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Review

Forecasting and preventing bankruptcy: A conceptual review

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The recent global financial crisis has caused the failure of many firms in several countries, renewing the interest of the literature towards forecasting models for default risk. Although these models have been developed since the 1960s, studies have been published in increased numbers during the last decades, proposing new approaches or comparing different existing models to understand which of them have the best predictive power. However, the recent financial crisis has underlined how important adopting early warning systems are. Although forecasting business failure and implementing warning systems are conceptually different, there is a risk of overlapping these concepts. Accordingly, this study aims to review the literature on these topics by using a conceptual review methodology, at the same time considering the trend to implement approaches aiming to facilitate corporate rescue.

Key words: Forecasting models, early warning systems, corporate rescue, literature review.

INTRODUCTION

The main motivation for this study relies on the relevance of business failure prediction, which is considered a crucial problem in economics and finance. Forecasting bankruptcy on time and preventing default could allow for adopting some actions to restore firms' financial situation.

Researchers have suggested several models to predict bankruptcy, such as discriminant analysis (Beaver, 1966; Altman, 1968), logit and probit models (Ohlson, 1980; Charitou et al., 2004; Jones and Hensher, 2007), artificial neural networks (Wilson and Sharda, 1994; Serrano-Cinca, 1997; Charalambous et al., 2000), genetic algorithms (Kingdon and Feldman, 1995), survival analysis (Luoma and Laitinen, 1991; Shumway, 2001; Gepp and Kumar, 2008) and recursive partitioning algorithm (RPA) (Marais et al., 1984; Frydman et al.,

1985).

These models aim to predict the risk of business failure and to classify firms accurately according to their financial health, selecting the most relevant financial ratios that influence the probability of default. Despite the differences between these models, they have an essential characteristic in common: the distressed state of a firm, expressed through a binary variable, has to be known *a priori* (that is, when the event of bankruptcy has already occurred: Amendola et al., 2017).

However, managers, financial institutions, practitioners and other interested stakeholders need to prevent the distress or, alternatively, accelerate the liquidation; avoiding letting assets of the distressed firms lose their value so as to keep the indirect costs of bankruptcy from

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increasing (Bisogno and De Luca, 2014). This aspect has been recently underlined by the proposal for a new EU directive labelled: 'Preventive restructuring frameworks, second chance and measures to increase the efficiency of restructuring, insolvency and discharge procedures'. Accordingly, implementing a model to *forecast* bankruptcy risk might not be enough. The actual economic scenario, profoundly affected by the global financial crisis, has underlined the importance of adopting early warning systems, in order to *prevent* bankruptcy.

It is important to underline the difference between forecasting models and early warning systems. The former are mainly focused on estimating the failure risk and understanding which variables could better predict the probability of default. They do not have any capacity to prevent a firms' possible crisis. Conversely, early warning systems consist of tools for monitoring and detecting warning events to predict and ward off an upcoming business crisis and implement a timely intervention. Therefore, implementing this kind of system means taking into consideration that business failure is a process that evolves through several troubling situations, with bankruptcy being only the final state.

Despite this difference, the expressions 'forecasting models' and 'early warning systems' are frequently used as synonyms, a practice that runs the risk of obscuring the dynamicity and complexity of business failure processes while at the same time paving the way for conceptually overlapping them. Accordingly, this study aims to review the literature concerning both models for forecasting default risk and early warning systems, considering them as complementary but different tools to support practitioners facing financial distress. Investigating previous studies and building on previous literature reviews (Alaka et al., 2018; Appiah et al., 2015; Bellovary et al., 2007; Gepp and Kumar, 2012), which were mostly based on forecasting models, this article adopts a broader perspective by also reviewing studies concerning early warning systems, at the same time paying attention to tools provided by legislation to put such systems into action (as in the case of the French 'safeguard procedure').

Findings from this conceptual review suggest that different forms of exiting the market, such as default of payment, insolvency proceedings and liquidation, should be taken into account while developing approaches to forecast and prevent default risk; more concretely, we would argue that additional studies are required to implement more dynamic models. Moreover, further investigations concerning the prevention of firms' financial distress are highly recommended, to assess positive and negative consequences of giving troubled businesses a second chance.

METHODOLOGY

As stated in the previous section, this study aims to review the literature, focusing not only on models suggested by researchers to

forecast bankruptcy and assess the default risk, but also on early warning systems, whose aim being to prevent bankruptcy.

As underlined in the previous section, *forecasting models* and *early warning systems* have been considered frequently as synonym; more specifically, taking into account that the objective to be achieved through the implementation of forecasting models is to select a set of indicators that best foresee distress, scholars have considered them as triggers events which, in turn, have been interpreted as warning signals. However, the expression 'early warning system' has a different meaning, since it is not focused only on the output of a model (namely indicators or financial ratios considered as warning signals or red flags) but also means implementing a procedure able to avoid the distress. This preliminary consideration helps us while selecting the appropriate methodology to be adopted while reviewing the existing literature.

According to Jesson et al. (2013), the literature review format depends on the purpose of the review, hence the process defines the type of the review being adopted over a continuum of approaches from the so-called traditional reviews to the systematic reviews. The 'traditional review' methodology is based on an iterative approach to search relevant articles, rather than a comprehensive and replicable search for a specific question (as in the case of systematic review approach). Although the traditional review could be considered too subjective, due to the personal selection of articles by the writer, this does not automatically imply that this approach is not scientific. Indeed, a traditional review is not merely descriptive, but is based on a critical approach, seeking to add new insight on the topic. Accordingly, both traditional and systematic reviews address a research question or problem, even if they use a different methodological approach. Having clarified that, it is worth observing that scholars have used different expressions to identify traditional review approaches, such as Jesson et al. (2013):

(1) *Traditional review*, frequently based on a critical analysis of methods and results of previous studies, with a focus on contextual materials;
(2) *Conceptual review*, which aims to synthesise conceptual knowledge in order to contribute to a better understanding of the investigated issues;
(3) *State-of-the-art review*, which intends to bring readers up to date on the most recent studies on the topic being investigated;
(4) *Expert review*, namely a review written by a recognized expert; and
(5) *Scoping review*, which depicts the scene for a future research agenda.

Bearing in mind the different aims to be pursued through these approaches, this study adopts a conceptual review methodology, which is particularly appropriate when the aim of the review is 'to compare and contrast the different ways in which authors have used a specific word or concept' (Jesson et al., 2013). Therefore, this approach is particularly useful since a risk of confusing and overlapping the expressions 'forecasting models to predict distress' and 'early warning systems to prevent distress' do exist since they have been used interchangeably (see, for example, the recent study of Wieprow and Barlik, 2017). Accordingly, this study aims to underline the conceptual differences between the above-mentioned expressions, contributing to a better understanding of these core concepts.

Forecasting models for default risk

The prediction of firm financial distress has been largely investigated since the 1930s. The first studies were based on the use of ratio analysis to predict bankruptcy,

evolving from univariate models (Beaver, 1966) to multivariate studies, with the best-known paper by Altman (1968). Following these seminal papers, several approaches have been developed, aiming at proposing more accurate and robust models to predict bankruptcy. More concretely, researchers have mostly implemented models based on a comparison between healthy and distressed firms (Du Jardin, 2010; Amendola et al., 2011), trying to select the best failure indicators. The approaches suggested by researchers for predicting business failure can be classified looking at both the model types used for distress forecasting and the factors that influence the risk of default (that is, the financial indicators selected in the study), as well as considering their different levels of predictive accuracy.

Forecasting model types: Main findings

The great depression of 1929 and the recent financial crisis that began in 2008 caused a significant increase in the number of companies in danger of bankruptcy, stimulating research on bankruptcy prediction. The literature classifies forecasting models into two categories (Alaka et al., 2018). The first one consists of *statistical models*, which analyse two samples of healthy and distressed firms, and where the selection of financial ratios having a predictive ability is based on empirical studies. The selected ratios are then used to estimate the parameters of the model and the probability of default. A drawback of these models is that they typically rely on some restrictive assumptions (Korol, 2013):

(1) Variables (that is, financial ratios) should have normal distributions, they must be independent and must have a high discriminative ability to separate healthy companies from distressed ones;
(2) Values for all indicators of all firms are required, that is, information for each unit (healthy and distressed firms) must be complete, in the sense that there are no missing values for any variables; and
(3) Classification of firms must be clearly defined (that is, a firm belonging to one group precludes its belonging to a different group).

The second group of approaches used to forecast the risk of default is based on *soft computing techniques*, whose primary assumption is that data can be incomplete and environmental conditions can change over time. Accordingly, these methods are designed to take into account that some parameters may be affected by changing environmental conditions; therefore, these models are dynamic and are often labelled as learning systems.

Statistical models

Statistical models consist of a set of approaches, which aims to estimate the probability of default and select the best predictors (namely ratios calculated on financial statements' items) of bankruptcy. The most straightforward models were primarily based on univariate approaches.

The first studies were proposed by Smith (1930) and FitzPatrick (1932). Smith (1930) investigated a sample of 29 failed firms belonging to different sectors, referring to 24 ratios, while FitzPatrick (1932) examined a sample of 20 companies, calculating 13 ratios. Several ratios were founded as good indicators of the unhealthy financial conditions of firms, notably Working Capital to Total Assets, Net Worth to Total Assets, Net Worth to Debt and Net Profits to Net Worth.

In the following years, other studies were published, representing the fruitful groundwork for further investigations. In particular, the research of Merwin (1942) was based on a large sample of 581 small firms for the period 1926-1936. Three ratios (Working capital/total assets; Net worthy/total liabilities; Current assets/current liabilities) were selected because of their high predictive ability. The article of Beaver (1966) represented the most widely recognised univariate study within the literature on bankruptcy prediction. He investigated a paired sample composed of 79 failed and 79 non-failed firms for the period 1954 to 1964. Thirty ratios, classified into six categories (1. Cash flow ratios; 2. Net-income ratios; 3. Debt to total assets ratios; 4. Liquid-assets to total assets ratios; 5. Liquid asset to current debt ratios; 6. Turnover ratios), were selected according to their relevance and adoption in previous studies.

Comparing the mean of these ratios, Beaver tested their predictive ability in classifying failed and non-failed firms: Net income to Total Debt gained the higher predictive ability, followed by Net Income to Sales, Net Income to Net Worth, Cash Flow to Total Debt and Cash Flow to Total Assets. Through a Dichotomous Classification Test, Beaver defined a cut-off point to minimise classification errors and correctly classify firms as healthy or distressed.

The research of Beaver was more rigorous than previous studies and underlined the importance of ratios as default risk estimators; however, as further development, Beaver suggested testing the predictive ability of multiple ratios instead of a single ratio. Therefore, forecasting models for default risks started to evolve, being based on the multivariate discriminant analysis.

