# THE INFLUENCE OF BES TERRITORIAL INDICATORS ON ECONOMIC PERFORMANCE OF MANUFACTURING FIRMS[1]

Romana Gargano, Ferdinando Ofria

## 1. Introduction

Labour productivity is amongst the most important and influential variables governing economic production activities. In the economic literature, numerous studies have estimated the determinants of productivity growth with an ever-increasing interest both for reasons of equity and social cohesion, due to the existence of large and persistent regional productivity gaps. The argument that productivity differences can be mainly attributed to the structural transformation process (the reallocation of work between sectors) has been empirically demonstrated in several studies (Roncolato and Kucera, 2014). Increasingly, the political objective of reducing disparities by increasing the competitiveness of the least productive regions has been seen as the solution to increase productivity levels and bridge the gap between competing territories. Focusing on productivity within the sector, several studies underline the importance of factors with supply-side implications, such as social and human capital, labour costs, R&D and personal security, (Millemaci and Ofria, 2016).

The study aims to verify whether manufacturing firms (in terms of regional labour productivity) are influenced by socio-environmental context, in addition to some well-known managerial factors (such as "investments per employee", "innovation, research and creativity" and "share of exports") which, in previous studies, have highlighted a significant role in productivity discrepancies between Italian regions. The socio-environmental factors considered are homicide rate (indicator of security), minimum economic conditions (indicator of economic well-being) and the indicator of innovation, research, and creativity. These indicators belong to the 12 dimensions of equitable and sustainable well-being (BES) developed by National Institute of Statistics (ISTAT).

Much research (Ofria and David, 2014; D'Agostino and Scarlato, 2015; Bristow and Healy, 2018; Alesina et al., 2019) has shown that the presence of negative

[1] This article was conceived and prepared by all the authors; however, Romana Gargano is the author of paragraphs 2 and 3, Ferdinando Ofria wrote paragraphs 1 and 4.

externalities, related to the social and institutional variables, impact on the innovative capacity of regional economic systems. Phenomena, such as criminal organizations in areas where they are strongly rooted (Calabria, Campania, Puglia and Sicily) impedes the development of a social fabric founded on trust and sharing (Acemoglu et al. 2020). Their illegal power has spread widely in these societies and has greatly influenced the legal economy, for instance through the phenomenon of corruption, especially in those economic sectors where the government is directly or indirectly involved (Nese and Troisi, 2019; Ofria and Mucciardi, 2021). Organized crime directly produces goods and services for the following reasons: 1) money laundering; 2) territorial control (by social and political consensus), managing labour market shares in labour-intensive sectors (construction, retail, transport and services for families and businesses). Furthermore, the criminal organisation imposes protection rackets and other illegal payments on local firms (Centorrino and Ofria, 2008)

The analysis is based on ISTAT time series data 2012-2016 relating to regional labour productivity, some well-known management factors, and BES indicators. A quantile regression model allowed us to verify the differences in the effects exerted on productivity by independent variables at various quantiles, to identify that labour productivity is heterogeneous and that the relationship between labour productivity, socio-environmental context and managerial characteristics is not constant between quantiles. The empirical results provided by our analysis support the theoretical thesis that the higher the level of uncertainty due to environmental factors, the lower the labour productivity.

The paper is structured as follows: section 2 introduces the data and the methodology adopted; section 3 presents the findings. Finally, Section 4 concludes and discusses the results in the light of some considerations.

## 2. Data and Methodology

### *2.1. Data*

This paper investigates Italian labour productivity across Nomenclature of Units for territorial statistics level 2 (NUTS 2) to 2012-2016. The data used are part of the "Report on the competitiveness of the productive sectors", produced by ISTAT. For our purpose, the report provides information on labour productivity, investments per employee, share of exports (impact of the sector on the region's total manufacturing exports). Labour productivity is measured as a log of ratio of the value added (output) by number of employees (see e.g., Ahlawat and Renu, 2018 and Mundakkad, 2018).

Investments per employee is a proxy for efficiency investments (Sylos-Labini, 2004), that is, the innovative investments made in response to the growth of the relative cost of labour. For Kaldor (1967), new investments represent endogenous technical progress. The share of exports is a proxy for competitiveness. Companies that export are stimulated to increase productivity to be competitive. This incentive to be competitive drives larger companies to invest in R&D (Castellani et al., 2017).

