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The role of bank analysts and scores in the prediction of financial distress: Evidence from French farms

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Abstract

The purpose of this paper is to explore the role of bank analysts and scores in the prediction of financial distress. For regulatory and economic reasons, banks are in the frontline for assessing financial distress through "hard" and "soft" criteria. While a large literature already exists on this topic, the agricultural sector has not been investigated. However, farms are risky businesses which mainly rely on bank loans for their development. Our analysis relies on a unique dataset of 1,045 farms which are customers of a French bank. Predictors of financial distress are based on risk scores and bank analysts' opinion. Zero-inflated negative binomial and logit regressions are used to assess their explanatory power of financial distress. Results show that scores, especially the one measuring the counterparty risk, are better predictors than analysts of the occurrence of an incident and its duration. Surprisingly, the duration of the customer-bank relationship does not allow us to predict future incidents. The analysis may be extended to other sectors such as small and medium-sized enterprises.

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1. Introduction

Finding themselves at the front line in the financing of economic activities, banks have to face a difficult trade-off between the magnitude of their expected profit and the control of specific risks related to their activity (Akins et al., 2016). Banks are thus strongly regulated given their crucial role in the economy and the risk they represent for financial stability (Hoque et al., 2015). In order to comply with both market and regulation constraints, banks play the role of a financial backer and as an ex-ante predictor of financial distress which can be defined as the "inability of a company to pay its financial obligations as they mature" (Beaver et al., 2011).

To do so, banks have to closely monitor their activities, especially regarding their customers' position. This can be done through a detection of potential sources of financial distress when a loan is requested. Facing information asymmetries, banks usually gather "hard" and "soft" information. "Hard" information relies on past accounting and financial figures related to activity, return, solvency, liquidity, and efficiency (Altman and Hotchkiss, 2010; Beaver et al., 2011). "Soft" information comes from an individual and prospective analysis of the customers' profiles and projects performed by bank analysts (Aristei and Gallo, 2017; Cassar et al., 2015). A very extensive literature in economics and finance has already tackled the issue of financial distress (see Altman and Hotchkiss, 2010, for a review), showing that industry-specific models get accurate predictability.

By contrast, only a few studies have addressed this topic for the agricultural sector (Dinterman et al., 2018). Farming is a capital-intensive activity, which requires a high level of cash in the short term and investments in the long term. Because most farms are sole proprietorship or family businesses (Aubert and Perrier-Cornet, 2009), their development relies on external financing. Therefore, most farms apply for bank loans (Wenner, 2010). Farming is also by nature a risky economic activity. Two unpredictable factors mainly influence farm income: yields and prices (Katchova and Ahearn, 2017; Kimura et al., 2010). In recent years, farming has been indeed weakened because of a fall in prices of agricultural commodities coupled with an increased volatility in yields due to natural hazards (Prager et al., 2018).

We propose a renewed study on financial distress which considers the key role of the bank as a predictor of financial distress for the farming sector. Existing studies consider individual data from national surveys and they measure financial distress through single indicators such as the debt-to-asset ratio or bankruptcy proceedings (Barry and Lee, 1983; Franks, 1998; Briggeman et al., 2009; Dinterman et al., 2018). Our contribution is to use precise banking data in order to compare the explanatory and predictive power of hard and soft information in the prediction of financial distress.

To that purpose, we use an original dataset obtained from a partnership with Crédit Agricole, a French bank that provides most farms with loans in this country. We focus more precisely on a sample of 1,045 farms located in the Auvergne-Rhône-Alpes region. The data were gathered at the regional headquarters of the bank, with the service in charge of bank loans. They include a wide set of individual, structural, accounting, and financial figures for each farm, which are processed automatically. They are combined with individual forms completed manually by bank analysts (individual data and comments) for each farm, especially when these farms request a loan.

Using this unique dataset, a comparison between hard and soft predictors of distress allows us to complement the existing literature on farms by offering a new insight into financial distress. We are then able to check whether the ex-ante risk of financial distress is confirmed ex-post. In practice, we assess financial distress through payment incidents noticed by the bank. The estimation of zero-inflated negative binomial and logit models allows us to explain distress measured ex-post according to distress indicators measured ex-ante.

This article is organized as follows. In the first part, we present more precisely the theoretical framework related to 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. In the fourth part, we conclude by presenting some perspectives related to this study.

2. Theoretical background

The literature on financial distress and bankruptcy has expanded since the seminal works of Altman (1968 and 1984). Some works focus on bankruptcy, which can be directly observed, while other studies rather focus on financial distress, a situation in between good health and bankruptcy (Farooq et al., 2018). Bankruptcy may happen suddenly as a direct consequence of a disaster, such as weather hazards in agriculture. In most cases, bankruptcy occurs at the end of a process of decline, which justifies the use of predictive models (de Andrés et al., 2012; Sun et al., 2014; Weiss, 1999).

The measure of financial distress is a critical issue for the banking sector because a poor 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 for the evaluation of whether it will 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).

2.1. Hard information – Ratios and scores

The literature emphasizes a set of financial criteria that may alert in advance on a possible financial distress. Some studies consider that this "hard" information can be summarized in one key criterion such as insufficient cash (Wruck, 1990) or negative equity (Ojala et al., 2016). Other works prefer the use of financial ratios such as liquidity and profitability which enable comparisons (Altman, 1968; Altman, 1984; Altman and Hotchkiss, 2010; Beaver, 1966; Sheng-Jung, 2009; Shepard and Collins, 1982). The preferred structural indicator is the debt-to-asset ratio which denotes the company's indebtedness (Altman, 1984): Debt plays an ambivalent role insofar as it serves to develop the firm by providing it with the resources needed for its development, but it can also turn against it if interest charges are too heavy.

