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Assessing the Impact of Credit Ratings and Economic Performance on Firm Default

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Assessing the Impact of Credit Ratings and Economic Performance on Firm Default*

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Abstract

The study of firms' default has attracted wide interest among both practitioners and scholars. However, attention has often been limited to a relatively small set of financial variables. In this work, we try to increase the scope of analysis extending the investigation to other possible determinants of default. In particular, we rely on credit ratings to summarize firms' financial conditions, and we address the potential predictive power of a set of economic dimensions – size, growth, profitability and productivity – which industrial economics suggest to be meaningful determinants of survival. We present novel results based on a large Italian dataset reporting credit ratings for all the firms in the sample. As far as financial conditions and default are concerned, we find that the firms displaying the worst credit ratings are quite turbulent, but also exhibit non-negligible chances to recover. Moreover, the analysis of the distribution of firms' economic performance reveals that profitability stands up as the only relevant economic variable telling apart defaulting firms from 'surviving' ones, at different time distance to default. Finally, probit and logit estimation of default probabilities, testing for the simultaneous effect of economic and financial dimensions, suggest that growth, in addition to credit ratings, significantly affects the likelihood of default, albeit in a positive (and as such unexpected) way in the manufacturing industry.

JEL codes: C14, C25, D20, G30, L11

Keywords: Default probability, Credit ratings, Firm growth dynamics, selection

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1 Introduction

Credit rating agencies have been playing an increasingly important role in debt and financial markets market, publishing credit ranking especially for large bonds' issuers. Ratings are employed both by private and institutional investors to get a concise picture of the financial soundness of the covered firms. As such, ratings play a relevant role under many respects, likely affecting the cost and the extent of access to credit of firms, and also contributing to shape firms' financial structure (Sengupta, 1998). More recently, banks are even more concerned with ratings, and credit risk in general, due to the need to cope with the capital-risk requirements of Basel II Accord (Altman and Sabato, 2005). As a result, a large body of academic literature has flourished within financial economics relating firms' default probability to financial indicators and credit rating. Drawing from the classical works by Beaver (1966) and Altman (1968), particular attention has been devoted to bankruptcy prediction based on financial variables such as leverage, liquidity or financial ratios, while much of the present effort is directed to estimation of credit migration matrices (see Crouhy *et al.* (2000), Jafry and Schuermann (2004), Schuermann (2007)).

In this paper, exploiting a confidential information on credit ratings and default events occuring in a large panel of Italian firms, we present an analysis of firm default taking a twofold perspective.

First, we exploit the informative content of credit ratings as a synthetic measure of firms' financial soundness. Whereas rating agencies typically produce their rankings for medium-big and listed firms, we instead have access to a database reporting credit ratings for all the included firms, irrespective of their size and of their being publicly-traded or not. Our study therefore offers an unprecedented - for breadth - account of the overall financial soundness of a broadly defined (Italian) 'economic system'.

Second, the fundamental contribution pursued in this article is an attempt to bridge two stream of research which have typically proceeded without interacting much, especially from an empirical viewpoint. On the one hand, the aforementioned financial studies, bankruptcy prediction in particular, are mainly concerned with relating firms' default with financial indicators and credit ratings, and only rarely consider non-financial factors. On the other hand, the large body of research – both theoretical and applied – conducted in the domain of industrial economics tend to pose the attention on economic, rather than financial determinants of firm dynamics, eventually stressing those factors which more closely relate with the ultimate economic activity of the firms, producing goods or services.

One is however aware that financial and economic conditions alone cannot offer but a partial account of firms' performance. It is indeed unquestioned that the financial stability as well as the probability to stay in the market are at least closely intertwined with, if not resulting from, firms' ability to perform well along the economic dimension of its operation. Despite these are commonly accepted considerations, the attempts to address the simultaneous effect of economic and financial performance on default probability are typically left aside (Grunert *et al.* (2005) is maybe a first exception).

From the theoretical side, although various and competing views are coexisting, most of the modern conceptualizations of firm dynamics share a common tenet whereby it is the action of some sort of selection mechanism, operating on the economic characteristics of heterogeneous firms, which ultimately determines firms' exit or, alternatively, growth and survival on the market. In Jovanovic (1982)'s model, selection operates on heterogeneous efficiency/productivity levels and through a process of passive learning by doing which enables firms to uncover their specific level of efficiency, randomly assigned to them from the beginning and assumed constant along the discovery process. Over time, those firms who realize to be efficient enough survive and grow, whereas the others exit. In Ericson and Pakes (1995), instead, the dynamics are driven by the active efforts of the firms themselves, who are allowed to 'choose' their own efficiency level through R&D investments. Then, selection operates on the resulting level of relative profitability which, in turn, is affected by the uncertainty inherently characterizing the exploration of different technological opportunities. In both the models, however, the decision to exit is conceived as an equilibrium solution for rational, profit maximizing firms. The models presented in Nelson and Winter (1982) and, to some extent, the whole stream of evolutionary flavored research (see Winter, 1971; Nelson and Winter, 1982; Dosi and Nelson, 1994; Metcalfe, 1998; Dosi, 2000; Bottazzi and Secchi, 2006) start from completely different premises. In this tradition, growth and exit events continuously occur in the course of a dynamic disequilibrium process where firm choose a satisfying, rather than an optimal, efficiency level. The latter, in turn, depends on asymmetries in the distribution of the basic building blocks of firm idiosyncratic characteristics (knowledge, capabilities, routines) and, similarly to Ericson and Pakes (1995), on the firms' effort to perform innovative (or imitative) activity. Then, competition forces create a powerful market selection mechanism whose complex interplay with efficiency and uncertainty of innovation determines an associated level of (satisfying) profitability and, ultimately, the relative balance between exit and growth. Whatever the specific model one might discuss, the implications in terms of the suggested key determinants of firm dynamics are rather similar: efficiency, profitability, size and growth are the key ingredients, all positively affecting the likelihood of success and survival in the market.

From the empirical side, size and growth, together with age, have been those variables receiving greatest attention by the studies investigating the dynamics of entry/exit and survival. The findings usually agree with the theory that they positively correlate with the probability of persisting in the market (see, among the many examples, the evidence reported in Evans, 1987; Hall, 1987; Dunne *et al.*, 1988; Geroski, 1995; Agarwal, 1997; Sutton, 1997; and Caves, 1998). The same has been repeatedly documented also with respect to technological characteristics, either measured in terms of innovative inputs such as R&D (Hall, 1987; and Doms *et al.*, 1995) or proxied via innovative output, such as patents (Cefis and Marsili, 2005). Remarkably, less work has been done to test for the existence of the selection mechanism itself, through a direct exploration of the relationship between survival, on the one hand, and efficiency or profitability, on the other, possibly under the implicit assumption, corroborated by theory but untested, that these variables are highly correlated with the other relevant economic characteristics.

For that matters in the context of our analysis, the message one can draw is that, at a rather general level, the likelihood of default is expected to be lower for firms displaying relatively sounder economic performance. Within such a perspective, we identify four basic relevant economic dimensions - size, growth, profitability and productivity - and relate them with a rather peculiar form of exit from the market, that is a declaration of default, and pose two interrelated research questions. One concerns the heterogeneities possibly existing both within and across defaulting vis a vis continuing firms. Relatedly, one wants to investigate the intertemporal patterns experienced by the two groups along the various economic dimensions considered. To take a fresh look on these issues, we will adopt a non parametric approach to estimate the empirical distribution of size, growth, profitability and productivity, and compare their characteristics during the transition to default for the two groups of firms.

What is more, the availability of credit ratings allows to shed light on more than the mere interaction between economic and financial dimensions. It also allows to provide novel evidence on the extent to which credit rationing types of mechanisms interact with the predicted effect of economic variables on survival. Indeed, starting from the seminal work of Fazzari *et al.* (1988), the empirical studies concerned with the identification of liquidity constraints in investment and growth dynamics have pervasively relied on cash flow as a proxy for capital markets imperfections (for reviews, see Hubbard, 1998; Fagiolo and Luzzi, 2006; and Whited, 2006). There are however reasons to suggest that liquidity may not be a good indicator for that kind of mechanisms (Kaplan and Zingales, 1997 and 2000). Eventually, it is a measure of the ability to generate ready to spend, merely *internal* resources, whereas capturing the existence of non-neutralities in the workings of financial markets would require to measure if external resources are rationed to certain types of firms. Credit ratings, embodying a forecast of firms' ability to pay back loans, represent a much more direct indicator of investors' (banks) propensity to bet on each firm, thereby offering a more reliable picture of heterogenous chances to access credit, in different amounts and at different costs. Noticeably, some peculiar characteristics of the credit ratings included in our dataset makes this attempt particularly promising.