BES indicators are useful for assessing the social and environmental progress of society. In this paper, we have used only a few BES indicators capable of providing information on economic well-being, safety and research of a given territory. Minimum economic conditions (MCE) are a composite indicator of economic well-being obtained by summarizing four indicators relating to the condition of serious material deprivation, quality of the home, economic difficulty in making ends meet and very low family work intensity. An increase in the MCE index indicates a reduction in the condition of discomfort. Innovation, research, and creativity (IRS) represents the domain with the same name and considers 3 elementary indicators: research intensity, knowledge workers and employees in creative enterprises. In the composition of this indicator, the indices that best capture social and economic progress were preferred. Homicide rate is one of the indicators that represents the domain of security. It has been standardized in such a way that its dynamics are in line with that of safety. A decrease in homicides corresponds to an increase in the standardized rate and therefore an increase in security, and vice versa. The choice of including this indicator is due to the observation that the safety of citizens is a key dimension in the construction of individual and collective well-being. The sense of insecurity of the population and the fear of being the victim of criminal acts can greatly influence the personal freedoms of each person, the quality of life and the development of the territories. The composite indices calculated for each dimension were obtained by applying Adjusted Mazziotta-Pareto Index (AMPI). It is a partially non-compensatory composite indicator based on a standardization of the individual indicators, at the reference time, that allows comparability of the data across units and over time (Mazziotta and Pareto, 2016).

### *2.2. Methodology*

Quantile regression (Buchinsky, 1998; Koenker and Hallock, 2001) estimates different conditional quantiles of the dependent variables minimizing the sum of absolute residuals. It can be specified by [1]:

$$y_{it} = \alpha + x'_{it}\beta_\tau + u_{\tau it} \tag{1}$$

for $0<\tau<1$, and with

$$Quant_\tau = (y_{it}|x_{it}) = x'_{it}\beta_\tau \tag{2}$$

where $y$ represents the dependent variable, $\mathbf{x}$ is a vector of all covariates, α is the term constant, β is the vector of parameters to be estimated and $u$ is the vector of residuals. $Quant_\tau = (y_{it}|x_{it})$ specifies the τ-th conditional quantile of y given **x**, with i=1, 2, …, 20 region and t=2012, …, 2016 years.

The τ-th regression quantile solves the following minimization problem for ρ:

$$\min(\beta)[(\textstyle\sum_{i=1}^{n} \rho_\tau(y_{it} - \beta'_\tau \mathrm{x}_{it}))] \tag{3}$$

where $\rho_\tau[\cdot]$ is the check function defined as $\rho_\tau(u\tau_{it}) = \tau u_{\tau it}$ if $u_{\tau it} \geq 0$ and otherwise $(\tau - 1)u_{\tau it}$ if $u_{\tau it} < 0$.

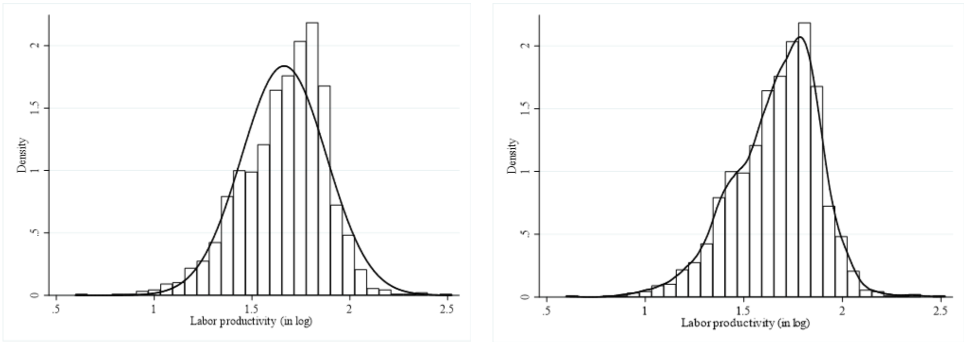
In this paper for log of labour productivity we estimated five different quantile regressions with $\tau$ = 0.1, 0.25, 0.5, 0.75 and 0.9. In addition, we addressed heteroscedasticity by means of robust standard errors. Equation 4 specifies the estimated model for our data:

$$\log(LP) = \alpha + \beta_1 \log(IL_{it-1}) + \beta_2(ER_{it}) + \beta_3(IRS_{it}) + \beta_4(MCE_{it}) + \beta_5(HR_{it}) + \varepsilon_{it} \tag{4}$$

where: LP is the labour productivity for each region *i* at time *t*; IL represents the investments per employee for each region *i* at time *t*-1; ER is a proxy for export ratio (incidence of the sector on the total manufacturing exports of the region) for each region at time *t*; IRS is the indicator of innovation, research and creativity for region *i* at time *t*; MCE is the indicator of minimum economic conditions for region *i* at time *t*; HR represents the indicator of homicide in each region *i* to the time *t*.

