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TOWARD AN INTEGRATED RATING METHODOLOGY FOR CORPORATE RISK DETECTION

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ABSTRACT

The need to innovate rating methodologies toward an integrated approach is crucial in the Italian financial contest. Currently, the banking system and the economic actors are unable to create effective and efficient information flows to react to the crisis. Banks weakness derives from the adopted rating models, which are mainly based on credit tendencies. They produce cyclical effects on credit availability and are not able to anticipate anti-cyclical firms' trends. The separation between financial and industrial analysis might be a driver of such an inefficient flow of information. The aim of the paper is to show a framework for an original rating methodology derived from the integration of industrial and financial analysis, in order to identify best performers in crisis scenarios (i.e. anti-cyclically). Industrial analysis is based on firm heterogeneity approaches to measure three dimension of analysis: innovation, internationalization and growth. Financial analysis focuses on operational return and risks measures and develops an integrated classification of firms using standardized XBRL financial data. Further integration of the two methodologies is used to create the effective set of information needed for an original rating system based on a certainty equivalent model. The case of the very competitive manufacturing firms in Vicenza was considered. The results suggest the efficacy of the proposed methodology in order to identify clusters of best performing firms in crisis scenarios, while the validation test on the post crisis timeframe confirms the anti-cyclical capacity of an integrated rating methodology.

1. INTRODUCTION

The financial crisis hit strongly the manufacture and made people aware of the existence of corporate risk. Through a very traumatic way, managers, bankers and regulators learnt that corporate risks must be managed mainly in an ex-ante approach. Only by managing according to this approach, you can *i)* avoid intolerable risks, *ii)* try to gain profits from risks that are compliant with the investor's risk aversion and *iii)* define the degree of risk sharing between the stakeholders of the firm. If managerial decisions are taken in this way, they can increase the long term corporate sustainability. But, how can corporate risk be soundly detected?

Techniques adopted in the classical financial risk approaches are often useless, since they are based on the heterogeneous nature of risks. Instead, in real terms, corporate risks have huge endogenous components, mainly related to corporate decisions and business model standards, as described by the competitive models in industries. Risk is continuously crafted by managerial decisions, including those adopted in order to manage them. The simple financial approach in corporate risk management is reductive for sure, missing the business model determinants along with the managerial decisions contribution. In order to soundly support the managerial choices, an integrated approach is required.

Two immediate consequences arise from the above framework: *i)* classical risk measures can distort the risk depicture inside companies, for both the absence of connection with more traditional corporate information system and their heterogeneity assumptions; *ii)* none of the measures can be efficiently adopted in real firms if they cannot be included into a business concept used to adopt sound managerial decisions regarding the entire business model (i.e. at all the levels). The integrated approach can solve the puzzle as Mantovani, Daniotti and Gurisatti (2013) demonstrate in the case of a specific industry in Italy.

To have a clear evidence of the corporate risk you must be able to unbundle it into more analytic measures, related to specific decisions that have to be taken in order to increase competitiveness. The industrial analysis will help you to re-bundle the measures, in order to have more insights about the return-to-risk ratios of the company. Such measures are usually outside the standard methodologies of the financial analysis. In fact, they aim to measure possible paths of corporate performance evolution (ex-ante), while financial reporting usually measures specific results (ex-post). Nonetheless, the endogenous nature of corporate risk may support measurement techniques that can even solve the adoption of data sourcing from the corporate information system. The close relationship between corporate risk and managerial decision is guarantee of risk persistence into the firm due to the stickiness of the decision impacts. Thus, indicators that are computed on accounting data can be helpful, if used to focus on the long term persistence of volatility (instead of specific results).

The paper aims to depict the inner benefits that may arise from an integrated rating approach, through the analysis of a sample of companies acting inside the very competitive Italian area of Vicenza, in North-Eastern Italy. To reach the target, the paper compares results arising from a traditional analysis at the industry level and the ones arising from the most advanced approaches of corporate risk management analysis. The latter consists in two steps: *i)* the return-risk analysis that evaluates single firm's operational strategy (Mantovani et al. 2013); *ii)* the development of the Lintner's (1965) certainty equivalent methodology in a financial rating perspective (Gardenal, 2011) following the confident equivalent methodology (Mantovani et al. 2014) based on the original formulas of the T-Ratio (Mantovani, 2011). The convergence of results lets us conclude that the integrated approach is robust. Furthermore, we demonstrate that, integrating a rating confident equivalent approach with the industrial classification, we can improve the prediction capacity of the model. The paper is organized as follows. After a literature review in Section 2, Section 3 depicts the main techniques of industrial analysis, adopted to detect risks embedded into different business models.

Section 4 presents the sample and its qualitative features. In Section 5 the methodology of financial analysis is reported. The empirical evidence at quantitative level (both ex-ante and ex-post) is shown insection 6 which compares results and demonstrates the superiority of the integrated approach. Section 7 concludes.

2. LITERATURE REVIEW

The great financial crisis of 2008 has shown all the weaknesses of a World Bank regulation that presents high levels of pro-cyclical effects. The evidence of such limits and threats incorporated in Basel II regulation, was extensively proved by the academic world (Kashyap 2003, Sironi et al. 2003), but representatives of states and governments of the G20 waited until the crisis boom for a regulation that improves the resilience of the financial markets. Starting from 1st January of 2014, "Basel III" regulation is active in the European Union bank system. However, many doubts on the pro-cyclicality of the regulation remain on the discussion table. In particular, the cyclical amplification effect is expected from small and medium enterprises (SMEs) rating systems. In fact, SMEs scoring is produced using a retail mechanism that evaluates credit tendency, creating a shift mechanism in asset allocation strategies from SMEs financing to low risk assets – i.e. government bonds (Blundell-Wignall Atkinson, 2010). Such a turnover is mainly dependent on bank's lack of capacity in measuring risk and return performance of SMEs, partially derived from an inefficient information flow among SMEs and banks. On one hand, most of SMEs do not present a complete and reliable report system. On the other, banks mostly consider firms' credit history to evaluate credit merit (Dainelli et al. 2013). In addition, Mantovani and Daniotti (2012) report how, in crisis periods, banks of Treviso district tend to finance bigger enterprises, reducing credit availability for smallest ones. It is evident that new methodologies of rating are needed, especially for SMEs. The Italian economy is a good field for testing new rating models for SMEs. In fact, Italy has the highest proportion of SMEs among OECD countries and SMEs are also responsible for the majority of Italian economic growth (Manfra 2002). The North-East - in particular - presents fundamental characteristics for new studies implementation: firms located in the North East of Italy produce 25% of national GDP, and generate among 33% of national total export, reporting the high GDP pro-capite rate of growth in Italy in the last 40 years (Bank of Italy 2011). The high proportion of SMEs and the high productivity of the North East drive our sample choice on the manufacturing firms of Vicenza, which is one of the main Italian manufacturing regions. The integration of a financial methodology with an industrial one puts our work in line with some precedent papers that underline the importance of adding soft information to standard financial approaches for a correct valuation of firms' merit of credit (Liberti 2005).

3. INDUSTRIAL ANALYSIS

In this section, we present the industrial analysis methodology used to classify firms by relevant structure and performance variables. This investigation was initiated with a survey sent to a sample of 309 industrial firms, selected by industry and size representativeness, located in Vicenza[1]. The aim of our analysis is to examine which business strategic feature can explain the different responses of firms to the financial and economic crisis. In other word, our research hypothesis refers to firm heterogeneity approaches (Bernard et al. 2012), where traditional variables – i.e. industry, size, location, etc. – are deemed insufficient to understand the different business dynamics. However, unlike other studies that immediately employ explanatory methods (regression analysis) based on the structure-performance relationship, our research takes an exploratory approach, with the purpose to identify different types of businesses in relation to three dimensions of firms' competitiveness: *i)* first of all, we look at innovation capabilities, collecting data on patents (with design and utility models too) and R&D offices; *ii)* secondly, we evaluate the international activities through information on firm's export, the occurrence of affiliates abroad and where firm see the main competitors; *iii*) finally, we measure the turnover and profit performance just after the 2008 crisis. Some control variables were also considered - such size and industry - but do not participate in the structural analysis. The choice is based on a theoretical framework of industrial analysis that considers competitiveness not just a sectors' matter, but a firm one (Porter 2000). More specifically, competitiveness is seen as interlinked between two dimensions: on one hand, the distinctive competences and the absorptive capacity of the firm; on the other, the economic ecosystem – i.e. local cluster, global value chain and markets – where the firm works (Buciuni et al. 2013).