The work is organized as follows. In Section 2 we present a short description of the dataset. Section 3 focuses on default and credit rating transition probabilities. Then, Section 4 investigates the interplay between economic variables and default. A formal (probit and logit) model estimating the impact of both economic and financial variables on default probability is presented in Section 5, while in Section 6 we sum up the results and suggest some possible interpretations.

2 Data sources and sample selection

The data come from the Centrale dei Bilanci (CeBi) database. Together with the information collected by the Italian national statistical office (ISTAT), this database represents the most detailed source of firm level information on Italy. This fact is due to the peculiar nature and history of CeBi. Nowadays a private company involved in services for financial analysis, it was instituted in 1983 by the Bank of Italy as a public agency with the assigned task of providing financial analyses to support the Bank of Italy itself within its activity of supervision of the banking system. It is in this perspective that CeBi is engaged in data collection, harmonization and cleaning since its foundation, in close relationship with leading Italian commercial banks.

Starting from the early 80's, the database contains the time series of balance sheets data of all the Italian *limited liability* firms, since these are the entities which face a legal obligation to make their annual accounting publicly available at the Chambers of Commerce. Initial reliability checks are performed by CeBi, and only balance sheets complying with the principles laid down by the IV EEC directive are considered reliable enough to enter the dataset. As a result, included firms operates in all the sector of activity and, contrary to what it often happens with other firm level panels (not only Italian ones) there are no thresholds imposed on firm size, in terms of number of employees. As such, the dataset is rich and detailed, and seems particularly suitable for the analysis of both large and small-medium sized firms.

Thanks to a collaboration between the Research Office "Strategie e Studi" of Unicredit Bank Group and the Laboratory of Economics and Management at Scuola Superiore Sant'Anna, we had access to a sub-sample of the CeBi database which covers about 50.000 firms operating in between 1996 and 2003. The way we have obtained the data is particularly important, since it contributed to shape some limitations of the analysis, but also opened up unique opportunities to exploit novel pieces of information which were never explored before by other studies making use of the same dataset.

On the one hand, the major limitation lies in the fact that we only have access to a subset of variables, rather than to the entire accounting book. Available items are: Total Sales (TS), Value Added (VA), Gross Operating Margins (GOM), Number of Employees (L), Gross Tangible Assets (K), Return on Investment (ROI), Leverage (Total Debt over Shareholders' Equity), Interest Expenses (IE), and the Debt over Revenues ratio. We sometimes had to face some problems in terms of freedom to choose the theoretically best proxy for the economic phenomenon one is willing to study. Still, the list is sufficiently rich and enabled us to check the results across some alternative way of capturing most of the dimensions considered in this work, such as size, efficiency, profitability, financial structure, and so on and so forth.

On the other hand, the collaboration with Unicredit Group is responsible for the two mostly remarkable features of our data, those which ultimately allow us to link the economic and the financial side of firms' structure and operation.

First, we have been provided with a dummy variable telling whether a group of firms, which were Unicredit customers during the period under analysis, incurred default at the end of the sample time window, in either 2003 or 2004. These firms (henceforth *defaulting firms*) were 155 in Manufacturing and 104 in Service, respectively. Second, Unicredit specific rights to access the database gave us the chance to exploit the credit ratings produced by CeBi.[1] Technically, this is an index issued once per year and allowed to change over time. The firms present in the database result ranked with a score ranging from 1 to 9, in increasing order of financial fragility: 1 is attributed to highly solvable firms, while 9 identifies firms displaying a serious risk of default. Table 1 reports the definitions given by CeBi itself to the the 9 classes. The actual methodology employed in computing the index has not been disclosed to us, as it is proprietary of CeBi. Though, it provides the same informative content of credit ratings issued by internationally well known agencies such as Moody's or Standard and Poor's. A large body of literature on credit rating engineering suggests that this kind of rankings should include many aspects characterizing the financial side of firms operations, including variables such as liquidity, leverage, debt structure and the associated maturity, and so on and so forth. CeBi ratings therefore convey a concise picture of the current financial conditions of a firm as well as a forecast of future sustainability.

There are however some specific characteristics which make the CeBi index particularly interesting as compared to ratings produced by international agencies. A remarkable feature is that the rating is assigned to each firm, rather than to single debt issues, justifying an interpretation as a proxy for firms' *overall* ability to meet debt positions on due time. In

[1] These informations, as well as the rest of the dataset, was provided to us thanks to a collaboration with the Research Office "Pianificazione, Strategie e Studi" of Unicredit Group, a large Italian bank. They are strictly confidential and have been provided under the mandatory condition of censorship of any individual information.

			Number of firms		
Class	**Rating**	**Definition**	1998	2000	2002
Low	1	high reliability	1114	1396	1531
	2	reliability	1293	1602	1664
	3	ample solvency	1483	1698	1671
Mid	4	solvency	4170	4549	4310
	5	vulnerability	2360	2621	2405
	6	high vulnerability	1969	2016	2083
	7	risk	2249	2691	2311
High	8	high risk	350	433	457
	9	extremely high risk	93	121	130
Total			15081	17127	16562

Table 1: Number of firms, total and by rating classes in 1998, 2000 and 2002 - Manufacturing.

addition to that, and more interestingly, the index seems a particularly reliable measure of actual (Italian) banks' propensity to invest in each firm, to be exploited as a measure of access to external financing. Indeed, due to the role played by CeBi as an institutional actor, the index has been for long a confidential information only available to the Bank of Italy and to the Italian banking system. One can therefore reasonably claim that (Italian) banks have a long experience in using CeBi credit ratings as a synthetic indicator, or at least as a benchmark, when deciding to open credit lines up. Finally, a third difference with respect to other ratings is that the latter usually apply to firms listed on the stock exchange. The CeBi index, on the contrary, is assigned to *all* the business firms present in the database, which might be either listed or not, with no particular limitations in terms of their size, sector of activity, and so on and so forth.

The cleaning procedures implemented in order to obtain an homogeneous dataset follow two strategies. On the one hand, we noted that the the first two years of the sample recorded a substantially lower number of non-missing observations, for reasons out of our control. We prefer working with similar sample sizes for the different years under analysis and, accordingly, we limit the study to the period 1998-2003. On the other hand, even if the raw data do not impose any threshold on the size of the firms considered, we tried to identify business units characterized by a minimum level of organizational structure and operation. We therefore discarded all those firms with only one employee, and all those reporting less than one million of euro of Total Sales in each year.

The specific cut imposed on the number of employees is chosen on the basis of preliminary investigations conducted on the properties of the original database. Indeed, explorative exercises conducted by Bottazzi *et al.* (2006) and Bottazzi *et al.* (2008) on the very same dataset has revealed that firms with one employee and firms with more than one employee fall into two categories representative of two different worlds, characterized by different properties which, from a statistical point of view, it would be safer to analyse separately. The economic rationale is simply that firms with only one employee capture all the phenomena connected to self-employment, a quite peculiar universe of economic activities/organizations, which we want to ignore here. The threshold imposed on annual revenues works along the same direction of working with "true firms", but it is also motivated by informal evidence emerged during discussions with Unicredit, suggesting that a threshold of one million of euro on Total Sales was a reasonable proxy for average Unicredit customers' size. This way we try to accomplish the specific need of enhancing comparability between the overall sample and the sub-sample of defaulting firms.

At the end of the day, we are left with around 15000 firms active in Manufacturing and 10000 operating in the Services, depending on the year. Table 1 shows, by way of example, the precise number of Manufacturing firms in three different years of the sample period, divided by CeBi rating classes.[2] The small number of defaults observed in the data prevents as simply unfeasible any attempt to look at finer levels of sectoral aggregation.

3 Transition to default and financial performance

In general, one would tend to argue that a positive relationship should be in place between sound financial records, on the one hand, and probability of survival, on the other: the lower the cost of debt, the more balanced the financial structure, for instance, and the lower the likelihood to incur default. Relatedly, it seems reasonable that time plays a role, as it is likely that an event as extreme as complete financial distress does not occur suddenly. Rather, one would expect to observe a deterioration of financial conditions, and therefore of the ratings, somewhere before.

In this section we exactly focus on such kind of dynamics, exploring the way in which overall financial conditions of firms, as summarized by their credit ratings, behave during the transition to default. One main point will be to understand how fast such a process occurs, and how well it is anticipated by the ratings. To do so, we first present descriptive evidence following how credit ratings of defaulting firms evolve over time. Then, we estimate the transition probabilities of moving across different rating classes or ending up defaulting. Comparative exercises will be run distinguishing firms active in Manufacturing and firms active in Service, allowing for a (minimum) control for possible industry specific differences.

