on the frontier or below it). This potential output is determined not by the deterministic matching function frontier $Af(.)$ but by the stochastic production frontier $A\,f(.)\exp(v_{it})$. In this way, random differences (captured by v_{it}) are not confused with systematic differences between potential and observed output (captured by u_{it}).

By rearranging Eq. (2) we obtain:

$$\frac{M_{it}}{A\,f(.)exp(v_{it})} = \exp(-u_{it}) = TE \qquad (3)$$

Where exp ($-u_{it}$) indicates the difference between the potential and the observed output (for the i office in the time t). We define this difference as the Technical Efficiency Index (TE) where $0 \leq \text{TE} \leq 1$ given that $u_{i>}$ 0.

Taking logarithms of Eq. (2) we have:

$$\ln\text{M}_{it} = \beta_0 + \ln f(U_{it}, V_{it}, C_{it}, E_{it}, \beta) + v_{it} - u_{it} \qquad (4)$$

Where $\beta_0 = \ln A$ and, as we have explained above, the matching function, M_{it}, depends on the inputs U, V, C and E. Finally, v_{it} is a two-sided, idiosyncratic error assumed to be independently and identically distributed to N $(0,\sigma_v^2)$ and u_{it} is a non-negative error assumed to follow some specific independently distributed distribution[2] $N^+(\mu,\sigma_u^2)$.

However, in (4) heterogeneity is *a priori* not taken into account in the one-side error component, that is, it is assumed that the error term has a constant variance. However in many cases the error term may be heteroskedastic, with a variance positively correlated with several characteristics of the observations. Given that, as already explained, it could prove a severe issue in a stochastic frontier context, in this paper we contrast whether heteroskedasticity is present in u_{it}.

To do this, we present a model that explores both the *observed* and *unobserved* heterogeneity in the inefficiency component of the distribution. With this aim, we follow Greene (2005) who models the unobserved firm characteristics in the inefficiency term u_{it}. Concretely, the variance of the one-sided error component is modelled as an exponential function of time variant covariates. Besides, the coefficients of the observed covariates are allowed to be firm specific and vary randomly. With this in mind, we include a random parameter in the inefficiency distribution (concretely in its variance), with a view to capturing any unobserved heterogeneity. This parameter has two main characteristics (Galán et al., 2014): it can be included simultaneously with observed covariates in the inefficiency distribution in order to distinguish observed from

[2]Usually, it is assumed a half-normal, exponential, truncated normal or gamma distribution.

unobserved heterogeneity; and it can indicate whether or not observed covariates do a good job in capturing the existing heterogeneity.

Concretely, the general model proposed for the stochastic matching frontier is as follows:

$$\ln M_{it} = \ln f(U_{it}, V_{it}, C_{it}, E_{it}, \beta) + v_{it} - u_{it} \quad (5)$$

$$v_{it} \sim \text{iid}N(0, \sigma^2_v) \quad (6)$$

$$u_{it} \sim \text{iid}N^+(0, \sigma^2_u \cdot (\exp(z_i \gamma\, I_2 + \tau_i\, I_3))^2) \quad (7)$$

Where τ_i is the random parameter that captures unobserved labour office effects in the inefficiency, γ is unknown parameter to be estimated, and I_1 and I_2 are indicator variables that can take the value 0 or 1. We will estimate three different models. First, we impose $I_1=I_2=0$ in equation 7 to obtain Model I, a heterogeneity free base model. Model II assumes that the variance of the inefficiency must be expressed as a function of observed covariates z_{it} ($I_1=1$ and $I_2=0$). In addition to the observed covariates in the variance of the inefficiency, Model III considers a random parameter τ_i in order to capture information omitted by the former, and then imposes $I_1=I_2=1$.

