Università della Calabria

Dipartimento Economia, Statistica e Finanza

Gruppo CALCOM

OVER-INDEBTEDNESS AND INNOVATION: SOME PRELIMINARY RESULTS

Damiana G. Costanzo
Damiano B. Silipo
Marianna Succurro

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Over-Indebtedness and Innovation: some preliminary results

Abstract
The paper studies the impact of firms' over-indebtedness on innovation. First, we build up an over-indebtedness index which takes account of the firm's financial structure as well as of its profitability conditions. Secondly, we investigate to what extent over-indebtedness explains firms' innovative activity by focusing on Italian manufacturing firms over the 2003-2010 period. Empirical evidence suggests that indebtedness plays an important role in explaining firms' innovative activity. Moreover, the relationship between debt and innovation is stronger for the over-indebted firms in the high tech industries.

JEL Classification: C10, D22, G20, G30, O30

Keywords: Over-indebtedness, Innovation, PCA

1 INTRODUCTION

Innovative activity may provide high rewards but is very uncertain. First, firms that undertake R&D do not know whether they succeed or not. Second, even if they succeed, they do not know whether will be the first in the patent race. Indeed, very often the innovation is a race to be the first, and the value to be second in the race may be the same than not succeeding at all. Given the nature of innovative activity, it is relevant for the firm to share the risk of innovation with other investors searching for high yields. So, it is reasonable to assume that the higher is the opportunity for the firm to share the risk of innovation with outside investors, the greater will be incentive to innovate. Indeed, Benfratello et al. (2008), among others, provided evidence that banking development affects the probability of process innovation, particularly for small firms and for firms in high(er) tech sectors and in sectors more dependent upon external finance.
In this paper we contribute to the literature on finance and innovation by extending the analysis to the role that banking loans As well as other forms of indebtedness play in spurring innovation. Although in Italy banking loans are the most important source of external finance for the firms, it is reasonable to assume that in making investments firms take account of all the sources of funding. So, if the risk sharing effect increases the incentive to innovate, we expect that the more indebted firms are also the most innovative ones, both because they have more access to external funds and they can share risk with several types of investors, and not only with banks.
To this aim, we build up a debt and over-indebtedness index, which takes account of the firm's financial structure as well as of its profitability conditions. Then, we estimate whether over-indebted firms are also more innovative. Notice that if the latter is the case, we may face a trade off between firm's financial stability and innovation, which arises puzzling issues on the relationship between finance and innovation.
Empirical evidence on a large sample of manufacturing Italian firms in the period 2008-2010 suggests that indebtedness plays an important role in explaining firms' innovative activity. Highly indebted firms are more innovative, and this relationship is even stronger for high tech firms.
Moreover, the relationship between debt and innovation is stronger among the over-indebted firms in the high tech industries. By contrast, over-indebted firms in other sectors show a significant but weaker relationship between finance and innovation. This suggests that over-

indebted firms in the high tech sectors would deserve special attention from banks, policy makers and even in courts, due to the greater beneficial effects of their indebtedness.
Further results suggest that banks loans seems to have a greater impact on innovation than other sources of funding, and the impact of the bank loans is greater for over-indebted firms. This may be due to nature of the Italian financial system centered around the banks, but also to a greater monitoring capability of the banks relatively to other investors with respect to the firms' investment decisions. Finally, the above results are even more robust for firms belonging to the high tech sectors.
Next section describes the construction and features of the over-indebtedness index and Section 3 the statistical methodology used to build up the index. Section 4 describes data sources and summary statistics, and Section 5 presents the econometric model and the empirical evidence. Section 6 provides some concluding remarks.

2 AN OVER-INDEBTEDNESS INDEX

Preliminary steps in the analysis of the effects of the firms' overindebtedness on innovation deal with: a) the definition of the variables capturing the financial conditions of the firm; b) the setting up of criteria which allow to establish when a firm may be considered overindebted.
With respect to the first issue, the financial and accounting literature suggest that to capture the firm's financial fragility it is more appropriate to consider a set of variables including several aspects of the indebtedness phenomenon (leverage, indebtedness capacity, form of the financial debt, net financial position, etc.). All together, the financial variables are able to provide a better understanding of the firm's financial condition than any single ratio of indebtedness.
Following this approach, to evaluate the financial condition of the firm we built up a debt index which includes the following ratios:

$$DEBT_{INDEX} = \alpha_1 \frac{TA}{N} + \alpha_2 \frac{FD}{N} + \alpha_3 \frac{CL}{FD} + \alpha_4 \frac{FD}{CF} + \alpha_5 \frac{TA}{WK} + \alpha_6 \frac{CL}{CA} + \alpha_7 \frac{NFP}{TA} + \alpha_8 \frac{CL}{PLAT} + \alpha_9 \frac{NFP}{PLAT} + \alpha_{10} \frac{NTCA}{N} + \alpha_{11} \frac{TFA}{LTD + N}$$

with $\frac{TA}{N}$ denoting firm's leverage, $\frac{FD}{N}$ is the inverse of the capitalization degree (indebtedness capacity), $\frac{CL}{FD}$ is the ratio between short-term financial debt (Current Liabilities) and total Financial Debt; $\frac{FD}{CF}$ is the ratio between total Financial Debt and Cash-Flow; $\frac{TA}{WK}$ is the ratio between Total Assets and Working Capital; $\frac{CL}{CA}$ is Current Liabilities over Current Assets, $\frac{NFP}{TA}$ measures the incidence of the net financial debt; $\frac{CL}{PLAT}$ is the rate of short-term financial debt over Profit (Loss) after Taxation; $\frac{NFP}{PLAT}$ indicates the ratio between Net Financial Position and Profit (Loss) after Taxation; $\frac{NTCA}{N}$ is the ratio between Net Technical Assets (Intangible Fixed Assets + Tangible Fixed Assets – Depreciation) and Shareholders Funds. Finally, $\frac{TFA}{LTD+N}$ is Total Fixed Assets over the sum of Long-Term Debt and Shareholders Funds.

However, firm's financial fragility is related not only to the degree of indebtedness but also to the capability of the firm to meet financial obligations with current income. So, we consider also indicators of profitability and we compare the latter with the cost of debt. Specifically, to measure firm's *debt sustainability,* we built up the following index*:*

$$NSD_{INDEX} = \delta_1 \frac{IP}{EBIT} + \delta_2 \frac{IP}{EBTDA} + \delta_3 \frac{IP}{CF}$$

which includes the following financial ratios: $\frac{IP}{EBIT}$, the ratio between Interest Paid and Earnings Before Interest and Taxes, $\frac{IP}{EBTDA}$ the ratio between Interest Paid and Earnings Before Interest, Taxes, Depreciation and Amortization, and $\frac{IP}{CF}$ the ratio between Interests Paid and Cash Flow.

A large amount of empirical evidence on the balance sheets conditions has demonstrated that there are threshold values for each of the above ratios, which allow to conclude when the firm is in good, normal and bad financial condition. Table 1 reports the three thresholds levels for each financial ratio used to build up the debt index and the firm's debt sustainability index.

