Performance analysis of Italian manufacturing companies: a multilevel linear approach

Silvia Bacci – Simone Terzani

Department of Economics – University of Perugia, Via Pascoli 20 - 06123 Perugia

Phone: +39-075-5855226 Fax: +39-075-5855950

E-mail: silvia.bacci@unipg.it, simone.terzani@unipg.it

Abstract

The Italian economy is the second biggest manufacturing power in Europe, surpassed only by Germany in terms of production value. After a long decline, the manufacturing activity is experiencing a revival in many countries and its development is one of the objectives of Agenda 2020 of the European Union. This study aims to assess the major determinants affecting companies performance by using the ROA (Return On Assets) index and by distinguishing between time-varying and time-constant company characteristics. The data are drawn from a sample of 897 Italian manufacturing companies of different sizes over a ten year period, from 2001 to 2011. A multilevel approach is adopted to take into account the longitudinal structure of the data. First, the analysis is performed under the normality of random effects and, then, such restrictive assumption is removed in favour of a semi-parametric approach based on the discreteness of random effects. Results show a positive impact of valued added production and a negative impact of high leverage on firm performance. In addition, company structure and size seems to have a significant impact on firm performance. Moreover, as a result of random effects estimation, a ranking of companies is obtained, which can be synthesised through homogenous latent classes that distinguish among low-, medium-, and high- performers.

Keywords: Italy, performance, manufacturing companies, latent class model, longitudinal data, mixed model, random coefficients model
Introduction

Italy's entrepreneurial sector is dominated by manufacturing companies which form the backbone of the Italian economy. Italy is still the second biggest European manufacturing power, surpassed only by Germany in terms of production value (Eurostat, 2014). After a long decline, due to an increasing growth in the servicesector of more developed economies (Obstfeld and Rogoff, 1996; Matsuyama, 2009), manufacturing activity is experiencing a revival in many countries and has recently attracted such considerable attention from policy makers that the European Commission has set it as its goal to increase the manufacturing share of GDP from the current 16% to 20% by 2020 (European Commission, 2014).

At the same time, Italian industry primarily relies on small and medium-sized family owned firms (Monducci, 2013), which are known to be less innovative (Bugamelli et al, 2011). Anyway, an industrial make-up of this nature, which has been heavily criticized (Ciocca, 2004), is still capable of being dynamic and competitive in international markets (Castellani and Zanfei, 2007). These features of growth and dynamism, which characterize small and medium-sized Italian companies, have been object of intense debate at international level (Alvarez and Vergara, 2013; Wiklund, 1998; Wiklund et al, 2003).

In such a production scenario, however, the economic circumstances brought about by the globalization of markets further increase competitive pressure at an international level, which works to the disadvantage of localism and small sized businesses. A careful analysis of the factors contributing to the competitive success of Italian manufacturing enterprises is therefore crucial in identifying best business practices.

This study aims to assess the extent to which different determinants affect the performance of business enterprises and to clarify how Italian firms have managed to deal with changes in the business environment over the last ten years. To this purpose an analysis of the performance of Italian enterprises is conducted, and the role played by different factors - including earnings, leverage, ownership structure and business size - in influencing business performance is assessed.

A sample of 897 business enterprises operating in the Umbria Region with annual turnovers exceeding EUR 1 million is selected and examined over a ten-year period, from 2001 to 2011, involving a total of 8000 observations. Given the considerable increase in economic competition, extending the time of observationof this study to a ten-year period emphasized the importance of the time variable in business performance analysis. The manufacturing sector was the key area of focus in this study as it provided homogenous sampling, and was characteristic of both Italy and Umbria entrepreneurial economy.

In recent years, there has been an increasing amount of literature on business performance and its determinants (Banos-Caballero et al, 2014; Minichilliet al, 2010). Accounting-based and market-based performance measures are generally the most used types of performance measurement (Teodori, 2008; Ou and Penman, 1989). Hutchinson and Gul (2004) claim that accounting-based performance measures reect the results of managers' actions and are thus better than market-based measures. However, both measures are open to criticism, as the results of accounting-based measures might be manipulated through accounting policy choices (Schipper, 1989), while, in the case of market-based measures, stockvalues can be influenced by speculative bubbles. As a result, a firm's stock price might not necessarily reflect the intrinsic value of its underlying assets.

In this study the performance analysis is accounting-based. Given the small number of listed companies in Italy, using a market-based measure would have resulted in a biased analysis of the complex reality of Italian enterprises. More specifically, ROA (Return on Assets) index is used as a measure of firm performance, as operating return is the primary goal of all business ventures. Without strong economic performance the business will not survive in the long run. ROA is considered one of the most commonly used accounting metrics in the literature (Bhagat and Bolton, 2008; Randya and Goel, 2003). It has been found to be effective in measuring the operating performance of manufacturing firms, which are dominant in Italy (Goodman and Bamford, 1989).