3. Data

This paper explores empirically the technical efficiency of employment offices in Asturias (Spain). In Spain, its provision is characterised by the decentralisation of active labour market policies (ALMP), which entails that Autonomous Communities are responsible for the management and/or execution of the ALMP. Our data belongs to the 25 employment offices in Asturias (Spain) that were fully operational during the months January 2013 to December 2013, being the most recent time period with data available for our study. Our database is sourced from the 2013 *Job seekers, positions and placements statistics*. Placement statistics offer complete information because they rely on data from the files of work contracts. These statistics provide information on the offers (vacancies) registered with the Public Employment Services and whether job vacancies were eventually filled by a job seeker (Toharia and Albert, 2007; Suárez and Mayor, 2012).

In this paper we use information from the register of job seekers (those subscribed to the services), comprising offers and placements. As far as we know, this is the first time that an article uses said information for a study of employment offices in Spain. The aggregated information of each employment office from the aforementioned files (demand, offers and placements) will be used in a complementary manner together with the information derived from the microdata of persons registered in the PESs.

In order to estimate Equations (5-7) we need to define the output and the inputs of the matching function. As regards output, we model it as the placements or jobs filled by a worker registered in the PESs (M) with the source of this information being the contracts presented by businesses to employment.

As regard the inputs used, these are represented by the demands for employment or workers registered in the PESs on the last working day of every month (U) and the supply or registered job vacancies registered in the PESs by businesses (V). But as explained above we consider an important issue to take into account one more input, namely “job counsellors per unemployed”. Job seekers visit PESs offices mainly in a voluntary way if they require information about vacancies (not only the ones registered in PESs but others announced in newspapers or online) or if they wish to participate in labour active programmes. However, it is compulsory to visit PESs if they are requested to participate in labour market programmes. In order to have access to PESs services, job seekers must be registered in the public employment offices. At registration, PESs offices staff will interview job seekers to determine their labour status, their needs and career aspirations. The registered data are personal and contact details, level of education and qualifications, languages skills, professional experience, and positions requested. After the interview, PESs counsellors are able to recommend training courses, professional orientation actions or self-employment support. Because of this, we also use as input the number of counsellors per job seeker in each office (C).

We have also include the environmental variable (E) which is defined as the number of other placements not managed by the PESs but accounted for in their zone of influence. In this sense, it represents a proxy of the economic climate of the locality where the office is situated.

Moreover, we have selected several variables that might explain the variance of the inefficiency of labour offices in Asturias (Spain) given that it is possible that jobseekers may possess different and peculiar characteristics that could affect the efficiency of the PESs offices. For example, some employment offices may use labour market policy measures more intensively than others depending on the profile of their jobseekers (Cueto and Suárez, 2011).

Because of this, we have taken into account the information available in order to know how these characteristics can affect the efficiency of the PESs offices. These factors are defined as follow:[3]

z_1=share of those 44 years or younger among jobseekers;

z_2= share of unemployment in construction among jobseekers;

z_3= share of unemployed skilled workers among jobseekers.

Table 1 shows the descriptive statistics for the data. As expected, the most populated municipalities are those with the greater number of registered unemployed. Thus, the jobcentres in Gijón and Oviedo (6 of 25 jobcentres) are the largest, on average, representing more than 50% of the jobseekers, whereas 8 of 25 jobcentres, all located in non-core areas, represent fewer than 10% of the jobseekers. The total number of workers in job centres is 116; furthermore, according to the data, each labour office manages on average more than 3,900 jobseekers.

4. EMPIRICAL RESULTS

The estimation results of the selected models are summarized in Table 2. All of the input variables that are included in the frontier (except the proportion of counsellors per job seekers -variable C- in Model I) are statistically significant at the 99% level and bear the expected signs. In contrast, and according to Models II and III, our findings indicate that the intensity of counselling also increases the productivity of the employment offices. In all the models, the environmental variable E (other placements not managed by the PESs in their zone of influence) was significant and positive at the frontier which indicates that the economic climate of the locality where the office is situated improves the productivity of labour PESs offices.

[3] We have tested other job-seekers characteristics as share of males, immigrants or share of those willing to move to gain employment. However, results indicate that these variables are not relevant in our model.