As summarized by Buchinsky (1998) the quantile regression provides robust estimates of the vector of coefficients, not sensitive to outliers in the values of the dependent variable; in the presence of non-normally distributed error terms, the estimators provided by the quantile regression can be more efficient than least squares estimators. Looking at different estimates for different quantiles it is possible to assess the different influence of covariates on the dependent variable, at the various points of the quantile conditioned distribution. Finally, the estimate, based on a linear combination of estimators of the various quantile regressions, is always more efficient than the estimator of the least squares. The quantile regression parameter estimates the change in a specific quantile of the response variable produced by a one-unit change in the covariate, making it possible to compare if and how covariates influence some percentiles of the dependent variable (Velucchi and Viviani 2011, Velucchi et al. 2014, Holmes et al. 2019). In this paper, we have chosen to estimate models by quantile regression for three main reasons. First, the standard least-squares assumption of normally distributed errors does not hold for this database because labour productivity in the Italian regions does not display a Gaussian distribution (Figure 1).

**Figure 1 –** *Histogram and Normal Density Plot (Panel A) and Kernel Density Plot (Panel B) of Labour Productivity (in log).*




Panel A Panel B

In addition, the quantile regressions describe all distributions of the dependent variable and do not focus on the mean (as OLS regression) and their use in the context of this study could be useful since high/low labour productivity regions are of interest for us and are not considered outliers. Finally, using this methodology and avoiding the assumption that the error terms are identically distributed it is possible to consider the regions' heterogeneity and the possibility that estimated slope parameters vary at different quantiles of the conditional distribution.

## 3. Results

Tables 1 and 2 report respectively descriptive statistics for selected variables in and the same descriptive statistics disaggregated on labour productivity quantiles. In the Appendix, in figures I-VI, we show the cartograms of the labour productivity median (in log) and of all variables considered in this study. The gap between the regions of the Centre-North and those of the South of the country in labour productivity is clear in manufacturing sectors, with the former showing better situations than the latter. There were similar results for all indicators considered.

**Table 1** – *Descriptive Statistics for Manufacturing.*

| Var. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| ln_LP | 3.755 | 0.478 | 1.380 | 5.050 |
| ln_IL | 1.502 | 0.965 | -9.210 | 4.120 |
| ER | 4.697 | 7.713 | 0.000 | 82.770 |
| HR | 102.132 | 7.425 | 72.300 | 113.800 |
| IRS | 98.407 | 9.600 | 79.300 | 124.100 |
| MEC | 95.324 | 11.061 | 65.800 | 109.100 |

**Table 2** – *Descriptive Statistics for Manufacturing by labour productivity quantiles.*

| Var. | | 10% | 25% | 50% | 75% | 90% |
|---|---|---|---|---|---|---|
| ln_PL | Mean | 3.045 | 3.300 | 3.637 | 3.950 | 4.192 |
| | *sd* | *0.064* | *0.092* | *0.100* | *0.087* | *0.059* |
| ln_IL | Mean | 0.738 | 0.854 | 1,353 | 1.721 | 2.045 |
| | *Sd* | *0.538* | *1.162* | *0.759* | *0.652* | *0.619* |
| ER | Mean | 1.935 | 2.969 | 3.780 | 5.296 | 7.312 |
| | *Sd* | *4.897* | *5.720* | *6.804* | *7.329* | *10.164* |
| HR | Mean | 96.675 | 99.219 | 102.393 | 103.342 | 103.957 |
| | *Sd* | *8.552* | *9.745* | *6.327* | *5.929* | *5.640* |
| IRS | Mean | 93.625 | 94.962 | 98.668 | 99.398 | 102.014 |
| | *Sd* | *8.090* | *8.115* | *9.851* | *9.396* | *9.382* |
| MEC | Mean | 86.304 | 89.417 | 95.515 | 97.631 | 99.241 |
| | *Sd* | *9.948* | *12.005* | *10.438* | *9.733* | *9.725* |

Table 3 reports the regression estimates for five different quantiles of the regional labour productivity distribution. Successively, in order to evaluate the importance of the differences in the quantile parameter estimates we test for the equality of coefficients between any two quantiles as well as jointly for all quantiles. The tests were performed using the F-statistic, the computation of which requires an estimate of the variance-covariance matrix of the quantile coefficients (table 4).