According to the available literature (Banos-Caballero et al, 2014; Mazzola et al, 2013; Lefort and Urzua, 2008; Dezi and Del Giudice, 2014) a set of variables has been identified as relevant determinants of manufacturing companies
performance, distinguishing between variables which are company characteristics that change over time and variables which are characteristics that do not change over time.

In order to properly account for the longitudinal structure of data at issue characterized by repeated measures (or level 1 units) within companies (or level 2 units), the relationship between ROA index and the possible time-varying and time-constant determinants is modelled through a multilevel linear approach (Goldstein, 2003; Skrondal and Rabe-Hesketh, 2004; Snijders and Bosker, 2012). Indeed, in a longitudinal context, one can expect that observations of the same variable in different time points within the same subject (i.e., company) are correlated to a greater extent rather than observations referred to different subjects. Differently from classical (linear) regression models, which ignore the hierarchical structure of longitudinal data (i.e., repeated measures within subjects), multilevel models (known also as hierarchical models, mixed models, and random coefficients or random effects (RE) models) provide a useful instrument to detect the effect of each level of hierarchy on the variability of the response variable, disentangling between variability among time points and variability among companies. Such an aim is reached by introducing one or more RE in the regression model, which capture that part of response variability unexplained by the covariates and due to unobserved characteristics of companies.

Usually, RE are assumed to be normally distributed, with mean zero and constant variance. The predictions of normal RE provide a ranking of the level 2 units, which allows us to make inference on the differences between companies. However, the misspecification of the parametric distribution may have negative consequences, mainly on the predictions of the RE, when the true distribution is highly skewed (Grilli and Rampichini, 2014, and the references therein). Moreover, it has also to be taken into account that the normality assumption can be very hard to check (Verbeke and Molenberghs, 2000; Grilli and Rampichini, 2014). Alternatively to the parametric specification of the RE distribution, a semi-parametric approach based on assuming the discreteness of the RE can be also applied. In practice, one works with a multinomial distribution with a number of support points much smaller than the number of level 2 units; for an exhaustive discussion, see Skrondal and Rabe-Hesketh (2004). See also Bartolucci et al (2014) and the references therein for an exhaustive review about the debate on which approach is more appropriate, between the continuous and the discrete ones, in some specific settings, such as that for the analysis of certain types of time-series data and in the setting of models for longitudinal data with time-varying individual RE.

The discrete approach has the advantage to very satisfactorily approximate any true continuous RE distribution, given a finite number of support points (Heckman and Singer, 1984). A first consequence of this result is that the introduction of possibly inappropriate and hardly verifiable assumptions about the true distribution of the RE is not necessary any more. Besides, the assumption of discrete RE has an interesting interpretative advantage concerning the unobserved heterogeneity, due to the possibility of classifying the level 2 units into a small number of unobserved (or latent) classes (Lazarsfeld, 1950; Lazarsfeld and Henry, 1968; Goodman, 1974; Hagenaars and McCutcheon, 2002) that share common homogeneous characteristics, and this fact may be more natural or more convenient in many settings than to place them on a continuous scale (Vermunt, 2003). In this study, both parametric and semi-parametric approaches are applied and their results are then compared.

The present study makes several noteworthy contributions to the current literature. Firstly, unlike many other studies, which are mainly focused on the observation of a single variable, it analyses a large number of performance determinants of Italian firms. Secondly, it provides deeper insight into how increasing international competition and the global economic and financial crisis have affected the performance of Italian enterprises over the last ten years. Last but not least, it provides evidence for a classification of Italian business organizations based not only on a single accounting number but on a complete set of variables determining a firm's competitive success as a whole. More in detail, the companies will be classified into three latent classes, distinguishing among low-, medium, and high-performers. The present article proceeds as follows. The second paragraph is concerned with the data. The third section describes the class of multilevel linear models used in what follows. The fourth section provides the main results and some final remarks conclude the work.
The data

Data are collected from a sample of 897 Italian firms grouped into four categories according to their size (annual turnover). Given the small average size of Italian companies, firms are grouped according to the European Union's definition of micro, small and medium-sized enterprises. As defined in the European Commission Recommendation of 6 May 2003 - 2003/361/EC, Art. 2 - a microenterprise is an enterprise whose annual turnover does not exceed EUR 2 million; a small enterprise is an enterprise whose annual turnover is between EUR 2 and EUR 10 million; and medium-sized enterprises have an annual turnover not exceeding EUR 50 million. Companies characterized by an annual turnover higher than 50 million have been classified as large enterprises.

