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Research article

Performance analysis of Italian manufacturing companies: a multilevel linear approach

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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 whichform the backbone of the Italian economy. Italy is still the second biggest Europeanmanufacturing power, surpassed only by Germany in terms of productionvalue (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 hasrecently attracted such considerable attention from policy makers that the European Commission has set it as its goal to increase the manufacturing share of GDPfrom the current 16% to 20% by 2020 (European Commission, 2014).

At the same time, Italian industry primarily relies on small and mediumsized 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 hasbeen heavily criticized (Ciocca, 2004), is still capable of being dynamic and competitivein international markets (Castellani and Zanfei, 2007). These features ofgrowth and dynamism, which characterize small and medium-sized Italian companieshave 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 broughtabout by the globalization of markets further increase competitive pressure at aninternational level, which works to the disadvantage of localism and small sizedbusinesses. A careful analysis of the factors contributing to the competitive successof Italian manufacturing enterprises is therefore crucial in identifying best businesspractices.

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

A sample of 897 business enterprises operating in the Umbria Region withannual turnovers exceeding EUR 1 million is selected and examined over a tenyearperiod, from 2001 to 2011, involving a total of 8000 observations. Given theconsiderable increase in economic competition, extending the time of observationof this study to a ten-year period emphasized the importance of the time variablein business performance analysis. The manufacturing sector was the key area offocus in this study as it provided homogenous sampling, and was characteristic ofboth 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 generallythe most used types of performance measurement (Teodori, 2008; Ou andPenman, 1989). Hutchinson and Gul (2004) claim that accounting-based performancemeasures reect the results of managers' actions and are thus better thanmarket-based measures. However, both measures are open to criticism, as theresults of accounting-based measures might be manipulated through accountingpolicy 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 haveresulted 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. ROAis considered one of the most commonly used accounting metrics in the literature(Bhagat and Bolton, 2008; Rand_ya 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; Mazzolaet 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 overtime.

In order to properly account for the longitudinal structure of data at issuecharacterized by repeated measures (or level 1 units) within companies (orlevel 2 units), the relationship between ROA index and the possible time-varyingand 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 a same variable in different time points within the same subject (i.e., company) are correlatedone other to a greater extent rather than observations referred to different subjects. Differently from classical (linear) regression models, which ignore the hierarchicalstructure of longitudinal data (i.e., repeated measures within subjects), multilevelmodels (known also as hierarchical models, mixed models, and random coefficients or random effects (RE) models) provide an useful instrument to detect the effectof each level of hierarchy on the variability of the response variable, disentanglingbetween variability among time points and variability among companies. Such anaim is reached by introducing one or more RE in the regression model, whichcapture that part of response variability unexplained by the covariates and due tounobserved characteristics of companies.

Usually, RE are assumed to be normally distributed, with mean zero and constantvariance. The predictions of normal RE provide a ranking of the level 2units, which allows us to make inference on the differences between companies. However, the misspecification of the parametric distribution may have negativeconsequences, mainly on the predictions of the RE, when the true distribution ishighly 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 hardto check (Verbeke and Molenberghs, 2000; Grilli and Rampichini, 2014). Alternatively to the parametric specification of the RE distribution, a semi-parametricapproach based on assuming the discreteness of the RE can be also applied. Inpractice, one works with a multinomial distribution with a number of supportpoints 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) andthe references therein for an exhaustive review about the debate on which approachis more appropriate, between the continuous and the discrete ones, in some specificsettings, such as that for the analysis of certain types of time-series data and inthe setting of models for longitudinal data with time-varying individual RE.