A necessary first step concerns to understand where defaulting firms stand in terms of credit rating in the years before default. In Figure 1 we take a picture of the distribution of defaulting firms into the 9 rating classes as it appears in 1998 and 2002, that is at the beginning of the sample period and in the very proximity of the default event, respectively.

Though simple, the exercise is quite informative about the length of the time horizon bringing firms to default. Indeed, look at Manufacturing, for instance, and compare the values computed for each class over time. In 2002, the number of firms is increasing with the rating, i.e. it is higher for badly rated firms, but not as much as one would expect to observe at a so short time distance to complete distress. Indeed most of the firms lies in between class 4 (solvency) and class 7 (risky), while only few experience severe financial troubles and fall into category 8 (high risk) and 9 (extremely high risk), those classes where one imagine to find the majority of defaulting firms, given that the default occurs just 1 to 2 years later. In

[2]In the CeBi database firms are classified in terms of the Ateco industrial classification, which is the standard adopted by the Italian statistical office, and substantially corresponding to the ISIC Rev 3.1 taxonomy. Codes 15-36 define the Manufacturing industry, whereas codes 50-74 identify the Service sector.

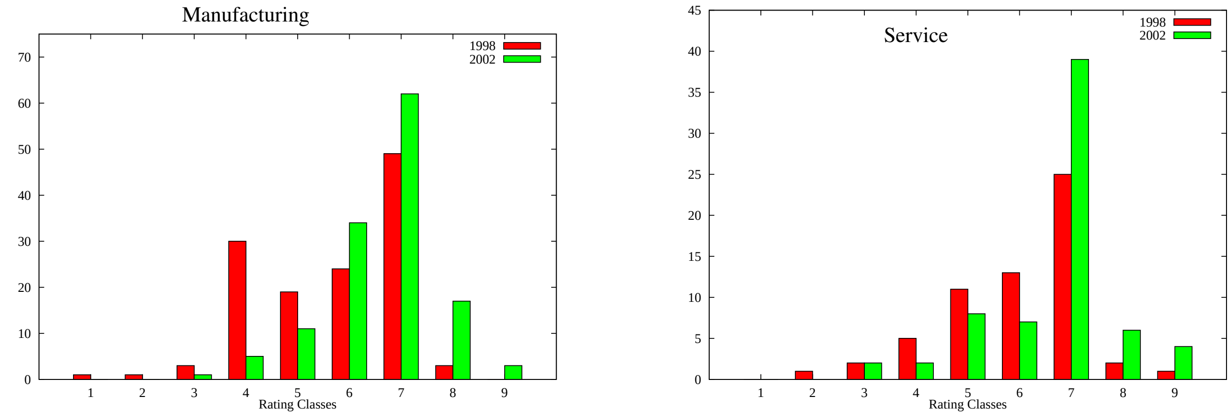

Figure 1: Number of Defaulting Firms in 1998 and 2002, by rating class - Manufacturing (**left**) and Service (**right**).

1998, 5 to 6 years before default, the credit ratings are slightly better, but the overall situation does not differ much: classes from 1 to 5 are more crowded than in 2002, but most of the firms still fall in between classes 4 and class 7, and none of them is receiving a 9. Looking at Services yields quite the same conclusion: credit ratings do deteriorate as the default event approaches, but jumps from solvency to default are not much less frequent than jumps from very bad financial conditions to complete distress.

A second interesting issue regards a comparison between defaulting firms and the rest of the sample. In Figure 2 we look again at defaulting firms broken down by rating classes in 1998 and 2002, but we now show their percentage over the overall number of firms (defaulting plus non-defaulting) active in each class in the same years. The picture emerging here is much more similar to the story one would guess a priori, that is to observe (i) an increasing percentage of defaulting firms when moving from class 1 to class 9, in each year; and (ii) an increasing relevance of the worst rating classes, as the time of default approaches. Consistently with such conjectures, we find that, in both sectors, the percentage of defaulting firms is much higher in classes from 6 (or 7) to 9 than in the other categories, and a clear rightward shift of mass does appear over time.

To improve the statistical reliance of the exercises performed so far, we estimate the transition probabilities of observing firms moving across the different rating classes, and from each of them into default. For ease of presentation of the results, we assign the firms included in the sample to three classes only, which we name Low Risk (with CeBi rating 1-3), Mid Risk (rated 4-7) and High Risk (rated 8-9). Notice that the term 'Risk' is just a shortcut for 'risk of default' and should not mislead the reader towards interpretations in terms of other definitions of risk which are more conventional to mean-variance frameworks of financial economics, such as, for instance, variability of prices, growth rates or stock returns. Rather, the particular grouping employed in this work is only intended to gather firms with similar financial profiles according to their original rating.[3]

Table 2 shows the "long-medium run" (5 to 6 years) transition matrix for Manufacturing.

[3] Following Bottazzi *et al.* (2006) and Bottazzi *et al.* (2008) we check robustness of results with respect to including class 7 into the High Risk category, since this is suggested to have lower discriminatory power as compared to the other classes. Yet, findings were never significantly affected.

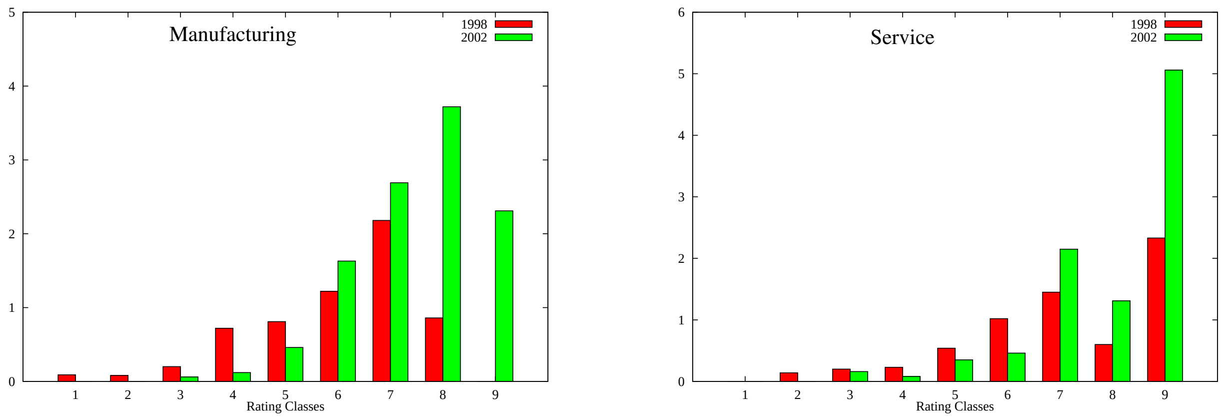

Figure 2: Percentage of Defaulting Firms in 1998 and 2002, by rating class - Manufacturing (**left**) and Service (**right**).

		2003			
		Low	**Mid**	**High**	**Default**
1998	**Low**	0.6969	0.2974	0.0048	0.0009
	Mid	0.1327	0.8247	0.0330	0.0096
	High	0.0909	0.6970	0.1991	0.0130

Table 2: Long-medium run transition to default - Manufacturing.

On the main diagonal one can read the estimated probability that a firm belonging to a specific rating class in 1998 ends up into the same class at the end of the sample period, whereas off-diagonal values capture the frequency of jumping from one class to another one, or to default. So, for instance, the first row tells that a firm classified as Low Risk at the beginning of the period has a probability of around 0.7 of remaining Low Risk five years later, an approximate 0.3 probability of becoming a Mid Risk firm, and negligible probabilities of either moving into the High Risk group or defaulting. Mid Risk firms, on the second row, display an even more stable pattern. The estimated probability of remaining in the same class is around 0.8, while they display an approximate 0.13 probability of improving their initial financial conditions and ending up into the Low Risk class, but a probability of only 0.03 and 0.01 to either move into the High Risk group or to default, respectively. However, the most interesting result emerge for those firms which were classified as High Risk in 1998. Indeed, we obtain that with a probability of around 0.7 and 0.09 they become Mid Risk and Low Risk firms, respectively, whereas the probability of either remaining High Risk or incurring default is much lower, 0.2 and 0.01 respectively. As a result, the estimated probability of recovering from a risky situation of bad financial conditions is much higher than the estimated probability of either remaining in the same bad situation or defaulting.

Even more surprisingly it is the fact that we face a quite similar result also when we look at the estimates of the "short run" (1 to 2 years) transition matrix, reported in Table 3. Given the quite short time span between the initial and the final instant of time considered, one would expect to observe a high degree of stability, with very few jumps across rating classes.

		2003			
		Low	**Mid**	**High**	**Default**
2002	**Low**	0.8219	0.1768	0.0013	0.0000
	Mid	0.0567	0.9064	0.0291	0.0078
	High	0.0064	0.4957	0.4742	0.0236

Table 3: Short run transition to default - Manufacturing.