More specifically, the analysis is conducted on all of the manufacturing enterprises operating in the Umbria Region on the basis of the ATECO 2007, a classification of economic activities. For the sake of homogeneity, enterprises characterized by totally different structures and activities, such as banks, insurance and service companies, are not included in this study. The source of all data is the Italian Digital Database of Companies (AIDA - Bureau Van Dijk).

As discussed in the introduction, ROA is selected as the dependent variable to measure business success. The selected independent variables fall into two categories: company characteristics that change over time (level 1 variables) and company characteristics that do not change over time (level 2 variables). Level 1 variables can be divided into the following sub-groups:

1. Economic determinants, which take into consideration the information deriving from profit and loss accounts, include:
   - ROI (Return on Investment), which measures the benefit obtained from an investment.
   - ROS (Return on Sales) is net profit as a percentage of sales revenues. This ratio indicates how much profit an entity makes after subtracting all costs. The higher the ROS the greater a company's ability to create added value.

2. Financial determinants, which take the financial structure of the balance sheet into consideration, include:
   - DTA (Total Debts/Totale Assets) indicates how the company is financed. The greater the ratio the higher the company's debt.
   - FATA (Fixed Assets/Total Assets) measures the extent to which fixed assets affect total assets. A high ratio often indicates a rigid organizational structure, and, consequently, higher fixed costs for the company, but can also indicate long term investments.
   - ROD (Return on Debt) which quantifies the cost of debt. Companies carrying a high amount of debt normally show a higher return on debt ratio, as banks generally tend to tighten credit measures and charge higher rates to companies they consider riskier.
   - DTE (Debt to Equity) is a measure of the relationship between a company's total debt and total equity.
   - END (Ebit/Net Debts) measures a company's ability to pay its debt by means of its operating profit.
   - ACR (Accounts Receivable/Sales) shows a company's ability to efficiently collect its receivables.
   - PEA (Personnel Expenses and Amortization/Sales) shows the flexibility of production processes, which is the percentage of sales revenue needed to cover personnel costs and amortization.
   - TA (Tangible assets/Total non-current assets), INTA (Intangible assets/Total non-current assets) and CA (Current assets/Total assets), show the relationship between different types of assets within a company.

Alongside the previously mentioned variables, the time of observation (Year), a categorical variable with 11 ordered values (2001, . . . , 2011) is also considered.

---

1. ATECO 2007 is the Italian classification of economic activities operated by the Italian Institute of Statistics (ISTAT). This classification is the national version of the European nomenclature, Nace Rev. 2 (Regulation EC No 1893/2006 of the European Parliament and of the Council of 20 December 2006).
Level 2 variables include the computed mean values of level 1 variables (e.g., average ROI, average ROS, and so on) as well as the following variables:

- Ownership structure: Based on the ownership structure, companies are classified as family firms or not family firms. A family firm is defined as a company where the control is in the hands of a family. In order to determine whether a company is a family business or not, both shareholdership and the composition of the board are taken into consideration.

- Firm size: According to their annual turnover, companies are classified as microenterprises, small enterprises, medium-sized enterprises, and large enterprises.

- Business activity: Based on the ATECO classification, companies are classified in eight macro-groups distinguishing for their core business (e.g., food, textile and clothing, electronic/IT and automobile companies, and so on).

- Business structure: According to their business structure companies are classified as joint-stock company, single member joint-stock company, limited liability company, single member limited-liability company.

**Multilevel linear models with normal and discrete RE**

In this section we illustrate the main characteristics of the multilevel linear regression model; for more details see, among others, Snijders and Bosker (2012). Let $y_{ti}$ denote the value of the continuous dependent variable (e.g., ROA) observed at time $t$ for subject $i$ (e.g., company), with $t = 1, \ldots, T$ and $i = 1, \ldots, n$. Let $x_{ti}$ be a level 1 (or time-varying) covariate, describing characteristics of firms that change over time, whereas $z_i$ denotes a level 2 (or time-constant) covariate, which refer to characteristics of firms constant over time.