The results indicate that there are statistically significant differences in the coefficients and among the various quantile regression estimates for most explicative variables. In particular, the coefficient of ln(IL) (investments per employee) varies significantly from 0.176 to 0.268 as we move from the lower quantile (0.10) to the upper quantile (0.90) of the labour productivity conditional distribution. Probably reflecting the fact that the most productive regions are more sensitive to investments intensity while the less productive ones are more indifferent.

**Table 3** – *Estimation results quantile regression model.*

| | 0.10 | 0.25 | 0.50 | 0.75 | 0.90 |
|---|---|---|---|---|---|
| ln_IL | 0.176** | 0.236** | 0.264** | 0.268** | 0.225** |
| | (0.023) | (0.020) | 0.012 | 0.022 | 0.029 |
| ER | 0.008** | 0.007** | 0.008* | 0.008** | 0.006* |
| | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| HR | 0.005* | 0.010** | 0.007* | 0.004 | 0.003 |
| | 0.003 | 0.003 | 0.002 | 0.003 | 0.003 |
| IRS | 0.012** | 0.009** | 0.005** | 0.002 | -0.001 |
| | 0.003 | 0.002 | 0.001 | 0.002 | 0.002 |
| MEC | 0.010** | 0.008** | 0.009* | 0.007* | 0.007* |
| | 0.002 | 0.002 | 0.001 | 0.002 | 0.002 |
| Cons | 0.833** | 0.672* | 1.263** | 2.168** | 2.933** |
| | 0.038 | 0.270 | 0.212 | 0.255 | 0.317 |
| Pseudo $R^2$ | 0.228 | 0.279 | 0.286 | 0.221 | 0.208 |

*Note: Standard errors (SEs) in parentheses. SEs for quantile regressions are derived via bootstrap techniques for 1000 replications. Significance levels: * p<0.05, ** p<0.01.*

**Table 4** – *Test for coefficient equality between pairwise quantiles and across all quantiles.*

| Quantile Group | *ln*_IL | ER | HR | IRS | *MEC* |
|---|---|---|---|---|---|
| Panel A | | | | | |
| 0.10-0.25 | 0.002 | 0.315 | 0.126 | 0.216 | 0.160 |
| 0.10-0.50 | 0.000 | 0.848 | 0.676 | 0.006 | 0.821 |
| 0.10-0.75 | 0.001 | 0.964 | 0.986 | 0.001 | 0.296 |
| 0.10-0.90 | 0.141 | 0.180 | 0.611 | 0.000 | 0.403 |
| 0.25-0.50 | 0.083 | 0.501 | 0.231 | 0.022 | 0.160 |
| 0.25-0.75 | 0.183 | 0.426 | 0.040 | 0.004 | 0.917 |
| 0.25-0.90 | 0.720 | 0.301 | 0.049 | 0.000 | 0.867 |
| 0.50-0.75 | 0.830 | 0.842 | 0.574 | 0.054 | 0.165 |
| 0.50-0.90 | 0.127 | 0.144 | 0.041 | 0.001 | 0.351 |
| 0.75-0.90 | 0.038 | 0.074 | 0.487 | 0.082 | 0.744 |
| Panel B | | | | | |
| Joint | 0.000 | 0.315 | 0.049 | 0.000 | 0.271 |

*Note: The null hypothesis is that the coefficients are equal between pairwise quantiles (panel A) and across all quantiles (panel B). Tests statistics are based on the variance-covariance matrix of the quantile coefficients estimated and reported in table 3. The table repots the p value foe the F-values; if the p-value is less than the level of significance (0.005), the hypothesis of equal coefficients is rejected.*

The opposite picture prevails in the IRS and HR coefficients, which seem to be a more important productivity enhancing factors for the less productive areas. The exportation rate and MEC are statistically significant to estimate the regional labour productivity but not vary across quantile distribution.

It is interesting to notice that the in-between coefficient differences of HR and IRS are significant in the joint test among all five quantiles. We can interpret these results as evidence that environmental factors do not matter among the very productive regions. It is in the less- middle productivity range that these factors confirm their superior efficiency by causing a productivity shift.

