The determinants of financial distress in French farms: Analysts versus Algorithms

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Abstract

This paper analyses the determinants of the financial distress observed on French farms. Using individual data collected in a French bank, we estimate an ex-ante risk of financial distress based not only using automatic algorithms and composite scores but also using the bank analysts' opinion. Effective distress is measured ex-post through payment incidents. One salient result is the strong correlation that exists between all the indicators considered in the analysis, and between these indicators and noticed distress. The estimation of tobit and logit models shows that all these indicators are able to predict the occurrence of an incident and its duration. While algorithms and composite scores seem to provide better predictions, information from analysts offers complementary perspectives. Such information may be useful for the bank by making explicit key indicators leading to distress such as capital structure.

Keywords: Financial distress, Agricultural finance, France

JEL Numbers: G21, G33, Q14

1 Introduction

For decades, French agriculture has been experiencing a decline in the number of professional farms. Between 2000 and 2010, one quarter of all farms disappeared, reducing their number to 490,000 in metropolitan France (Butault and Delame, 2003; Giroux, 2011). One salient fact is the almost exclusive fading of small farms, mainly in cattle breeding and wine-growing. In return, medium and large farms continued to expand their acreage, which denotes a search for a critical size. A similar trend has been noticed in the U.S. (Katchova and Ahearn, 2017). This evolution was confirmed in 2015 and 2016 because of the fall in prices of agricultural commodities, which was coupled with the drop in yields due to natural hazards (Kalkuhl *et al.*, 2016).

The analysis of the literature emphasizes the economic context as a key factor of farm growth and decline. Legislation on farm bankruptcy also appears to be a factor of preservation (Stam and Dixon, 2004). The influence of agricultural policies through subsidies helps farms to modernize their equipment and successfully negotiate technological changes (Huffman and Evenson, 2001). At the farm level, large or growing farms are more likely to survive (Van de Gucht *et al*, 2000). Weather conditions are also key factors leading to drop in yields, thus resulting in income losses and therefore financial distress. The characteristics of the owner are decisive in the development of farms, such as the owner's personal investment in the activity. While young ones are mostly growth-oriented, older ones are tempted to prepare their retirement by disinvesting (Gale, 1994; Rizov and Mathijs, 2003). Furthermore, the degree of personal investment of the holder in his activity is essential for the future of the company (Aubert and Perrier-Cornet, 2009). A farmer focused primarily on his farm is more attached to ensure its continuity. Finally, specialization has a significant impact on the process of decline, as some sectors are flourishing less than others (Blanchard *et al*, 2012).

The financial situation of farms appears to be another key determinant of their decline because a precarious situation, potentially denoted over several years, could lead to a business interruption (Weiss, 1999). A wide literature exists in finance and economics related to firm distress, which stresses the conjunction of several financial parameters. Three criteria emerge particularly in the literature. The first criterion is the level of activity that determines the size and resilience of a firm to a shock (Bernanke and Gertler, 1987). The largest firms are naturally the best prepared to resist in this configuration. The second criterion is indebtedness (Altman, 1984). Debt plays an ambiguous role insofar as it serves to expand the firm by providing the capital necessary for its development, but it can also turn against it if interest charges are too heavy. The third criterion is the level of profitability that measures the profitability from the point of view of the holder (Shepard and Collins, 1982): a low or negative profitability inevitably leads to the end of the farming activity.

However, when considering agricultural economics, financial factors such as indebtedness and profitability appear to have been studied less than structural factors. The reason for this is often the absence of individual data relating to agricultural accounting. From a methodological point of view, financial distress is usually identified using ratios and scores, which compute and combine financial-key parameters (Colson *et al.*, 1993; Desbois, 2008; Aubert and Enjolras, 2016). Such

scoring methodology is indeed commonly used in the banking sector to offer a synthetic indicator of default risk. However, access to banking data is very often restricted, which leads to estimate the financial distress by processing individual data the Farm Accountancy Data Network (FADN) and comparing the obtained indicators to common thresholds (Aubert and Enjolras, 2016). Although it remains possible to define and measure the financial difficulty of each farm, such limitation is a significant barrier to a precise identification and assessment of financial distress.

In order to overcome this difficulty, our work relies on data obtained from a partnership with Crédit Agricole, a French bank which provides loans to most of farms in this country. We focus more precisely on 677 farms located in the Auvergne-Rhône-Alpes region, the fourth producing area in France, which is characterized by a diversity of agricultural productions and a representativeness of the French agriculture (Agreste Auvergne-Rhône-Alpes, 2016). The data were gathered at the regional seat of the bank, with the service in charge of bank loans. They include a wide set of individual, structural, accounting and financial components (balance sheets and income statements) over 3 years for each farm. In addition to these figures which are processed automatically, we compiled individual forms filled manually by bank analysts (individual data and remarks) for each farm, especially when these farms request a loan.

By combining the elements emphasized by the literature and the elements included in our database, we are able to examine various aspects of the measure of financial distress. Each distress is indeed the result of a combination of several financial parameters, such as a high level of indebtedness or low profitability that can be associated with individual fragilities. It can also be appreciated through the analysts' experience. Consequently, we simultaneously consider various ways to measure the financial distress risk, which are used in the banking sector:
- 16 specific risk ratios (Altman and Hotchkiss, 2006) which include measures of activity, return, solvency, liquidity and efficiency. Key ratios are compared to a reference level, so as to define a degree of distress. A synthetic score can then be computed in order to count the number of critical ratios.
- 2 composite indicators: Basel II solvability test and Anadefi®, a software solution designed by the bank, which takes into account the whole financial situation of a farm through algorithms. This type of indicators is commonly used in the banking sector to summarize default risk.
- The personal opinion of financial analysts in charge of the risk analysis of borrowing farms. This opinion consists in two measures: Firstly, 6 positive and 5 negative indicators (*e.g.* fragile structure, bad weather conditions) can be noticed by these analysts and translate their personal opinion regarding a farm wealth. These indicators are then transformed into dummies and scores through a counter. Secondly, the financial analyst provides his opinion regarding loans requested by farms.