The general idea on which a multilevel model is based consists in assuming a specific linear model for each level 2 unit. Let us begin considering just a level 1 covariate, then a level 1 model is specified for each time occasion $t$ and subject $i (t = 1, \ldots, T; i = 1, \ldots, n)$ as follows

$$y_{ti} = \beta_0 + \beta_1 x_{ti} + \epsilon_{ti} \sim N(0, \sigma^2_{\epsilon}),$$  \hspace{1cm} i.t.d. \hspace{1cm} (1)

With respect to a classical linear model, now intercept $\beta_0$ and slope $\beta_1$ are subject specific. In the RE approach, which we adopt in the following empirical analysis, it is usually assumed that $\beta_0$ and $\beta_1$ are bivariate normally distributed with means equal $(\gamma_0, \gamma_1)$ and constant variance and covariance matrix; besides, they are also independent of $\epsilon_{ti}$. Given these assumptions, we may formulate a level 2 model as follows

$$\begin{align*}
\beta_0 &= \gamma_0 + u_{0i} \\
\beta_1 &= \gamma_1 + u_{1i}
\end{align*} \hspace{1cm} (2)$$

with $u_{0i}$ denoting the deviation of the intercept for subject $i$ from the average value of all subjects, that is $\gamma_0$, and $u_{1i}$ denoting the deviation of covariate effect for subject $i$ from the average effect common to all subjects, that is $\gamma_1$. Besides, $u_{0i}$ and $u_{1i}$ are random residuals with a normal distribution with mean equals $(0, 0)$ and variance and covariance matrix given by

$$\Sigma_u = \begin{bmatrix} \sigma^2_{u0i} & \sigma_{u0i} \\ \sigma_{u0i} & \sigma^2_{u1i} \end{bmatrix}$$

Substituting model (2) in model (1) the following two-level random intercept and random slope linear model is obtained:

$$y_{ti} = \gamma_0 + \gamma_1 x_{ti} + u_{0i} x_{ti} + u_{0i} + \epsilon_{ti}$$  \hspace{1cm} (3)
Note that this model is composed by a fixed part \((\gamma_{00} + \gamma_{10}x_{it})\), similar to any classical linear model, and by a random part \((u_{i}x_{it} + u_{0i} + \epsilon_{it})\), characterized partly by residuals at level 1 \((\epsilon_{i1})\) and partly by residuals at level 2 \((u_{0i} \text{ and } u_{1i})\).

A special case of model (3) is obtained by constraining \(\beta_{1t}\) to be fixed, that is \(\beta_{1t} = \gamma_{10}\) and

\[
\Sigma_u = \begin{bmatrix}
\sigma_{u0i}^2 & 0 \\
0 & 0
\end{bmatrix}
\]

It results a two-level random intercept linear model as follows

\[
y_{it} = \gamma_{00} + \gamma_{10}x_{it} + u_{0i} + \epsilon_{it}
\]  

(4)

which identifies a set of \(n\) parallel lines, with intercepts \(\gamma_{00} + u_{0i}\). Such type of model is particularly appealing because it allows us to rank subjects on the basis of the values of \(u_{0i}\), which explain that part of the total variance of \(y_{ti}\), given by

\[
\text{Var}(y_{it}|x_{it}) = \sigma_{u0i}^2 + \sigma_{\epsilon_{it}}^2,
\]  

(5)

due to the longitudinal structure of data and, therefore, imputable to some unobservable elements characterising the level 2 units and constant over time.

A relevant assumption of the model at issue is the absence of endogeneity, consisting in the fact that \(u_{0i}\) are not correlated with the level 1 covariates. An alternative approach which do not require the absence of endogeneity is known as fixed effects (FE) approach and it distinguishes from the RE one by the fact that \(u_{0i}\) are considered as fixed parameters rather than as random parameters. The main advantage of the FE approach is that the corresponding parameters estimator is always consistent, whereas the parameters estimator under the RE approach is biased in presence of endogeneity. However, in absence of endogeneity, both the estimators are consistent, but only the RE one is asymptotically efficient. We also outline that the FE approach cannot be generalised to model (3) to account for random slopes and it does not allow to insert level 2 covariates. As far as this last point, under the RE approach the random intercept model (4) is immediately extended as follows

\[
y_{it} = \gamma_{00} + \gamma_{10}x_{it} + \gamma_{01}z_{it} + u_{0i} + \epsilon_{it}
\]  

(6)

where \(\gamma_{01}\) denotes the regression coefficient of level 2 covariate \(z_{i}\). It has to be noted that the introduction of \(z_{i}\) modifies only the fixed part of the model, whereas the random part and the corresponding distributive assumptions are unchanged.

The two-level random intercept model in equation (6) is immediately extended to account for any number of covariates at levels 1 and 2:

\[
y_{it} = \gamma_{00} + x_{it}' \gamma_{10} + z_{i}' \gamma_{01} + u_{0i} + \epsilon_{it},
\]  

(7)

with \(x_{i}\) and \(z_{i}\) column vectors of level 1 and level 2 covariates, respectively, and \(\gamma_{10}\) and \(\gamma_{01}\) the corresponding vectors of regression coefficients.