In general, the aim of a multivariate discriminant analysis is to classify the observations into two (or more) groups, minimising the classification errors (more specifically, two misclassification errors can occur: a *type I error*, which means that a failing firm is misclassified as a healthy firm, or a *type II error*, which means that non-failing firm is misclassified as a failing firm). This goal is achieved by adopting the decision rule of maximising the

between-group variance relative to the within-group variance. Following this rule, the discriminant score calculated for each firm is compared to an optimal cut-off value, in order to determine the group to which the firm belongs. If this score is less than the cut-off point, the firm is assigned to the failing group; otherwise, it is assigned to the non-failing group (Amendola et al., 2011).

The study of Altman (1968) can be considered as a milestone in the field since he is the first author who applied discriminant analysis to the prediction of business failure. He developed the so-called 'Z-score model', a five-factor model to forecast bankruptcy of manufacturing firms, and investigated the financial statements of a sample of 66 companies, divided into two groups (failed and non-failed firms) through the estimation of a linear combination of five variables:

$$Z = 0.012 \, X_1 + 0.014 \, X_2 + 0.033 \, X_3 + 0.006 \, X_4 + 0.999 \, X_5$$

where:
X_1 = Working capital / Total assets;
X_2 = Retained earnings / Total assets;
X_3 = EBIT / Total assets;
X_4 = Market value of equity / Total liabilities; and
X_5 = Sales / Total assets.

His model showed a higher predictive ability compared with previous models one year before bankruptcy; however, this capacity was considerably lower in two to five years before failure: for example, the type I error varies from 6% (one year before failure) to 28% (two years before failure). The cut-off point (Z = 2,675) was calculated as a mean of the average values of z-score for both groups, which allowed for reducing the misclassification errors. The author also defined a grey area that takes into account any uncertainty when classifying firms. Altman further enhanced and improved his model (Altman et al., 1977; Altman, 2000), also considering the Basel 2 environment (Altman and Heine, 2002).

Studies on bankruptcy prediction increased considerably after Altman's research, and several statistical models have been developed, such as logit and probit regression, and survival analysis. Logit analysis is used when the dependent variable is binary, assuming only two values, 0 and 1, which in our case represent healthy and failed firms. The use of logistic regression is a way of overcoming restrictive assumptions of discriminant analysis, such as normality and equal covariances between groups. Among the studies that use the logit model for the business failure prediction, we mention the most relevant. Ohlson (1980) pioneered the use of logit analysis in failure prediction. He analysed a sample of 105 failed firms and 2,058 non-failed firms in the period 1970 to 1976, and the predictive ability of the model, based on nine ratios, was over 92% of the bankrupt firms two years earlier. Therefore, the logit model predicting corporate failure performs well.

Zavgren (1985) investigated a sample of industrial firms for predicting bankruptcy 1-5 years in advance. His model was based on seven indicators and used factor analysis to obtain the independent variables for the logit model. Its predictive ability for one-year prediction was about the same as Ohlson (1980). The error rates for longer predictions were similar to or slightly lower than those reported in the previous bankruptcy prediction studies using multivariate discriminant analysis.

Peel (1987) examined a sample of non-listed firms, and the predictive ability of the model was satisfactory in the last five years before the bankruptcy. Finally, the highest predictive ability (around 98%) was achieved by Dambolena and Shulman (1988), whose model was based on fourteen ratios. The main problem of discriminant analysis and logistic regression is that they are cross-sectional models and assume that the underlying failure process remains stable over time. This assumption is usually violated in the real world (Luoma and Laitinen, 1991). Therefore, researchers have suggested using survival analysis to forecast business failure.

Survival analysis differs from the other approaches since it deals with business failure prediction, not as a classification problem, but as a timeline, representing firms through lifetime distributions (Gepp and Kumar, 2008). Accordingly, survival analysis is more flexible, allowing for taking into account 'the relationship between survival and a set of explanatory (prognostic or covariate) variables, (which) may also describe changes in the status as a function of time' (Luoma and Laitinen, 1991).

The pioneering study on survival analysis for financial distress prediction was the paper of Lane et al. (1986). They found that the use of Cox models was empirically comparable to discriminant analysis, but with fewer Type I errors. Luoma and Laitinen (1991) achieved less satisfactory results than those of discriminant analysis. Then the accelerated time survival analysis proposed by Shumway (2001) got better results compared to those of previous approaches. However, as Gepp and Kumar (2008) have underlined, comparing time-series survival analysis with cross-sectional models is not easy. Indeed, only the former takes into account the longitudinal nature of business failure prediction, while the latter are static models (Shumway, 2001) *de facto* ignoring that firms can change over time.

Soft computing models

Soft computing models (also named *artificial intelligence models*) try to deal with the incompleteness and uncertainty of data, as well as changes affecting them, because of evolving environmental conditions. Accordingly, while variables entered into statistical models are supposed to be reliable, accurate and precise, soft computing models accept that data may be

partially inaccurate and imprecise. In so doing, these models take into account that precision and certainty mean sustaining costs and that the decision-making process is expected to tolerate uncertainty and approximation of data. Several approaches can be included in the artificial intelligence models, such as the recursive partitioning algorithm (RPA), genetic algorithms, and neural networks.

After some applications in the medical context, scholars (Marais et al., 1984; Frydman et al., 1985) implemented RPA to forecast bankruptcy risk. The model of Marais et al. (1984) was based on both financial and non-financial indicators and aimed to estimate the misclassification costs. Frydman et al. (1985) investigated a sample of 200 firms (58 failed and 142 healthy) in the period 1971-1982, implementing both RPA and the classical multivariate discriminant analysis, and compared their predictive ability. The results showed that RPA on average performed better than the discriminant analysis.

Genetic algorithms (GAs) try to imitate the Darwinian logic of evolution through a natural selection while selecting predictors of failure. This approach was first implemented to forecast bankruptcy by Kingdon and Feldman (1995), according to whom GAs can be considered as a class of probabilistic optimisation techniques. More specifically, GAs are similar to the Monte Carlo simulations, drawing a set of inputs from different domains randomly and calculating a result from these inputs. These results, in turn, are used to measure the fitness by using a specific function, with the main aim being to evolve to better solutions (Egan, 2007). GAs are frequently used in conjunction with artificial neural networks (ANNs), whose implementation to forecast bankruptcy progressively increased in the last decades.

ANNs consist of different layers of nodes, starting from one (or several) layers in the input, at least one hidden layer and final output. The set of inputs is used to train the network so as to get a target output by changing the weights assigned to the different nodes. Several studies were published (Rahimian and Singh, 1993; Serrano-Cinca, 1997; Laitinen and Kankaanpaa, 1999; Zhang et al., 1999; Charalambous et al., 2000; Neves and Vieira, 2006), sometimes comparing results with those of the classical discriminant analysis. The predictive accuracy of network models is, on average, quite high (Serrano-Cinca, 1997; Laitinen and Kankaanpaa, 1999; Zapranis and Ginoglou, 2000), although their generalizability can be lower than that of multivariate discriminant analysis because they require a high number of parameters to improve predictive accuracy. For this reason, researchers have suggested simplifying neural network (Sen and Stivason, 2004).

Forecasting model ratios: Main findings

Models adopted in previous studies can be classified in accordance with the selection of factors, that is, financial

ratios used to predict bankruptcy. These factors are usually classified into several groups, expressing the performance of a firm (Maksimovic and Phillips, 2001), its liquidity and solvency (Rege, 1984), the leverage (Heiss and Köke, 2004), the size (Bethel et al., 1998; Heiss and Köke, 2004) and so on. It is also worth noting that many studies have classified ratios into several categories. The most common are:

(1) *Profitability ratios*, such as Return on Equity (ROE), Return on Assets (ROA), Return on Sales (ROS), Net Income to Total Assets, Net Income to Total Debts, Sales to Fixed Assets, Finance Charges to Net Sales and so on;
(2) *Liquidity and solvency ratios*, such as Current Ratio, Quick Ratio, Current Assets to Fixed Assets, Inventory to Current Assets, Working Capital to Total Assets, Liquid Assets to Total Assets, Cash Flow and so on;
(3) *Size and capitalisation*, such as Total Assets, Long-term Assets to Total Assets, Net Worth to Fixed Assets, Net Worth to Total Debts, Total Debts to Total Assets and so on;
(4) *Turnover ratios*, such as Inventory to Sales, Accounts Receivable to Sales, Accounts Payable to Sales, Total Debts to Sales; and
(5) *Operating structure ratios*, such as Labour Cost to Production Cost, Labour Cost to Net Sales, Finance Charges to Debt, Finance Charges to Financial Debt.

The primary aim of this classification is to facilitate the interpretation of ratios, supporting the selection of those having a good predictive ability. Additionally, several recent studies (that is, Liao and Mehdian, 2016 and references therein) have adopted an aggregation process, to build an aggregate bankruptcy index which ranges between 0 and 1, ranking firms by their relative financial distress. Several studies have also found that corporate governance indicators influence the prediction of bankruptcy (Liang et al., 2016; Bredart, 2014; Chen, 2014). These indicators can be classified into five groups, including board structure, ownership structure, cash flow rights, key person retained and others. Even if some authors (Lin et al., 2010; Chen, 2014) have shown that combinations of financial ratios and corporate governance indicators can improve models' performance, there is not a unanimous consensus on the best set of variables to be used in the model estimation for predicting business failure. The choice of the most significant predictors usually depends on some details, such as the aim of the study, the activity sector under investigation and the data availability (Amendola et al., 2017).

Early warning systems and safeguard procedure: Main findings

The models aiming to forecast bankruptcy, described in

the previous section, adopt different approaches (statistical vs. soft computing techniques) and select ratios to be used as predictors of financial distress. Notwithstanding the differences, these models are substantially based on an ex-post perspective, comparing samples of distressed and healthy firms, namely firms whose status is already known.

Accordingly, these models are not necessarily able to support the decision-making process of practitioners who are involved (or are going to be involved) in transactions with a firm experiencing a decline. Indeed, as previously stated, financial distress is a dynamic process (Volkov et al., 2017) which evolves over time, and bankruptcy is only the final step when there are no other alternatives. This would mean that other ways of exiting the market should be taken into consideration, to understand and assess whether a troubled firm has future chances of survival by implementing a restructuring strategy. Consistently, legislation in many countries is evolving in the direction of introducing timely intervention, sometimes without the direct involvement of the courts, with the main aim being corporate rescue.

Focusing on the European context, notable legislative innovations in insolvency laws have taken place in countries like Germany (1999 and 2012), England (Enterprise Act 2002), Poland and Romania (2003 and 2006), Spain (2004 and 2013), France (2006 and 2014), Finland (2007), Greece (2007 and 2012; see Paulus et al., 2015); Italy (2017[1]) and so on. Although several differences still exist between these legislations, a common orientation towards corporate rescue can be observed, as an alternative to liquidation procedures (Tollenaar, 2017).