Such analysis allows to complement the literature by offering a new insight of financial distress in the agricultural sector. Our approach is original insofar we compare the evaluation of financial distress both through algorithms, composite scores and bank analysts. Moreover, we are able to check whether the *ex-ante* risk of financial distress is confirmed *ex-post* through payment incidents. The banking activity offers a unique vantage point insofar the solvency of the farm and its ability to pay back each month the principal and the interests are critical for this sector (Briggeman *et al.*, 2009). Banking is also a commercial activity which belongs to a competitive sector. Usually, banks

and their customers have close relationships because of the long duration of credits, thus reinforcing the role of analysts (Heider and Inderst, 2012).

This paper aims at contributing to the literature on farm financial situation and distress in three ways. Firstly, we use direct bank information, which allows improving precision regarding the individual, structural and financial characteristics of studied farms. Secondly, we take into account both the objective and the subjective dimensions in evaluating distress, by analysing various definitions of distress. Thirdly, we explain distress measured *ex-post* through observed payment incidents using econometric models (tobit and logit) which take into account both the various dimensions of distress above-mentioned measured *ex-ante*.

This article is organized as follows. In the first part, we present more precisely the framework and the methodology of this study by proposing measures of financial distress. In the second part, we develop the empirical framework used for this analysis. In the third part, we detail the results, especially correlations among indicators and the econometric models. In the fourth part, we conclude by presenting the perspectives related to this study.

2 The measure of financial distress

This section proposes measures of financial distress, which are adapted to farms. The measure of financial distress is a critical issue for the banking sector since a bad financial situation can lead to a default from the borrower. Consequently, banks perform systematic *ex-ante* analyses when a loan is requested in order to gather information whether it has to be fully granted, partially granted or denied. Such information is primarily used to reduce information asymmetries and especially adverse selection (Berger and Udell, 2006; Gustafson, 1989).

As a first step, we present specific risk ratios which allow to explore specific dimensions of financial distress. In a second step, we develop algorithms used in the banking sector. In a third step, we detail the measure of distress through the banking analysts' opinion. In a fourth step, we expose control variables, which appear relevant for the farm sector.

2.1 Specific risk ratios

The literature in agricultural economics emphasizes a set of criteria which may alert in advance on a possible financial distress (Altman, 1968; Altman, 1984; Altman and Hotchkiss, 2006; Beaver, 1966; Desbois, 2008). Considered criteria specifically encompass complementary facets of financial analysis. They are defined by ratios of indicators of the balance sheet and the income statement so as to consider both the farm structure and activity (Table 1).

Table 1. Financial distress criteria used in the analysis

Based on the literature and interviews with bank analysts, we were able to identify 6 main categories of ratios that are relevant for the banking sector: financial independence (or solvency), economic performance, productivity, profitability, debt servicing and liquidity. 16 individual ratios were specifically considered. Some of them may overlap, for example Equity/Total Assets and Debt/Total Assets. Others may provide different overviews of the same reality, for example Equity/Total Assets and Debt/Equity.

For each indicator, a critical threshold identified by the literature or banking practices defines a so-called at risk position. One should note that the analysis of ratios is relevant to compare companies among a given sector, by taking explicitly into account the economic structure.

2.2 Algorithms

Because a firm cannot be solely judged on one criterion in particular, financial distress may be defined by computing a risk score (Aubert and Enjolras, 2016; Colson *et al.*, 1993; Desbois, 2008). Banks use scoring methods as a convenient way to aggregate available information. Globally speaking, the literature shows that the "hard", quantitative information in credit scores provides a cost-effective method for lenders to assess loan applications and monitor borrowers (Akhavein *et al.*, 2005; Berger *et al*., 2005; Frame *et al.*, 2001).

The creation of scores requires a harmonization of different criteria that refer to different units. The overall score is then a linear combination of the dichotomous criteria identified previously. Weights may be unbalanced according to the importance of some source of difficulties. Composite indicators and algorithms rely on this technique (Table 2).

Table 2. List of variables used in the analysis

The implementation of Basel II regulation leads to a specific risk assessment, which takes into account doubts on the ability of the borrower to repay, the existence of arrears, bankruptcy proceedings and disputed trade receivables if so. The bank uses a ranking internal software, which allows classifying customers into 5 grades of risk, from 0 (very low) to 4 (proven risk), which correspond to a counterparty risk. By default, the measure of the risk of failure is in a year using previous accounting documents. Based on this "Basel II" score, the banks define both the commitment and delegation levels, the interest rate and the eventual automatic renewal of some lines of credit. It is computed based on the customers' banking practice and some key financial statements.

Anadefi®[1] is a software specifically designed for banks. This package manages customers' data as well as accounting records (balance sheet, income statement and statement of cash flows). The software is able to compute customized ratios and scores based on the financial risk and counterparty risk associated with the farm, using previous accounting and collected documents. A

[1] See a presentation on the official website of the software:
http://www.orsystem.com/site/?p=83&lang=en

synthetic score called "Anadefi" summarizes the financial position of the company, from 0 (excellent condition) to 3 (poor condition). A special score (4) is attributed to farms whose annual value of sales is lower than €76,300 and which benefit from a special tax system (lump sum payment). Due to their small activity, these farms are mostly considered at risk.

The bank may also assess risk at a given time using some individual indicators, which are automatically computed every day: the occurrence and duration of payment incidents, the number of days of arrear and the corresponding arrears, the average credit balance, a debt rescheduling and a break in debt payback.

2.3 Personal analysts' opinion

In contrast to the former "automated" figures, bank analysts can assess by themselves the degree of financial distress risk, by meeting the economic reality beyond the numbers. In practice, this is performed for each loan request, which is examined manually. The analyst states his own opinion regarding the project and its feasibility as well as other criteria such as his knowledge of individual customers. In the end, a credit committee decides whether granting or not a loan.