The statistical model processed data in two steps. First, by a multiple correspondence analysis, we built a structural framework to study the main relations among variables and firms; then, by a cluster analysis, we identified five groups with peculiar features and a good quality of statistical representation. With the multiple correspondence analysis, we got that the 70% of the whole variability is explained by two axes: one discriminates firms by innovation capabilities and international position, and the other by performance. This means that best competitive features (i.e. innovation activities and openness) are not associated with good economic results. At the same time, weak innovation capacity and local markets are not associated with poor performance. For this reason, it is necessary to deepen the analysis with cluster analysis and by collecting more data on firms' balance sheet series.

[1] The survey was implemented from the 15th to the 22th of June 2011. The statistical universe was the set of firms joining the Industrial Association of the Vicenza Province (Associazione Industriali Provincia di Vicenza).

We identified five groups and named them as follows[2] - according to the emerging characteristics:

- **G1** - *International and reactive firms* (about 20% of the sample): the group collects firms with the best innovation capabilities and with a strong international position (high export propensity and often with foreign investments) and good performances even during the crisis;

- **G2** - *International but not reactive firms* (15% of the sample): this group shows firms that, despite the good structural variables (specially in terms of innovation and exports), have had negative performance;

- **G3** - *Local reactive firms* (20% of the sample): this group classifies small firms with weak innovation activities and for which local market is crucial but that have shown good economic performance during the crisis. In this group there are suppliers and service businesses linked to the value chain of local or national leader firms.

- **G4** - *National or local not reactive firms* (15% of the sample): this group pulls together firms with the worst conditions, i.e. either structural and performance variables are bad;

- **G5** - *Average or standard firms* (30% of the sample): as usual, correspondence analysis detaches those firms with no significant differentiations related to the variables set. So, this group pulls companies that present average performance and structural variables in comparison to other classifications.

In Appendix A figures, the five groups are described through several structural and performance variables. In the next section, we assume these groups as the industrial side of the analysis. For instance, we will try to understand if the belonging of firms in each group, may be explained by different risk management strategies adopted in previous years. Graphs D to G (in Appendix A) clearly describe the structural conditions of each competitive group on the first ax (innovation capabilities and international position), in line with the characterization summarized here above. G1 and G2 have a strong international attitude, while G3 and G4 are almost exclusively concentrated on the national market, with low rate of investment in R&D and innovation systems. To these key parameters, before any other comment on the performance ax, it's important to associate further details about the economic sector. Manufacturing is prevalent in the first two groups, with a remarkable role played by Mechanics. Differently Construction and Services play an important role in all the other groups, mainly G3. The Construction sector has a strong influence on performance of these groups. In Italy, and Vicenza, the sector has followed a very peculiar evolution: running very fast, far beyond the market saturation before 2008, and literally collapsing during the period 2009-2012.

[2] Specific group features of the, resulting from survey, are reported in Appendix A.

Performance data are highly informed by this sector's trend and by the downturn of the Italian consumption, also affecting Services. Furthermore, the first two groups are characterized by larger companies, competing head to head with advanced competitors, while the other groups are characterized by smaller companies, far less exposed to real competition (see Tables A and B in Appendix A).

Having this structural framework in mind, it is easier to interpret the performance data, presented in Graph B and C (Appendix A). Negative turnover variation is impressing in G2 and G4, with high rates of net losses, while G1 and G3 (the most reactive companies) travel in more safe waters. Reactivity, in using available competitive advantages (at the international and local level), comes out as the key asset of G1 and G3 by statistical analysis. Manufacturing specialization is the second key asset, beyond the specific situation of the Construction system in Italy during the period considered by the survey.

4. THE SAMPLE

The survey sent out to manufacturing firms located in Vicenza[3] also reported the "authority[4] identification code". Using identification codes, by the AIDA database[5] "research" function, we could extract complete balance sheets for the financial analysis implementation. The analysis was performed on a sample data containing continuous and complete standard financial reports from 2004 to 2012 (Table 1).

The first extraction was made on November, 22 2011 (software version, 179) and the criteria were: 309 firms' identification codes; continuous and complete 2004-2010 standard financial reports. The second extraction, to include the 2012 up-date, was made on October, 3 2013 (software version, 200) and the criteria were: 309 firms' identification codes; continuous and complete 2004-2012 standard financial reports. The first extraction delivered 182 firms' data, while the second extraction only 159 firms' data (Table 1).

Table 1: Search criteria* for extraction of sample database on AIDA software on 2012 up-date.

Variable	Criteria	Number of Firms selected
Identification code	BG0336110, MI0057076, MI1509019, MI1662809, MI1686807, …	225
Continuous years with available account	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012	159

* Elaboration from AIDA Bureau van Dijk "research" function.

[3] The statistical universe was the set of firms members of the Industrial Association of the Province of Vicenza.

[4] In Italy all firms with a limited responsibility must file their balance sheets (at least once a year) to the Chamber of Commerce. The Chamber represent the authority that monitors the correctness of such documents and gives to each firm an identification code.

[5] Software with fee, edited by Bureau van Dijk, available at Ca'Foscari University in Venice.

For missing balance sheets in 2011 and 2012, further data was extracted from In.balance[6] database, by searching identification codes and checking the correspondence of data values for the last year of AIDA available accounts. The check on values confirms the possibility to integrate the two databases. Data from In.balance showed that 4 firms defaulted in 2012, balance sheets for 6 active firms were found and 1 firm was acquired by another firm in 2012.

The availability of data for the 2004-2010 timeframe covered 58% of firms that answered to the survey, with a percent that varies from 34% of G3 to 77% of G1 (Table 2). Differences come from the composition of each group. The majority of Italian small firms have no balance sheet on the AIDA database. For such a reason, G3 - that is composed by the majority of small firms - presents the smaller sample coverage. For the 2004-2012 timeframe, searches on AIDA and In.balance software produced a loss of data for 17 firms: 3 in G1, 5 in G2, 5 in G4, 4 in G5. G3 does not register any loss of data availability. As reported above, 4 of the 17 firms defaulted in 2011 or 2012: 1 in G1, 2 in G2 and 1 in G5. Such firms were considered as KO in the financial analysis and completed the final sample composition. During the post crisis timeframe, 169 firms were considered, covering the 93% of the sample for 2004-2010 financial analysis (Table 2). The firm acquired in 2012 was in G1.

Table 2: Original samples and update on 2013 – number of firms.

	Original samples			**Sample update** (26th September 2013)		
Groups	**Survey sample**	**2004-2010 financial sample**	**Cover percentage**	**2004-2012 financial sample**	***Defaulted (+acquired)***	**2004-2012 analysis sample**
G 1	61	**47**	77%	44	*1(+1)*	**45**
G 2	45	**30**	67%	25	*2*	**27**
G 3	62	**21**	34%	21	*0*	**21**
G 4	46	**23**	50%	18	*0*	**18**
G 5	91	**61**	67%	57	*1*	**58**
TOTAL	**313**	**182**	**58%**	**165**	***4***	**169**

Summarizing, data loss is present in particular in G2 (3 firms data loss and 3 defaults) and G4 (5 firms data loss), which are the groups of bad performers in the industrial analysis. G1 and G3 - that are considered the group of best performers in the industrial analysis - register the least loss of data

[6]In.balance is edited by Info Camere and collects data from Chambers of Commerce data base. Data is available starting from 2008, for firms that report balance sheets in XBRL format. We thank the Chamber of Commerce of Treviso, for the access to In.balance data base.

5. FINANCIAL ANALYSIS

In this section we present a quantitative financial model used to classify the sample according to return and risk indicators[7]. The intuition behind this model is the need to give an appropriate emphasis to risk dimensions in classifying a "performing" firm. The resulting matrix (Figure 1) classifies the sample into six quadrants: "OK firms", "KO firms", two quadrants identified as "Critic Firms" and two quadrants identified as "Anomalous Firms to be reclassified."

Figure 1: Financial Model Framework for the classification of Firms in the sample

		RETURNS		
		INCREASING ROC (ROC 2010 > ROC 2007)		DECREASING ROC (ROC 2010<ROC 2007)
		STEADY TREND (ROC 2010>ROC 2008)	UNSTEADY TREND (ROC 2010<ROC 2008)	WORSENING
RISK	DECREASING RISK	Ok	Anomalous Firms to be reclassified-Group B	Critic firms
	INCREASING RISK	Anomalous Firms to be reclassified-Group A	Critic firms	Ko

First, to capture the return dimension, we use a measure of return on capital "ROC", defined as:

$$ROC_t = \frac{EBIT_{\ t}}{FA_{\ t} + WKCA_t} \qquad \text{Eq. 1}$$

Where:

ROC = Return on Capital

$EBIT$ = Earnings before interest and taxes

FA = Fixed Assets

$WKCA$ = Working Capital[8]

Further, the return dimension is divided into three sub-dimensions to capture a steady increasing trend, an unsteady increasing trend and a decreasing trend. Specifically, if $ROC_{2010} > ROC_{2007}$ two classifications were possible: if $ROC_{2010} > ROC_{2008}$, the state is defined as "steady increasing trend"; if $ROC_{2010} < ROC_{2008}$ it is defined as "unsteady increasing trend". Finally, if $ROC_{2010} < ROC_{2007}$ the state is defined as "worsening."

