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INTERNAL AND EXTERNAL DETERMINANTS OF CORPORATE FAILURE

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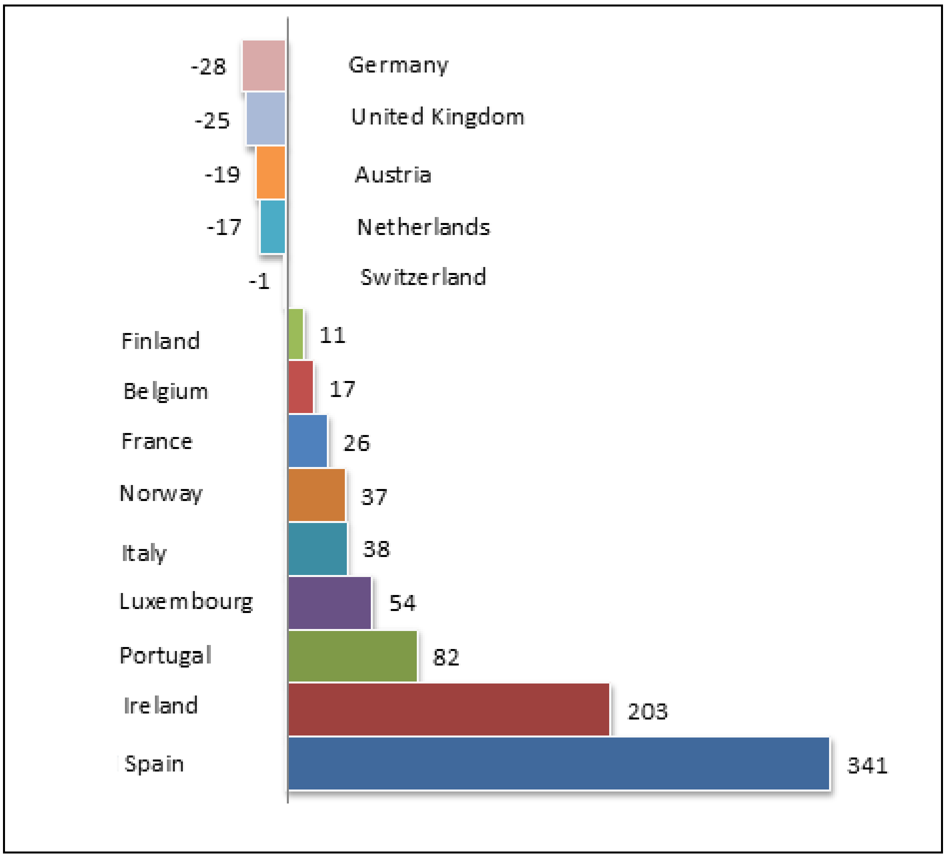
Introduction

This PhD thesis is composed of three chapters having the aim to contribute to the literature about corporate bankruptcy and firm's exit. The choice to investigate this phenomenon is due to the importance of this subject since corporate failure leads to relevant costs for the whole economy, and, especially after the financial crisis, it tended to involve several aspects and actors of business life. The relevant number of bankruptcies, together with the growing incidence of major companies collapse, in the last years, led to a rise in the number of insolvency related job losses. Indeed, failures can be characterized by insolvencies which undermine the creditors of defaulting companies and create chain of bankruptcies. Furthermore, the default is likely to affect company's shareholders since the opening of a collective procedure leads to direct costs management systems: compensation for dismissal, lawyers' fees, costs of procedures, etc. These costs weigh on the business value and particularly on insiders. Indeed, at first glance, it is quite obvious that business failures cause losses for the agents directly concerned, in particular employees, creditors and owners of companies which tends to suggest an overall negative assessment of failures from the point of view of the community. But bankruptcy can also generate indirect costs consisting in losses for the company partners, increase of unemployment and decrease of incomes in a given area, or supplier credits and difficulties in obtaining financing. The indirect costs can be high and should not be ignored in the analysis of the consequences of corporate bankruptcy. This is all the more justified that, according to the concept of *Corporate Social Responsibility*, the objectives of a business go far beyond the insiders' interest. Firm should thus achieve a sustainable development in the broad sense of economic development that, in addition to creating value for shareholders, maintains a conservation of the natural and social environment and human capital. As the impact of corporate failures concern a large number of agents, an important attention must be paid to this important and expanding phenomenon.

The declining trend in business insolvencies initiated in 2010, has continued in 2016 for the seventh consecutive year. Companies have absorbed the 2008 crisis shock at the global level but they remain vulnerable to the lack of solid macroeconomic and financial environment and to local hot spots. In 2016 they faced three major global headwinds: (i) the sluggish global economy, with real GDP growth posting only +2.5% in 2016 (versus +2.7% in 2015); (ii) the sharp slowdown in global trade, with export volume growth reaching an unprecedented blow at +1.9% (+3.1% in 2015); (iii) fierce price competition, which has put turnovers under pressure; and (iv) volatility in exchange rates and international financial flows, which have kept financing under constraints (Euler Hermes, 2017). Western Europe is the only region to record a sizable decline in bankruptcies in 2016 (-5% after -13% in 2015), thanks to the gradual improvement of the economic situation. Despite these positive results, the level of bankruptcies in Western Europe remains high. As Figure 1 shows many countries still report more insolvencies in 2016 than their 2003-2007 average. In 2016, for instance, Spain and Portugal recorded 341% and 82 % more bankruptcies than before the crisis. The picture is already less troubling for Italy (+38%) and France (+27%), where the decline is supported by the recovery of corporate margins and strong fiscal boosters.

Figure 1: 2016 Insolvencies compared to 2003-2007 average (% change)



Source: National Statistics, Euler Hermes

Keeping firms alive is a public policy target since bankruptcy has not only financial consequences but industrial ones too, linked to the loss of precious intangible assets and know-how that represents a source for the whole economy. It represents, thus, a phenomenon which has a negative influence on the competitiveness of the business environment.

Exit is a common consequence of firm's poor performance. Firms that underperform as they compete in the market will, sooner or later, exit the market. It is a process of selection results from a (passive) process of post-entry Bayesian learning: those firms which discover to be efficient enough to ensure non-negative profitability, rationally choose to continue their operations and grow, while the others quit the market (Jovanovic, 1982). This process is better worth knowing for a main reason: the Shumpeterian concept of creative destruction, which describes the process of transformation that is linked to radical innovation, which supposes the replacement of established companies by new entrants, involves the exit of a certain number of existing firms. Besides this renewal of productive system it ensures, exit can also have a positive value since individuals who have closed down the company they owned or managed in the previous year are more likely to engage successfully in a future entrepreneurial activity (Levratto, 2013).

Different studies have, thus, attempted to identify the causes of corporate bankruptcy. A comprehensive vision of the possible causes of failure is provided by Bradley and Rubach (2002) who remind the different families of the factors identified as causes of insolvency. Management, marketing, or financial reasons are the main ones, but additional elements may intervene, such as outside and inside business condition, tax issues or disputes with a particular creditor. Starting with the seminal work of Altman (1968), a large body of literature has investigated corporate bankruptcy with a focus on firm-specific features, searching to predict insolvency through the application of several statistical methods on economic and accounting data. In his seminal study on bankruptcy detection, Altman improved research methodology by usage of multiple discriminate analysis (MDA) where the discrimination was determined by a score–the «*Z-score*»–calculated on the basis of five accounting ratios. Recently, some authors have resorted to artificially intelligence expert system (AIES) models for bankruptcy prediction. These recent artificially intelligence expert system models would lightly outperform discriminant and logistic analysis but they are based on complex underlying model structures. Hence, standard implementations have to be modified to allow the estimation of realistic default propensities. A correct measure of firms' insolvency risk is very important both for internal monitoring purpose and for the potential investors, stockholders, actual or potential firm's competitors.

The first chapter of this PhD thesis goes in the direction of this strand of literature, with the purpose to provide an instrument able to predict corporate bankruptcy. The study is entitled *"Predicting corporate bankruptcy by a composite indebtedness index. An application to Italian manufacturing firms*", and proposes a Composite Indebtedness index of financial ratios, estimated by a Robust Principal Component Analysis for skewed data, that allows to classify firms according to two dimensions: their indebtedness degree and their solvency capability. Furthermore, the study presents a logit model aimed at investigating if and to what extent the proposed index is able to correctly predict firms' financial bankruptcy probabilities. The econometric results are compared with those of the popular Altman Z-score for different lengths of the reference period. The empirical evidence suggests a good performance of the proposed Composite Indebtedness index which, therefore, could be used as an *early warning signal* of bankruptcy. This study contributes to the literature in several ways. First, since small sample size appears to be a limitation, it considers the Italian manufacturing companies as a whole and includes small, medium and large firms in a large industry sample. Secondly, I attempt to improve the research model by implementing a composite analysis based on both Principal Component Analysis (PCA) and logit model, demonstrating that the combined method of PCA and logit estimation is promising in evaluating firms' financial conditions. Thirdly, I attempt to evaluate the efficiency of the model, that is its economic and organizational usability in an operational context.

Generally, the focus of the accounting and finance literature has typically considered only the internal features of a company (financial and non-financial information) to determine its likelihood of failure. Only very recently, a small number of studies analysed the influence of institutional features of the *local context* to understand the exit behaviour across geographical regions. This is a relevant issue to address since the likelihood of firm's exit is likely to be determined by how much favourable are market conditions to sustaining businesses primarily dependent on local demand.

The second chapter of this PhD thesis entitled *"New firms' bankruptcy: does local banking market matter?*" tries to fill this gap. It analyses the role that local context and particularly the role that local banking market, may exert in shaping new firm's bankruptcy. The novelty of this study results from three main elements: the emphasis put on the relationship between insolvency and the organization of the local credit market, the estimation technique used (Logit Multilevel Model) and the sample of companies considered in the empirical analysis based on Italian new firms (incorporated between 2008 and 2013). According to many research studies on bankruptcy, new firms are more likely to exit from the market than other firms (Thornhill and Amit, 2003) and are very vulnerable to the macroeconomic environment (Bonaccorsi di Patti and Gobbi 2001). New and young companies are the primary source of job creation in economies, contributing to economic dynamism by injecting into the market competition and innovation. At the same time, these firms are the most financially vulnerable in the market. This weakness leads to questioning the role played by the financial system and, more precisely, by banks, in the local economic activity and as a driver of the performance of local firms. The results suggest that a higher level of financial development in a province decreases the likelihood of a new firm's bankruptcy. In addition, the estimations suggest that the effect of local financial development and bank concentration is shaped by size. The effect that local financial development exerts in reducing corporate bankruptcy is stronger for small start-ups, which traditionally suffer from great difficulty in accessing credit, whereas local banking concentration reduces the probability of bankruptcy for large, new firms.

The third chapter of this PhD thesis entitled "*Spatial patterns and determinants of firm's exit in France*" is also in line with the strand of literature which investigates the effect that location specific determinants may have in shaping the exit risk in the local area. The purpose of the study is to understand the relevance of the domino effect in firm's exit among neighbour locations with a focus on two regional variables: local specialisation and local financial development. Indeed, the influence of location can be considered also looking at the effect of agglomeration economies and spatial dependences. The observation that economic activity tends to be clustered in space (Porter, 1998; Cooke, 2002), suggests that agglomeration economies are relevant and can compensate for the negative effect of density such as intense competition from other firms located in the vicinity which may lead to relatively intense competition on the input-side as well as on the output-side of the market. The analysis refers to the Exit Rate of French Departments (corresponding to NUTS3 in the EU classification) over the period 2009-2013. I propose an econometric study based on a dataset combining different sources computed at the Department level based, and on the application of spatial econometric techniques to consider the spatial dependence in business failure. The results suggest that firm's exit is characterized by positive spatial autocorrelation, so that locations with high exit rates tend to be surrounded by similar ones. In addition, similarly to the second chapter, I find that a higher local financial development reduces the exit rate of a department whereas local specialisation seems not to exert any effect. Therefore, by highlighting the clustering phenomena, I contribute to the spatial literature that emphasizes the neighbouring effect and states the idea that what happens in a certain area not only depends on the local context but also on what happens in the nearby areas. Some policy implications conclude each chapter of the thesis.

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CHAPTER 1

Predicting Corporate Bankruptcy by a Composite Indebtedness Index. An Application to Italian Manufacturing Firms.

Abstract

Starting from a series of financial ratios analysis, I build up two indices which take into account both the firm's debt level and its sustainability. The construction of a Composite Indebtedness index, based on an original use of Robust Principal Component Analysis for skewed data, allows to classify firms according to their indebtedness degree and nature. This is a first tool to evaluate firms' financial health. Secondly, a model aimed at investigating if and to what extent the proposed indices are able to correctly predict firms' financial bankruptcy probabilities is proposed. The econometric results are compared with those of the popular Altman Z-score for different lengths of the reference period. The empirical evidence would suggest a good performance of the proposed Composite Indebtedness index which, therefore, could also be used as an *early warning signal* of bankruptcy.

Keywords: Financial Ratios, Bankruptcy, Robust PCA, *Z*-score, Logit.

1. Introduction

Due to the international financial crisis, both the number and the average size of bankrupt firms has increased dramatically with the consequent greater interest from governments, financial institutions and regulatory agencies.

A correct measure of firms' insolvency risk is very important both for internal monitoring purpose and for the potential investors, stockholders, actual or potential firm's competitors. The purpose of this study is to construct, analyse and test a new bankruptcy prediction model which can be easily applied as early warning instrument. The potential application of this model is in the spirit of predicting bankruptcy and aiding companies' evaluation with respect to going-concern considerations, among others, since the early detection of financial distress facilitates the use of rehabilitation measures. Insolvency is mostly a consequence of a sharp decline in sales which can be caused by several and different factors like a recession, deficiencies of management, relevant changes in market dynamics, shortage of a row material, changes in lending conditions, etc. An early warning signal of probable bankruptcy is very important since it will allow to adopt preventive and corrective measures. This study aims to contribute to the elaboration of efficient and effective corporate failure prediction instruments in order to prevent bankruptcy through the adoption of reorganization strategies. Failure, indeed, is not identifiable in a specific episode but in a process of progressive worsening of the financial health of a company. Given the dynamic nature of firms' financial crisis, it is necessary to build an early warning index for firms' insolvency which could signal a critical level of over-indebtedness behind which the financial status of the firm becomes pathological, therefore very difficult to rehabilitate.

Most of the past studies concentrate on specific industrial sectors and/or used a relatively small sample of firms. These studies include models for manufacturers by Beaver (1968), Altman (1968), Wilcox (1971, 1976), Deakin (1972, 1977) and Edmister (1972), among others, and models for specific industries such as Altman on railroads (1973), Sinkey on commercial banks (1975), Korobow and Stuhr (1975) and Korobow et al. (1976) on commercial banks, Altman and Lorris on broker/dealers (1976) and Altman (1977) on savings and loan associations.

Beaver (1966), Altman (1968) and Van Frederikslust (1978) argue that, although a failure may be caused by several circumstances, the development of some financial ratios can be a signal of the firm's financial health. Previous studies indicate that, with few financial ratios, corporate bankruptcy can be predicted with success for at least five years before failure. Important shortcomings, however, characterize previous works. First, financial ratios are chosen if they perform well, so without a specific reference to financial theory. Moreover, a very small sample of firms are considered in the empirical analysis. Therefore, the results obtained in these works cannot be generalized.

This study contributes to the literature in several ways. First, since small sample size appears to be a limitation and "… any new model should be as relevant as possible to the population to which it will eventually be applied" (Altman et al., 1977, p.30), it considers the Italian manufacturing companies as a whole and includes small, medium and large firms in a large industry sample. Secondly, I attempt to improve the research model by implementing a composite analysis based on both Principal Component Analysis (PCA) and logit model. I demonstrate that the combined method of PCA and logit estimation is promising in evaluating firms' financial conditions. Thirdly, apart from effectiveness, I also attempt to evaluate the efficiency of the model, that is its economic and organizational usability in an operational context (Cestari et al., 2013). With reference to the actual usability of the model on the part of the potential users, this model proposes two steps/instruments in the analysis: 1) an accurate, but rather simple, bankruptcy prediction instrument which allows to classify firms in different categories with respect to their solvency status on the base of financial ratios; 2) a more complex logit model, based on both the first step computed indices and additional non-financial variables, which allows to compute specific bankruptcy scores (predicted probabilities) for each firm included in the analysis. Finally, the logistic regression estimates are compared with those of the popular Altman Z-score for different lengths of the reference period. Hence, in addition to several models that have been tested by the relatively short one-year prediction horizon, the predictive power of the index several years prior to bankruptcy is tested.

In brief, I extend previous methodology by building a very large sample of firms and paying attention to both financial and non-financial firms' characteristics. Moreover, I examine how the model can be used in practice to analyze the risk of failure. In this context, I first derive a simple decision rule to classify firms as either at high risk of failure or at low risk of failure. I then propose a more complete model to predict the risk of failure as early warning signal of bankruptcy. The chapter is organized as follows. Section 2 summarizes the related literature, Section 3 illustrates the methodology, Section 4 shows an application to Italian manufacturing firms and illustrates the empirical findings. Section 5 concludes.

2. Literature review

Bankruptcy has been the subject of numerous studies over the past years[2]. Researchers have investigated both the causes and the legislative and financial tools available to start a process of recovery/rehabilitation of the firm. Especially after the recent international financial crisis, there has been a general need to predict insolvency and financial failure on-time in order to take corrective and remedial measures for protecting business from the problem of bankruptcy.

A broad international field of study has focused on predicting bankruptcy using statistics and economic-financial indicators. Prior to the development of quantitative measures of company performance, agencies were established to supply qualitative information assessing the creditworthiness of firms. During the 1930s many models were developed to help banks decide whether or not to approve credit requests (Smith, 1930; FitzPatrick, 1932; Ramser and Foster, 1931; Smith and Winakor, 1935; Wall, 1936). Bellovary et al. (2007) traced a brief historical summary of the early studies (1930 to 1965) concerning ratio analysis for bankruptcy prediction that laid the groundwork for the studies that followed.

At the end of the 1960s, several applications of univariate and multivariate statistical methods were developed. One of the classic works in the area of ratio analysis and bankruptcy classification was performed by Beaver (1968). His univariate analysis of a number of bankruptcy predictors set the stage for the multivariate attempts. Beaver found that a number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure, but he completed a discriminant analysis on a single ratio (cash flow/total debt).

Altman (1968) and Deakin (1972) applied multivariate analysis, followed by several authors (Blum, 1974; Elam, 1975; Libby, 1975; Alberici, 1975; Taffler, 1976, 1982; Altman et. al., 1977, 1993; Wilcox, 1976; Argenti, 1976; Appetiti, 1984; Forestieri, 1986; Lawrence and Bear, 1986; Aziz, Emanuel and Lawson, 1988; Baldwin and Glezen, 1992; Flagg, Giroux and Wiggins, 1991; Bijnen and Wijn, 1994; Kern and Rudolph, 2001; Shumway, 2001; Hillegeist, et. al., 2004; Altman, Rijken, et. al., 2010). In his seminal study on bankruptcy detection, Altman (1968) improved research methodology by usage of multiple discriminate analysis (MDA) where the discrimination was determined by a score–the «*Z-score*»– calculated on the basis of five accounting ratios. Thus, only five financial ratios were enough

[2] For comprehensive reviews on predicting corporate bankruptcy methodologies, see Aziz and Dar (2006), Bellovary et al. (2007) and Ravi Kumar and Ravi (2007).

to distinguish healthy from unhealthy companies. The first research on SMEs failure was done by Edminister (1972) who also used MDA as statistical technique to discriminate among loss and non-loss SME borrowers. The empirical analysis, based on a MDA model with seven financial ratios, revealed that the models with industry relativized ratios were characterized by higher classification accuracy in comparison with models based on classical ratios.

After Altman's seminal study, the linear discriminant analysis has been intensively used in practice mainly because of the simplicity of its application. However, Johnson (1970) and Joy and Tollefson (1975) have criticized the excessive broadness of the so-called grey area and the difficulty of application in predicting bankruptcy *ex ante*. Guatri (1995) has stressed how predictions using multiple discriminant analysis could be a self-realizing prophecy since, if adopted by banks, it would be harder for a company with a low score to have access to external finance, causing it to be insolvent and to go bankrupt. Others have questioned that multiple discriminant analysis implies the respect of some strict statistical restrictions such as the normality of the distribution of the explanatory variables and requirement for the same variance-covariance matrices for both groups of bankrupt and non-bankrupt companies.

As a consequence, later studies have tried to upgrade the methodology and improve the predictive power of the models. Several authors have used logit and probit models - instead of MDA- depending on whether the residuals follow a logistic or normal distribution. Ohlson (1980) was the first one who used the logit model, followed by several authors (Mensah, 1984; Zavgren, 1985; Aziz, Emmanuel and Lawson, 1988; Bardos, 1989; Burgstahler et al., 1989; Flagg, Giroux and Wiggins, 1991; Platt and Platt, 1991; Bardos and Zhu, 1997; Bell et al., 1998; Premachandra et al., 2009; Bhargava et al., 1998; Nam and Jinn, 2000; Vuran, 2009; Pervan et al., 2011). In other studies, the probit models have been implemented (Zmijewsji, 1984; Gentry et al., 1985; Lennox, 1999). Similar methodologies – like duration models – have been developed in order to consider several periods in the analysis (Shumway, 2001; Duffie et al., 2007). But, apart from statistical methodology, previous studies have been focused only on financial ratios. The recent empirical evidence indicates that prediction of insolvency and credit risk management can be improved by incorporating nonfinancial information (management, employees, clients, industry, etc.) in failure prediction models. Nevertheless, only few papers (Grunert et al., 2004; Berk et al., 2010, Pervan and Kuvek, 2013) explicitly use non-financial variables to predict failure.

More recently, some authors have resorted to artificially intelligence expert system (AIES) models for bankruptcy prediction. Several types of AIES models have been implemented such as recursively partitioned decision trees, case-based reasoning models (Kolodner, 1993), neural networks (Odom and Sharda, 1990; Yang et al., 1999; Kim and Kang, 2010), genetic algorithms (Varetto, 1998; Shin and Lee, 2002), rough sets model (Dimitras et al., 1999) or "new age" classifiers. Ravi Kumar and Ravi (2007) present a comprehensive review of the work done in the application of intelligent techniques showing, for each technology, the basic idea, advantages and disadvantages. These recent artificially intelligence expert system models would lightly outperform discriminant and logistic analysis (see, among others, Behr and Weinblat, 2016; Jones et al. 2017) but they are based on complex underlying model structures. Hence, standard implementations have to be modified to allow the estimation of realistic default propensities. Logit models, on the contrary, are universally known, easily applicable and clearly understandable.

Note that, independently from the methodology applied, both statistical and AIES models focus on firms' symptoms of failure and are mainly drawn from company accounts.

Theoretical models, on the contrary, focus on the causes of bankruptcy and are mainly drawn from information that could satisfy the proposed theory. See Aziz and Dar (2006) for a clear description of the different types of theoretical models and their main characteristics.

On the whole, the above mentioned literature indicates that there have been many empirical applications of the bankruptcy prediction models. Despite the differences in the methodologies applied, they show high predictive ability. Further, despite the vast amount of literature and models that have been developed, researchers continue to look for "new and improved" models to predict bankruptcy. As argued by Bellovary et al. (2007) in their review of bankruptcy prediction studies, "… the focus of future research should be on the use of existing bankruptcy prediction models as opposed to the development of new models. Future research should consider how these models can be applied and, if necessary, refined" (Bellovary et al., 2007, pp.13-14). This contribute to the literature goes in this direction by applying a methodology based on both an original use of robust PCA and logit model. The review also suggests important insights and some areas for model improvement, incorporated in the analysis. First, much past research has employed relatively small samples of firms; recent evidence suggests that large samples are critically necessary to generalize empirical results. Second, financial ratios have been dominant explanatory variables in most research to date; it may be worthwhile to include nonfinancial variables and corporate governance structure in addition to financial variables. Third, several models have been tested by the relatively short one-year prediction horizon; it would be desirable to test the predictive power several years prior to bankruptcy. It is very important to consider how far ahead the model is able to accurately predict bankruptcy. Clearly, a model that is able to accurately predict bankruptcy earlier becomes more valuable for the investors and, at the same time, for the adoption of effective policies.

Moreover, previous studies have mainly focused on the development of models with high level of reliability. However, it is important to identify the parameters that can measure both effectiveness, in terms of reliability, and efficiency, in terms of organizational and economic sustainability, of prediction instruments (Cestari et al. 2013). For this reason, I also attempt to evaluate this model in terms of its practical implementation. The first part of the study proposes a simple and efficient tool to evaluate firms' financial health. The second part illustrates a more complex model aimed at predicting firms' default risk.

3. Methodology

This section describes the methodology including conceptual and operational definition of the variables used in the study. This two steps method is based on the idea to maintain and treat separately the debt level of a firm and its sustainability. Indeed, companies might be characterized by similar level of indebtedness but different degrees of vulnerability. Therefore, it is important to take into account the ability to generate cash flows sufficient to cover the cost of debt and its principal amount.

For this reason, in the first step of the analysis, a debt index and a sustainability index of such debt are independently defined and estimated. The estimation of such indices is obtained through a Robust Principal Component Analysis of different financial ratios. These two indices are then combined in a synthetic one, the Composite Indebtedness index, which can classify firms according to their indebtedness degree and insolvency risk.

In the second step, the reliability of the Composite Indebtedness index as early warning signal of financial bankruptcy is evaluated by applying a logistic regression technique which allows to specify the probability of default as a function of such indices and other explanatory variables.

3.1 Assessment of the financial health of the firms

3.1.1 The Composite Indebtedness Index

The financial and accounting literature suggests that a firm's financial condition is better evaluated by considering several aspects of the indebtedness phenomenon (leverage, indebtedness capacity, form of the financial debt, net financial position, etc.). Following this approach (Bartoli, 2006; Brealey and Myers, 2001; Fridson, 1995), I build up a debt index which considers the multifaceted aspects of debt. More precisely, I assume:

$$\boldsymbol{DEBT_{INDEX}} = \boldsymbol{\alpha_1} \frac{\boldsymbol{FD}}{\boldsymbol{N}} + \boldsymbol{\alpha_2} \frac{\boldsymbol{CL}}{\boldsymbol{FD}} + \boldsymbol{\alpha_3} \frac{\boldsymbol{FD}}{\boldsymbol{CF}} + +\boldsymbol{\alpha_4} \frac{\boldsymbol{CL}}{\boldsymbol{CA}} + \boldsymbol{\alpha_5} \frac{\boldsymbol{NTCA}}{\boldsymbol{N}} + \boldsymbol{\alpha_6} \frac{\boldsymbol{TFA}}{\boldsymbol{LTD+N}} \;; \quad \alpha_i \in \mathrm{R}; \; i = 1,2,\dots,6$$

where FD/N is the inverse of the capitalization degree; CL/FD is the ratio between Current Liabilities and Total Financial Debt and gives information on the form of financing of the firm; FD/CF is the ratio between Total Financial Debt and Cash-Flow and represents the inability of firm’s internal finance to cover the total debt; CL/CA is Current Liabilities over Current Assets, that is the inverse of the current ratio; NTCA/N is the ratio between Net Technical Assets and Shareholders Funds and indicates the inverse of the capitalization rate of technical assets. Finally, TFA/(LTD+N) is Total Fixed Assets over the sum of Long-Term Debt and Shareholders Funds and represents the equilibrium between fixed assets and long term liabilities. High values indicate that the firm may be forced to find more financial sources through short-term debt, usually subject to higher interest rates.

While a moderate level of debt can spur firm performance, an important element to consider when assessing firms’ creditworthiness is the vulnerability of such debt. The maturity structure of assets and liabilities can provide valuable information about their vulnerability to changes in financing conditions. However, at the euro area level and in Italy in particular, short-term funding accounts for a small proportion of total funding, thus the maturity structure has a limited informative power (European Central Bank, 2013). Hence, an important factor for the assessment of the sustainability of debt is the debt service burden of firms, which indicates the proportion of their income needed for servicing debt. For this reason, I assume the following index describing firm’s weakness to cover the amount of interests on debt:

$$\boldsymbol{WKN_{INDEX}} = \boldsymbol{\delta_1} \frac{\boldsymbol{IP}}{\boldsymbol{EBIT}} + \boldsymbol{\delta_2} \frac{\boldsymbol{IP}}{\boldsymbol{EBITDA}} + \boldsymbol{\delta_3} \frac{\boldsymbol{IP}}{\boldsymbol{CF}} \;; \quad \delta_i \in \mathrm{R}; \; i = 1,2,3$$

where IP is the Interest Paid, EBIT the Earnings Before Interest and Taxes, EBITDA the Earnings Before Interest, Taxes, Depreciation and Amortization. CF indicates cash-flow.