Because a firm cannot be solely judged on one criterion in particular, financial distress may be defined by computing a risk score (Altman, 1984; Desbois, 2014). Banks use scoring methods as a convenient way to aggregate available information (Berger et al., 2005). Globally speaking, the literature shows that the hard, quantitative information in credit scores provides lenders with a cost-effective method of assessing loan applications and monitoring borrowers (Akhavein et al., 2005; Berger and Udell, 1995; Frame et al., 2001).

Banks are intensive score users given the implementation of the Basel II regulation (Thomas et al., 2017). They have to perform a specific risk assessment, which considers doubts on the ability of the borrower to repay, the existence of arrears, bankruptcy proceedings, and disputed trade receivables if any. Based on this "Basel II" score, banks define both the commitment and delegation levels, the interest rate, and the eventual automatic renewal of some lines of credit. These are based on the customers' banking practices and some key financial statements.

2.2. Soft, prospective and selective information - Analysts' opinion

In contrast to the former figures, bank analysts can assess by themselves financial distress risk, by scrutinizing the economic reality beyond the numbers. In practice, this is performed for each loan request, which is examined manually. Information is collected directly from customers who have to disclose "private" information related to their profile and their project (Moro et al., 2014). 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 fully verifiable by outsiders (Cassar et al., 2015). However, such information appears essential given that analysts may report issues even if risk ratios and scores meet the usual standards (Gustafson, 1989).

Among the main criteria considered in the literature, the personal opinion of the analyst is first related to the knowledge of the customer: the person's character (honesty, integrity, and reliability), skills, and ability to operate the business (Gustafson, 1989). Second, loyalty and past transactions provide additional information on the attitude toward risk. Consequently, past dealings with a borrower may provide superior information for assessing the borrower's creditworthiness (Diamond, 1991; Petersen and Rajan, 1994). All these elements directly reduce information asymmetries.

Analysts may also focus on the financial situation of the farm, *e.g.* financial structure, while putting emphasis on criteria that are not considered by standard indicators, e.g., diversification of activities and sources of income, and the existence of guarantees. They also have to assess the feasibility of the funded project and use not only past information but also prospective information. Bank analysts may combine this soft information with hard information in order to improve the quality of information (Berger et al., 2001) and to reduce manipulation issues (Godbillon-Camus and Godlewski, 2013).

3. Empirical framework

The proposed empirical framework helps in measuring financial distress through the different aspects identified above. As a first step, we present the data collection and the context. Then we detail variables used in the analysis. Finally, we present the econometric modeling.

3.1. Data collection

We use unique dataset obtained from a partnership with Crédit Agricole - the second largest commercial bank in France, which provides eight farms out of 10 with loans, representing more than €7 billion in 2018 (Crédit Agricole, 2019). Our dataset consists of 1,045 farms located in the Auvergne-Rhône-Alpes region, the fourth largest producing area in France, whose agricultural production is fairly close to the observed distribution for the whole of French agriculture (Agreste Auvergne-Rhône-Alpes, 2019).

The data include for each farm a wide set of individual, structural, accounting, and financial components (latest balance sheets and income statements). Data collection consisted of the compilation of individual forms completed either automatically (financial data, ratios and scores) or manually by bank analysts (individual data and remarks) during the period 2012-2017. All of this information was gathered within the bank and remains private. For the sake of analysis, data were anonymized, and no information was provided regarding the precise location of the farm and characteristics of the farm owner.

3.2. Variables used in the analysis

The comprehensive list of variables used in the analysis is provided by Table 1.

Table 1. List of variables used in the analysis

Variable		Unit	Definition
Year		-	Year of the study
Specialization		-	Economic and technical orientation (in 9 classes = field crops, market gardening, fruits & wine, cattle, granivores, mixed crops, mixed livestock, mixed crops & 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 productions on the farm (e.g. different crop types and livestock species)
Tax situation		-	Flat tax vs. regular
Payment incidents		Number	Cumulated days of payment incidents over the last year (from 0 to 365)
Scores	**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, not assessed)
Analysts	**Strengths**	-	6 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, farmer's experience) + 1 counter of noticed strengths from 0 to 6
	Weaknesses	-	5 specific items (fragile capital structure, low profitability, high indebtedness, poor season, no guarantee) + 1 counter of noticed strengths from 0 to 5
	Overall opinion	-	Ranking of a requested loan (favorable without guarantees, favorable with guarantees, partial acceptance, refusal)
Customer-bank relationship	**Loyalty**	Years	Duration of the customer-bank relationship
	Amount already borrowed	€	Amount already borrowed by the farmer
	Amount of requested loans	€	Amount of money requested by the farmer during the last application
	Maturity of requested loans	€	Maturity of the requested loan during the last application

Source: Own database.

First, we consider the "hard" information, by focusing on risk scores. The "Basel II" score is computed by an internal software in accordance with the international banking regulations. This score classifies automatically customers into five grades of risk, from 0 (very low) to 4 (proven risk), which correspond to a counterparty risk. The "Anadefi" score is provided by a software application specifically designed for banks. This package manages customers' data as well as accounting records (balance sheet, income statement, and statement of cash flows). The outcome is a synthetic score which summarizes the financial position of the company, from 0 (excellent condition) to 3 (poor condition). A special score (4) is attributed to small farms (value of sales lower than €76,300) which benefit from a special tax system (lump sum payment).

"Soft" information relies on the analysts' comments, which were freely written on individual forms. Comments include the own analyst's opinion regarding the project and its feasibility as well as other criteria such as the analyst's knowledge about individual customers. Because these comments, either positive or negative, express similar ideas among application files and among analysts, we could group them into main dummy variables, e.g., "good capital structure".