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[7] The methodology is presented for the 2007-2010 timeframe. In other timeframes (2004-2007 and 2010-2012) it was used the same process.

[8] It is to note that in our calculation for Working Capital, the account "Creditors" was missing for some companies in the sample. To solve for this problem, Creditors for some companies was estimated based on method and data from a prior paper authored by Mantovani et al. (2011)

Second, the risk dimension is identified by three accounting indicators:

$$DOL = \frac{AV_t}{EBIT_t} \qquad \text{Eq. 2}$$

$$DPL = \left[\frac{\frac{AV_t}{OpRev_t}}{\frac{AV_t}{OpRev_t} - x} - 1\right] * 100 \qquad \text{Eq. 3}$$

$$WKCA\ Intensity = \frac{WKCA_t}{OpRev_t} \qquad \text{Eq. 4}$$

Where:

DOL = Degree of Operating Leverage

DPL = Degree of Price Leverage

AV = Added Value

$EBIT$ = Earnings Before Interest and Taxes

$OpRev$ = Operating Revenues

$WKCA$ = Working Capital

x = price variation for DPL calculation (1%)

Within this realm, a firm will be classified as having a "decreasing risk", if two out of three indicators present a value at the end of the period (year 2010) that is lower than the value at the beginning of the analysis (year 2007). Conversely, if two out of three indicators present the end value greater than the beginning one, the firm will be classified as having an "increasing risk." The intersection within the return and the risk dimensions creates five categorizations and six quadrants as follows (Figure 1):

1. "OK" firms, if return is increasing with a steady trend and risk is decreasing
2. "KO" firms if return is decreasing while risk in increasing
3. "Critic" firms if either both return and risk is decreasing or if return is increasing with an unsteady trend and risk is increasing
4. "Anomalous" firms Group A if return and risk are increasing
5. "Anomalous" firms Group B if return is increasing with an unsteady trend and risk is decreasing

Moreover "Anomalous" firms are to be reclassified based on an additional analysis as follows:

1. For Group A, if two out of three individual "return to risk" ratios calculated at the end of the period are superior the value at the beginning of the period, they are reclassified as "OK firm", otherwise as "Critic firm".

2. For Group B, it has to be checked the decreasing "steadiness" of risk in the intermediate year of 2008. If it is decreasing steadily, it will be classified as "OK firm", otherwise as "Critic firm".

3. For firms that present ambiguous data, the "Anomalous" classification was confirmed.

The above analysis is performed over three timeframes: the pre-crisis period (2004-2007), the crisis period (2007-2010) and the post-crisis period (2010-2012). The pre and crisis periods are considered as the "in sample" period while the post-crisis period serves as the "out of sample" (or verification) period. Table 3 shows the distribution of the firms classified according to the above methodology. What it is interesting is the fact that, during the crisis period (2007-2010), the number of OK firms more than halved, while the number of KO firms doubled. Further, the post-crisis period shows a progressive normalization of the sample classification, in line with the pre-crisis.

Table 3: Descriptive statistics of firms' financial analysis by three timeframes selected.

2004 - 2007	**OK**	**KO**	**Critical**	**Anomalous**	**Total**
#	74	54	28	13	169
%	44%	32%	17%	8%	100%
2007 - 2010	**OK**	**KO**	**Critical**	**Anomalous**	**Total**
#	31	105	32	1	169
%	18%	62%	19%	1%	100%
2010 - 2012	**OK**	**KO**	**Critical**	**Anomalous**	**Total**
#	51	76	40	2	169
%	30%	45%	24%	1%	100%

In addition, we apply Mantovani et al (2013) methodology also to identify anomalous data, by considering single index distribution. In practice we looked at the years in which a firm presents an extreme data (outside 2 standard deviations) and excluded all the indexes of such a year from the data-set.

6. INTEGRATION OF RESULTS

To integrate the industrial and the financial classifications, we propose to use a rating methodology based on an original development of the the certainty equivalent method elaborated by Lintner (1965). Mantovani et al (2013) defined such a methodology by the adoption of a confident equivalent indicator as follows

$$CE = E(ROC) - \mathrm{z} * \sigma_{ROC} \qquad \text{Eq.5}$$

Where:

z = identify the firm's threshold ROC, with the 90% of confidence.

To estimate σ_{ROC} the Authors focus on five measures of corporate risk (Gardenal, 2011) and the autoregressive component of ROC in order to find the future expected ROC.

In addition, we apply further Mantovani et al (2013) to identify anomalous data, by considering single index distribution. In practice we looked at the years in which a firm presents an extreme data (outside 2 standard deviations) and excluded all the indexes of such a year from the data-set.

We present the results of financial classification by industrial analysis clustering and the average levels of indexes for each group, in order to identify best performers groups and quantify the aggregate level of performance. We expect, in fact, that the best performers cluster presents the highest percentage of OK firms and the best aggregate relationship between return and risk indexes. In the second part, we show the changes in classification of firms by groups, in order to identify if the proposed scoring methodology of manufacturing firms presents an internal coherence also in the classification migration. We expect, in fact, that best performers' clusters of firms register the highest percentage of firms that improve their classification in comparison with the others groups and the lowest percentage of firms that worsen their classification in the timeframes considered.

6.1. Aggregate Analysis

For timeframe 2004-2007, any group presents a similar financial classification composition (Table 4) with an unexpected result: G1 firms - the international best performing firms - present the lowest percentage of OK firms and the highest percentage of KO. The other groups present similar percentages of OK firms, with G5 and G3 having the highest percentages of OK firms before the crisis period. G3 is also characterized by a high presence of anomalous firms - with a not clear trend in return and risk changes. Such a result may depend on the presence of many small firms in this cluster.

Table 4: Financial analysis results on 2004-2007 timeframe - number and percentage of firms by group.

2004-2007		OK	KO	Critical	Anomalous	TOT
G 1	#	16	18	9	2	45
	%	36%	40%	20%	4%	100%
G 2	#	11	8	4	4	27
	%	41%	30%	15%	15%	100%
G 3	#	10	5	1	5	21
	%	48%	24%	5%	24%	100%
G 4	#	8	6	4	0	18
	%	44%	33%	22%	0%	100%
G 5	#	29	17	10	2	58
	%	50%	29%	17%	3%	100%
TOTAL	#	74	54	28	13	169
	%	44%	32%	17%	8%	100%

Moving to the crisis timeframe (2007-2010), significant variations are produced. G1firms move from the lowest to the highest percentage of OK firms (33%), while all the other groups reduce significantly the percentage of OK firms. Best industrial clusters present the lowest difference of OK percentage (Table 5):

- G1 move from a 36% to a 33%;
- G3 move from a 48% to 19%;
- G5 move from 50% to 17%;
- G2 move from 41% to 7%;
- G4 presents 0% of OK firms, from an initial 44%.

During the crisis period, any group of firms show an increase of KO classification and a reduction in the percentage of critical firms.

Aggregate return and risk values integrate financial and industrial analysis results by completing the framework of information.

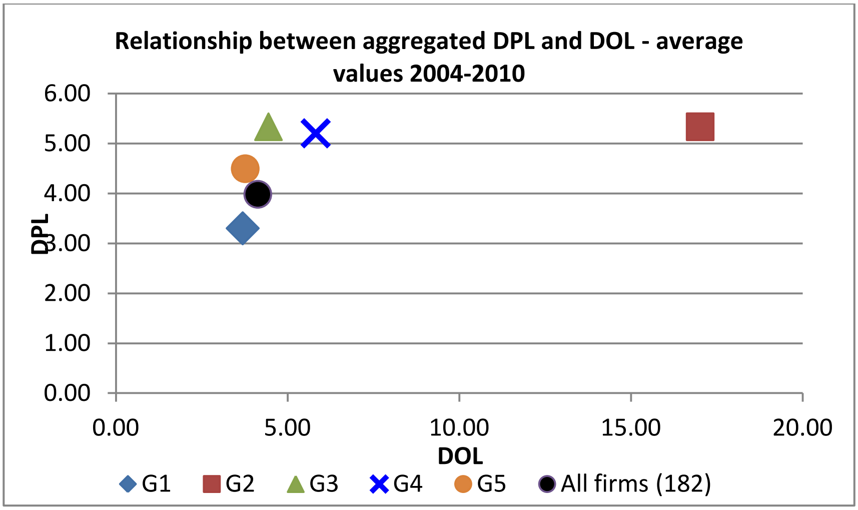
Table 5: Financial analysis results on 2007-2010 timeframe - number and percentage of firms by group.