Note that higher values of the WKN index indicate lower sustainability of debt, hence higher firms' debt vulnerability.

The accounting theory (Bartoli 2006, Brealey and Myers 2001, Fridson 1995, among others) and numerous specialized websites[3] suggest - for each financial ratio - specific threshold values which allow us to define when a firm is in a good, normal or bad financial condition, as shown in Table 1.

Table 1 Financial ratios and threshold values

Good financial status (<threshold 1)	*Normal financial status*	*Bad financial status (> threshold 2)*
Threshold 1		Threshold 2
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
0.9	$0.9 < \frac{CL}{CA} < 1.1$	1.1
1	$1 < \frac{NTCA}{N} < 2$	2
1.25	$1.25 < \frac{TFA}{LTD + N} < 3.33$	3.33
0.25	$0.25 < \frac{IP}{EBIT} < 0.58$	0.58
0.18	$0.18 < \frac{IP}{EBITDA} < 0.5$	0.5
0.33	$0.33 < \frac{IP}{CF} < 0.5$	0.5

[3] See, for example, http://www.investopedia.com/articles/investing/080113/understanding-leverage-ratios.asp; http://www.materialitytracker.net/standards/financial-thresholds/; https://www.gov.mb.ca/agriculture/business-and-economics/transition-planning/pubs/ch3-t7-financial-performance.pdf; https://www.oldschoolvalue.com/blog/valuation-methods/cash-flow-ratios/; http://www.suredividend.com/ratios-metrics/.

For example, a value of the financial ratio FD/N ranging between 1 and 1.6 denotes a normal financial status of the company. On the contrary, a value below 1 or over 1.6 usually denotes a good or a bad financial condition respectively.

Note that, through the substitution of the threshold values for each financial ratio included in the $DEBT_{INDEX}$ and in the WKN_{INDEX} , it is possible to define the corresponding threshold values for such two indices and classify the firms according to their degree of indebtedness.

More specifically, after estimating the α and δ coefficients, it's possible to compute the DEBT score and WKN score for every firm. By crossing in a two-way table these two different dimensions we obtain the *Composite Indebtedness Index* (***CI***), a classification tool that takes into account both a firm's indebtedness level and its vulnerability at the same time.

Table 2 reports the suggested classification. Let us indicate with +, . (dot) and – the situation in which the considered index is lower than threshold 1, the case in which it is between threshold 1 and threshold 2 and the condition in which it is higher than threshold 2 respectively. If the first subscript refers to the column index and the second one to the row index, then $\boldsymbol{CI}^{++}$ indicates the best financial status of a firm. $\boldsymbol{CI}^{\cdot\cdot}$ signals a common indebtedness level of a firm, therefore denoting a normal financial health of a company. The financial health of the firm tends to deteriorate when the firm is highly indebted ($\boldsymbol{CI}^{-+}$) or unable to cover the cost of its debt ($\boldsymbol{CI}^{+-}$). $\boldsymbol{CI}^{\cdot-}$ and $\boldsymbol{CI}^{-\cdot}$ denote a very fragile financial status. Finally, $\boldsymbol{CI}^{--}$ indicates the situation in which the firm has a relatively high level of debt and it is not able to cover the cost of interests ("pathologic" status).

Table 2 Firm's financial health classification by CI index

	WKN< threshold1	thr. 1<WKN<thr. 2	WKN> threshold2
$DEBT$<threshold1	$\boldsymbol{CI}^{++}$ optimal	$\boldsymbol{CI}^{+\cdot}$	$\boldsymbol{CI}^{+-}$
thr.1<$DEBT$<thr. 2	$\boldsymbol{CI}^{\cdot+}$	$\boldsymbol{CI}^{\cdot\cdot}$ normal	$\boldsymbol{CI}^{\cdot-}$
$DEBT$>threshold 2	$\boldsymbol{CI}^{-+}$	$\boldsymbol{CI}^{-\cdot}$	$\boldsymbol{CI}^{--}$ bad

Source: own elaborations

3.1.2 Robust Estimation of the CI Index

After the pioneering work of Altman (1968), the multivariate approach to failure prediction spread worldwide among researchers in finance, banking and credit risk.

The classical multivariate methods, however, are based on the assumption of normal distribution of variables while financial data are often characterized by asymmetric distribution. For this reason, the traditional multivariate statistical models are not the proper methods to treat such data since the strong asymmetry could bring the researcher to consider too many observations as outliers.

Therefore, to estimate the DEBT and WKN indices I use a robust version of Principal Component Analysis (PCA), through which we obtain the values of the coefficients α_i and δ_i associated to each financial ratio.

PCA is one of the best known procedures of multivariate statistics. It is a dimension reduction technique which transforms the observed variables into a small number of new variables while retaining as much information as possible. These new variables are linear combinations of the original variables which explain most of the variation in the data, they are uncorrelated and maximize variance, an important information underlying the data. PCA is often the first step of a data analysis, followed by further multivariate analysis like cluster analysis, discriminant analysis, regression or other statistical and/or econometrics techniques.

Let $\mathbf{X}$ be a $n \times p$ observed data matrix with n observations and p variables assumed to be correlated. By applying a PCA we obtain a $n \times p$ matrix $\mathbf{Y}$, composed by p new variables, called the principal components (PCs), uncorrelated among them, which are linear combinations of the original variables, according to the following linear transformation:

$$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{A}$$

where $\boldsymbol{A}$ is an orthonormal $p \times p$ matrix whose columns are the eigenvectors of $\sum$, the covariance matrix of $\mathbf{X}$. In particular, the first principal component $\boldsymbol{y_1} = \boldsymbol{X}\boldsymbol{a_1} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{p}} a_{\boldsymbol{1k}}\boldsymbol{x_k}$ is the linear combination of the p original variables $\mathbf{x}_k$ (column vectors of $\mathbf{X}$) with maximal variance whose coefficients are given by the first column vector of $\mathbf{A}$; that is the eigenvector $\boldsymbol{a}_1$ associated to the largest eigenvalue l_1 of $\sum$. Successive p-1 components $\mathbf{y}_2$, $\mathbf{y}_3$, …, $\mathbf{y}_p$ are the linear combinations whose coefficients are given by the successive eigenvectors $\boldsymbol{a}_2$, $\boldsymbol{a}_3$, … $\boldsymbol{a}_p$ of $\sum$ associated to successive eigenvalues $l_2<l_3<\ldots<l_p$. The variances of the principal components (PCs) are equal to the l_i.

Since classical PCA makes use of eigenvalues and eigenvectors of the classical (from sample or population) covariance matrix, this technique is sensitive to outliers and asymmetric distribution of variables. Various robust alternatives have been proposed in the literature (see Hubert et al. 2005 for a review). Here, in order to robustly estimate the α and δ coefficients of the DEBT and WKN indices, a robust PCA technique - called modified *ROBPCA for skewed data* - suggested by Hubert et al. (2009) is applied. As in the classical case, these new PC_s are linear combinations of original variables, they are uncorrelated and they are extracted according to their importance in terms of explained variance of the original variables. Hence, the first principal component explains a percentage of variance greater than the second one and so on. The number of extractable PCs is equal to the number of original variables, but eigenvectors and eigenvalues solutions of principal component analysis problem is based on a robust estimate of the covariance matrix of the data (Hubert et al. 2005, 2009).

In real applications, when a PCA analysis is performed, if the original variables have a good degree of correlation, so that a high percentage of the original variance can be explained by few PCs, the first principal component (PC_1) is considered a good approximation of the data matrix **X**. Indeed, the explained variance, l_1, represents a measure of the summary power of the data given by the first component and it is high if there is a good degree of correlation between the original variables. Usually, a percentage around 50-60 % of explained variance by the first principal component is considered a good value of summary power.

Since accounting data tend to move in the same direction, and more or less proportionately, it is believed that collinearity is always present (Horrigan, 2000). Therefore, I expect the first PC of the two sets of financial ratios to explain a proper percentage of variability, so that $DEBT_{INDEX}$ and WKN_{INDEX} can be properly estimated with the coefficients given by the eigenvector defining the first robust principal component (RPC_1) of the firm's financial ratios data matrix.

Once the RPC_1 is computed, the combination of the threshold values shown in Table 1 and the value of the coefficients given by the first eigenvector for each financial ratio included in the $DEBT_{INDEX}$ and in the WKN_{INDEX}, allows us to define the final threshold values for the two indices:

$$Threshold1_{DEBTINDEX} = \sum_{i=1}^{10} \alpha_i \; Threshold1_i$$

$$Threshold2_{DEBTINDEX} = \sum_{i=1}^{10} \alpha_i \; Threshold2_i$$

$$Threshold1_{WKNINDEX} = \sum_{i=1}^{3} \delta_i \; Threshold1_i$$

$$Threshold2_{WKNINDEX} = \sum_{i=1}^{3} \delta_i \; Threshold2_i$$

These threshold values allow us to build the ***CI*** index and classify the firms according to their degree of indebtedness ($DEBT_{INDEX}$) and vulnerability (WKN_{INDEX}).

3.2 Assessment of the probability of default

To evaluate the reliability of the Composite Indebtedness index as early warning signal of financial bankruptcy, a logistic regression technique is applied with the aim to specify the probability of default as a function of a set of explanatory variables. Specifically, the dependent variable is a dichotomous variable that takes value 1 for defaulting firms (the firm is under bankruptcy procedure, it has filed for bankruptcy or it is subject to liquidation in 2011), 0 otherwise (the firm is still active in 2011). In formal terms:

$$p_{i,t} = \Pr(Y_{i,t} = 1) = F(x_{i,t-n}\beta) \quad (1)$$

where $p_{i,t}$ is the probability that the dependent variable Y=1 for individual firm at time t=2011, F(_) is the logistic cumulative distribution function, $x_{i,t-n}$ is the set of explanatory variables thought to affect $p_{i,t}$ with n=1…5; β are the regression coefficients. The explanatory variables are expressed as follows:

$$\begin{aligned}\Pr(Y_{i,t} = 1) = F(&\beta_0 + \beta_1 DEBT_{i,t-n} + \beta_2 WKN_{i,t-n} + \beta_3 SIZE_{i,t-n} + \beta_4 AGE_{i,t-n} \\ &+ \beta_5 D\_own_{i,t-n} + \beta_6 D\_mult_{i,t-n} + \beta_7 PROD_{i,t-n} + \beta_8 X\_region_{i,t-n} \\ &+ \beta_9 Y\_sector_{i,t-n})\end{aligned} \quad (2)$$

i = 1… m where i is the i*th* firm, n=1…5.

In accordance with the general literature on bankruptcy, the model considers the financial structure of the firm. The first two explanatory variables, given by the DEBT and WKN scores computed in the first step of the analysis, take into account the financial health of the firm by measuring both the debt level and its vulnerability. Several works find a significant relation between the financial structure of the firms and their probability of default or exit from the market (see, among others, Molina, 2005; Hovakimian et al. 2012; Graham et al. 2011; Bonaccorsi di Patti et al. 2014).

The model includes other regressors in order to control for additional non-financial characteristics of the firms, expected to be relevant in determining their probability of default. Both the theoretical and empirical literature suggest that age and size of the firms impact significantly on their performance (for a review, see Klepper and Thompson 2006). More recent studies also analyze the effects of productivity, industrial organization and ownership structure on firm performance (Beck et al. 2006, 2008; Disney et al. 2003; Dunne et al. 1988, 1989; Foster et al. 2006).

Therefore, equation (2) includes additional nonfinancial variables reported hereafter.

The variable $SIZE_i$ is computed in terms of a firm's annual turnover[4] and measured in hundred thousands of Euros.

The variable AGE_i is the age of a firm since its foundation.

D_own_i is a dummy variable equal to 1 for fully concentrated ownership (unique partner), 0 otherwise (fragmented ownership, several partners). It is a signal of corporate governance since firms in countries with weaker investor protection also have more concentrated ownership (La Porta et al., 1998; La Porta et al., 1999).

D_mult_i is a dummy variable equal to 1 for multinational firms, 0 otherwise. Multinational firms have been identified through the analysis of ownership data, by selecting companies owning foreign subsidiaries (ownership share equals 51% by default).

The variable $PROD_i$ indicates labor productivity and it is given by value added per employee.

Finally, to take into account the characteristics of the institutional and financial environment in which the firms operate and the specificities of the industrial sectors, I consider both regional dummies and sector dummies as explanatory variables, included in the vectors X and Y respectively. The manufacturing sectors are defined to include firms in the NACE Rev.2 primary codes 10-32. Hence, the model includes 20 regional dummies and 23 sector dummies.

Notice that the two-way Table 2 would also suggest an interaction effect between the DEBT index and the WKN index. This will be explicitly analyzed in section 4.3.

[4] In order to measure the size of a firm, different variables could be used like the number of employees, total assets and turnover. However, the accounting data on "turnover" are more reliable than those on total number of employees reported in the balance sheets, and there are less missing data.

4. An Application to Italian firms

This section illustrates the results of the analysis applied to Italian firms. Despite the easing of the economic situation and the fall in the number of business failures in the Eurozone, the number of corporate insolvencies in Italy is still relatively high and characterized by a positive trend. Table 3 and Table 4 show respectively the absolute values of corporate insolvencies and the year-on year percentage variation in total bankruptcies in Western European countries over the 2006-2014 years. Italy is the only country always characterized by positive percent change in failures over previous year since the 2007-2008 international financial crisis.

As it is illustrated in Figure 1, only Italy and Norway register year-on-year increases in corporate insolvencies 2014. Italy, in particular, shows the highest yearly percentage variation in corporate failures (+12.8 percent).

Table 3 Corporate insolvencies in Western Europe (2006-2014), absolute values

	2014	**2013**	**2012**	**2011**	**2010**	**2009**	**2008**	**2007**	**2006**
Austria	5600	5626	6266	6194	6657	7076	6500	6362	6854
Belgium	10736	11739	10587	10224	9570	9382	8476	7678	7617
Denmark	4049	4993	5456	5468	6461	5710	3709	2401	1987
Finland	2954	3131	2956	2944	2864	3275	2612	2254	2285
France	60548	60980	59556	49506	51060	53547	49723	42532	40360
Germany	24030	26120	28720	30120	32060	32930	29580	29150	34040
Greece	330	392	415	445	355	355	359	524	532
Ireland	1164	1365	1684	1638	1525	1406	773	363	304
Italy	16101	14272	12311	10844	10089	8354	6498	5518	8827
Luxembourg	845	1016	1033	961	918	698	590	680	634
Netherlands	6645	8375	7373	6176	7211	8040	4635	4602	5941
Norway	4803	4564	3814	4355	4435	5013	3637	2845	3032
Portugal	7200	8131	7763	6077	5144	4450	3267	2123	2400
Spain	6392	8934	7799	5910	4845	4984	2528	880	853
Sweden	7158	7701	7737	7229	7546	7892	6298	5791	5243
Switzerland	5867	6495	6841	6661	6255	5215	4222	4314	4528
United Kingdom	15240	16021	17765	18467	17468	19908	16268	12893	13686
Total	179662	189855	188076	173219	174463	178235	149675	130910	139123

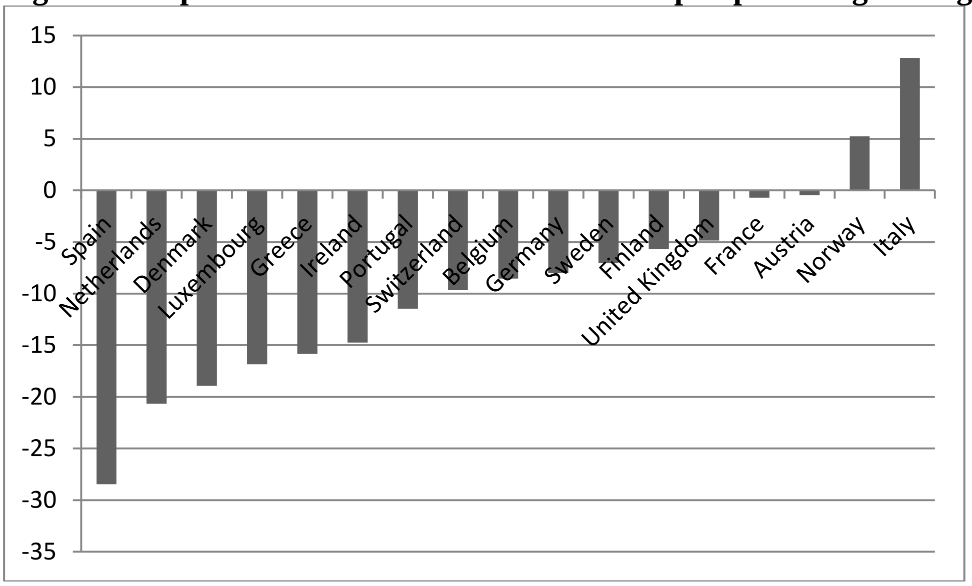
Source: own elaborations on Creditreform data

Table 4 Corporate insolvencies in Western Europe (2006-2014), year-on-year % variation

	14/13	13/12	12/11	11/10	10/09	09/08	08/07	07/06
Austria	-0.46	-10.21	1.16	-6.96	-5.92	8.86	2.17	-7.18
Belgium	-8.54	10.88	3.55	6.83	2.00	10.69	10.39	0.80
Denmark	-18.91	-8.49	-0.22	-15.37	13.15	53.95	54.48	20.84
Finland	-5.65	5.92	0.41	2.79	-12.55	25.38	15.88	-1.36
France	-0.71	2.39	20.30	-3.04	-4.64	7.69	16.91	5.38
Germany	-8.00	-9.05	-4.65	-6.05	-2.64	11.33	1.48	-14.37
Greece	-15.82	-5.54	-6.74	25.35	0.00	-1.11	-31.49	-1.50
Ireland	-14.73	-18.94	2.81	7.41	8.46	81.89	112.95	19.41
Italy	12.82	15.93	13.53	7.48	20.77	28.56	17.76	-37.49
Luxembourg	-16.83	-1.65	7.49	4.68	31.52	18.31	-13.24	7.26
Netherlands	-20.66	13.59	19.38	-14.35	-10.31	73.46	0.72	-22.54
Norway	5.24	19.66	-12.42	-1.80	-11.53	37.83	27.84	-6.17
Portugal	-11.45	4.74	27.74	18.14	15.60	36.21	53.89	-11.54
Spain	-28.45	14.55	31.96	21.98	-2.79	97.15	187.27	3.17
Sweden	-7.05	-0.47	7.03	-4.20	-4.38	25.31	8.75	10.45
Switzerland	-9.67	-5.06	2.70	6.49	19.94	23.52	-2.13	-4.73
United Kingdom	-4.87	-9.82	-3.80	5.72	-12.26	22.38	26.18	-5.79
Total	-5.37	0.95	8.58	-0.71	-2.12	19.08	14.33	-5.90

Source: own elaborations on Creditreform data

Figure 1 Corporate insolvencies in Western Europe - percentage change 2014/2013



Source: own elaborations on Creditreform 2015

The international comparison highlights significant differences among countries in terms of corporate insolvencies and suggests some distinguishing features of Italian companies, which are worth to analyze. Since firm-level data can provide critical information on firms' behavior that complements traditional macro analysis, this empirical analysis is based on accounting data of Italian manufacturing firms taken from the Aida Database, published by Bureau Van Dijk. After dealing with missing data,I build up an appropriate database including 31958 Italian small, medium and large manufacturing firms.

The work is carried out on the balance sheet and income statement over the 2006-2010 period in order to analyze the characteristics of firms affecting their probability of default after 5 years, in 2011. An important issue concerns the definition of default. I consider the group membership in 2011, during which some firms failed or were subject to liquidation procedure that brings to failure. Business failure has been defined in many different ways in the empirical literature (Crutzen and Van Caillie, 2008), therefore it is important to clarify the meaning of bankruptcy adopted in this study. Specifically, I focus on companies that have undertaken the juridical procedure of bankruptcy because of permanent financial distress. Therefore, a firm is considered to have defaulted if it is under bankruptcy procedure, if it has filed for bankruptcy or it is in liquidation; I exclude firms with temporary financial problems or companies which have voluntary chosen liquidation for economic opportunity, mergers or acquisition.

The information on the legal status of the firms with respect to bankrupt procedures has been collected from the AIDA database.

By applying the default definition provided, the work focuses on two groups of firms: defaulting firms and non-defaulting firms. The composition of the sample is provided in Table 5.

Table 5 Sample Composition, 2010

	Total n. of firms		Defaulting Firms		Non-defaulting firms	
	Number	Percentage	Number	Percentage	Number	Percentage
Total	31958	100	1856	5.81	30102	94.19
Geographical Area						
North	23659	74.03	1225	5.18	22419	94.82
Center	5038	15.76	367	7.28	4671	92.72
South	3261	10.20	264	8.09	2997	91.91
Turnover						
2-10 million euros	21246	66.48	1207	5.68	20039	94.32
10-50 million euros	8226	25.74	271	3.29	7955	96.71
>50 million euros	2486	7.78	378	15.2	2108	84.8
Age						
<15	11049	34.57	882	7.98	10167	92.02
16-24	7550	23.62	371	4.91	7179	95.09
25-32	6342	19.84	271	4.27	6071	95.73
>33	7017	21.96	332	7.35	6685	92.65

Source: own elaborations on Aida database

The manufacturing firms included in the sample operate in different geographical areas, in different sectors and they significantly differ in size. Since both large companies and SMEs are considered, in order to mitigate the effect of firm size on selected variables, I first consider large, medium and small enterprises separately; then divide each financial variable by the average turnover of the corresponding group and, finally, build up the financial ratios.

As mentioned above, the full sample includes 31958 firms. The defaulting firms' group includes 1856 firms failed in 2011 and represents 5.81% of the firm population, while the non-failed group consists of 30102 companies representing 94.19% of the total. With reference to the geographical area in which the firms are located, the population includes 23644 firms in the North, 5038 in the Center and 3257 in the South of Italy. The distribution of failed firms among the different geographical areas mirrors the composition of the whole population. Most of defaulting firms, at least in absolute terms, are concentrated in the North (1225), while default firms in the Center and in the South of the country are 367 and 264 respectively. Looking at percentage values, the distribution of the two groups of firms shows a prevalence of default firms in the South of Italy.

Table 5 also shows the composition of the sample with respect to firm size and age. As mentioned above, as measure of size I consider the annual turnover, one of the parameters adopted by the Basel II Committee to define SMEs, while age is in terms of years of activity since firm foundation. Data show a relatively higher concentration of bankruptcies among SMEs and young firms.

In Europe, the distribution of insolvency among the different branches of the economy can vary considerably. Southern European countries usually register large numbers of defaulting firms in manufacturing sectors. In 2010, for example, Italy registers 24.1 percent of default firms belonging to manufacturing sectors, a value above the European average.

Table 6 shows the percentage of corporate insolvencies across the manufacturing sectors, identified following the NACE Rev.2 classification and structured, for a descriptive purpose, following the Intermediate level SNA/ISIC-A*38 aggregation.

Within the manufacturing industry, the incidence of failure is relatively higher in the sectors of motor vehicles and transport equipment (8.44%), repair and installation of machinery and equipment (8.25%), followed by manufacture of wood, paper products and printing (7.42 %). The manufacture of chemical and chemical products and the manufacture of pharmaceuticals, medicinal, chemical and botanical products show the lowest percentages of corporate failures, registering 2.70% and 2.91% of insolvencies respectively.

Table 6 Percentage of corporate insolvencies by sector, year 2010

NACE Rev.2 code	Sector Description	N of defaulting firms	Total N of firms	% of corporate insolvencies
10, 11, 12	Manufacture of food products, beverage and tobacco products	117	2855	4.10
13, 14, 15	Manufacturing of textiles, apparel, leather and related products	265	3953	6.70
16, 17, 18	Manufacture of wood, paper products and printing	174	2345	7.42
19	Manufacture of coke and refined petroleum products	5	155	3.23
20	Manufacture of chemical and chemical products	38	1406	2.70
21	Manufacture of pharmaceuticals, medicinal, chemical and botanical products	9	309	2.91
22, 23	Manufacture of rubber and plastics products, and other non-metallic mineral products	234	3750	6.24
24, 25	Manufacture of basic metals and fabricated metal products, except machinery and equipment	408	6737	6.06
26	Manufacture of computer, electronic and optical products	60	1096	5.47
27	Manufacture of electrical equipment	70	1564	4.48
28	Manufacture of machinery and equipment n.e.c.	217	4670	4.65
29, 30	Manufacture of motor vehicles, trailers and semi-trailers Manufacture of transport equipment	83	983	8.44
31, 32	Manufacture of furniture Other manufacturing; repair and installation of machinery and equipment	176	2134	8.25

Source: own elaborations on Aida database

4.1 Analysis of the financial health of Italian manufacturing firms through the CI index

In this paragraph the results obtained by applying the Robust PCA analysis to the Italian case are firstly presented and discussed, and then the classification obtained through the estimated ***CI*** index is illustrated.

Notice that, to estimate DEBT e WKN coefficients, the Robust PCA algorithm has been applied to average values of financial ratios over the 2006-2010 years in order to increase the stability and the reliability of such financial indices.

After applying the Robust PCA method, I obtain new RPCs variables that are linear combination of original financial ratios, they are uncorrelated and maximize variance. The percentage of variance explained by each Robust PC is computable from the robust eigenvalues given by the Robust PCA algorithm (Appendix, Table A.1).

As expected, the first robust principal component represents the most important dimension in explaining changes of financial conditions since it explains 72.5% of the total variance. Thus, I retain RPC_1 to estimate the coefficients α_i for $DEBT_{INDEX}$:

$$\boldsymbol{DEBT_{INDEX}} = 0.9192\frac{FD}{N} + 0.0045\frac{CL}{FD} + 0.0885\frac{FD}{CF} + 0.0254\frac{CL}{CA} + 0.3706\frac{NTCA}{N} + 0.0657\frac{TFA}{LTD+N}$$

With reference to financial ratios included in the WKN_{INDEX}, the first robust principal component is also the most important dimension in explaining changes in sustainability of firms' debt. It explains 56.2% of the total variance of the financial ratios (Appendix, Table A.2). As for $DEBT_{INDEX}$, the coefficients δ_i for WKN_{INDEX} are estimated by retaining only RPC_1:

$$\boldsymbol{WKN_{INDEX}} = 0.1572\frac{IP}{EBIT} + 0.2515\frac{IP}{EBITDA} + 0.9550\frac{IP}{CF}$$

Using the threshold values shown in Table 1, I can define the final threshold values for both $DEBT_{INDEX}$ and WKN_{INDEX}, derive the ***CI*** index and then classify the firms according to their degree of indebtedness and vulnerability:

$$Threshold1_{DEBTINDEX} = \sum_{i=1}^{7}\alpha_i\ Threshold1_i = 1.65$$

$$Threshold2_{DEBTINDEX} = \sum_{i=1}^{7}\alpha_i\ Threshold2_i = 3.06$$

$$Threshold1_{WKNINDEX} = \sum_{i=1}^{3}\delta_i\ Threshold1_i = 0.29$$

$$Threshold2_{WKNINDEX} = \sum_{i=1}^{3}\delta_i\ Threshold2_i = 0.69$$

Table 7 illustrates the distribution of the Italian manufacturing firms in 2010 according to this classification.

Table 7 Distribution of firms by CI index, year 2010

$\boldsymbol{WKN_{INDEX}}$ $\boldsymbol{DEBT_{INDEX}}$	**Good** WKN< 0.29	**Normal** 0.29<WKN<0.69	**Bad** WKN> 0.69	**Total**
Good $DEBT$<1.65	9096 (28.46%) $\boldsymbol{CI}^{++}$	2480 (7.76%) $\boldsymbol{CI}^{+\cdot}$	3331 (10.42%) $\boldsymbol{CI}^{+-}$	14907 (46.65%)
Normal 1.65<$DEBT$<3.06	1483 (4.64%) $\boldsymbol{CI}^{\cdot+}$	1217 (3.81%) $\boldsymbol{CI}^{\cdot\cdot}$	4492 (14.06%) $\boldsymbol{CI}^{\cdot-}$	7192 (22.50%)
Bad $DEBT$>3.06	1822 (5.70%) $\boldsymbol{CI}^{-+}$	982 (3.07%) $\boldsymbol{CI}^{-\cdot}$	7055 (22.08 %) $\boldsymbol{CI}^{--}$	9859 (30.85%)
Total	12401 (38.80%)	4679 (14.64%)	14878 (46.55%)	31958 (100%)

Source: own elaborations on Aida database

According to the classification based on the $\boldsymbol{CI}$ index, the percentage of Italian manufacturing firms in the best financial status $\boldsymbol{CI}^{++}$ is 28.46%; these firms have a low level and a good sustainability of debt. 22.08% of firms are classified in the worst financial status $\boldsymbol{CI}^{--}$; these firms are characterized by a high level of debt and a bad sustainability of the debt, therefore the risk to fail is expected to be high.