## 4. Conclusions

As stated, organized crime influences the market economy in the South, influencing its development in a negative way (Calamunci and Drago, 2020). Mafia activity within legitimate markets “confuses” other competitors, as it creates barriers which prevent numerous industries from entering both production markets and work markets. In many respects, these markets are much less competitive in those regions affected by organized crime in comparison to other regions. In some extreme cases, where the mafia manages to control both the supply and demand of goods supplied by the State, the markets (both corrupt and normal markets) are suppressed and there is a hierarchic economic organization, in which those businesses outside the cartel, or those potential candidates for entry, are forced to deal with very high transaction costs. This institutional environment is a source of inefficiency and low productivity growth (Felli and Tria, 2000).

According to Centorrino and Ofria (2008), crime is interested in productive sectors that are directly or indirectly reached by State interventions, that are not very open to external competition (since they are non-tradable sectors), with high labour intensity rather than capital intensity, in such a way as to leave wider margins for money laundering, and also to guarantee some forms of social consensus, through the distribution of work opportunities.

Such circumstances discourage entrepreneurs to invest in these territories. (Detotto and Otranto, 2010, Daniele and Marani, 2011, Brown and Hibbert, 2019).

Starting from this premise, the aim of research is to examine whether some territorial indicators of equitable and sustainable well-being (BES), proxies of the socio-environmental context, can contribute to influencing the Italian regional labour productivity in manufacturing sector. As proxies for socio-environmental factors we used some equitable and sustainable well-being composite indicators that ensuring temporal and territorial comparability. The choice to use these indicators stems from the awareness that measuring well-being, also and above all, from an economic point of view, requires a multifaceted statistical approach since no single measurement can summarize the multidimensional value of something as complex as the well-being of society. By adopting quantile regression approach, we highlighted that labour productivity is heterogeneous and that the relationship between labour productivity, socioeconomic context, managerial factors, and a firm's characteristics is not constant across quantiles. In particular, the empirical answers provided by our analysis support the theoretical proposition that the higher the social and environmental well-being of a territory, the more efficient the production is. We can interpret these results as evidence that environmental factors do not matter among the regions with firms very productive. It may be that companies are negatively influenced to invest and operate in areas of the Italian territory where the population insecurity sense and the fear of being a victim of criminal acts are high. In our opinion, to increase economic performance in less productive Italian regions, it is essential to invest in safety and to improve the minimum economic condition to remove all the factors that hinder the will or the ability to invest of a firm. Furthermore, it is important to continue investing in innovation and research which has proved to be a growth factor in areas where labour productivity is lower but also in investments per employees which, on the contrary, is a factor whose importance increases as it grows productivity.

## Appendix

*Cartograms of all variables considered in Italian regions.*


*Figure I - Maps of ln(LP) median*


*Figure II - Maps of ER Median*


*Figure III - Maps of ln(IL)*


*Figure IV - Maps of HR median*


*Figure V - Maps of MEC median*


*Figure VI - Maps of IRS median*

## References

ACEMOGLU D., DE FEO G., DE LUCA G.D. 2020. Weak states: Causes and consequences of the Sicilian mafia. *The Review of Economic Studies*, Vol. 87, pp. 537-581.

AHLAWAT V., RENU. 2018. An analysis of growth and association between labour productivity and wages in Indian textile industry. *Management and Labour Studies*, Vol. 43, No. 1-2, pp. 78-87.

ALESINA A., PICCOLO S., PINOTTI P. 2019. Organized crime, violence, and politics. *The Review of Economic Studies*, Vol. 86, No. 2, pp. 457-499.

BRISTOW G., HEALY A. 2018. Innovation and regional economic resilience: an exploratory analysis. *The annals of regional science*, Vol. 60, No. 2, pp. 265-284.

BROWN L, HIBBERT K, 2019. The Incidence of crime on industry-level foreign direct investment: An assessment of OECD member countries. *Social Science Quarterly*, Vol. 100, No. 4, pp. 1228-1240.

BUCHINSKY M., 1998. Recent advances in quantile regression models: A practical guide for empirical research, *Journal of Human Resources*, Vol. 33, pp. 88-126.

CALAMUNCI F., DRAGO F. 2020. The economic impact of organized crime infiltration in the legal economy: Evidence from the judicial administration of organized crime firms. *Italian Economic Journal*, Vol. 6, pp. 275-297.