2007-2010		OK	KO	Critical	Anomalous
G 1	#	15	24	5	1
	%	33%	53%	11%	2%
G 2	#	2	22	3	0
	%	7%	81%	11%	0%
G 3	#	4	13	4	0
	%	19%	62%	19%	0%
G 4	#	0	10	8	0
	%	0%	56%	44%	0%
G 5	#	10	36	12	0
	%	17%	62%	21%	0%
TOTAL	#	31	105	32	1
	%	18%	62%	19%	1%

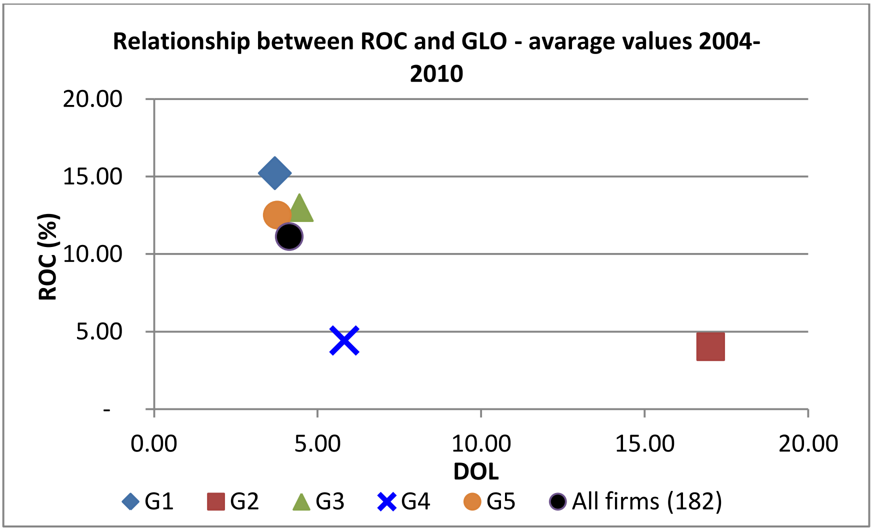
G1 presents the lowest risk exposure for both price and volumes variations (Graph 8) and the highest return rate (Graph 9). Differently, G2 - which groups international firms with bad performance - presents a high level of operational risk indexes. The differences among G1 and G2 firms are based on a different ability to manage risk in the international contest. G3 and G5 do not present relevant differences in risk composition, just G4 - gathering worst performers - reveals a significant level of DOL (Graph 8). Worst clusters - G2 and G4 - in crisis period, present the lowest level of ROC, while G4 high risk exposure is relevant in determining financial classification changes. It can be noticed how the financial analysis of firms confirms the industrial one. In fact, financial analysis confirm that G1 are the best performers in crisis period, followed by G3 and G5. G2 and G4 are the worst and, between them, G4 has no firms that react positively to the crisis.

The implementation of the model on the 2010-2012 timeframe is used as an out of sample timeframe for definitive model confirmation. In fact, the sample update gives some additional evidence on the default tendency. The presence of defaulted firms in G1, G2 and G5 and the lack of defaulted firms in G3 and G4 point out an higher tendency of default in international or partially international firms, in comparison to local or national ones. Among them, G2 presents the highest percentage of defaulted firms (6,7%), confirming itself as one of the riskiest clusters.

Graph 8: Relationship between aggregated DPL and DOL – average values on 2004-2010 timeframe.



Graph 9: Relationship between aggregated DPL and DOL – average values on 2004-2012 timeframe.



Financial analysis for the post-crisis timeframe confirms G1 as the best performing - with 42% of firms that are classified OK - while G3 is confirmed to be a good performing cluster - with 33% of OK firms. The anomalous data represents the 37% of OK firms in G2 - international bad performing firms - which represents a significant improvement of firms' classification for a non performing cluster (Table 6).

G2 firms' results may be due to the significant reduction of DOL, with an aggregate level of return and risk indicators that, instead, confirms the low performance of the cluster (Graph 10). Overall, G1 and G2 show the highest percentage of OK firms, signaling a good reaction to the crisis by firms playing on an international market.

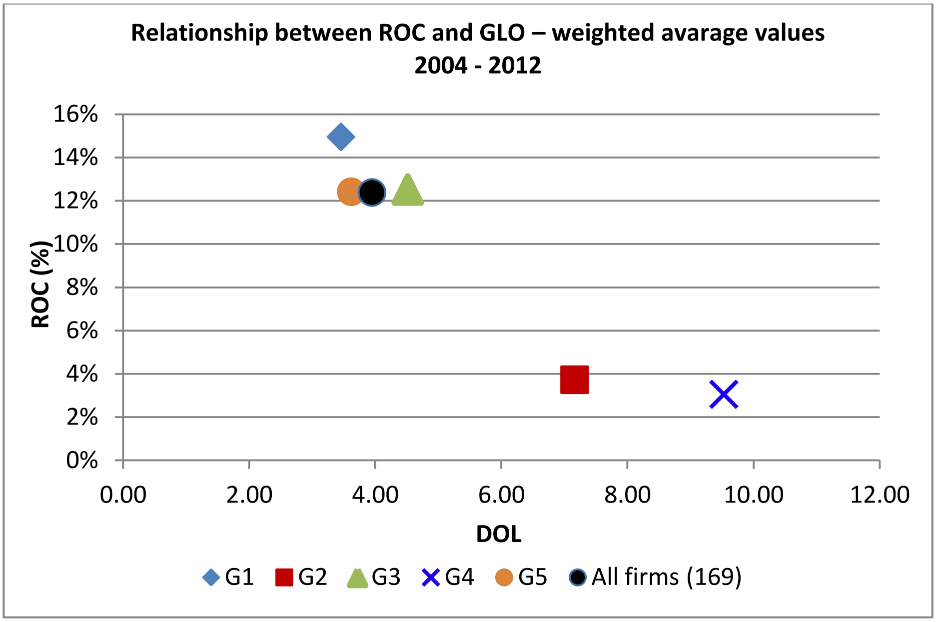
All clusters report an increase in OK firms (Table 6) after the crisis, while G5 presents the lowest improvement. All clusters keep a higher rate of KO firms than the pre-crisis level, even if it is decreasing. Such results depend on the firms' risk exposure. Excluding DOL for G2, all other clusters present a level of risk unchanged or increased in the last two years: G3 reports an increase only in DPL risk while G4 in both DOL and DPL risk; G2 presents a higher level of DPL (Graph 11). Such results point out an increased average risk - despite the high rate of OK firms - after the crisis, depicting a scenario with no definitive overcoming of the crisis.

Table 6: Financial analysis results on 2004-2007 timeframe - number and percentage of firms by group.

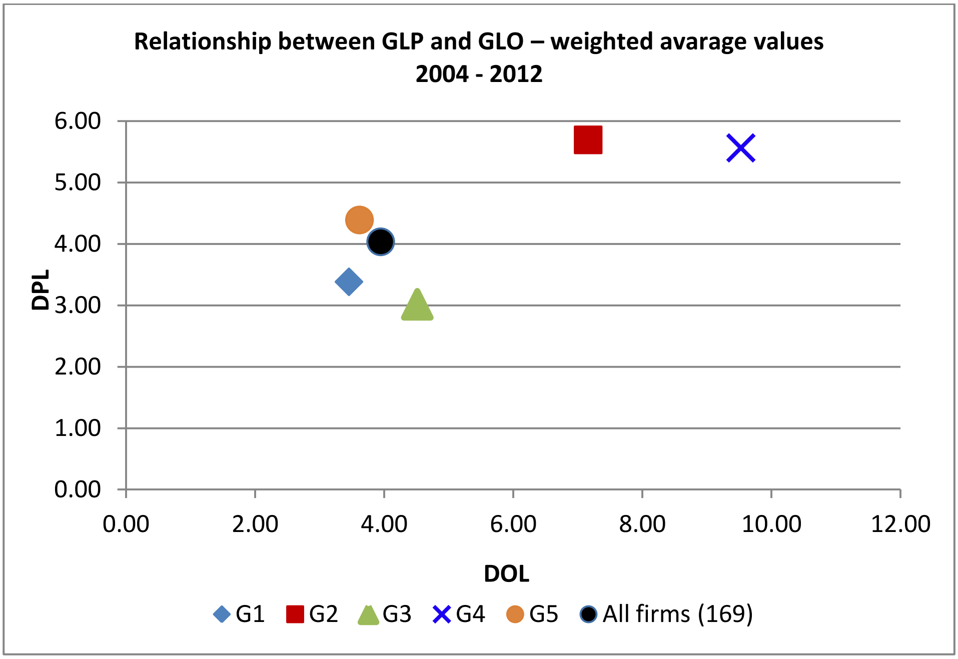
2010-2012		OK	KO	Critical	Anomalous
G 1	#	19	21	5	0
	%	42%	47%	11%	0%
G 2	#	10	12	4	1
	%	37%	44%	15%	4%
G 3	#	7	8	6	0
	%	33%	38%	29%	0%
G 4	#	4	10	4	0
	%	22%	56%	22%	0%
G 5	#	11	25	21	1
	%	19%	43%	36%	2%
TOTALE	#	51	76	40	2
	%	30%	45%	24%	1%

Summarizing, we can say that the industrial analysis produces a consistent method to identify best performers. On one hand, the industrial method identifies firms with high return rate and low risk exposure (i.e. G1, G3 and G5) and firms with low return rate and high risk exposure (i.e. G2 and G4). On the other, the financial method confirms the ability to react to the crisis by best performing groups (G1 and G3). Finally, the expectations about cluster performance are also confirmed after the crisis. Hence, the industrial methodology is able to detect long-term trends of firms' performance.