4.2 Econometric Results

Table 8 shows the logistic regression estimates for different lengths of the reference period, in particular for 1, 2, 3, 4 and 5 years before failure.

Those variables performing well in the latest year before failure will not necessarily perform well in the other years prior to failure. Some variables, however, can play an important role in more than one regression given the long run nature of some factors leading to failure.

Given the non-linearity of the first-order conditions with respect to parameters, a solution of numerical approximation is adopted that reaches the convergence after five reiterations. Table 8 reports the maximized value of the log-likelihood function for all the regressions.

LR Chi-square (50) is the asymptotic version of the F test for zero slopes. The p-value allows the rejection of the null hypothesis that all the model coefficients are simultaneously equal to zero. Therefore, the model as a whole is statistically significant. To avoid the risk of multicollinearity among variables, the computed bivariate correlation test has been carried out. It does not reveal any linear relation among variables. To further corroborate this result two additional measures, namely the ‘‘tolerance’’ (an indicator of how much collinearity a regression analysis can tolerate) and the VIF (variance inflation factor, an indicator of how much of the inflation of the standard error could be caused by collinearity) have been computed. Since both measures are close to 1 for the considered variables, any multicollinearity can be excluded.

Turning to the analysis of the estimates, the empirical findings show that both the DEBT score and the WKN score are statistically significant at 1% level with the expected positive sign. An increase in firm’s debt level and/or in its unsustainability significantly increases the probability of default.

Table 8 also reports the odds ratio of the logistic regression, which coincides with the exponential value of the estimated parameters. Considering one year prior to failure (2010), for a unit increase in the DEBT score, the odds of bankruptcy increases by 44%, holding the other variables constant. Likewise, a unit increase in the WKN score raises the odds by 67.9%. In other words, firms that are exposed to high debt are more than 1.44 times ($e^{0.365}$) likely to fail than the other firms; firms with an unsustainable debt are more than 1.68 times ($e^{0.518}$) likely to go to bankrupt than the other firms.

From these results it is clear that the level of indebtedness and its nature are important factors in explaining firms' default risk. Interestingly, both indices enter with the highest coefficients in all the regressions, that is for different lengths of the reference period. Moreover, the coefficient associated to the vulnerability of debt is always greater than that related to the absolute level of debt[5]. Hence, it is certainly true that total amount of debt and its composition signal the financial health of the company, but the capacity/potential of the firm to sustain such debt is a more important factor to consider in firms’ creditworthiness evaluation. In this context, an early warning signal of default risk would assume a pivotal role in the adoption of effective reorganization procedures.

With reference to the other explanatory variables, firm size enters with negative sign at 10% level of significance, therefore larger companies would face lower probability of default. Note, however, that firm size is not significant when we consider long period prior to failure. Age enters at 1% level with negative sign, suggesting that younger firms are more likely to go to bankruptcy than larger companies. These results confirm previous empirical findings on the impact of age and size on firm performance (European Central Bank, 2013; Hurst and

[5] Note that the relatively higher coefficient associated to the variable WKN cannot be ascribed to scale differences because, as mentioned above, financial ratios have been standardized.

Pugsley, 2011; Haltiwanger, 2013; Fort et al. 2013). In a recent work on Italian manufacturing firms, Ferretti et al. (2016) obtain similar results.

Ownership concentration would enter with negative sign in the first year prior to failure suggesting that alignment of interests in fully concentrated ownership firms reduces the probability of financial instability and default. The variable, however, is not significant in explaining the probability of default in the majority of regressions.

On the contrary, being a multinational firm would impact significantly and negatively on the probability of bankruptcy, presumably due to the diversification of risk among different markets worldwide.

Labor productivity, on the contrary, does not seem to influence the probability of default.

As it is expected, the pseudo R-square increases when the reference period before failure reduces.

Moreover, both the coefficients (thus the odds ratios) and, for some regressors, the significance levels decrease when an increasing number of years is considered before failure. However, the estimates suggest that while some variables (like the annual turnover) are strongly significant in the latest year before failure but less significant - or not significant - in the other years prior to failure, the DEBT and WKN scores always enter at 1% level of significance with the expected positive sign. They play an important role in determining the probability of default for several years before bankruptcy, mainly due to their long run nature within the process leading to failure.

For a comparison, I have also estimated the model including the Altman (1983) Z-score (see the Appendix A.3 for a short description) instead of the DEBT and WKN scores. Empirical findings, reported in Table 9, show that the Altman Z-score enters significantly with the expected negative sign. The rest of the results are quite similar both in sign and level of significance.

Table 8 Probability of default: Logit estimates

	Year -1 2010		Year -2 2009		Year -3 2008		Year -4 2007		Year -5 2006	
	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}
DEBT	0.365***	1.440***	0.338***	1.402***	0.286***	1.331***	0.373***	1.452***	0.275***	1.317***
	(0.057)	(0.083)	(0.047)	(0.067)	(0.037)	(0.049)	(0.040)	(0.058)	(0.042)	(0.055)
WKN	0.518***	1.679***	0.469***	1.599***	0.513***	1.671***	0.562***	1.755***	0.529***	1.698***
	(0.045)	(0.075)	(0.035)	(0.057)	(0.032)	(0.054)	(0.034)	(0.059)	(0.034)	(0.057)
SIZE	-0.134*	0.874*	-0.063	0.938	0.013	1.014	-0.001	0.999	0.075	1.077
	(0.065)	(0.057)	(0.053)	(0.050)	(0.044)	(0.045)	(0.042)	(0.041)	(0.041)	(0.044)
AGE	-0.262***	0.769***	-0.201***	0.817***	-0.186***	0.829***	-0.128***	0.879***	-0.060	0.940
	(0.066)	(0.050)	(0.052)	(0.043)	(0.044)	(0.037)	(0.043)	(0.038)	(0.044)	(0.042)
D_own	-0.034*	0.965*	0.144	1.155	0.157	1.170	0.232	1.261	0.244	1.276
	(0.150)	(0.145)	(0.123)	(0.142)	(0.104)	(0.122)	(0.096)	(0.121)	(0.097)	(0.124)
D_mult	-0.258*	0.772*	-0.297***	0.742**	-0.581***	0.559***	-0.403***	0.668***	-0.547***	0.578***
	(0.141)	(0.109)	(0.120)	(0.089)	(0.106)	(0.059)	(0.095)	(0.063)	(0.094)	(0.054)
PROD	0.074	1.077	0.139	1.149	-0.032	0.967	-0.087	0.915	-0.127	0.880
	(0.124)	(0.134)	(0.097)	(0.112)	(0.082)	(0.079)	(0.084)	(0.077)	(0.086)	(0.076)
Regional dummies	included	included	included	included	included	included	included	included	included	included
Sector dummies	included	included	included	included	included	included	included	included	included	included
Constant	-3.415**		-4.272***		-2.846***		-2.260***		-3.280***	
	(1.258)		(1.210)		(0.946)		(0.813)		(0.791)	
N of obs.	14486		14225		15466		16674		15809	
Log-likelihood	-1529.44		-2071.53		-2790.83		-3159.92		-3095.08	
Pseudo R^2	18.77		16.59		15.84		16.34		15.31	
LR Chi-square(50)	530.06		596.74		749.93		889.94		789.07	
Prob>Chi-square	0.000		0.000		0.000		0.000		0.000	

Notes: All variables in logs. Standard errors in parenthesis. Significance levels: *10%; **5%; ***1%.

Table 9 Probability of default: Logit estimates, Z-score

	Year -1 2010		Year -2 2009		Year -3 2008		Year -4 2007		Year -5 2006	
	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}
Z-score	-0.611*** (0.050)	0.542*** (0.027)	-0.470*** (0.040)	0.624*** (0.025)	-0.576*** (0.038)	0.561*** (0.021)	-0.687*** (0.039)	0.503*** (0.019)	-0.614*** (0.040)	1.698*** (0.057)
SIZE	-0.124** (0.063)	0.883** (0.056)	-0.049 (0.052)	0.951 (0.050)	0.006 (0.042)	1.006 (0.042)	0.033 (0.039)	1.033 (0.040)	0.073 (0.039)	1.077 (0.044)
AGE	-0.365*** (0.063)	0.693*** (0.043)	-0.353*** (0.048)	0.702*** (0.034)	-0.244*** (0.041)	0.783*** (0.032)	-0.156*** (0.039)	0.855*** (0.033)	-0.130*** (0.041)	0.940 (0.042)
D_own	-0.018* (0.149)	0.981* (0.146)	0.054 (0.121)	1.056 (0.128)	0.115 (0.098)	1.122 (0.110)	0.215 (0.089)	1.240 (0.111)	0.136 (0.095)	1.276 (0.124)
D_mult	-0.580*** (0.140)	0.559*** (0.078)	-0.483*** (0.116)	0.616*** (0.072)	-0.739*** (0.100)	0.477*** (0.048)	-0.592*** (0.088)	0.553*** (0.048)	-0.677*** (0.090)	0.578*** (0.054)
PROD	0.151 (0.119)	1.163 (0.139)	0.146 (0.099)	1.157 (0.114)	0.063 (0.080)	1.065 (0.086)	-0.145* (0.080)	0.864* (0.069)	-0.120 (0.084)	0.880 (0.076)
Regional dummies	included	included	included	included	included	included	included	included	included	included
Sector dummies	included	included	included	included	included	included	included	included	included	included
Constant	-2.477* (1.259)		-3.228*** (1.172)		-2.422*** (0.904)		-1.532*** (0.761)		-2.782*** (0.850)	
N of obs.	14491		14129		16165		17307		16342	
Log-likelihood	-1587.12		-2193.33		-3111.58		-3622.11		-3381.13	
Pseudo R^2	14.30		11.30		10.82		11.37		10.57	
LR Chi-square(49)	364.60		345.35		455.79		576.66		475.82	
Prob>Chi-square	0.000		0.000		0.000		0.000		0.000	

Notes: All variables in logs. Standard errors in parenthesis. Significance levels: *10%; **5%; ***1%.

4.3 Interaction effect between DEBT and WKN

In this paragraph the interaction effect between DEBT and WKN is estimated to infer how the effect of DEBT (WKN) on the dependent variable depends on the magnitude of WKN (DEBT). I compute the interaction term in the logit model following Ai and Norton (2003). As highlighted by the authors, the intuition from linear models does not extend to nonlinear models. To compute the magnitude of the interaction effect in logit model and to test for its statistical significance, it is necessary to compute the cross derivative of the expected value of the dependent variable. Moreover, the odds-ratio interpretation of logit coefficients cannot be used for interaction terms. The correct marginal effect of a change in the two interacted variables and the correct standard errors have been computed in accordance with Norton et al. (2004). Estimates are based on the same variable list reported in eq.(2) plus the interaction term between DEBT and WKN.

The interaction effects and the z-statistics are illustrated in Figure 2 and Figure 3 respectively. Both DEBT and WKN are statistically significant at conventional levels, as well as their interaction. Hence, the effect of DEBT (WKN) on the probability of default depends on the level of WKN (DEBT), as well as on other covariates.

The main effects imply that firms with higher debt and vulnerability are more likely to go bankrupt and the mean interaction effect is positive (0.0028482) (Table 10). Note, however, that the interaction effect varies widely. For some observations it is positive and for others it is negative. For firms whose predicted probability of bankruptcy is low (toward the left end of Figure 2), the interaction effect between DEBT and WKN is positive, thus the association between one of the two predictors and the dependent variable increases if the other predictor increases. Hence, the more positive DEBT is, the more positive effect of WKN on probability of default becomes.

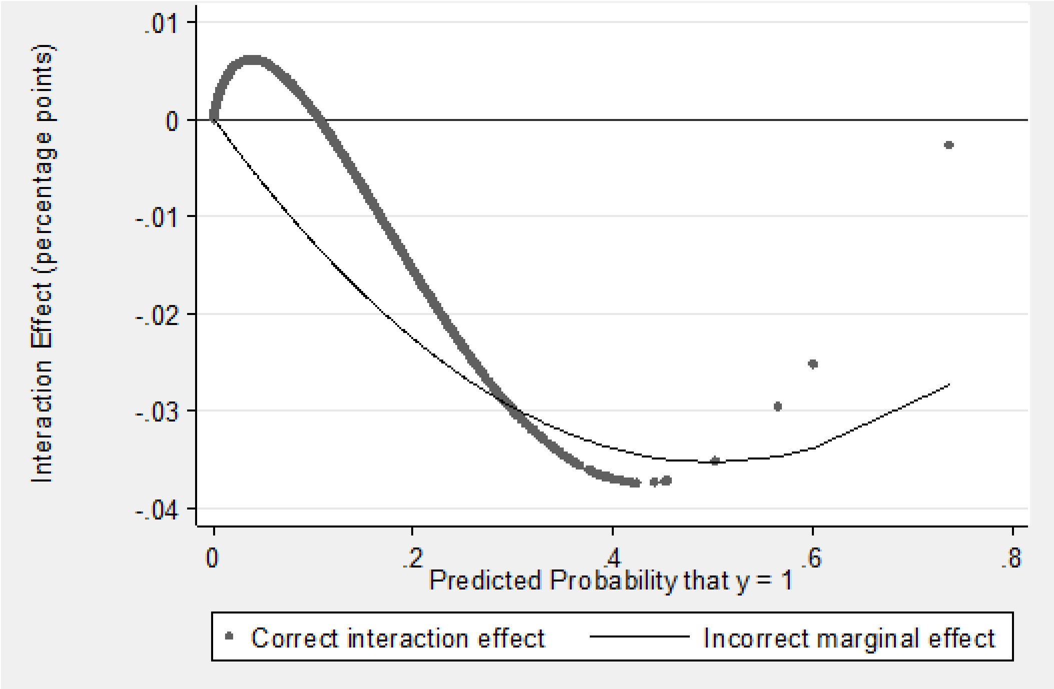
Where firms have a predicted probability of bankruptcy relatively higher, their interaction effects are all negative. That means there is “negative synergy” between the two interacted variables, so their presence at the same time dampens the effect. As debt increases, the effect of WKN on the probability of bankruptcy gets lower and lower. Put it differently, debt and WKN behave like substitutes: it is sufficient that one of them increases - for a given level of the other - in order to increase bankruptcy probability.

Table 10 Interaction effect, standard error and z-statistic – summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
_logit_ie	27702	0.0028482	0.0042808	-0.037341	0.0060973
_logit_se	27702	0.0007213	0.0010507	1.44e-09	0.0117573
_logit_z	27702	11.9979	8.075172	-16.42664	26.45633

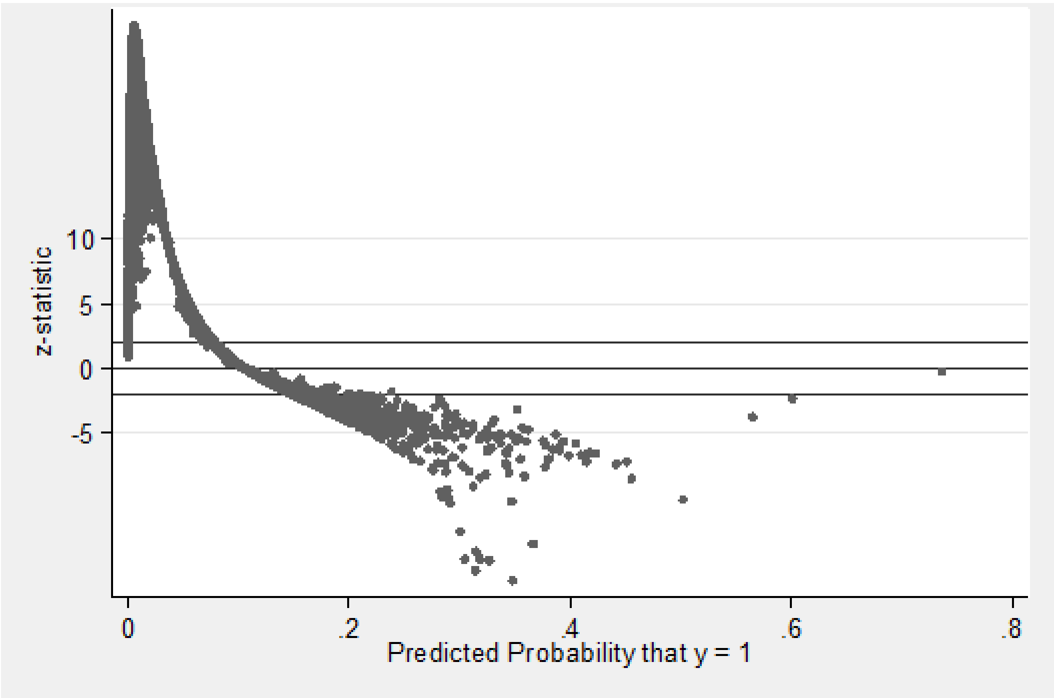
Source: own elaborations

Figure 2 Interaction Effects after Logit



Source: own elaborations

Figure 3 z-statistics of Interaction Effects after Logit



Source: own elaborations

5. Reliability of the model

To evaluate the model the percentage of overall correct classifications is computed, which gives the percent of correct predictions of thie model (Table 11). In total, 97.24% of predicted probability is correctly classified in 2010. More specifically, in 2010, 400 firms are misclassified, consisting of 389 non-failed firms, and 11 failed firms. Hence, the estimated chance of *misclassification* is 2.76 percent. Misclassification increases when the length of the reference period increases. For the second, third, fourth and fifth years prior to failure, the estimated chance of misclassification is 4.23 percent, 5.30 percent, 5.74 percent and 5.84 percent respectively.

Note that, in terms of classification accuracy, this model and the Altman Z-score perform similarly in the first two years before failure. However, a greater discrepancy occurs in the third, fourth and fifth years prior to failure with expected overall accuracy rates of 94.71 percent, 94.28 percent and 94.17 percent for DEBT-WKN scores *versus* 94.65 percent, 93.92 percent and 94.11 percent for the z-score.

At a deeper analysis, the empirical findings indicate that this model and the Altman Z-score show different percentages of first and second type errors. Type I errors refer to firms that are actually defaulting, but are classified as non-default firms. Type II errors refer to non-defaulting firms that are incorrectly classified by the model as default firms. As argued by Bottazzi et al. (2011) and Modina and Pietrovito (2014), it is standard to prefer prediction models that reduce the Type I error, that is models that maximize the percentage of correctly classified defaults. For a bank, and from a social point of view as well, it is more costly to fail to predict a default than to classify a non-default firm as a default firm.

Interestingly, these empirical findings show that the first type crucial error rates for misclassifying failed firms as non-failed firms for the first five years prior to failure are always lower in this model in comparison with the Altman Z-score.

I have further assessed the model's ability to accurately classify observations using a receiver operating characteristic (ROC) curve. A ROC curve is constructed by generating several classification tables for cutoff values ranging from 0 to 1 and calculating the sensitivity and specificity for each value. Sensitivity is plotted against 1, to make a ROC curve. The area under the ROC curve (AUC) is a measure of discrimination; a model with a high area under the ROC curve suggests that the model can accurately predict the value of an observation's response. This model provides outstanding discrimination since the AUC for the first five years prior to failure is 0.83, 0.80, 0.79, 0.78, 0.77 respectively (Table 11). Note that, as it is shown in Figure 4, the area under the ROC curve computed with the DEBT-WKN scores is always greater than the area computed with the Altman Z-score.

To test the model fit, Hosmer and Lemeshow's test was evaluated. A good fit will yield a large p-value. With a p-value of 0.42, this model fits the data well.

Finally, I have checked the presence of any specification error using the linktest. The idea behind linktest is that if the model is properly specified, one should not be able to find any statistically significant additional predictors, except by chance. The linktest uses the linear predicted value (_hat) and linear predicted value squared (_hatsq) as the predictors to rebuild the model. Since the variable _hat is a statistically significant predictor, the model is not misspecified. On the other hand, if the model is properly specified, variable _hatsq should not have much predictive power except by chance. Since, _hatsq is not significant, I have not omitted relevant variables and the equation is correctly specified.

In brief, the overall evidence suggests that, in terms of classification accuracy and reliability, this model would outperform Altman Z-score for prediction of corporate failure (see Van Frederikslust 1978). This is especially true in the third, fourth and fifth years prior to failure indicating DEBT-WKN indices to be good early warning signals of probable bankruptcy.

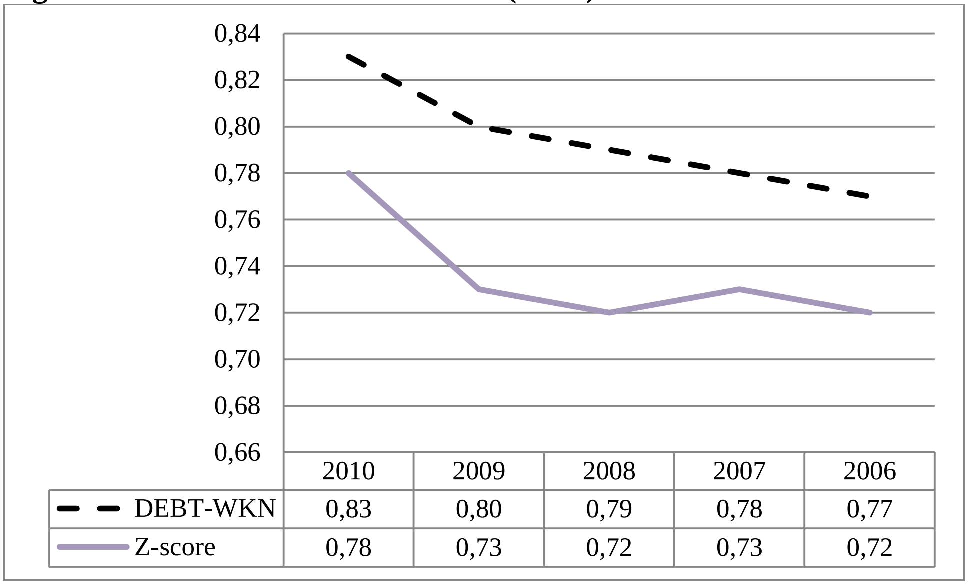
The proposed ***CI*** index, therefore, is an efficient alternative to the Altman z-score and can be used as an early warning signal of financial bankruptcy.

Table 11 Model reliability

	Year -1 2010		Year -2 2009		Year -3 2008		Year -4 2007		Year -5 2006	
	DEBT-WKN	Z-score	DEBT-WKN	Z-score	DEBT-WKN	Z-score	DEBT-WKN	Z-score	DEBT-WKN	Z-score
Correctly classified	97.24%	97.22%	95.98%	96.00%	94.71%	94.65%	94.28%	93.92%	94.17%	94.11%
Type I error	2.69%	2.74%	3.94%	3.99%	5.18%	5.27%	5.58%	5.95%	5.72%	5.80%
Type II error	0.07%	0.04%	0.09%	0.02%	0.12%	0.09%	0.16%	0.15%	0.12%	0.10%
AUC	0.83	0.78	0.80	0.73	0.79	0.72	0.78	0.73	0.77	0.72

Notes: A firm is classified as default whenever its estimated probability of default (p_i) is higher than 0.5; it is classified as non-default otherwise. We refer to first type errors when the model classifies as healthy a critical firm. We refer to second type errors when the model classifies as critical a healthy firm.

Figure 4 Area under the ROC curve (AUC)



Source: own elaborations

Finally, Table 12 illustrates the distribution of *ex-post* predicted probability of default for each group of firms characterized by the same composite indebtedness index $\boldsymbol{CI}$. Interestingly, for each level of the DEBT index, the probability of default increases as the WKN index increases; at the same time, for each level of the WKN index, the probability of default increases as the DEBT index increases. The best ideal companies ($\boldsymbol{CI}^{++}$) deal with a very low probability of default, equal to 0.62%; the worst companies ($\boldsymbol{CI}^{--}$) face a very high bankruptcy probability equal to 76.8%. As expected, the evidence as a whole indicates a significant increase in the probability of default as the firms' financial status deteriorates.

Table 12 Predicted Probability of Default, year 2010

$\boldsymbol{WKN_{INDEX}}$ $\boldsymbol{DEBT_{INDEX}}$	**Good** $WKN < 0.29$	**Normal** $0.29 < WKN < 0.69$	**Bad** $WKN > 0.69$
Good $DEBT < 1.65$	Prob. 0.62% $\boldsymbol{CI}^{++}$	Prob. 0.73% $\boldsymbol{CI}^{+\cdot}$	Prob. 0.76% $\boldsymbol{CI}^{+-}$
Normal $1.65 < DEBT < 3.06$	Prob. 1.12% $\boldsymbol{CI}^{\cdot+}$	Prob. 2.66% $\boldsymbol{CI}^{\cdot\cdot}$	Prob. 9.68% $\boldsymbol{CI}^{\cdot-}$
Bad $DEBT > 3.06$	Prob. 1.43% $\boldsymbol{CI}^{-+}$	Prob. 4.45% $\boldsymbol{CI}^{-\cdot}$	Prob. 76.8% $\boldsymbol{CI}^{--}$

6. Conclusions

The aim of this study is to develop a new bankruptcy prediction model which can be used in practice to analyze and promptly signal the risk of failure of a firm. In this context, I first derive a simple decision rule to classify firms as either at high risk of failure or at low risk of failure. Taking into account both the firms' debt level and its vulnerability, I develop a new Composite Indebtedness index based on a Robust Principal Component Analysis for skewed financial ratios. I derive an accurate instrument to assess the financial health of the firms. Second, I estimate a more complex logit model, based on both the first step computed indebtedness indices and additional non-financial firms' characteristics, which allows to compute specific bankruptcy scores (predicted probabilities of default) for each firm included in the analysis.

The main findings of this application to Italian manufacturing firms show that the level of indebtedness and its sustainability are significant factors in explaining firms' default risk. The coefficient associated to the vulnerability of debt, however, is always greater than that related to the absolute level of debt indicating that the capacity of the firm to sustain a certain amount of debt is a relevant factor to consider in firms' creditworthiness evaluation. Moreover, the interaction effect between debt and its sustainability varies widely. For firms whose predicted probability of bankruptcy is low, the interaction effect is positive, while where firms have a predicted probability of bankruptcy relatively higher, their interaction effects are all negative. The majority of the other non-financial explanatory variables enters significantly with the expected sign. In addition to several models that have been tested by the relatively short one-year prediction horizon, I test the predictive power of the index several years prior to bankruptcy and compare it with the popular Altman z-score. The empirical evidence suggests a good performance both in terms of classification accuracy and reliability. Hence, the proposed Composite Indebtedness index is a good predictor of firm default, it is an efficient alternative to the Altman z-score and can be used as an *early warning signal* of financial bankruptcy. An early warning signal of over-indebtedness assumes a pivotal role in the adoption of effective reorganization procedures. From this perspective, this accounting-based research can also contribute to a critical understanding and policy formulation on small firms, which are non-publicly traded firms.

The practical use of the empirical results, based on a very large sample size, is valuable for entrepreneurs, managers and financiers. However, the research can be developed following several directions. First, it would be interesting to compare the proposed composite index with other rating systems, apart from the Z-score, to evaluate companies' financial stability and their creditworthiness. Second, it may be worthwhile developing a more general model of company default prediction including also managerial practices and other qualitative information. Finally, as the analysis as a whole would indicate that this classifier outperforms individual techniques that constitute the ensemble classifiers, it would be worthwhile investigating new methodologies in order to amplify the advantages of the individual models and minimize their limitations.