It is important to note that, from the results obtained for Model III we observe that the random component is capable of capturing part of the heterogeneity of the inefficiency even though in this case that the three z_i variables (the share of unemployed persons 44 years or younger in U; the share of skilled workers in unemployment; and the share of unemployment in construction) are significant. In sum, the results obtained in Model III indicate that both observed and unobserved heterogeneity are present.

In this context, we see that when the unobserved component is included in the inefficiency distribution, the criteria for the comparison of the models improves. Figure 1 shows different information criteria that are used as selection tests to choose the preferred model: the traditional AIC and BIC and some of their variants, the modified AIC criterion (AIC3), the corrected AIC (AICc) or the consistent AIC (CAIC), which can be considered a variation of the AIC and the BIC (see Fonseca and Cardoso, 2007). All the presented criteria show an improvement in the goodness of fit of the estimates when unobserved heterogeneity is addressed in the model through a random parameter model approach (Model III).

According to these results, we focus on the results obtained from the estimation of the most efficient model (Model III). In this model, we can interpret the estimated coefficient as elasticities given that the variables used in the estimation are defined in logarithms and these variables have been divided by the geometric mean. In this sense, the number of workers registered (U variable) shows a positive and significant elasticity meaning that, as expected, a larger number of jobseekers would generate an increase in the productivity of the labour offices. Specifically, keeping constant the rest of the variables, if the U were increased by 1%, the jobs filled (M) would increase by aproximately 0.06%. Similarly, the V variable shows a positive and significant coefficient indicating that increases in the registered job vacancies also increase PESs offices output. More specifically, a potential increase in the job supply would imply an improvement in placements of 0.27%. Finally, the C variable (number of counsellors) also presents a positive elasticity indicating a direct relationship between counsellors and jobs filled. Concretely, if C variable were increased by 1%, the productivity of PESs offices would increase by aproximately 0.41%, ceteris paribus.

As regards the environmental variable (E), a larger number of other placements not managed by the PESs offices but accounted for in their zone of influence are indicative of more productive PESs offices. According to this result we can say that if E increase by 1%, labour offices productivity would rise by aproximately 0.61.

On the other hand, as already explained above, in order to explain the variance of the error term u (Equation 7), we have included a set of variables with the aim of controlling the differences between the jobseekers administered by the PESs offices. Table 2 displays the estimated coefficients. Let us recall that increases in the variance of u represent increases in the distance to the frontier (and vice versa). Results indicate that if a labour office has both, a high percentage of workers aged 44 years or younger and a high percentage of skilled workers, it reduces the distance to the matching frontier, that is to say, inefficiency decreases. In contrast, a high share of unemployed in construction significantly increases inefficiency.

As regards the technical inefficiency index, as mentioned previously and in accordance with Equation (3), from Model III we observe that the mean value of efficiency is around 87%, with little variability among the observations, except for the minimum value of 58% (Teverga). The most efficient employment offices, during the analysed period, were Gijón-Montevil (93.8%), Oviedo-G. Elorza (91.3%), Pravia (91.2%), Langreo (90.5%) and Navia (90.2%).

Table 3 shows the employment offices ranked under the different models, ordered according to the estimated efficiency. For Model III the Spearman's rank correlation with Model I is 0.77. These models differ essentially from the base model in the middle positions of the offices, preserving broadly the relative position of better and worse offices. In contrast, Model II differs widely from the base model and the Spearman's rank correlation is only 0.49.

Figure 2 confirms the result obtained in Table 2 as regards the inverse relationship between average technical efficiency indices (TE) of each employment office and unobserved inefficiency heterogeneity coefficient (τ_i).

Lastly, it is worth noting that in line with the parameters obtained with Model III, the presence of scale economies is rejected. This result indicates that the matching process exhibits decreasing returns-to-scale. In tests for returns to scale the coefficient for

Model III is 0.75.[4] Interestingly, similar results have been reported, e.g. Hynninen and Lahtonen (2007).