The discrete approach has the advantage to very satisfactorily approximate anytrue continuous RE distribution, given a finite number of support points (Heckmanand Singer, 1984). A first consequence of this result is that the introductionof possibly inappropriate and hardly verifiable assumptions about the true distributionof the RE is not necessary any more. Besides, the assumption of discreteRE has an interesting interpretative advantage concerning the unobserved heterogeneity,due to the possibility of classifying the level 2 units into a small numberof unobserved (or latent) classes (Lazarsfeld, 1950; Lazarsfeld and Henry, 1968;Goodman, 1974; Hagenaars and McCutcheon, 2002) that share common homogeneouscharacteristics, and this fact may be more natural or more convenientin many settings than to place them on a continuous scale (Vermunt, 2003). Inthis study, both parametric and semi-parametric approaches are applied and theirresults 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 observationof a single variable, it analyses a large number of performance determinants of Italian firms. Secondly, it provides deeper insight into how increasing internationalcompetition and the global economic and financial crisis have affected the performanceof 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 asingle accounting number but on a complete set of variables determining a firm'scompetitive success as a whole. More in detail, the companies will be classified inthree latent classes, distinguishing among low-, medium, and high-performes.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 microenterpriseis an enterprise whose annual turnover does not exceed EUR 2 million; a smallenterprise is an enterprise whose annual turnover is between EUR 2 and EUR 10million; and medium-sized enterprises have an annual turnover not exceeding EUR50 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 enterprisesoperating in the Umbria Region on the basis of the ATECO 2007[1], section C (Classification of Economic Activities). For the sake of homogeneity, enterprises characterized by totally different structures and activities, such as banks, insurancesand service companies, are not included in this study. The source of all datais the Italian Digital Database of Companies (AIDA - Bureau Van Dijk).

As discussed in the introduction, ROA is selected as the dependent variable to measurebusiness success. The selected independent variables fall into two categories:company characteristics that change over time (level 1 variables) and companycharacteristics that do not change over time (level 2 variables). Level 1 variablescan 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. Thisratio 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 sheetinto 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 organizationalstructure, and, consequently, higher fixed costs for the company, but canalso indicate long term investments.
- ROD (Return on Debt) which quantifies the cost of debt. Companies carryinga high amount of debt normally show a higher return on debt ratio, asbanks generally tend to tighten credit measures and charge higher rates tocompanies they consider riskier.
- DTE (Debt to Equity) is a measure of the relationship between a company'stotal 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 efficientlycollect its receivables.
- PEA (Personnel Expenses and Amortization/Sales) shows the flexibility ofproduction processes, which is the percentage of sales revenue needed tocover personnel costs and amortization.
- TA (Tangible assets/Total non-current assets), INTA (Intangible assets/Totalnon-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.

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[1] ATECO 2007 is the Italian classification of economic activities operated by the ItalianInstitute of Statistics (ISTAT). This classification is the national version of the Europeannomenclature, Nace Rev. 2 (Regulation EC No 1893/2006 of the European Parliament and ofthe 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 companywhere the control is in the hands of a family. In order to determine whether acompany is a family business or not, both shareholdership and the compositionof the board are taken into consideration.
- Firm size: According to their annual turnover, companies are classified asmicroenterprises, 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, limitedliabilitycompany, 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 yti denote the value of the continuous dependent variable (e.g., ROA) observed at time t for subject i (e.g., company), with t = 1, …,T and i = 1, …,n. Let x_{ti} be a level 1 (or time-varying) covariate, describing characteristics of firms that changeover 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 1covariate, then a level 1 model is specified for each time occasion t and subject i(t = 1, …,T; i = 1, …,n) as follows

$$y_{ti} = \beta_{0i} + \beta_{1i}x_{ti} + \epsilon_{ti}\epsilon_{ti} \sim N\left(0,\sigma^2_{\epsilon_{ti}}\right), \epsilon_{ti}\ i.i.d. \tag{1}$$

With respect to a classical linear model, now intercept β_{0i} and slope β_{1i} are subject specific. In the RE approach, which we adopt in the following empirical analysis,it is usually assumed that β_{0i} and β_{1i} are bivariate normally distributed withmeans equal $(\gamma_{00}, \gamma_{10})$ and constant variance and covariance matrix; besides, theyare also independent of ϵ_{ti}. Given these assumptions, we may formulate a level 2model as follows

$$\begin{cases}\beta_{0i} = \gamma_{00} + u_{0i}\\ \beta_{1i} = \gamma_{10} + u_{1i}\end{cases} \tag{2}$$

withu_{0i} denoting the deviation of the intercept for subject i from the averagevalue of all subjects, that is γ_{00}, and u_{1i} denoting the deviation of covariate effectfor subject i from the average effect common to all subjects, that is γ_{10}. 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

$$\Sigma_u = \begin{bmatrix}\sigma^2_{u_{0i}} & \sigma_{u_{01i}}\\ \sigma_{u_{01i}} & \sigma^2_{u_{1i}}\end{bmatrix}$$

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

$$y_{ti} = \gamma_{00} + \gamma_{10}x_{ti} + u_{1i}x_{ti} + u_{0i} + \epsilon_{ti} (3)$$