Under the assumption of normality of \(u_{0i}\), parameters of model (7) are estimated through maximum likelihood based methods (for details, see Snijders and Bosker, 2012). Here we outline that the estimation process provides estimates of fixed parameters \(\gamma_{00}, \gamma_{10}, \gamma_{01}\), and of random parameters \(\sigma_{u0i}^2\) and \(\sigma_{\epsilon_{it}}^2\). Moreover, as the random effects \(u_{0i}\) are not parameters, but random variables, they are not obtained as output of the estimation process. However, predicted values of \(u_{0i}\) are usually a posteriori extrapolated by combining in a suitable way information from subject \(i\) with information from the population. According to the specific criterion adopted, we may distinguish several types of...
estimates, being the empirical Bayes estimates (used in the following study) among the most known ones (Efron and Morris, 1973; Morris, 1983).

As outlined in the introduction, an alternative to the normal RE approach consists in relaxing such restrictive parametric assumption in favour of a semi-parametric approach based on the discreteness of the RE. In theory, we may adopt the assumption of discreteness to both level 1 and level 2 residuals or to just one of them (Vermunt, 2003). In practice, in what follows we consider that only residuals $u_{0i}$ in equation (7) may assume a multinomial distribution, characterised by $k$ components (or support points) $\xi_c$ having probabilities $\pi_c$, with $c = 1, \ldots, k$, that substitute the random parameter $\sigma^2_{u0i}$. In this way, $k$ mutually exclusive and homogeneous groups or latent classes of level 2 units (i.e., companies) are detected, which share common unobservable characteristics, so that each level 2 unit may be classified in one of the latent classes on the basis of the a posteriori probabilities. It is important to outline that the value of $k$ is not a model parameter, but it has to be fixed a priori. Typically, data driven procedures are adopted, which are based on information criteria, unless theoretical considerations suggest a given value.

**Results and Discussion**

In this section we describe the main results obtained by the estimation of the multilevel linear model in equation (7).

First, the normality assumption is taken into account and, then, it is relaxed in favour of a semi-parametric approach.

**Random intercept linear model under normality assumption**

The longitudinal analysis is performed on a subset of 456 companies, which are characterized from a minimum of three observations to a maximum of nine observations of all the variables of interest in the period 2001-2011. In the following, a two-level analysis is performed, where the companies represent the level 2 units and the repeated observations over the period of interest are the level 1 units.

We begin the study with two preliminary analyses. Firstly, we estimate a null random intercept linear model for ROA, that is a two-level model without covariates, in order to test the signficativity of level 2 variance and, therefore, to justify the choice of a multilevel linear model instead of a classical linear model. The Lagrangian multiplier test for RE of Breusch and Pagan (1979) allows us to strongly reject the hypothesis of level 2 variance equals zero (test statistics = 1083.19, $p$-value < 0.0001), so corroborating the multilevel analysis. Secondly, we need to verify the hypothesis of absence of endogeneity. For this aim, we specify a multilevel linear model characterised by all the level 1 covariates described above and we perform the Hausman test (Hausman, 1978), which provides a reliable tool for comparing the parameter estimators under the FE and the RE approaches. The Hausman test provides a test statistic equals 9.93 and a $p$-value equals 0.0773. Then, we cannot reject the null hypothesis of absence of endogeneity and we conclude that the RE estimator gives parameter estimates similar to those obtained under the FE approach, but more efficient, and we prosecute the analysis adopting an RE approach.

As concerns the model selection, we first selected the significant level 1 covariates and, then, the level 2 covariates. The main results concerning the parameter estimates of the selected model, which contains only the statistically significant covariates (at 5% level), are illustrated in Table 1.
Table 1 - Random intercept linear model with normal RE: estimates of regression parameters $\gamma_{10}$ and $\gamma_{01}$ (column coef.) with standard errors, z-values, p-values, and inferior and superior limits ($l_1$ and $l_2$) of confidence intervals at 95%; estimates of level 1 and level 2 variances ($\sigma^2_{\epsilon_{it}}$ and $\sigma^2_{u_{0i}}$, respectively) with standard errors.