This kind of "soft" information is subjective in the sense that it is hard to quantify and communicate to others, and it may not be verifiable by outsiders (Cassar *et al.*, 2015). However, this information appears essential given that analysts may report issues even if risk ratios and scores respect usual standards (Gustafson, 1989). Subjective measures of financial distress can be addressed either through a range of individual indicators, through scores combining these indicators or through an overall opinion.

The personal opinion of the analyst is firstly related to the knowledge of his customer: his character (honesty, integrity and reliability), his skills and ability to operate his business. Secondly, loyalty and past transactions provide additional information on his attitude towards risk. Consequently, past dealings with a borrower may provide superior information for assessing his worthiness (Diamond, 1991; Petersen and Rajan, 1994). All these elements directly reduce information asymmetries. However, a long-term relationship may also lock-in customers within an unfavourable relationship (Bharat et al., 2011).

Analysts may also focus on the financial situation of the farm, *e.g.* financial structure, while putting emphasis on parameters that are not taken into account by automata, *e.g.* diversification of activities and sources of income, and the existence of guarantees. Other criteria, that are specific to the farming sector are also of interest to explain potential issues. For instance, unfavourable weather conditions and low prices during may help to identify or predicts a potential distress situation that a single financial analysis may not emphasize.

Finally, the personal opinion of an analyst can be observed directly through his decision regarding a requested loan. Basically, a loan granting decision can be examined through 4 modalities: full acceptation, with or without guarantees, partial acceptation and refusal. The analyst takes his decision according to the project's potential while taking into account the farm position and its ability to pay back.

2.4 Control variables

The introduction of control variables allows to put in perspective the measure of financial distress. Structural indicators, such as acreage (UAA) characterize the size of the farm. Considering a static analysis, a farm of significant size appears more able to protect itself against a failure. For that reason, an indicator of diversification is taken into account (Aubert and Perrier-Cornet, 2012). Tax situation is also an indicator of size, according to the tax regime chosen by the farmer: small French farms pay a flat tax while bigger ones pay a regular tax based on their effective income.

Individual and objective indicators such as the age and gender of the farm holder may be considered. A young farmer may be more able to contribute to the development of his farm while an older farmer may consider discontinuation of its activity. The personal property as well as the diversification of productions and activities represents factors decreasing both the occurrence of a distress and its consequences (Cary and Wilkenson, 1997).

As stated before, the banking relationship is a key parameter. It can be measured directly through the loyalty to the bank. Indirect measures include the amount already borrowed as well as requested new loans and their maturity.

3 Empirical framework

The proposed empirical framework helps measuring financial distress through the different aspects identified above. As a first step, we present the data collection and the context. Then, we expose the econometric modelling.

3.1 Database

We use data obtained from a partnership with Crédit Agricole, the second commercial bank in France, which provides loans to 9 farms out of 10, representing a total of 7.2 billion euros in 2014 (Crédit Agricole, 2015). Crédit Agricole was indeed created in 1894 to grant loans to farms. The group diversified later on its customers and customers, but it remains organized nowadays with the form of 39 independent regional branches, which are in turn divided into 2,474 credit unions.

Credits are granted by regional branches, our study being focused on Crédit Agricole Sud-Rhône-Alpes, which encompasses 3 departments (Ardèche, Drôme, Isère) in the South-East part of France. Our dataset consists in 677 farms located in the Auvergne-Rhône-Alpes region, the fourth producing area in France, which is characterized by a diversity of agricultural productions and a representativeness of the French agriculture (Agreste Auvergne-Rhône-Alpes, 2016).

The data were gathered at the regional seat of the branch, with the service in charge of bank loans. They include a wide set of individual, structural, accounting and financial components (balance sheets and income statements) up to a 3-year period for each farm. Data collection consisted in the compilation of individual forms filled either automatically (financial data, Basel II and Anadefi

scores) or manually by bank analysts (individual data and remarks). All these information is gathered within the bank and remains private. For the sake of analysis, data were anonymized.

Starting from these information, we could process collected data in several ways. Firstly, we computed the main ratios identified by the literature and analysts. Secondly, we grouped the analysts' comments, which were already freely written on the forms, into main dummy variables, *e.g.* "good capital structure". Then, overall scores of positive and negative opinions were created by adding the former dummy variables. The assumption made is that high negative scores are related to the financial distress risk.

3.2 Econometric modelling

This section extends previous analysis by explaining a situation of *ex-post* distress by a set of key indicators, which are measured *ex-ante*. More specifically, it seeks to understand which critical elements may predict an effective distress. To do so, we consider a dependent variable which relies on payment incidents. Such indicator appears appropriate since it offers a continuous measure of distress. We are then able to observe farms that face various stages of financial distress, from no difficulty to a series of difficulties.

Figure 1. Cumulated days of payment incidents in a year for each studied farm

As shown in Figure 1, most farms exhibit at least one day of payment incident each year. However, 20% of farms have no payment incident. The dependent variable is thus censored at 0 for the lower bound and at 365 for the upper bound. In that case, the ordinary least square methods (OLS), which assumes that the dependent variable is normally distributed, appears inappropriate. Consistent estimates are obtained by the maximum likelihood estimation of a Tobit model (Maddala, 2001).

Formally, the model can be synthesized as follows:

$$y_i^* = \propto + X_i'\beta + \varepsilon_i \text{ with } \varepsilon_i \sim N(0, \sigma^2) \text{ and } i = 1, \dots, n \quad (1)$$

$$y_i = \begin{cases} t_i^* \text{ if } t_i^* > 0 \\ 0 \text{ if } t_i^* < 0 \end{cases} \quad (2)$$

Where y_i^* is the latent endogenous distress variable which corresponds to the quality of the financial position of the farm, and y_i is the observed endogenous variable. X is a matrix of farm and farmer's characteristics, and β is the corresponding vector of parameters to be estimated. ε_i is assumed to be the normally and independently distributed error terms. Because our analysis relies on observations at a given point in time, we are not able to estimate a panel data analysis.