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APPENDIX

Table A.1 Robust Principal Components and robust eigenvalues for $DEBT_{INDEX}$

Variable	*RPC1*	*RPC2*	*RPC3*	*RPC4*	*RPC5*	*RPC6*	*RPC7*
FD/N	0.9192	0.0252	-0.3911	-0.0352	0.0026	0.0021	-0.0141
CL/FD	0.0045	0.0086	-0.0246	0.0141	-0.0570	0.2103	0.9755
FD/CF	0.0885	0.9563	0.2607	0.0982	0.0112	-0.0042	-0.0022
CL/CA	0.0254	-0.0074	0.0810	-0.1113	-0.1599	0.9540	-0.2114
NTCA/N	0.3706	-0.2861	0.8327	0.2203	0.1937	-0.0172	0.0337
TFA/LTD+N	0.0657	-0.0486	0.1291	0.1736	-0.9597	-0.1584	-0.0211

Robust Eigenvalues	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
	33.3526	5.9613	4.0668	1.6916	0.7494	0.1324	0.0296
Explained Cumulate Variance[6]	0.725	0.855	0.943	0.980	0.996	0.999	1

Source: own elaborations on Aida database

Table A.2 Robust Principal Components and robust eigenvalues for WKN_{INDEX}

Variable	*RCP1*	*RCP2*	*RCP3*
IP/EBIT	0.1572	-0.6957	0.7009
IP/EBITDA	0.2515	-0.6581	-0.7097
IP/CF	0.9550	0.2878	0.0715

Robust Eigenvalues	λ_1	λ_2	λ_3
	13.2803	5.9266	4.4327
Explained Cumulate Variance	0.562	0.812	1

Source: own elaborations on Aida database

[6] The variance explained by the first PC is computable as $\frac{\lambda_1}{\lambda_1+\lambda_2+\cdots+\lambda_7}$

A.3 Altman Z-score

The Altman *Z-Score* (1983) for Private Firms is defined as follows:

$$\boldsymbol{Z = 0,717X_1 + 0,847X_2 + 3,107X_3 + 0,420X_4 + 0,998X_5}$$

X1 is defined as Working Capital/Total Assets (WC/TA).

The working capital/total assets ratio, frequently found in studies of corporate problems, is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

X2 is defined as Retained Earnings/Total Assets (RE/TA).

Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. It should be noted that the retained earnings account is subject to "manipulation" via corporate quasi-reorganizations and stock dividend declarations. The age of a firm is implicitly considered in this ratio. For example, a relatively young firm will probably show a low RE/TA ratio because it has not had time to build up its cumulative profits.

X3 is defined as Earnings Before Interest and Taxes/Total Assets (EBIT/TA).

This ratio is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure.

X4 is defined as Book Value of Equity/Book Value of Total Liabilities (BVE/TL).

The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. For example, a company with a value of its equity of $1,000 and debt of $500 could experience a two-thirds drop in asset value before insolvency. However, the same firm with $250 equity will be insolvent if assets drop only one-third in value.

X5 is defined as Sales/Total Assets (S/TA).

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capacity in dealing with competitive condition.

CHAPTER 2

New firms' bankruptcy: does local banking market matter?

Abstract

This chapter investigates the role of local context, with regard to the effect of local financial development and banking concentration, on a new firm's probability of bankruptcy. The empirical setting is based on the Logit Multilevel Model that better allows the treatment of data referring to different levels of aggregation (firm and local variables) applied to new firms located in Italian provinces. I find that a higher level of financial development in a province decreases the likelihood of a new firm's bankruptcy. This result is robust considering a 2SLS regression in which I use instruments for the local financial development and for the concentration of bank branches. In addition, the estimations suggest that the effect of local financial development and bank concentration is shaped by size. Local financial development is particularly significant for small start-ups, which traditionally suffer from great difficulty in accessing credit, whereas local banking concentration reduces the probability of bankruptcy for large, new firms.

Keywords:

Probability of bankruptcy, new firms, multilevel model, local banking structure

1. Introduction

Since the work of Guiso et al. (2004), there has been a renewed interest in the differences at the local level of financial development affecting a firm's financial activities. While it appears well stated that local financial development and, in general, institutional features of the local context, shape the financial decisions of firms (Cariola et al 2010, Deloof and La Rocca 2014, Deloof et al. 2016), with particular regards to small and medium-sized enterprises (SMEs), it is a first-order problem to investigate how the differences in the local market can affect the SMEs' quality of life in the short-run and their capability to access growth opportunities and operate for long-term success. In particular, local financial development can provide valuable support at the time firms are more fragile, as in their early stages. New and young companies are the primary source of job creation in economies (Haltiwanger et al. 2013), contributing to economic dynamism by injecting competition into markets and spurring innovation (Wiens and Jackson 2015). At the same time, these firms are the most financially vulnerable in the market. This weakness leads to questioning the role played by the financial system and, more precisely, by banks, in the local economic activity and as a driver of the performance of local firms.

This research addresses this question focusing on new firms' survival, one among many proxies describing the robustness of the companies. The analysis is centred on the role of local financial markets as determinants of firm bankruptcy. Considering that small and young firms are mainly hit by strong difficulties in the take-off years, I consider that the post-creation period is the moment where the local financial context provides the more valuable support to new firms. As new firm, I mean a newly incorporated company, independent from any group, not related to any industrial spin-off, and operating in market sectors. The objective of this study is thus to investigate whether the local financial market influences new firm bankruptcies to enhance our understanding of the drivers of this failure, to explore potential areas of interventions and to transform business failures into learning opportunities for future improvements in entrepreneurship.

The novelty of this research results from several features: the emphasis put on the relationship between insolvency and the organization of the local credit market, the sample of companies considered in the empirical analysis based on new firms, and the estimation technique used. Examining the sources of the regional disparities in the probability of corporate bankruptcy, it rapidly appears that the structure of the local debt market matters. A strand of the literature shows that credit rationing and institutional features vary across regions (Bonnet et al., 2005; Andriani 2013 and 2015), suggesting that the regional dimension is more important when companies are small (Bonnet and Le Pape 2012).

This study is in accordance with the strand of literature (Glauben et al. 2006; Fotopoulos and Louri 2000; Buehler et al. 2012) finding that a firm's bankruptcy is shaped by differences in the *local context* where the firms are based. The difference from the previous research originates from the restriction of the field of the analysis to *new firms,* which, according to many research studies on bankruptcy, are more likely to exit from the market than other firms (Kale and Arditi, 1998; Thornhill and Amit, 2003) and are very vulnerable to the macroeconomic environment (Petersen and Rajan 1995; Bonaccorsi di Patti and Gobbi 2001). Another novelty of this study is due to the estimation technique used since the empirical setting is based on the logit multilevel model, which has never been used in bankruptcy studies. This novelty allows to consider the hierarchical structure of the data and to better consider the effect of local variables.

The analysis is based on a unique sample covering all firms incorporated in Italy between 2008 and 2012. Italy represents an interesting case for studying this question, since it is characterized by cross-regional differences although all the regions are subject to the same formal institutions such as rules of law, constitution, civil, and criminal codes (Andriani, 2015; Guiso et al. 2004). The results suggest that a higher level of local financial development decreases new firms' bankruptcy likelihood, particularly in the case of small firms, whereas concentration in the local banking market reduces the probability of bankruptcy of large, new firms.

The remainder of the chapter is organized as follows. First, the literary review about firm bankruptcy, local financial development and bank concentration is presented. This presentation is followed by a description of the model, the sample, the variables employed, and their descriptive statistics. Next, the empirical results are reported. Finally, the main findings are synthesized, and considerations for future research are offered.

2. Literature review and hypotheses

2.1 Firm's bankruptcy

Financial distress, bankruptcy and general firm exits from the market have been the theme of several research studies in recent years. Beginning with the pioneering work of Altman

(1968), a large body of literature has investigated corporate bankruptcy with a focus on firm-specific features, searching to predict insolvency through the application of several statistical methods on economic and accounting data. Many authors seek to introduce new methodologies to obtain a more specific forecasting of firm's exit from the market (Blum, 1974; Elam, 1975; Libby, 1975; Alberici, 1975; Taffler 1982; Altman et. al., 1977, 1993; Wilcox, 1976; Lawrence and Bear, 1986; Flagg et al. 1991; Hillegeist et al., 2004; Altman et al., 2010). The recent empirical evidence indicates that prediction of insolvency and credit risk management can be improved by including *corporate nonfinancial information* in prediction models. Several researchers argue that economic and financial data alone don't give sufficient predictive power of insolvency, being therefore necessary to include variables representative of ownership and corporate governance characteristics in order to improve the predictive power of models (Lee & Yeh, 2004; Deng and Wang, 2006; Fich and Slezak, 2008).

The focus of this area of the accounting and finance literature has typically considered only the internal features of a company (financial and non-financial information) to assess its likelihood of failure. Only very recently, a small number of studies analysed the influence of institutional features of the *local context* to understand the exit behaviour across geographical regions. Fotopoulos and Louri (2000) examine the determinants of hazard rates of new firms entering Greek manufacturing industries in the 1982–1992 period. They propose a survival model in which the hazard faced by new firms in different locations is considered, with the results that firms located in the country's largest urban environment, Athens, face better survival prospects. This appears to be particularly relevant for smaller firms located in Athens when compared to their counterparts elsewhere in Greece. Glauben et al. (2006) study exit rates in agriculture across 326 counties in Western Germany. They find significant differences in the exit rates of farms across regions, with a higher exit rates in region with smaller firms. Buehler et al. (2010) find that bankruptcy rates tend to be lower in the central municipalities of agglomerations, in regions with favorable business conditions (where corporate taxes and unemployment are low and public investment is high) and that private taxes and public spending at the local level have little impact on bankruptcy rates. This last contribution is the only one who takes into account the relationship between the local economic development and firm's survival using duration models.

These papers suggest that there is a link between a firm's bankruptcy risk and its geographic location. This contribution differs from previous studies, because it focuses on the role of the local banking market in determining the access to credit and its consequence on new firms' survival.

2.2 Local financial development and corporate insolvency

The idea that the financial sector has the potential to influence patterns of innovation and growth dates to Schumpeter (1961), who argued that the services provided by financial intermediaries are essential for technological innovation and economic development. In the 1990s, beginning with the studies by King and Levine (1993a, 1993b, 1993c), a new body of literature has provided empirical evidence about a positive relation between the level of development achieved by the banking system and the growth rates of real variables (per-capita GDP, per-capita productivity, value added of individual industrial sectors, and sales by individual firms).

The last two decades a huge literature investigated the finance-growth nexus using cross-country data and new econometric tools. A number of observations, backed by empirical evidence, have emerged. Levine (2004) summarizes these as follows: (i) countries with better functioning banks and financial markets grow faster; (ii) simultaneity bias (i.e., the reverse causality) does not seem to drive this conclusion; and (iii) better-functioning financial systems ease the external financing constraints that impede firm and industrial expansion, suggesting that this is one mechanism through which financial development matters for growth. This positive relation prevails, despite the absence of complete unanimity of results (De Gregorio and Guidotti 1995, Guariglia and Poncet 2008, Brunnemeier and Pedersen 2009)

Considering the effect of financial development at the micro level, many studies investigating the relationship between financial development and firm performances demonstrate that a more developed banking system and a higher degree of bank penetration are significantly correlated with a lower probability that borrowers are financially constrained. Love (2003) brings evidence about the effect that financial development has on the severity of financial constraints facing firms, while Demirgüç-Kunt and Maksimovic (2002), using firm level data, find that financial development is robustly linked with firm access to external markets. Other researches find evidence that bank system development leads to more credit availability, and

more growth (Black and Strahan 2001; Beck et al. 2004; Cetorelli and Strahan 2006, Bertrand et al. 2007, Presbitero and Rabellotti, 2016).
Furthermore, analyzing the influence of financial development on new firms' performance, Aghion, Fally and Scarpetta (2007) using firm-level data for 16 industrialized and emerging economies, find that financial development promotes post-entry growth, even after controlling for the initial size at entry. Similarly, using panel data on French manufacturing firms over the 1996-2004 period, Musso and Schiavo (2008) show that an easier access to external funds lowers the probability that firms exit the market.

Considering the local dimension of bank credit market, another part of literature, however, documents that distance matters in the provisions of funds, especially for small firms. Petersen and Rajan (2002), for instance, document the importance of distance in the provision of bank credit to small firms due to the reducing impact of asymmetric information and transaction costs. Indeed, borrowers' actions are harder to observe when lender and borrower are far apart, leading to adverse selection (of potential borrowers) and moral hazard (for current borrowers). Starting from this perspective, Guiso et al. (2004) emphasize the importance of finance at the local level, defining local financial development as the "ease with which subjects in need of external funds can access them and the premium they have to pay for these funds" and "enables a more efficient allocation of capital reducing borrowing and financing constraints". A well-developed financial system at the local level can thus facilitate the ability of a company to gain access to external financing, providing cheaper finance to worthy companies (Guiso et al., 2004).
In general, it is suggested that banks operating locally have more knowledge and control over local firms and entrepreneurs (Alessandrini and Zazzaro, 1999). Consequently, local small businesses are very sensitive to the behaviour of local banks or branches.
The locally restricted relationships between banks and companies are confirmed by papers in the field of spatial economics which insist upon the importance of the local context in financing (Pollard, 2003; Argawal and Hauswald, 2010).
The previous empirical findings demonstrate that local financial development is positively related to growth (Guiso et al. 2004; Gagliardi 2009), enhances the probability of individuals starting their own businesses, favours the entry of new firms (Guiso et al. 2004) and affects firm's financial activities in different fields. It is suggested that, in more financially developed areas inside a country, firms use more debt (Cariola et al. 2010) and more trade credit (Deloof and La Rocca 2014). These features strongly affect the financial decisions of

new firms (Deloof et al. 2016). A greater availability of bank credit with a higher level of post-entry growth for new firms should thus result in a lower risk of bankruptcy. In contrast, financial constraints are likely to be more severe in the presence of a poorly developed financial system.

Consistent with these considerations, it’s possible to formulate the first hypothesis:

> **H1a**: a higher level of local financial development reduces new firm’s probability of bankruptcy.

The availability and cost of bank loans is crucial for many small businesses because they often do not have other possibilities for external funding (Berger and Udell, 1998; Robb and Robinson 2014; Miller and al., 2016). According to Titman et al. (2003), key determinants of the financial constraint, influencing firm’s capital-structure, may be the existence of asymmetric information and the cost of contracting between companies and potential providers of external financing (Diamond 1993)

In the literature on bankruptcy, the firm size is considered to have a positive effect on access to debt on the assumption that as the size increases the probability of financial distress is lower. Bates and Nucci (1989) found that the size of firm is a key factor affecting failure rates. Their research shows that a large group of very small firms was most responsible for high failure rates among small firms in general and that the larger and growing firms were less likely to exit from the market. The evidence provided by Titman and Wessels (1988) indicates that small firms tend to use significantly more short-term financing than large firms. This difference in financing practices may reflect the high transaction costs that small firms confront when they issue long-term debt or equity. Their finding that small firms use more short-term financing may also provide some insights about possible risk factors underlying the "small-firm effect." By borrowing more short term, these firms are more sensitive to temporary economic downturns than larger firms that are less leveraged and use longer term financing.

If small firms find it more difficult to access financial services due to greater information and transaction costs, the financial development that ameliorates these frictions will exert a particularly positive impact on small firms (Cestone and White 2003, Guiso et al 2004). Other arguments are provided by additional papers. Larger new firms can more easily raise funds in markets far from their main headquarters. Therefore, if finance affects growth we expect the effect of financial development to be mostly concentrated among smaller new firms. Consistently with these considerations the results provided by Guiso et al. (2004) support the hypothesis that financial development constrains more severely the growth of small and medium enterprises. According to Beck et al. (2008), different explanations could hide behind this greater effect of financial development on growth of small firms: one possibility is that small firms are more informationally opaque than large firms, consequently financial improvements lowering the marginal costs of acquiring information disproportionately facilitate the flow of capital to small firms; another possibility is that small firms rely more on intangible assets, so that financial innovations that reduce the need for collateral ease credit constraints on small firms more than large ones. Nevertheless, their results indicate that financial development still exerts a disproportionately positive impact on small-firm industries even when controlling for cross-industry differences in informational opacity, asset intangibility, industry concentration, and growth prospects. This suggests that financial development affects small-firm industries beyond opacity, collateral, and growth prospects.

Finally, bank debt represents a critical source of external financing for new firms (e.g., Bates, 1997; Cassar, 2004; Robb and Robinson, 2014; Hanssens et al. 2015). The results of these empirical findings could suggest that local financial development may influence the extensive margin by allowing new small firms to access financial services and thus reduce their risk of bankruptcy.

Consistent with these considerations, I formulate the following hypothesis.

> **H1b**: the effect of local financial development on new firms' probability of bankruptcy is stronger for small firms.

2.3 Local banking concentration and corporate insolvency

According to Petersen and Rajan (1995), two opposite perspectives are available. The Structure-Conduct-Performance (noted SCP below) paradigm states a positive relationship between the level of concentration and the interest rates. In line with the mainstream view, according to, more competition grants lower prices, this literature considers that bank competition relaxes financing constraints and, consequently, pushes down the risk of bankruptcy. An alternative point of view is supported by the information approach. It argues that a higher concentration deters banks to develop information systems, leads them to prefer long-term customer relationships that grant them an advantage coming from the accumulation of private information about potential borrowers who, in turn, have a better access to credit (Dell'Ariccia, and Marquez, 2006).

So far, the empirical research did not bring definite evidence, even if a vast majority of papers leads to consider that the probability of bankruptcy decreases when the banking sector becomes more competitive. This relation is supported by some papers finding that a higher concentration deters firm creation, limits economic growth, and causes a higher rate of unemployment (e.g., Jayaratne and Strahan, 1996, Black and Strahan, 2002, Cetorelli and Strahan, 2006). All these factors could lead to a higher risk of failure.

Still in this direction, Boyd and De Nicolo (2005) argue that, as competition becomes lower, banks earn more thanks to their market power that allows them to charge higher loan rates. This increases bankruptcy's probability for borrowers who are forced to face higher interest costs and, consequently, lower profits, trying to find the optimal solution of their investment policies in favor of more risk. Similarly, Koskela and Stenbacka (2000) suggest that, by lowering interest rates, greater competition increases the likelihood that borrowers are able to remain solvent and repay their loans. In line with these conclusions Agostino et al. (2012) find that bank concentration positively affects SMEs' default risk when credit relationships are very concentrated, that is when firms borrow heavily from their main bank and have few credit relationships with other intermediaries.

The favorable influence of competition on firm functioning is supported by a cross-country investigation performed by Beck, Demirgüc-Kunt, and Maksimovic (2004). They find a positive impact of bank concentration on financing obstacles. The same result is obtained by Love and Martinez Peria (2012) using an alternative measure for bank competition, the Lerner index. Although competition alleviates financing obstacles they find the effect depends on the economic and financial environment. Carbo-Valverde, Rodriguez-Fernandez, and Udell (2009) analyze the relation between bank competition and credit availability, measured at the firm level by the dependence on trade credit, on a sample of Spanish small and medium-sized enterprises (SMEs). They, too, find that greater bank competition is associated with lower credit constraints. Ryan, O'Toole and McCann (2014) examine the impact of bank competition measured by the Lerner index on credit constraints for a sample of firms from 20 European countries. They identify financial constraints through sensitivity of investment to the availability of internal financing. Their findings indicate that bank competition diminishes credit constraints. However, Cetorelli also finds that the positive effect of bank concentration on small firm financing is substantially weakened in developed countries.

Other pieces of research find favorable effects of bank concentration, such as higher growth rates and greater access to credit by new firms and other SMEs (e.g., Petersen and Rajan, 1995, DeYoung, Goldberg, and White, 1999, Bonaccorsi di Patti and Gobbi, 2001, Cetorelli and Gambera, 2001, Zarutskie, 2003, Bonaccorsi di Patti and Dell'Ariccia, 2004, Beck et al., 2004).

The favorable effects of concentration on the survival of firms are more evident when firms are very young. In fact, considering the case of young firms, Petersen and Rajan (1994, 1995), note that when a firm is young, the potential for future cash flows may be high while current cash flows are low. A monopolistic lender may be willing to subsidize such firms with cheap loans because the lender can extract rents later when the firms' cash flows become high. This finding means that a monopolistic bank might financially support firms with the objective of exploiting rents from eventually successful borrowers. When a bank adopts this kind of strategy, it has the objective of maintaining the lending relationships in the future, certain that the firm will not be attracted by rival banks. In contrast, in a competitive credit market, banks cannot expect to share the future firm's surplus and may be forced to charge a premium to cover the riskiness of young or distressed firms.

However, this effect is strictly linked to this specific context; therefore, the second hypothesis is inspired by research showing the advantages resulting from a more intense concentration in the local banking market.

> **H2a**: a higher local banking concentration reduces bankruptcy probability for new firms.

It is however important to note that firm size can shape the previous relationship. Indeed, two major papers by Beck et al. (2004) and Bonaccorsi di Patti and Gobbi (2001) find that competition in the bank market has a different effect on the credit volume of small and medium size enterprises that traditionally suffer from greater difficulty in accessing credit, compared to the impact on large firms. As argued by Berger and Udell (1998) small firm finance is more vulnerable to the external environment. This problem involves a variety of issue including: the fragility of private equity markets and their strong reactions to the different events in the equity markets; the effects of monetary policy changes; bank credit crunches caused by changes in the regulatory system, macroeconomic conditions; and the consequences of the consolidation of financial institutions. More recently, the stronger effect of competition on smaller companies is documented by Sääskilahti (2016) who proposes an empirical analysis of the relationship between competition environment and changes in lending during the crisis comparing Lerner and Herfindahl indices. He concludes to the superior sensitivity of smaller companies.

This finding leads to hypothesize:

H2b: The influence of concentration on the probability of new firms' bankruptcy is higher for smaller companies.

3. Method

3.1 Sample and data

The dataset of this study is derived from various sources. Data on the local banking market are from the Bank of Italy; data on economic development, population, and crime rates in the 103 Italian provinces are provided by the Italian National Institute of Statistics (ISTAT). Firms' data are extracted from the Orbis database, compiled by Bureau Van Dijk (BvD), which is a great resource for company data. The database contains the financial statements of privately held and publicly traded global firms, including more than 1 million Italian firms.

Firms needed to satisfy different requirements to be part of our sample. First, I included all firms that were legally incorporated in Italy in the years from 2008 to 2012, to avoid certain events in a specific year of incorporation driving our estimations. Second, with the objective of only considering real new firms not born from industrial spinoffs, only stand-alone companies with at least 1 employee and fewer than 50 employees are considered. I also exclude firms having a previous company name. These criteria are used with the objective of excluding *ghost* firms (that often exist only for fiscal reasons) and companies that are unlikely to be new firms. Third, I excluded public-owned firms because these firms' policies may be influenced by regulatory issues; we also excluded firms operating in different sectors (agriculture, financial and insurance activities, real estate activities, public administration, education, social services and human health services) because they may be subjected to particular failure regimes. Fourth, I excluded observations for which the total assets are less than 2,500 euros, which is the minimum equity requirement to found a firm in Italy. Fifth, I excluded from the dataset all firms whose status was unknown, inactive or dissolved and did not request official bankruptcy procedures. Finally, I only selected firms for which all information needed to calculate our variables is available. The final sample includes 94,118 firms.

3.2 Model and Variables

Since the dependent variable is a firm's probability of bankruptcy and our data refer to various levels of aggregation, it's possible to study the different sources of variability by means of the Logit Multilevel Model.

Companies operate in a socio-economic context, which significantly affects the performance of business processes (Audretsch and Dohse 2007, Garsaa and Levratto 2016). This finding is highlighted, as apparently weak ties between the organization and external parties can have a relevant impact on competitiveness and business performance but also on institutional structures and entrepreneurial purposes. In other words, firms located in the same territory share the same external environment; consequently, they are likely to be more similar to each other than firms operating in other geographical areas. From an econometric perspective, the most important effect of this similarity is that the assumption of independence of standard error is violated. This problem is resolved by the multilevel approach, which provides efficient estimates of coefficients since it controls for spatial dependence and correct standard errors of variables. Specifically, whereas standard logit regression has an overall mean coefficient, the logit multilevel model considers, in addition, group-level variance explicitly through the incorporation of random coefficients.

The model allows the simultaneous consideration of individual variables (X_{hij}, where *h* is the number of covariates and *i* is the firm located in the *j-th* province) and local variables that represent a 'higher level' (Z_{kj} where *k* is the number of local covariates and *j* the province). An econometric specification of the Logit Multilevel model can be written as the logistic function of the general model with a continuous dependent variable (Snijders and Bosker, 1999):

$$p_{ij} = \Pr\left(Y_{ij} = 1\right) = F[\alpha + \textstyle\sum_{h=1}^{r} \beta_h X_{hij} + \sum_{k=1}^{s} \gamma_k Z_{kj} + (u_j + e_{ij})] \qquad (1)$$

where *F(_)* is the logistic cumulative distribution function, u_j and e_{ij}, are the so called second and first level residuals, normally distributed with variance σ_u^2 and σ_e^2. In particular, u_j represents the difference between the j-province and the total average. As said, we may distinguish the errors resulting from differences across firms or clusters. To this end, it is necessary to consider the *empty model*, that is, a multilevel model in which there are no explanatory variables:

$$p_{ij} = \Pr\left(Y_{ij} = 1\right) = F[\alpha + u_j + e_{ij}] \qquad (2)$$

From Equation (2), it is possible to identify two different components of the variance of Y_{ij}, that is, the variance of the random error e_{ij} (σ_e^2), the within group variance, and the variance of u_j (σ_{u0}^2), the between group variance. A useful way to exploit this information is to compute the intra-class correlation (ICC), which represents the proportion of variance underlying each level of the model hierarchy. The ICC at the provincial level is computed as the ratio between the provincial variance and the total variance, that is:

$$ICC_{u0} = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_e^2} \tag{3}$$

Consequently, the firm ICC is the ratio of the firm variance to the total variance[2]:

$$ICC_e = \frac{\sigma_e^2}{\sigma_{u0}^2 + \sigma_e^2} \tag{4}$$

Table 1 provides the definitions of the variables used to test the model.

Table 1- Variables' names and definition

Explained variable	Probability of bankruptcy up to 2 years after incorporation
Explanatory variables	
Local variables	
FinDev	Private Credit/Gross Domestic Production
HHI	$\sum_{i=1}^{n}\left(\frac{\text{number of branches of bank i}}{\text{number of total branches}}\right)^{2}$
Crime	Number of extortions / Thousands inhabitants
GdpPerCapita	Gross Domestic Production / Thousands inhabitants
Firm's variables	
Size	Logarithm of Total Assets
StdTa	Short term Debt / Total Assets
LtdTa	Long term Debt / Total Assets
Tangibility	Tangible Assets / Total Assets
Intangible	Intangible Assets/ Total Assets
ROA	Ebit / Total Assets
WCTA	Working Capital / Total Assets
Interestcov	Ebitda / Interest paid
DifferentTaxShield	(Ebitda-Ebit)/ Total Assets
Majority_sh	Dummy variable= 1 if there's a majority shareholder
Sole_propr	Dummy variable=1 if there's a unique shareholder

The dependent variable used in the empirical model is the *Probability of bankruptcy*, a dummy variable that takes value 1 if a new firm requested an official bankruptcy procedure and 0 if it is normally operating. I focus on companies that have undertaken an official juridical procedure because of permanent financial distress to a maximum of 2 years after incorporation, because new firms that survive over the second year after incorporation are more likely to generate revenue and remain on the market. To check the robustness of the results, I also consider the probability of bankruptcy for 1 and 3 years after incorporation. We exclude firms with temporary financial problems or companies that have voluntarily chosen liquidation for economic opportunity, mergers or acquisition. Firms whose status was unknown or dissolved without precision were dropped from the sample.

Table 2 provides a description for the bankruptcy ratio of new firms calculated in our sample. As shown by Table 2, the sample is well-balanced, since the default ratios among firms born in the different years of the analysis, are similar.

Table 2. Description of the bankruptcy ratio for new firms

	(1) Number of new firms	(2) Bankrupted firms up to 1 year	(3) Bankrupted firms up to 2 years	(4) Bankrupted firms up to 3 years
Year of incorporation				
2008	22630	135	546	1150
		(0.60%)	(2.41%)	(5.08%)
2009	16984	126	508	1028
		(0.74%)	(2.99)	(6.05%)
2010	21637	44	443	1247
		(0.20%)	(2.05%)	(5.76%)
2011	14940	41	389	996
		(0.27%)	(2.60%)	(6.67%)
2012	17927	78	578	1175
		(0.44%)	(3.22)	(6.55%)
Total	94118			

Source: own elaboration on Orbis dataset

Regarding the local variables, it is worth specifying that I consider the "local" unit, the province (NUT3 code), similar to what is done by the large majority of empirical works based on Italy (Guiso et al. 2004, Deloof and La Rocca 2014) and because, citing Guiso et al. (2004): "According to the Italian Antitrust authority the "relevant market" in banking for antitrust purposes is the province, a geographic entity very similar to a US county. This is also the definition the Central Bank used until 1990 to decide whether to authorize the opening of new branches."