Graph 10: Relationship between aggregated ROC and DOL – average values during 2004-2012.



Graph 11: Relationship between aggregated DPL and DOL – average values during 2004-2012.



6.2. Migration analysis

A further in-depth analysis on singular firm classification for each timeframe will highlight the specific reaction of firms to the crisis and - at the same time - will test the coherence of the model. First of all, we notice that G1 keeps a high and constant level of OK firms in all three timeframes while the most volatile performance is registered in G2 and G4 (Tables 7).

Table 7: Resume of industrial and financial analysis output (percent of firms per group)

		OK	KO	Critical	Anomalous
G 1	2004-2007	36%	40%	20%	4%
	2007-2010	33%	53%	11%	2%
	2010-2012	42%	47%	11%	0%
G 2	2004-2007	41%	30%	15%	15%
	2007-2010	7%	81%	11%	0%
	2010-2012	37%	44%	15%	4%
G 3	2004-2007	48%	24%	5%	24%
	2007-2010	19%	62%	19%	0%
	2010-2012	33%	38%	29%	0%
G 4	2004-2007	44%	33%	22%	0%
	2007-2010	0%	56%	44%	0%
	2010-2012	22%	56%	22%	0%
G 5	2004-2007	50%	29%	17%	3%
	2007-2010	17%	62%	21%	0%
	2010-2012	19%	43%	36%	2%
TOTAL	2004-2007	44%	32%	17%	8%
	2007-2010	18%	62%	19%	1%
	2010-2012	30%	45%	24%	1%

Between the pre-crisis and crisis periods, a total of 28 firms confirms their classification, 95 worsen their position and 43 improve their status. G1 presents the highest percentage (33%) of improving performance firms during the crisis timeframe, followed by G5 (28%) and G3 (25%). G1 also registers the lowest percentage of worsening firms' performance during the crisis (42%) with all the other groups that register a percentage near 60% (Table 8). In the post crisis period, a total of 59 firms confirms the previous classification, 40 firms worsen their status, while 68 firms improves it (Table 9). Firms that improve performance are located more in G2 and G3 - 52% of each group - and less in G1 and G4 - 33% of each group. For G1, the low statistic depends on the high presence of good performers already in the crisis period. For G4, the result is a signal of the absence of firms that are able to react to crisis. In fact, in G4 there is also the highest percentage of firms that confirms the crisis classification (44%) while 33% of G4 firms confirms a KO position (Table 9).

The crisis and post-crisis timeframes present the highest correspondence of classification - 35% of firms do not change status - confirming the capacity of the model to predict crisis and post crisis performance. Between pre- and post-crisis timeframes the correspondence is also significant: 31% of firms restores the status before the crisis (Table 10).

Table 8: Detail on classification changes between two timeframes: 2004-2007 and 2007-2010

2004-2007 and 2007-2010		Group					Total
Classification		1	2	3	4	5	
Confirmed	OK	1	0	2	0	0	3
	Critical	2	1	0	1	1	5
	Anomalous	0	0	0	0	0	0
	KO	6	6	1	2	5	20
	TOTAL	9	7	3	3	6	28
Worsened	From OK to KO	14	10	7	5	25	61
	From OK to Critical	1	1	1	3	4	10
	From Critical to KO	3	2	1	3	5	14
	From Anomalous to KO	1	4	4	0	1	10
	TOTAL	19	17	13	11	35	95
Improved	From Critical to OK	3	1	0	0	4	8
	From KO to OK	11	1	1	0	6	19
	From KO to Critical	1	1	3	4	6	15
	From Anomalous to OK	0	0	1	0	0	1
	TOTAL	15	3	5	4	16	43
Others	Others	2	0	0	0	1	3

Table 9: Detail on classification changes between two timeframes: 2007-2010 and 2010-2012

2007-2010 and 2010-2012		Group					Total
Classification		1	2	3	4	5	
Confirmed	OK	8	0	1	0	1	10
	Critical	0	0	1	2	4	7
	Anomalous	0	0	0	0	0	0
	KO	11	8	3	6	14	42
	TOTAL	19	8	5	8	19	59
Worsened	From OK to KO	6	2	3	0	4	15
	From OK to Critical	1	0	0	0	5	6
	From Critical to KO	4	2	2	4	7	19
	From Anomalous to KO	0	0	0	0	0	0
	TOTAL	11	4	5	4	16	40
Improved	From Critical to OK	1	1	1	2	1	6
	From KO to OK	9	9	5	2	9	34
	From KO to Critical	4	4	5	2	12	27
	From Anomalous to OK	1	0	0	0	0	1
	TOTAL	15	14	11	6	22	68
Others	Others	0	1	0	0	1	2

Table 10: Detail on classification changes between two timeframes: 2004-2007 and 2010-2012

2004-2007 and 2010-2012		Group					Total
Classification		1	2	3	4	5	
Confirmed	OK	4	5	2	2	8	21
	Critical	0	1	0	1	7	9
	Anomalous	0	0	0	0	0	0
	KO	7	3	1	3	8	22
	TOTAL	11	9	3	6	23	52
Worsened	From OK to KO	8	4	4	5	15	36
	From OK to Critical	4	1	4	1	6	16
	From Critical to KO	5	2	1	2	1	11
	From Anomalous to KO	1	3	2	0	1	7
	TOTAL	18	10	11	8	23	70
Improved	From Critical to OK	4	1	0	1	2	8
	From KO to OK	10	3	2	1	1	17
	From KO to Critical	1	2	2	2	7	14
	From Anomalous to OK	1	1	3	0	0	5
	TOTAL	16	7	7	4	10	44
Others	Others	0	1	0	0	2	3

Summarizing, 63% of firms (106 firms) presents a correspondence between at least two periods of analysis. Only 11 firms present the same classification for all the three timeframes: 1 OK, 9 KO and 1 critical. Firms classified as OK in all the three periods belong to G1 while the one classified as critical is in G5. The 9 KO firms in all the timeframes belong to four of the five groups: 3 firms belong to G1, 2 firms to G2, 2 to G4 and 2 to G5. Only G3 does not present a firm classified KO for all the timeframes (Table 11).

Any elaboration of the financial analysis(aggregate and migration) demonstrates that the industrial classification correctly identifies the G1cluster as containing the best performers: G1 firms have the best capacity to react to crisis and the highest percentage of OK firms during the crisis and post-crisis period. At the same time, G4 is also correctly identified as the worst performing group. In fact, G4 firms have the lowest percentage of improving firms and the highest percentage of worsening firms in crisis and post crisis timeframes. As the industrial model predicts, G3 and G5 are clusters of good performers, even if the result is due to different features: in G5 firms, the partial presence of good structural variables and the partial openness to international markets compensate the lower rate of performance in comparison to G3.

The most interesting cluster is G2, the group of international firms with low performance. During the crisis, G2 suffered a high degree of risk exposure, being that one also the reason of the low performance during the three timeframes. However, the international openness of G2 firms permitted to reduce risk exposure after the crisis.

In fact, G2 firms report an improvement in financial classification, despite conserving low ROC levels. Differently, G4 firms do not present such improvement in risk exposure because of the geographic context of competition: the national one does not give the opportunity to react promptly to the crisis as the international one.

Concluding, financial analysis confirms the industrial classification (especially in crisis and post-crisis periods): G1 firms have the best performance also during crisis, followed by G3 and G5; G2 and G4 are the worst performing firms' clusters.

Table 11: Index matches by cluster and number of firm with 2 or 3 matches.