In order to measure the difference between distressed farms and non-distressed farms during one year of observation, we could transform the original dependent variable into a dichotomous one. The new variable allows to distinguish farms (20%) which exhibit at least one day of payment incident from farms which do not (80%). In that case, the econometric approach relies on a standard binomial logit model, with a dichotomous endogenous variable (Mc Fadden, 1984).

$$Y_i = \begin{cases} 0 \; if \; no \; payment \; incident \; is \; reported \\ 1 \; if \; at \; least \; one \; payment \; incident \; is \; reported \end{cases} \quad (3)$$

To the extent that this variable is related to another latent non-observable random variable y_{it}^*, which takes the form:

$$Y_i^* = \alpha + X'_i \; \beta + \varepsilon_i \quad (4)$$

Where ε_i conditional upon X_i follows a logistic distribution, *i.e.,* $F(a)=1/(1+\exp(-a))$.

If also the relationship is of the type $Y_i = 1$ if $Y_i^* > 0$, and zero otherwise, we obtain:

$$Prob(Y_i = 1 \; / \; (X_i)) = Prob(Y_i^* > 0 \; / \; (X_i)) = F(\alpha + X'_i \; \beta) \quad (5)$$

Where, therefore, Prob (y_i=1/(x_i)) is the probability of being distressed.

The variable y_i^* can be understood as the quality of the financial position of the farm, which is a function of the farm and farmer's characteristic. A farm is to be distressed when unfavourable parameters exceed favourable parameters, namely when $y_i^* > 0$.

Regression parameters determine the extent to which the latent variable y_i^* increases with the independent variables. A positive sign increases the probability that the farm is distressed and decreases subsequently the quality of the financial position.

4 Results

This section considers the choice of relevant financial distress indicators among the ones identified in the previous sections. To do so, we study the correlation between these indicators. Then, we characterize farms according to their degree of financial difficulties. Econometric models allow to check for the predictive power of *ex-ante* distress indicators regarding *ex-post* payment incidents.

4.1. Financial distress indicators

The first step of the analysis consists in examining the correlations among the various *ex-ante distress* indicators (Table 3). Although Anadefi and Basel II indicators are expressed in classes, the continuity in classes (ordered by ascending order of estimated risk) allows to consider these indicators as continuous variables. A similar reasoning applies for counters of the numbers of strengths and weaknesses, as well as for the difference between these two counters, for the analyst opinion regarding a requested loan and for distress scores.

Table 3. Correlations among financial distress indicators

Examination of the tables demonstrates an overall consistency: algorithms, counters and ratios are positively correlated when risks measures are both on increasing/decreasing scales and negatively correlated when risk measures are expressed on opposite scales. For instance, Basel II ranking is increasing with risk and so is Ratio1a (significant positive correlation), while Ratio1b is decreasing with risk (significant negative correlation).

Moreover, most indicators are closely correlated with each other. Notable is the strong correlation between aggregate scores and counters, whether computed through automatic algorithms or the combination of information gained from analysts. A negative Anadefi or Basel II score is therefore associated to a larger number of weaknesses noticed by the analyst and to a smaller number of strengths, and conversely. Such result was not obvious *prima facie* given that strengths and weaknesses mostly encompass non-financial criteria, such as the loyalty and the knowledge they have of their customers.

It also appears that Anadefi and Basel II algorithms exhibit the strongest correlations (0.48), which may indicate a redundancy. The weakest (but significant) correlation is found between the number of strengths and weaknesses noticed by bank analysts, which may imply that they do not base their positive and negative opinions on the same criteria. Even the manual "distress score" computed according to the main ratios (and the corresponding thresholds) considered by Crédit Agricole analysts is significantly correlated with all the other indicators.

Figure 2. Proportion of farms facing financial difficulties by criteria and ETO

Figure 2 allows to observe the main *ex-ante* financial distress risk indicators (Anadefi, Basel II, Number of strengths and Number of weaknesses) according to the farm specialization. On average, between 20-30% farms are very risky according to the bank and its analysts (Anadefi $\geq$ Poor, Basel II $\geq$ High risk, Strenghts ≤ 1, Weaknesses ≥ 2). We observe some heterogeneity in productive orientation. For example, farms specializing in "field crops", "dairy cattle" or "meat cattle" are perceived as riskier than farms specializing in "wine-growing" or "market gardening". This observation seems consistent with the reality in some sectors. Over the last years, prices of cereals and meat dropped, while volatility in yields increased (Kalkuhl et al., 2016).

4.2 Farms facing financial distress

In itself, effective financial distress can only be noticed *ex-post*, according to the occurrence of disorders on the farmer's bank account. As stated before, a convenient way to monitor and measure difficulties is to observe payments incidents. Using this criterion, we can split farms in two categories, whether they have exhibited or not at least one day of payment incident over the last 365 days at the time of observation. Then we observe the distress criteria that were measured during a previous state of play (e.g. considering the latest accounting documents).

Table 4. Ex-post payment incidents versus ex-ante distress criteria

The results emphasize that farmers displaying payment incidents were considered significantly more at risk by algorithms (Anadefi and Basel II). Not surprisingly, the distress score based on key

financial ratios appears to be significantly higher for distressed farms. Purely financial algorithms and composite indicators are therefore reliable predictors of a future distress.

Distressed farms were also granted more weaknesses and less strengths by analysts. However, the ranking providing by analysts regarding a loan request does not appear to be significant in the detection of a distress situation. Despite the amount of collected information before a loan is granted, this result may indicate an overconfidence of bank analysts in their final decision. Yet, amounts already borrowed are higher for farms exhibiting payment incidents.

Unexpectedly, all control variables included in our analysis, such as the acreage, the technical and economic orientation of the farm, the age and gender of the farm holder do not significantly differ according to the occurrence of a payment incident.