Table 1 Financial ratios and thresholds

Good status (< threshold 1)	**Normal financial status**	**Bad status** (>threshold 2)
threshold 1		**threshold 2**
3	3 < $\frac{TA}{N}$ < 5	5
1	1 < $\frac{FD}{N}$ < 1.6	1.6
0.6	0.6 < $\frac{CL}{FD}$ < 0.8	0.8
2.85	2.85 < $\frac{FD}{CF}$ < 6.7	6.7
2.5	2.5 < $\frac{TA}{WK}$ < 3.3	3.3
0.9	0.9 < $\frac{CL}{CA}$ < 1.1	1.1
0.20	0.20 < $\frac{NFP}{TA}$ < 0.35	0.35
0.15	0.15< $\frac{CL}{PLAT}$ <0.30	0.30
0.10	0.10< $\frac{NFP}{PLAT}$ <0.50	0.50
1	1< $\frac{NTCA}{N}$ <2	2
1.25	1.25< $\frac{TFA}{LTD+N}$ <3.33	3.33
Good status (< threshold 1)	**Normal financial status**	**Bad status** (>threshold 2)
threshold 1		**threshold 2**
0.25	0.25 < $\frac{IP}{EBIT}$ < 0.58	0.58

0.33	$0.33 < \frac{IP}{CF} < 0.5$	0.5
0.18	$0.18 < \frac{IP}{EBITDA} < 0.5$	0.5

We want to stress that these threshold values have only empirical foundations, and therefore their estimations are subject to systematic as well as random errors. However, the choice of the threshold level does not affect the relevance of our approach.

To establish when a firm may be considered overindebted, we estimated in both indexes the weights associated to each financial ratio (i.e.; the values of the coefficients α_i and δ_i), using the principal component analysis (PCA) methodology (see next paragraph).

Finally, substituting the estimated coefficients of α_i and δ_i and the threshold values for each ratio reported in Table 1 in the above equations $DEBT_{INDEX}$ and NSD_{INDEX}, we are able to identify the two indexes' values which allow to classify firms according to their degree of indebtedness.

The possible outcomes in which a firm may end up are reported in Table 2.

Table 2 Over-Indebtedness Index and Financial Status

	NSD<threshold 1	thr 1< NSD<thr 2	NSD >threshold 2
Debt<threshold 1	**OI=1 Optimal**	**OI=2**	**OI=3**
thr 1<Debt< thr 2	**OI=4**	**OI=5 Normal**	**OI =6**
Debt>threshold 2	**OI=7**	**OI=8**	**OI=9 Pathological**

The best financial condition of the firm is when both the $DEBT_{INDEX}$ and the NSD_{INDEX} are lower than the computed threshold 1. This is an optimal financial status (OI=1).

When both DEBT and NSD indices are between threshold 1 and threshold 2, the corresponding financial status can be considered normal (OI=5). All the other cases are illustrated in Table 2. Notice that in the classification of the firm's financial condition we assume the Debt index values are more important than the NSD index to define an over-indebtedness condition.

Therefore, given our definition, the OI_{INDEX} can rank from 1 to 9 signaling 9 different financial status levels. When the OI_{INDEX} takes values from 1 to 5, the firm cannot be considered over-indebted. On the contrary, when the OI_{INDEX} takes values from 6 to 9, the firm's financial status is fragile and it deteriorates as the OI index increases.

The worst situation for a firm is when both the $DEBT_{INDEX}$ and the NSD_{INDEX} are greater than the computed threshold 2. This condition, which is associated to the highest over-indebtedness degree, can be considered as a pathological financial status (OI=9).

So, we assume the firm is *over-indebted* if the overall debt of the firm – defined by the $DEBT_{INDEX}$ - is greater than the calculated threshold 2 level and/or the overall unsustainable level of debt - calculated by the NSD_{INDEX} – is greater than the calculated threshold 2.

Specifically, we define OVER-INDEBTEDNESS a firm's financial condition characterized by:

$$\mathbf{OI_{INDEX}} = \{\boldsymbol{DEBT_{INDEX}} > threshold\ 2; \mathbf{NSD}_{\boldsymbol{INDEX}} > threshold\ 2\}$$

However, in the empirical investigation, to get a larger sample, we included in the category of overindebted firms those in categories 8 and 9 in Table 2.

3 STATISTICAL METHOD AND RESULTS

In order to estimate the weights associated to each financial ratio in both the DEBT index and the NSD index, we use the Principal Component Analysis (PCA). It is a standard multivariate technique developed in early 20th century (Pearson 1901b, Hotelling 1933) in psychometrics and multivariate statistical analysis for similar purposes of aggregating information scattered in many numeric measures, such as student scores on several tests. It is described in many multivariate and dedicated textbooks such as Anderson (2003), Mardia, Kent & Bibby (1980), Jolliffe (2002) and Rencher (2002).

The last several years have seen a growth in the number of publications in economics that use Principal Component Analysis. In economics, the method has been applied to the studies of cointegration and spatial convergence (Harris 1997, Drakos 2002), development (Caudill, Zanella & Mixon 2000), panel data (Bai 1993, Reichlin 2002), forecasting (Stock & Watson 2002), simultaneous equations (Choi 2002) and economics of education (Webster 2001). Filmer and Pritchett (1998, 2001) used PCA to construct socioeconomic indices.

Principal Component Analysis (PCA) is a data-driven modeling technique that transforms a set of correlated variables into a smaller set of new variables (principal components) that are uncorrelated and retain most of the original information. More precisely, the aim of PCA is to reduce the dimensionality of a set of variables while retaining the maximum variability in terms of the variance-covariance structure. In other, words PCA tries to explain the variance-covariance structure of a data set using a new set of coordinate systems that is lesser in dimension than the number of original variables: mathematically, PCA is based on an orthogonal decomposition of the covariance matrix of the process variables along the directions that explain the maximum variation of the data.

Given a set of p variables, say X, a principal component (PC) model transforms these variables into a new set lesser in dimension, i.e., $k < p$, and yet can capture most of the variability in the original data set. Such a transformation will usually be accompanied by a loss of information. The goal of PCA is, therefore, to preserve as much information contained in the data as possible. The optimal number of PCs needed to achieve this task is not known *a priori*. The task is to find a set of k principal components with eigenvalues that have a significantly larger value than the remaining $p - k$. This procedure requires the definition of a threshold for the retrieved eigenvalues beyond which the rest of the PCs are regarded to be insignificant. In other words, we discover an effective number of variables in the PC model that explains the original data sufficiently well. This is known as the intrinsic dimensionality. Since PCA finds linear combinations of original variables that describe major trends in data set, given a PC model, we hope to be able to interpret the first few principal components in terms of the original variables, and thereby have a greater understanding of the data. However, just as many methods of statistical inference, the application of PCA requires a preprocessing stage in which the original variables are transformed in a way that the general assumptions about the data set will hold best.