Defining financial development is a challenging task (Giovannini et al. 2013). Among the diverse indicators in use, I measure local financial development (*FinDev*) by Private Credit/GDP. This measure captures the amount of credit channelled through financial intermediaries to the private sector, and it has been used in several cross-country and within country studies on financial development (Rajan and Zingales 1998; Kendall 2012). Levine, Loayza and Beck (2000) show that Private Credit/GDP is a suitable predictor of economic growth.

Figure 1 displays the magnitude of our variable FinDev across Italian provinces.

As shown in this figure, the distribution of financial development reflects the duality in the Italian economy. Higher levels of financial development characterize the Nord and Central provinces, whereas in the south of the country, it is relatively low (with the exceptions of Bari and Messina provinces).

The measure of concentration in the local bank market is the Herfindahl-Hirschman on bank branches (*HHI*), a traditional and very used measure of bank concentration in the literature. Figure 2 displays the level of concentration across Italian provinces. According to the magnitude of this variable, the level of concentration is heterogeneously distributed. The highest values are recorded in the region of Sardinia with a peak in the province of Nuoro having a value of *HHI* equal to 0.52.

Moreover, considering that the local banking market is related to local crime (Bonaccorsi di Patti 2009), we included in the analysis a proxy of criminality. Financial contracts require trust, which is negatively affected by crime. However, the lending relationship between banks and the firm also requires trust (Fisman and Love 2003). The variable *Crime,* as a proxy of the business climate, is a measure that is based on the average number of extortion crimes reported by police to the judicial authority per 1000 inhabitants at the province level over the period considered. In addition, I include *GDPpercapita* as a measure of macroeconomic conditions in the different provinces defined as GDP per thousand inhabitants.

In accordance with the general literature on bankruptcy, the analysis includes the main firm's internal features at the first level of the model. Table 1 also displays the control variables at the first level. I include firm *Size* as proxy for firm creditworthiness[7]. Firm's age is not included in the model because the sample only contains new companies, but I add year fixed effects dummy variables to control for specific events that could occur in the year of incorporation. The model considers the financial structure and debt maturity of the firm. The variables *LtdTa* and *StdTa* explain debt maturity. I also consider the value of tangible assets introducing a variable named *Tangibility*, which measures the capacity to provide collateral and, consequently, obtain financing to restructure the business. Similarly, it is essential to consider the role of the variable *Intangible* (i.e., intellectual resources: trademarks, patents and licenses) because these kinds of assets are more likely to form the basis for competitive advantage and growth. I also consider the return on assets (*ROA*), a measure of firm's profitability, which allows us to understand how profitable a company's assets are in generating revenue. The variable WCTA as a measure of a firm's internal financing is also included. Another essential element to consider when assessing firms' creditworthiness is the vulnerability of such debt. In fact, certain companies may be characterized by similar levels of indebtedness while presenting different degrees of vulnerability. Hence, it is important to consider the ability to generate sufficient income to cover the cost of debt. Therefore, in the model, I add a debt sustainability variable, *Interestcov*. I include also the variable *DifferentTaxShield*, to understand the influence of different tax regimes and different amounts of amortization on the probability of bankruptcy. The model considers other explanatory variables to control for additional non-financial characteristics of the firms, expected to be relevant in determining their bankruptcy. In this study, I include information about ownership structure with two dummy variables: *Majority_sh* takes value 1 if there is a shareholder owning more than 50% of the firms and 0 otherwise, and *Sole_pr* that takes value 1 for firms owned and run by a unique shareholder and 0 otherwise. Industry dummies are included to capture industry-specific unobserved characteristics. Moreover, since the centre-north of Italy is more developed than the south and to explain the possibility that a firm's location influences its financial decisions, I include the dummies *North* and *South* to capture the location of a firm in a specific Italian macro-area.

[7] To measure the size of a firm, different variables could be used, such as the number of employees, total assets and turnover. However, the accounting data on "turnover" are more reliable than those on total number of employees reported in the balance sheets, and there are less missing data.

Figure 1 - Level of Financial Development (Average Values 2008-2012)

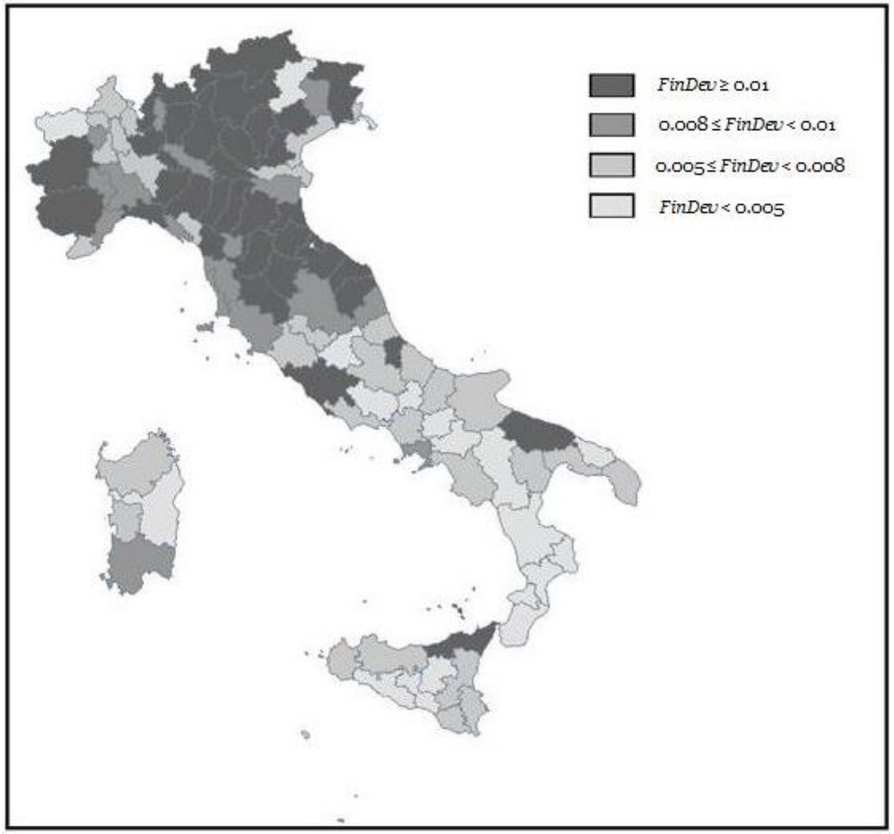
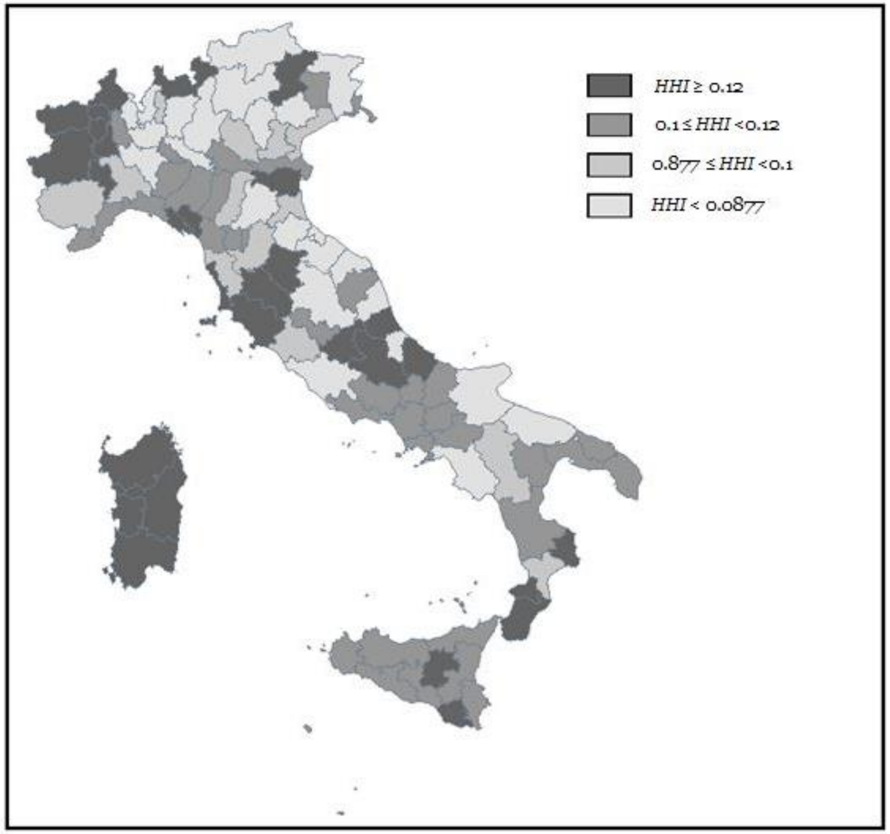


Figure 2- Level of Concentration in the banking market (Year 2009)



3.3 Descriptive statistics

The descriptive statistics concerning local and companies' variables are presented in Table 3, separately for active and bankrupt firms. The t tests for mean comparison for each variable is also presented.

Table 3 - Descriptive statistics

Variable	Active firms (n=91654) Mean	Media	STD	Bankrupt firms (n=2464) Mean	Media	STD	t-test Mean Compariso
FinDev	0.034	0.113	0.034	0.026	0.114	0.037	8.061***
HHI	0.100	0.094	0.041	0.101	0.096	0.040	-1.182
Crime	10.33	9.725	4.152	10.33	9.575	4.321	0.073
GDPpercapita	22.61	21.966	9.822	22.57	21.966	9,530	0.208
Size	4.807	4.770	1.344	4.482	4.469	1.323	11.843***
Stdebt	0.053	0.000	0.131	0.061	0.000	0.150	-3.212 **
Ltdebt	0.038	0.000	0.129	0.030	0.000	0.115	3.124***
Tangibility	0.144	0.058	0.195	0.125	0.041	0.177	4.760***
Intangible	0.088	0.029	0.145	0.103	0.040	0.149	-4.829***
ROA	0.021	0.024	0.297	-0.119	-0.004	0.499	22.585***
WCTA	0.072	0.029	0.355	0.045	0.000	0.359	3.709***
Interestcov	512.5	12.932	1122	18.53	2.161	4905.	2.179**
DifferentTaxShiel	0.063	0.019	0.854	0.042	0.020	0.141	1.197
Majority_sh	0.404	0.000	0.491	0.48	0.000	0.480	4.324***
Sole_propr	0.188	0.000	0.391	0.401	0.000	0.401	-1.694*

Source: own elaboration on Orbis, Banca d'Italia and ISTAT dataset

Concerning the mean value of local variables, it can be noticed that bankrupt firms, as expected, are more concentrated in provinces with a lower presence of financial development with a significance of the t test of mean comparison at 1%, while the mean value of Herfindahl-Hirschman index on bank concentration (*HHI*) and *Crime* index is almost equal between the two subsamples. Descriptive statistics about *GDPpercapita* shows that active firms are located in provinces with a higher level of richness per capita. Furthermore, we can see that the mean difference is statistically significant for almost all firm's variables and the value of means for bankrupt and active firms is in line with expectations: for example, the mean value of *Size* is higher for active firms, thing that confirms that a larger size is considered as a protection against insolvency;

regarding at debt maturity variables it seems that bankrupt firms make a larger use of short term debt, a classical form of financing that is used by Italian firms. The variable *Intangible* shows a higher mean value for bankrupt firms, showing that bankrupt firms make greater investments in intangible assets compared to firms that are active two years after startup, but it's necessary to consider if the variable is statistically significant in the model to make further considerations. The mean value of the profitability measure (*ROA*) is positive for active firms and negative for bankrupt firms, that is in line with our expectations. The mean value of the variable tangibility, a measure of the capacity to provide collateral and, consequently, obtain financing to restructure the business, is higher, as expected, for actives firms with a statistical significance of mean and median comparison between the two subsamples. As expected, descriptives on *WCTA* and *Interestcov* show a better financial health of active firms with a statistical significance in mean and median difference while the mean difference of *DifferentTaxShield* variable is not statistically different between the two subsamples.
VIF test, reported in appendix, suggests the lack of multicollinearity problems.

4. Empirical results

4.1 From the empty model to the effect of local variables

This section refers to the estimations obtained running the Logit Multilevel model to our data. Firstly, I consider the empty model that allows to evaluate how much of the variation in outcomes can be attributable only to unobserved factors operating at each level. In our case, the two levels are as follows: firms and province. Secondly, I present the result obtained when the model is augmented with firm-specific and provincial variables, the principal aim of our analysis.

This part of the chapter refers to the estimations obtained when considering the empty model. The empty multilevel model permits to understand how much of the variation in outcomes might be attributable to unobserved factors at each level. In our case study, there could be four levels: firm, province, Italian macro-areas (Nord, Centre and South) and sectors. Since we have 3 macro-areas and 8 sectors, this prevents us from considering them as levels of the model (see note 1). For this reason, I restrict the data hierarchy only to two levels: firms and province. As a consequence, the macro-area and

sector effect have been controlled using dummies. So, I choose the model specification that treats provinces as sources of randomness in the intercepts, while macro-area and sectors are considered as fixed effects. I consider provinces (NUTS3 code) as local units and not regions (NUTS2), following the suggestion of Italian Antitrust authority who considered the province as the "relevant market" in banking for antitrust purposes.
Table 4 displays the results obtained when running the empty model.

Table 4 – Explaining firms' heterogeneity in bankruptcy. Empty model

Constant	-3.642***
Random effects	
Variance	
Firms	3.290
Province	0.068
Total	3.358
ICC(%)	
Firms	97.96
Province	2.04
LR test	141.17***
Log-likelihood	-11336.647
Observations	94118
N. of groups	103

Notes: Results from multilevel regressions run with the command xtmelogit, available in Stata13 version
***Significance at the 1% level, **Significance at the 5 % level, * Significance at the 10% level

The most relevant result to be discussed is the value of the likelihood ratio test (LR test), that compares the empty multilevel model to the standard logit regression: under the null hypothesis H_0 σ_{u0}^2=0, this means that there is no random intercept in the model. If the null hypothesis is true, the logistic regression can be used instead of a mixed model. In our results, the test is highly significant, supports the use of Logit Multilevel Model and consequently, the intercepts related to the different clusters should be treated as a group by group variant coefficients. As can be seen from the table 4, provincial-specific factors capture 2.04% of new firms' probability of bankruptcy, while, the remaining (97.96%) is attributable to firm specific features.
Furthermore, with the aim to provide consistency in our estimations, it's essential to consider the role of Italian macro-area and sectors in the empty model. Since prior

studies on financial development in Italy have found significant differences between Northern, Central, and Southern Italy (Angelini et al. 1998; Ferri and Messori 2000; Alessandrini et al. 2009), we will include North and South dummies (with Center as reference group) in the empty model and all further regressions in which we augment the model with individual and local variables, to ensure that any effect of local banking development is not driven by the north–central–south divide. All regressions will also include sector dummies. With an improper number of clusters (3 macro-areas and 8 sectors) we decide to consider the fact that a firm is located in north, center or south Italy and the fact that the firm operates in a certain sectors as fixed effects. Table 5 shows the results obtained when running the empty model with fixed effects.

Table 5 - Heterogeneity in firm's bankruptcy. Empty model with fixed effects

	(1)	(2)	(3)
Constant	-3.619***	-3.552***	-3.531***
Fixed effects			
North	-0.0028		-0.0029
South	-0.0841		-0.0829
Manufacture		-0.2101***	-0.2139***
Utilities		-0.1219	-0.1231
Construction		-0.4300***	-0.4312***
Accommodation and food		0.2279***	0.2256***
ICT		-0.0709	-0.0735
Service to firms		-0.0101	-0.0132
Arts entertainments		0.1890	0.185
Random effects			
Variance			
Firms	3.290	3.290	3.290
Province	0.068	0.069	0.069
Total	3.358	3.359	3.359
ICC			
Firms	97.96%	97,94%	97.94%
Province	2.04%	2.06%	2.06%
LR test	141.84***	147.09***	147.67***
Log-likelihood	-11336.173	-11291.484	-11290.191
Observations	94118	94118	94118
N. of groups	103	103	103

Notes: Results from multilevel regressions run with the command xtmelogit, available in Stata13 version

***Significance at the 1% level, **Significance at the 5 % level, * Significance at the 10% level

In column 1, it can be observed that the result remains almost unchanged when the empty model is augmented with *North* and *South* dummy variables: the province-specific factors captures 2.04% of variability, the remaining is attributable to the firms while the macro-area effect is not significant. When I model sectors as fixed effects through dummy variables (column 2), the share of variability in firm's probability of bankruptcy remains also unchanged: firm's features record 97,94% of variability while provincial factors explain the remaining percentage (2.06%). However, the estimated parameters of sector dummies confirm that there are considerable differences in probability of bankruptcy among the different sectors: it would be less frequent in Manufacturing and Construction sectors and more probable in Accommodation and food sector. Again, when I consider both macro-area and sectorial dummies (column 3) the percentage of heterogeneity explained by firms and province remains the same (97.94% and 2.06% respectively). All equations show the evidence in favor of the Logit multilevel approach, since the LR test is always highly significant.

To sum-up, what we learn from Table 4 and Table 5 is the robustness of the provincial effect, even if the main part of heterogeneity is explained by firm's level. The percentage of variability explained by local features, in fact, remains the same whatever the model used, ranging from 2.04 % to 2.06%.

Table 6 shows the results obtained when the Logit Multilevel Model is augmented through a set of province and individual variables. Province level regressors inserted in the model are *FinDev, HHI*, *Crime* and provincial *GDPpercapit*a. At the firm level we include *Size*, *Stdebt*, *Ltdebt*, *ROA*, *Tangibility*, *Intangible*, *DifferentTaxShield*, *WCTA*, *Interestcov*, *Majority_Sh*, *Sole_Propr*. They have already been presented.

Column 1 in Table 6 shows estimations obtained for our sample of new firms. Focusing on the specific objective of the study it is worth discussing the empiric findings about how provincial features, and specifically local financial development and bank concentration (second level variables) affect new firms' bankruptcy.

The variable *FinDev* has a negative sign at the 1% level of statistical significance. Since the dependent variable is a dummy taking value 1 if the firm is in the default status and 0 otherwise, the negative sign of *FinDev* means that a firm incorporated in a province with a higher level of financial development has a lower probability to go bankrupt in the first years of its life. This empirical finding confirms the hypothesis H1a that a higher level of local financial development reduces new firms' probability of bankruptcy. This effect of local financial development on firm's probability of default is consistent with previous findings about local financial development in the literature. Local financial development is positively related to growth (Guiso et al. 2004; Gagliardi 2009) and affects firm's financial activities in different fields. In more financially developed areas inside a country, firms use more debt (Cariola et al. 2010), more trade credit (Deloof and La Rocca 2014) and these features strongly affect financial decisions of start-ups (Deloof et al. 2016). A greater availability of bank credit brings thus new firms to have a higher probability of survival and a greater potential to grow.

To test the hypothesis H1b concerning small firms, I divide the sample of firms into two groups depending on the size: small firms and large firms. To identify these groups, I split the population of firms considering the distribution of the variable *Size* and composed two subsamples (above and below the median value). The results for Small and Large new firms are displayed in column 2 and 3, respectively. It is worth noting that the magnitude of *FinDev* coefficient declines, in absolute value, as we move from small firms to large ones, moving from -6.578 to -3.646; it is statistically significant at 1% and 5% for the subsample of small and large start-ups, respectively. This empirical finding confirms the hypothesis H1b that the effect of local financial development on new firms' bankruptcy is stronger for small new firms[2]. This finding is consistent with previous findings on financial development and different firm's performance according to the size. If small firms find it more difficult to access financial services due to greater information and transaction costs, then financial development that ameliorates these frictions can exert a particularly positive impact on small firms (Cestone and White 2003, Guiso et al 2004) more strongly reducing their probability to exit from the market.

The variable describing concentration in the local banking market *HHI* is not significant in the estimations concerning the whole sample. This finding means that, considering the total sample of Italian new firms, our hypotheses H2a and H2b are not confirmed since HHI is significant only for the subsample of large firms. This result is consistent with the standard flight-to-quality of credit from smaller (and relatively opaquer) firms to larger (and relatively more transparent) ones because of negative shocks hitting the banking sector over the studied period. The economic turmoil that hit the Italian economy after Lehman's collapse induced a contraction of credit supply (Albertazzi and

Marchetti, 2010; European Central Bank, 2014) that particularly concerned small and more opaque firms, for which a long-term relationship with their main bank has been the most effective means of overcoming financial constraints (Arnaudo et al., 2016). This bank-borrower relationship is more likely when the credit market is more concentrated so that, for smaller companies the flight to quality effect overpassed the advantages resulting from concentration. Consequently, our results exhibit no correlation between the rate of bankruptcy and the Herdindahl Hirschman index for this this size class, whereas larger companies continue to benefit from a strong customer relationship.

The negative and statistically significant sign associated with *HHI* for large firms, is consistent with our expectations; concentration in the bank market reduces the probability of bankruptcy of new firms. In accordance with Petersen and Rajan (1995), a bank operating in a concentrated market may offer more credit and at lower rates to young firms than may a bank operating in a competitive market. The other local variables, *Crime* and *GDPpercapita,* show no statistical significance in the model.

Table 6: Empirical results

	(1) Whole sample	(2) Small new firms sub-group sample	(3) Large new firms sub-group sample
Local Variables (2nd level)			
FinDev	-4.700***	-6.578***	-3.646**
	(1.436)	(1.610)	(1.433)
HHI	-1.241	-0.794	-2.592**
	(0.769)	(0.879)	(1.190)
GDPperCapita	-0.00221	-0.00414	-0.000946
	(0.00341)	(0.00424)	(0.00445)
Crime	0.00348	0.00558	-9.78e-05
	(0.0124)	(0.0142)	(0.0156)
Firm's variable (1st level)			
Size	-0.158***	-0.142***	-0.146***
	(0.0176)	(0.0380)	(0.0407)
Stdta	0.554***	0.669***	0.320
	(0.145)	(0.191)	(0.222)
Ltdta	-0.241	-0.177	-0.0970
	(0.188)	(0.281)	(0.253)
Tangibility	-0.730***	-0.290*	-1.273***
	(0.130)	(0.170)	(0.210)
Intangible	-0.0379	0.374**	-0.548**
	(0.148)	(0.189)	(0.248)
ROA	-0.556***	-0.432***	-1.978***
	(0.0430)	(0.0467)	(0.146)
WCTA	-0.118*	0.0909	-0.318***
	(0.0651)	(0.0852)	(0.101)
Interestcov	-3.34e-06	-1.65e-05**	1.76e-06
	(2.65e-06)	(7.78e-06)	(1.69e-06)
DifferentTaxShield	-0.510***	-0.496***	-2.017***
	(0.158)	(0.166)	(0.626)
Majority_sh	-0.146***	-0.263***	0.0345
	(0.0464)	(0.0596)	(0.0749)
Sole_pr	0.0446	-0.110	0.255***
	(0.0561)	(0.0763)	(0.0846)
Year of incorporation FE	YES	YES	YES
Sector FE	YES	YES	YES
North/South FE	YES	YES	YES
Constant	-2.479***	-2.524***	-2.420***
	(0.218)	(0.280)	(0.352)
Variance			
Firms	3.29	3.29	3.29
Province	0.051	0.055	0.037
LR test	58.70***	27.33***	8.73***
Log-likelihood	-11049.287	-6335.5944	-4632.3457
Observations	94,118	47,059	47,059
Number of groups	103	103	103

Notes: Results from multilevel regressions run with the command xtmelogit, available in Stata13 version

***Significance at the 1% level, **Significance at the 5 % level, * Significance at the 10% level

Concerning individual firm’s feature at the first level, it is possible to argue that all variables have the intended sign in estimation.

Firm *Size* enters with a negative sign at the 1% level of significance; therefore, larger companies would encounter a lower probability of bankruptcy. Short-term debt is associated with a positive sign at the 1% level of significance. This finding confirms our expectations that new firms have limited cash flows and low profits and rely more heavily on short-term debt finance and therefore, are most likely to be subject to financial distress and financial restrictions. *ROA* enters, as expected, with a negative sign at the 1% level of statistical significance, indicating that more profitable companies encounter a lower bankruptcy risk. The estimated coefficient of the variable *Tangibility* is negative at the 1% level of significance. The proportion of tangible fixed assets in the total of all assets is confirmed as a measure of the capacity to provide collateral and, consequently, obtain financing to restructure the business. *DifferentTaxShield* enters the regression with a negative sign at the 1% significance level, indicating that growing firms that are subject to higher levels of amortizations and taxes are less subject to financial distress and bankruptcy risk. The coefficient of (*WCTA*) has a negative sign in the estimation with a significance at 10%, indicating that a higher level of working capital helps the internal financing of a firm’s activity, reducing its probability of exit from the market. The dummy variable *Majority_sh* enters with a negative sign at the 1% level, suggesting that, for firms with an alignment of interests in more concentrated ownership, the probability of financial instability and bankruptcy is reduced. The variables *Ltd*, *Intangible*, *Interestcov* and *Sole_propr* show no statistical significance, suggesting that long-term debt, the equipment of intangible assets, sustainability of debt and fully concentrated ownership do not appear to affect the probability of new firms’ bankruptcy. The regressions are controlled for Italian macro-area, year of incorporation and industry fixed effects to avoid that specific issues would drive our estimations.

4.2 Robustness checks

A potential problem with the previous findings is that the observed effect that local financial development and banking concentration have on a firm’s bankruptcy may actually reflect omitted factors that affect both the local banking market and firms’ performance, such as the local economic development. This finding means that estimations could suffer omitted variable bias. To ascertain the effect that the local banking market has on a firm's bankruptcy, I use exogenous determinants of the degree of banking development as instruments in 2SLS regressions. In accordance with Guiso et al. (2004) and Deloof and La Rocca (2014), I use measures of the local supply of credit in 1936 as determinants of the local banking development in the 2000s. While local banking structures in 1936 were largely determined by factors unrelated to local economic development, a new banking law in 1936 severely constrained the growth of the banking system. Since this law affected certain types of banks more than others and the type of banks in the system differed across regions, the law created significant local differences in banking development that may persist to the present day. Consistent with this argument, Guiso et al. (2004) find that local banking development in 1936 is strongly correlated with the current local banking market, but it is only weakly correlated with contemporary local economic development. First, I identify five measures of banking development in 1936 that significantly affect the current local banking development: the number of bank branches and banks in the province, the total number of mutual banks in the province, and the number of banks and bank branches over the population in the region in which a firm is located. The results of robustness tests are displayed in Table 7.

The regression in column 1 of Table 7 is based on 2SLS estimation in which I use certain instrumental variables for *FinDev* and *HHI*. The results fully confirm the previous findings; a higher level of financial development at the province level reduces the probability of bankruptcy for new firms. The magnitude of the variable's coefficients is highly different, for multilevel logit, the coefficient of explanatory variables does not correspond to the marginal effect on the dependent variable but is the effect on the Logit function. In contrast, in the 2SLS regression, the coefficient is the marginal effect on the dependent variable, because I run a regression with instruments without restrictions on the distribution of the dependent variable (linear probability model)[4]. Standard errors are clustered by province level.[8]

[8] Appendix A2 reports other robustness checks: Logit regression with cluster of standard errors on provinces, logit multilevel regression in which I use the number of bank branches on km^2 as proxy of Local Financial Development.