4.3. Econometric models

To confirm and further develop these results, econometric models using tobit and logit regressions are implemented for explaining *ex-post* financial distress as a function of the ex-ante distress indicators and farm characteristics. In order to avoid any endogeneity bias, it is important to recall that the explained variable (payment incidents) was not used in the computation of any explicative variables and, in any case, distress indicators are computed with previous available information.

2 classes of econometric models are estimated according to the nature of the dependent variable (Table 5 and Table 6): number of days in a year with payment incidents (tobit) or existence of at least one day with payment incident in a year (logit). Given the strong correlation observed between *ex-ante* distressed criteria, we estimate, for each class, 9 different models, one with a different estimation of *ex-ante* distress. A large set of control variables is included in each model.

Table 5. Econometric models (tobit)

Table 6. Econometric models (logit)

We firstly notice that results of both econometric models (tobit and logit) converge, which implies that considering the occurrence of a payment incident is, in itself, as relevant as considering the number of days of incidents, for the measure of effective distress.

Not surprisingly, results from descriptive statistics are confirmed, especially regarding algorithms. A higher Anadefi or Basel II score leads to a higher risk of payment incidents. The Basel II score appears to be very discriminant: a high or a proven risk indicate that a farmer's bank account may have payment incidents at least half a year. Coefficients associated to the distress score computed manually are also significant, but of a lesser magnitude.

Similarly, the number of strengths noticed by the bank analyst decreases the likelihood to be distressed. Only in the tobit model, the number of weaknesses increases the number of days of incidents. In detail, capital structure appears to be a very discriminant parameter in the occurrence

and extent of an effective distress. On the whole, control variables are not significant, which implies that risk distress criteria may not need to be targeted among farm specializations.

While the explanative power of all models is validated using a Chi2 test, a comparison between them can be done according to the Bayesian Information Criterion – BIC (Schwarz, 1978). Although this criterion is not very different among models, both the tobit and the logit regressions indicate that the Anadefi, Basel II and Distress Score have the best predictive power. This result indicates that algorithms and purely financial criteria anticipate the most the occurrence of a payment incident. Despite the statistical relevance of the information gathered by analysts, the estimated models seem to be less predictive. This result suggest that banks may still rely on automatic monitoring indictors even if analysts bring a complementary dimension to risk analysis.

5 Conclusion

In this article, we proposed a study of French farms facing financial difficulties. In the current context of farm distress and exit, this work aimed at complementing the literature about financial distress, especially in the agricultural sector. Unlike many of the existing empirical literature, we used precise individual data from Crédit Agricole, the main bank of French farms. We focused on a sample of 677 farms and gathered individual, structural and financial data from the information systems of the bank. We took into account the analysts' opinion which was provided in a free-form format and then added to our database.

Consequently, we were able to estimate an *ex-ante* risk of financial distress based not only using automatic algorithms and composite scores but also using the bank analysts' opinion. Effective distress was measured *ex-post* through payment incidents, a continuous variable. One salient result is the strong link that exists between all the indicators considered in the analysis. In particular, the aggregate criteria (Basel II, Anadefi and composite scores) are strongly correlated to the personal opinion of financial analysts (number of strengths and weaknesses). One could argue that financial analysts are very sensitive to indicators of financial distress. Yet, they also take into account other aspects such as the loyalty and the knowledge they have of their customers.

The estimation of tobit and logit models shows that all these indicators are able to predict the occurrence of an incident and its duration. Algorithms and composite scores seem to provide better predictions, which validates current banking practices on risk monitoring. Information gained from bank analysts is also a relevant predictor of a future distress. Their analysis provides complementary perspective, especially regarding some specific criteria (*e.g.* capital structure) and the farmer' projects. While financial distress unequally affects farms according to their specialization, the latter does not seem to affect payment incidents.

This work offers many perspectives for future studies, such as helping to find more precisely weak signals leading to financial distress, especially over a longer observation period. The use of time series would also help identifying financial trajectories of potentially distressed farms. While our findings highlight the importance of taking into account precise individual data, information gained

would be of use at the aggregate scale of banks in order to monitor more accurately the solvency of the banking sector. The issue is salient insofar as banks represent a major source of financing for farmers in France and in Europe.

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7 Appendix

Table 1. Financial distress criteria used in the analysis

Criteria	Method of calculation	Risk threshold	Interpretation
1. Financial independence	***1a.*** Equity / Total assets ***1b.*** Debt / Equity ***1c.*** Debt / Total assets ***1d.*** Debt / Production	<25% >100% >75% >150%	Measure of dependence towards creditors
2. Economic performance	***2a.*** EBIDTA / Production ***2b.*** Profit / Production ***2c.*** Repayment capacity / Production	<15% <3% /	Operational performance of the farm
3. Productivity	***3.*** Production / Total assets	/	Ability of the farm to sell products regarding invested capital
4. Profitability	***4a.*** EBITDA / Debt ***4b.*** Return on Capital Employed ***4c.*** Return on Equity	<15% / /	Rate of return regarding the money invested
5. Debt servicing	***5a.*** Annuities / Production ***5b.*** Annuities / EBITDA ***5c.*** (Annuities + Private expenses) / EBIDTA ***5d.*** Annuities / Total assets	/ >60% >100% /	Sustainability of credit terms granted to farms
6. Liquidity	***6.*** Working Capital / Production	< 0	Safety margin ensured by the farm to pay for its current expenditures
Score	***Ratio 1a + Ratio 1d + Ratio 2a + Ratio 2b + Ratio 4a + Ratio 5b + Ratio 5c***	/	Overall risk score based on criteria closely monitored by Crédit Agricole

Note: thresholds without an asterisk denote a level of proven risk (over-indebtedness, inability to repay the debt, negative profitability) and are used in practice in the banking sector.