In fact PCA, was originally developed for multivariate normal data, and it is a classical technique which can do something in the linear domain; applications having linear models are suitable. Further, its performance and applicability in real scenarios are limited by a lack of robustness to outlying observations. In fact, both the variance (which is being maximized) and the covariance matrix (which is being decomposed) are very sensitive to anomalous observations. Consequently, the first components are often attracted towards outlying points, and may not capture the variation of the regular observations. Therefore, data reduction based on PCA becomes unreliable if outliers are present in the data, as it was in our case.

For all these reasons we present in this paper results from a preliminary analysis based on the "most regular observations". That is, we decided to "estimate" principal components DEBT and NSD indices considering the observations lying between the first and the third quartiles, for all financial ratios simultaneously. In fact, a preliminary step of data preprocessing allowed us to establish that just these observations met quite well all the requirements previously outlined; that is why when consider all of the observations a number of outlying observations obscured the normal, linear and in particular the correlation structures both of the original variables and financial ratios. The following tables 3 and 4, where we present main statistics for financial ratios for the two geographical areas, highlight on some of these aspects.

Table 3 Main descriptive statistic for financial ratios in South of Italy

	N	Minimo	Massimo	Media	Deviazione std.	Interquartile Range
TA/N	22454	-13488,18	29665,00	11,7176	292,23595	7,37
FD/N	22454	-13489,18	29664,00	10,7182	292,23617	7,37
CL/FD	22320	-6,43	48,42	,7757	,39967	0,31
FD/CF	20416	-74132,00	347312,00	40,3622	2705,24678	22,56
TA/WK	21297	-44297,50	10059,06	-14,3303	612,43411	5,28
CL/CA	22440	-14,98	90417,00	6,6243	605,24978	0,48
NFP/TA	22326	-3,92	90416,00	5,4652	606,31166	0,33
CL/PLAT	22265	-118171,50	262315,00	29,0660	2443,89622	46,83
NFP/PLAT	22170	-114043,00	263518,00	33,7991	2825,39093	57,53
NTCA/N	20345	-11362,09	21138,83	2,9089	182,97073	1,75
TFA/(LTD+N)	22454	-11926,55	23221,67	2,3905	186,90501	1,26
IP/EBIT	20813	-667,21	814,00	,1895	11,73634	0,48
IP/EBITDA	19678	-206,00	1198,00	,2955	11,33244	0,28
IP/CF	19678	-1005,00	3598,00	,6690	36,83229	0,41
Validi (listwise)	19131					

Source: own elaborations on Amadeus Database

Table 4 Main descriptive statistic for financial ratios in Centre-North of Italy

	N	Minimo	Massimo	Media	Deviazione std.	Interquartile Range
TA/N	103227	-26100,36	84808,70	13,1883	456,17710	8,23
FD/N	103227	-26101,36	84807,71	12,1875	456,17733	8,23
CL/FD	103094	-1835,89	16,27	,7395	5,72410	0,27
FD/CF	99299	-98214,22	77087,00	22,1228	813,64227	22,90
TA/WK	100915	-119875,50	69244,00	-3,8445	866,22187	4,04
CL/CA	103209	-13,03	41570,71	2,3598	153,89316	0,43
NFP/TA	102712	-1,85	41569,71	1,5480	135,16821	0,38
CL/PLAT	102843	-414677,00	712957,00	18,9658	3176,03410	42,37
NFP/PLAT	102420	-653208,00	962564,00	45,1760	4916,81468	52,68
NTCA/N	99212	-5001,63	14846,50	2,0941	75,57791	1,62
TFA/(LTD+N)	103228	-4920,67	48221,15	2,3329	166,91858	1,13
IP/EBIT	99855	-2376,00	6192,46	,1937	26,85982	0,52
IP/EBITDA	97532	-848,36	4882,00	,2259	18,98461	0,31
IP/CF	97535	-2947,50	1900,33	,3553	20,40808	0,52
Validi (listwise)	95703					

Source: own elaborations on Amadeus Database

The PCA method applied to both data sets of the companies operating in the South of Italy and companies operating in the Centre-North regions has given quite similar results despite the different economic structure of the companies of these two macro areas and also the different number of companies comprised between the two 25% quartiles.

In the case of South Italy we restricted our analysis to 328 companies lying to the first and third quartiles; the two first principal components of the two data sets of financial ratios explained 85,61 and 91,61 of the total variance respectively. As results of such analysis, in Table 1 and 2 we present the correlations between the financial ratios and the (first) component and the corresponding weights (coefficients) α_i 's that allowed us to the define the DEBT and the PROF indices.

Table 5a

Financial Ratios	CORRELAT.	α_i
TA/N	.196	0.029
FD/N	.196	0.029
CL/FD	-.030	0.00025
FD/CF	.621	0.225
TA/WK	.012	0.0014
CL/CA	.155	0.0014
NFP/TA	.257	0.0019
CL/PLAT	.981	0.6347
NFP/PLAT	.988	0.7381
NTCA/N	.146	0.0045
TFA/(LTD+N)	.135	0.0034

Source: own elaborations on Amadeus Database

Table 5b

Financial Ratios	Correlations	δ_i
IP/EBIT	.932	0.561
IP/EBITDA	.988	0.595
IP/CF	.951	0.572

Source: own elaborations on Amadeus Database

We observe that the financial ratios that mostly contribute to define the DEBT index are NFP/PLAT, CL/PLAT and FD/CF, while all the three financial ratios we considered to define PROF index contribute almost the same.

In the case of Centre-North regions we restricted our analysis to the 1794 observations lying between the first and third quartiles; the two first principal components of the two data sets of financial ratios explained 85,82 and 93,20 of the total variance respectively. As results of such analysis, in Table 3 and 4 we present the correlations between the financial ratios and the (first) component and the corresponding weights (coefficients) α_i 's that allowed us to the define the DEBT and the PROF indices for Centre-Nord regions.

Table 5c

Financial Ratios	Correlations	α_i

TA/N	.241	0.042598
FD/N	.241	0.042598
CL/FD	.010	0.000101
FD/CF	.690	0.252467
TA/WK	.011	0.001208
CL/CA	.157	0.001611
NFP/TA	.234	0.002216
CL/PLAT	.987	0.621349
NFP/PLAT	.989	0.739678
NTCA/N	.117	0.004028
TFA/(LTD+N)	.093	0.002417

Source: own elaborations on Amadeus Database

Table 5d

Financial Ratios	Correlations	δ_i
IP/EBIT	.948	0.567665
IP/EBITDA	.991	0.593413
IP/CF	.957	0.573054

Source: own elaborations on Amadeus Database

We observe that also in the Centre-Nord regions the financial ratios that mostly contribute to define the DEBT index are NFP/PLAT, CL/PLAT and FD/CF, while all the three financial ratios we considered to define PROF index contribute almost the same.
Further developments in progress consider both a robust version of PCA (the goal is to obtain principal components that are not influenced much by outliers; this could avoid to sacrifice too much observations for our analysis) and a sensitivity analysis.