		2003			
		Low	**Mid**	**High**	**Default**
1998	**Low**	0.7017	0.2847	0.0121	0.0014
	Mid	0.1589	0.7972	0.0381	0.0057
	High	0.1144	0.6617	0.2139	0.0100

Table 4: Long-medium run transition to default - Service.

Moreover, it would be hard to imagine bad firms to recover in only one or two years: our ex-ante conjecture is that, if jumps happened to occur for the High Risk firms, they should lead to default. Though, the results only partially meet our hypotheses. On the one hand, the probabilities on the main diagonal are all higher than they were for the long-medium run transition: not surprisingly, the probability of changing rating class is lower than what observe above. On the other hand, however, we still observe that, exactly as before, High Risk firms display a probability of switching to better financial conditions which is not much different (roughly 0.5) than that of either remaining in the same group or defaulting.

Note however that such a turbulence does not prevent to identify a clearcut and expected result about the relationship between financial conditions and default probabilities. The estimates reported in the last column of the two matrices indeed reveal that a precise mapping characterizes the data, with the probability of default decreasing as the quality of the initial financial conditions increases: default is more likely for High Risk firms than for the other two groups, then Mid Risk firms come second, and Low Risk firms are those least likely to incur complete distress. Such a ranking shows up in both the matrices, but a closer comparison between them reveals that the time distance to default does anyway play a role. Indeed, while the default probabilities estimated for Low Risk and Mid Risk firms are quite comparable between the two transitions considered, the probability that High Risk firms end up defaulting almost doubles when one looks at the short run transition matrix.

In spite of some difference in the values, the estimates for Service firms, reported in Table 4 and Table 5, are substantially in accordance with the results just outlined for Manufacturing. We again observe that credit ratings are more stable along the short run transition than along the long-medium run transition, but also a strikingly high probability that High Risk firms experience an inter-temporal improvement of their conditions, irrespective of the time span considered. As compared to Manufacturing, the only difference emerges with respect to the estimated transition probabilities of ending up into default, which in Service are comparable across time not only for Low and Mid Risk firms, but also for the High Risk group.

		2003			
		Low	**Mid**	**High**	**Default**
2002	**Low**	0.8178	0.1795	0.0021	0.0006
	Mid	0.0750	0.8838	0.0361	0.0051
	High	0.0219	0.5570	0.4101	0.0110

Table 5: Short run transition to default - Service.

Summarizing, we robustly observe that the credit ratings for Low Risk and Mid Risk firms are very stable, meaning that, both along the short and the medium-long run transition, there is a very small probability that these groups experience changes in the quality of their financial conditions. On the contrary, the dynamics of the credit rating of firms classified as High Risk are much more turbulent, in a rather unexpected way: especially over the medium-long rum, but also very close to default, they display a surprising tendency to recover from initially bad financial records, with an estimated probability of jumping back to better ratings which is comparable or even higher as compared to the estimated probability of remaining High Risk. Nevertheless, it always holds true that the firms rated as High Risk in the initial year have an higher probability to end up defaulting than the other firms in the sample: CeBi credit ratings still retains an informative content in terms of firms' expected ability to meet their financial obligations.

4 Transition to default and economic performance

Looking at the credit rating allowed to carry on a concise analysis of how the diverse financial conditions of firms are related with default. In this section we pursue a different, *real* rather *financial*, perspective. We now ask how the event of default correlates with, and to some extent is determined by, some dimensions of firms' economic operation and performance as crucial as size-growth dynamics, profitability and productive efficiency.

In parallel with the perspective adopted above in exploring the linkages between financial conditions and default probabilities, we will be addressing two specific research questions. On the one hand, we follow the intertemporal patterns experienced along such economic dimensions by the defaulting firms, in the years before default. The issue will be tackled comparing the statistical properties of the empirical distribution of size, growth, productivity and profitability measured at the beginning of the sample period (in1998) with those emerging 1 to 2 years before the default event (in2002). On the other hand, a second point concerns whether, and to what extent, defaulting firms differ from the other firms present in the sample. For this purpose, we will estimate the empirical distribution of the same economic variables for *all* the firms present in the database in 1998 and 2002, and we will try to identify how defaulting firms rank within the entire sample.

From a methodological point of view, a common characteristic with respect to both the research questions resides in the choice of adopting non parametric (kernel) techniques which focus on the entire distribution of the different economic dimensions, rather than more traditional, parametric approaches which are mainly concerned with estimating average behavior. Such a decision avoids to impose any structure to the data, allowing to take a fresh look

Variable	Sample	Mean 1998	Mean 2002	V.C. 1998	V.C. 2002
Total Sales	Defaulting	24681	34482	2.26	2.18
	Aggregate	23882	27314	3.94	6.29
Growth	Defaulting	0.11	-0.17	4.02	-1.80
	Aggregate	0.03	-0.01	6.87	-17.11
Profitability	Defaulting	0.07	0.02	1.64	5.67
	Aggregate	0.10	0.09	0.95	1.16
Productivity	Defaulting	46.68	44.58	0.55	1.29
	Aggregate	55.80	59.00	0.66	0.80

Table 6: Mean and Variation Coefficient (VC) of Total Sales, Growth, Profitability and Labour Productivity, in 1998 and 2002. Defaulting firms and entire sample, Manufacturing.

on the heterogeneities possibly existing both within and across defaulting *vis a vis* surviving firms.

A note is also due on measurement issues. Indeed, for all of the relevant economic variables we will be discussing, several different proxies have been proposed in the literature. The findings presented in Bottazzi *et al.* (2006) and Bottazzi *et al.* (2008) on the very same dataset which is used in the present work, however, suggest that the use of alternative measures is not very likely to significantly affect the results. Therefore, we consider here one single proxy for each of the economic dimensions. Firm size is measured in terms of Total Sales (TS), and, accordingly, the simple log-difference of Total Sales, g^{TS}, is used to measure firm growth. Then, we proxy profitability with the Returns on Sales (ROS), that is the ratio between operating margins and revenues. Finally, efficiency in production is captured by a standard proxy of Labour Productivity, i.e. in terms of value added per employee. Descriptive statistics on these variables are shown in Table 6 for defaulting firms vis a vis the entire sample of firms. Note that here, as well as in the rest of the section, we show results only for Manufacturing, since the evidence from Service firms, which we did explore, was supportive of very similar conclusions.

Let us start with the analysis of firm size distributions. In the two panels of Figure 3 we plot, on a double logarithmic scale, the kernel density of TS estimated for defaulting firms and for the overall sample in 1998 and in 2002. To help comparability between the two groups, in the bottom part of each figure we also depict the actual values of TS for each defaulting firm.

First look at 1998. The most apparent feature is that the two distributions are very similar in both the supports spanned and in the shapes, which is remarkably right-skewed, a property repeatedly found in the literature of firm size distribution. Together, these two characteristics tell us that, somewhat contrary to what one might conjecture on the basis of theory and empirical research on firm survival, defaulting firms are neither less heterogeneous nor smaller with respect to the entire sample. Actually, we find that default events could even be more frequent among medium-big sized firms, rather than at small sizes: consistently with the figures in Table 6, the mean seems even higher for defaulting firms, and their density turns out to be even more concentrated in the right part of the support, as compared to the others.

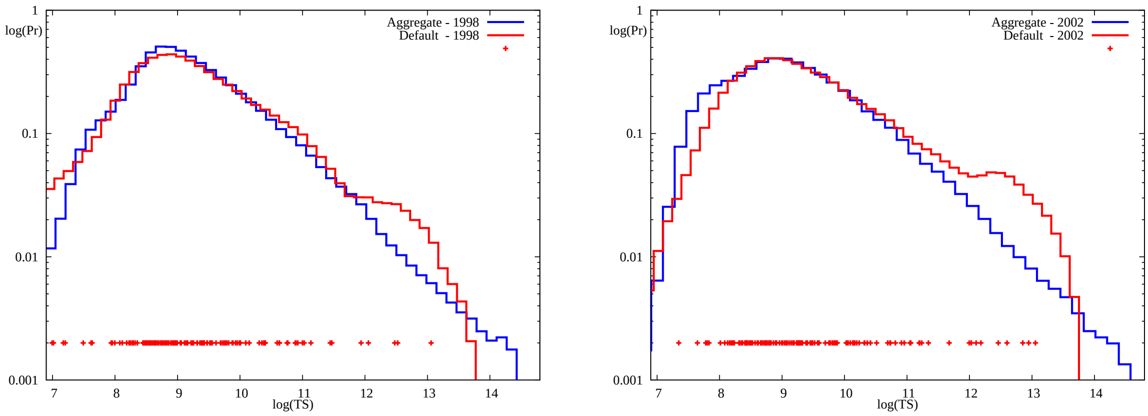

Figure 3: Empirical density of Total Sales (TS) in 1998 (**left**) and 2002 (**right**): Defaulting Firms and entire sample - Manufacturing.