The EU itself has recently proposed a new directive, aiming to implement preventive restructuring frameworks, in order to give firms a second chance and increase the efficiency of restructuring, insolvency and discharge procedures. Even if this proposal has been criticised from a juridical perspective (Tollenaar, 2017), from an economic point of view, it intends to facilitate timely interventions.

From a theoretical viewpoint, this would mean investigating and implementing models to prevent financial distress. Indeed, in the light of a timely intervention, the main problem is not to *forecast* default risk but mainly to *prevent* it. Accordingly, from a practitioners' perspective, we would argue that the central point is to understand how a safeguard procedure can be implemented and how its efficiency can be assessed.

France has a long tradition of implementing such a procedure. The legislation is specifically designed to stimulate managers to become aware of the financial difficulties of the firm at an early stage, and consequently to adopt the necessary measures to recover the position. The legislation regulates three forms of pre-insolvency

situations (Kastrinou, 2016): the safeguard-preservation procedure (*sauveguarde*), the conciliation procedure (*conciliation*) and the *ad hoc* mandate (*mandate ad hoc*).

The first procedure is based on a safeguard plan, which could provide several solutions to overcome the financial difficulties, such as a change in the control of the company, the sale of certain assets or dismissal of a business area, a rescheduling of the debt and so forth. The principal aim of the *safeguard-preservation procedure* is to stimulate managers to take a timely initiative to rescue the firm; they have to demonstrate the difficulties their company is experiencing, asking to begin the procedure to solve them. However, there is a fundamental pre-condition to start the procedure: the firm cannot be insolvent. The principal actor is an administrator, appointed by the Court, who is expected to serve as a sort of temporary manager, with the main aim being to assist the management of the firm in redesigning the strategy and implementing the plan.

The *conciliation procedure* aims to facilitate the rehabilitation of firms experiencing legal, financial or economic difficulties. While the safeguard procedure requires that firms not be insolvent, the conciliation procedure asks for a more precise requirement: firms can access the conciliation if they have ceased payments for no more than 45 days (Kastrinou, 2016). The Court appoints a conciliator, who supports the management of the troubled firm to negotiate with creditors in order to conclude an agreement, whose primary aim is to guarantee the going concern of the firm.

The *ad hoc mandate* intends to ensure the rescue of a distressed firm. It starts at the initiative of the firm, asking the Court to appoint a mandatee; the request must be based on a plan, where managers illustrate the measures to implement, in order to restructure the business and to repay the firm's debts. The ad hoc mandate is less formal and more flexible than the safeguard procedure, which means that achieving an agreement with the creditors should be facilitated. Other contexts provide similar procedures: for example, the UK's insolvency law provides the company with a voluntary arrangement, a debtor in possession procedure which aims to make easy the rehabilitation of firms experiencing financial difficulties.

A recent reform (2017) approved in Italy has regulated a procedure close to the French 'sauveguarde', providing a new tool to firms experiencing financial difficulties, in order to make a timely intervention possible. More generally, it is worth recalling that, in the EU context, a proposal of a new directive has been approved, with the main aim being to give firms experiencing financial difficulties a second chance, supporting them in restructuring the business. This directive also intends to harmonise the legislation, considering that several relevant differences can be observed in the European context.

The literature has paid comparatively little attention to these timely – intervention procedures: while a large

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[1] Before this last reform, the Italian Parliament introduced several innovations since 2005 (Di Carlo and Bisogno, 2016).

number of studies have investigated models to forecast bankruptcy, early warning systems seem to be under-investigated. Indeed, scholars have analysed safeguard procedures principally by adopting a judicial perspective (Kastrinou, 2016; Paulus et al., 2015; Tollenaar, 2017), aiming at investigating legal problems (such as the absolute priority rule) rather than the economic and financial implications of the tools being investigated, with a few exceptions (Di Carlo et al., 2009) but focused on specific contexts.

DISCUSSION

Forecasting model types: Discussion of main findings

It is noteworthy that newer and more complex models do not necessarily have a higher predictive ability than older and simpler ones (Bellovary et al., 2007); moreover, in several studies, the highest success rates have been shown by both multivariate discriminant analysis and neural network models. This means that both statistical methodologies and soft computing approaches allow for achieving good results, although the second ones are more complex than the first. Along this line of thought, Alaka et al. (2018) propose an integrated framework based on 13 criteria (including accuracy, result transparency, ability to use and small sample size), emphasising that the selection of an appropriate tool to predict bankruptcy should be based on its strengths and weaknesses rather than on its popularity (as has frequently occurred).

However, it should also be observed that it is not easy to compare models, taking into account that different definitions of business failure have been adopted. While many papers define this concept as actually filing for bankruptcy, others adopt larger definitions, considering as "unhealthy" all firms that are suffering financial distress or are not able to pay obligations.

It is also important to note that bankruptcy is only one of the possible ways of exiting the market, as Schary (1991) has pointed out. Accordingly, researchers (Esteve-Pérez et al., 2010; Chancharat et al., 2010; Balcaen et al., 2012; Jones and Hensher, 2007; Amendola et al., 2015) suggest focusing on the different forms of exiting the market, considering not only bankruptcy but also voluntary liquidation as well as merger and acquisition (M&A),[2] which constitute out-of-court exit procedures. These studies have appreciably improved our knowledge in this field, highlighting that these different forms of exit are likely to be caused by

various factors.

It should be further observed that the vast majority of previous studies, with few exceptions (Amendola et al., 2017), have adopted an ex-post perspective, testing the predictive accuracy of the model they propose on a sample of failed and non-failed firms, that is, firms whose status is already known. However, in several circumstances (e.g. when a bank is going to decide whether or not to lend money to a firm), an ex-ante perspective is required. Therefore, there is a need to investigate from an ex-ante viewpoint the probability of moving from healthy status to another (for example, liquidation or bankruptcy), and scholars are highly encouraged to examine these issues by adopting a dynamic approach.

More specifically, considering the above and bearing in mind that the failure of a company is a process which evolves over time, we would argue that several statuses should be taken into consideration while forecasting the risk of default:

(1) *Default of payment*, which occurs when a firm (more generally, a debtor) starts not to pay its debts regularly;
(2) *Insolvency proceedings*, which occur when a firm is unable to pay its debts. In this case, even if the insolvency is declared, the firm remains active, though it is in administration or receivership or under a scheme of arrangement (US - Chapter 11). During this period, the firm is usually placed under the protection of the law, continues operating and repaying creditors, while trying to reorganise its operating activities. At the end of the procedure, the firm will alternatively (a) return to normal operating (the default of payment was thus temporary), (b) be reorganised (parts of its activity can be restructured or sold) or (c) be liquidated;
(3) *Bankruptcy*, which occurs when a firm is formally declared distressed since it is not able to pay its creditors. The court will appoint an insolvency expert, whose main aim is to sell the assets and repay the debts. At the end of the procedure, the firm will be dissolved; and
(4) *In liquidation*, which occurs when all the assets of the company are being sold, and the firm will be dissolved.
Considering these steps is essential when assessing the financial and economic condition of a firm, with the main aim being to compare two alternatives. The first one regards the liquidation of a company, through a judicial procedure (such as bankruptcy) aiming at selling all the assets and paying all the debts of the distressed company, which will disappear from the market. The second alternative concerns the rescue of a firm, through a turnaround process: in this case, the firm is experiencing a decline, and a timely intervention would mean reducing losses and restoring the company, making the creation of new value possible. This would mean emphasising more the dynamic nature of the failure process, at the same time enhancing the connection with early warning systems: instead of focusing merely on

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[2] Nevertheless, it should be noted that M&A is quite different from the other statuses. Indeed, M&A might not be caused by financial distress; moreover, the productive capacity of a firm remains in the industry with an M&A, while it is supposed to be removed from the industry in both voluntary liquidation and bankruptcy (Balcaen et al., 2012).

predicting bankruptcy, implementing one or several models and selecting those having a higher predictive ability, it would be highly desirable to take into account all the steps preceding the final distress.

Forecasting model ratios: discussion of main findings

The findings from this review show that the most adopted factor is Net Income to Total Assets, followed by Current Ratio and Working Capital to Total Assets. However, it can be observed that increasing the number of factors to be included in a model does not necessarily improve its predictive accuracy. Moreover, a ratio can have a high predictive ability one year before bankruptcy and a lower one in the previous years. This means that other factors should be taken into account.

One of the elements deserving attention is the legal requirements (namely the bankruptcy or safeguard procedures provided by the insolvency law), which can strongly affect the formal declaration of bankruptcy as well as the characteristics of timely intervention. Furthermore, management skill can also influence the financial distress (Platt and Platt, 2008). More generally, apart from the factors showing a high predictive ability, financial distress and/or bankruptcy can be defined and influenced by the context where a firm is managed. Following this line of thought, another important factor to consider could relate to the differences in the accounting rules to be adopted, which can have a relevant influence on the way of translating economic transactions into accounting numbers. Accordingly, taking into account different contexts and comparing them could be of great interest to both researchers and practitioners. To select countries to be examined, future studies could relate to international accounting classifications (Alexander and Nobes, 2002), which group countries according to different factors, such as:

(1) Commercially driven vs. government-driven and tax-dominated corporate financial reporting;
(2) Large vs. small stock exchange;
(3) Shareholder vs. creditor orientation;
(4) Strong vs. weak profession;
(5) Professional-driven vs. government-driven accounting standards; and
(6) Common law vs. civil law system.

Although several characteristics are evolving, due to the international accounting harmonisation at a global (and especially European) level, reducing the accounting differences between countries, these criteria could be useful to identify different clusters because of the persistence of some dissimilarities.

Finally, bearing in mind the contradictory results concerning the role of corporate governance variables, further studies are recommended to investigate these issues, assessing their role in both listed and non-listed firms. In this way, it could be possible to implement models and use ratios which are not based on stock market data, as frequently occurred where listed firms are investigated. Indeed, as Tobback et al. (2017) underline, data regarding firms' managers and directors are highly desirable while investigating small- and medium-size entities.

Finally, it is worth observing that the vast majority of previous studies have used a unique prediction rule, with the consequence being that they could not take into account the diversity of the different components upon which the performance model has been built. This would imply that such a model could not capture the complexity governing bankruptcy; accordingly, as suggested by du Jardin (2016), combinations of classifiers are desirable since they tend to be more accurate than those based on a single prediction rule. Therefore, further research could investigate these issues.

Early warning systems and safeguard procedures: discussion of main findings

The main point deserving attention is that several countries are paying attention to early warning systems, considering them as an alternative to bankruptcy. This article points out that in the current context there is a need to investigate and propose tools able to prevent financial distress rather than merely predict it.

Following Volkov et al. (2017), it is worth reaffirming that financial distress is a dynamic process; accordingly, the faster a remedy is appointed, the higher the probability of solving troubling situations, avoiding the distress and safeguarding the going concern of the firm experiencing financial difficulties. However, only a few studies (Amendola et al., 2017) have emphasised this aspect.