4 DESCRIPTIVE ANALYSIS

Substituting the estimated coefficients of α_i and δ_i in previous section and the threshold values for each ratio reported in Table 1 in the equations $DEBT_{INDEX}$ and NSD_{INDEX}, we identify the indexes' values which allow to classify firms according to their degree of indebtedness. In Tables 6 and 7 we present results of such "classification" for Centre-North and South respectively.

Table 6 Distribution of firms by DEBT Index and NSD Index, Centre-North

NSD_{INDEX} / $DEBT_{INDEX}$	**good** **NSD≤0.441**	**normal** **0.441< NSD<0.912**	**bad** **NSD ≥0.912**	Total
good **Debt≤1.069**	23100 *(24%)*	4154 *(4.3%)*	12397 *(13%)*	39651 (41%)
normal **1.069<Debt< 2.552**	1802 *(1.9%)*	35 *(0.04%)*	46 *(0.05%)*	1883 (2%)
bad **Debt≥2.552**	34218 *(35.6%)*	11056 *(11.6%)*	8895 *(9.3%)*	54169 (57%)
Total	59120 (62%)	15245 (16%)	21338 (22%)	95703 (100%)

Source: own elaborations on Amadeus Database

Table 7 Distribution of firms by DEBT Index and NSD Index, South

NSD_{INDEX} / $DEBT_{INDEX}$	**good** **NSD≤0.439**	**normal** **0.439<NSD<0.909**	**bad** **NSD≥0.909**	Total
good **Debt≤0.940**	5149 *(26.9%)*	653 *(3.4%)*	1949 *(10.2%)*	7751 *(40.5%)*
normal **0.940<Debt< 2.286**	180 *(0.9%)*	7 *(0.0%)*	8 *(0.0%)*	195 *(1.0%)*
bad **Debt≥2.286 (*bad*)**	7127 *(37.3%)*	2401 *(12.6%)*	1657 *(8.7%)*	11185 *(58.5%)*
Total	12456 *(65.1%)*	3061 *(16.0%)*	3614 *(18.9%)*	19131 *(100%)*

Source: own elaborations on Amadeus Database

Tables B1-B10 in Appendix B show the main descriptive statistics for each ratio separately for $DEBT_{INDEX}$ and NSD_{INDEX}, for the Centre-North and the South respectively (B1, B2 and B6, B7) and for each cell along the main diagonal of Table 6 and Table 7 (B3, B4, B5 and B8, B9, B10). In all the tables, the mean of the ratios result quite different. In particular, the inspection of the ratio statistics related to frequencies along main diagonal of Tables 6 and 7 - that is in the three case *optimal*, *normal* and *pathological* - show that the ratio means are very different for all the ratios and for both geographical areas, with the exception of ratios CL/FD, CL/CA and NFP/TA which get, by the way, very low weights in the definition of $DEBT_{INDEX}$.

Table 8 shows the evolution over 2003-2010 years of the loans over financial debt ratio (L/TA) and of the financial debt over total assets ratio (FD/TA). The percentage of the loans in the composition of financial debt is relatively low, in particular in the high-tech sectors. Financial debt over total assets, on the contrary, is always greater than 50% in all the sectors, both in the Centre-North and in the South of the country.

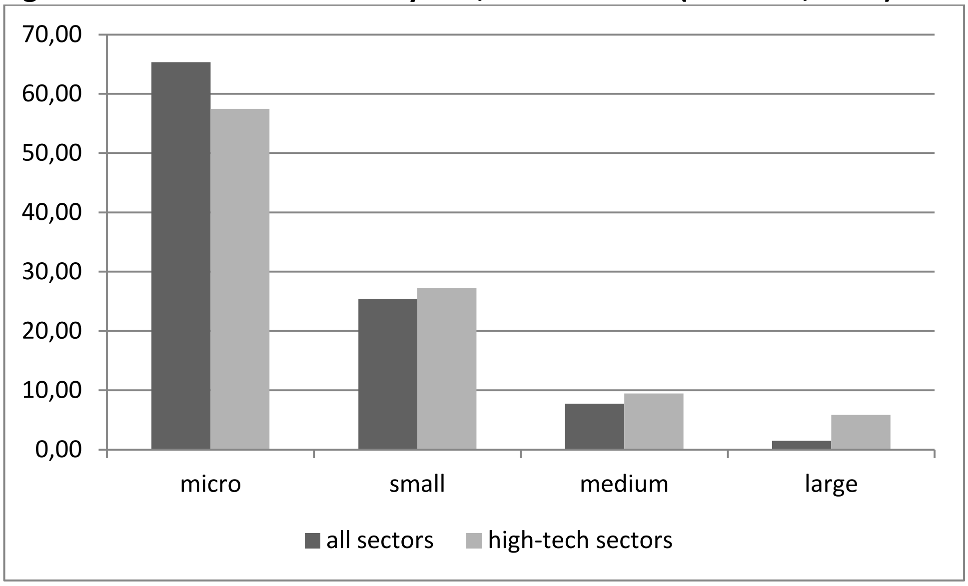
Table 8 Loans/FD and FD/TA (years 2003-2010)

Centre-North	2003	2004	2005	2006	2007	2008	2009	2010
all sectors								
Loans/FD	0.115	0.099	0.164	0.165	0.171	0.159	0.161	0.166
FD/TA	0.711	0.729	0.736	0.742	0.743	0.719	0.722	0.733
high-tech sectors								
Loans/FD	0.108	0.089	0.154	0.153	0.162	0.151	0.150	0.151
FD/TA	0.715	0.735	0.742	0.747	0.749	0.724	0.725	0.736
South	2003	2004	2005	2006	2007	2008	2009	2010
all sectors								
Loans/FD	0.099	0.060	0.116	0.123	0.120	0.108	0.104	0.116
FD/TA	0.694	0.710	0.718	0.725	0.727	0.726	0.725	0.729
high-tech sectors								
Loans/FD	0.081	0.047	0.108	0.121	0.124	0.101	0.103	0.110
FD/TA	0.697	0.714	0.718	0.719	0.725	0.719	0.725	0.733