Table 7: Robustness checks

	(1) 2sls	(2) Bankruptcy up to 1 year	(3) Bankruptcy up to 3 years
Local variables (2nd level)			
FinDev	-0.0904**	-3.563	-6.004***
	(0.0391)	(2.363)	(1.436)
HHI	-0.0132	0.347	-1.340**
	(0.0862)	(1.446)	(0.626)
GDPperCapita	-9.20e-05	0.000340	0.000415
	(6.82e-05)	(0.00654)	(0.00276)
Crime	0.000117	0.0336	0.00373
	(0.000286)	(0.0235)	(0.0109)
Firm's variables (1st level)			
Size	-0.00355***	-0.172***	-0.127***
	(0.000621)	(0.0425)	(0.0118)
Stdta	0.0119***	1.078***	0.480***
	(0.00404)	(0.307)	(0.100)
Ltdta	-0.00643*	-0.932*	-0.318**
	(0.00336)	(0.537)	(0.127)
Tangibility	-0.0188***	-0.510*	-0.753***
	(0.00369)	(0.293)	(0.0879)
Intangible	-0.00644*	-0.445	0.0741
	(0.00385)	(0.372)	(0.100)
ROA	-0.0364***	-0.506***	-0.607***
	(0.00468)	(0.0623)	(0.0363)
WCTA	-0.00104	-0.511***	-0.133***
	(0.00167)	(0.153)	(0.0441)
Interestcov	1.04e-08	-6.30e-06**	-3.02e-06
	(1.72e-08)	(2.61e-06)	(1.94e-06)
DifferentTaxShield	-0.00140*	-0.953	-0.442***
	(0.000749)	(0.589)	(0.0965)
Year of incorporation FE	YES	YES	YES
Sector FE	YES	YES	YES
North/South FE	YES	YES	YES
Constant	0.0523***	-4.309***	-1.912***
	(0.0103)	(0.439)	(0.179)
Variance			
Firm		3.29	3.29
Province		0.107	0.059
LR Test		15.55***	168.29***
Log-likelihood		-2575.936	-20531.5
Observations	94,118	94,118	94,118
R-squared	0.009		
Number of groups		103	103

Notes: Results from multilevel regressions run with the command xtmelogit, available in Stata13 version,; Results from 2SLS regression run with the command ivreg2

***Significance at the 1% level, **Significance at the 5 % level, * Significance at the 10% level

Moreover, columns 2 and 3 of Table 7 show the estimations obtained when modifing the dependent variable that corresponds to the probability of bankruptcy over a period of 2 years after the year of incorporation. In particular, I want to investigate the effect of the local banking market (local financial development and local banking concentration) in influencing the probability of a firm's bankruptcy 1 and 3 year after incorporation. These regressions show that the effect of the local banking market is not relevant in the first year of a firm's life and that it does not appear to affect the probability of bankruptcy, since the coefficients of *FinDev* and *HHI* are not significant. Conversely, if we consider bankruptcy over a period of 3 years after incorporation, the effect of local financial development is stronger in reducing a new firm's bankruptcy, since the coefficient associated with the variable *FinDev* extends from -4.700 to -6.004. In the third year of life, the concentration in the local banking market also has a relevant role in reducing a new firm's bankruptcy, since the coefficient associated with *HHI* is negative and statistically significant. This finding means that the effect of the local banking market is relevant as the bank intends to be present in a firm's financial structure, and this effect is increasingly stronger over time.

5. Conclusions

The empirical investigation undertaken in this research targets estimating the impact of local financial development and bank concentration on new firms' bankruptcy. It is an issue for entrepreneurs who need to find financial resources to expand their business, for lenders who find an interest in maintaining relationships with secure borrowers, and for policy makers who are responsible for providing the best environment to enterprises.

Local financial development appears to play a role in shaping bankruptcy risk, since it reduces the probability of bankruptcy of new firms. Local financial development is positively related to growth and affects firm's financial activities in different fields. In more financially developed areas inside a country, firms use more debt, and this feature strongly affects the financial decisions of new firms. A greater availability of bank credit provides new firms with more potential to grow and survive. This effect is stronger for small new firms. The reason underlying this topic is that, if small firms find it more difficult to access financial services due to greater information and transaction costs, financial development that ameliorates these frictions can exert a particularly positive impact on small firms.

Furthermore, these results suggest that local banking concentration reduces the probability of bankruptcy only for large, new firms. A bank operating in a more concentrated market may financially support new firms with the objective of exploiting rents from eventually successful borrowers. When a bank adopts this kind of strategy, it has the objective of maintaining lending relationships in the future, certain of the fact that the firm will not be attracted to rival banks.

In terms of policy, a first indication offered by the current research is that the regulation of the bank sector at the local level plays a key role in a firm's early stage life, and a more stable financing relationship could represent an advantage for newly established firms. Second, agencies supporting business creation should define specific criteria in the selection of investment projects and the subsequent attribution of credit to create a stable lending relationship.

A limit of this study is represented by the observation that I consider the probability of bankruptcy over the early years after start-ups. I found that the effect of local financial development and bank concentration is relevant as the bank pursues a presence in a firm's financial structure, and this effect is stronger over time; however, this study cannot obtain further evidence about the direction of this relationship in future years. Furthermore, it would be interesting to investigate the relative importance of local features in a study that includes a sample of firms operating in different countries, to understand the level of heterogeneity in insolvency and its determinants across European countries and regions.

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Appendix

A1-Correlation matrix

	VIF	FinDev	HHI	Crime	GDPper capita	Size	Stdebt	Ltdebt	ROA	Tangibility	Intangible	DifferentTax Shield	WCTA	Interest cov	Majority sh	Sole propr
FinDev	1.38	1														
HHI	1.15	-0.313	1													
Crime	2.67	-0.071	0.020	1												
GDPpercapita	1.39	-0.061	-0.014	-0.420	1											
Size	1.20	0.001	-0.034	-0.084	0.069	1										
Stdebt	1.07	-0.015	-0.019	-0.114	0.082	0.149	1									
Ltdebt	1.10	-0.017	-0.004	-0.074	0.053	0.167	0.031	1								
Tangibility	1.24	-0.066	0.029	-0.002	0.008	0.113	0.037	0.206	1							
Intangible	1.19	0.066	-0.027	-0.027	0.002	-0.140	0.007	0.071	-0.008	1						
ROA	1.11	-0.002	0.003	-0.002	0.003	0.105	-0.080	-0.046	-0.091	-0.182	1					
WCTA	1.22	-0.011	-0.007	-0.066	0.040	0.104	0.131	0.027	-0.273	-0.179	0.151	1				
Interestcov	1.01	-0.001	-0.003	-0.004	0.002	0.037	-0.017	-0.013	-0.014	-0.023	0.100	0.007	1			
DifferentTaxShield	1.01	-0.004	0.008	0.007	-0.010	-0.079	-0.011	-0.009	-0.007	0.048	-0.018	-0.019	0.004	1		
Majority_sh	1.19	0.030	-0.014	0.003	-0.006	-0.021	-0.010	-0.030	-0.012	-0.017	0.022	-0.016	0.006	-0.0001	1	
Sole_propr	1.20	-0.018	-0.002	-0.015	0.025	0.075	-0.004	-0.013	0.011	-0.032	0.007	0.020	0.003	-0.004	-0.395	1

A2- Other robustness checks

	(1) Logit with province clustering	(2) Multilevel with Branch/km2 as proxy of FinDev
Local Variables (2nd level)		
FinDev	-5.577***	-0.038***
	(0.689)	(0.147)
HHI	-1.067	-1.231
	(0.929)	(0.879)
GDPperCapita	-0.005	-0.001
	(0.004)	(0.003)
Crime	0.009	0.006
	(0.011)	(0.013)
Firm’s variable (1st level)		
Size	-0.153***	-0.158***
	(0.021)	(0.018)
Stdta	0.539***	0.556***
	(0.132)	(0.145)
Ltdta	-0.245	-0.241
	(0.171)	(0.188)
Tangibility	-0.751***	-0.730***
	(0.172)	(0.129)
Intangible	-0.017	0.040
	(0.153)	(0.148)
ROA	-0.564***	-0.555***
	(0.065)	(0.043)
WCTA	-0.117*	0.118*
	(0.0651)	(0.065)
Interestcov	-3.23e-06	-3.32e-06
	(1.40e-06)	(2.64e-06)
DifferentTaxShield	-0.514***	-0.509***
	(0.184)	(0.158)
Majority_sh	-0.148***	-0.147***
	(0.043)	(0.046)
Sole_pr	0.042	0.045
	(0.052)	(0.056)
Year of incorporation FE	YES	YES
Sector FE	YES	YES
North/South FE	YES	YES
Constant	-2.450***	-2.525***
	(0.218)	(0.280)
Variance		
Firms		3.29
Province		0.056
LR test		67.79***
Log-likelihood	-11078.639	-11050.83
Observations	94,118	94118
Number of groups	103	103

***Significance at the 1% level, **Significance at the 5 % level, * Significance at the 10% level

CHAPTER 3

Spatial Patterns and Determinants of firm's exit in France

Abstract

The purpose of this research is to study the role of spatial agglomeration economies as drivers of firm's exit in France over the period 2009-2013 with a focus on two regional variables: local financial development and local specialisation. I apply spatial econometric techniques (Spatial Dynamic Panel data and Spatial GMM) to consider the spatial dependence in firm's exit. I show that the firm's exit is characterized by positive spatial autocorrelation, so that locations with high exit rates tend to be surrounded by similar ones. In addition, the results suggest that a higher local financial development reduces the exit rate of a department whereas local specialisation seems not to exert any effect.

Keywords: Firm's exit, spatial econometric, local financial development, local specialisation

1. Introduction

Firm exit is one of the most debated issues in industrial organization. The related literature has mostly focused on firm-and industry specific determinants (Audretsch and Mahmood, 1995; Santarelli and Vivarelli, 2007). Whereas location has often been introduced in papers focusing on firm creation (Cala et al. 2016; Audretsch et al., 2015), and growth (Levratto and Garsaa, 2016), location specific determinants have not been much investigated in this literature with some exceptions (Keeble and Walker, 1994; Fotopoulos and Louri, 2000; Cainelli et al. 2014). This is a relevant issue to address since the likelihood of firm's exit is likely to be determined by how much favourable are market conditions to sustaining businesses primarily dependent on local demand. The importance of local specific factors is linked to the issue of spatial agglomeration of firms, a topic that needs to be deeply investigated. Spatial agglomeration has been proved to be a relevant source of both positive and negative externalities, whose effect on local performances depends also on their impact on firm's exit. Accordingly, the role of spatial externalities for firm exit might receive more direct study than the indirect one it mainly gets in regional and urban economics researches (Frenken et al., 2007; Boschma and Iammarino, 2009). The determinants of the spatial differences in the rates of business exit have been the subject of some researches carried out at the local level for UK (Keeble and Walker, 1994), Greece (Fotopoulos and Louri, 2000) and Italy (Cainelli et al 2014) whereas this topic has never been carried out for France, a country where, despite business insolvencies are decreasing in the last years, total insolvencies are still 25% higher than pre-crisis level with the persistence of high regional divergences (Euler Hermes, 2017)

This study contributes to the empirical stream of literature with the objective to understand the relevance of the domino effect in firm's exit among neighbour locations, with a focus on two local variables susceptible to be subjected to spatial interdependencies and playing a relevant role in influencing the emerging of agglomeration economies: local financial development and local specialisation. Indeed, concerning the level of financial development, the availability of external finance tends to mitigate financing constraints on entrepreneurial enterprises, which hastens economic growth. Further, certain entrepreneurial firms, or emergent industries, are subject to agglomeration economies so that when the growth of one firm or one industry attracts related or complementary activities local industry expands, workers are drawn in, and urban growth follows (Glaeser and Gottlieb 2009). Similarly, specialization represents a central role in the emergence of agglomeration economies since it is related to the presence of both static externalities, associated with cost efficiencies, and dynamic externalities, related to knowledge spillovers. Both types of externalities are potentially related to Marshall-Arrow-Romer (MAR) localization economies which encourage growth via industrial specialisation (Marshall, 1890; Arrow, 1962; Romer, 1986).

Generally, business exit is a phenomenon that spreads among firms through the channel of financial and commercial debts. Conversely, in presence of difficulties due to the last financial crisis, it could be important to understand the role played by other potential drivers in the spreading of firm's exit within a certain country, including spatial interdependences. It is relevant to understand which channels are responsible for the spreading of this phenomenon, since business exits causes, above all, losses for the economic agents directly concerned, in particular employees, creditors and shareholders of companies (Coface, 2016).

The empirical analysis refers to the Exit Rate of French Departments (corresponding to NUTS3 in the EU classification) over the period 2009-2013. In accordance with Dunne, Klimek, Roberts, & Xu (2013), the Exit rate includes firms characterized by the dissolution of a combination of production factors, and not only firms facing official bankruptcy procedure.

The purpose of this study is thus to fill a gap in the business businesses exit studies on French economy investigating three issues. What is the role of spatial dependencies in spreading business exit? Is the local context relevant to shape the risk of business exit? Is the local financial development able to reduce the Exit rate of firms located in a certain department? And last, does local specialisation have an influence in determining business survival?

To deal with these questions, I propose an econometric study based on a dataset combining different sources computed at the Department level (NUTS3 classification) applying spatial econometric techniques to consider the spatial interdependence in business exit. I show that the firm's exit is characterized by positive spatial autocorrelation, so that locations with high exit rates tend to be surrounded by similar ones. In addition, I find that a higher local financial development reduces the exit rate of a department whereas local specialisation seems not to exert any effect. Therefore, by highlighting the clustering phenomena, this study contributes to the spatial literature that emphasizes the neighbouring effect and states the idea that what happens in a certain area not only depends on the local context but also on what happens in the nearby areas. Finally, the contribution to local public policies is in informing on the spillover effect which spreads across different locations (Levratto, 2015). This study, thus, emphasises the need for policies adopted in a given area, to be harmonized with the actions implemented in neighbouring areas.

The chapter is organized as follows. Section 2 reviews the relevant literature about firm's exit and its potential link with agglomeration economies, financial development and local specialisation. Section 3 presents the dataset and the variables used in the empirical analysis.

Section 4 presents the spatial explorative analysis on firm Exit Rate. Section 5 presents the econometric specification and the empirical results. Section 6 concludes.

2. Literature review

This section presents a review of the relevant literature. A first subsection reviews the main literature about the previous studies which analyze the role that local feature and spatial issues may exert in shaping the business exit risk. The second and third subsections review the main previous studies about our interest local variables: local financial development and local specialization.

A spatial perspective of firm's exit

Firm's exit has been the theme of different research studies in the past years. Starting with the work of Altman (1968), a large body of literature has investigated the determinants of corporate bankruptcy, searching to predict insolvency through the application of several statistical methods on economic and accounting data. Many authors seek to introduce new methodologies to obtain a more specific forecasting of firm's exit from the market. The focus of this area of the accounting and finance literature has typically considered only the internal features of a company (financial and non-financial information) to assess its likelihood of exit.

Only very recently, a small number of studies analysed the influence of the *local context* to understand the exit behaviour across geographical regions. Fotopoulos and Louri (2000) examine the determinants of hazard rates of new firms entering Greek manufacturing industries in the 1982–1992 period. They propose a survival model in which the hazard faced by new firms in different locations is considered, with the results that firms located in the country's largest urban environment, Athens, face better survival prospects. This appears to be particularly relevant for smaller firms located in Athens when compared to their counterparts elsewhere in Greece. Glauben et al. (2006) study exit rates in agriculture across 326 counties in Western Germany. They find significant differences in the exit rates of farms across regions, with a higher exit rates in region with smaller firms. Buehler et al. (2010) find that bankruptcy rates tend to be lower in the central municipalities of agglomerations, in regions with favorable business conditions (where corporate taxes and unemployment are low and public investment is high) and that private taxes and public spending at the local level have little impact on bankruptcy rates.

The influence of location can be considered also looking at the effect of agglomeration economies and spatial dependences. The observation that economic activity tends to be clustered in space (Audretsch and Feldman, 1996 ; Porter, 1998; Cooke, 2002); suggests that agglomeration economies are relevant and can compensate for the negative effect of density such as intense competition from other firms located in the vicinity which may lead to relatively intense competition on the input-side as well as on the output-side of the market. Such advantages of setting up a business in a great agglomeration could include the availability of large, differentiated labor markets and of specialized services, easy access to research institutions, spatial proximity of large numbers of customers as well as other firms in the industry that may facilitate knowledge spillovers. It is, however, unclear whether these advantages are the effect of the proximity to firms that are related to the same industry (localization economies) or to diverse kinds of actors and institutions (urbanization economies) (Fritsch et al 2011).

Some studies found evidence about the positive effects of being located in an agglomeration on firm survival (Keeble and Walker, 1994; Fotopoulos and Louri, 2000), other studies (e.g., D. Audretsch and Vivarelli, 1995; Gerlach & Wagner, 1994) identified a significant negative impact. Hence, the impact of agglomeration as such is a priori unclear.

A main reason for the unclear effect of agglomeration on firm's exit may be the correlation with the business environment approximated by indicators such as population density and other measures like qualification structure of employees, regional R&D intensity, or intensity of regional competition (Fritsch et al 2011). Although less investigated, spatial agglomeration can be argued to affect firm exit on the ground of different theoretical interpretations and with the support of different empirical evidence.

Financial development and firm's exit

The idea that the financial sector has the potential to influence patterns of innovation and growth dates to Schumpeter (1934), who argued that the services provided by financial intermediaries are essential for technological innovation and economic development. In the 1990s, beginning with the studies by King and Levine (1993), a new body of literature has provided empirical evidence about a positive relation between the level of development achieved by the banking system and the growth rates of real variables (per-capita GDP, per-capita productivity, value added of individual industrial sectors, and sales by individual firms). The last two decades a huge literature investigated the finance-growth nexus using cross-country data and new econometric tools. A number of observations, backed by empirical evidence, have emerged. Levine (2005) summarizes these as follows: (i) countries with better functioning banks and financial markets grow faster; (ii) simultaneity bias (i.e., the reverse causality) does not seem to drive this conclusion; and (iii) better-functioning financial systems ease the external financing constraints that impede firm and industrial expansion, suggesting that this is one mechanism through which financial development matters for growth. This positive relation prevails, despite the absence of complete unanimity of results (Brunnermeier & Pedersen, 2009; De Gregorio & Guidotti, 1995; Guariglia & Poncet, 2008). The methods used at the aggregate level in the previous studies are quite uniform. The main tool applied is the cross-country growth regression, in which financial variables of a large set of countries together with a set of additional determinants are regressed on a proxy of economic developments. A significant and positive sign is interpreted as evidence of a positive impact of financial variables on economic development. Financial variables often display indicators of the magnitude or level of financial activity. The most prominent variables are bank loans to the private sector, stock market capitalisation and stock market turnover, all expressed in relation to GDP. The dependent variable mainly consists of the real rate of economic growth, on capital accumulation or productivity growth.

Considering the effect of financial development at the micro level, many studies investigating the relationship between financial development and corporate performances demonstrate that a more developed banking system and a higher degree of bank penetration are significantly correlated with a lower probability that borrowers are financially constrained. Love (2003) brings evidence about the effect that financial development has on the severity of financial constraints faced by firms, while Demirgüç-Kunt and Maksimovic, 2002 using firm level data, find that financial development is robustly linked with firm access to external markets. Other researches find evidence that bank system development leads to more credit availability, and more growth (Black & Strahan, 2001; Bertrand et al. 2007; Black and Strahan, 2001; Cetorelli and Strahan, 2006; Presbitero and Rabellotti, 2016)

Furthermore, analyzing the influence of financial development on new firms' performance, Aghion et al. (2007) using firm-level data for 16 industrialized and emerging economies, find that financial development promotes post-entry growth, even after controlling for the initial size at entry. Similarly, using panel data on French manufacturing firms over the 1996-2004 period, Musso and Schiavo (2008) show that an easier access to external funds lowers the probability that firms exit the market.

Considering the local dimension of bank credit market, another part of literature, however, documents that distance matters in the provisions of funds, especially for small firms. Petersen and Rajan (2002), for instance, document the importance of distance in the provision of bank credit to small firms due to the reducing impact of asymmetric information and transaction costs. Indeed, borrowers' actions are harder to observe when lender and borrower are far apart, leading to adverse selection (of potential borrowers) and moral hazard (for current borrowers). In general, it is suggested that banks operating locally have more knowledge and control over local firms and entrepreneurs (Alessandrini and Zazzaro, 1999). Consequently, local small businesses are very sensitive to the behaviour of local banks or branches and this effect is amplified when significant difference in financial constraints persist between the different regions. This is the case of France, where financial constraints are differentiated within French regions, despite the relative homogeneous nature of the banking sector (Bonnet et al 2005). The locally restricted relationships between banks and companies are confirmed by papers in the field of spatial economics which insist upon the importance of the local context in financing (Pollard, 2003; Agarwal and Hauswald, 2010). The previous empirical findings demonstrate that financial development at the local level is positively related to growth (Guiso et al. 2004; Gagliardi, 2009) enhances the probability of individuals starting their own business, favours the entry of new firms (Guiso et al. 2004) and affects firm's financial activities in different fields. It is suggested that, in more financially developed areas inside a country, firms use more debt (Cariola et al. 2010) and more trade credit (Deloof and La Rocca, 2015).

A greater availability of bank credit with a higher level of growth for firms should thus result in a lower Exit rate in a certain department. In contrast, financial constraints are likely to be more severe in the presence of a poorly developed financial system. Consistently with these considerations it's possible to expect that a higher level of financial development reduces the firm's exit rate in a given area.

Local specialization and firm's exit

Specialization represents a central role in the emergence of agglomeration economies. Its consequences have been mostly connected to the scale of activity of an industry in a certain area (Cainelli et. al 2014). Regional specialization may increase the sharing of resources among firms and produce a better matching between employers and employees (Rosenthal and Strange, 2001). When workers are specialized in analogous activities, firms can take advantages from a larger labor pool and a higher workers' mobility. The impact of specialization economies at the local level appears confirmed by the empirical evidence (Beaudry and Schiffauerova, 2009; Breitenecker & Schwarz, 2011). At the regional level, specialization may provide firms a form of proximity creating a common knowledge, which can either complement or substitute their geographical and social one. Because of growing specialization, the knowledge bases of firms diverge to such an extent that interactive learning is stimulated (Boschma, 2005).

On the one side, supposing a certain association between firm productivity and density, more productive firms might choose, ex-ante, denser areas to locate. On the other side, tougher competition in denser regions allows only the most productive firms to survive (Combes et al. 2012). Two different perspectives are possible. Through the positive effects exerted on firm productivity, specialization is expected to negatively impact on firm exit rates. However, considering the effects in terms of higher competition (Combes et al., 2012), higher costs for commuting and for recruiting local production input (Higano and Shibusawa, 1999; Tabuchi, 1998) the impact of specialization on firm exit rates could be positive.

Some of the few studies analyzing the effect of specialization on the probability of firm exit, support the first negative effect. Cainelli et al. (2014) provide evidence that specialization economies reduce firm's exit at the local level. This effect turns out to be significantly negative already in the short-run. Indeed, in their study, the structure of the Italian economic systems seems able to more than compensate the diseconomies—e.g. in terms of tougher competition and/or pressures on the cost of local inputs—that could interfere with the productivity advantages that specialization normally grants them as time passes. Indeed, this productivity effect appears available to them since agglomeration occurs. Other studies find evidence about the second, positive effect (i.e. increasing firm-exit). Staber (2001), in particular, finds that belonging to a specialized industrial district reduces firm survival, because of competition effects on local resources. However, this could still be consistent with a positive effect, via labor productivity, when short and long-run effects are distinguished.

3. Sample and variables

The empirical analysis refers to French economy and makes use of data collected by different sources. I extracted data about the number of exited, created and operating firms in the 96 French Departments (corresponding to NUTS3 in the EU classification) over the period 2009-2013 from the archives of Eurostat, the statistical office of the European Union. Data on GDP and population at NUTS3 level are also extracted from Eurostat dataset, data on Total Credit provided by banks to the private sector are provided by Bank of France. Finally, data on firms' establishments by sectors are extracted from Acoss Dataset (Agence Centrale des Organismes de Securité Sociale). Using these data I built up a balanced panel of 480 observations at the department's level (96 x 5). Table 1 displays the variables used in the empirical analysis. All variables are defined at the Department level.

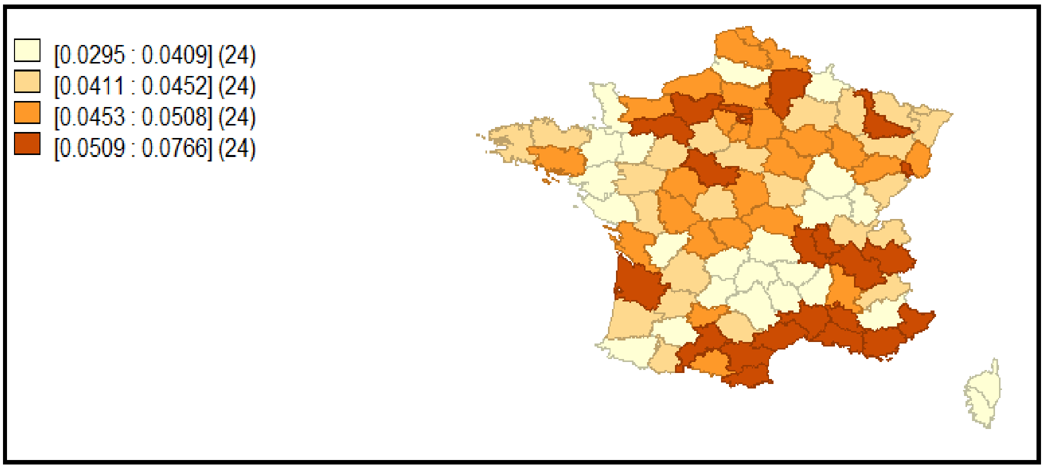
Table 1: Variables

Variable	Definition	Source
Y (Exit rate)	N exited firms/N total firms	Eurostat
Birth_rate$_{t-1}$	(N new firms/N total firms)$_{t-1}$	Eurostat
FinDev	Private Credit/GDP	Bank of France - Eurostat
Specialisation	$\sum_{r=1}^{k} \lvert S_{ri} - X_r \rvert$	Acoss
GdpPerCapita	GdP/N inhabitants	Eurostat
Pop_density	N inhabitants/Area	Eurostat

To compute the departmental exit and birth rates, this study considers the firms operating in the sectors of Industry, Trade and Services except insurance activities of holding companies. According to the definition provided by Eurostat, in this study firm's exit "amounts to the dissolution of a combination of production factors with the restriction that no other enterprises are involved in the event". Ghost firms without any employee have not been considered. The exit rate does not include exits from the population due to mergers, take-overs, break-ups or restructuring of a set of enterprises. It does not include exits from a sub-population resulting only from a change of activity. An enterprise is included in the count of deaths only if it is not reactivated within two years. Equally, a reactivation within two years is not counted as a birth. For death firms, I retain here the definition commonly used in the literature since the pioneering papers by (Dunne, Roberts, & Samuelson, 1988) and (Baldwin & Gorecki, 1991) and frequently included in economic demography articles (Bartelsman, Scarpetta, & Schivardi, 2005, Blanchard, Huiban, & Mathieu, 2012), which defines discontinued firms in relation to active firms. The definition of active enterprise is characterized by its presence in the registers during the current year, t, and the following year t + 1 whereas a firm is considered in cessation if its activity is interrupted between t and t + 1, thus causing its disappearance from the registers.

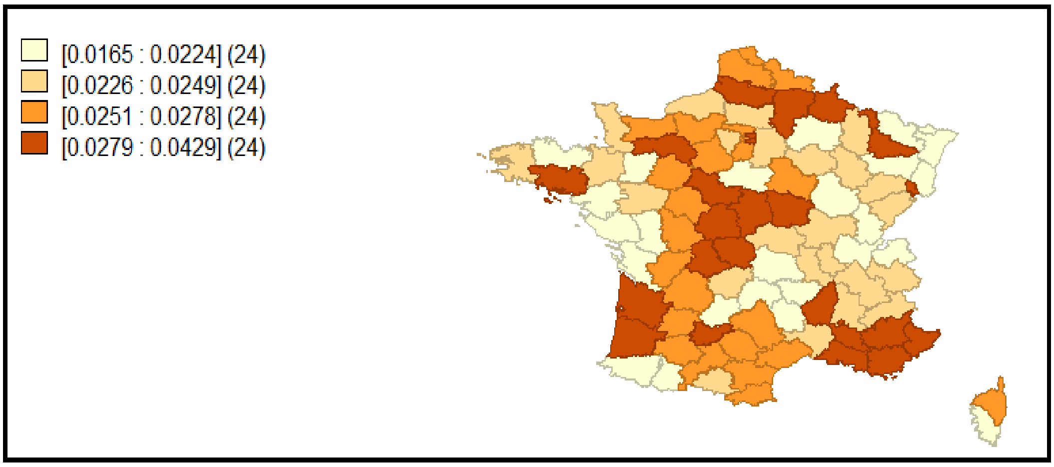
The dependent variable of this econometric specification is the *Exit rate* of the department *i*, defined as the ratio between the number of firms exiting from the market in year *t* and the number of active firms in the same year. Figure 1a and 1b show the distribution by quartiles of the *Exit rate* across French Department in the first and last year of the analysis.