Table 2. List of variables used in the analysis

Variable		Unit	Definition
Year		-	Year of the study
ETO		-	Economic and technical orientation (in 9 classes = cereals, vegetables & market gardening, fruits & wine, cattle & sheep & goats, pigs & chickens, polyculture, mixed livestock, polyculture & mixed livestock, other farms)
Acreage		Hectare	Cultivated area of the farm
Personal property		Hectare	Cultivated area of the farm belonging to the farm holder
Diversification		Number	Number of different crops on the farm
Age		Year	Age of the farm holder
Gender		-	Gender of the farm holder
Tax situation		-	Flat tax vs. regular
Payment incidents		Number	Cumulated days of payment incidents in a year
Risk ratios		-	See Table 1
Algorithms	**Basel II**	-	Counterparty risk (Basel II score, in 5 classes = very low risk, low risk, medium risk, high risk, proven risk)
	Anadefi	-	Financial position (Software ranking, in 5 classes = excellent, good, fair, poor, other)
Analysts	**Strengths**	-	Counter + Specific items (good capital structure, sources of income outside the farm, farmer's wealth, feasibility of the project, good relationships between the bank and the farmer, experience of the farmer)
	Weaknesses	-	Counter + Specific items (fragile capital structure, low profitability, high indebtedness, poor season, no guarantee)
	Overall opinion	-	Ranking of a requested loan (favorable without guarantees, favorable with guarantees, partial acceptance, refusal)
Banking relationship	**Loyalty**	Years	Loyalty to the bank
	Amount already borrowed	€	/
	Amount of requested loans	€	/
	Maturity of requested loans	€	/

Table 3. Correlations among financial distress indicators

	Anadefi	Basel II	Number Strengths	Number Weaknesses	Ratio 1a	Ratio 1b	Ratio 1c	Ratio 1d	Ratio 2a	Ratio 2b	Ratio 2c	Ratio 3	Ratio 4a	Ratio 4b	Ratio 4c	Ratio 5a	Ratio 5b	Ratio 5c	Ratio 5d	Ratio 6
Anadefi	1.00																			
Basel II	0.48***	1.00																		
Strengths	-0.28***	-0.31***	1.00																	
Weaknesses	0.18***	0.23***	-0.09***	1.00																
Ratio 1a	-0.38***	-0.28***	0.09**	-0.16***	1.00															
Ratio 1b	-0.00	-0.05	0.01	-0.04	0.00	1.00														
Ratio 1c	0.20***	0.12***	-0.02	0.09**	-0.87***	0.04	1.00													
Ratio 1d	0.03	0.08**	-0.09**	0.09**	-0.10**	0.24***	0.31***	1.00												
Ratio 2a	-0.25***	-0.17***	0.05	-0.15***	0.08**	0.03	0.07*	0.17***	1.00											
Ratio 2b	-0.21***	-0.21***	0.10***	-0.19***	0.07*	0.01	-0.03	0.16***	0.75***	1.00										
Ratio 2c	-0.12***	-0.10**	0.12***	-0.12***	0.05	-0.08*	-0.09**	-0.34***	0.22***	0.33***	1.00									
Ratio 3	0.12***	0.03	0.07*	0.02	-0.58***	-0.04	0.53***	-0.26***	-0.08**	0.05	0.16***	1.00								
Ratio 4a	-0.23***	-0.19***	0.05	-0.16***	0.15***	-0.02	-0.14***	0.22***	0.33***	0.37***	0.27***	0.28***	1.00							
Ratio 4b	-0.11***	-0.09*	0.10**	-0.08*	0.53***	0.00	-0.54***	-0.11**	0.13***	0.13***	0.12**	0.08*	0.46***	1.00						
Ratio 4c	0.00	0.02	0.03	-0.00	-0.01	0.02	-0.01	0.03	0.02	0.06	-0.02	0.01	0.10**	-0.01	1.00					
Ratio 5a	0.04	0.07*	-0.08**	0.10**	-0.05	0.13***	0.21***	0.71***	0.23***	-0.13***	-0.53***	-0.23***	-0.18***	-0.06	-0.00	1.00				
Ratio 5b	0.03	-0.03	0.00	-0.02	0.00	0.03	0.02	0.09**	0.03	0.03	-0.10**	-0.04	-0.04	0.01	0.01	0.14***	1.00			
Ratio 5c	0.02	-0.05	0.01	-0.04	0.00	0.01	0.00	0.03	0.02	0.07*	-0.14***	-0.04	-0.03	0.021	0.03	0.06*	0.90***	1.00		
Ratio 5d	0.15***	0.09**	0.05	0.05	-0.67***	0.00	0.70***	0.00	0.04	0.00	-0.10**	0.79***	0.14***	-0.02	0.03	0.25***	0.06	0.03	1.00	
Ratio 6	-0.48***	-0.32***	0.09*	-0.12***	0.31***	0.00	-0.08**	0.18***	0.19***	0.14***	-0.01	-0.19***	0.05	-0.02	0.03	0.11***	-0.03	-0.05	-0.17***	1.00

	Anadefi	**Basel II**	**Number of strengths**	**Number of weaknesses**	**Difference btw strengths and weaknesses**	**Analyst opinion**	**Distress score**
Anadefi	1.00						
Basel II	0.48***	1.00					
Strengths	-0.28***	-0.31***	1.00				
Weaknesses	0.18***	0.23***	-0.09***	1.00			
Diff. btw S and W	-0.32***	-0.37***	0.85**	-0.59***	1.00		
Analyst Opinion	0.17***	0.19***	-0.24***	0.14***	-0.27***	1.00	
Distress Score	0.30***	0.22***	-0.13***	0.24***	-0.23***	0.22***	1.00

Source: Own database.

Key: Significances are the following: * p<0.05, ** p<0.01, *** p<0.001.