<table>
<thead>
<tr>
<th>Variable</th>
<th>coef</th>
<th>s.e.</th>
<th>z-value</th>
<th>p-value</th>
<th>$l_1$</th>
<th>$l_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>1.294</td>
<td>0.184</td>
<td>7.010</td>
<td>0.000</td>
<td>0.932</td>
<td>1.655</td>
</tr>
<tr>
<td>roi</td>
<td>0.355</td>
<td>0.004</td>
<td>82.870</td>
<td>0.000</td>
<td>0.347</td>
<td>0.364</td>
</tr>
<tr>
<td>ros</td>
<td>0.274</td>
<td>0.007</td>
<td>40.500</td>
<td>0.000</td>
<td>0.261</td>
<td>0.288</td>
</tr>
<tr>
<td>dtp</td>
<td>-1.624</td>
<td>0.168</td>
<td>-9.660</td>
<td>0.000</td>
<td>-1.953</td>
<td>-1.294</td>
</tr>
<tr>
<td>inci</td>
<td>0.394</td>
<td>0.150</td>
<td>2.620</td>
<td>0.009</td>
<td>0.099</td>
<td>0.689</td>
</tr>
<tr>
<td>year</td>
<td>-0.025</td>
<td>0.010</td>
<td>-2.600</td>
<td>0.009</td>
<td>-0.044</td>
<td>-0.006</td>
</tr>
<tr>
<td>familiar company</td>
<td>0.308</td>
<td>0.084</td>
<td>3.670</td>
<td>0.000</td>
<td>0.143</td>
<td>0.472</td>
</tr>
<tr>
<td>sales class (&gt;10 mlm)</td>
<td>0.246</td>
<td>0.080</td>
<td>3.080</td>
<td>0.002</td>
<td>0.090</td>
<td>0.402</td>
</tr>
<tr>
<td><strong>Random effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2_{\epsilon_{it}}$</td>
<td>0.831</td>
<td>0.025</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>$\sigma^2_{u_{0i}}$</td>
<td>0.865</td>
<td>0.055</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

We first observe that several variables initially taken into account in the first stages of this study, are not included in the final model, as they are not statistically significant. These include ROD, DTE, END, ACR, PEA, TA, INTA and CA. Within level 2 variables, the type of business activity and the business structure are also taken into consideration but neither of the two is statistically significant. As regards the former, the lack of significance might derive from the fact that it is a sub-classification within a single manufacturing sector and the difference in terms of business performance between sub-sectors is not statistically significant. The lack of statistical significance for the business structure variable does not come as a surprise. Although it is true that business structure can be used as a proxy for business size - more complex business structures tend to be characteristics of bigger enterprises - it is also the case that firm size is merely one of the reasons - alongside other factors including economic reasons - why a specific business structure is chosen. As a result, whereas the business-structure variable is not statistically significant, the firm size variable is.

As concerns the significant covariates, the analysis of results is first conducted by taking into account the extent to which economic factors affect firm performance. Results show a positive effect of ROI on ROA, indicating the relevance of good investments on companies performance. The value of ROS coefficient, which is positive and similar to ROI coefficient, indicates how a company's added value affects its overall performance and suggests companies to improve the development of value added products.

As a second step, the financial determinants of firm performance are analysed. The markedly negative coefficient (-1.624) of DTA shows that the higher a company's debt ratio, the lower its performance. This is probably due to the financial burden incurred by the company as a result of its high level of debt. These findings are particularly relevant for the Italian corporate sector and should encourage Italian companies, which are traditionally deep in debt, to reconsider their financing policies in favour of a higher balance between internal and external financing. As for the composition of total assets, the results of the FATA variable are interesting as they show that the higher the impact of fixed assets on total assets, the better the firm performance ($\beta_1 = 0.394$). Results reveal that the advantages deriving to companies from high long term investments are higher than the disadvantages coming from a more rigid capital structure. The manufacturing sector is capital intensive and, therefore, a substantial share of fixed assets is to be considered positively as it indicates significant investment in the core business. By contrast, enterprises with a low
share of capital assets show poorer firm performance probably due to unsold stock, unrecoverable receivables and few strategic investments. The results of time-constant variables are also noteworthy. Variable Year shows a slightly negative coefficient and a progressive deterioration of firm performance over the investigated time horizon (2001-2011), which includes also the years of the global economic crisis. It is also worth noting that a quadratic time trend has been tested as well as a random slope of variable Year, but both such effects are not statistically significant. The result is, therefore, not surprising and perfectly in line with Italian economic situation. Data show how the manufacturing sector has been impacted by general economic developments even though the trend, over the years, has been only slightly negative thus indicating a stagnation rather than a real decline.

As for Ownership structure variable, family ownership positively affects firm performance, which shows the importance and the high performance of family businesses for Italian economy, which is partially in line with other studies conducted at the international level. To conclude, Firm size variable indicates how firm size is fundamental towards achieving good firm performance. The positive coefficient shows that firm performance improves as the company’s turnover increases.

As concerns the random part of the model, the Lagrangian multiplier test of Breusch and Pagan repeated on the selected model allows us to reject the hypothesis of null level 2 variance \( \sigma_{u_0}^2 \) (test statistic = 1189.28, \( p \)-value < 0.0001).