Source: own elaborations on Amadeus Database

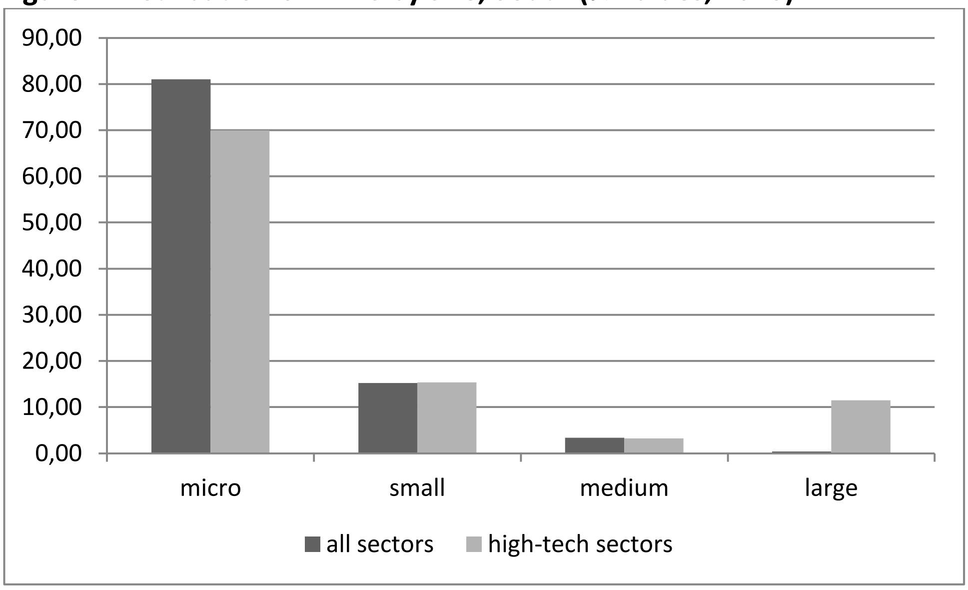
Figure 1 and Figure 2 show the distribution of the Italian manufacturing firms by size in the two considered areas of the country. Data reflect the traditional Italian industrial structure, essentially made up of micro and small firms. Figure 1 and Figure 2 show that the percentage of medium and large firms is relatively higher in: a) the Centre-North of the country; b) the high-tech sectors.

Figure 1 Distribution of firms by size, Centre-North (% values, 2010)



Source: own elaborations on Amadeus Database

Figure 2 Distribution of firms by size, South (% values, 2010)



Source: own elaborations on Amadeus Database

5 ECONOMETRIC ANALYSIS

5.1 Econometric Specification

This study is mainly based on firms' accounting data taken from the Amadeus database, published by *Bureau van Dijk*. It is a European financial database which includes more than 4 million firms' accounting data in a standardized balance sheet format. The database includes both SME and large firms operating in all industries.

Our analysis focuses on the Italian manufacturing firms in two macro areas: the South of Italy and the Centre-North of the country.

The computation of the $DEBT_{INDEX}$ and the NSD_{INDEX} for all the Italian manufacturing firms allows us to estimate if and to what extent firms' innovative activity depends on their over-indebtedness degree.

The econometric analysis is based on the estimation of the following function:

$$IA_{it} = \beta_0 + \beta_1 DEBT_{it} + \beta_2 NSD_{it} + \beta_3 X_{it} + \beta_4 Z_{it} + \beta_5 W_{it} + \gamma_t + u_i + \varepsilon_{it} \quad (1)$$

where *i* indicates firms, observed over the 2003-2010 period;

$\gamma_t$indicates time effects, u_i indicates firms' effects and ε_{it} are the stochastic residuals.

The dependent variable measures the innovative activity of the firm and it is given by the ratio between Intangible Fixed Assets and Total Fixed Assets. We use Intangible Fixed Assets as proxy variable for the intangible production factors. These include R&D expenditures, patents, copyrights, software, employees training, trademarks and other similar items (Marrocu et al., 2011). We have considered only firms with a positive innovative activity over the 2003-2010 years, that is only firms with IA/TA greater than zero.

The variables *DEBT* and *NSD*, defined in paragraph 2, indicate firms' indebtedness degree and their capacity to sustain debt.

The additional explanatory variables include firm-level, industry-level and region-level controls.

Specifically, the X matrix includes the following relevant firm-level variables:

L/TA which is the ratio between loans and total assets and it is used as a proxy of bank financing of innovative activity;

Size of the firm, measured as the log of total revenues;

Age, measured as the log of the difference between the last available year and the foundation date of the company;

Legal form, which takes value 1 if the firm is a joint stock company, 0 otherwise.

The Z matrix includes industry-level controls. In particular:

23 D_I industry dummies so that each dummy takes the value of one if the firm's main activity is in that industry and zero otherwise (see Table A1 in the appendix for the list of industries);

D_{HT} dummy which takes the value of one for high-tech industries and zero otherwise (see Table A2 in the appendix for details);

C_4 which indicates 4-firms concentration rate for each industry.

Finally, our model includes the W matrix which considers relevant regional-level controls:

TK which is a measure of technological capital, computed as 3 years patents stock (source: *Ufficio Italiano Brevetti e Marchi*) over 1000 population (source: Istat);

R&D which indicates total research and development expenditure as percentage of regional gross domestic product (source: Istat, *Statistiche sulla ricerca scientifica*);

HK as a measure of human capital, calculated as the number of people with a scientific degree over 1000 residents aged 20-29 (source: Istat);

Firm Density, computed as the average number of firms over 1000 inhabitants (source: Istat), which indicates the vitality of the economic system considered that firms' density can be a significant stimulus for competition and innovation;

GDP which indicates per-capita gross domestic product (source: Istat);
Infr which is a proxy of public infrastructures computed as kilometers of highway network in each region (over 1000 km^2 of regional territory) (source: Istat);
Criminality which is a proxy of social cohesion. It is computed as the number of people denounced for crimes (over 100000 inhabitants) (source: Istat);
Judicial efficiency which indicates the quality of the court system and it is measured as the number of years a first degree trial takes to complete (source: Ministry of Justice);
In alternative to regional-level controls, we include a dummy variable for each region.
Some descriptive statistics are reported in Table A3 in the Appendix.

5.2 Empirical Evidence

We drop all firms with at least one of the chosen financial ratios missing and, in order to correct for significant outliers, we eliminate all observations in the lowest and highest 1% percentiles. As mentioned in the previous paragraph, we estimate function (1) for all Italian manufacturing firms characterized by a positive ratio between intangibles and total assets, that is by considering only firms that invested in innovation in our period of investigation.
The analysis gives the following results, illustrated separately for Centre-North (Table 9) and Southern regions (Table 10).
As shown in Table 9 and in Table 10, the F test null hypothesis that all the coefficients are jointly equal to zero is always rejected at 1% level.
The pooled cross-section specification might generate biased and inconsistent results, since it does not take into account unobserved heterogeneity among firms like managerial ability, degree of risk-aversion, ownership structure, etc. In all the relevant specifications, indeed, the Breusch-Pagan test indicates that pooled cross-section is not the correct specification of the model since there are significant differences across firms. Individual shocks should be taken into account with a panel data estimation.
The Hausman specification test is then performed to investigate the correlation between the unobserved individual effect and the observed explanatory variables. As reported in Table 9 and in Table 10, we always reject the null hypothesis both for the Centre-North and the South of the country; therefore, the correct specification of the model is Fixed Effect.
All time-invariant variables are not considered with fixed effects estimation.
Empirical evidence for the Centre-North of the country shows that the DEBT index enters at 1 percent level of significance with the expected positive sign and a coefficient equal to 0.06 (Table 9, reg.(5)), suggesting that indebtedness plays an important role in explaining firms' innovative activity. Higher indebtedness is associated to higher values of intangibles over total assets highlighting that indebtedness is an incentive, not an obstacle, to innovation.
The coefficient of the NSD variable is significant at 1 percent level with an expected positive sign. Thus firms characterized by high interest rates compared to income and cash flow, which are probably also those firms with higher access to credit, are the most innovative ones[1].
We then augment this specification with a set of firm level variables such as loans over total assets, size and age to control for firms' characteristics (Table 9, reg.(6))[2]. The estimation results confirm both the sign and the significance level of DEBT and NSD. Relatively to the other explanatory variables, L/TA is significant at 1% level with positive sign. As expected, firms with higher access to credit invest more in innovative projects. Size is a significant determinant of