			OK	KO	Critical	No. corr.
G 1	2 ind.	#	10	15	2	18
		%	22%	33%	4%	40%
	3 ind.	#	1	3	0	41
		%	2%	7%	0%	91%
G 2	2 ind.	#	5	11	2	9
		%	19%	41%	7%	33%
	3 ind.	#	0	2	0	25
		%	0%	7%	0%	93%
G 3	2 ind.	#	5	5	1	10
		%	24%	24%	5%	48%
	3 ind.	#	0	0	0	21
		%	0%	0%	0%	100%
G 4	2 ind.	#	2	5	4	7
		%	11%	28%	22%	39%
	3 ind.	#	0	2	0	16
		%	0%	11%	0%	89%
G 5	2 ind.	#	9	21	9	19
		%	16%	36%	16%	33%
	3 ind.	#	0	2	1	55
		%	0%	3%	2%	95%
TOTAL	2 ind.	#	31	57	18	63
		%	18%	34%	11%	37%
	3 ind.	#	1	9	1	158
		%	1%	5%	1%	93%

6.3 Confident Equivalent Analysis

In this section, we show the confident equivalent estimation for any group, in order to measure the soundness of industrial and financial classifications. In fact, by using the confident equivalent methodology, we are able to produce a value of firms' investment by group, derived from expected return and risk estimations.

Table 12 presents the expected return on capital and the respective estimated standard deviation for every group as well as the total of the firms, derived from regressions on all available data:

- G1, G3 and G5 confirm industrial and financial classifications for the expected return level;
- national firms (G3 and G4) present the highest level of volatility of ROC;
- G3 and G4 present the lowest confident equivalent – lower than the total firms' one.

Table 12: Expected ROC, ROC volatility and confident equivalent – total data-set.

	G1	G2	G3	G4	G5	TOTAL
$\boldsymbol{\sigma_{ROC}}$	10.3%	11.6%	30.0%	21.9%	17.5%	20.4%
$\boldsymbol{E(ROC)}$	14.7%	9.7%	13.0%	8.1%	15.0%	13.3%
$\boldsymbol{CE}$	1.5%	-5.2%	-25.5%	-20.0%	-7.4%	-12.9%
R-squared	*0.256*	*0.392*	*0.832*	*0.745*	*0.449*	*0.524*

The result could depend strongly on fewer anomalous values and, for this reason, we repeated the confident equivalent's estimation by cutting from the data-set the firm's data in the year in which it presents at least one anomalous index. Table 13 shows the statistics of the anomalous data distribution by group and year. As we can see from Table 13, G3 presents the highest level of outlier data with more than 1 outlier index per firm, followed by G5 and G2. Furthermore, it is evident that the highest concentration of anomalous data is in 2012 and not, as it could be expected, during the crisis period. Hence, we can conclude that outliers' data are not linked to a particular economic contingency but maybe on data reliability or availability. These considerations represent a further reason that supports the exclusion of the outliers' data from the final regressions' data-set.

Table 13: Average of Outlier Data (AOD) per firm.

	AOD TOT	AOD 2012	AOD 2011	AOD 2010	AOD 2009	AOD 2008	AOD 2007	AOD 2006	AOD 2005	AOD 2004	AOD (%)
G1	0.34	0.09	0.00	0.00	0.05	0.02	0.07	0.02	0.05	0.05	4%
G2	0.68	0.16	0.04	0.04	0.08	0.04	0.04	0.12	0.08	0.08	8%
G3	1.10	0.33	0.10	0.10	0.14	0.14	0.05	0.05	0.10	0.10	12%
G4	0.33	0.17	0.00	0.06	0.06	0.00	0.06	0.00	0.00	0.00	4%
G5	0.91	0.25	0.07	0.07	0.05	0.11	0.11	0.07	0.09	0.11	10%
TOTAL	0.68	0.19	0.04	0.05	0.07	0.07	0.07	0.05	0.07	0.07	8%

The AOD total represents the average number of outlier data per firm, i.e. the sum of AOD for each year; the AOD percentage represents the percentage of outlier data on the total of data.

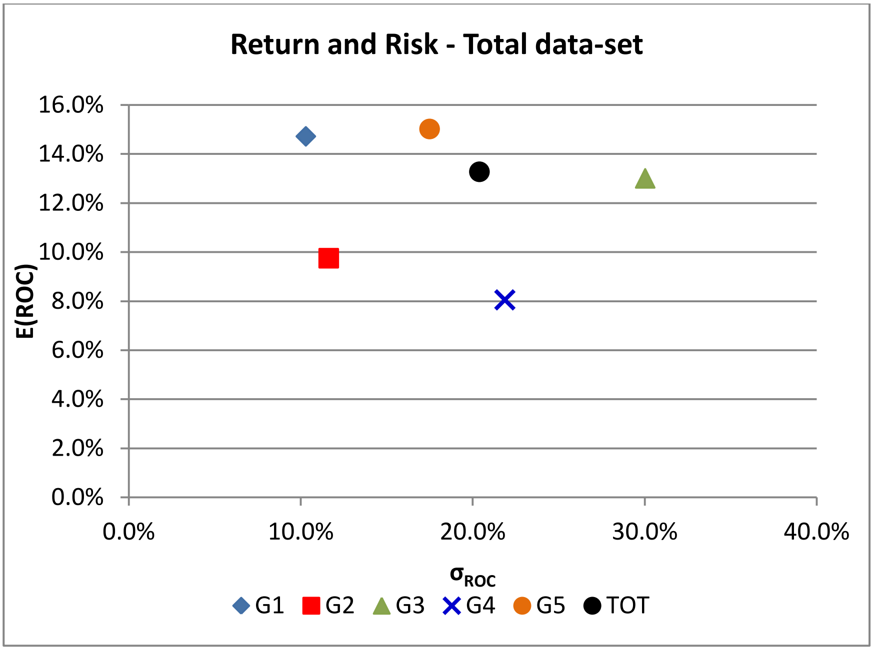
After outliers' data exclusion, re-estimated regressions (Appendix B) show a higher level of R-squared, thus giving the possibility to produce a more efficient estimation of expected ROC, ROC volatility and the confident equivalent. In fact, as we can see from Table 14, new regressions give a more coherent and sound confident equivalent classification:

- G1, G3 and G5 still present higher levels of expected return than total firms;
- the volatility is not too different from one group to another, and only G4 present a level of ROC volatility higher than total firms' estimation, while G1 has the lowest one.

Hence, the confident equivalent classification confirms industrial and financial ones: estimating the highest level for G1, followed by G3, G5, G2 and G4. Also, the financial classification presented in previous section produced the same results.

Graph 12 and 13 summarize the return-risk classification produced through the regressions' output, by which we can easily find that G1 firms present an absolute dominance in return-risk combination for both the firm evaluation and the investment choice perspective and for both the data-sets considered.

Graph 12: Expected ROC and ROC volatility by group – total data-set.



Graph 13: Expected ROC and ROC volatility by group – anomalous data excluded.

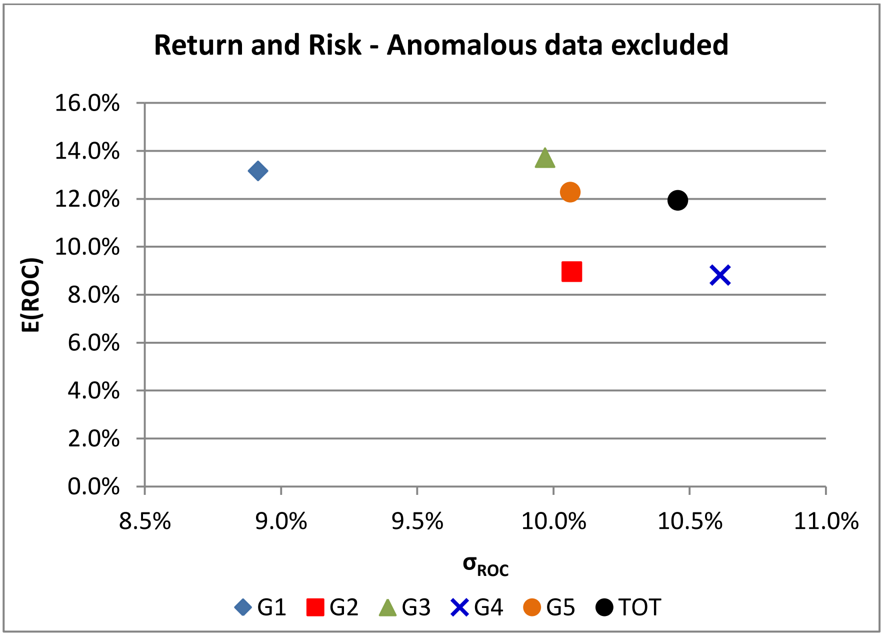


Table 14: Expected ROC, ROC volatility and certainty equivalent – anomalous data excluded.