Note that this model is composed by a fixed part ($\gamma_{00} + \gamma_{10}x_{ti}$), similar to anyclassical linear model, and by a random part ($u_{1i}x_{ti} + u_{0i} + \epsilon_{ti}$), characterizedpartly by residuals at level 1 (ϵ_{ti}) and partly by residuals at level 2 (u_{0i} and u_{1i}).
A special case of model (3) is obtained by constraining$\beta_{1i}$to be fixed, that is $\beta_{1i} = \gamma_{10}$and

$$\Sigma_u = \begin{bmatrix} \sigma^2_{u_{0i}} & 0 \\ 0 & 0 \end{bmatrix}.$$

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

$$y_{ti} = \gamma_{00} + \gamma_{10}x_{ti} + u_{0i} + \epsilon_{ti} \tag{4}$$

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

$$Var(y_{ti}|x_{ti}) = \sigma^2_{u0i} + \sigma^2_{\epsilon_{ti}}, \tag{5}$$

due to the longitudinal structure of data and, therefore, imputable to some unobservableelements 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. Analternative 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 factthat u_{0i} are considered as fixed parameters rather than as random parameters. Themain advantage of the FE approach is that the corresponding parameters estimatoris always consistent, whereas the parameters estimator under the RE approach isbiased in presence of endogeneity. However, in absence of endogeneity, both theestimators are consistent, but only the RE one is asymptotically efficient. We alsooutline that the FE approach cannot be generalised to model (3) to account forrandom slopes and it does not allow to insert level 2 covariates. As far as thislast point, under the RE approach the random intercept model (4) is immediatelyextended as follows

$$y_{ti} = \gamma_{00} + \gamma_{10}x_{ti} + \gamma_{01}z_i + u_{0i} + \epsilon_{ti} \tag{6}$$

whereγ_{01} denotes the regression coefficient of level 2 covariate z_i. It has to benoted that the introduction of $z_i$modifies only the fixed part of the model, whereasthe random part and the corresponding distributive assumptions are unchanged.
The two-level random intercept model in equation (6) is immediately extended toaccount for any number of covariates at levels 1 and 2:

$$y_{ti} = \gamma_{00} + \boldsymbol{x}_{ti}\boldsymbol{\gamma}'_{10} + \boldsymbol{z}_i\boldsymbol{\gamma}'_{01} + u_{0i} + \epsilon_{ti}\ , \tag{7}$$

with$\boldsymbol{x}_{ti}$ and $\boldsymbol{z}_i$ column vectors of level 1 and level 2 covariates, respectively, and$\boldsymbol{\gamma}_{10}$and $\boldsymbol{\gamma}_{01}$ the corresponding vectors of regression coefficients.
Under the assumption of normality of u_{0i}, parameters of model (7) are estimatedthrough maximum likelihood based methods (for details, see Snijders andBosker, 2012). Here we outline that the estimation process provides estimates of fixed parameters $\gamma_{00}, \boldsymbol{\gamma}_{10}, \boldsymbol{\gamma}_{01}$, and of random parameters σ^2_{u0i} and $\sigma^2_{\epsilon_{ti}}$. Moreover, as the random effects u0i are not parameters, but random variables, they arenot obtained as output of the estimation process. However, predicted values of $u_{0i}$are usually a posterior extrapolated by combining in a suitable way informationfrom subject i with information from the population. According to the specific criterionadopted, we may distinguish several types of

estimates, being the empiricalBayes estimates (used in the following study) among the most known ones (Efronand Morris, 1973; Morris, 1983).