[1] The coefficient of correlation between NSD and Loans over Total Assets equals 0.40.
[2] Legal form is not considered with Fixed Effects specification since it is time-invariant.

innovation and this result holds also if we use total assets or the number of employees as measure of size. Age enters at 1% level with a negative sign suggesting that the innovative activity decreases with age, may be because younger firms invest an higher percentage of financial resources in R&D, employees training and software than older and more established firms[3].
We also control for industry concentration (Table 9, reg(7)). The coefficient of concentration rate is significant at 1% level with an expected positive sign. With imperfect capital market, firms are forced to finance their innovative projects from internal funds; therefore, there is a clear presumption that industrial concentration is positively correlated with innovative activity. Moreover, innovation is often used as a barrier to entry in a market characterized by a relatively high monopolistic power.
The results do not change when we add regional control variables (Table 9, reg.(7)).
The F test on the time dummies variables allows us to reject the hypothesis that all the coefficients are jointly equal to zero; therefore time fixed effects are explicitly considered in our model specification.

Table 9 Debt and Innovation, Centre-North – all sectors (2003-2010)

Dependent variable: IA_{it}							
	Random Effects				**Fixed Effects**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DEBT_{it}$	0.047***	0.058***	0.057***	0.059***	0.060***	0.057***	0.057***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)
NSD_{it}	0.077***	0.077***	0.079***	0.077***	0.063***	0.072***	0.072***
	(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.012)
L/TA_{it}		0.024***	0.026***	0.027***		0.023***	0.023***
		(0.004)	(0.004)	(0.004)		(0.004)	(0.005)
$Size_{it}$		0.108***	0.113***	0.101***		0.136***	0.137***
		(0.007)	(0.007)	(0.007)		(0.007)	(0.027)
Age_{it}		-0.332***	-0.336***	-0.335***		-0.239***	-0.233***
		(0.091)	(0.009)	(0.009)		(0.009)	(0.009)
Legal $form_{it}$		0.212***	0.194***	0.195***			
		(0.029)	(0.029)	(0.029)			
D_{HT}			0.226***				
			(0.022)				
C_4			0.108***				0.162***
			(0.016)				(0.049)
Industry dummies			no	yes			
Regional controls			yes	no		no	yes
Regional dummies				yes			
constant	-4.66***	-3.09***	-7.84***	-11.18**	-4.69***	-3.92***	-11.18
	(0.030)	(0.064)	(1.510)	(5.630)	(0.039)	(0.220)	(7.15)
F test[a]	901.14***	2781.12***	3351.58***	3739.79***	95.84***	53.62***	34.17***
Firm effects (F test)	-	-	-	-	7.18***	7.18***	7.12***
Time effects (F test)	389.08***	43.98***	42.94***	24.76***	69.87***	14.70***	3.97***
Hausman test		179.43***	197.23***	188.48***			
Breusch-Pagan test		44085.14***	43323.30***	42524.83***			
N obs.	107384	76175	76142	76142	107384	76175	76142
R^2	0.016	0.051	0.061	0.072	0.010	0.042	0.05

All variables are considered in log (except dummy variables). Robust standard errors in parenthesis.
Significance levels: *10%; **5%; ***10%.
[a] It refers to Wald test when random effect model is considered

[3] Also Benfratello et al. (2008) find that a probability of introducing a product innovation starts to decline after age 57.

Empirical evidence for the South of the country shows both some analogies and some differences with respect to the Centre-North.

The DEBT index and the NSD index enter at 10% and 1% level of significance respectively with a positive sign; loans over total assets, on the contrary, are not significant in explaining innovative activity in the South of the country. The stronger financial constraints shared by southern firms (Sarno, 2008; Sarno 2007) could be a possible reason explaining these results: given the greater difficulties to access to credit, the innovative activity is mainly explained by other forms of external financing and the availability of internal funds.

Size enters significantly with a positive sign, while age and concentration rate of the sector are not significant when we augment the model specification with regional controls (Table 10, reg.(7)).

Table 10 Debt and Innovation, South – all sectors (2003-2010)

Dependent variable: IA_{it}							
	Random Effects				**Fixed Effects**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DEBT_{it}$	-0.020	0.017	0.017	0.040**	0.006	0.012*	0.014*
	(0.014)	(0.019)	(0.019)	(0.019)	(0.017)	(0.028)	(0.030)
NSD_{it}	0.010	0.084***	0.086***	0.093***	0.056**	0.123***	0.137***
	(0.013)	(0.022)	(0.022)	(0.022)	(0.022)	(0.039)	(0.041)
L/TA_{it}		0.017*	0.017*	0.019*		-0.005	-0.005
		(0.010)	(0.010)	(0.010)		(0.016)	(0.016)
$Size_{it}$		0.225***	0.227***	0.255***		0.242***	0.210***
		(0.018)	(0.018)	(0.020)		(0.075)	(0.077)
Age_{it}		-0.180***	-0.181***	-0.140**		-0.170**	-0.028
		(0.025)	(0.025)	(0.026)		(0.081)	(0.105)
Legal $form_{it}$		0.174*	0.142	0.180*			
		(0.101)	(0.101)	(0.100)			
D_{HT}			0.053				
			(0.064)				
C_4			0.167***				0.136
			(0.043)				(0.166)
Industry dummies			no	yes			
Regional controls			yes	no		no	yes
Regional dummies				yes			
constant	-4.63***	-2.78***	8.37	-5.17***	-4.59***	-2.61***	3.89
	(0.080)	(0.150)	(9.840)	(1.240)	(0.114)	(0.517)	(10.76)
F test[a]	22.19***	385.99***	403.55***	567.82***	6.39**	7.98***	3.16***
Firm effects (F test)	-	-	-	-	6.11***	6.06***	6.03***
Time effects (F test)	20.34***	2.78	9.32	3.44	7.57***	1.53	1.08
Hausman test		22.01***	53.10***	14.49**			
Breusch-Pagan test		5206.19***	4782.26***	5009.75***			
N obs.	17913	10553	9921	10553	17913	10553	9921
R^2	0.013	0.061	0.072	0.083	0.010	0.061	0.014

All variables are considered in log (except dummy variables). Robust standard errors in parenthesis.
Significance levels: *10%; **5%; ***10%.
[a] It refers to Wald test when random effect model is considered.