To make this central point clearer, we would argue that selecting an appropriate tool to prevent failure would mean taking into account several criteria, essentially based on the analysis of strengths and weaknesses, as Alaka et al. (2018) suggest. Table 1 illustrates the recovery rate, its time and costs and the strength of insolvency framework index regarding several European countries and the US.

The strength of insolvency framework index is calculated (only in 2016) as the sum of the scores concerning four sub-indices: the commencement of proceedings index, the management of debtor's assets index, the reorganisation proceedings index and the creditor participation index. According to the World Bank, this index ranges from 0 to 16: the higher the value of the index, the better the insolvency legislation is designed for rehabilitating viable firms and liquidating nonviable ones.

As can be easily observed, several differences exist between countries, especially regarding the recovery rate (which ranges from 32.1% in Poland to 90.1% in Finland)

Table 1. Insolvency data (years 2006, 2011, 2016).

Country	Year	Resolving insolvency			
		Recovery rate	Time (years)	Cost (% of estate)	Strength of insolvency framework index (0-16)
Austria	2006	73.3	1.1	18	-
	2011	73.1	1.1	18	-
	2016	82.7	1.1	10	11
Belgium	2006	86.6	0.9	3.5	-
	2011	87.6	0.9	3.5	-
	2016	89.3	0.9	3.5	11.5
Denmark	2006	67.2	3.3	4	-
	2011	89.4	1.1	4	-
	2016	87.8	1.0	4	12
Finland	2006	89.0	0.9	3.5	-
	2011	89.4	0.9	3.5	-
	2016	90.1	0.9	3.5	14.5
France	2006	47.5	1.9	9	-
	2011	45.0	1.9	9	-
	2016	77.5	1.9	9	11
Germany	2006	81.3	1.2	8	-
	2011	81.9	1.2	8	-
	2016	83.7	1.2	8	15
Greece	2006	45.9	2	9	-
	2011	43.2	2	9	-
	2016	34.9	3.5	9	12
Italy	2006	63.6	1.8	22	-
	2011	58.0	1.8	22	-
	2016	63.1	1.8	22	13.5
Poland	2006	32.1	3	15	-
	2011	35.8	3	15	-
	2016	58.3	3	15	12.5
Portugal	2006	74.7	2	9	-
	2011	72.6	2	9	-
	2016	73.4	2	9	14.5
Spain	2006	74.1	1.5	14.5	-
	2011	70.5	1.5	11	-
	2016	71.2	1.5	11	12
Sweden	2006	74.9	2	9	-
	2011	77.3	2	9	-
	2016	76.6	2	9	12

Table 1. Cont'd.

UK	2006	85.3	1	6	-
	2011	88.6	1	6	-
	2016	88.6	1	6	11
US	2006	80.2	1.5	7	-
	2011	81.5	1.5	7	-
	2016	81.5	1.5	7	15

Source: Adapted from EU (2016).

and the strength of insolvency framework index. Focusing on the case of France previously examined, where early warning systems have a long tradition, we can observe that the recovery rate was quite low in 2001 and 2006; however, bearing in mind that important reforms concerning early warning procedures were implemented in 2014, the recovery rate of 2016 increased a lot. Accordingly, these procedures testify how relevant having a proactive approach towards firms experiencing financial difficulties could be.

Indeed, managers are required to develop a culture of default risk, since experiencing financial problems should be considered as a 'physiological' condition during the life-cycle of a firm. In other words, managers are required to manage *the risk of crisis* rather than the *state of crisis* of their company. This means developing a positive approach toward this risk, prearranging the strategic and operational paths to follow to solve troubling conditions. This would imply also adopting early warning systems through which triggers events can be promptly perceived and timely interventions can be carried out. From a theoretical perspective, this would call for further research based on an interdisciplinary approach, merging law, economics, accounting and finance.

However, the effectiveness of these procedures should not be taken for granted. Accordingly, we call for further research, to provide models through which the evolving condition of a firm experiencing financial difficulties can be forecast. Furthermore, additional efforts are required to assess the efficacy of timely intervention procedures, also comparing different countries, to take into account the effects of the legislation as well as other factors (such as those illustrated in the previous section) that could play a role in guaranteeing the rescue of the firm or accelerating its liquidation, reducing the (indirect) costs of bankruptcy (Bisogno and De Luca, 2014).

Conclusion

The high number of failed firms because of the global financial crisis has renewed the interest of researchers towards forecasting models for default risk. Although

these models have been developed since the 1960s, even more of such studies have been published during the last decades, proposing new approaches or comparing different existing models, to understand which of the models have the best predictive power. Among other things, recent studies have adopted an aggregate approach (Liao and Mehdian, 2016) or a more efficient method to select the explanatory variables (Amendola et al., 2017). Consistently, the first aim of this article was to depict the state of the art of the research in this field.

Unlike previous reviews, this study takes into consideration not only forecasting models for default risk but also early warning systems. Additionally, by discussing model types and factors, it emphasises the critical role of timely intervention procedures, even in the light of the remedies provided by legislation in several countries and the movement to harmonise the different acts in the EU context. Therefore, building on previous research and considering the outcome of prior reviews on the topic, we would argue that this study highlights several important points.

First, there is no one method which unquestionably provides better results than others. Accordingly, instead of proposing new methodologies, future studies are encouraged to adopt different existing systems in different contexts, through comparative analysis (Korol, 2013) or considering several geographical areas (Alaminos et al., 2016), at the same investigating the influence of the legislation (i.e. considering how insolvency procedures are regulated in different contexts).

Second, the methods proposed mostly adopt an ex-post perspective. However, the lesson we are learning from the global financial crisis is that in many cases the financial difficulties experienced by many firms can be overcome through timely intervention. Accordingly, further research is highly desirable to investigate the possibility of implementing methodologies based on an ex-ante perspective. Indeed, the recent juridical innovations introduced in many countries have emphasised how relevant providing corporate rescue mechanisms could be, with the main aim being to get over financial difficulties restoring the profitability of the

firm. Along these lines, the literature on the economics of insolvency can support a process of cultural integration between different disciplines, such as law, economics, accounting and finance, although, according to Penman (2010, p.11), 'financial forecasting, risk determination and valuation are a matter of accounting'.

Third, introducing safeguard procedures could positively affect the recovery ratio, because of a timely intervention; however, their positive impact should not be taken for granted. Further research on the effectiveness of early warning systems are highly encouraged, to assess their repercussion on the recovery ratio, the time and the costs of the procedures implemented in different countries. Additionally, further studies could investigate the effect on these procedures caused by other factors, such as differences in accounting rules, the approach of insolvency legislation towards the insolvent firm or to its creditors, the role of corporate governance variables and so on.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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The research of innovation efficiency of government's fund and enterprises' R&D investment in China

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In this paper, the panel data of China from 2003 to 2012 and stochastic frontier and threshold regression models were used to analyze the impact of government's fund and enterprises' research and development (R&D) investment on China's innovation efficiency and the optimal intensity of different R&D investment and their interval analysis. This research indicates that in the process of innovation in China, the impact of government R&D funding on innovation efficiency is negative, called "government failure"; enterprises' R&D investment can promote innovation efficiency, meaning "market failure" phenomenon will be less. The optimal interval of investment intensity is 0.288 or above and the optimal interval of R&D investing intensity coefficient is between 0.688 and 0.775.

Key words: Government R&D fund, enterprise R&D investment, innovation efficiency.

INTRODUCTION

With the rise of Chinese economy and increasing cash accumulation of enterprises, in addition to meeting daily operation, enterprises will have more money to invest in research and development; while the current domestic and international market competition is fiercely increasing, in order to increase product competitiveness, enterprises need not only to improve the domestic and oversea market participation, but also need to increase investment in research and development, and thus enhance the overall innovation efficiency (Innovation efficiency refers to the input-output ratio of innovation behavior). Therefore, enterprise's research and development (R&D) investment refers to R&D activities conducted by the enterprises themselves or through self-raised funds. Government R&D investment refers to R&D activities supported by financial funds. In recent years, the scale of government R&D funds has been greatly expanded in

China and has always played a basic and important role in promoting innovation efficiency. In particular, since the reform and opening up policy, the government has set up a number of national research programs to support scientific research and development, mainly as follows: National Spark Program, National Natural Science Foundation, "863" plan, Torch Plan, and "973" plan. These government's research programs promote the development of China's scientific research to some extent and provide an important guarantee for innovation efficiency. However, compared with the developed countries, China's innovation efficiency is still at a low level, which is still an indisputable fact. Therefore, assuring efficiency optimization of government R&D funding and enterprise R&D investment has become the key factor to the impact of innovation efficiency.

A country's R&D funding sources are mainly self-

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financing or government funding. The two kinds of models as part of innovation system play an important role in promoting economy growth. Enterprises' R&D investment follows market-oriented principle; it applies new technologies, uses new products and then seeks competitive advantage for the purpose. So enterprises' R&D investment may be more efficient than government's R&D investment (Wang, 2011). However, due to the existence of "market failure", the monopoly of R&D resources, externalities and information asymmetry will interfere with enterprises' R&D investment, which gives theoretical explanation for government funding enterprise's research and development (Guellec and Van, 2003). At the same time, the government's investment on enterprise's R&D will also be affected by imperfect information and market imperfection; there may be "government failure" problem, namely government's market response signals is numb and slow, inefficient and rent-seeking corruption problems (Jian and Qi, 2007). So what are the roles of a country's innovation efficiency? Are there any differences? How do we coordinate R&D fund structure and make a country's innovation efficiency to come to the optimal? These issues are our major concern.

Based on the earlier considerations, this paper focuses on the following two aspects: first, utilizing transcendental logarithmic random frontier model to study the overall impact of government's funding and enterprises' R&D investment on the efficiency of innovation; second, with the help of threshold regression model to seek the optimization zone of government's funding and enterprises' R&D investment to effectively avoid "market failure" and "government failure". The contributions of this paper include: (1) establish dual failure framework of government and market at first, then analyze a country's innovative efficiency; (2) provide beneficial experiences on how to adjust the relationship between government and market for the promotion of innovation efficiency.

THEORETICAL REVIEW

Government's R&D fund and enterprises' R&D investment as two kinds of important sources of R&D funding have raised and promoted innovation efficiency. However, due to the co-existence of "government failure" and "market failure", both of them do not only show the difference between the innovative output effects, but also show a "complementary relationship" and "alternative relationship" coexistence phenomenon.

Analysis on the different influence of government's R&D funding and enterprises' R&D investment on innovation efficiency

In the process of innovation in a country, government's funding is an important guarantee for R&D investment and enterprises' investment as an important source of R&D funds; both kinds of funds have impact on the improvement of innovation efficiency. However, due to the differences between the two kinds of bodies, government's R&D funding and enterprises' R&D investment have different influence. This paper mainly summarizes three aspects: the degree of participation, the impact field and the impact style.