Table 4. Ex-post payment incidents versus ex-ante distress criteria

Variables	All farms	Distress measured through payment incidents		Differences in distributions (Chi2 test)
		Never	At least one day in the year	
Anadefi Score				
Excellent	13.23%	29.73%	9.21%	
Good	17.46%	22.52%	16.23%	
Fair	47.27%	37.84%	49.56%	***
Poor	15.87%	3.60%	18.86%	
Other	6.17%	6.31%	6.14%	
Basel II Score				
Very low risk	18.20%	42.31%	11.81%	
Low risk	24.96%	40.00%	20.98%	
Medium risk	40.42%	16.15%	46.84%	***
High risk	15.62%	1.54%	19.35%	
Proven risk	0.81%	0.00%	1.02%	
Strengths & Weaknesses				
Number of strengths (counter)	2.07	2.39	1.99	***
Number of weaknesses (counter)	0.78	0.57	0.83	***
Diff btw strengths and weaknesses (counter)	1.29	1.82	1.16	***
Loan ranking				
Favorable without guarantees	51.31%	53.17%	50.82%	
Favorable with guarantees	32.52%	35.71%	31.69%	
Partial acceptance	6.70%	7.14%	6.58%	
Refusal	9.48%	3.97%	10.91%	
Distress score	2.27	1.68	2.43	***
Amount already borrowed	100,208	88,989	103,193	***
Loyalty (years)	19.55	20.60	19.26	
Usable Agricultural Area (UAA, hectares)	84.97	97.23	81.79	
UAA belonging to the farmer (%)	39.07%	43.45%	37.95%	
Tax situation (flat tax/regular)	94.61%	94.78%	94.56%	
Age of the farm holder (years)	46.84	46.46	46.94	
Gender of the farm holder (ref = man)	93.31%	93.89%	93.16%	
Diversification	1.86	1.92	1.84	
Technical and Economic Orientation of the farm				
Cereals	24.58%	34.52%	21.99%	
Vegetables / Market gardening	3.54%	5.17%	0.00%	
Fruits / Wine	29.93%	17.24%	31.70%	
Cattle / Sheep / Goats	20.52%	25.86%	9.75%	
Pigs / Chickens	5.24%	1.72%	9.75%	
Polyculture	6.48%	3.44%	4.87%	
Mixed livestock	2.00%	1.72%	4.87%	
Polyculture & Mixed livestock	6.48%	3.44%	17.07%	
Other farms	1.23%	6.89%	0.00%	

Source: Own database.

Key: A Chi2 test is performed to compare the differences in distributions for each variable according to the decision taken by the bank. A Kruskal-Wallis equality-of-populations rank test is specifically estimated for continuous variables. Significances are the following: n.s. not significant, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 5. Econometric models (tobit)

	Anadefi	Basel II	Number of strengths	Number of weaknesses	Difference btw strengths and weaknesses	Analyst opinion	Distress score	Detail of weaknesses	Detail of strengths
Anadefi 1	46.104**								
Anadefi 2	58.447***								
Anadefi 3	86.503***								
Anadefi 4	7.757								
Basel II 1		26.056**							
Basel II 2		87.726***							
Basel II 3		190.848***							
Basel II 4		237.340***							
Number of strengths			-18.434***						
Number of weaknesses				17.745***					
Diff btw S and W					-16.278***				
Analyst opinion 1						-4.024			
Analyst opinion 2						-4.456			
Analyst opinion 3						44.563**			
Distress score							8.692***		
Fragile capital structure								42.549***	
Low profitability								39.366***	
High indebtedness								-2.874	
Poor season								-8.591	
No guarantee								-7.368	
Good capital structure									-48.774***
Income outside the farm									3.994
Farmer's wealth									-15.906
Feasibility of the project									-32.001***
Good relationships									-5.530
Experience of the farmer									-4.909
Age	0.612	0.384	0.823	0.790	0.775	0.707	0.265	0.794	0.619
Gender	-18.331	7.953	-0.490	-5.150	0.339	-10.649	2.643	-2.114	-1.271
Acreage	-0.253**	-0.043	-0.202*	-0.260**	-0.207*	-0.245**	-0.199*	-0.233**	-0.148
Personal property	-15.826	-1.305	-8.723	-9.038	-7.588	-5.631	3.182	-14.736	1.312
Loyalty	-0.043	-0.202	0.020	0.025	0.037	-0.053	-0.048	-0.067	0.031
Amount borrowed	-0.009	0.001	-0.011	-0.010	-0.009	-0.012	-0.269***	-0.009	-0.010
Diversification	-0.036	6.176*	0.309	-0.414	0.095	0.382	-0.691	-0.707	0.515
Vegetables	-29.033	-54.084**	-40.400	-44.487	-41.821	-58.198*	-40.464	-44.188	-37.941
Fruits & wine	-23.035	-4.818	-27.225*	-27.055*	-25.865*	-27.736*	-21.249	-27.707*	-18.987
Cattle & sheep & goats	22.157	7.250	9.953	20.922	13.021	11.203	20.253	17.389	9.622
Pigs & chicken	26.343	4.038	33.576	31.177	30.339	31.547	37.018	20.352	39.502*
Polyculture	-14.706	-23.612	-23.601	-30.098	-27.166	-24.009	-21.480	-28.438	-21.883
Mixed livestock	26.126	31.482	39.855	35.462	40.050	38.203	17.341	33.142	35.353
Polyculture & livestock	-3.524	1.663	-14.212	1.456	-10.191	-1.639	2.057	2.899	-3.832
Other farms	-3.138	26.952	-32.334	-15.828	-27.924	-49.134	-31.500	-6.203	-25.541
Intercept	18.972	-48.033*	77.514*	32.496	60.376	52.986	49.268	37.250	75.988*
/sigma	83.058***	61.036***	84.514***	86.156***	83.683***	86.285***	87.399***	83.990***	82.067***
LR Chi2	69.91	341.60	64.31	47.66	72.91	39.44	60.53	70.67	93.17
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BIC	4384.8	4549.5	4716.9	4746.3	4696.4	4661.5	4368.1	4748.0	4718.9

Source: Own database.

Key: * p<0.05, ** p<0.01, *** p<0.001.