Figure 1a: Exit rate of French Departments (Year 2009)



Source: own elaboration on Eurostat dataset

Figure 1b: Exit rate of French Departments (Year 2013)

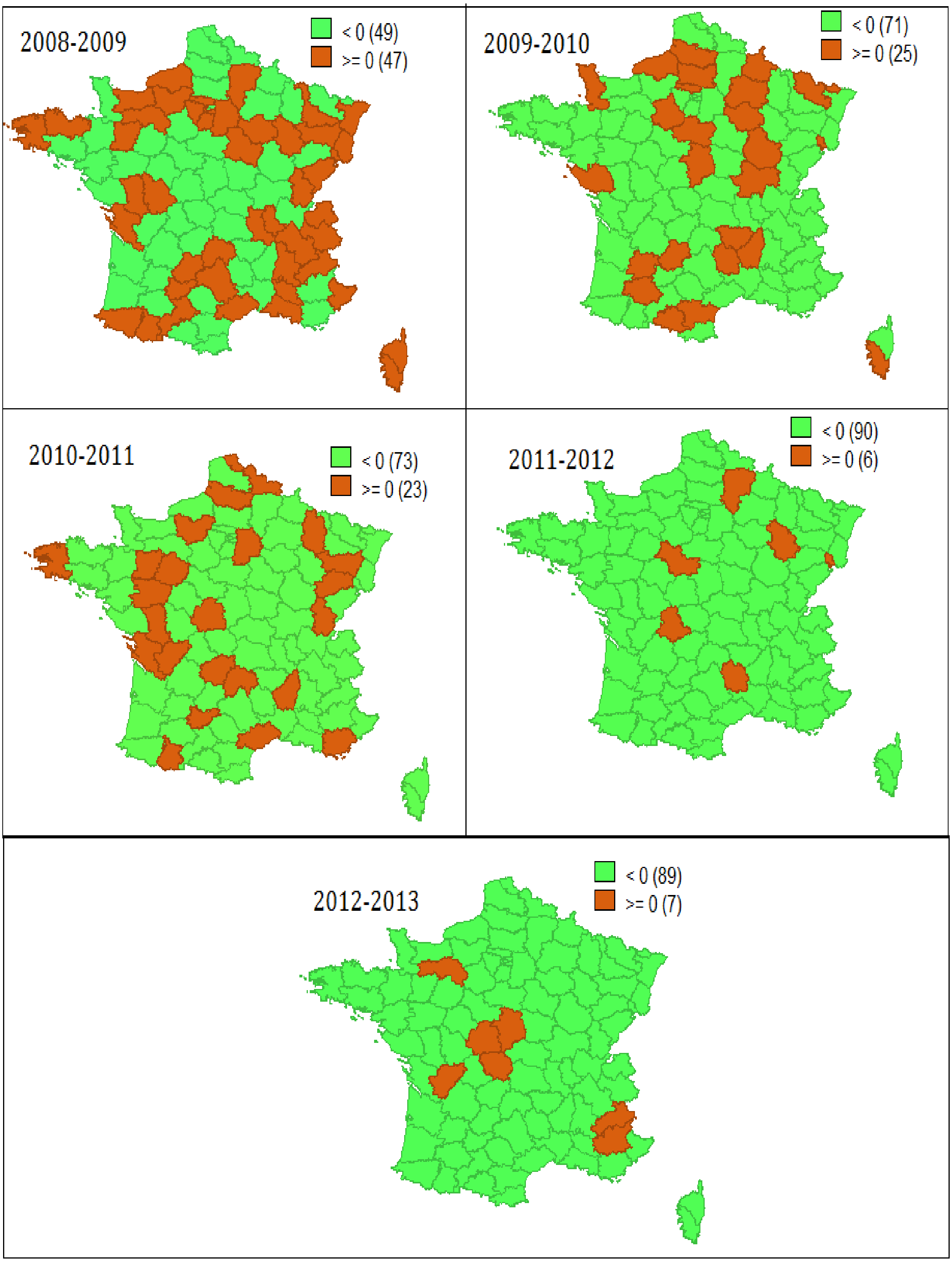


Source: own elaboration on Eurostat dataset

The first element to underline is that the Exit rate of French firms is higher in the first year of the analysis compared to exit rate in 2013. The min and max value of Exit rate in 2009 are 2,95% and 7,66% respectively, whereas the same value for Exit rate in 2013 are significantly lower (1,65% and 4,29%). This great difference in Exit rate may be explained as a consequence of the global crisis that hit French economy in 2008, that led many challenges and difficulties in the entrepreneurial environment. With the crisis that begun in 2008, the economic and financial conditions of French companies rapidly deteriorated and corporate crises became more frequent. For many companies it has exacerbated pre-existing economic-financial imbalances, especially a high level of indebtedness. In France, Firm's exit rate knew a peak of 63,500 on twelve months in November 2009 near to the maximum value of 64,000 recorded in October 1993. The paper by Fougere et al. (2013) allows to understand the impact of the 2008 crisis on firms' bankruptcy. The econometric approach used in their study makes it possible to dissociate, among the 2008-2010 bankruptcies, those resulting from the crisis and those which are derived mechanically from demography. The authors conclude that the proportion of exits attributable to the crisis is of the order of 27% to 46% according to the sector of activity. Dolignon (2011) also highlights an important impact of the crisis: the collapse of the activity linked to crisis became the predominant factor, compared to business demography, starting from the fourth quarter of 2008. As figure 1a shows, the higher Exit rates are recorded in South-East Departments of the country.

Additional information is given by the variation of Exit rate over the period under study (Figure 2). In 2009, due to the international financial crisis, 47 Departments recorded an increase in the Exit rate compared to the previous year with a peak of +33% in the Department of Savoie whereas the year 2013 was generally characterized by a decrease in the Exit rate for almost all Departments. This trend decreased over time, with only 6 and 7 Departments recording an increase in the Exit rate in the last 2 years of the analysis. In 2013 the highest increase in the exit ratio was recorded by the Department of Creuse (+33%).

Figure 2: Variation of Exit rate of French Departments



Source: own elaboration on Eurostat dataset

Local specific factors have a relevant role in influencing firm's bankruptcy, together with firm and industry specific one. For this reason, it's necessary to proxy these phenomena by introducing in the estimates other explanatory variables. I include in the analysis the variable *Birth_rate*, the stock of new firms on the total number of firms in year *t*. Entry and exit rates in the same sector are often highly correlated, i.e., high entry industries are often also characterized by a high number of exits. Then again, incentives to enter the market, such as high profit margins and market growth, may also serve as disincentives to exit (Carree and Thurik, 1996). Johnson & Parker (1994) describe the possible interdependence between firm births and deaths over time, discriminating between a multiplier (or demonstration) effect and a competition effect. Audretsch (1995) distinguishes between a displacement and revolving door effect as two different mechanisms that explain the positive relationship between entry and exit. Displacement occurs when new firms force less efficient incumbent firms out of the market. The revolving door effect captures the short life expectancy of new firm.

The key regressors in this research, refer to location-specific factors. The variables of interest are two measurements of financial development and specialisation inside a certain department. Defining financial development is a challenging task as shown by in a survey on literature on this question by Giovannini et al., (2013). Among possible indicators in use, I choose to measure local financial development (*FinDev*) by Private Credit/GDP equals the value of credits by financial intermediaries to the private sector divided by GDP at the Department level. This ratio captures the amount of credit channelled through financial intermediaries to the private sector and it has been used in several cross-country and within country studies on financial development (Kendall, 2012; Rajan and Zingales, 1998). Levine, Loayza and Beck (2000) show that Private Credit/GDP is a good predictor of economic growth. To measure the *Specialisation* inside a certain Department, I introduce the Krugman specialisation index according to the following specification: $\sum_{k=1}^{n}|S_{ri} - X_r|$, where S_{ri} is the share of the industry *r* in the *i*-th department and X_r is the share of the industry *r* at the national level (calculated on the number of establishments and following the Intermediate level SNA/ISIC-A*38 aggregation). The other variables used as control and included in the analysis are *GdpPerCapita*, catching the richness effect that influences demand, and *PopDensity* as a proxy of external agglomeration economies. Table 2 displays the main descriptive statistics for the variable of our analysis

Table 2: Descriptive Statistics

Variable	Mean	Std dev	Min	Max
Y (Exit rate)	0.0379	0.0098	0.0165	0.0766
$Birth\_rate_{t-1}$	0.1074	0.0199	0.0622	0.1555
FinDev	0.0090	0.0020	0.0037	0.0219
Specialisation	0.1590	0.0499	0.0584	0.3403
GdpPerCapita	0.0283	0.0161	0.0041	0.1161
Pop_density	553.7095	2432.77	14.8974	21288.74

4. Spatial distribution of Exit Rates

To model spatial interactions, it's necessary to specify the spatial connectivity between each department in the sample. The spatial weight matrix is the major tool used to represent the spatial connectivity between departments. More precisely, each department is connected to a set of neighbour departments through a purely spatial pattern introduced exogenously in this spatial weight matrix $\boldsymbol{W_N}$. It is a square matrix with as many rows and columns as there are locations in the sample. The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the department *i* is spatially connected to the department *j*. These elements are non-stochastic, non-negative, and finite. To normalize the outside influence upon each region, the weight matrix is standardized such that the elements of a row sum up to 1. The spatial weight matrix $\boldsymbol{W_N}$ used in this study is row-standardized contiguity weights matrix and the general form of the k-nearest neighbours weight matrix W(k) is defined as follows:

$$\begin{cases} w_{ij}(k) = 0 \; if \; i = j \\ w_{ij}(k) = 1 \; if \; department \; i \; and \; department \; j \; have \; a \; common \; boarder \\ w_{ij}(k) = 0 \; if \; department \; i \; and \; department \; j \;\; don'thave \; a \; common \; boarder \end{cases}$$

So far, the weights considered are purely cross-sectional. To extend their use in a panel data setting, they are assumed to remain constant over time. The measurement of global spatial autocorrelation is usually based on Moran's I statistic (Cliff and Ord 1981). For each year of the period 2009–2013, this statistic is written in the following form:

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(y_{it} - \bar{y}_t) * (y_{jt} - \overline{y_t})}{\sum_i (y_{it} - \overline{y_t})^2} \quad (1)$$

where w_{ij} is the weight between observation i and j, S_0 is a scaling factor equal to the sum of all the elements of $\boldsymbol{W_N}$. For row-standardized spatial weights, S_0=n and expression (1) consequently simplifies. Statistical inference, is based on the permutation approach and is derived from conditional randomization using a sample of 10,000 permutations[9] (Anselin 1995). Table 3 displays the values of the Moran's I statistic, using contiguity spatial weight matrix, for the Exit Rate of 96 French Departments in the whole period of analysis.

Table 3: Moran's I statistic

Year	Morans' *I*	Mean	St Dev	Standardized value	P-value
2009	0.2987	-0.0103	0.0672	4.6001	0.0001
2010	0.3317	-0.0112	0.0677	5.0683	0.0002
2011	0.3334	-0.0100	0.0668	5.1417	0.0001
2012	0.2070	-0.0120	0.0673	3.2530	0.0018
2013	0.2389	-0.0108	0.0676	3.6932	0.0009

Source: own elaboration on Eurostat dataset

The expected value of I under the null hypothesis of no autocorrelation is t given by $I_0 = -1/(n-1)$. If the observed value of I is significantly greater than I_0 , than values of y are positively autocorrelated, whereas if I < I_0 this will indicate negative autocorrelation.

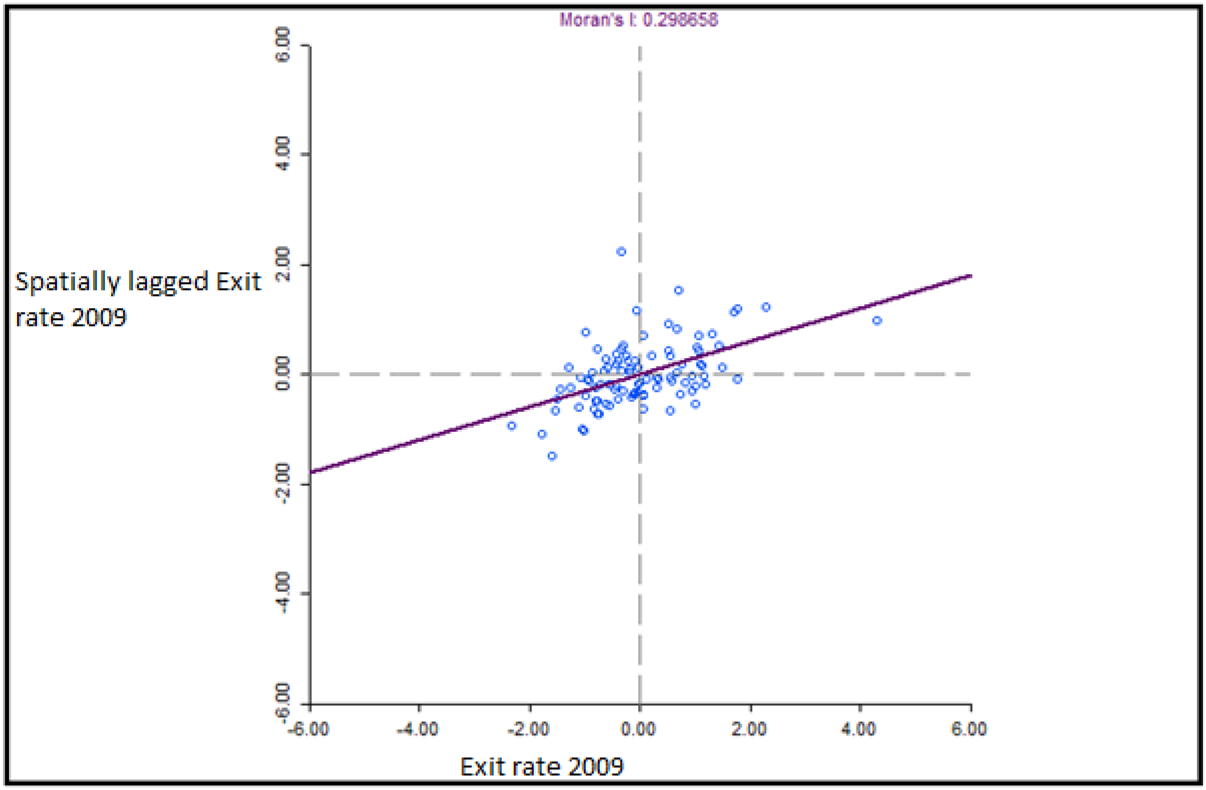
It appears that Department's exit ratios are positively spatially autocorrelated because the statistics are significant at 1% for each year. This means that the distribution of *Exit_rate* is by nature clustered over the whole period. In other words, the regions with relatively high *Exit_rate* (resp. low) are localized close to other regions with relatively high *Exit_rate* (resp. low). It thus indicates a globally significant tendency toward geographical clustering of similar regions in terms of firm's exit from the market.

Moran's diagram (Figure 3a and 3b) compares the value of *Exit_rate* in the 96 French departments with the neighbor' average, so we can visualize the spatial dependence of such variable. Its horizontal axis is based on the values of the observations and is also known as the response axis.

[9] More precisely, the sample consists of the original observed value of the statistic and the values computed for 9,999 conditionally randomized data sets

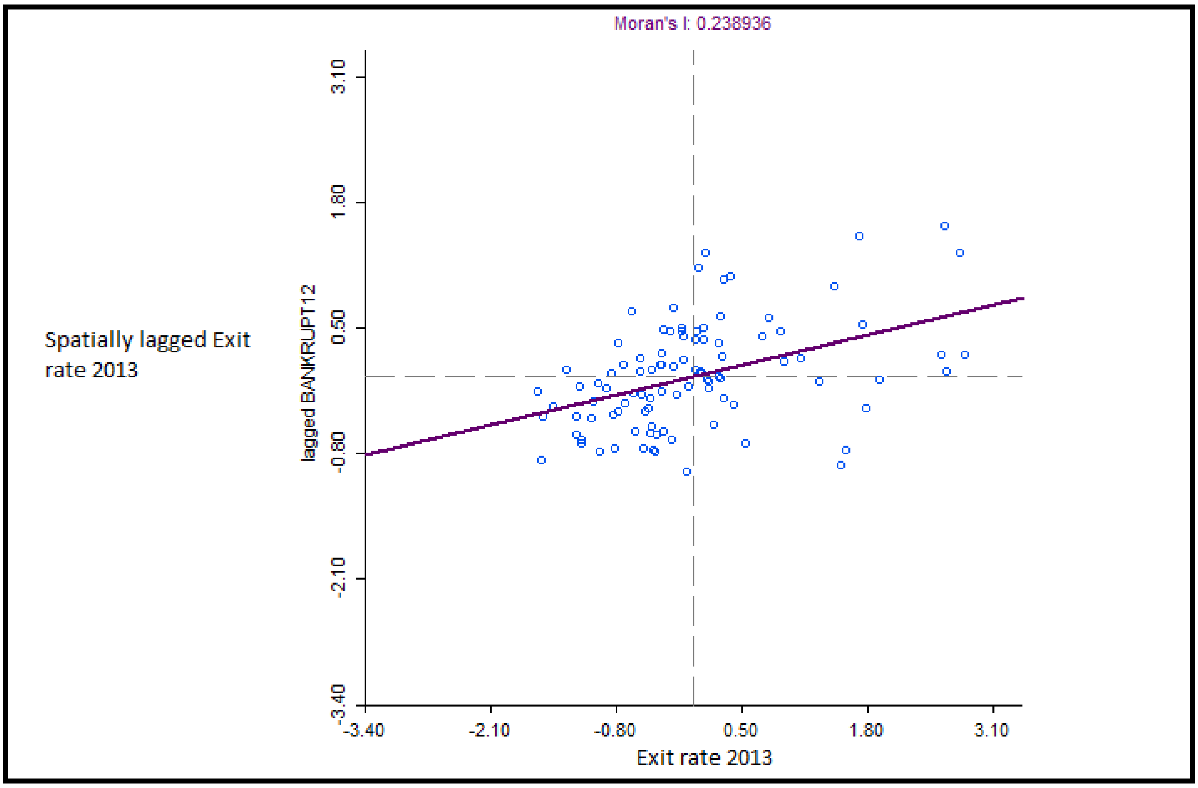
The vertical Y axis is based on the weighted average or spatial lag of the corresponding observation on the horizontal X axis. The observations are represented by their standardized values. Depending on their position on the plot, the Moran plot data points express the level of spatial association of each observation with its neighboring ones. We can find the data points on the Moran scatter plot in any of the four quadrants defined by the horizontal line y=0 and the vertical line x=0. Points in the upper right (or high-high) and lower left (or low-low) quadrants indicate positive spatial association of values that are higher and lower than the sample mean, respectively. The lower right (or high-low) and upper left (or low-high) quadrants include observations that exhibit negative spatial association; that is, these observed values carry little similarity to their neighboring ones.

Figure 3a - Moran Scatter Plot for the normalized value of Exit Rate-2009



Source: Own elaboration on Eurostat dataset

Figure 3b - Moran Scatter Plot for the normalized value of Exit Rate - 2013



Year 2013. Source: Own elaboration on Eurostat dataset

While the strength of Moran's I lies in its simplicity, its major limitations is that it tends to average local variations in the strength of spatial autocorrelation. This has prompted statisticians to develop local indices of spatial association. This category of tools examines the local level of spatial autocorrelation in order to identify areas where values of the variable are both extreme and geographically homogeneous. This approach is most useful when, in addition to global trends in the entire sample of observations, there exist also pockets of localities exhibiting homogeneous values that do not follow the global trend. This leads to identification of so-called hot spots -regions where the considered phenomenon is extremely pronounced across localities- as well of spatial outliers.

The index fast becoming the standard tool to examine local autocorrelation is Luc Anselin's LISA (Local Indicator of Spatial Association), which can be seen as the local equivalent of Moran's I. The sum of all local indices is proportional to the (global) value of Moran's statistic.

The local value of a LISA is computed as:

$$I_i = \frac{y_{it} - \bar{y}_t}{m_0} \sum_{j=1, j \neq i}^{n} w_{ij} \left(y_{jt} - \bar{y}_t \right) \quad (2)$$

Where $m_0 = \frac{\sum_{j=1, j \neq i}^{n} (y_{jt} - \bar{y}_t)}{n}$

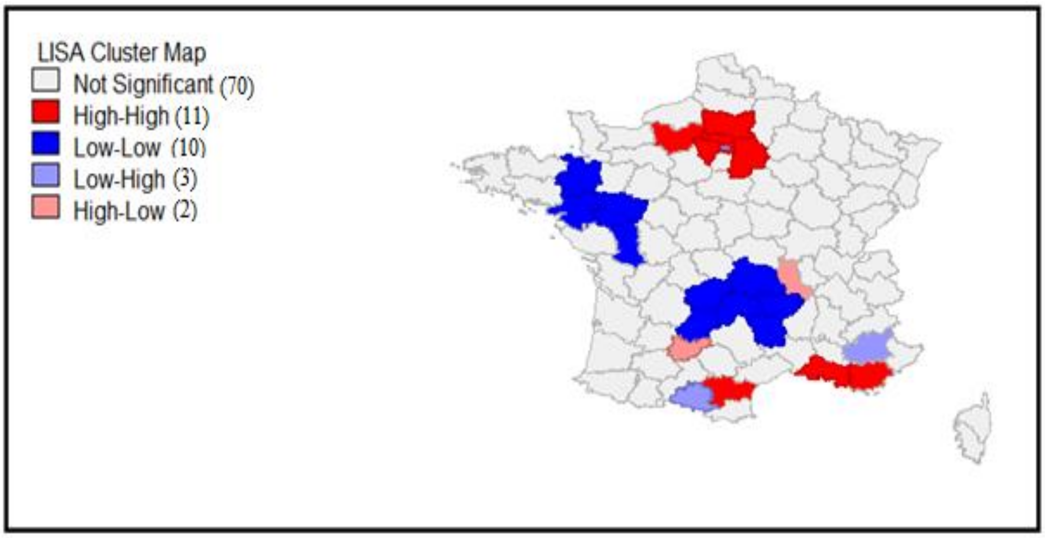
For each location, LISA values allow for the computation of its similarity with its neighbors and also to test its significance. Five scenarios may emerge:

- Locations with high values with similar neighbors: high-high (HH). Also known as *hot spots* (positive spatial autocorrelation).
- Locations with low values with similar neighbors: low-low (LL). Also known as *cold spots* (positive spatial autocorrelation).
- Locations with high values with low-value neighbors: high-low (HL). Potential *spatial outliers* (negative spatial autocorrelation).
- Locations with low values with high-value neighbors: low-high (LH). Potential *spatial outliers* (negative spatial autocorrelation).
- Locations with no significant local autocorrelation.

A positive value for I_i indicates a spatial concentration of similar values (HH or LL) whereas a negative value indicates a spatial concentration of dissimilar values (HL or LH). These statistics can represent the basis of a null hypothesis test about the lack of local spatial association. However their distribution remains unknown, statistical inference must therefore be based on the permutation approach with 10,000 permutations that as well as presented in the case of Global Moran. Figures 4a and 4b show the LISA cluster map in which it's possible to identify hot spot, cold spot and spatial outliers. Results are obtained using the same row-standardized weights matrix, as for the global measure[10]. Only Departments with a significance of 10 % for the LISA statistic are considered.

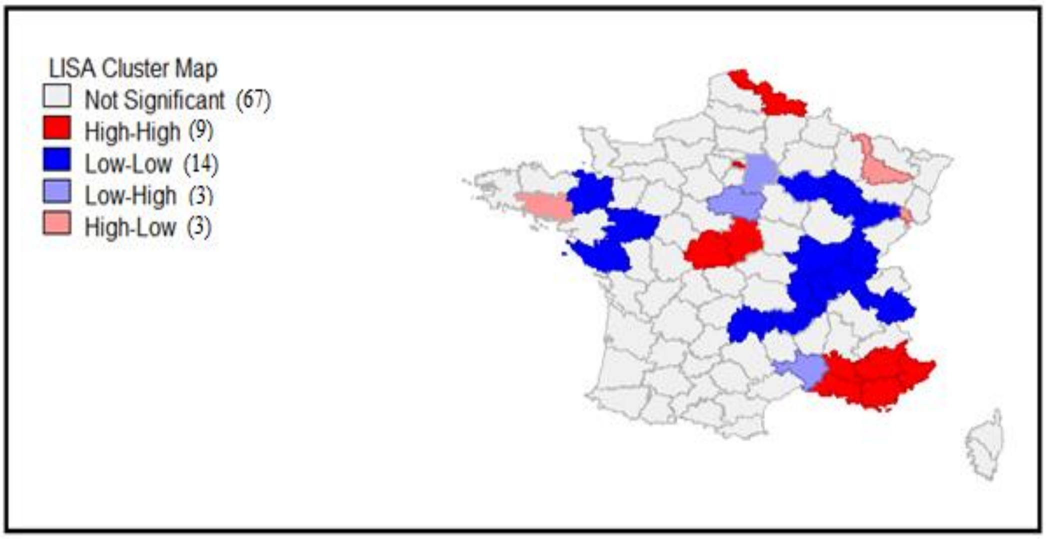
[10] LISA indicators for each Department are reported in appendix A2

Figure 4a: LISA cluster Map. Exit rate of French Departments (Year 2009)



Source: own elaboration on Eurostat dataset

Figure 4b: LISA cluster Map. Exit rate of French Departments (Year 2013)



Source: own elaboration on Eurostat dataset

The maps represent the spatial autocorrelation of the firm's *Exit_rate* by department corresponding to the situation and the evolution of the French economy over the period. The macroeconomic shock that hit the whole productive fabric, and in particular the industry, in 2008 is reflected in dissimilar ways in the different territories (Poupard and Baude, 2014). Firm's exit rates are structurally higher in the departments of southern France and Ile-de-France, which also have the highest proportions of small and very small enterprises (Rau, 2013) on the one hand, and young companies on the other one. These populations are more exposed to exit, which explains the clustering of HH type in the south-east and the Ile-de-France at the beginning of the period. The evolution between 2009 and 2013 highlights a change in clustering that corresponds to a change in the differentiated economic climate at the local level. In the west, the agri-food crisis in Bretagne reduced the economic success of the region, which explains the reduction in the number of LL-type departments. The good performance of the Rhône-Alpes region resulted in the appearance of a large area of departments characterized by a LL correlations that spills over into Bourgogne. Finally, the emergence of a group of HH-type departments comprising departments of northern France reveals the difficulties, especially industrial, characterizing this region.

5. Econometric Strategy and Empirical results

In order to estimate the impact of spatial agglomeration on firm's exit rate, it is essential to properly account the complex temporal and spatial patterns exhibited by the dependent variable. Furthermore, in order to analyse the effects of local-specific determinants on firms exit, it is necessary to account for the possible endogeneity of the regressors included in the analysis. At this aim, Dynamic Panel Models can solve two relevant issues: the serial dependence between observations of each unit in time, and the presence of unobservable time-invariant specific factors. However, they do not accommodate two other crucial aspects that are: the spatial dependence at each point of the time, and the unobservable effects specific to space and time period. Given that these effects are relevant in this study I make use of a Spatial Dynamic Panel Data model (see Elhorst 2010 for a survey).

A general specification for Spatial Dynamic Panel Data model is given by the following equation:

$$y_{it} = \alpha + \tau y_{it-1} + \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{c=1}^{k} x_{itc}\beta_c + \sum_{c=1}^{k}\sum_{j=1}^{n} w_{ij} x_{jtc}\theta_c + \mu_i + \gamma_t + v_{it}$$

$v_{it} = \lambda \sum_{j=1}^{n} m_{ij} v_{it} + \epsilon_{it}$ i=1…..n t =1…..T

- if $\lambda = 0$ and θ =0, we have the Spatial Autoregressive Model (SAR) where y_{it} is influenced by its temporal lagged value τy_{it-1}, its spatial lagged values $w_{ij}x_{jt}$ and the covariates in location *i*

- if $\tau = 0$, $\rho = 0$ and θ =0, we have the Spatial Error Model (SEM) where y_{it} is influenced only by spatial correlation in the error term v_{it}.

- if $\tau = 0$ and θ =0, we have the Spatial Autoregressive Model with Auto regressive disturbances (SAC), where y_{it} is influenced by its spatial lagged values $w_{ij}x_{jt}$ and the spatial correlation in the error term v_{it}.

- if if $\lambda = 0$ we have the Spatial Durbin Model (SDM) where y_{it} is influenced by its temporal lagged value τy_{it-1}, its spatial lagged values $w_{ij}x_{jt}$, the covariates in location *i* , and the covariates of neighbour locations (spatially lagged dependent variables).

The spatial weight matrix ***W*** used to estimate econometric results is the row-standardized contiguity weights matrix, as in the explorative analysis. This section presents estimation results which are obtained when the data are modelled through the setting of Spatial Dynamic Panel Models estimated via (Quasi Maximum) Likelihood. In a further step, as robustness, the estimations in which the Spatial Lag Term is estimated via SYS-GMM are provided in order to correct for the potential endogeneity.