As the main body of technology innovation, enterprises' R&D investment plays a leading role in the innovation process of a country. While government's funding plays a more important role in standardization and management. As the competition between enterprises increases, in order to obtain higher profits and seek competitive advantage and based on market demand-oriented, enterprises mainly obtain the application of new technologies and new products and introduce foreign technology at the same time, enlarge R&D self-investment, improve their own R&D technology and product technology. Therefore, enterprises concern more on the utilization of investment funds; the utilization efficiency of enterprises' R&D funds may be higher than the government's R&D funding (Miao, 2011).

Government's funding is mainly concentrated on the field of basic research and enterprises' R&D investment mainly focuses on application research. These have different effects and influences in different innovation areas. In the short term, application research often targets R&D and technology acquisition, as business mainstay; in order to obtain commercial technology and new products and seek competitive advantage, enterprises' R&D investment frequently focuses on more efficient innovative projects that are market-oriented; R&D results output is faster (Yan and Gong, 2013). However, basic research has much more and relatively large impact on the radiation and guidance of other research areas in long term, often brings greater economic and social value, and improves the overall innovation level; government's R&D funding is much more efficient on overall innovation efficiency.

Government's R&D funding based on original R&D resources and enterprises' R&D investment can bring breakthrough on R&D funds' structure. Government's R&D funding mainly provide funds directly, with relatively large funds support to ease the pressure of enterprises' investment shortage. When the government exists within the rent-seeking corruption, the existence of internal effects, making the "government failure" phenomenon continues to affect the usage efficiency of government's funds (Yue et al., 2002). Enterprise can bring knowledge overflow through market information feedback, bring new technology and knowledge "learning by doing" such as staff exchange and demo imitation, guide enterprises to allocate innovative resources much more effectively and promote innovation efficiency (Fang et al., 2011). The incomplete and asymmetry information caused by the "market failure" phenomenon misleads their own R&D investment, affects the rational allocation of R&D

resources and improves innovation efficiency (Xing, 2004).

Analysis on the optimal intensity interval between Government's R&D funding and enterprises' R&D investment

Government's R&D funding and enterprises' R&D investment complement with each other in the whole innovation process. The intensity of government R&D funding and the intensity of enterprise's R&D investment indicate in this paper the weighting of government and enterprises' investment in innovation and R&D activities. However, limited nature of government's R&D funding and enterprises' R&D investment will result in government's R&D funding and enterprises' R&D investment push out with each other and form "alternative relations"; this has negative impact on the overall innovation efficiency.

The "complementary relationship" between government's R&D funding and enterprises' R&D investment can improve the usage efficiency of government's R&D funding. First of all, government's R&D funding has an effect on enterprises' R&D investment. Spence (1984) studied European experiences and found that government's R&D funding directly reduces the cost of enterprise technology innovation, reduces the risk of enterprise's R&D investment; thereby could enhance the motivation and enthusiasm of enterprises' devotion to research and development. Czarnitzki and Licht (2006) have confirmed the positive incentive of government's R&D funding on enterprises' R&D investment through empirical research from German enterprises, and R&D funding has also increased the likelihood of enterprises acquiring patents. Li and Wang (2010) pointed out that crowding-out effect between Chinese government R&D funding and enterprises' R&D investment does not exist, but effectively stimulated the motivation and enthusiasm of enterprises' devotion to research and development.

Secondly, enterprises' R&D investment has an "incentive effect" on government's R&D funding. Enterprises' R&D investment does not only improve their own research and development capabilities and ensure the realization of expected purpose of government's funds support; but also fully demonstrate the consistency between enterprises and national interests, and further attract government's R&D funding. Liu (2000) and Wu (2006) indicate that: by strengthening R&D investment, enterprises improve their own technology innovation and product innovation, and improve their competitiveness and profits. At the same time, that improves the level and progress of whole society's technology. In this beneficial process of self-realization, the role of enterprises in national innovation system has become increasingly prominent and government will further increase government's R&D funds to promote the role of enterprises in national innovation system (Perkmann and Walsh, 2009).

The "alternative relationship" between governments' funding and enterprises' investment in research and development is mainly embodied in mutual "crowding-out effect". Firstly, government's R&D funding will squeeze out enterprises' R&D investment. If enterprises are relatively easy to obtain government's R&D funding, then they will be in loss of competitiveness and enthusiasm on R&D activities. Klette et al. (2000) and Schreyer (2000) found that government is generally inclined to support the projects with high success probability and high returns, which are exactly what enterprise itself is ready to implement. If the subsidized enterprise directly utilizes government grant funds to replace its own R&D investment or adjust to carry out the new subsidized R&D projects, to give up the unsupported R&D projects, government's funding for enterprise will produce "crowding out effect" (Cheng and Zhao, 2009). In addition, the increasing of government's funding also increases enterprises' demand for scarce R&D fund resources. If the determinants of R&D (such as high-level labor) are insufficiently supplied, market mechanism will increase the salary level of R&D personnel and then reduce the enthusiasm of enterprises in employing R&D personnel, and change their R&D investment behavior. Goolsbee (1998) confirmed that when R&D expense and cost increase, enterprises will abandon some R&D projects and turn to other profitable projects, lead to squeeze some enterprise's R&D investments. This "squeeze effect" in the country with scarce scientific and technological resources becomes especially serious.

Secondly, enterprises' R&D investment will reduce government's R&D funding. Enterprise, as main-bodies in market, could be aware of enormous and various market information. At present, R&D investment from Chinese enterprises has achieved good results, which have significantly improved R&D innovation efficiency, and led enterprises to expand their R&D investment scale (Zhu et al., 2014). With the continuing improvement of enterprises' R&D, the scale of enterprise R&D investment is expanding, will be part of government R&D funds, that makes the scale of government funds gradually to be narrowed, the ration of China's enterprises' R&D investment accounted in the total social R&D investment from less than 60% in 2000 to about 75% in 2010 (Kang, 2013).

EMPIRICAL MODEL SETTING AND VARIABLE DEFINITION

Empirical model setting

Basic model settings

In choice of production function, most commonly used

two kinds of function are Cobo-Douglas and beyond logarithmic forms. Although the former is with simple form, but its assumption of technology is neutral and output elasticity is fixed (Pai et al., 2009). The latter relaxes these hypotheses, which are more flexible in form and can better avoid estimate deviation due to misuse of functions (Fu and Wu, 2007).

In order to examine the effect of government's R&D funding and enterprises' R&D investment on China innovation efficiency, according to Battese and Coelli (1995) model setting, this paper utilizes stochastic frontier model of beyond logarithmic production function as regression model, as follows:

$$lnPatent_{it}=\beta_0+\beta_1+lnK_{it}+1/2\beta_2(lnK_{it})^2+1/2\beta_3+(lnL_{it})^2+\beta_4lnK_{it}lnL_{it}+v_{it}+u_{it} \quad (1)$$

$$u_{it}=\delta0+\delta1+lnGRD_{it}+\delta_2lnBRD_{it}+\delta_3lnTMT_{it}+\delta_4lnLabor_{it}+\delta_5lnInf_{it}+\delta_6lnOpen_{it}+w_{it} \quad (2)$$

In Equation 1, β_i (i=0,1…5) is the coefficient of regression variable, $Patent_{it}$, K_{it}, and L_{it}, respectively denote patent output, R&D capital stock and R&D personnel input at i-region in t-year, v_{it} denotes random disturbance items, and u_{it} denotes technical inefficiency. In Equation 2, r_i (i=0,1…5) is the coefficient of the regression variable, GRD_{it}, BRD_{it}, TMT_{it}, $Labor_{it}$, Inf_{it} and $Open_{it}$, respectively represent the level of government's R&D funding, enterprises' R&D investment, technology innovation environment, human capital level, region infrastructure level and opening up level, and ω_i denotes random error term.

Threshold model setting

Based on the threshold regression model developed by Hansen (1999), this paper selects government's R&D funding intensity ω_{it}^G and enterprises' R&D investment intensity ω_{it}^B as threshold variable; t^G, t^B is the threshold value of these two threshold variables, take dual-threshold as example to build a regression model:

$$U_{it}=\delta_0+\eta lnX_{it}+\kappa_1 lnGRD_{it}*I(\omega_{it}^G\leq\tau_1^G)+\kappa_2lnGRD_{it}*I(\tau_1G<\omega_{it}^G<\tau_2^G)+\kappa_3lnGRD_{it}*I(\omega_{it}^G>\tau_2^G)+\omega_{it} \quad (3)$$

$$U_{it}=\delta_0+\eta lnX_{it}+\rho_1 lnBRD_{it}*I(\omega_{it}^B\leq\tau_1^B)+\rho_2lnBRD_{it}*I(\tau_1^B<\omega_{it}^B\leq\tau_2^B)+\rho_3lnBRDi_t*I(\omega_{it}^B>\tau_2^B) \quad (4)$$

where i denotes unit entity, t denotes time, u denotes explained variable, LnX denotes other variable that significantly affects explained variable, and I(•) denotes exponential function, $\omega_{it}\sim idd$ (0, σ^2). In the model (Equation 3), $lnGRD$ is the explanatory variable affected by threshold variable, w_{it} denotes intensity of government's R&D funding, κ_1, κ_2, κ_3, respectively denote influence coefficients of explain variable influence on

explained variable when the threshold variables with the terms of $\omega_{it} <\tau_1^G$, $t_1 <\omega_{it} <t_2$, $\omega_{ii}> t_2$,. In Equation 4, $lnBRD_{it}$ is explanatory variable affected by threshold variable. ω_{it}^B is the intensity of enterprises' R&D investment. ρ_1, ρ_2 and ρ_3, respectively denote the regression coefficients of explain variable influence on explained variable when the threshold variables with terms of $\omega_{it}^B<\tau_1^B$, $\tau_1^B<\omega_{it}^B<\tau_2^B$, $\omega_{it}^B> \tau_2^B$.

Variable definition and data source

Variable definitions

(1) K_{it} and L_{it}: This paper takes perpetual inventory method to calculate the R&D funds stock K_{it}, $K_{it}=(1-\delta)*K_{it-1}+E_{it}$. The R&D capital stock in 2003 is: $K_{i2003}=E_{i2003}/(g+r)$; g denotes the region average annual growth rate of internal investment in R&D, r denotes depreciation rate, here δ=15% (Wu, 2006). While, E_{it} denotes the actual annual R&D expenditure in each region, the value takes reference to R&D expenditure price index (R&D expenditure price index = 0.55 × Consumer Price Index + 0.45 × fixed asset investment price index) fabricated by Zhu and Xu (2003); 2003 is the base period; it reduces the nominal R&D expenditure of internal expenses. R&D personnel investing takes definition of R&D staff in equivalent full-time in each region and every year.

(2) $Patent_{it}$: In measuring R&D output, this paper selects the number of patents as assessment index. The patent number of $Patent_{it}$ is measured by the number of patents granted in China over the years.