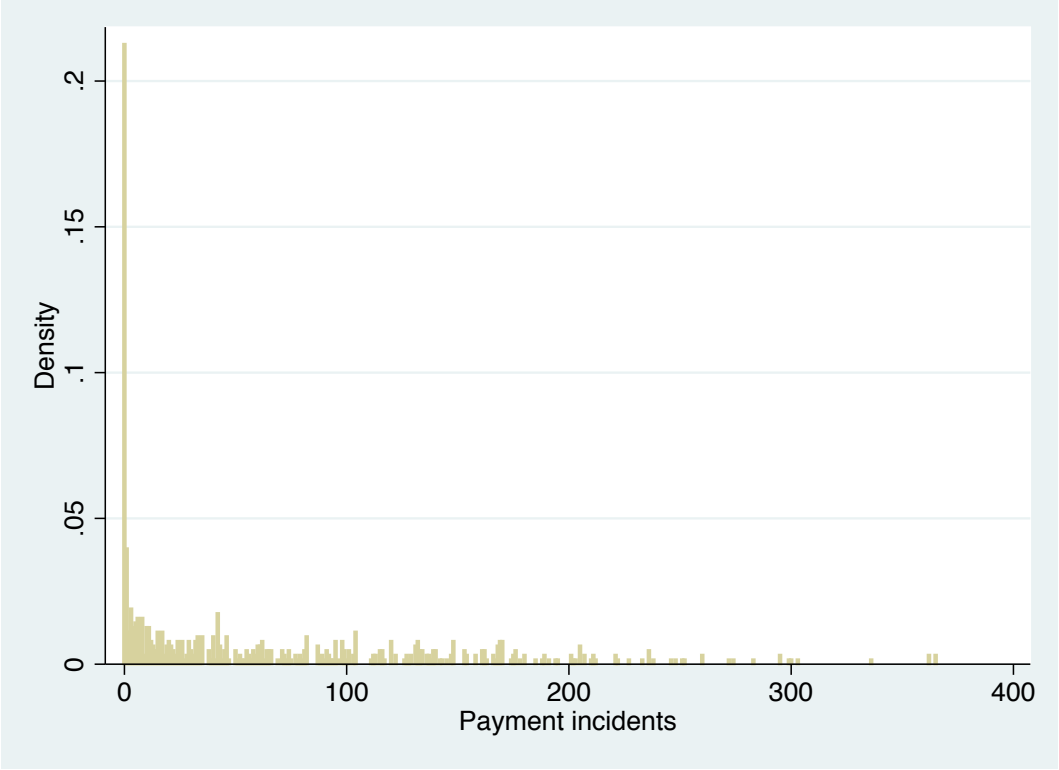
Table 6. Econometric models (logit)

	Anadefi	Basel II	Number of strengths	Number of weaknesses	Difference btw strengths and weaknesses	Analyst opinion	Distress score	Detail of weaknesses	Detail of strengths
Anadefi 1	0.743								
Anadefi 2	1.146***								
Anadefi 3	2.629***								
Anadefi 4	0.723								
Basel II 1		0.599*							
Basel II 2		2.270***							
Basel II 3		3.407***							
Basel II 4		0.000							
Number of strengths			-0.243*						
Number of weaknesses				0.263					
Diff btw S and W					-0.221**				
Analyst opinion 1						-0.262			
Analyst opinion 2						-0.224			
Analyst opinion 3						0.836			
Distress score							0.280***		
Fragile capital structure								1.387**	
Low profitability								0.555	
High indebtedness								-0.303	
Poor season								-0.130	
No guarantee								0.134	
Good capital structure									-1.297***
Income outside the farm									0.386
Farmer's wealth									-0.120
Feasibility of the project									-0.183
Good relationships									0.259
Experience of the farmer									-0.368
Age	0.006	0.006	0.006	0.006	0.006	0.007	-0.002	0.005	0.003
Gender	-0.088	0.585	0.211	0.178	0.242	0.108	0.647	0.113	0.230
Acreage	-0.006*	-0.003	-0.005*	-0.006**	-0.005*	-0.005*	-0.006*	-0.005*	-0.004
Personal property	-1.057*	-1.026*	-0.753*	-0.701	-0.733	-0.654	-0.427	-0.790*	-0.641
Loyalty	-0.011	-0.019	-0.013	-0.013	-0.013	-0.011	-0.021	-0.014	-0.011
Amount borrowed	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.005***	-0.000	-0.000
Diversification	-0.018	0.174	0.010	-0.004	0.008	0.059	-0.056	0.007	0.034
Vegetables	0.946	0.364	0.297	0.193	0.302	-0.077	0.262	0.083	0.459
Fruits & wine	-0.149	-0.049	-0.353	-0.333	-0.338	-0.345	-0.153	-0.325	-0.134
Cattle & sheep & goats	0.061	-0.277	-0.100	0.032	-0.064	-0.084	0.112	-0.039	-0.069
Pigs & chicken	0.018	-0.426	0.316	0.091	0.277	0.452	0.450	0.022	0.440
Polyculture	-0.152	-0.575	-0.808	-0.873	-0.849	-0.781	-0.611	-0.846	-0.715
Mixed livestock	0.848	0.787	1.011	0.969	1.020	1.020	0.605	1.021	0.982
Polyculture & livestock	-0.259	-0.167	-0.312	-0.071	-0.274	-0.052	0.199	0.021	0.090
Other farms	-0.823	-0.451	-1.372	-1.147	-1.317	-1.487	-1.830	-0.932	-1.303
Intercept	1.476	0.220	2.603**	1.922*	2.342**	1.947*	1.866	2.076*	2.611**
LR Chi2	48.38	96.13	29.24	25.62	31.44	24.60	52.78	39.09	53.43
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BIC	514.7	524.0	581.6	588.9	578.9	591.9	522.8	600.2	588.4

Source: Own database.

Key: * p<0.05, ** p<0.01, *** p<0.001.

Figure 1. Cumulated days of payment incidents in a year for each studied farm



Source: Own database.

Figure 2. Proportion of farms facing financial difficulties by criteria and ETO