More precisely, the longitudinal structure of data explains more than 50% of the variance of ROA, as the estimated intraclass correlation coefficient (Snijders and Bosker, 2012) corroborates:

\[
ICC = \frac{\sigma_{u_0}^2}{\sigma_{u_0}^2 + \sigma_{\epsilon t}^2} = \frac{0.865}{0.865 + 0.831} = 0.510,
\]

where the denominator of ICC is the total variance of equation (5) and the numerator denotes that part due to the longitudinal data.

To conclude, in Figure 1 we represent a ranking of the top 20 and the last 20 private companies (out of the total of 456 companies involved in the analysis) based on the estimated random intercept model: the empirical Bayes estimates of \( \hat{u}_{0i} \) and the upper and lower extremes for the confidence interval at 95% level are given for each company. It should be remembered that two companies are to be considered significantly different from each other if their respective confidence intervals do not coincide (Goldstein and Healy, 1994).

![Fig. 1 - Random intercept linear model: estimated random intercepts (\( \hat{u}_{0i} \)) for the top 20 and the last 20 companies.](image)
A comparison between ranks of companies based on $u_{0i}$ ($i = 1, ..., 456$) and ranks based on the average ROA provides statistically significant Spearman's and Kendall's correlation coefficients equal 0.2784 and 0.1945, respectively ($p$-value < 0.0001), which denote a weak positive correlation between the two types of rankings. This result warns the use of “raw” average values of a variable of interest (i.e., ROA) to rank a sample of level 2 units (i.e., companies) instead of the level 2 RE resulting from a multilevel regression analysis, that account for all the significant covariates.

**Random intercept linear model under discreteness assumption**

In order to skip the limits linked with the normality assumption of the RE (Section 1), we remove such an hypothesis in favour of a semi-parametric specification of the level 2 RE. We specify a random intercept model with $k = 3$ mixture components, so as to possibly identify a latent class of high performers, a latent class of low performers, and an intermediate latent class. We also evaluated the possibility to add one more component, but such a choice singled out a class with a very low weight.

In Table 2 are illustrated results concerning the fixed part of the selected mixture random intercept model with $k = 3$ and the related level 1 variance. Comparing with the estimates described in Table 1, the results are in line even though $\hat{\beta}_i$ values are lower. The sign of single coefficients does not change and DTA and Year are the only variables with a negative coefficient. It is also noteworthy that the FATA and Year variables, whose coefficients are close to 0, do not show any statistical significance.

**Table 2** - Mixture random intercept linear model, $k = 3$: estimates of regression parameters (column coef.) with standard errors, $z$-values, $p$-values, and inferior and superior limits ($l_1$ and $l_2$) of confidence intervals at 95%; estimates of level 1 variance ($\hat{\sigma}^2_{\epsilon_{ti}}$), with standard errors.

<table>
<thead>
<tr>
<th>Variable</th>
<th>coef.</th>
<th>s.e.</th>
<th>z-value</th>
<th>p-value</th>
<th>$l_1$</th>
<th>$l_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>0.910</td>
<td>0.149</td>
<td>6.100</td>
<td>0.000</td>
<td>0.617</td>
<td>1.202</td>
</tr>
<tr>
<td>roi</td>
<td>0.359</td>
<td>0.004</td>
<td>84.970</td>
<td>0.000</td>
<td>0.351</td>
<td>0.368</td>
</tr>
<tr>
<td>ros</td>
<td>0.266</td>
<td>0.007</td>
<td>40.260</td>
<td>0.000</td>
<td>0.253</td>
<td>0.279</td>
</tr>
<tr>
<td>dtp</td>
<td>-1.068</td>
<td>0.129</td>
<td>-8.270</td>
<td>0.000</td>
<td>-1.321</td>
<td>-0.815</td>
</tr>
<tr>
<td>inci</td>
<td>0.167</td>
<td>0.157</td>
<td>1.060</td>
<td>0.290</td>
<td>-0.142</td>
<td>0.475</td>
</tr>
<tr>
<td>year</td>
<td>-0.015</td>
<td>0.010</td>
<td>-1.490</td>
<td>0.136</td>
<td>-0.034</td>
<td>0.005</td>
</tr>
<tr>
<td>familiar company</td>
<td>0.139</td>
<td>0.051</td>
<td>2.740</td>
<td>0.006</td>
<td>0.040</td>
<td>0.238</td>
</tr>
<tr>
<td>sales class (&gt;10 mlm)</td>
<td>0.207</td>
<td>0.053</td>
<td>3.930</td>
<td>0.000</td>
<td>0.103</td>
<td>0.310</td>
</tr>
<tr>
<td><strong>Random effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\sigma}^2_{\epsilon_{ti}}$</td>
<td>0.991</td>
<td>0.028</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

In Table 3 are shown the estimates of support points $\hat{\xi}_c$ ($c = 1, 2, 3$) of the mixture random intercept model and the corresponding weights $\hat{\pi}_c$. 
The distribution of the RE is substantially symmetric. In class 2 is grouped the main part of companies (82.3%) with average performances, whereas the other companies are equally distributed in the remaining classes. Class 1 collects companies with low levels of performance and class 3 involves companies with high levels of performance. For the reader's convenience, in Table 3 are also shown the average values of the normal RE $u_{0t}$, computed separately for each latent class (and denoted by $\hat{u}_{0t|c}$). We observe that these values are perfectly aligned with the support points $\xi_c$.