(3) GRD_{it}, BRD_{it}, TMT_{it}, $Labor_{it}$, Inf_{it} and $Open_{it}$: GRD_{it} denotes government's R&D funding and is expressed as the amount of government funds in each region and every year of a country's annual R&D expenditure. BRD_{it} denotes enterprises' R&D investment funds and is expressed as the amount of enterprise's investment in each region and every year of a country's annual R&D expenditure. Technology Innovation Environment TMT_{it} is measured by annual technical market total turnover in each region of China. The level of human capital $Labor_{it}$ is measured by average annual number of years of education in each region of China. This paper classifies education level into five categories: uneducated (0 years), primary education (6 years), junior middle school education (9 years), high school education (12 years) and college education (16 years), to denote the average age of education in each region ($Labor_{it}$). The formula is: $Labor=pri×6+jun×9+sen×12+col×16$. Infrastructure level Inf_{it} is measured by annual post and telecommunications business in each region of China. Opening up level $Open_{it}$ is measured by the actual usage of foreign direct investment in each region of China.

Data sources

The empirical data of this paper are mainly from panel data of each region in China between 2003 and 2012. The amount of internal expenses incurred by R&D personnel, the total amount of R&D personnel, the R&D internal expenses, the enterprises' funds and the government's R&D funds are derived from the "China Science and Technology Statistics Yearbook"; the data obtained by per year of education are derived from "China Labor Statistics Yearbook". The total amount of the postal and telecommunications business, the consumer price index and the fixed asset investment price index are from "China Statistical Yearbook"; the actual usage of

Table 1. Test results of impacts on innovation efficiency.

Code	Model 1 (Delay a year)	Model 2 (Delay 2 years)	Model 3 (Delay 3 years)	Model 4 (Delay 4 years)
lnK_{it}	2.563 (3.663***)	2.457 (2.652***)	3.485 (4.027***)	4.517 (5.077***)
lnL_{it}	-4.575 (-7.693***)	-4.137 (-5.398***)	-4.545 (-6.075***)	-5.827 (-6.458***)
$[lnK_{it}]^2$	0.629 (3.403***)	0.647 (3.091***)	0.690 (2.879***)	0.826 (4.275***)
$[lnL_{it}]^2$	0.836 (4.356***)	0.810 (3.451***)	0.996 (4.003***)	1.219 (5.488***)
$[lnK_{it}][lnL_{it}]$	-0.591 (-3.043***)	-0.599 (-2.594***)	-0.746 (-3.044***)	-0.936 (4.595***)
Constant term β_0	19.319 (16.146***)	17.244 (18.005***)	5.063 (17.034***)	19.932 (3.624***)
$lnGRD_{it}$	0.484 (2.901***)	0.432 (3.653***)	0.116 (3.817***)	0.137 (3.333***)
$lnBRD_{it}$	-0.214 (-2.526***)	-0.068 (-1.968***)	0.073 (1.451)	0.067 (1.186)
$lnTMT_{it}$	-0.021 (-0.484***)	-0.163 (-4.100***)	-0.121 (-4.180***)	-0.122 (-3.811***)
$lnLabor_{it}$	-4.729 (-3.675***)	-2.229 (-3.263***)	-0.302 (-0.528)	-0.611 (-0.937)
$lnInf_{it}$	-0.697 (-6.277***)	-0.517 (-5.600***)	-0.407 (-6.874***)	-0.424 (-7.340***)
$lnOpen_{it}$	-0.141 (-2.941***)	-0.104 (-2.626***)	-0.037 (-1.289)	-0.028 (-0.762)
Constant term δ_0	15.514 (5.177***)	8.998 (6.581***)	5.063 (4.415***)	5.736 (3.624***)
σ	0.288 (10.112***)	0.148 (8.284***)	0.122 (10.873***)	0.123 (9.731***)
γ	0.648 (10.173***)	0.375 (3.612***)	0.999 (11.887***)	0.999 (8.759***)
Log function value	-119.342	-101.039	-80.432	-72.937

T in the brackets for test value; ***, **, *, respectively, denote that variables pass 1, 5, and 10% of significance level test.

foreign direct investment is from the "China Statistics Yearbook "; some data are from regional statistical yearbook. In addition, due to the lack of data in Tibet Autonomous Region, the country data of China exclude Tibetan file data.

ANALYSIS OF EMPIRICAL RESULTS

Basic model test and analysis of empirical results

There is a certain time lag in the process of innovation from R&D investment to patent output. Liu and Guan (2002) set the lag time to 1 year, Furman et al. (2002) set to 2 years, Li (2009) studied and found that would take about 3 years between invention application to patent authorization in China. For the sake of comprehensive consideration, this paper will test the stochastic frontier model with four consideration of no time lag, lag 1 year, lag 2 years and lag 3 years.

The regression results between the input and the output are lagging 0 year, lagging 1 year, lagging 2 years and lagging 3 years that are shown in models 1, 2, 3 and 4 (Table 1). From the estimation results, r^2 and y of models 1 to 4 passed the 1% significance level test, which indicates that technology inefficiency is significant in the R&D innovation process. At the same time, it confirms the rationality of application of SFA technology in this paper.

The regression coefficients of $lnGRD_{it}$ in models 1 and 4 are positive and the 1% significance level test shows that government's R&D funding does not promote innovation efficiency, but does have significant negative effect.

The main reasons for this analysis are: government's R&D funding is too low. Government, as an important part in national innovation system, plays an important role in a

country's innovation activities. The purpose of government's R&D funding is to guide the main direction of enterprises' R&D investment, reduce cost of enterprises' R&D investment, and solve the problem of unequal investment caused by technology spillovers between private investment and social benefits. At present, because of lack of vitality of the market economy in China, enterprises' R&D investment capacity and desire are inadequate; government, as a strong backing power for R&D activities, greatly needs to provide necessary and enough financial support for R&D activities. However, few government's R&D funds result in lack of financial support for enterprises' R&D activities and reduces their R&D scale, thereby reduces their research and development capabilities and affects the improvement of national innovation efficiency.

On the other hand, the intensity of government's R&D funding is too high. If the intensity of government's R&D funding is too high, it will encourage the increase in demand for R&D resources and elements, but the shortage in the supply of scarce R&D resources will lead to increase in R&D decision-making elements, thereby increasing the cost of enterprises' research and development. Some enterprises will give up part of R&D activities and turn to other profitable projects; this "crowding out" phenomenon is particularly serious in countries that lack R&D resources (Li and Wang, 2011). In short, inappropriate government intervention, that is, if government's funding is too low or too high will both be detrimental to the improvement of innovation efficiency.

The regression coefficients of enterprises' R&D input variable $lnBRD_{it}$ in models 1 and 2 are significantly negative through the 5% significance test. The regression coefficients are positive in models 3 and 4, but not

significant, which indicates that enterprises' investment has played a catalytic role in improving innovation efficiency. With the improvement of economic development level and technical level, Chinese market economy is becoming increasingly active and dynamic; enterprises' R&D investment is gradually increasing. The capabilities and level of R&D are continuously improving. Chinese market economy develops very stable, "market failure" phenomenon appears less, enterprises can accurately and completely grasp market information, reasonably adjust their own R&D funds scale to ensure a reasonable proportion of enterprise R&D investment, making the level of innovation efficiency of the whole country gradually improve.

But, with the deepening of government's intervention, the influence of "market failure" on R&D innovation has been effectively regulated by government policy strategy, and enterprises' R&D investment can guarantee correct investment direction and investment scale under the guidance of government policy. To ensure that enterprises' R&D funds can be invested into high level of innovation and with scarce R&D resources areas, the overall efficiency of Chinese innovation needs to be improved.

Among other explanatory variables, $lnTMT_{it}$, which represents the technology innovation environment, $lnLabor_{it}$ represents the human capital level, $lnInf_{it}$ represents the infrastructure level, and $lnOpen_{it}$ represents the opening up level. In the four models of the regression coefficients, the above four coefficients are significantly negative; it indicates that they significantly promote the improvement of innovation efficiency; the better the technological innovation environment, the higher the level of human capital; the better the conditions of infrastructure, the higher the level of opening up and the innovation efficiency.

The analysis shows that R&D investment can promote the improvement of innovation efficiency level, but the impact of government's R&D funding on innovation efficiency is negative. It can be seen that the intensity of enterprises' R&D investment in China is relatively reasonable, but government's R&D funding is with too low or too high proportion. Is there an optimal interval between them that can make our innovation efficiency to be optimal? To this end, this paper continues to use the valve regression model to test the existence of strength of government's R&D funding and enterprises' R&D investment strength; it further discusses government's R&D funding strength and enterprises' R&D investment strength threshold characteristics. Finally, there is a comprehensive analysis on the optimal interval of government's R&D funding strength and enterprises' R&D investment strength.

Threshold model test and empirical analysis

Through the previous analysis, this paper further explores whether there is an optimal interval in the process of government's R&D funding and enterprises' R&D investment influencing innovation efficiency to minimize the "market failure" and "government failure" to ensure maximum innovation efficiency. In order to test the intensity of government's R&D funding and the optimal range of enterprises' R&D investment intensity, then we need to improve the innovation efficiency of China. This paper will take the intensity of government's R&D funding and enterprises' R&D investment as the threshold variables.

Threshold test

Firstly, in order to determine the number of thresholds, we need to examine the threshold effect. This paper examines models 3 and 4 in the absence of the threshold, the existence of a threshold, the existence of a double thresholds and the existence of a triple thresholds. The specific test results are shown in Table 2.

It can be seen from Table 2 that the threshold effect test shows that the intensity of government's R&D funding in model 3 and the intensity of enterprises' R&D investment in model 4 are significantly different from each other. The regression results of each threshold are shown in Table 3.

It can be seen from Table 3 that the w^G thresholds of model 3 are respectively estimated by Bootstrap to be 0.161, 0.208 and 0.282. According to the threshold value, the innovation efficiency is affected by different government subsidy intensity. The intensity of government's R&D subsidy can be divided into four intervals: low government's R&D subsidy intensity ($w^G <= 0.161$), sub-low government's R&D subsidy intensity ($0.106 < w^G <= 0.208$), sub-high intensity of government's R&D subsidy ($0.208 < w^G < 0.282$) and high intensity of government's R&D subsidy ($w^G > 0.282$). Similarly, the respectively estimated value by Bootstrap of w^B from model 4 is 0.688, 0.775 and 0.838. According to the threshold, it can be seen that the intensity of enterprise's R&D investment that can affect innovation efficiency can be divided into four intervals: low enterprises' R&D investment intensity ($w^B <= 0.688$), sub-low enterprises' R&D investment intensity ($0.688 < w^B < 0.775$), sub-high intensity of enterprises' R&D investment ($0.775 < wB < 0.838$) and high intensity of enterprises' R&D investment ($wB > 0.838$).