As outlined in the introduction, an alternative to the normal RE approach consistsin relaxing such restrictive parametric assumption in favour of a semi-parametricapproach based on the discreteness of the RE. In theory, we may adopt the assumptionof discreteness to both level 1 and level 2 residuals or to just one ofthem (Vermunt, 2003). In practice, in what follows we consider that only residualsu_{0i} in equation (7) may assume a multinomial distribution, characterised by $k$components (or support points) ξ_c having probabilities π_c, with c = 1, …,k, that substitute the random parameter σ^2_{u0i}. In this way, k mutually exclusive and homogeneousgroups 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 posterior probabilities. Itis 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 themultilevel linear model in equation (7). First, the normality assumption is takeninto 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 arecharacterized from a minimum of three observations to a maximum of nine observationsof all the variables of interest in the period 2001-2011. In the following, atwo-level analysis is performed, where the companies represent the level 2 unitsand 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 nullrandom intercept linear model for ROA, that is a two-level model without covariates, in order to test the significativity of level 2 variance and, therefore, to justifythe choice of a multilevel linear model instead of a classical linear model. The Lagrangianmultiplier test for RE of Breusch and Pagan (1979) allows us to stronglyreject the hypothesis of level 2 variance equals zero (test statistics = 1083.19, p-value < 0.0001), so corroborating the multilevel analysis. Secondly, we need toverify the hypothesis of absence of endogeneity. For this aim, we specifya multilevel linear model characterised by all the level 1 covariates described above and we perform the Hausman test (Hausman, 1978), which providesa reliable tool for comparing the parameter estimators under the FE and the REapproaches. The Hausman test provides a test statistic equals 9.93 and a p-valueequals 0.0773. Then, we cannot reject the null hypothesis of absence of endogeneityand we conclude that the RE estimator gives parameter estimates similar tothose obtained under the FE approach, but more efficient, and we prosecute theanalysis adopting an RE approach.

As concerns the model selection, we first selected the significant level 1 covariatesand, then, the level 2 covariates. The main results concerning the parameterestimates of the selected model, which contains only the statistically significantcovariates (at 5% level), are illustrated in Table 1.

Table 1 - Random intercept linear model with normal RE: estimates of regression parameters γ_{10} and γ_{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 ($\hat{\sigma}^2_{\epsilon_{ti}}$ and $\hat{\sigma}^2_{u0i}$, respectively) with standard errors.

Variable	coef.	s.e.	*z*-value	*p*-value	l_1	l_2
Fixed effects						
constant	1.294	0.184	7.010	0.000	0.932	1.655
roi	0.355	0.004	82.870	0.000	0.347	0.364
ros	0.274	0.007	40.500	0.000	0.261	0.288
dtp	-1.624	0.168	-9.660	0.000	-1.953	-1.294
inci	0.394	0.150	2.620	0.009	0.099	0.689
year	-0.025	0.010	-2.600	0.009	-0.044	-0.006
familiar company	0.308	0.084	3.670	0.000	0.143	0.472
sales class (>10 mlm)	0.246	0.080	3.080	0.002	0.090	0.402
Random effects						
$\hat{\sigma}^2_{\epsilon_{ti}}$	0.831	0.025	--	--	--	--
$\hat{\sigma}^2_{u0i}$	0.865	0.055	--	--	--	--

We first observe that several variables initially taken into account in the firststages 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 structureare 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 interms of business performance between sub-sectors is not statistically significant. The lack of statistical significance for the business structure variable does not comeas a surprise. Although it is true that business structure can be used as a proxyfor business size - more complex business structures tend to be characteristics ofbigger enterprises - it is also the case that firm size is merely one of the reasons- alongside other factors including economic reasons - why a specific businessstructure is chosen. As a result, whereas the business-structure variable is notstatistically significant, the firm size variable is.

As concerns the significant covariates, the analysis of results is first conductedby taking into account the extent to which economic factors affect firm performance. Results show a positive effect of ROI on ROA, indicating the relevance ofgood investments on companies performance. The value of ROS coefficient, whichis positive and similar to ROI coefficient, indicates how a company's added value affects its overall performance and suggests companies to improve the developmentof 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'sdebt ratio, the lower its performance. This is probably due to the financialburden incurred by the company as a result of its high level of debt. These findingsare particularly relevant for the Italian corporate sector and should encourage Italiancompanies, which are traditionally deep in debt, to reconsider their financingpolicies in favour of a higher balance between internal and external financing. Asfor the composition of total assets, the results of the FATA variable are interesting asthey show that the higher the impact of fixed assets on total assets, the better the firm performance ($\hat{\beta}_l = 0.394$). Results reveal that the advantages deriving to companiesfrom high long term investments are higher than the disadvantages comingfrom a more rigid capital structure. The manufacturing sector is capital intensiveand, therefore, a substantial share of fixed assets is to be considered positively as it indicates significant investment in the core business. By contrast, enterpriseswith a low

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share of capital assets show poorer firm performance probably due tounsold 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 performanceover the investigated time horizon (2001-2011), which includes also the years ofthe global economic crisis. It is also worth noting that a quadratic time trend hasbeen 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 perfectlyin line with Italian economic situation. Data show how the manufacturing sectorhas been impacted by general economic developments even though the trend, overthe years, has been only slightly negative thus indicating a stagnation rather thana real decline.