Then, following the scoring methodology, we created overall counters of positive and negative opinions by computing a linear combination of these dummy variables, assuming that each factor is of equal importance. We assume that high negative scores are related to a high perceived risk of financial distress and conversely that conversely high positive scores are related to a low perceived risk of financial distress.

Files at our disposal also include control variables that allow us to put the measure of financial distress into perspective. Structural indicators, such as the usable agricultural area (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 (Bernanke and Gertler, 1990). Personal property as well as the diversification of production and activities represent factors decreasing both the occurrence of a distress and its consequences (Cary and Wilkenson, 1997). 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. Specialization has also a significant impact on distress, as some sectors are flourishing less than others (Blanchard et al., 2012).

As stated before, the customer-bank relationship is a key criterion. It can be measured directly through loyalty to the bank. Indirect measures include the amount already borrowed as well as requested new loans and their maturity. Within a loan granting process, the analyst proposes a decision which is validated by a credit committee along four modalities: full acceptance with no guarantees, acceptance with guarantees, partial acceptance, and refusal.

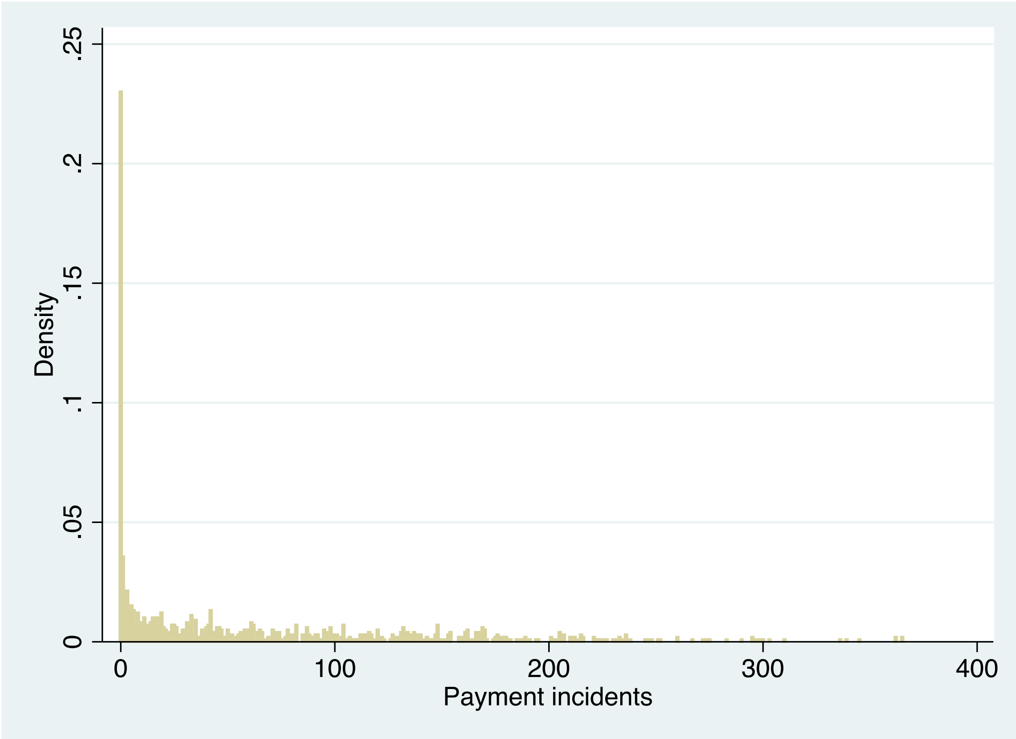
According to the definition of the financial distress made by Beaver et al. (2011), we chose to consider a dependent variable that relies on payment incidents which are defined according to the French Monetary and Financial Code (article D. 133-5) as “any rejection of a payment order received by the payer’s payment service provider due to default or insufficient provision, regardless of the means of payment used”. In practice, incidents are related to rejections of checks, transfers and debits. Measured over the previous 365 days, payment incidents provided a continuous measure of distress and was available for all farms in our sample. We were then able to observe farms that face various stages of financial distress, from no difficulty to a series of difficulties.

3.3. Econometric modelling

This section extends previous analyses by explaining a situation of ex-post distress, namely days of payment incidents, 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.

The choice of a relevant econometric modelling is driven by the characteristics of the dependent variable, which is a counter of payment incidents over the last 365 days before data were collected for each farm. As shown in Figure 1, the dependent variable is censored at 0 for the lower bound and at 365 for the upper bound. 23% of farms have no payment incident, which denotes an exemplary cash flow control. The standard deviation of the dependent variable (73.999) is also significantly greater that its average (59.685), which denotes an overdispersion in the data. In that case, the most suitable model is zero-inflated negative binomial regression, which accounts for overdispersed count variables with excessive zeros. Such model assumes that excess zeros are generated by a separate process from the count values (Cameron and Trivedi, 2013; Scott, 1997). In our models, we consider that excess zeros can be predicted by the Basel II score, which measures the counterparty risk.