Parameter estimation and empirical results analysis

The threshold variables are added to models 3 and 4 and regression analysis. The results are shown in Table 4. The test results of model 3 show that the negative effect of government subsidy on innovation efficiency can be reduced only when the intensity of government's R&D funding breaks through certain thresholds, thus reduce the impact of "government failure" on innovation level.

Table 2. Test of the threshold effect.

Test	Model (3)		Model (4)	
	F value	P value	F value	P value
Single threshold check	20.981***	0.000	51.448***	0.000
Double threshold test	12.632**	0.040	17.746**	0.017
Triple threshold check	10.363**	0.050	8.795*	0.067

***, **, *, respectively, denote that variables pass 1, 5, and 10% of significance level test.

Table 3. Regression results of the threshold value.

Indicator	Threshold Value		Threshold Value		Threshold Value	
	Estimated value	95% significance interval	Estimated value	95% significance interval	Estimated value	95% significance interval
Model 3	0.161	[0.088, 0.532]	0.208	[0.161, 0.281]	0.282	[0.088, 0.533]
Model 4	0.688	[0.606, 0.727]	0.775	[0.760, 0.798]	0.838	[0.609, 0.882]

Table 4. Regression results of the model's parameters.

Parameter	Model 3	Model 4
$lnTMT_{it}$	-0.0686 (-5.00***)	-
$lnLabor_{it}$	2.633 (2.22***)	-
$lnInf_{it}$	-0.102 (-5.56***)	-
$lnOpen_{it}$	0.032 (1.77*)	-
$lnBRD_{it}$	-0.262 (-8.87***)	-
p_1	-	-0.226 (-8.27***)
p_2	-	-0.270 (-9.66***)
p_3	-	-0.256 (-9.30***)
p_4	-	-0.237 (-8.72***)
$lnGRDit$	-	0.103 (2.82***)
k_1	0.161 (4.25***)	-
k_2	0.216 (5.36***)	---
k_3	0.197 (4.93***)	---
k_4	0.177 (4.55***)	---
C	-4.056 (-1.58)	-1.488 (-0.60)
R^2	0.53	0.57

***, **, *, respectively, denote that variables pass 1, 5, and 10% of significance level test.

Specifically, when the intensity of government's R&D funding is less than 0.161, although the negative impact of government's R&D funding on innovation efficiency is the smallest, the elasticity coefficient is -0.161; but because of the current government funding in our country has been basically higher than this ratio, here we need to seek a higher proportion. When the intensity of government's R&D funding reaches 0.161 to 0.208, the negative effect of government's R&D funding on innovation efficiency is larger, and its elasticity coefficient is -0.216. However, when the intensity of government's R&D funding is 0.208-0.282, the negative effect of government's R&D funding on innovation efficiency is reduced and the elasticity coefficient is increased to -0.197. When the intensity of government's R&D funding reaches 0.282, the negative effect of government's R&D funding in the innovation process is relatively small, its elasticity coefficient is -0.177; the elasticity is lower than the first interval, but the gap is small, and the government's R&D subsidy strength is also in line with the current development trend of innovation efficiency in China.

The regression of model 4 shows that it is obvious that there is threshold for the impact of enterprises' R&D investment on innovation efficiency. Overall, only the enterprises' R&D investment intensity is in a reasonable range; the enterprises' R&D investment can promote the innovation efficiency to a full role; when the enterprises' R&D investment intensity is too low or too high, it will both reduce the positive effects of enterprises' R&D investment on innovation efficiency. Specific performance is: when the enterprises' R&D investment intensity is lower than 0.688, enterprise cuts down investment in R&D innovation; though enterprises' R&D investment on the innovation efficiency is relatively small, its flexibility coefficient is only 0.226; when the enterprise R&D investment strength increased to 0.688-0.775, enterprises' R&D investment promote the innovation efficiency to be optimal; the significantly elastic coefficient is 0.270. However, when the intensity of enterprises' R&D investment increased to 0.775-0.838, the role of enterprise's R&D investment in innovation efficiency began to decline; and when the intensity of enterprises' R&D investment exceeds 0.838, the promotion of enterprise' R&D investment to innovation efficiency is weakened, and its elasticity coefficient is reduced to 0.237, but still higher than the elasticity of first interval is 0.226.

Based on the threshold characteristics of government's R&D and enterprises' R&D investment, this paper argues that China is currently setting the intensity of government's R&D funding above 0.282, and the intensity of enterprises' R&D investment is controlled between 0.688 and 0.775. This can reduce the "market failure" and "government failure" on the innovation efficiency, and thus improve the overall level of innovation in China.

CONCLUSION AND POLICY RECOMMENDATIONS

This paper summarizes the impact mechanism of government's R&D funding and enterprises' R&D investment on innovation efficiency from the perspective of "double failure". Then, this paper analyzes the impact of government's R&D funding and enterprises' R&D investment on innovation efficiency based on the data of Chinese region panel data between 2003 and 2012. On the whole, the impact of government's R&D funding on innovation efficiency is negative, and enterprises' R&D investment can promote the improvement of innovation efficiency. This shows that in Chinese overall innovation system, there is a certain degree of "government failure", but less "market failure" phenomenon. At present, the optimal interval of intensity of government R&D funding based on over 0.161, and over 0.282, and the optimal range intensity of enterprises' R&D investment is between 0.668 and 0.775.

And further, the threshold regression method is used to define government R&D funding and enterprises' R&D investment of the optimal strength. This study finds that

only the government's R&D funding and enterprises' R&D investment is in a reasonable interval, that is, the intensity of government R&D funding is above 0.282, enterprises' R&D investment intensity is constrained into 0.668 and 0.775, in order to minimize the impact of "government failure" phenomenon on innovation efficiency, and improve the role and importance of enterprises' R&D investment in promoting innovation efficiency.

Therefore, we should fully understand the role of government and the market- mechanism in the innovation system, providing rich amounts of funds resources and a good environment for the purpose of Chinese innovation well developed. First of all, the government should continue to expand the scale of government's R&D funds, so that it is close to the level of funding in developed countries to ensure the intensity of government R&D funding in a reasonable range, and prevent the occurrence of inefficient "government failure" phenomenon. Secondly, it should increase the support of strength to innovative enterprises, improve enterprises' innovation investment preferential policies to mobilize the enthusiasm of enterprises' R&D investment; at the same time, enterprises should strengthen their own R&D investment, introduce external advanced technology and high-quality personnel, improve the competitiveness of their products, and fully play their own role in the innovation system.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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Full Length Research Paper

Effects of employees' commitment on organizational performance at Arjo Didessa Sugar Factory

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Presently, no organization can perform at peak levels unless each employee is committed to the organizations objectives. Hence, it is important to understand the concept of commitment and its feasible outcome. The employees in sugar industry play decisive role in transferring the theory to practical in order to enhance development of industry. The objective of this study was to determine the effects of employee commitment on performance of organization based on a case study of Arjo Didessa Sugar Factory. To attain this, the study determined factors that affect employee commitment in the study area and also attempted to identify the relationship and their effect between employees' commitment, and factors affecting employee's commitment, as well as the relationship and their effect between employees' commitment models and organizational performance at Arjo Didessa Sugar Factory. The research is a cross-sectional study. 261 employees and four management members were selected as sample of the study. Standardized questionnaires were distributed, filled, and collected. Statistical package for social sciences (SPSS) was used to process and analyze the data collected from the respondents through correlation; and regression analyses were performed to determine the association between dependent and independent variables. Additionally, employees' commitments were found to have effects on the organizational performance in the study area. Based on the regression results, employees' commitments models have effects on performances for the organization at Arjo Didessa Sugar Factory. Thus, recommendations have been provided to increase commitment by designing motivational package, and establishing sustainable regular training program in the company.

Key words: Employee's commitment, organizational performance, motivation, training and development.

INTRODUCTION

In today's competitive world, every organization is faced with new challenges regarding sustained productivity and creating committed workforce. Hence, it is important to understand the concept of commitment and its feasible outcome (Dixit and Bhati, 2012). It is no longer good enough to have employees who come to work faithfully every day and do their jobs independently. Employees now have to think like entrepreneurs while working in teams and have to prove their worth. People are the most important drivers of a company competitive advantage

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(Maugo, 2013).

People management is an important aspect of organizational processes. This emanate from the recognition that the human resources of an organization and the organization itself are synonymous. A well-managed business organization normally considers the average employee as the primary source of productivity gains. These organizations consider employees rather than capital as the core foundation of the business and contributors to the firm's development (Kabir and Parvin, 2011).

To ensure the achievement of firm goals, the organization creates an atmosphere of commitment and cooperation for its employees through policies that facilitate employee satisfaction. Satisfaction of human resource finds close links to highly motivated employees. Motivated employees then develop loyalty or commitment to the firm resulting to greater productivity and lower turnover rates (Kabir and Parvin, 2011).

The workforces today are filled with various mindsets. Over the past few years, there have been numerous supports on human capital development, lifelong learning and continuous attention on soft skill development. Nevertheless, many a times, issues are only attended to at the surface level but not to the roots of the cause. Human beings are highly associated with emotion and intelligence. Therefore, the requirement to fulfill human need hierarchy is rather an important aspect especially on satisfaction and motivation (Yukthamarani et al., 2013).

Employee commitment always plays a very key role in improving the organizational performance. The organizational performance can be measured through a lot of ways for example, company employee turnover, return on equity etc. Employee commitment can be enhanced through their involvement in assessment construction and providing them with the chance for better insight on the whole procedure of the organization performance measurement (Dost and Ahmed, 2011).

Igella (2014) recommended that the research should be carried out in another sector in order to broaden the understanding of the term commitment in relation to that sector. The reason for carrying out further research in that direction is that the factors that may strongly influence employee commitment in the service industry could differ in the production industry. Being able to understand these factors in the production industry as well would be very helpful in shedding light on other organizational.

In manufacturing industry especially in sugar industry, there is limited research related to commitments of human resource. As the industry needs technical staffs from its nature there should be investigation about the employee's attitude towards their organization, how the commitments have been influenced and the practical effects of employees' commitment in order to attain the desired organizational goal effectively.

Therefore, the purpose of this study is to investigate factors affecting employees' commitments, identify relationship between employee's commitment and organizational performance and finally, identify the effects of employees' commitment upon the organizational performance in the case of Arjo Didessa Sugar Factory.

Hypothesis

H1: Employees' commitment has no significant relation with demographic factors; work environment; motivation and training and development.
H2: There is no significant relationship between employees' commitment models and organizational performance in the study area.
H3: Factors affecting employees' commitment have no effect on employees' commitment in the study area.
H4: Employees' commitment models have no effects on organizational performance in the study area.

Significance of the study

This study provides guidance to the management at different level and employees of Arjo Didessa Sugar Factory, and other similar sugar industries to understand factors that affects employees' commitment and effects of employees' commitments to organizational performance. Moreover, there is lack of studies concerning employees' commitment in the study area. Thus, this study makes suggestions to the management for further implementation, and gives a better understanding on the work environment for Arjo Didessa Sugar Factory as manufacturing industry. In addition, the study makes a contribution to future research in human resource management.