This kind of story is robust across time: if anything, the right tail of the defaulting firms' distribution is even heavier in 2002, when it takes only 1 to 2 years to the default event, as compared to 1998, 5 to 6 years before default. The actual values of TS attained by defaulting firms clarify that the sort of second modes appearing in the right tails are essentially due to a limited number of very big firms. Still, the overlap in the central part of the densities, where most of the observations are placed, is almost perfect, so that, if not bigger, defaulting firms are for sure not smaller than the others, at least on average. This is enough to conclude that there is a lack of a clearcut relationship between size and the event of default: operating above a certain size threshold does not seem to be a relevant warranty in preventing default.

Next we focus on firms' growth rates. Figure 4 shows the kernel density of g^{TS} estimated in deviation from the annual sectoral (Manufacturing) average, that is in terms of market shares. Again, we propose a comparison between defaulting firms and the overall sample in both 1998 and 2002, and report actual values for the growth rates of defaulting firms below the estimated densities.

As far as the central part of the distribution is concerned, that is where one finds the most of the probability mass (approximately in $[-1, 1]$), the shape estimated for defaulting firms is not very different from the estimates obtained for the entire sample. This is clearly the case, for both the years, in the right part of this portion of support (consider the interval $[0, 1]$, i.e. at above average values of growth rates), while at below average values (about the interval $[-1, 0]$) defaulting firms are more concentrated in 2002, in accordance with the lower mean reported in Table 6. Though, when one considers the entire distribution, rather than the central part, a distinctive feature emerges: the support spanned are indeed different, with defaulting firms displaying a considerably lower degree of heterogeneity than the overall sample. This fact is reflected in both the left and the right tail, where the presence of defaulting firms is much less relevant, when not nil. Indeed, on the one hand, only 'non-defaulting' firms are present at extremely bad growth records in both the years. On the other, only few defaulting firms are responsible for the peaks observed at the top extreme in 1998, whereas extremely good performances in 2002 are attained only by firms which will not default one or two years later.

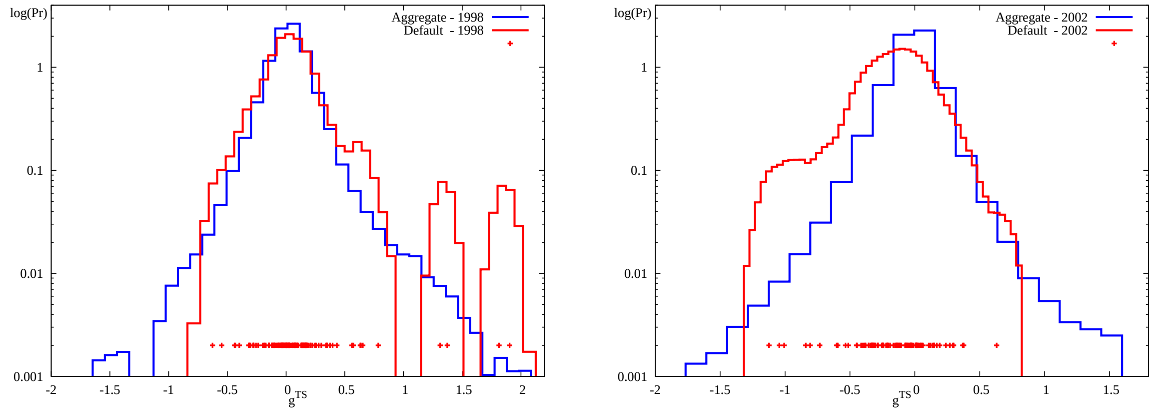

Figure 4: Empirical density of Total Sales Growth (g^{TS}) in 1998 (**left**) and 2002 (**right**): Defaulting firms and entire sample - Manufacturing.

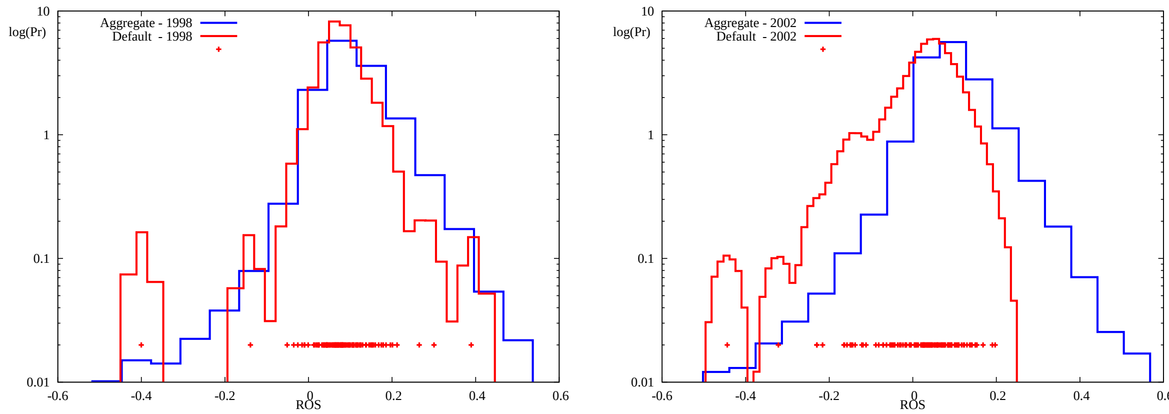

Figure 5: Empirical density of Profitability (ROS) in 1998 (**left**) and 2002 (**right**): Defaulting Firms and entire sample - Manufacturing.

The conclusion one can draw is that, overall, defaulting firms do not grow systematically slower than the other firms, independently from the distance to default: similarly to what we observed with size, we do not find clearcut peculiarities characterizing this sub-sample of firms as a particularly suffering group, as compared to the rest of the sample.

We then explore if similar results emerge also with respect to profitability, looking at the kernel densities of the ROS. Figure 5 reports estimates and actual values for defaulting firms in 1998 and 2002. Once again, we compare the latter with the densities estimated for the entire population of firms active in Manufacturing in the very same years.

In 1998, the two distributions display very similar shapes, and are substantially overlapping in the negative part of the support, whereas there are clear differences for what concerns the extent of heterogeneity and the weight of positive performances. Indeed, apart from few single cases on the far left end of the support, defaulting firms have shorter tails, meaning that they are less heterogenous than the overall sample. Moreover, their distribution lies below the

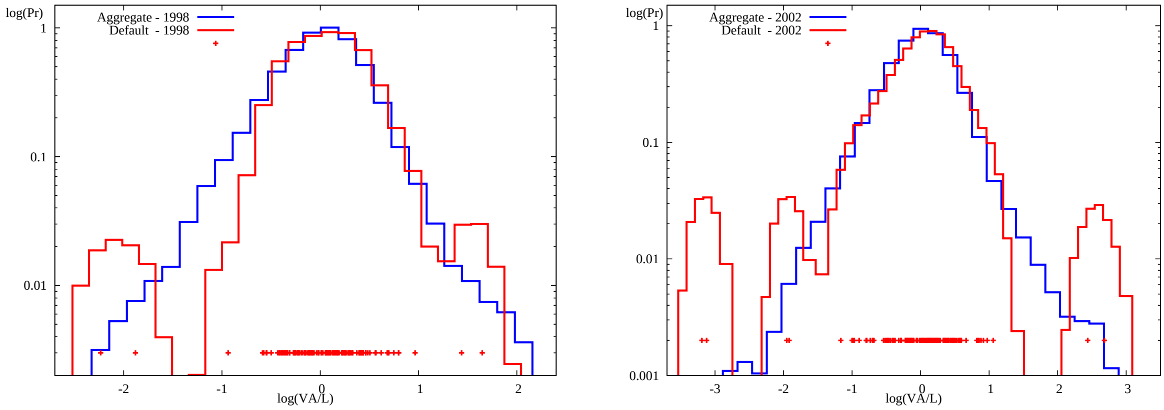

Figure 6: Empirical density of Labour Productivity (VA/L) in 1998 (**left**) and 2002 (**right**): Defaulting firms and entire sample - Manufacturing.

aggregate one in the positive part of the support, as reflected in the lower mean shown in Table 6. The same differences are present, and somewhat reinforced, in the estimates for 2002. The profitability density of defaulting firms turns out to be clearly shifted towards the left of the density estimated for the overall sample: the latter is more symmetric, whereas much of the probability mass of defaulting firms is concentrated at negative values. As a result, the distance between the two distributions in the right part of the support is even more apparent than in 1998, and a significantly heavier left tail for defaulting firms also emerges. Despite negative performance is experienced also by non-defaulting firms, there is nevertheless sufficiently robust evidence to conclude that defaulting firms are, on average, less profitable than the rest of the sample.