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

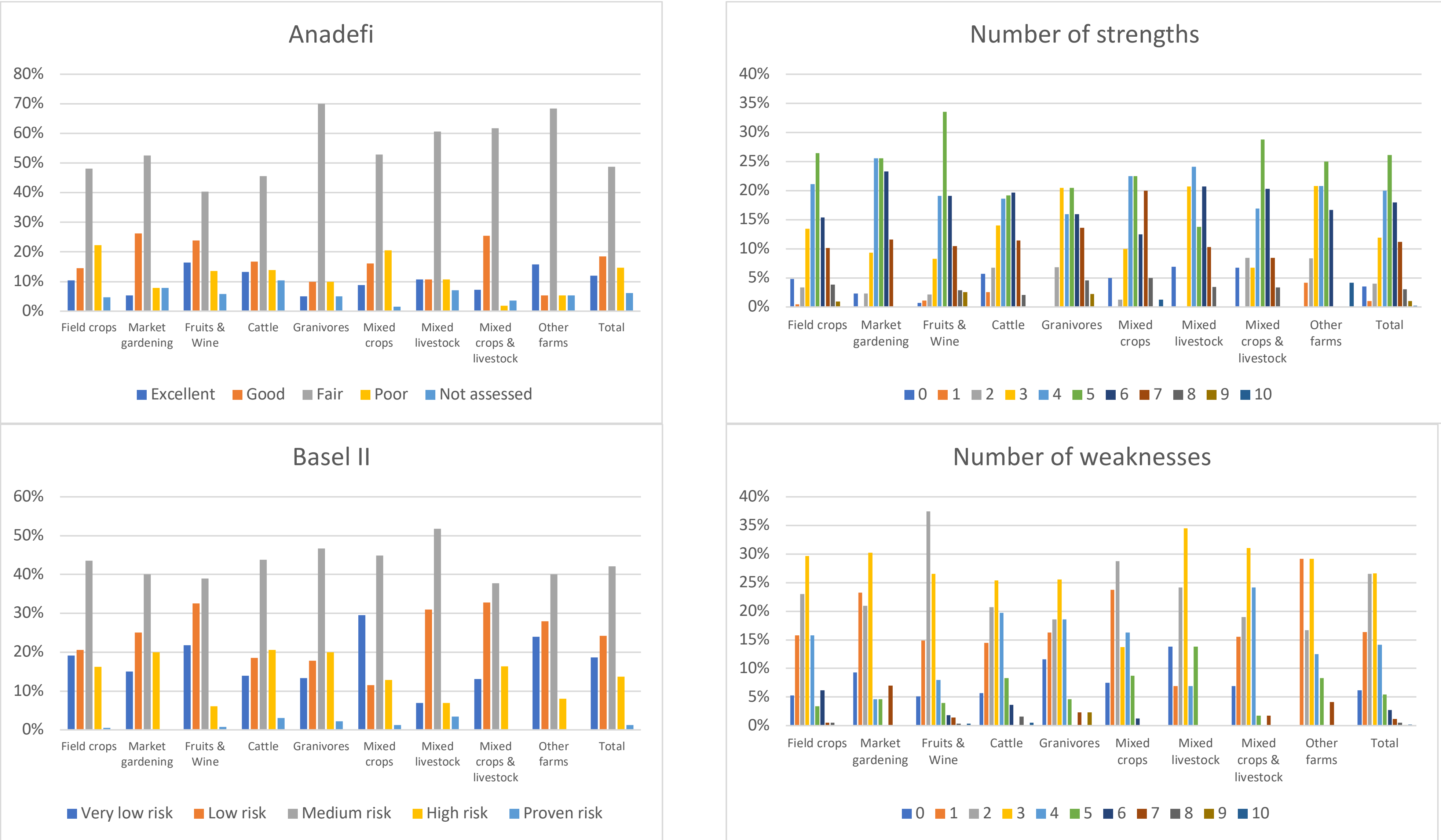


Source: Own database.

Three classes of econometric models are estimated according to the nature of the dependent variable (Tables 3a, 3b, 3c). We estimate, for each class, 4 models based on the Anadefi score and 4 models based on the Basel II score, considered as independent variables. These models include additional independent variables related to the bank analyst's opinion on a loan, the number of strengths and weaknesses, and the detail of these strengths and weaknesses. A large set of control variables referring to the farm structure (acreage, specialization), the amount borrowed, banking relationship, and the year of the analysis is included in each model.

Because our analysis relies on observations at a given point in time, we are not able to estimate a panel data model. In order to assess more precisely the difference between distressed farms and non-distressed farms, we transformed the original dependent variable into two dichotomous one. The first variable allows us to distinguish farms that exhibit at least one day of payment incident (77%) from farms that do not (23%). The second variable considers the eventuality of limited payment incidents and distinguishes farms that exhibit at least seven day of payment incidents (67%) from farms that do not (33%). In both cases, the econometric approach relies on a standard logit model, with a dichotomous endogenous variable (McFadden, 1984).

Figure 2. Proportion of farms facing financial distress by criteria and specialization



4. Results

This section considers the choice of relevant financial distress indicators among the ones identified in the previous sections. To do so, we characterize farms according to their distress level. Econometric models allow us to check the predictive power of ex-ante distress indicators regarding ex-post payment incidents.

4.1. Financial distress indicators

In the first step of the analysis, we consider the main ex-ante financial distress risk indicators (Anadefi, Basel II, number of strengths, and number of weaknesses) according to the farm specialization (Figure 2). On average, between 10-20% farms are very risky according to the bank and its analysts (Anadefi ≥ Poor, Basel II ≥ High risk, Strengths ≤ 3, Weaknesses ≥ 5). We observe some heterogeneity in productive orientation. For example, farms specializing in field crops or cattle breeding are perceived as riskier than farms specializing in wine and fruit production or mixed livestock. This observation seems consistent with the reality in some sectors. Over the last years, prices of cereals and meat have dropped, while volatility in yields have increased (Prager et al., 2018).

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 distress is to observe payment incidents. Using this criterion, we can split farms into two categories: whether or not they have exhibited at least one day of payment incident noted over the previous 365 days. Then we observe the distress criteria that were measured during a previous state of play (e.g. considering the latest accounting records).