METHODOLOGY

An explanatory approach has been used to examine the relationship between commitment of employees and organizational performance in sugar industry, in the case of Arjo Didessa Sugar Factory by Pearson correlation. Additionally, the relationship of the variables, and the influence of independent variable (employees' commitment) upon dependent variable (organizational performance) undertaken through linear regression analysis were investigated.

The research approach that is used for this study is both quantitative and qualitative research approach. The reason for choosing quantitative research approach is due to the fact that it involves data that uses statistical analyses to obtain their findings. Similarly, there was qualitative data gathered through interview from management that cannot be analyzed statistically but interpreted accordingly to attain the desired objectives. Focus was on a sample size of 265 employees ranging from top management personnel, middle managers, supervisors and the lower level employees.

To determine an adequate sample size that estimate the population prevalence with a good precision Daniel (1999) formula was used. This is because if this proportion is larger than 5% (n/N >0.05), the formula with finite population correction should be used

Table 1. Correlation of factors affecting employee's commitment (EC).

Variable		Employees' commitment
Motivation	Pearson correlation (R)	0.538**
Work environment	Pearson correlation (R)	0.545**
Training and development opportunity	Pearson correlation (R)	0.628**
Demographic factors	Pearson correlation (R)	0.442**

Source: SPSS output from survey data (2017).

Table 2. Correlation of Employees' commitment models and OP.

Model of commitments		OP
Affective commitment	Pearson correlation	0.478**
	Sig. (2-tailed)	0.000
Continuous commitment	Pearson correlation	0.648**
	Sig. (2-tailed)	0.000
Normative commitment	Pearson correlation	0.756**
	Sig. (2-tailed)	0.000

Source: SPSS output from survey data (2017).

(Naing et al., 2006).

$$n' = \frac{NZ^2P(1-P)}{d^2(N-1)+Z^2P(1-P)}$$

(1)

where n' = Sample size
N= population size
Z= Z statistical for a level of confidence (95%)
P= expected population (in proportion of one) (0.5)
d= precision (in population of one) (5%).

In this study, primary data were collected through questionnaires from employees and interview with top management. Mainly quantitative data were collected using likert scale questions to obtain relevant information from the sample employees. From distributed questionnaires, 100% of them were filled by respondents and collected from the respondents. In addition, officials were interviewed and observation of the researcher was deployed. From secondary sources; statistics of employees and allowance package documents have been reviewed. The questionnaire is the most appropriate means to involve large sample population to collect the necessary information within a given time frame. In the design of these instruments, the researcher made use of the literature review as a base from studies of Njenga et al. (2017), Jaros (2007), Irefin and Mechanic (2014), and Oluyinka (2012). The questionnaires were prepared for 261 employees of Arjo Didessa Sugar Factory. Once the data were collected, the researcher used statistical techniques to analyze the information. Data were entered and analyzed using recent statistical package for social sciences (SPSS) version 20.0. Correlation analysis statistical tools were used to align with the objectives of the research, and to test the relationship between the variables.

DISCUSSION

The first objective of this study was to examine the factors that affect employees' commitment. The findings obtained from the study shows that factors like motivation, work environment, demographic factors and training, and development opportunity have strong influence on employees' commitment even though the scale of influence varied depending on a survey of respondent's results (Table 1).

As described by Andy (2006), correlation is a commonly used measure for the size of an effect: values of 0±0.1 represent a small effect, 0±0.3 is a medium effect and 0±0.5 is a large effect. Here, correlation analysis conducted in the light of each research objectives and hypotheses were developed. The relationship between factors employee commitment and employees' commitment was analyzed using correlation analysis that indicates the strength and direction of relationship.

Hence, the correlation result on Table 1, clearly revealed that motivation has moderate positive relation r = 0.538 with employees' commitment. Accordingly, work environment has a moderate positive correlation coefficient of r = 0.545, which implies that it has strong positive relation with employees' commitment. Similarly, training and development indicates a correlation coefficient of r = 0.628, which implies that training and development opportunity has a strong positive correlation with the dependent variable employees' commitment. As clearly stipulated on the same Table 1, demographic factors have a positive relationship with employees' commitment with coefficient of r = 0.442.

The second objective of the study was to identify the relationship between employee's commitment models, and organizational performance. The relationship between employees' commitment models and organizational performance are described in the Table 2. As described, affective commitment is moderately r= 0.478, and both continuous commitment and normative commitment are strongly correlated to be r= 0.648 and 0.756, respectively to organizational performance.

The regression analysis was conducted to know how much the independent variable explains the dependent variable. It is also used to understand how much each independent variable (Factors influencing Employees' commitment) explains the dependent variable (Employee commitment). Therefore, regression analysis of employees' commitment and factors influencing employee

Table 3. Coefficients /Results of regression analysis of factors affecting EC.

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	8.269	1.653	-	5.001	0.000
	Motivation (M)	0.446	0.077	0.305	5.772	0.000
1	Work environment (WE)	0.201	0.078	0.149	2.567	0.001
	Training and development opportunity (TD)	0.346	0.063	0.358	5.455	0.000
	Demographic factors (DF)	0.255	0.119	0.124	2.150	0.003

EC= 8.269+ (0.446)M+ (0.201)WE+ (0.346)TD + (0.255)DF + E.
Source: SPSS output from survey data (2017)

Table 4. Regression of EC on OP.

					Model 1 summary				
Model	R	R square	Adjusted R square	Std. Error of the estimate	Change statistics				
					R Square change	F change	df1	df2	Sig. F change
1	0.724[a]	0.525	.517	4.62596	0.525	70.636	4	256	0.000

[a]Predictors: (Constant), demographic factors, motivation, work environment, training and development opportunity.
Source: SPSS output from survey data (2017).

Table 5. Coefficients of ECM.

Coefficients[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	13.962	1.443	-	9.674	0.000
	Affective commitment	0.359	0.105	0.217	3.405	0.001
1	Continuous commitment	0.265	0.143	0.149	1.846	0.006
	Normative commitment	0.454	0.100	0.339	4.536	0.000

[a]Dependent variable: Employees' commitment. Yii = 13.962 + 0.359AC + 0.265 CC + 0.454 NC +E.
Source: SPSS output from survey data (2017).

commitment was conducted, and the results of the regression analysis are presented.

The third objective of the study was to identify the effects of factors affecting employees' commitment on the employees' commitment. There is an effect of motivation, work environment, training and development and demographic factors on employees' commitment which was analyzed using correlation and regression analysis (Table 3).

As stated in Table 3, the third hypothesis is that motivation, work environment, training and development and demographic factors are significant predictors of employee commitment. The results of the regression analysis indicated the B value for motivation was 0.446 at t = 5.772 (p-value <= 0.00) for work environment, Beta values 0.201 at t = 2.567 (p-value <= 0.01) for training and development, Beta value is 0.346 at t = 5.455 (p-value <= 0.00) and demographic factors Beta value 0.255 at t=0.255 (p-value 0.003).

Accordingly, an increase in one percent of motivation result in 44.6% (sig. 0.000) changes shows the effect on employees' commitment, while an increase in one percent work environment result in a 20.1% (sig. 0.001) effect on employees' commitment. Similarly, as one percent of demographic factors (like education background, age and work experience) increase, it can result in a 25.5% increase in employees' commitment (Table 4).

Finally, the fourth objective of this study was to identify the effects of employees' commitment models on the organizational performance. There is an effect of affective, normative, and continuous commitment on organizational performance which was analyzed using correlation and regression analysis (Table 5).

In addition, regression analysis result revealed an increase in one percent of affective commitment result in 35.9% effect on organizational performance, while an increase in one percent normative commitment result in a

Table 6. Model summary of R square of ECM on OP.

Model	R	R Square	Adjusted R Square	Std. Error of the estimate	Change statistics				
					R square change	F change	df1	df2	Sig. F change
1	0.762[a]	0.581	0.576	5.39471	0.581	118.724	3	257	0.000

[a]Predictors: (Constant), normative commitment, affective commitment, continuous commitment.
Source: SPSS output from survey data (2017).

45.4% effect on organizational performance, similarly, a 1% increase in continuous commitment has a 26.5% effect on organizational performance.

According to the regression analysis in Table 6, the independent variables: employees' commitment models (affective, continuous and normative commitment) have 58.1% ($R^2 = 0.581$) effect on dependent variable organizational performance. Thus, all the four null hypotheses are rejected and alternative hypothesis are accepted.

Conclusion

The study has identified the general information of respondents such as age, gender, work experience in the company and educational background. The result indicates that there are young age groups, qualified and majorities are male. Researcher identifies the factors that influence employee commitment and the relationship between employees' commitments through correlation. Similarly, the relationship between employees' commitment models and organizational performance has been reviewed. The researcher examines the effects of factors that influence the employees' commitment on the intentions/commitment of the employees in the study area. Hence, motivation, work environment, training and development and demographic factors have effects on the commitments of employees. Finally, the researcher examines the effects of employee commitment models on performance of the organization.

RECOMMENDATIONS

This study provides useful contribution for the Sugar Corporation of Ethiopia, Arjo Didessa Sugar Factory, which has value in ensuring employees commitment to attain the desired performance economically. Nowadays, human development and their readiness to engage in the organizational operations are crucial for business organization in order to use competitive advantage. To achieve the desired performance at organizational level, the treatment taken at individual level has its own contribution. Thus, the following recommendations are necessary:

1. Organizations are facing several challenges as a result

of the dynamic nature of the environment. One of the many challenges for a business is to satisfy its employees in order to cope up with the ever changing and evolving environment, and to achieve success and remain in competition. Hence, Arjo Didessa Sugar Factory (ADSF) advised to give attention to work environment such as proper work environment, fair and transparent treatment among staff members during promotion and other opportunity given to attract professional staff from outside.

2. If the empowerment and recognition of employees is increased, their motivation to work will also improve, as well as their accomplishments and the organizational performance. Thus to get maximum performance from staff, ADSF should emphasize on developing motivational package in order to encourage creativity and competition among the staff.

3. Industries are required to meet standard set. To ensure this training and development opportunity, ADSF ought to establish and maintain regular training program and should design training and development system.

4. Committed employees bring added value to the organization through their determination, proactive support, relatively high productivity and awareness of quality; hence ADSF emphases on employee commitment.

SUGGESTION FOR FUTURE RESEARCH

Since the current research considered only Arjo Didessa Sugar Factory, Ethiopian Sugar Corporation found it difficult to generalize employee's commitment in the sugar industry as a whole. Only some factors that affect employee's commitment and models of employees' commitment at individual level towards organizational performance have been studied. Thus, future researchers can replicate insights gotten from the current study, and consider other possible factors that affect organizational performance in sugar factory.

CONFLICT OF INTERESTS

The author has not declared any conflict of interests.

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