More in detail, we may define three groups of companies on the basis of the centiles of $u_{0t}$ corresponding to the weights assessed through the mixture model, that is, centiles -1.199 and 0.955 of order 0.088 and 0.911, respectively. Let group 1 denote all companies having $u_{0t} \leq -1.199$, let group 2 denote the companies with $-1.199 < u_{0t} \leq 0.955$, and let the remaining companies with $u_{0t} > 0.955$ be in group 3. As shown in Table 4, the resulting classification of companies very closely resembles that based on the discrete RE (Cramer's V equals 0.9255; p-value < 0.0001). We then conclude about a substantial agreement between the ranking of companies resulting by the parametric approach and their classification resulting by the semi-parametric approach.

### Table 3 - Mixture random intercept linear model, $k = 3$: estimates of support points ($\xi_c$) and weights ($\pi_c$) and average values of $\hat{u}_{0t}$ given the latent class ($\hat{u}_{0t|c}$).

| $c$ | $\xi_c$ | $\pi_c$ | $\hat{u}_{0t|c}$ |
|-----|---------|---------|------------------|
| 1   | -1.879  | 0.088   | -1.700           |
| 2   | -0.017  | 0.823   | -0.093           |
| 3   | 1.960   | 0.091   | 1.612            |

### Table 4 - Cross-classification of companies based on $\hat{\xi}_{0c}$ ($c = 1$, $c = 2$, $c = 3$) and on centiles of the empirical distribution of $\hat{u}_{0t}$ (group 1, group 2, group 3); absolute frequencies.

<table>
<thead>
<tr>
<th></th>
<th>$c = 1$</th>
<th>$c = 2$</th>
<th>$c = 3$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>37</td>
<td>3</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>Group 2</td>
<td>3</td>
<td>369</td>
<td>4</td>
<td>376</td>
</tr>
<tr>
<td>Group 3</td>
<td>0</td>
<td>1</td>
<td>39</td>
<td>40</td>
</tr>
<tr>
<td>Total</td>
<td>40</td>
<td>373</td>
<td>43</td>
<td>456</td>
</tr>
</tbody>
</table>

**Conclusion**

In this paper we analysed the performance of Italian manufacturing companies over a ten year period, from 2001 to 2011. This study aims to assess the extent to which different determinants affect the performance of business enterprises and to clarify how Italian firms have managed to adapt to changes in the business environment over the last ten years.

To this purpose a multilevel linear model is developed to analyse the performance of Italian enterprises and to investigate the role played by different determinants. The paper focuses exclusively on manufacturing companies for two main reasons: the relevance of this sector in the Italian economy and the growing importance given to this sector by the European Commission.

Our results provide firms and governments some useful insight into the determinants of manufacturing company performances. More specifically, we find a significant positive impact of valued added production and a negative impact of higher level of debts on firm performance. Such results should encourage Italian firms, which normally have a high level of debt, to reduce their debt while also leading the Italian government to adopt fiscal instruments aimed to increase firm capital (Bugamelli et al, 2011). Another important point is the positive impact of fixed assets on business success. Our results show that the higher the impact of fixed assets on total assets, the better the firm performance, which should drive firms to increase both their tangible and intangible investments in fixed
Moreover, results show a slightly negative coefficient for the year variable and a progressive deterioration of firm performance over the investigated time horizon (2001-2011), which includes the years when the global economic crisis was at its worst, that is, from 2007 onwards. Firm size and ownership play a fundamental role in determining firm performance. It is noteworthy the extent to which firm size is fundamental towards achieving good firm performance. The positive coefficient of this variable shows that firm performance improves as the company’s turnover increases. At the same time, we find that family ownership positively affects firm performance thus demonstrating the dynamic nature of Italian family businesses. We conclude outlining the utility of classifying companies in homogeneous classes, so that, on one side, enterprises belonging to the class of the worst performers may be object of specific public policies and, on the other side, enterprises belonging to the class of the best performers represent the gold standard to imitate.

References


[38] Vermunt JK, Multilevel latent class models. Sociological Methodology 33, 2003, 213-239