Table 2 emphasizes that farms displaying payment incidents were considered significantly riskier by scores (Anadefi and Basel II). Not surprisingly, these financial algorithms are therefore reliable predictors of a future distress. Distressed farms were also granted more weaknesses and fewer strengths by analysts. Moreover, the ranking providing by analysts regarding a loan request is also significant in the detection of a distress situation. Indeed, a large majority of farmers who did not exhibit any payment incident were granted loans with or without guarantee. When making decisions related to loans, bank analysts predict implicitly but accurately the probability that the borrower will face some incident. Moreover, amounts already borrowed are higher for farms exhibiting payment incidents.

Unexpectedly, most control variables included in our analysis, such as the acreage and the economic and technical orientation of the farm, do not significantly differ according to the occurrence of a payment incident. However, loyal bank customers and farmers who own their own land are less likely to exhibit payment incidents.

Table 2. Ex-post payment incidents vs. ex-ante distress criteria

Variables	All farms	Distress measured through payment incidents: Never	Distress measured through payment incidents: At least one day in the year	Differences in distributions (Chi2 test)
Anadefi Score				
Excellent	11.92%	27.32%	7.85%	
Good	18.63%	26.78%	16.62%	
Fair	48.50%	36.07%	51.08%	***
Poor	14.58%	2.73%	18.15%	
Not assessed	6.37%	7.10%	6.31%	
Basel II Score				
Very low risk	18.62%	45.45%	8.93%	
Low risk	24.38%	37.73%	19.94%	
Medium risk	42.08%	14.55%	51.88%	***
High risk	13.68%	2.27%	17.57%	
Proven risk	1.23%	0.00%	1.67%	
Strengths & weaknesses				
Number of strengths	4.74	5.31	4.56	***
Number of weaknesses	2.63	2.10	2.80	***
Analyst' opinion				
Favorable without guarantees	44.37%	51.20%	42.41%	
Favorable with guarantees	40.55%	40.67%	40.54%	***
Partial acceptance	5.84%	4.78%	5.73%	
Refusal	9.24%	3.35%	11.32%	
Amount already borrowed	91.978	88.664	92.733	***
Loyalty (years)	21.33	29.79	18.91	*
Usable Agricultural Area (UAA, hectares)	84.73	96.74	81.03	
UAA belonging to the farmer (%)	38.08%	42.40%	36.93%	*
Tax situation (flat tax/regular)	94.29%	94.64%	94.05%	
Diversification	1.90	1.94	1.89	
Economic and Technical Orientation of the Farm				
Field crops	22.11%	18.47%	23.28%	
Market gardening	4.34%	3.15%	4.76%	
Fruits & wine	28.73%	37.39%	26.06%	
Cattle	20.04%	15.32%	22.09%	
Granivores	4.54%	3.15%	4.89%	
Mixed crops	8.09%	10.81%	7.01%	
Mixed livestock	2.86%	2.25%	3.17%	
Mixed crops & livestock	6.32%	5.86%	5.82%	
Other farms	2.96%	3.60%	2.91%	

Source: Own database.

Notes: Percentages for each variable and type of distress are in column. 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, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

4.3. Econometric models

To confirm and further develop these results, econometric models using zero-inflated negative binomial and logit regressions are implemented for explaining ex-post financial distress as a function of the ex-ante distress indicators and farm characteristics. In all models of Table 3a, the parameter *ln(alpha)* is significant, which validates the use of a zero-inflated negative binomial compared to a zero-inflated Poisson regression. As anticipated, the *Basel II score* (counterparty risk) provides a significant explanation of the excess zeros.

We first notice that most results of the econometric models converge, which implies that considering the occurrence of payment incidents 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 scores. In all models, a higher Anadefi or Basel II score leads to a higher risk of payment incidents.

Similarly, bank analysts provide a clear insight on the financial distress of their customers that mainly reinforces indications provided by the Anadefi score. A negative opinion on a loan requests translates into a higher risk of distress. The number of weaknesses noticed by the bank analyst also increases the likelihood of being distressed and the number of days of incidents, while the number of strengths has the opposite effect. In detail, the evaluation of the quality of capital structure by bank analysts appears to be a very discriminant criterion in the occurrence and extent of an effective distress: the identification of a good structure significantly decreases the occurrence and extent of distress (all models) whereas the opposite can be observed for a strong capital structure (logit model). Only with zero-inflated negative binomial models we observe that the feasibility of the farmer's project and the quality of the relationship between the farmer and the bank decrease the number of days of incidents.

In most models, some control variables appear to reduce payment incidents. Large farms are less likely to be distressed, probably because of their increased ability to cope with financial shocks and their facilities act as a collateral. Only market gardeners and to some extent fruit and wine, and mixed-crop producers exhibit significantly fewer days of incidents compared to field crop producers. The reason may lie in the high production value of market gardeners and the existence of stocks for wine producers, which can smooth annual yield variations. This result may indicate that risk distress criteria could be targeted for some farm specialization. Conversely, annual effects play only a significant role for farms exhibiting less than 7 days of payment incidents.

While the explanatory power of each model is validated using a Chi2 test, a comparison between each model can be done according to the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Schwarz, 1978). Although these criteria are not notably different among models, all models indicate that incorporating Basel II scores provides the best explanatory power (*i.e.* the lowest AIC/BIC). Moreover, the results show that analysts do not provide significant value added in the explanation of financial distress compared to scores (AIC and BIC are very similar among models including Basel II).