In this respect, the conjectures put forward by the theories of firm dynamics are confirmed by the analysis: some sort of selection on profitability seems to be at work. Interestingly, time plays an important role in the story, as defaulting firms are not different from surviving firms five years before default, but, rather, their performances seem to worsen over time until they become quite weak in the very short run (1-2 years) before default.

As a final step, we ask whether selection operates also on productive efficiency. The densities of Labour Productivity, estimated in (log) deviations from sectoral average, suggest that this might not be the case: efficiency does not act as a sharp discriminatory factor telling apart defaulting firms from surviving ones. Indeed, as Figure 6 shows, we observe something similar to what we noted above for size and growth. That is, defaulting firms are substantially identical to the entire sample in the most relevant part of the support (approximately in $[-1.5, 1.5]$), where one nets out the effect of some outliers possibly present among both extremely inefficient and extremely efficient firms. Again, the time distance to default does not play any role: the same picture is emerging both in 1998 and in 2002.

5 Estimation of default probabilities

The analysis conducted in the previous section on the distribution of economic performance has suggested that profitability stands up as the only relevant economic variable which is able to definitely discriminate between defaulting firms and surviving ones. Size, growth and productive efficiency, on the contrary, do not display any clearcut relationship with default, in spite of the major role attributed to these dimensions in theoretical and applied research.

To gain in statistical precision about how economic performance affect firm distress, we now turn to a more standard parametric analysis of default probabilities. This exercise, at the same time, will allow to control for the way the economic and financial dimensions of firm dynamics interact in explaining, or determining, firm default.

Given the dichotomous nature of the event which we are focusing on, namely the occurrence of default, binary choice models must be chosen in order to study the response probability of observing the outcome, conditional upon a set X of k explanatory variables. Let y be a binary index so that $y = 1$ when a certain event (default, in our case) occurs, and 0 otherwise. Then, a binary choice model reads

$$P(X) = P(y = 1 \mid X) = P(y = 1 \mid x_1, x_2, \ldots, x_k) \qquad . \tag{1}$$

The interest lies primarily in estimating the partial (or marginal) effect of each x_j on the response probability, that is the approximate change in $P(y = 1 \mid X)$ when x_j increases, holding all the other variables constant. For continuous variables, this is given by

$$\frac{\partial P(X)}{\partial x_j} = \frac{\partial P(y = 1 \mid X)}{\partial x_j} \qquad . \tag{2}$$

If, instead, x_j is a discrete variable (for instance, a 0-1 covariate), one is interested into

$$P(x_1, x_2, \ldots, x_{j-1}, 1, x_{j+1}, \ldots, x_k) - P(x_1, x_2, \ldots, x_{j-1}, 0, x_{j+1}, \ldots, x_k) \qquad . \tag{3}$$

which tells us the difference in the response probability computed when x_j switches from 0 to 1, keeping all the other variables fixed.

Traditionally, binary choice response models have been estimated via two alternative ways, namely probit and logit models. They both specify (1) as

$$P(X) = P(y = 1 \mid X) = F(X\beta) \qquad , \tag{4}$$

that is, they assume $P(X)$ is a function of the covariates X only through a linear combination of the latter, $X\beta$, which, in turn, is mapped into the response probability via a certain function F. Then, the probit model is a special case of (4) with F given by

$$\begin{aligned} F(z) &= \Phi(z) \\ &= \int_{-\infty}^{x} \phi(v) dv \qquad , \end{aligned} \tag{5}$$

where $\Phi(z)$ is the cumulative distribution function of a standard normal variable, and $\phi(z)$ the associated density. The logit model, on the other hand, assumes F to follow a logistic distribution

$$\begin{aligned} F(z) &= \Lambda(z) \\ &= \frac{exp(z)}{1 + exp(z)} \qquad . \end{aligned} \tag{6}$$

In practical applications, however, it is very uncommon to observe that the two alternative models yield contrasting results in terms of estimated partial effect of the covariates on the response probabilities. This indeed holds true for all the analyses we will be performing in this section and, accordingly, we limit the discussion to probit estimation. For completeness, the results of logit regressions are reported in the Appendix at the end of the work.

In order to understand what binary choice actually estimate, a crucial point concerns a proper interpretation of the coefficients β_j and, more importantly, their relationship with the ultimate object of interest, that is the partial (or marginal) effect of each covariate on the response probability $P(X)$. For the probit model, when the explanatory variable is continuous, one can compute

$$\frac{\partial P(X)}{\partial x_j} = \phi(X\beta)\beta_j \qquad , \tag{7}$$

which clarifies that the partial effect of x_j depends on all the other covariates through $\phi(X\beta)$. Therefore, if one is interested into the magnitudes of the effects, a choice is required in order to evaluate the latter expression at some meaningful value of X, for instance at the sample average of the covariates, $\phi(\bar{X}\beta)$. On the contrary, if the interest only lies in the sign of the effects, the estimates of the β_j's alone are able to tell what is needed. Indeed, since the standard normal distribution has a strictly increasing cumulative distribution function, one has that $\phi(z) > 0$ for all z and, thus, the sign of the partial effect is just the same as the sign of β_j.[4]

To see how this framework can apply in the context of our exercise, it is essential, recall that we have information about default only for 2003, the last year in the sample. This means that, unfortunately, we are not able to apply panel data versions of the probit model, where one would exploit the time dimension of the data to control for firms unobserved heterogeneity. Rather, we will focus on a model of the form

$$P(X) = P(\text{Default}_{03} = 1 \mid X) = F(X\beta) \qquad , \tag{8}$$

and attempt several specifications with X including different sets of explanatory variables.

The time dimension will be used to explore the possible lagged effect of the explanatory variables on default. Specifically, in order to facilitate comparison with the evidence presented so far, we will pay attention to the predictive ability of variables measured in 2002, 1 to 2 years before default, and at the beginning of the sample period, that is in 1998, 5 to 6 years before default. In the same spirit of reproducing what done in the previous sections, we will also keep the distinction between Manufacturing and Service firms, running separate estimation within each of these two 'macro-sectors'. In addition, all the specifications we will be presenting include a full set of 2-digit sectoral dummies, intended to capture sector specific effects at a finer level of aggregation.[5]

The first two columns of Table 7 present our first specification of equation (8), where the effect of the economic variables *alone* is investigated. In this case the set of explanatory

[4] Something similar holds also true when x_j is a discrete variable.

[5] Due to consideration of space and to enhance readability, we will not present the corresponding estimates in the reported tables. Obviously, for some industries it was not possible to estimate the corresponding coefficient due to a relatively small, or null, number of default, and to collinearity problems. Though, when we were able to get an estimate, some of the dummies were indeed found to be statistically significant, suggesting industry effects might play a role.

Independent Variables	**Economic Variables and Lags** Manufacturing	Services	**Economic Variables, Lags and Rating** Manufacturing	Services
TS_{02}	0.000	0.000	0.000	0.000
	(0.865)	(0.722)	(0.854)	(0.849)
TS_{98}	0.000	0.000	0.000	0.000
	(0.988)	(0.301)	(0.678)	(0.280)
$PROD_{02}$	0.000	**-0.00002**	0.000	0.000
	(0.931)	(0.027)	(0.212)	(0.941)
$PROD_{98}$	-0.0001	0.000	0.000	0.000
	(0.053)	(0.693)	(0.525)	(0.388)
$PROF_{02}$	**-0.0246**	0.0011	-0.0008	0.00105
	(0.000)	(0.368)	(0.696)	(0.275)
$PROF_{98}$	0.0080	-0.0014	0.0017	-0.0004
	(0.380)	(0.532)	(0.712)	(0.616)
$GROWTH_{02}$	-0.0023	**-0.0111**	-0.0002	**-0.0023**
	(0.480)	(0.003)	(0.684)	(0.029)
$GROWTH_{98}$	**0.0029**	0.000	**0.0010**	0.000
	(0.000)	(0.848)	(0.001)	(0.597)
$RATING_{02}$			**0.0024**	**0.00114**
			(0.000)	(0.000)
$RATING_{98}$			-0.0001	0.00027
			(0.673)	(0.101)
Pseudo R^2	0.076	0.065	0.194	0.192
Obs.	12266	7840	12199	7786

Table 7: Probit estimates of default probabilities, marginal effects. Coefficients significant at 5% level are in bold. P-value for each coefficient in parenthesis.

variables X includes, for 1998 and 2002, the values of size (measured in terms of Total Sales, TS in the Table), efficiency (Labour Productivity, PROD in the Table), profitability (PROF, measured through the ROS), and growth (in terms of g^{TS}, GROWTH in the Table). To give a figure of the magnitudes, we report partial effects computed at the average values of the covariates, together with the associated *p-value* derived applying heteroskedasticity-robust standard errors.[6]

As already argued, theoretical models, supported by the extant empirical studies, tend to predict that all of the variables should reduce the probability of default. Though, the analysis of the empirical distribution of economic variables performed so far has suggested that such an interpretation might not be so obvious when looking at the data. Indeed, drawing upon the results obtained in Section 4, one would expect that, on average, only Profitability presents

[6]The same will apply throughout all the section.

a clear inverse relationship with default.