5.2.1 Debt and Innovation in HIGH-TECH sectors

In this paragraph, we focus attention on the relationship between firms' indebtedness and innovation in high-tech sectors[4]. The Hausman specification test is performed to investigate the

[4] For a list of the high-tech sectors, see Table A2 in the Appendix A.

correlation between the unobserved individual effect and the observed explanatory variables both for the Centre-North and the South of the country. The results for the Hausman test, not reported in Table 11, are 46.28 (p-*value*>0.000) for the Centre-North and 16.20 (p-*value*>0.000) for the South respectively. Therefore, also for the high-tech sectors the correct specification of the model is Fixed effect.

Empirical results seem more or less confirmed for the high-tech sectors in the Centre-North, but the industry concentration rate (Table 11, reg (3)).

With reference to the South, the impact of the DEBT index in explaining firms' innovative activity is stronger for the most innovative firms; NSD, on the contrary, is not significant. Size enters positively at 1% level, while age is not significant in explaining innovative activity in high-tech sectors (Table 11, reg (6)).

Table 11 Debt and Innovation (2003-2010), High-Tech Sectors

Dependent variable: IA_{it}						
	Fixed Effects			**Fixed Effects**		
	Centre-North			**South**		
	(1)	(2)	(3)	(4)	(5)	(6)
$DEBT_{it}$	0.030**	0.032**	0.028*	0.078**	0.075*	0.091**
	(0.012)	(0.015)	(0.016)	(0.031)	(0.040)	(0.042)
NSD_{it}	0.096***	0.110***	0.115***	-0.010	0.048	0.079
	(0.015)	(0.019)	(0.020)	(0.031)	(0.044)	(0.050)
L/TA_{it}		0.015*	0.015*		0.030	0.034*
		(0.008)	(0.008)		(0.020)	(0.020)
$Size_{it}$		0.076**	0.157**		0.193***	0.230***
		(0.039)	(0.044)		(0.038)	(0.039)
Age_{it}		-0.333**	-0.143**		-0.128**	-0.088
		(0.053)	(0.066)		(0.056)	(0.059)
C_4			-0.172			0.250**
			(0.184)			(0.099)
Regional controls		no	yes		no	yes
constant	-4.40***	-3.01***	-17.04	-4.98***	-3.21***	3.63
	(0.067)	(0.325)	(12.32)	(0.151)	(0.319)	(7.20)
F test	31.70***	27.36***	11.58***	6.71***	4.33***	3.03***
Firm effects (F test)	7.14***	7.15***	7.15***	6.24***	6.26***	7.33***
Time effects (F test)	21.82***	5.98**	2.24**	7.29	0.40	3.51
N obs.	34419	24343	24334	3756	2182	2070
R^2	0.007	0.037	0.04	0.002	0.052	0.053

All variables are considered in log (except dummy variables). Robust standard errors in parenthesis.
Significance levels: *10%; **5%; ***10%.

5.2.2 Debt and Innovation for over-indebted firms

To investigate the impact of over-indebtedness on innovation, we have then focused on the firms with a pathological or near-pathological financial status (OI_{INDEX}=8 and OI_{INDEX}=9), that is firms that satisfy both the conditions $DEBT_{INDEX}$>2.55 and NSD_{INDEX}>0.437 in the Centre-North and $DEBT_{INDEX}$>2.245 and NSD_{INDEX}>0.437 in the South of the country.

The percentage of over-indebted firms is relatively higher for high-tech industries in both areas. Indeed, with respect to the Centre-North, the 19.17% of the firms are over-indebted in all the sectors, while the 23.51% of the firms are over-indebted in the high-tech sectors. In the South of

the country, the 21.14% of the firms are over-indebted in all the sectors, while the 29.29% % of the firms are over-indebted in the high-tech sectors.
For the Centre-North, empirical evidence for the over-indebted firms confirms the importance of the DEBT index and the NSD index independently from the sector, while Loans over total assets is significant only for over-indebted firms in the high-tech sectors.
For the South of the country, previous results are confirmed for over-indebted firms in the high tech industries. Compared to previous estimations, the coefficient of DEBT increases suggesting that the impact of a change in the debt structure on innovative activity would be greater for high tech firms.

Table 10 Debt and Innovation: Over-indebted Firms (2003-2010)

Dependent variable: IA_{it}				
	Centre-North		South	
	All sectors	High-tech	All sectors	High-tech
	(1)	(2)	(3)	(4)
$DEBT_{it}$	0.066***	0.046*	-0.032	0.296***
	(0.027)	(0.024)	(0.073)	(0.090)
NSD_{it}	0.110*	0.260*	0.216	-0.309
	(0.061)	(0.082)	(0.213)	(0.247)
L/TA_{it}	0.008	0.035*	0.001	0.096
	(0.018)	(0.019)	(0.058)	(0.061)
$Size_{it}$	0.116**	0.009	0.180	0.257***
	(0.049)	(0.049)	(0.165)	(0.027)
Age_{it}	-0.240***	-0.308***	0.094	-0.100
	(0.119)	(0.031)	(0.292)	(0.115)
C_4	0.084	0.197***		0.234
	(0.085)	(0.050)		(0.162)
Regional controls	yes	yes	yes	yes
constant	-13.18***	-5.42*	-23.92	-9.74
	(7.133)	(3.342)	(19.35)	(26.08)
F test	5.84***	2.87***	2.64***	2.28**
Firm effects (F test)	5.90***	6.91***	5.95***	5.57***
Time effects (F test)	1.31	1.46	2.61**	1.17
N obs.	20593	8094	3787	1108
R^2	0.04	0.04	0.02	0.06

All variables are considered in log (except dummy variables). Robust standard errors in parenthesis.
Significance levels: *10%; **5%; ***10%.

5.3 Dealing with endogeneity

As it is known, fixed effects in panel data model allow us to solve the omitted variable problem by controlling for the unobservable individual effect but the endogeneity problem is still present. Endogeneity could be produced by several factors like systematic shocks (period effects), omitted variables (unobserved heterogeneity), simultaneity, measurement error. Here, because of potential simultaneity, one could think that also the innovative activity determines firms' over-indebtedness degree. More specifically, the firms' debt and profitability, as well as the other potential endogenous explanatory variables, could be determined jointly with the dependent variable. Under endogeneity, the FE-estimator will be biased. The traditional approach to solve the endogeneity problem consists in instrumental variables regression with external instruments and fixed or random effects estimators. An alternative approach to tackle the endogeneity issue uses internal instruments by exploiting panel data structure. More specifically, we use a Generalized Method of Moment (GMM) estimator (Arellano and Bond 1991; Blundell and Bond 1998) treating all explanatory variables as potentially endogenous. Thus, we rewrite Eq. 1 in dynamics terms, as follows:

$$IA_{it} = \beta_0 + \beta_1 IA_{i,t-1} + \beta_2 DEBT_{it} + \beta_3 NSD_{it} + \beta_4 X_{it} + \beta_5 Z_{it} + \beta_6 W_{it} + u_i + \varepsilon_{it} \quad (2)$$

Equation 2 is a dynamic panel model with fixed effects (u_i) and a lagged dependent variable which allows us to take into account the dynamic nature of the innovative activity.