The predictive power of each model is then tested using two out-of-sample techniques: a "leave-one-out cross validation" and a "5-fold cross validation" (Arlot and Celisse, 2010). A comparison of the root-mean-square errors (RMSE) and mean absolute errors (MAE) is then performed among models. The estimations from the zero-inflated negative binomial models (Table 3a) clearly show that the Basel II-only model is the best predictive one (lowest and convergent values of RMSE and MAE). By contrast, models with Anadefi and the analysts' opinion display high values of RMSE and MAE, possibly emphasizing some overfitting issue (Moore, 2012). Logit models (Tables 2b and 2c) also confirm that the Basel II-only model is the best predictive one while no overfitting issue is detected with other models.

The combination of all these results suggest that banks can rely on automatic monitoring indicators based on past accounting and financial data at the business level (hard information) in order to prevent financial distress. In turn, analysts may provide some insight on information that is difficult to include in those models. For instance, they can highlight some individual and prospective dimensions (soft information) that are prone to reduce financial distress, such as the perception of the capital structure and the feasibility of the project.

Table 3a. Econometric models (Zero-inflated negative binomial regression)

	Anadefi	Basel II	Anadefi + Analyst	Basel II + Analyst	Anadefi + Counters	Basel II + Counters	Anadefi + W/S	Basel II + W/S
Anadefi - Good	0.454**		0.447**		0.293*		0.454**	
Anadefi - Fair	0.653***		0.587***		0.412**		0.370**	
Anadefi - Poor	0.813***		0.790***		0.518***		0.403**	
Anadefi - Not assessed	0.560**		0.544**		0.219		0.143	
Basel II - Low risk		0.759***		0.663***		0.730**		0.757**
Basel II - Medium risk		1.802***		1.792***		1.747***		1.825***
Basel II - High risk		2.638***		2.620***		2.534***		2.674***
Basel II - Proven risk		2.855***		2.875***		2.701***		2.871***
Analyst - Favorable with guarantees			0.083	-0.041				
Analyst - Partial acceptance			-0.086	-0.133				
Analyst - Refusal			0.358**	-0.050				
Analyst - Number of strengths					-0.142***	-0.021		
Analyst - Number of weaknesses					0.164***	0.043*		
Analyst - Good capital structure							-0.377***	0.011
Analyst - Income outside the farm							0.040	-0.022
Analyst - Farmer's wealth							-0.096	0.060
Analyst - Feasibility of the project							-0.377***	0.073
Analyst - Good relationships							-0.298***	-0.059
Analyst - Farmer's experience							0.024	-0.001
Analyst - Fragile capital structure							0.081	-0.001
Analyst - Low profitability							0.190*	0.049
Analyst - High indebtedness							-0.036	0.070
Analyst - Poor season							0.140	0.175
Analyst - No guarantee							-0.122	-0.097
Acreage	-0.002***	-0.001**	-0.002***	-0.001***	-0.002***	-0.001**	-0.001**	-0.001*
Personal property	0.110	0.160	0.161	0.158	0.055	0.117	0.134	0.128
Loyalty	0.003	0.002	0.002	0.003	-0.005	0.003	0.008	0.004
Amount borrowed	-0.001**	0.000	-0.001**	0.000	-0.001**	0.000	-0.001**	0.000
Diversification	0.001	-0.011	-0.001	-0.031	-0.025	-0.029	-0.020	-0.019
Market gardening	-0.965***	-0.537***	-0.963***	-0.510***	-0.693***	-0.467***	-0.868***	-0.539***
Fruits & wine	-0.399***	-0.061	-0.333**	0.029	-0.238*	-0.001	-0.360**	-0.073
Cattle	0.337***	0.192*	0.327**	0.204*	0.354***	0.181	0.263**	0.172
Granivores	0.231	0.100	0.245	0.137	0.378	0.181	0.177	0.080
Mixed crops	-0.096	-0.121	-0.063	-0.071	0.012	-0.091	-0.123	-0.180
Mixed livestock	0.247	0.167	0.341	0.288	0.323	0.215	0.276	0.201
Mixed crops & livestock	0.136	-0.045	0.188	0.081	0.174	0.052	0.052	-0.008
Other farms	-0.116	-0.080	-0.095	0.038	-0.263	-0.067	-0.148	-0.153
2013	-0.250	-0.125	-0.185	-0.116	-0.280	-0.149	-0.283	-0.144
2014	-0.052	0.332**	-0.066	0.296**	-0.097	0.313**	0.063	0.308**
2015	-0.160	0.083	-0.159	0.047	-0.363**	0.005	-0.201	0.009
2016	-0.067	0.011	-0.047	-0.023	-0.305*	-0.038	-0.053	-0.040
2017	-0.128	0.110	-0.136	0.127	-0.332**	0.062	-0.067	0.078
Intercept	3.919***	2.206***	3.873***	2.224***	4.416***	2.292***	4.320***	2,201***
Basel II - Low risk	*-0.791****	*-0.750****	*-0.751****	*-0.720****	*-0.748****	*-0.695****	*-0.793****	*-0.717****
Basel II - Medium risk	*-2.961****	*-2.670****	*-2.989****	*-2.666****	*-2.823****	*-2.595****	*-2.861****	*-2.620****
Basel II - High risk	*-4.214****	*-3.069****	*-4.103****	*-2.982****	*-3.610****	*-2.970****	*-3.647****	*-3.003****
Basel II - Proven risk	*-19.710****	*-20.171****	*-21.585****	*-21.231****	*-20.673****	*-20.339****	*-19.468****	*-21.328****
Intercept	*-0.021*	*0.013*	*-0.050*	*-0.003*	*-0.033*	*-0.027*	*-0.018*	*-0.016*
Ln(alpha)	*0.258****	*-0.160****	*0.258****	*-0.168****	*0.165****	*-0.202****	*0.167****	*-0.205****
Number of observations	729	830	692	786	703	795	712	806
LR Chi2	111.20	716.63	113.59	704.80	179.31	715.36	201.45	771.59
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC/N	9.201	8.771	9.208	8.734	9.141	8.766	9.174	8.790
BIC/N	9.383	8.936	9.417	8.923	9.341	8.948	9.430	9.023
RMSE (leave-one-out)	1911.203	57.868	152.015	434.262	76177.752	390.279	13700.221	993.828
RMSE (5-fold, average)	140.942	56.487	65.757	205.928	74400.005	79.562	16369.485	647.688
MAE (leave-one-out)	120.778	39.534	54.856	54.493	2920.425	52.416	5134.850	74.316
MAE (5-fold, average)	49.948	39.606	50.195	40.623	1090.733	49.011	1667.324	52.163