The choice of the proper specification of Spatial Dynamic Panel data is linked to the results of Lagrange Multiplier test, as ignoring spatial dependencies in the dependent variable and residuals leads to potentially misleading estimates and incorrect statistical inferences. This test allows to choose among the SAC ($\rho \neq 0$ and $\lambda \neq 0$), SAR ($\rho \neq 0$ and $\lambda = 0$) and SEM ($\rho = 0$ and $\lambda \neq 0$) models. The LM statistic tests the following null hypotheses: H0(1) absence of spatial auto-correlation the error term ($\lambda = 0$); H0(2) absence of auto-correlation in the spatial lag ($\rho = 0$). Results for Lagrange Multiplier test are provided in Table 4.

Table 4: Spatial Dependence tests

Lagrange Multiplier SEM	49.8448
	(0.000)
Robust Lagrange Multiplier SEM	673.2729
	(0.000)
Lagrange Multiplier SAR	61.1266
	(0.000)
Robust Lagrange Multiplier SAR	684.5547
	(0.000)

P-values in parentheses

As shown by Table 4 the results for the LM test and its robust version lead to refuse the two null hypotheses suggesting that the terms λ and ρ are statistically different from 0.

Consequently, the proper version of SPDP that needs to be used to obtain evidences in this empirical analysis is the Spatial Autoregressive Model with Auto regressive disturbances (SAC), where y_{it} is influenced by both its spatial lagged values $w_{ij}y_{jt}$ and the spatial correlation in the error term v_{it} (both ρ and λ are different form 0). The results for the SAC model are presented in column 1 of Table 5. As reference, I present in columns 2 and 3, the results obtained when running the SAR and SEM model that consider only spatial dependence in the dependent variable and error respectively. Finally, since the SAC and the more general SDM (that includes spatially lagged dependent variables) are not nested models, information criteria can be used to test if the most appropriate model is the SAC[11] (Belotti et al. 2017) .

Overall, a fixed effect model is the most preferable estimation procedure as suggested by the Hausman test, which measures the difference between FE and RE estimators of coefficients. It yelds a χ^2 value of 20.27 and a p-value of 0.00. This leads to reject the null hypothesis, according to which differences in coefficients are not systematic, and to conclude that the FE estimator is consistent.

[11] As expected, in this case Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) point toward the application of SAC model.

Table 5: Empirical results (SPDM models)

	(1) SAC	(2) SAR	(3) SEM
ρWExit_rate	0.877***	0.554***	
	(0.018)	(0.033)	
Exit_rate$_{t-1}$		0.528***	
		(0.043)	
Birth_rate$_{t-1}$	0.215***	0.148***	0.185***
	(0.043)	(0.057)	(0.061)
FinDev	-1.135***	-1.274**	-1.151*
	(0.349)	(0.057)	(0.610)
Specialisation	-0.034	0.009	-0.049
	(0.037)	(0.046)	(0.045)
GdpPerCapita	0.023	0.013	0.031
	(0.020)	(0.026)	(0.026)
Pop_density	-7.10e-07	-1.54e-06	1.29e-06
	(7.12e-06)	(0.001)	(0.001)
λ	-0.646***		0.867***
	(0.077)		(0.018)
Spatial FE	YES	YES	YES
R^2 within	0.7465	0.8009	0.5225
R^2 between	0.0644	0.4293	0.4137
R^2 overall	0.3237	0.6164	0.2514
Observations	480	480	480
Log-likehood	2088.5215	2052.1774	2033.1221

Standard errors in parentheses
Notes: Results from SDPM regressions run with the command xsmle.
***Significance at the 1% level, **Significance at the 5% level, * Significance at the 10% level

The results for the SAC model, suggested by the application of the LM test, shows the significance of the spatially lagged variable associated with the coefficient ρ. This positive coefficient shows the relevance of agglomeration economies in firm's Exit Rate since a mortality increase of firms located in neighbour departments increases the likelihood exit of companies operating in a certain Department. The significance of the spatially dependent variable is confirmed when I run the SAR model even if with a lower coefficient. The coefficient associated with the variable *Birth_rate*$_{t-1}$ is positive and statistically significant for the SAC, SAR and SEM models: a higher Entry rate of firms in a certain location in the previous year increase the Exit rate of the companies in year *t*. This result confirms the displacement and revolving door effects as two possible mechanisms that explain the positive relationship between entry and exit (Audretsch, 1995).

Coming to the core issue of the study, first of all, the analysis provides evidence on the effect that financial development (*FinDev*) exerts in reducing firm exit at the local level. The variable *FinDev* is negative and statistically significant at 1% for the SAC model. The relevance of this effect is confirmed with a significance of 5% for the SAR model and while it is weaker (10%) for the SEM model. This empirical finding means that a higher level of financial development in a department brings to a lower mortality of companies. This effect of financial development on firm's exit rate is consistent with previous findings about local financial development in the literature. Local financial development is positively related to growth (Guiso et al. 2004; Gagliardi 2009) and affects firm's financial activities in different fields. In more financially developed areas inside a country, firms use more debt (Cariola et al. 2010), more trade credit (Deloof and La Rocca 2014) and these features strongly affect financial decisions of start-ups (Deloof et al. 2016). A greater availability of bank credit brings, thus, firms to have a higher probability of survival and a greater potential to grow. Conversely, specialisation economies seem not to exert any effect in affecting firm's exit in France since the coefficient associated with the variable *Specialisation* is never significant. [12]

In general, Spatial Dynamic Panel Models are estimated via (Quasi Maximum) Likelihood (e.g. Elhorst 2005, Su and Yang 2007, Yu et al. 2008, Lee and Yu 2010 a, b, c). However, this method cannot correct for the potential endogeneity of the explanatory variables in addition to the endogeneity of the spatially lagged dependent variable. In order to correct for this kind of potential endogeneity, an alternative method is to rely on GMM estimators (Arellano and Bover 1995, Blundell and Bond, 1998) as done in some other studies (Kukenova and Monteiro 2009, Bouayad-Agha and Vedrine 2009, Cainelli et al. 2014).

Following the GMM logic, the spatial lag is a strictly endogenous variable; the first time lag is a predetermined variable while I consider *Findev*, *Specialisation*, *GdpPerCapita,* and *Pop_density* as

[12] I didn't add Year dummies in the estimations to control for macroeconomic shocks (as suggested by Coad and Rao, 2008), since the effect of economic conjuncture in France, in the years of the analysis, differently affected the various sectors (Fougère et al. 2013). However, estimations with year dummies, available in appendix, confirm the relevance of the clustering effect.

strictly endogenous variables since there could be omitted variable and reverse causality bias. Accordingly, one can use the following moment condition (Bond 2002):

- If $x_{i,t}$ is strictly exogenous:

$E\ (x_{i,s}\Delta\varepsilon_{i,t})$=0 for *s=1, …., T* and *T=3,…..,T*

- If $x_{i,t}$ is weakly endogenous:

$E\ (x_{i,s}\Delta\varepsilon_{i,t})$=0 for *s=1, …., T-1* and *T=3,…..,T*

- If $x_{i,t}$ is strictly endogenous:

$E\ (x_{i,s}\Delta\varepsilon_{i,t})$=0 for *s=1, …., T-2* and *T=3,…..,T*

Table 6 shows estimations obtained when I run the SYS-GMM model (Blundell and Bond, 1998). The results fully confirm the ones obtained for the SAC model estimated via (quasi) maximum likelihood.

Table 6: Empirical results (GMM results)

	(1) SYS-GMM
$Exit\_rate_{t-1}$	0.194***
	(0.064)
ρWExit_Rate	0.783***
	(0.052)
$Birth\_rate_{t-1}$	0.209**
	(0.090)
FinDev	-1.000**
	(0.382)
Specialisation	0.019
	(0.0339)
GdpPerCapita	0.016
	(0.035)
Pop_density	-2.64e-07
	(3.40e-07)
N of instruments	44
N of Observations	480
AR1	-4.75
P-value	(0.000)
AR2	1.18
P-value	(0.238)
Hansen test	39.04
P-value	(0.335)
Sargan Test	44.85
P-value	(0.148)

Standard errors in parentheses
Notes: Results from GMM regressions run with the command xtabond2.
***Significance at the 1% level, **Significance at the 5% level, * Significance at the 10% level

The consistence of the GMM estimator relies on the validity of the lagged values of the autoregressive and spatial autoregressive terms as instruments for the regression. Using an orthogonality condition between the first-differenced error terms and lagged values of the dependent variables, I have to ensure, with specification tests, that these assumptions are justified. The Arellano-Bond (AR1) test for autocorrelation of the residuals rejects the null hypothesis that the errors are not autocorrelated, which is expected since differencing generates autocorrelation of order 1. The Arellano-Bond (AR2) test is not significant, this is needed in order not to reject the hypotheses that the errors in the level equation are not correlated, an assumption that ensure that the orthogonality conditions and the Arellano-Bond specifications are correct. The Hansen and Sargan tests of overidentifying restrictions also suggest that the instruments are appropriate.

The results of the estimations obtained running the SYS-GMM model, also shows the significance at 1 % of the spatially lagged Exit rate associated with the coefficient ρ. This confirms the relevant influence of the domino effect due to the clustering phenomenon. In fact, also controlling for potential endogeneity, I may state that an increasing mortality of firms located in neighbour areas brings to a higher likelihood of exit for companies operating in a certain Department. The coefficient associated with the variable $Birth\_rate_{t-1}$ is positive and statistically significant at 5 %: a higher Entry rate of firms in a department is confirmed to have a positive effect in increasing the Exit rate of the companies in the subsequent years. Also in the GMM model, financial development exerts a relevant effect in reducing firm exit at the local level since the variable *FinDev* is negative and statistically significant at 5%. All other local variables included in the analysis (as in the estimations obtained through SPDM models) seem not to exert any effect in affecting firm's exit in France.

6. Conclusions

This study has the aim to analyse the relevance of spatial agglomeration economies and other local features as drivers of firm's exit in France after the financial crisis that hit the country in 2008.

The macroeconomic shock that hit the whole productive tissue, and in particular the industry, in 2008 reflected in dissimilar ways in the different territories. The spatial distribution of firm's exit rate suggests that exit rates are structurally higher in the departments of southern of the country and Ile-de-France, which also have the highest proportions of small and very small enterprises on the one hand, and young companies on the other one. These populations are more exposed to exit, which explains the clustering of locations with high value of Exit rate. The evolution between 2009 and 2013 highlights a change in clustering that corresponds to a change in the differentiated economic climate at the local level.

Furthermore, the empirical results state the presence of a spatial domino effect in firm's exit among neighbour locations. In fact, firm's exit is characterized by positive spatial autocorrelation, so that locations with high exit rates tend to be surrounded by similar ones. The contribution to local public policies is in informing on the spillover effect which spreads across different locations. This study, thus, emphasises the need for policies adopted in a given area, to be harmonized with the actions implemented in neighbouring area.

In addition, I find that local financial development appears to play a role in shaping business exit risk, since it reduces the exit rate of a certain department. Local financial development positively affects business growth and firm's financial activities in different fields. In more financially developed areas, firms use more debt with the ability to better exploit the effect of leverage. A greater availability of bank credit provides firms with more potential to grow and survive. This is an issue for entrepreneurs who need to find financial resources to expand their business, for lenders who find an interest in maintaining relationships with secure borrowers, and for policy makers who are responsible for providing the best environment to enterprises.

A first limitation of this study is that I do not have evidence about the source of the domino effect that spread as shock in neighbour locations. Further research with the availability of many local variables could deeply investigate the reason underlying this phenomenon. A second limitation of this study is that I consider the Department as unit of analysis. However, this territorial level is defined from an administrative point of view and, because of this institutional background, does not systematically correspond to the effective economic division. Further researches based on Employment areas (*zone d'emploi)* could overcome this issue.

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Appendix

A1. Correlation Matrix

Variable	$Birth\_rate_{t-1}$	*FinDev*	*Specialisation*	*GdpPerCapita*	*Pop_density*
$Birth\_rate_{t-1}$	1				
FinDev	-0.2270	1			

Specialisation	-0.1077	0.0627	1		
GdpPerCapita	0.0584	0.2866	0.0518	1	
Pop_density	0.2425	0.3348	0.4202	0.5088	1

A2. LISA indicators

LISA Year 2009

Department	LISA	P-value
Ain	0,039011	0,431
Aisne	-0,1300278	0,473
Allier	-0,0019564	0,371
Alpes-de-Haute-Pce	-1,0022494	0,017
Hautes-Alpes	-0,1605347	0,068
Alpes-Maritimes	0,1395141	0,333
Ardèche	0,4375203	0,238
Ardennes	-0,1698221	0,307
Ariège	-0,0445266	0,047
Aube	-0,0011952	0,448
Aude	0,0921017	0,376
Aveyron	1,0372452	0,039
Bouches-du-Rhône	1,0935476	0,069
Calvados	0,0045781	0,487
Cantal	2,4428872	0,001
Charente	0,1106457	0,412
Charente-Maritime	-0,0075685	0,421
Cher	-0,0885792	0,274
Corrèze	0,4892113	0,07
Côte-d'Or	0,1026574	0,389
Côtes-d'Armor	0,2425467	0,081
Creuse	0,0155944	0,18
Dordogne	0,0671137	0,149
Doubs	0,0093305	0,5
Drôme	0,1836542	0,192
Eure	0,8951104	0,032
Eure-et-Loir	-0,2499872	0,038
Finistère	0,4032633	0,041
Corse-du-Sud	-0,630685	0,08
Haute-Corse	-0,0185529	0,462
Gard	-0,719252	0,092
Haute-Garonne	-0,3307697	0,2
Gers	-0,0699914	0,404
Gironde	-0,4560286	0,163

Hérault	-0,0127086	0,463
Ille-et-Vilaine	0,4973688	0,064
Indre	-0,1057011	0,247
Indre-et-Loire	-0,0347585	0,461
Isère	0,4170487	0,159
Jura	0,0878381	0,425
Landes	0,0571052	0,122
Loir-et-Cher	-0,0943951	0,415
Loire	-1,138082	0,003
Haute-Loire	0,8678046	0,163
Loire-Atlantique	0,5739606	0,027
Loiret	-0,4638188	0,055
Lot	0,7726433	0,116
Lot-et-Garonne	0,3775272	0,089
Lozère	1,8857341	0,001
Maine-et-Loire	0,1098917	0,381
Manche	0,7190805	0,084
Marne	0,0033333	0,482
Haute-Marne	0,0273031	0,264
Mayenne	0,2453017	0,291
Meurthe-et-Moselle	-0,3074863	0,177
Meuse	0,1524881	0,202
Morbihan	-0,0477986	0,049
Moselle	0,0035697	0,479
Nièvre	0,0855787	0,274
Nord	0,6295153	0,007
Oise	0,0814417	0,003
Orne	-0,0986377	0,477
Pas-de-Calais	0,3081576	0,098
Puy-de-Dôme	0,567756	0,117
Pyrénées-Atlantiques	0,1396949	0,355
Hautes-Pyrénées	0,1254805	0,253
Pyrénées-Orientales	0,8687376	0,09
Bas-Rhin	-0,1959892	0,223
Haut-Rhin	-0,0164652	0,468
Rhône	-0,3492794	0,158
Haute-Saône	0,0064338	0,417
Saône-et-Loire	-0,0267597	0,461
Sarthe	0,0301771	0,394
Savoie	-0,1658194	0,356
Haute-Savoie	0,0125386	0,488
Paris	-0,5911157	0,001
Seine-Maritime	-0,0253869	0,076
Seine-et-Marne	0,570255	0,015
Yvelines	0,6417329	0,03
Deux-Sèvres	0,0990936	0,351

Somme	-0,747981	0,019
Tarn	0,0167455	0,5
Tarn-et-Garonne	-0,2791847	0,133
Var	0,6667846	0,11
Vaucluse	0,9638336	0,021
Vendée	0,8009956	0,104
Vienne	-0,0248689	0,217
Haute-Vienne	0,0240879	0,302
Vosges	-0,0549701	0,258
Yonne	-0,0774814	0,304
Territoire de Belfort	-0,4567433	0,316
Essonne	0,7755709	0,002
Hauts-de-Seine	1,3074203	0,001
Seine-Saint-Denis	4,5958897	0,003
Val-de-Marne	2,4832764	0,001
Val-d'Oise	3,5046787	0,004

Source: Own elaboration on Eurostat dataset

LISA Year 2013

Department	LISA	P-value
Ain	0,8797566	0,035
Aisne	-0,1167823	0,495
Allier	-0,2410197	0,18
Alpes-de-Haute-Pce	0,461167	0,001
Hautes-Alpes	-0,0895494	0,307
Alpes-Maritimes	1,6340365	0,028
Ardèche	-0,1221488	0,291
Ardennes	0,4737718	0,114
Ariège	-0,1059195	0,137
Aube	0,1873592	0,066
Aude	0,0063065	0,437
Aveyron	-0,0846609	0,119
Bouches-du-Rhône	1,7280258	0,063
Calvados	-0,0156013	0,407
Cantal	0,8190947	0,034
Charente	0,0357811	0,345
Charente-Maritime	-0,0105002	0,452
Cher	0,2832461	0,314
Corrèze	-0,0049883	0,46
Côte-d'Or	0,3306287	0,313
Côtes-d'Armor	0,5612786	0,124
Creuse	0,3519115	0,244
Dordogne	0,0052368	0,135
Doubs	0,3250704	0,051

Drôme	0,0196647	0,484
Eure	-0,0370627	0,233
Eure-et-Loir	0,0190338	0,141
Finistère	0,2771961	0,066
Corse-du-Sud	-1,6481621	0,002
Haute-Corse	-0,040823	0,087
Gard	0,0122924	0,482
Haute-Garonne	0,0255767	0,215
Gers	0,0656473	0,29
Gironde	-0,7933951	0,068
Hérault	-0,0361926	0,427
Ille-et-Vilaine	0,1854829	0,118
Indre	0,4525246	0,005
Indre-et-Loire	-0,0216843	0,333
Isère	0,0497223	0,455
Jura	0,8790074	0,076
Landes	-0,0464944	0,386
Loir-et-Cher	0,9612466	0,156
Loire	0,2189004	0,113
Haute-Loire	0,513251	0,151
Loire-Atlantique	0,4075876	0,072
Loiret	-0,3381765	0,131
Lot	-0,1625094	0,285
Lot-et-Garonne	-0,0213095	0,316
Lozère	0,3092443	0,213
Maine-et-Loire	0,2040602	0,159
Manche	0,310669	0,081
Marne	-0,3502451	0,16
Haute-Marne	0,3291636	0,028
Mayenne	-0,226629	0,349
Meurthe-et-Moselle	-0,6053294	0,223
Meuse	0,0801544	0,353
Morbihan	-0,371277	0,03
Moselle	0,330267	0,175
Nièvre	-0,0095228	0,492
Nord	0,0723289	0,007
Oise	-0,2781151	0,008
Orne	-0,5079813	0,291
Pas-de-Calais	0,0000984	0,454
Puy-de-Dôme	0,3524868	0,228
Pyrénées-Atlantiques	0,1508586	0,356
Hautes-Pyrénées	0,1365482	0,428
Pyrénées-Orientales	0,0036084	0,464
Bas-Rhin	0,4797539	0,214
Haut-Rhin	0,6334137	0,066
Rhône	0,1759739	0,021

Haute-Saône	0,2266377	0,202
Saône-et-Loire	0,5091638	0,004
Sarthe	0,01064	0,451
Savoie	0,1968999	0,125
Haute-Savoie	0,8713593	0,011
Paris	0,0828528	0,086
Seine-Maritime	-0,0348736	0,394
Seine-et-Marne	-0,2048519	0,091
Yvelines	-0,1101702	0,213
Deux-Sèvres	0,35464	0,271
Somme	-0,0712118	0,43
Tarn	-0,0371866	0,24
Tarn-et-Garonne	-0,0914971	0,499
Var	2,6409379	0,008
Vaucluse	0,9793118	0,071
Vendée	0,4446229	0,097
Vienne	-0,0022657	0,429
Haute-Vienne	0,1909241	0,303
Vosges	0,2983648	0,218
Yonne	-0,1126307	0,094
Territoire de Belfort	-1,5079384	0,006
Essonne	0,1099528	0,039
Hauts-de-Seine	0,2306631	0,042
Seine-Saint-Denis	0,7232555	0,272
Val-de-Marne	0,3731182	0,14
Val-d'Oise	0,1964367	0,035

Source: Own elaboration on Eurostat dataset

A3. Estimations with time dummies

	(1) SAC	(2) SAR	(3) SEM
ρWExit_rate	0.402***	0.226***	
	(0.140)	(0.061)	
Exit_rate$_{t-1}$		0.270***	
		(0.050)	
Birth_rate$_{t-1}$	0.228***	0.189***	0.218***
	(0.043)	(0.059)	(0.061)
FinDev	-0.487	-0.210	-0.486
	(0.527)	(0.556)	(0.568)
Specialisation	0.020	0.026	-0.004
	(0.044)	(0.045)	(0.045)
GdpPerCapita	0.033	0.035	0.033
	(0.024)	(0.025)	(0.025)
Pop_density	-5.57e-06	-8.94e-07	-3.70e-06
	(9.40e-06)	(0.001)	(0.001)
λ	-0.197		0.247***
	(0.291)		(0.018)
Spatial FE	YES	YES	YES
Year dummies	YES	YES	YES
R^2 within	0.8654	0.8595	0.8641
R^2 between	0.0292	0.5193	0.0011
R^2 overall	0.0481	0.7244	0.2139
Observations	480	480	480
Log-likehood	2128.2233	2127.8698	2126.9125

Standard errors in parentheses
Notes: Results from SDPM regressions run with the command xsmle.
***Significance at the 1% level, **Significance at the 5% level, * Significance at the 10% level

	(1) SYS-GMM
Exit_rate$_{t-1}$	0.189**
	(0.089)
ρWExit_Rate	0.630***
	(0.160)
Birth_rate$_{t-1}$	0.256**
	(0.112)
FinDev	-1.049**
	(0.407)
Specialisation	0.030
	(0.037)
GdpPerCapita	0.024
	(0.034)
Pop_density	-2.88e-07
	(4.03e-07)
N of instruments	44
N of Observations	480
Year dummies	YES
AR1	-5.01
P-value	(0.000)
AR2	1.44
P-value	(0.151)
Hansen test	39.03
P-value	(0.183)
Sargan Test	40.62
P-value	(0.141)

Standard errors in parentheses
Notes: Results from GMM regressions run with the command xtabond2.
***Significance at the 1% level, **Significance at the 5% level, * Significance at the 10% level

Conclusions

The chapters that compose this PhD Thesis are in vein with the strand of literature having objective to understand the different determinants of Business Failure. The choice to investigate this phenomenon is due to the importance of this subject since corporate failure leads to relevant costs for the whole economy. Indeed, the objectives of a business go far beyond the insiders' interest. Firms have to achieve a sustainable development in the broad sense of economic development that, in addition to creating value for shareholders, maintains a conservation of the natural and social environment and human capital. As the impact of corporate failures concern a large number of agents, an important attention must be paid to this important and expanding phenomenon, trying to understand its main determinants.

The first chapter has provided the elaboration of an index which targets to predict corporate bankruptcy and can, thus, used as *early warning* signal. Taking into account both the firms' debt level and its vulnerability, this work presents the elaboration of a new Composite Indebtedness Index based on a Robust Principal Component Analysis for skewed financial ratios. In this context, I first derive an accurate instrument to assess the financial health of the firms. Second, I estimate a more complex logit model, based on both the first step computed indebtedness indices and additional non-financial firms' characteristics, which allows to compute specific bankruptcy scores (predicted probabilities of default) for each firm included in the analysis. The main findings of this application to Italian manufacturing firms show that the level of indebtedness and its sustainability are significant factors in explaining firms' default risk. I test the predictive power of the index several years prior to bankruptcy and compare it with the popular Altman z-score. The empirical evidence suggests a good performance both in terms of classification accuracy and reliability. Hence, the proposed Composite Indebtedness index is a good predictor of firm failure, it is an efficient alternative to the Altman z-score and can be used as an *early warning signal* of financial bankruptcy.

The second chapter goes further the internal determinants of corporate bankruptcy trying to investigate which is the role exerted by the external environment, with a focus on the organisation of local credit market. In particular, this chapter has studied the effects that local financial development and banking concentration may exert on the probability of bankruptcy of new firms. I focused on this research question since new and young companies are the primary source of job creation in economies, they contribute to economic dynamism but, at the same time, they are the most financially vulnerable in the market. This weakness leads to questioning the role played by the financial system and, more precisely, by banks, in the local economic activity and as a driver of the performance of local firms. Local financial development can provide valuable support at the time firms are more fragile, as in their early stages. It is an issue for entrepreneurs who need to find financial resources to expand their business, for lenders who find an interest in maintaining relationships with secure borrowers, and for policy makers who are responsible for providing the best environment to enterprises. Previous studies found that local financial development is positively related to growth and affects firm's financial activities in different fields. In more financially developed areas inside a country, firms use more debt, and this feature strongly affects the financial decisions of new firms. Coherently with previous findings, the empirical evidence of this study, based on Italian new firms, shows that a greater availability of bank credit allows new firms to have more potential to grow and survive. This effect is stronger for small new firms. The reason underlying this topic is that, if small firms find it more difficult to access financial services due to greater information and transaction costs, financial development that ameliorates these frictions can exert a particularly positive impact on small firms. Furthermore, the results suggest that local banking concentration reduces the probability of bankruptcy only for large, new firms. A bank operating in a more concentrated market may financially support new firms with the objective of exploiting rents from eventually successful borrowers. When a bank adopts this kind of strategy, it has the objective of maintaining lending relationships in the future, certain of the fact that the firm will not be attracted to rival banks

The third chapter of the thesis is also in line with the strand of literature which investigates the effect that location specific determinants may have in shaping the exit risk in the local area. The specific purpose of the research is to study the relevance of the domino effect in firm's exit among neighbour locations with a focus on two regional variables: local specialisation and local financial development. The analysis has been carried out on data aggregated at the NUTS3 level for France, a country where, despite business insolvencies are decreasing in the last years, total insolvencies are still higher than pre-crisis level with the persistence of high regional divergences. The explorative analysis has shown that the macroeconomic shock that hit the whole productive tissue, and in particular the industry, in 2008 reflected in dissimilar ways in the different territories. The spatial distribution of firm's failure rate suggests that exit rates are structurally higher in the departments of southern of the country and Ile-de-France, which also have the highest proportions of small and very small enterprises on the one hand, and young companies on the other one. These populations are more exposed to failure, which explains the clustering of locations with high value of Exit rate. The evolution between 2009 and 2013 highlights a change in clustering that corresponds to a change in the differentiated economic climate at the local level. The empirical results state the presence of a spatial domino effect in firm's exit among neighbour locations. In fact, firm's failure is characterized by positive spatial autocorrelation, so that locations with high exit rates tend to be surrounded by similar ones. In addition, I find that local financial development appears to play a role in shaping business failure risk, since it reduces the exit rate of a certain department whereas specialisation at the local level seems not exert any effect.

Trying to understand the different determinants of business failure is a relevant issue for business community and policy maker. The focus of the first chapter on the internal determinants of bankruptcy, suggest that an early warning signal of over-indebtedness may assume a pivotal role in the adoption of effective reorganization procedures. From this perspective, the accounting-based research can also contribute to a critical understanding and policy formulation on small firms, which are non-publicly traded firms. The practical use of the empirical results, is valuable for entrepreneurs, managers and financiers. However, the research can be developed following several directions. First, it would be interesting to compare the proposed composite index with other rating systems, apart from the Z-score, to evaluate companies' financial stability and their creditworthiness. Second, it may be worthwhile developing a more general model of company default prediction including also managerial practices and other qualitative information. Finally, as the analysis as a whole would indicate that this classifier outperforms individual techniques that constitute the ensemble classifiers, it would be worthwhile investigating new methodologies in order to amplify the advantages of the individual models and minimize their limitations. The study on the external determinants of business failure (Chapters 2 and 3) may also give indications in terms of policy. A first indication offered by the current research is that the regulation of the bank sector at the local level plays a key role in a firm's early stage life, and a more stable financing relationship could represent an advantage for newly established firms. Second, agencies supporting business creation should define specific criteria in the selection of investment projects and the subsequent attribution of credit to create a stable lending relationship. Finally, the contribution to local public policies is in informing also on the spillover effect which spreads across different locations. This study, thus, emphasises the need for policies adopted in a given area, to be harmonized with the actions implemented in neighbouring area.