It can be properly estimated through the first differences GMM (GMM-DIFF) estimator proposed by Arellano and Bond (1991) which uses all the available lags of each independent variable in levels as instruments. However, the levels are poor instruments when variables exhibit strong persistence, as in the analyzed model (weak instruments). For this reason, we employ the estimation of the system of equations (GMM-SYS) implemented by Blundell and Bond (1998). It combines the first differenced regression used in GMM-DIFF and the Eq.2 in levels, whose instruments are the lagged differences of the endogenous variables.

Table 11 shows the empirical results and some specification tests.

We report the results of the tests proposed by Arellano and Bond (1991) to detect first and second-order serial correlation in the residuals[5]. As shown in Table 11, the absence of second-order serial correlation, which is a necessary condition for the validity of the instruments, is satisfied in our analysis.

A second specification test is a test of overidentifying restrictions. Since $p>0.05$, the null that the population moment conditions are correct is not rejected, therefore overidentifying restrictions are valid.

The coefficient of the lagged dependent variable is significant with a positive sign both for Centre-North and South of the country, for all the sectors and high-tech sectors, showing the opportunity of the dynamic specification of the model.

With respect to the other explanatory variables, the GMM-System confirms our previous estimation results. The empirical evidence shows the importance of the DEBT index, for all the sectors and areas of the country. The DEBT index, indeed, enters positively with a high level of significance in all specifications of the model.

Table 11 Debt and Innovation (2003-2010), GMM-system

Dependent variable: IA_{it}				
	Centre-North		**South**	
	All sectors	High-tech	All sectors	High-tech
	(1)	(2)	(3)	(4)
IA_{it-1}	0.752***	0.820***	0.722***	0.416**
	(0.031)	(0.030)	(0.103)	(0.040)
$DEBT_{it}$	0.046**	0.027*	0.080	0.108***
	(0.022)	(0.022)	(0.059)	(0.035)
NSD_{it}	0.011	0.012**	0.014	0.029***
	(0.003)	(0.006)	(0.010)	(0.008)
L/TA_{it}	0.002	-0.009	0.016	0.011
	(0.005)	(0.009)	(0.016)	(0.012)

[5] If ε_{it} are not serially correlated, the differenced residuals should show autocorrelation of first-order and absence of second-order serial correlation.

$Size_{it}$	0.010**	0.002**	0.440**	0.001
	(0.006)	(0.001)	(0.210)	(0.002)
Age_{it}	-0.043**	0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
C_4	0.013	0.031	0.041	0.021
	(0.016)	(0.022)	(0.042)	(0.042)
Regional controls	yes	yes	yes	yes
constant	-0.15	0.164	-1.033*	-1.051**
	(0.113)	(0.175)	(0.437)	(0.535)
Sargan test (*p* value)	0.723	0.100	0.42	0.456
AR (1) (*p* value)	0.000	0.000	0.005	0.002
AR (2) (*p* value)	0.153	0.328	0.259	0.191
N obs.	27791	9147	2352	718

Significance levels: *10%; **5%; ***10%. WC-Robust standard errors in parenthesis.

6 Conclusions

The aim of this paper is to build up an over-indebtedness index which takes account of the firm's financial structure as well as of its profitability conditions. Secondly, this research aims at verifying if and to what extent indebtedness explains firms' innovative activity by focusing on Italian manufacturing firms over the 2003-2010 period.

Empirical evidence for the Centre-North of the country suggests that indebtedness plays an important role in explaining firms' innovative activity. Over-indebtedness remains a very significant determinant of innovation also when we introduce industry and regional controls. Also for southern firms, indebtedness plays an important role in explaining their innovative activity. Empirical results are confirmed for high-tech firms, both in the Centre-North and in the South of the country.

To investigate the impact of over-indebtedness on innovation, we have then focused on the firms with a pathological or near-pathological financial status. The percentage of over-indebted firms is relatively higher for high-tech industries in both areas. For the Centre-North, the empirical evidence confirms the importance of the DEBT index and the NSD index independently from the sector, while Loans over total assets is significant only for over-indebted firms in the high-tech sectors. For the South of the country, previous results are confirmed for over-indebted firms in the high tech industries. Compared to previous estimations, the coefficient of DEBT increases suggesting that the impact of a change in the debt structure on innovative activity would be greater for high tech firms.

Our previous estimation results are confirmed also when we control for endogeneity. The empirical evidence shows the importance of the DEBT index, for all the sectors and areas of the country. The DEBT index, indeed, enters positively with a high level of significance in all specifications of the model.

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APPENDIX A

Table A1 List of industries

10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment nec
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing

Table A2 High Tech industries

Manufacture of chemicals and chemical products
Manufacture of basic pharmaceutical products and pharmaceutical preparations
Manufacture of computer, electronic and optical products
Manufacture of electrical equipment
Manufacture of machinery and equipment nec
Manufacture of motor vehicles, trailers and semi-trailers
Manufacture of other transport equipment

Table A3 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
CENTRE-NORTH				
All firms				
IA/TA	0.0293089	0.0525232	8.12e-07	0.6056765
DEBT	34.67076	39.9429	-76.17413	169.8895
NSD	0.2609796	0.2358971	-0.3555776	1.263622
L/TA	0.1011353	0.1119731	-0.7825242	0.7848015
Over-indebted firms				

IA/TA	0.0317235	0.052495	8.12e-07	0.5108737
DEBT	73.32877	39.20781	3.504613	169.3219
NSD	0.6124415	0.1303232	0.4370039	1.168917
L/TA	0.1911688	0.1319392	-0.3740467	0.6337065
SOUTH				
All firms				
IA/TA	0.0307316	0.0546403	1.79e-06	0.60082
DEBT	42.04124	41.41717	-62.88465	183.68
NSD	0.2654674	0.2373368	-0.2739496	1.061725
L/TA	0.0659298	0.0926253	-0.2543886	0.7378192
Over-indebted firms				
IA/TA	0.028647	0.0484712	1.79e-06	0.4726366
DEBT	73.02834	41.33216	3.542508	183.1677
NSD	0.6256344	0.1379924	.4375404	1.061725
L/TA	.1346382	.1122562	0	.5854046
HIGH TECH INDUSTRIES				
All firms				
IA/TA	0.0326268	0.0578321	1.58e-06	0.6056765
DEBT	35.11507	39.22121	-76.09116	169.3219
NSD	0.2491596	0.2296222	-0.2972364	1.25188
L/TA	0.0941572	0.1072458	-0.209506	0.6336448
Over-indebted firms				
IA/TA	0.0365848	0.0595556	6.22e-06	0.5014945
DEBT	73.00336	38.93299	3.504613	169.3219
NSD	0.6078619	0.1269962	0.4370039	1.131343
L/TA	0.1862265	0.1314155	-0.0540058	0.6336448

Source: own elaborations on Amadeus Database