5. CONCLUSIONS

This paper explores empirically the technical efficiency of employment offices in Asturias, a region situated in Northern Spain. To do this, we present a model that explores both the *observed* and *unobserved* heterogeneity in the inefficiency component of the distribution. With this aim, we follow Greene (2005) who models the unobserved firm characteristics in the inefficiency term u_{it}. Concretely, the variance of the one-sided error component is modelled as an exponential function of time variant covariates. Besides, the coefficients of the observed covariates are allowed to be firm specific and vary randomly. With this in mind, we include a random parameter in the inefficiency distribution (concretely in its variance), with a view to capturing any unobserved heterogeneity. Results indicate that when both, observed and unobserved components are included in the inefficiency distribution, the criteria for the comparison of the models improves. Concretely, when we analyse the goodness of fit of the estimates we found that it improves by introducing unobserved heterogeneity. In conclusion, a random parameter model approach that takes into account both observed and unobserved heterogeneity appears to be more appropriate for our aims.

Furthermore, our analysis allows us to identify the most efficient employment offices. The results indicate that the relative technical efficiency of the employment offices is an acceptable level (87% on average). Moreover, with respect to the relationship between vacancies, jobseekers and placements, we find a positive and significant effect. As we explained above, the intensity of counselling in terms of number of counsellors per unemployed person increases the productivity within PESs offices. Consequently, the implementation of policies by regional governments aimed at the management of human resources at the labour offices may serve to increase their efficiency.

[4] The $\chi^2(1)$ statistic for the hypothesis that $(\beta_{LnU} + \beta_{LnV} + \beta_{LnC}) = 1$ is 12.0643 with a p-value of 0.0051.

Therefore, the reader should not conclude that some PESs offices are useless. To the contrary, results would appear to indicate that it is the different characteristics of the jobseekers that prevent them from providing jobseekers with adequate job search assistance. In this sense, some factors such as the share of unemployed skilled workers or the share of unemployed persons aged 44 years or younger exerts a positive influence in terms of reducing the degree of inefficiency.

In addition, we have seen that the economic climate of the locality is an important factor in order to understand the PESs offices productivity. Here we observe something of a “worse-case scenario”, given that the data used for 2013, probably represents the worst year for the Spanish labour market since 2007, during which PESs offices were flooded beyond capacity by jobseekers. Because the future prospects for the economy are rather bleak and unemployment is expected to remain high, there is an urgent need for reforms to improve the job search assistance that unemployed workers receive at PESs offices.

In summary, our analysis of the efficiency of PESs offices could help policymakers to redesign labour offices. No decision should be made without first conducting an exhaustive analysis of the strengths and weaknesses of each PESs office and its environmental factors in order to improve the dismal behaviour of labour markets and alleviate the problems caused by high unemployment nationwide.

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Table 1. Descriptive statistics