As for Ownership structure variable, family ownership positively affects firmperformance, which shows the importance and the high performance of familybusinesses for Italian economy, which is partially in line with other studies conductedat 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.

This element should be considered alongside the family company resultsand highlights the important role played by medium-sized family businesses in theItalian economy.

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 $\sigma^2_{u_{0i}}$ (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:

$$ICC = \frac{\sigma^2_{u_{0i}}}{\sigma^2_{u_{0i}} + \sigma^2_{\epsilon_{ti}}} = \frac{0.865}{0.865 + 0.831} = 0.510,$$

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).

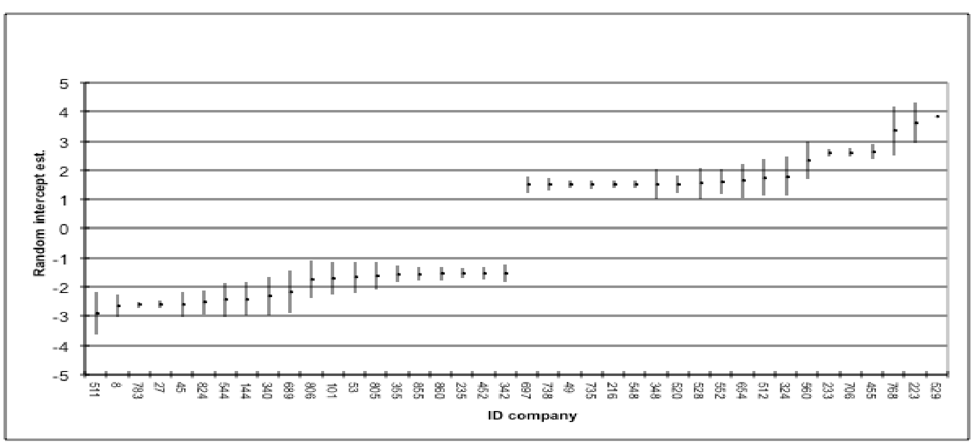

Fig. 1 - Random intercept linear model: estimated random intercepts ($\hat{u}_{0i}$) for the top 20 and the last 20 companies.

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A comparison between ranks of companies based on $\hat{u}_{0i}$ (i = 1, …, 456) and ranks based on the average ROA provides statistically signify cant 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 $\hat{\beta}_l$ 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.

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

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 $\hat{\pi}_c$.

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

	c = 1	c = 2	c = 3
$\hat{\xi}_c$	-1.879	-0.017	1.960
$\hat{\pi}_c$	0.088	0.823	0.091
$\bar{\hat{u}}_{0i\|c}$	-1.700	-0.093	1.612

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 $\hat{u}_{0i}$, computed separately for each latent class (and denoted by $\bar{\hat{u}}_{0i|c}$). We observe that these values are perfectly aligned with the support points$\hat{\xi}_c$. More in detail, we may define three groups of companies on the basis of the centiles of $\hat{u}_{0i}$ 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 $\hat{u}_{0i} \leq -1.199$, let group 2 denote the companies with $-1.199 < \hat{u}_{0i} \leq 0.955$, and let the remaining companies with $\hat{u}_{0i} > 0.955$ 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 4 - Cross-classification of companies based on $\hat{\xi}_{0c}$ (c = 1, c = 2, c = 3) and on centiles of the empirical distribution of $\hat{u}_{0i}$ (group 1, group 2, group 3); absolute frequencies.

	c = 1	c = 2	c = 3	Total
Group 1	37	3	0	40
Group 2	3	369	4	376
Group 3	0	1	39	40
Total	40	373	43	456

Conclusion

In this paper we analysed the performance of Italian manufacturing companiesover 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 businessenvironment over the last ten years.

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

Our results provide firms and governments some useful insight into the determinantsof 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 alsoleading the Italian government to adopt fiscal instruments aimed to increase firmcapital (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

assets.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 itsworst, 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 showsthat firm performance improves as the company's turnover increases. At the same time, we find that family ownership positively affects firm performance thus demonstratingthe dynamic nature of Italian family businesses.
We conclude outlining the utility of classifying companies in homogeneousclasses, 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, enterprisesbelonging to the class of the best performers represent the gold standard to imitate.

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