	G1	G2	G3	G4	G5	TOT
$\boldsymbol{\sigma_{ROC}}$	8.9%	10.1%	10.0%	10.6%	10.1%	10.5%
$\boldsymbol{E(ROC)}$	13.2%	9.0%	13.7%	8.8%	12.3%	11.9%
$\boldsymbol{CE}$	1.7%	-3.9%	0.9%	-4.8%	-0.6%	-1.5%
R-squared	*0.503089*	*0.614092*	*0.882785*	*0.853525*	*0.832314*	*0.760715*

7. CONCLUSIONS

Results from the empirical analysis are clear: an integrated approach in corporate risk detection is more efficient than standard financial (i.e. Basel) approaches. By adopting such a methodology, you can measure the impact of risks that do persist into the firm, along with their impact as a bundle. This means that you reduce short-termism and pro-cyclicality, looking through the real business risk. The choice of the indicators must be done according to both critical drivers arising from a sound business analysis and their ability to intercept corporate information. The first finding of this paper is that any efficient corporate risk measure in private (i.e. non-listed) companies must be conceived into a return-to-risk framework. The efficacy of the proposed measures is tested by comparing the results arising from a qualitative survey, mainly based on the industry analysis tools, with those arising from a more quantitative detection of corporate risks. Evidence clarifies the overlapping conclusions of the two approaches, thus demonstrating the soundness of the integrated rating approach.

In order to test the predictability of previous results, we ran an additional quantitative analysis on a more updated data set to verify how many companies remain in the same cluster years later. The persistency emerging from this test supports the soundness of the integrated rating approach even in an ex-post framework (i.e. in the long run). The opportunity to include the data sourced from industrial analysis into the integrated rating approach, increases the efficacy of the estimation. The result demonstrates the relevance of including qualitative industrial analysis in a rating system elaboration. In fact, the confident equivalent, produced for each group, presents an increase in regression outputs and estimations significance measured by R-squared statistic. Furthermore, $E(ROC)$, σ_{ROC} and CE estimations confirm industrial and financial results, depicting an efficient methodology for long-run financial merit estimation. This paper gives the proof that industrial analysis and financial elaborations are fundamental to develop an effective and efficient rating confident equivalent system. Future research must be aimed at applying the proposed methodology here to a wider set of firms, and integrate the survey used for industrial analysis with more qualitative information.

Appendix A – Results of Survey Data Collection

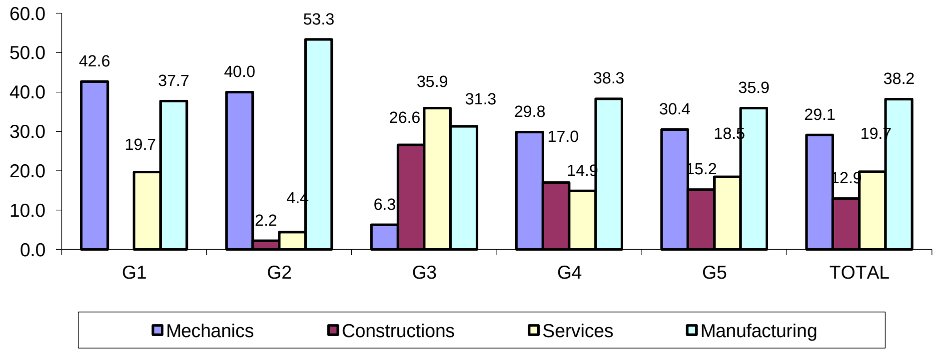
Table A: Group and firms' size (by number of employees)

Number of employees	G1	G2	G3	G4	G5	TOTAL
0-10	6.6	22.2	48.4	40.4	29.3	29.4
11-20	14.8	24.4	17.2	31.9	20.7	21.0
21-50	31.1	24.4	23.4	14.9	29.3	25.6
51-100	19.7	20.0	6.3	12.8	13.0	13.9
100+	27.9	8.9	4.7		7.6	10.0
TOTAL	100.0	100.0	100.0	100.0	100.0	100.0

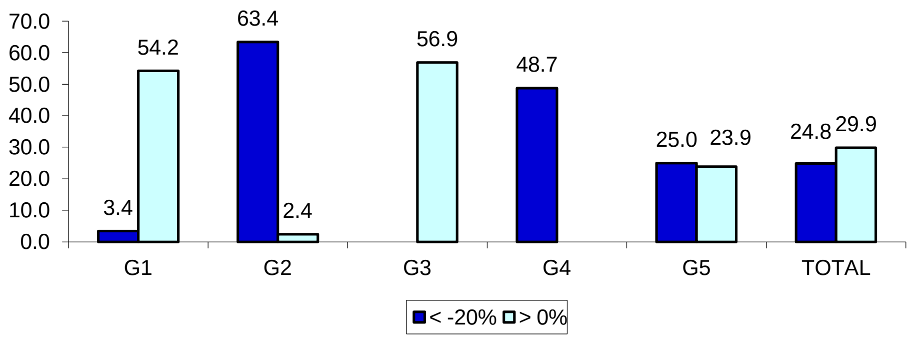
Table B: Firms typology of competitors - percentage per group.

	G1	G2	G3	G4	G5	**TOTAL**
Only advanced competitors	45.9	22.2	6.3		8.7	**16.2**
Only entering competitors		28.9		2.1	7.6	**6.8**
Advanced and entering competitors	21.3	11.1			1.1	**6.1**
No competitors	32.8	37.8	93.8	97.9	82.6	**70.9**
TOTAL	100.0	100.0	100.0	100.0	100.0	**100.0**

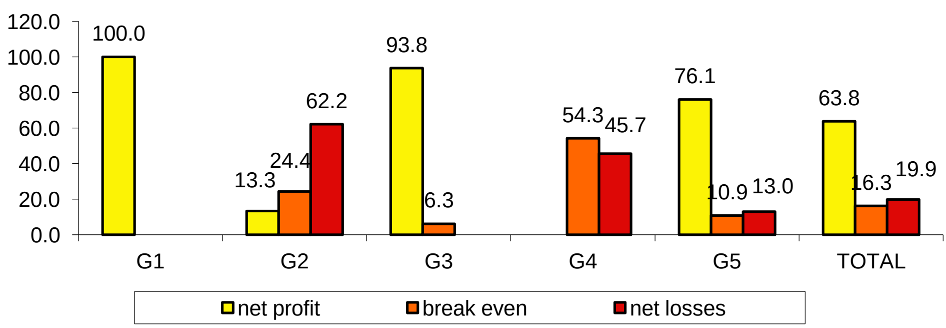
Graph A: Economic sector of firms - percentage per group.



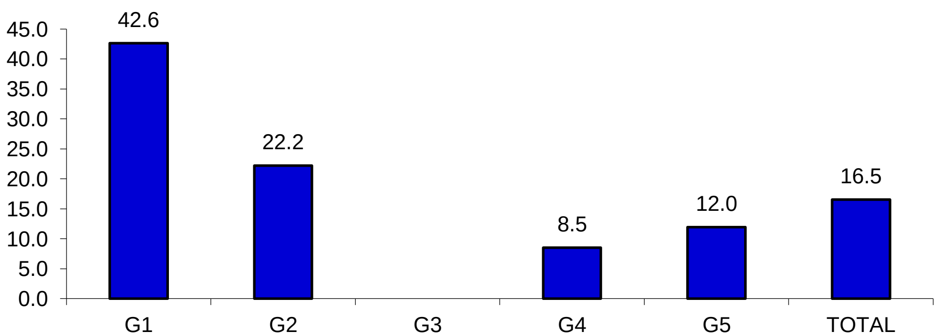
Graph B: Firms' turnover variation class on 2010 - percentage per group.



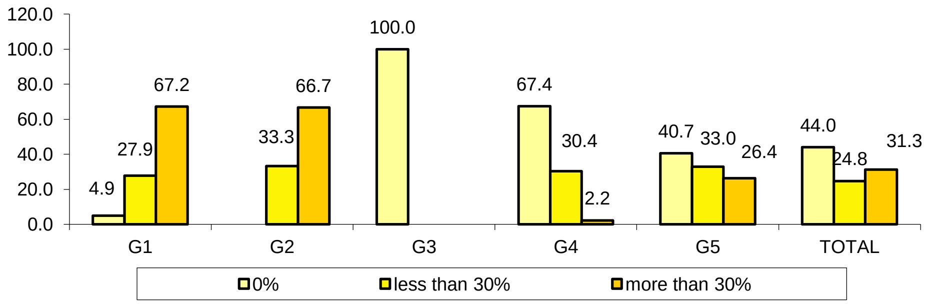
Graph C: Firms net income class - percentage per group.