Employment office	M (units)	U (persons)	V (units)	C (persons)	E (units)	z_1	z_2	z_3
ALLER	899	1,259	5	1	1,028	0.520	0.122	0.131
AVILÉS-G. ABARCA	5,496	4,247	194	6	7,445	0.558	0.140	0.217
AVILÉS-S. AGUSTÍN	9,141	7,850	304	10	12,555	0.610	0.145	0.216
C. NARCEA	1,186	1,401	59	3	1,269	0.493	0.148	0.132
C. ONÍS	1,873	1,379	27	2	3,097	0.511	0.164	0.133
GIJÓN-F. CANELLA	9,150	8,460	195	12	12,422	0.494	0.109	0.225
GIJÓN-G. MALLADA	7,202	6,723	120	8	10,100	0.511	0.113	0.263
GIJÓN-J. AUSTRIA	7,288	6,320	57	8	11,776	0.552	0.127	0.182
GIJÓN-MONTEVIL	8,458	7,088	104	5	8,959	0.577	0.141	0.181
GRADO	1,507	1,475	82	2	1,775	0.583	0.190	0.177
INFIESTO	1,852	1,640	37	2	2,861	0.543	0.149	0.138
LANGREO	7,905	8,602	165	7	9,957	0.550	0.145	0.148
LENA	1,062	1,182	47	2	991	0.551	0.172	0.180
LLANES	3,074	2,291	104	3	3,372	0.525	0.184	0.140
VALDÉS	884	854	33	1	1,073	0.558	0.180	0.193
MIERES	4,118	4,830	99	5	4,734	0.541	0.128	0.151
NAVIA	1,839	1,516	58	2	2,004	0.627	0.183	0.241
OVIEDO-ELORZA	12,894	10,636	372	10	17,023	0.535	0.115	0.276
OVIEDO-ZUBILLAGA	10,782	9,619	245	12	15,180	0.538	0.132	0.235
PRAVIA	2,007	1,874	63	3	1,973	0.573	0.151	0.175
SIERO-LUGONES	3,901	2,987	188	5	5,252	0.564	0.141	0.189
SIERO-POLA	4,774	4,534	73	3	6,620	0.580	0.143	0.217
TEVERGA	91	109	1	1	116	0.438	0.113	0.119
TINEO	680	721	55	1	911	0.576	0.129	0.138
VEGADEO	889	868	36	2	897	0.609	0.178	0.231
Asturias Mean	**4,358**	**3,939**	**109**	**4,6**	**5,736**	**0.546**	**0.135**	**0.205**
Asturias Total	**108,952**	**98,465**	**2,723**	**116**	**143,390**			

Table 2. Parameter estimates of the frontier matching function

	Model I (Base model)			*Model II (Heteroscedasticity in the inefficiency)*			*Model III (Random parameter in the inefficiency)*		
Variable	***Coeff.***		***t-ratio***	***Coeff.***		***t-ratio***	***Coeff.***		***t-ratio***
Production Frontier									
Intercept	-0.534	***	-2.90	-0.959	***	-5.45	-0.243		-1.64
ln U	0.076	***	4.52	0.059	***	4.37	0.059	***	5.21
ln V	0.347	***	8.72	0.372	***	10.26	0.275	***	8.57
ln C	-0.165		-1.50	0.751	***	4.67	0.414	***	2.73
ln E	0.578	***	16.85	0.582	***	18.84	0.611	***	20.20
Inefficiency									
Intercept (σ^2_u)				24.916	***	3.36			
z_1 (σ^2_u)				-45.927	**	-2.34	-13.224	***	-4.39
z_2 (σ^2_u)				-20.498		-0.79	10.839	**	2.25
z_3 (σ^2_u)				-21.129		-0.66	-9.216	***	-2.60
τ_i							6.981	***	6.61
$\sigma^2\tau_i$							0.667	***	4.39
σ_u	0.195			0.204			0.169		
Mean efficiency	0.846			0.941			0.871		
S.d. efficiency	0.072			0.153			0.101		
Number of observations	300			300			300		

Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 3. Efficiency rankings

Model I		*Model II*		*Model III*	
office	**Effic.**	**office**	**Effic.**	**office**	**Effic.**
GIJON-Montevil	0.897	NAVIA	0.999	GIJON-Montevil	0.938
PRAVIA	0.888	VEGADEO	0.998	OVIEDO-G. Elorza	0.913
NAVIA	0.877	AVILES-S.	0.996	PRAVIA	0.913
LENA	0.877	GRADO	0.993	LANGREO	0.905
VEGADEO	0.870	SIERO-Pola	0.992	NAVIA	0.902
LLANES	0.861	LUARCA	0.988	LENA	0.899
AVILES-G. Abarca	0.858	GIJON-Montevil	0.988	SIERO-Pola	0.899
OVIEDO-G. Elorza	0.856	PRAVIA	0.987	OVIEDO-Zubillaga	0.899
SIERO-Lugones	0.854	AVILES-G. Abarca	0.987	GIJON-F. Canella	0.897
SIERO-Pola	0.851	OVIEDO-G. Elorza	0.984	GIJON-G. Mallada	0.897
GIJON-G. Mallada	0.849	SIERO-Lugones	0.984	AVILES-G. Abarca	0.897
GIJON-F. Canella	0.848	LENA	0.983	AVILES-S.	0.896
LANGREO	0.848	OVIEDO-Zubillaga	0.980	MIERES	0.896
GRADO	0.847	TINEO	0.976	LLANES	0.890
GIJON-J. Austria	0.847	GIJON-J. Austria	0.974	GIJON-J. Austria	0.888
ALLER	0.846	LANGREO	0.968	SIERO-Lugones	0.887
MIERES	0.846	GIJON-G. Mallada	0.967	GRADO	0.877
OVIEDO-Zubillaga	0.845	LLANES	0.961	VEGADEO	0.877
AVILES-S.	0.844	INFIESTO	0.959	ALLER	0.872
CANGAS	0.844	MIERES	0.955	CANGAS	0.860
INFIESTO	0.832	GIJON-F. Canella	0.927	INFIESTO	0.857
CANGAS DE	0.820	CANGAS DE	0.919	LUARCA	0.838
LUARCA	0.817	ALLER	0.914	CANGAS DE	0.834
TINEO	0.795	CANGAS	0.871	TINEO	0.811
TEVERGA	0.763	TEVERGA	0.331	TEVERGA	0.580

Figure 1. Model selection tests

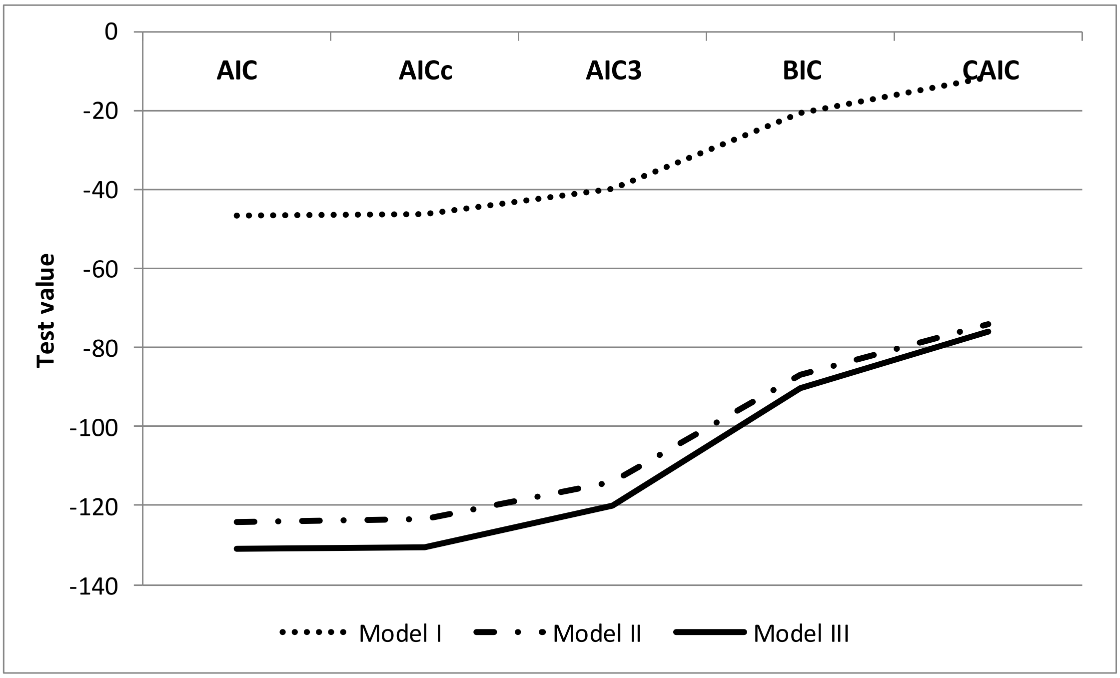

Figure 2. Relationship between τ_i and TE indices