The picture emerging from the present probit analysis partially corroborates such a conjecture, but also offers some novel insights. These mainly concern the role played by time to default, and the comparison between the different patterns characterizing Manufacturing (second column of Table 7) and Services (third column). In the latter we observe that Productivity and Growth, as of 2002, are the only significant variables, whereas Profitability is not. The sign of the effects are coherent to what one might expect, as an increase in both these variables entail a reduction (very small one for Productivity) in the probability of default. Conversely, the estimates for Manufacturing suggest something very different. Here the effect of profitability in the short run (PROF_{02}) is significant, with the expected negative sign, but a long-medium run role of growth (GROWTH_{98}) also shows up, with a positive effect on the probability of default. Two are the puzzles. A first one has to do with the sign, as one would expect higher growth rates to be a signal of good performance in firms' core operational activities and, therefore, to observe a negative effect on default probabilities. Of course, an important caveat applies at the present stage of the analysis. We are indeed neglecting the possible impact of variability of growth rates, which might be related to another important issue, namely firm age, unfortunately not measured in our data. Secondly, there is a matter about the timing of the effect, since growth records at the beginning of the sample period are the only significantly affecting default, whereas short run growth seems not enough to help firms to recover.

Looking for additional insights, we propose a second specification wherein the CeBi rating index is added to the covariates. This allows to apply a robustness check for the previous results and, at the same time, provides a first attempt to see how the economic and financial dimensions interact in explaining default. Since the index is purposedly built as a measure of default risk, what we expect to observe is that it should take much of the explanatory power of the model.

The estimation results, shown in the fourth and fifth column of Table 7 for Manufacturing and Services respectively, tell us that this is indeed the case. The negative and significant effect of PROF_{02} observed for Manufacturing in the first specification actually vanishes, as well as the small effect of PROD_{02} observed for Services disappears. In addition, the partial effect of the rating index turns out to be highly significant in the short run (RATING_{02}), and a considerable increase in the goodness of fit of the model (Pseudo R^2 increases) is achieved with respect to the first specification. The more interesting result, however, is represented by the fact that growth keeps on playing a statistically significant role on default probability, in the same directions estimated above. Indeed, we still obtain a negative short term effect ($\mathrm{GROWTH}_{0}2$) in Services, but a puzzling positive impact of GROWTH_{98} among Manufacturing firms.

The relevance of the result is reinforced by its survival through the additional specifications presented in Table 8. Here, we broaden the scope of our analysis to include a set of financial indicators. As explained during the presentation of the dataset, we had the chance to access yearly figures about Interest Expenses (IE), leverage (in terms of Total Debt/Shareholders' Equity ratio, TD/SE), and Total Debt/Total Sales ratio (TD/TS). These are unfortunately not enough to fully describe financial structures, and quite less numerous than the wide number of financial variables or ratios traditionally used in bankruptcy prediction models. Their inclusion here is essentially meant to integrate the information content of the CeBi credit rating and, thus, to provide a wider account of the financial status of firms.

Independent Variables	Economic & Fin. Variables		Economic, Fin. &, Rating	
	Manufacturing	Services	Manufacturing	Services
TS_{02}	0.000	0.000	0.000	0.000
	(0.168)	(0.150)	(0.239)	(0.517)
TS_{98}	0.000	0.000	0.000	0.000
	(0.875)	(0.115)	(0.654)	(0.394)
$PROD_{02}$	0.000	**-0.0001**	0.000	0.000
	(0.963)	(0.046)	(0.482)	(0.944)
$PROD_{98}$	-0.0001	0.000	0.000	0.000
	(0.018)	(0.170)	(0.391)	(0.333)
$PROF_{02}$	**-0.017**	0.002	-0.001	0.000
	(0.001)	(0.839)	(0.910)	(0.370)
$PROF_{98}$	0.006	0.001	0.001	0.000
	(0.391)	(0.862)	(0.825)	(0.906)
$GROWTH_{02}$	-0.008	**-0.009**	0.000	-0.002
	(0.534)	(0.005)	(0.698)	(0.041)
$GROWTH_{98}$	**0.003**	-0.001	**0.001**	0.000
	(0.000)	(0.213)	(0.002)	(0.247)
IE_{02}	**1.80e-06**	**8.24e-07**	**6.00e-07**	0.000
	(0.001)	(0.049)	(0.001)	(0.074)
IE_{98}	**-9.06e-07**	0.000	**-3.00e-07**	0.000
	(0.046)	(0.199)	(0.034)	(0.555)
TD/SE_{02}	0.000	0.000	**-5.5e-06**	0.000
	(0.094)	(0.149)	(0.020)	(0.815)
TD/SE_{98}	0.000	0.000	**3.36e-06**	0.000
	(0.320)	(0.485)	(0.016)	(0.999)
TD/TS_{02}	**0.0001**	0.000	**0.0001**	0.000
	(0.000)	(0.386)	(0.003)	(0.943)
TD/TS_{98}	0.000	0.000	0.000	0.000
	(0.403)	(0.120)	(0.483)	(0.167)
$RATING_{02}$			**0.002**	**0.001**
			(0.000)	(0.000)
$RATING_{98}$			0.000	0.000
			(0.888)	(0.148)
Pseudo R^2	0.116	0.083	0.209	0.200
Obs.	12264	7836	12197	7782

Table 8: Probit estimates of default probabilities, marginal effects. Coefficients significant at 5% level are in bold. P-value for each coefficient in parenthesis.

In the first specification presented (second and third columns of Table 8) the financial indicators enter together with the economic variables, but without the credit ratings. This should substantially mimic the exercise performed in our first specification (column 2 and 3 of Table 7 above) and, indeed, the results are quite the same. In Manufacturing, $GROWTH_{98}$ displays again a strikingly positive sign and, in addition, we also get an expected negative effect of short run profitability, while in Services an equally expected negative sign is found for both short run efficiency and short run growth. The magnitudes are also very similar to the findings emerged from our first specification. Moreover, none of the financial variables seem to play a role, with the minor exception of IE, whose effect is anyway fairly small.

Lastly, we perform probit estimates of a fourth specification, where we consider the wider possible set of regressors, including both economic and financial variables, together with credit rating.

As shown in the last two columns of the same Table 8, the basic conclusions are not affected. Indeed, even if some of the financial variables turn significant in Manufacturing, their effect is very small, so that the single major result concerns the fact that short run credit ratings and growth are the only variables playing a role in predicting default. Once again, however, the estimates obtained for growth in Manufacturing are quite intriguing, with respect to both the negative sign and the medium-long run timing of the effect. Noticeably, nothing changes if one tries to improve the modeling of growth dynamics: both the sign and the timing of the effect of growth were preserved when we tried and re-estimate the last column of Table 8 with all the possible additional lags of growth.

6 Conclusion

Economic models of firm dynamics put the greatest attention on the selection process which results from the interactions of market pressures with heterogeneities in firms' economic characteristics such as size, growth, productivity and profitability. The effect of these variables on default is, instead, much less explored in standard frameworks of bankruptcy prediction originated within financial economics. The ultimate goal of this paper has been to try and bridge the predictions coming from the two strands of research, focusing on the respective role played by financial and economic dimensions of firm operations, in view of a multidimensional and empirically driven description about the possible determinants of default. We address important questions like: is it true that default is mainly a financial phenomenon, as suggested by standard financial literature, or rather, some economic variable turns out to be important? And, if it is so, are there economic dimensions where this is the case and other which contradict such conjectures? How does time distance to default interplay with all of these issues?

Some of the analyses have provided pieces of evidence which certainly agree with the findings of previous studies and also with what theory suggests. At the same time, other results, although still at a preliminary stage, are less expected and opens up space for further research.