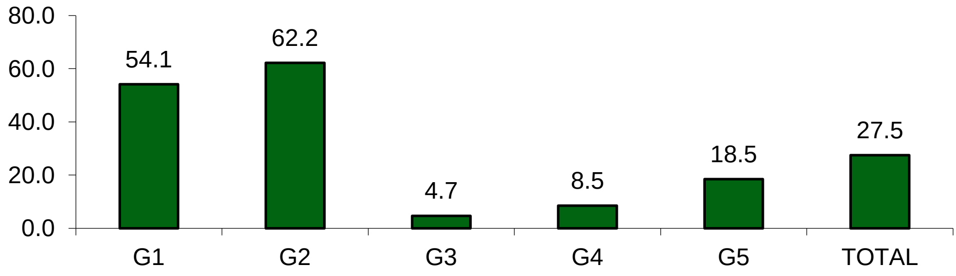
Graph D: Firms with foreign branches - percentage per group.



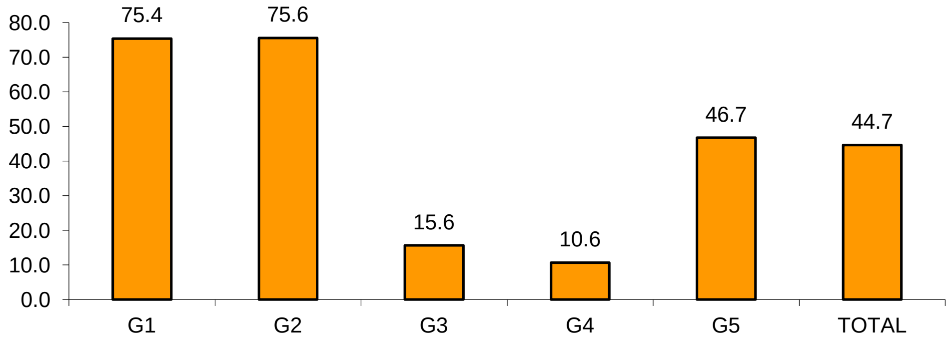
Graph E: Firms export rate on turnover class - percentage per group.



Graph F: Firms that register patents, or models - percentage per group.



Graph G: Firms with a R&D office - percentage per group.



Appendix B – Regression Estimated Outputs for Total Sample of Firms and the Five Goups – Outlier Data Excluded.

Table C: Total sample of firms

Dependent Variable: D(ROC)
Method: Panel Least Squares
Date: 02/13/14 Time: 10:02
Sample: 2004 2012 IF ANOM_TOT=0
Periods included: 8
Cross-sections included: 160
Total panel (unbalanced) observations: 1181

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.120097	0.004856	24.73267	0
DPL(-1)	-0.00151	0.000732	-2.05744	0.0399
DOL(-1)	-0.0001	4.28E-05	-2.36704	0.0181
NFP_I(-1)	-0.18824	0.015961	-11.7933	0
ROC(-1)	-0.83156	0.013604	-61.1258	0

R-squared	0.760715	Mean dependent var	0.014177
Adjusted R-squared	0.759901	S.D. dependent var	0.233772
S.E. of regression	0.114548	Akaike info criterion	-1.49142
Sum squared resid	15.43057	Schwarz criterion	-1.46994
Log likelihood	885.6846	Hannan-Quinn criter.	-1.48332
F-statistic	934.6605	Durbin-Watson stat	1.113558
Prob(F-statistic)	0		

Table D: Industrial analysis' G1 firms.

Dependent Variable: D(ROC)
Method: Panel Least Squares
Date: 02/13/14 Time: 10:02
Sample: 2004 2012 IF GROUP=1 AND ANOM_TOT=0
Periods included: 8
Cross-sections included: 43
Total panel (unbalanced) observations: 329

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.048837	0.014812	3.29722	0.0011
WKCA_I(-1)	0.142054	0.040998	3.46488	0.0006
NFP_I(-1)	-0.24655	0.035035	-7.03718	0
ROC(-1)	-0.59846	0.034197	-17.5005	0

R-squared	0.503089	Mean dependent var	-0.00298
Adjusted R-squared	0.498502	S.D. dependent var	0.156232
S.E. of regression	0.110638	Akaike info criterion	-1.55303
Sum squared resid	3.978231	Schwarz criterion	-1.50688
Log likelihood	259.473	Hannan-Quinn criter.	-1.53462
F-statistic	109.6801	Durbin-Watson stat	1.268532
Prob(F-statistic)	0		

Table E: Industrial analysis' G2 firms.

Dependent Variable: D(ROC)
Method: Panel Least Squares
Date: 02/13/14 Time: 10:01
Sample: 2004 2012 IF GROUP=2 AND ANOM_TOT=0
Periods included: 8
Cross-sections included: 24
Total panel (unbalanced) observations: 175

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.159592	0.028459	5.607703	0
DPL(-1)	-0.01092	0.004377	-2.49391	0.0136
DOL(-1)	-9.34E-05	5.37E-05	-1.7378	0.0841
NFP_I(-1)	-0.13302	0.040226	-3.30667	0.0012
ROC(-1)	-0.83265	0.051786	-16.0786	0
RL_FIAS(-1)	-0.00266	0.001351	-1.97146	0.0503

R-squared	0.614092	Mean dependent var	-0.01284
Adjusted R-squared	0.602675	S.D. dependent var	0.18485
S.E. of regression	0.116518	Akaike info criterion	-1.42786
Sum squared resid	2.294406	Schwarz criterion	-1.31936
Log likelihood	130.938	Hannan-Quinn criter.	-1.38385
F-statistic	53.78566	Durbin-Watson stat	1.472669
Prob(F-statistic)	0		

Table F: Industrial analysis' G3 firms.

Dependent Variable: D(ROC)
Method: Panel Least Squares
Date: 02/13/14 Time: 10:01
Sample: 2004 2012 IF GROUP=3 AND ANOM_TOT=0
Periods included: 8
Cross-sections included: 20
Total panel (unbalanced) observations: 146

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.166687	0.013782	12.09486	0
DPL(-1)	-0.00841	0.00294	-2.85908	0.0049
DOL(-1)	-0.00123	0.000629	-1.95986	0.052
NFP_I(-1)	-0.16376	0.054948	-2.98031	0.0034
ROC(-1)	-0.92168	0.028703	-32.111	0

R-squared	0.882785	Mean dependent var	0.044791
Adjusted R-squared	0.87946	S.D. dependent var	0.316865
S.E. of regression	0.110012	Akaike info criterion	-1.54281
Sum squared resid	1.706475	Schwarz criterion	-1.44063
Log likelihood	117.6249	Hannan-Quinn criter.	-1.50129
F-statistic	265.4791	Durbin-Watson stat	1.190828
Prob(F-statistic)	0		

Table G: Industrial analysis' G4 firms.

Dependent Variable: D(ROC)
Method: Panel Least Squares
Date: 02/13/14 Time: 10:01
Sample: 2004 2012 IF GROUP=4 AND ANOM_TOT=0
Periods included: 8
Cross-sections included: 18
Total panel (unbalanced) observations: 132

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.076249	0.017901	4.259473	0
WKCA_I(-1)	0.150351	0.070272	2.139554	0.0343
DPL(-1)	-0.00612	0.002568	-2.38302	0.0187
NFP_I(-1)	-0.14887	0.051451	-2.89338	0.0045
ROC(-1)	-0.94281	0.03507	-26.8836	0

R-squared	0.853525	Mean dependent var	0.029488
Adjusted R-squared	0.848911	S.D. dependent var	0.257731
S.E. of regression	0.10018	Akaike info criterion	-1.72655
Sum squared resid	1.274585	Schwarz criterion	-1.61735
Log likelihood	118.9521	Hannan-Quinn criter.	-1.68217
F-statistic	185.0102	Durbin-Watson stat	1.219034
Prob(F-statistic)	0		

Table H: Industrial analysis' G5 firms.

Dependent Variable: D(ROC)
Method: Panel Least Squares
Date: 02/13/14 Time: 10:01
Sample: 2004 2012 IF GROUP=5 AND ANOM_TOT=0
Periods included: 8
Cross-sections included: 55
Total panel (unbalanced) observations: 396

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.122865	0.006224	19.742	0
NFP_I(-1)	-0.18299	0.023883	-7.66205	0
ROC(-1)	-0.85886	0.019452	-44.1521	0

R-squared	0.832314	Mean dependent var	0.023875
Adjusted R-squared	0.83146	S.D. dependent var	0.260599
S.E. of regression	0.106985	Akaike info criterion	-1.62471
Sum squared resid	4.498209	Schwarz criterion	-1.59454
Log likelihood	324.6919	Hannan-Quinn criter.	-1.61276
F-statistic	975.3308	Durbin-Watson stat	1.052165
Prob(F-statistic)	0		

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