Source: Own database. Notes: * p<0.05, ** p<0.01, *** p<0.001. W/S is for Weaknesses and Strengths. N is the number of observations. A significant ln(alpha) validates the choice of a zero-inflated negative binomial regression compared to a zero-inflated binomial regression. Parameters of the main model are written in upright letters, parameters of the inflated model are written in italic.

Table 3b. Econometric models (Logit, ref = 0 incident)

	Anadefi	Basel II	Anadefi + Analyst	Basel II + Analyst	Anadefi + Counters	Basel II + Counters	Anadefi + W/S	Basel II + W/S
Anadefi - Good	0.140**		0.116*		0.085		0.090	
Anadefi - Fair	0.271***		0.249***		0.210***		0.161***	
Anadefi - Poor	0.401***		0.373***		0.335***		0.266***	
Anadefi - Not assessed	0.126		0.116		0.023		0.064	
Basel II - Low risk		0.222***		0.219***		0.196***		0.185***
Basel II - Medium risk		0.501***		0.503***		0.471***		0.439***
Basel II - High risk		0.521***		0.519***		0.489***		0.448***
Basel II - Proven risk		0.000		0.000		0.000		0.000
Analyst - Favorable with guarantees			0.024	0.011				
Analyst - Partial acceptance			-0.012	-0.070				
Analyst - Refusal			0.110*	0.024				
Analyst - Number of strengths					-0.030***	-0.001		
Analyst - Number of weaknesses					0.026**	0.008		
Analyst - Good capital structure							-0.125***	-0.049
Analyst - Income outside the farm							0.042	0.032
Analyst - Farmer's wealth							-0.039	-0.005
Analyst - Feasibility of the project							-0.036	0.022
Analyst - Good relationships							-0.000	-0.027
Analyst - Farmer's experience							-0.024	-0.047
Analyst - Fragile capital structure							0.064	0.071
Analyst - Low profitability							0.074	0.017
Analyst - High indebtedness							-0.036	-0.046
Analyst - Poor season							0.094	0.063
Analyst - No guarantee							-0.030	-0.021
Acreage	-0.001***	-0.000**	-0.001***	-0.000**	-0.030***	-0.000**	-0.001**	-0.000*
Personal property	-0.078	-0.083	-0.083	-0.093	-0.093	-0.094	-0.074	-0.086
Loyalty	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Amount borrowed	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Diversification	-0.004	0.023	-0.002	0.028	-0.003	0.025	-0.002	0.026
Market gardening	0.025	-0.017	0.022	-0.018	0.013	-0.014	-0.013	-0.006
Fruits & wine	-0.121**	-0.091**	-0.109**	-0.085**	-0.088*	-0.085**	-0.113**	-0.089**
Cattle	0.010	-0.055	0.012	-0.058	0.007	-0.060	-0.007	-0.046
Granivores	-0.050	-0.095	-0.013	-0.047	-0.053	-0.112	-0.041	-0.060
Mixed crops	-0.172**	-0.168***	-0.150**	-0.150***	-0.136*	-0.173***	-0.166**	-0.171***
Mixed livestock	0.006	0.063	-0.016	-0.068	0.003	0.065	-0.035	0.053
Mixed crops & livestock	-0.022	-0.065	-0.028	-0.066	-0.022	-0.066	-0.031	-0.052
Other farms	-0.046	-0.074	-0.079	-0.103	-0.093	-0.079	-0.051	-0.072
2013	-0.083	-0.106	-0.101	-0.132*	-0.086	-0.103	-0.101	-0.122*
2014	-0.001	-0.007	0.003	-0.008	-0.001	-0.010	-0.003	-0.011
2015	-0.034	-0.032	-0.033	-0.035	-0.051	-0.037	-0.045	-0.056
2016	0.005	-0.047	0.002	-0.062	0.001	-0.048	0.005	-0.068
2017	-0.031	-0.035	-0.045	-0.051	-0.053	-0.032	-0.030	-0.046
Number of observations	743	825	706	783	717	791	726	801
LR Chi2	78.45	160.09	77.84	148.66	90.58	152.31	113.53	181.55
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC/N	0.978	0.867	0.994	0.879	0.966	0.880	0.963	0.881
BIC/N	1.125	0.996	1.167	1.032	1.130	1.026	1.184	1.080
RMSE (leave-one-out)	0.401	0.373	0.404	0.375	0.398	0.376	0.398	0.379
RMSE (5-fold, average)	0.400	0.376	0.407	0.380	0.398	0.375	0.394	0.390
MAE (leave-one-out)	0.308	0.268	0.311	0.271	0.302	0.272	0.297	0.270
MAE (5-fold, average)	0.307	0.269	0.308	0.270	0.300	0.273	0.296	0.274

Source: Own database. Notes: Marginal effects are reported. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. W/S is for Weaknesses and Strengths.