CASTELLANI D., MONTRESOR S., SCHUBERT T., VEZZANI A. 2017. Multinationality, R&D and productivity: Evidence from the top R&D investors worldwide. *International Business Review,* Vol. 26, No. 3, pp. 405-416.

CENTORRINO M., OFRIA F. 2008. Criminalità organizzata e produttività del lavoro nel Mezzogiorno: un'applicazione del "modello Kaldor-Verdoorn". *Rivista economica del Mezzogiorno,* Vol. 22, No. 1, pp. 163-188.

D'AGOSTINO G., SCARLATO M. 2015. Innovation, socio-institutional conditions and economic growth in the Italian regions. *Regional Studies,* Vol. 49, No. 9, pp. 1514-1534.

DANIELE V., MARANI U. 2011. Organized crime, the quality of local institutions and FDI in Italy: A panel data analysis. *European Journal of Political Economy,* Vol. 27, No. 1, pp. 132−142.

DETOTTO C., OTRANTO E. 2010. Does crime affect economic growth? *Kyklos,* Vol. 63, pp. 330−345.

FELLI E., TRIA G. 2000. Produttività e crimine organizzato: un'analisi delle regioni italiane, *Sviluppo Economico,* Vol. 1, pp. 79-101.

GANAU R., RODRÍGUEZ-POSE A. 2018. Industrial clusters, organized crime, and productivity growth in Italian SMEs. *Journal of Regional Science,* Vol. 58, pp. 363-385.

HOLMES M., DOAN T., HASSAN G. 2019. Does foreign investment enhance domestic manufacturing firms' labour productivity? Evidence from a quantile regression approach. *Economic Change and Restructuring*, pp. 1-18.

KALDOR N. 1967. *Causes of the slow rate of economic growth in the United Kingdom: An inaugural lecture*. Cambridge University Press. Cambridge.

KOENKER R., HALLOCK K.F. 2001. Quantile regression. *Journal of Economic Perspectives,* Vol. 15, No. 4, pp. 143-156.

MAZZIOTTA M., PARETO A. 2016. On a generalized non- compensatory composite index for measuring socio-economic phenomena. *Social Indicators Research*, Vol. 127, pp. 983–1003.

MILLEMACI E., OFRIA F. 2016. Supply and demand-side determinants of productivity growth in Italian regions. *Structural Change and Economic Dynamics,* Vol. 37, pp. 138-146.

MUNDAKKAD P. 2018. Firms' leverage and labour productivity: A quantile regression approach. *Economics Bulletin,* Vol. 38, No. 4, pp. 2331-2344.

NESE A., TROISI R. 2019. Corruption among mayors: Evidence from Italian court of cassation judgments. *Trends in Organized Crime*, Vol. 22, No. 3, pp. 298-323

OFRIA F., DAVID P. 2014. *L'economia dei beni confiscati*, Franco Angeli, Milan.

OFRIA F., MUCCIARDI M. 2021. Government failures and non-performing loans in European countries: a spatial approach, *Journal of Economic Studies*, ahead-of-print. https://doi.org/10.1108/JES-01-2021-0010

RONCOLATO L., KUCERA D. 2014. Structural drivers of productivity and employment growth: A decomposition analysis for 81 countries. *Cambridge Journal of Economics,* Vol. 38, No. 2, pp. 399-424.

SYLOS LABINI P. 2004. *Torniamo ai classici. Produttività del lavoro, progresso tecnico e sviluppo economico*. Laterza. Rome-Bari.

VELUCCHI M., VIVIANI A. 2011. Determinants of the Italian labor productivity: A quantile regression approach, *Statistica*, Vol. 71, No. 2, pp. 213-238.

VELUCCHI M., VIVIANI A., ZELI A. 2014. Italian manufacturing and service firms labor productivity: A longitudinal quantile regression analysis. *Statistica*, Vol. 74, No. 3, pp. 267-293.

**SUMMARY**

**The influence of BES territorial indicators on economic performance of manufacturing firms**

The research aims to verify whether some BES territorial indicators influence the Italian regional labour productivity in the manufacturing sector. The quantile regression approach allows us to highlight that labour productivity is heterogeneous that the relationship between labour productivity and environmental and firm's characteristics is not constant across quantiles. Our results show that labour productivity is affected by negative externalities such as the homicide rate and minimum economics conditions and that these indicators have a greater influence in regions with lower labour productivity.

Romana GARGANO, Department of Economics, rgargano@unime.it
Ferdinando OFRIA, Department of Economics, ofriaf@unime.it