We proceeded in three steps. We first focused on how default relates with a credit rating index associated to all the firms present in the database, which we use as a synthetic measure of financial conditions. Transition probabilities of moving across different rating classes or defaulting confirmed that the likelihood of default decreases with the quality of firms' initial financial conditions. Moreover, time distance to deafult seems also to act in the expected direction. Indeed, consistently with what one might conjecture a priori, the probability that financially unstable firms incur default increases as the default time approaches. However, the unexpected finding was that the firms characterized by the worst financial situation display a transition probability of improving their credit worthiness which is higher than the probability of either remaining in the same bad situation or defaulting. This finding is notably robust across Manufacturing and Service firms.

Secondly, we turned the attention to economic variables, and compare the kernel densities of size, growth, productivity and profitability estimated for a sub-sample of firms defaulting at the end of the sample period, with the characteristics of those obtained for the entire sample. The results were particularly intriguing, since the existing empirical evidence, based on traditional regression approaches, tend to support the idea that, at least *on average*, the likelihood of survival should be increasing in all the dimensions considered. Instead, our analysis based on techniques concerned with the *entire* distribution of performances, rather than with average effects, shows that selection operates more tightly on profitability than on the other relevant dimensions, at least for the Italian case. Indeed, we found that only the empirical distribution of profitability is much more concentrated around very poor performances for the subsample of defaulting firms, as compared to the estimates obtained for the entire sample. At the same time, defaulting firms were not found to display any distinctive characteristic in terms of systematically smaller sizes, slower rates of growth, or lower productivity. Interestingly, time distance to default, as well as the sector of activity considered, did not add any remarkable insight on these points.

Finally, to gain in statistical precision, and also to recompose the picture about the *simultaneous* effect of both economic and financial indicators on firm default, we tackle a more standard, parametric approach and estimate default probabilities via binary choice models. A series of alternative specifications of probit and logit regressions, also controlling for 2-digit industry effects, showed robust evidence supportive of the following conclusions. On the one hand, as predicted by many studies in financial economics, we found that credit ratings and, relatedly, financial conditions, are confirmed to significantly affect the probability of default. Remarkably, their effect is relevant only in the very short run, that is 1 to 2 years before default occurs. On the other hand, the analyses revealed that growth, rather than profitability, turns out as the only economic variable significantly affecting default, once financial fragility are controlled for. Though, the way growth impinges on default might be more complex than expected: the effect differs across sector of activity and over time, and presents a puzzling sign in some instances. Indeed, short run growth (occurring 1 to 2 years before default) negatively affects default probabilities in Services, but it is medium-long run growth (measured 5 to 6 years before default) which significantly impacts on default in Manufacturing, with a puzzling positive sign.

7 Appendix: logit analysis

For completeness, we report here the results obtained with logit estimation. Table 9 reports the first and second specification of the model, that is including economic variables alone and economic variables plus CeBi rating, respectively. In Table 10, instead, we show the two alternative specifications which also include the financial indicators among the covariates.
In the logit specification the probability of the outcome $y = 1$ is modeled as

$$\begin{aligned} P(X) = P(y = 1 \mid X) &= \Lambda(X\beta) \\ &= \frac{exp(X\beta)}{1 + exp(X\beta)} \quad , \end{aligned} \tag{9}$$

with corresponding marginal effect of the each covariate x_j given by

$$\frac{\partial P(X)}{\partial x_j} = \Lambda\left(X\beta\right)\left[1 - \Lambda\left(X\beta\right)\right]\beta_j \quad . \tag{10}$$

Therefore, as we already noted for the probit model, the sign of the effects is directly given by the sign of the estimated β_j's, whereas their magnitudes depend on the values of all the explanatory variables. As for the case of probit estimation, a choice is required in order to evaluate expression 10 at some meaningful value of X, for instance at the sample average $\bar{X}$. The logit model, however, offers an alternative and convenient way to present the results based on the odds of the outcome $y = 1$. Define the latter as

$$O(y = 1 \mid X) = \frac{P(X)}{1 - P(X)} = e^{X\beta} \quad . \tag{11}$$

Then, given two realizations of X, say X_0 and X_1, one can define the odds ratio

$$\frac{O(y = 1 \mid X_1)}{O(y = 1 \mid X_0)} = e^{(X_1 - X_0)\beta} \quad , \tag{12}$$

which captures a change in the odds of observing the outcome $y = 1$ induced by a change of X from X_0 to X_1. Therefore, for each covariate x_j, one has that e^{β_j} tells us how the odds of $y = 1$ changes when x_j changes by one unit

- if $e^{\beta_j} > 1$ the variable x_j increases the odds of $y = 1$
- if $e^{\beta_j} < 1$ the variable x_j decreases the odds of $y = 1$.

All the results in the Tables are reported in this format and must be read accordingly.

Independent Variables	**Economic Variables and Lags** Manufacturing	Services	**Economic Variables, Lags and Rating** Manufacturing	Services
TS_{02}	0.9999	0.9999	0.9999	0.9999
	(0.967)	(0.665)	(0.608)	(0.569)
TS_{98}	1.0000	0.9999	1.0000	0.9999
	(0.850)	(0.387)	(0.435)	(0.516)
$PROD_{02}$	0.9974	0.9969	1.0016	0.9998
	(0.705)	(0.066)	(0.171)	(0.924)
$PROD_{98}$	0.9935	0.9998	0.9982	1.0003
	(0.158)	(0.959)	(0.626)	(0.555)
$PROF_{02}$	**0.1196**	1.3025	1.2167	2.6028
	(0.016)	(0.135)	(0.740)	(0.198)
$PROF_{98}$	2.2805	0.7187	1.7028	0.7219
	(0.428)	(0.296)	(0.782)	(0.468)
$GROWTH_{02}$	0.7003	**0.1001**	0.9363	0.2791
	(0.453)	(0.003)	(0.698)	(0.069)
$GROWTH_{98}$	**1.3876**	0.9768	**1.3492**	0.9693
	(0.000)	(0.795)	(0.004)	(0.732)
$RATING_{02}$			**2.2715**	**2.1771**
			(0.000)	(0.000)
$RATING_{98}$			0.9936	1.2051
			(0.939)	(0.091)
Pseudo R^2	0.068	0.063	0.186	0.187
Obs.	12266	7840	12199	7786

Table 9: Logit estimates of default probabilities, odds ratios. Coefficients significant at 5% level are in bold. P-value for each coefficient in parenthesis.

Independent Variables	**Economic & Fin. Variables** Manufacturing	Services	**Economic, Fin. &, Rating** Manufacturing	Services
TS_{02}	0.9999	0.9999	0.9999	0.9999
	(0.165)	(0.410)	(0.210)	(0.517)
TS_{98}	1.0001	0.9999	1.0000	0.9999
	(0.671)	(0.385)	(0.484)	(0.394)
$PROD_{02}$	0.9989	0.9969	1.0009	0.9996
	(0.852)	(0.014)	(0.394)	(0.944)
$PROD_{98}$	0.9929	0.9991	0.9974	0.9994
	(0.085)	(0.330)	(0.500)	(0.333)
$PROF_{02}$	**0.1505**	1.1138	1.4377	2.2228
	(0.017)	(0.761)	(0.530)	(0.370)
$PROF_{98}$	2.1097	1.1271	1.2597	1.0530
	(0.451)	(0.899)	(0.894)	(0.906)
$GROWTH_{02}$	0.8518	**0.1086**	0.9552	0.2843
	(0.574)	(0.004)	(0.676)	(0.041)
$GROWTH_{98}$	**1.4202**	0.8155	1.3798	0.8183
	(0.002)	(0.491)	(0.014)	(0.247)
IE_{02}	**1.0002**	1.0001	**1.0002**	1.0001
	(0.001)	(0.108)	(0.000)	(0.074)
IE_{98}	0.9999	1.0001	0.9999	1.0000
	(0.052)	(0.148)	(0.011)	(0.555)
TD/SE_{02}	0.9985	1.0004	**0.9998**	1.0000
	(0.284)	(0.140)	(0.007)	(0.815)
TD/SE_{98}	1.0013	1.0001	**1.0013**	1.0000
	(0.095)	(0.396)	(0.009)	(0.999)
TD/TS_{02}	**1.0083**	1.0005	**1.0050**	0.9998
	(0.001)	(0.443)	(0.006)	(0.943)
TD/TS_{98}	0.9987	1.0017	0.9986	1.0015
	(0.582)	(0.126)	(0.569)	(0.167)
$RATING_{02}$			**2.1324**	**2.1593**
			(0.000)	(0.000)
$RATING_{98}$			1.0122	1.1868
			(0.894)	(0.148)
Pseudo R^2	0.102	0.078	0.199	0.194
Obs.	12264	7836	12197	7782

Table 10: Logit estimates of default probabilities, odds ratios. Coefficients significant at 5% level are in bold. P-value for each coefficient in parenthesis.

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