Table 3c. Econometric models (Logit, ref = less than 7 incidents)

	Anadefi	Basel II	Anadefi + Analyst	Basel II + Analyst	Anadefi + Counters	Basel II + Counters	Anadefi + W/S	Basel II + W/S
Anadefi - Good	0.182***		0.171***		0.126**		0.121**	
Anadefi - Fair	0.319***		0.299***		0.236***		0.198***	
Anadefi - Poor	0.489***		0.453***		0.390***		0.276***	
Anadefi - Not assessed	0.217***		0.207***		0.123		0.045	
Basel II - Low risk		0.315***		0.305**		0.306***		0.307***
Basel II - Medium risk		0.684***		0.676***		0.670***		0.675***
Basel II - High risk		0.753***		0.743***		0.724***		0.731***
Basel II - Proven risk		0.000		0.000		0.000		0.000
Analyst - Favorable with guarantees			0.033	0.011				
Analyst - Partial acceptance			0.027	-0.020				
Analyst - Refusal			0.135*	0.014				
Analyst - Number of strengths					-0.046***	-0.007		
Analyst - Number of weaknesses					0.055***	0.014		
Analyst - Good capital structure							-0.161***	-0.046
Analyst - Income outside the farm							0.090	0.059
Analyst - Farmer's wealth							-0.033	0.019
Analyst - Feasibility of the project							-0.023	0.063
Analyst - Good relationships							-0.012	-0.011
Analyst - Farmer’s experience							-0.006	-0.058
Analyst - Fragile capital structure							0.090	0.049
Analyst - Low profitability							0.133***	0.002
Analyst - High indebtedness							0.011	-0.004
Analyst - Poor season							0.107	0.073
Analyst - No guarantee							-0.044	-0.028
Acreage	-0.001***	-0.000	-0.001***	-0.000	-0.001**	-0.000	-0.001**	-0.000
Personal property	-0.040	-0.067	-0.031	-0.072	-0.051	-0.088	-0.018	-0.076
Loyalty	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
Amount borrowed	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000
Diversification	-0.003	-0.019	0.002	0.022	-0.003	-0.021	0.001	0.022
Market gardening	0.077	0.104	0.120	0.142*	0.136	0.131*	0.091	0.128*
Fruits & wine	-0.142***	-0.066	-0.125**	-0.058	-0.084*	-0.041	-0.125**	-0.051
Cattle	0.064	0.012	0.066	-0.008	0.061	-0.009	0.038	-0.003
Granivores	-0.043	-0.078	-0.001	-0.036	-0.027	-0.025	-0.033	-0.039
Mixed crops	-0.217	-0.130**	-0.191**	-0.107*	-0.155**	-0.111*	-0.212***	-0.128*
Mixed livestock	0.072	0.008	0.061	0.013	0.087	0.020	0.044	0.003
Mixed crops & livestock	-0.047	-0.108	-0.033	-0.078	-0.061	-0.075	-0.054	-0.047
Other farms	-0.088	-0.074	-0.041	-0.040	-0.167	-0.081	-0.108	-0.006
2013	-0.160**	-0.172**	-0.185**	-0.210***	-0.146**	-0.167**	-0.143**	-0.170**
2014	-0.071	-0.081	-0.071	-0.082	-0.073	-0.079	-0.054	-0.080
2015	-0.117*	-0.113*	-0.109*	-0.111**	-0.144**	-0.114**	-0.131**	-0.126**
2016	-0.134**	-0.146**	-0.139**	-0.156***	-0.160***	-0.159***	-0.114*	-0.153***
2017	-0.103*	-0.124**	-0.111*	-0.131***	-0.152***	-0.138***	-0.112**	-0.143***
Number of observations	743	825	706	783	717	791	726	801
LR Chi2	85.20	221.59	77.84	209.15	89.76	210.76	124.81	233.79
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC/N	1.199	0.966	1.215	0.983	1.155	0.965	1.159	0.961
BIC/N	1.341	1.091	1.382	1.131	1.314	1.107	1.374	1.154
RMSE (leave-one-out)	0.456	0.393	0.458	0.398	0.443	0.393	0.446	0.396
RMSE (5-fold, average)	0.460	0.395	0.459	0.400	0.445	0.396	0.446	0.394
MAE (leave-one-out)	0.400	0.301	0.404	0.306	0.378	0.324	0.377	0.314
MAE (5-fold, average)	0.403	0.302	0.401	0.306	0.379	0.298	0.375	0.294

Source: Own database. Notes: Marginal effects are reported. * p<0.05, ** p<0.01, *** p<0.001. W/S is for Weaknesses and Strengths.

5. Conclusion

In this article, we proposed a study of French farms facing financial distress. In the current context of farm distress and exit, this work aimed to complement the literature about financial distress, especially in the agricultural sector. Unlike many of the empirical studies in the literature, we were able to use a unique dataset of 1,045 farms and gathered individual, structural, and financial data from the information systems of a French bank. We also considered the analysts' opinions, which were 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 on automatic scores but also on the bank analysts' opinion. Effective distress was measured ex-post through payment incidents, a continuous variable. The estimation of zero-inflated negative binomial and logit models shows that all these indicators are able to predict the occurrence of an incident and its duration. Scores alone seem to provide both a better explanation and prediction, which validates current banking practices on risk monitoring that rely mostly on "hard" and past information. Nonetheless, "soft" and prospective information gained from bank analysts can provide some perspective, especially regarding some specific criteria (e.g. capital structure) and the quality of farmer's projects which are relevant predictors of financial distress.

This work offers many perspectives for future studies, such as helping to more precisely find weak signals leading to financial distress, especially over a longer observation period. The use of time series would also help in identifying financial trajectories of potentially distressed farms. While our findings highlight the importance of considering 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 farms in France and in Europe.

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