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Highlights

- We propose to model the probability of bank failure with the GEV model.
- We propose to model the probability of receiving capital injections with GEV model.
- We propose the longitudinal binary generalised extreme value (LOBGEV).
- The temporal structure of the probability of failure is modelled by the LOBGEV.
- A unique dataset on the Troubled Asset Relief Program is analysed.

The effectiveness of TARP-CPP on the US Banking Industry: a new copula-based approach

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Abstract

Following the 2008 financial crisis, regulatory authorities and governments provided distressed banks with equity infusions in order to strengthen national banking systems. However, the effectiveness of these interventions for financial stability has not been extensively researched in the literature. In order to understand the effectiveness of these bailouts for the solvency of banks this paper proposes a new model: the Longitudinal Binary Generalised Extreme Value (LOBGEV) model. Differing from the existing models, the LOBGEV model allows us to analyse the temporal structure of the probability of failure for banks, for both those that received a bailout and for those that did not. In particular, it encompasses both the flexibility of the D-vine copula and the accuracy of the generalised extreme value model in estimating the probability of bank failure and of banks receiving approval for capital injection. We apply this new model to the US banking system from 2008 to 2013 in order to investigate how and to what extent the Troubled Asset Relief Program (TARP)- Capital Purchase Program (CPP) reduced the probability of the failure of commercial banks. We specifically identify a set of macroeconomic and bank-specific factors that affect the probability of bank failure for TARP-CCP recipients and for those that did not receive capital under TARP-CCP. Our results suggest that TARP-CPP provided only short-term relief for US commercial banks.

Keywords: Binary data, D-vine copula model, Banking, TARP-CPP, Failure.

1 Introduction

Monitoring and evaluating banking stability is an important and reoccurring theme on the agenda of policy makers. A number of recent influential studies have contributed to the analysis of systemic banking crises in the operational research literature (see for a literature review Kumar & Ravi, 2007; Fethi & Pasiouras, 2010; Demyanyk & Hasan, 2010; Ioannidis et al., 2010). These studies on distressed banks develop models that detect risky banks prior to failure. They also attempt to identify banks for which regulatory authorities may have to take corrective actions (DeYoung & Torna, 2013). However, little attention has been devoted so far to the analysis of the effectiveness of bailouts for the stability of a banking system. An understanding of this subject is important in order to minimize the cost of failure and rescue for stakeholders and taxpayers.

At present, this issue is of great concern for policy makers and researchers because of the peculiarities of the 2008 financial crisis. Compared to the past, the financial crisis led to extraordinary policy interventions in terms of both the range of policy measures adopted, the speed and scale of the interventions, and the implementation of those resolutions (Laeven & Valencia, 2010). Starting from the onset of the financial crisis, US and EU regulatory authorities or governments bailed-out numerous commercial and investment banks in order to reduce the fragility of the banking system and to restore confidence in the financial markets. During this time, several financial institutions failed. These events led to a proliferation of new studies on the determinants and the consequences of bank failures and bailouts (e.g. Demyanyk & Hasan, 2010; Dam & Koetter, 2012; Bayazitova & Shivdasani, 2012; Cole & White, 2012; Berger & Bouwman, 2013; Calderon & Schaeck, 2015). While the availability of government safety nets and rapid intervention policies can have beneficial effects in resolving crises, their use is not free from criticism. Implicit and explicit guarantees can strengthen the perception that big-banks will be bailed-out if they find themselves in a distressed situation, thus encouraging moral hazard behaviour (Hakenes & Schnabel, 2010), thereby decreasing the stability of the banking system. Consequently, understanding whether regulatory interventions and capital support enhance banking stability is critical for regulatory authorities and policymakers.

From a statistical perspective, many relevant theoretical and empirical contributions to this topic employ the use of logistic (e.g. Bayazitova & Shivdasani, 2012; Cole & White, 2012; Berger & Bouwman, 2013) or probit models (Croci et al., 2015). However, the use of probit and logit link is not appropriate when modelling rare events. If we classify the rare events as ones, the major drawback of these approaches is that they underestimate the probability of binary rare events for values close to one, such as bank defaults or bail-outs (Calabrese & Osmetti, 2015; King & Zeng, 2001; Wang & Dey, 2010). To overcome this limitation, a model has been proposed in the operational research literature (Andreeva et al., 2016; Calabrese & Osmetti, 2013; Marra et al., 2014; Calabrese & Osmetti, 2015) - the Binary Generalised Extreme Value Additive model, BGEVA (GEV model in the parametric form). This approach is particularly suitable for binary rare events data, i.e. when the observed number of ones in the sample is very low.

In particular, the BGEVA model has been proven to outperform the logistic regression model when predicting failure events, such as bank and firm defaults.

This paper adds to the operational and banking literature by proposing a new model that enables us to measure the effectiveness of bailout interventions for the financial stability of banks. Specifically, the aim of this paper is to develop a statistical tool to better analyse and monitor (i) the probability of default depending on bailouts over time; and (ii) the temporal dependence structure of the probability of the failure of a bank.

From a methodological viewpoint, this paper contributes to the operational research literature in three ways. First, we estimate the probability of bank distress and the probability of being bailed out using the GEV model. Calabrese & Giudici (2015) show the advantages of the GEV model in their study of distressed Italian banks. Second, we analyse the effects of a bailout over time on a bank's probability of default. To achieve this, we develop an extension of the GEV model for use with longitudinal data. We call this new model the Longitudinal Binary Generalised Extreme value (LOBGEV) model. Third, we employ the LOBGEV to analyse the temporal dependence structure of the probability of failure for banks that either received or did not receive ad-hoc bailouts. This enables us to analyse how and to what extent bailouts were effective in reducing the probability of default for banks.

Several models have been proposed for correlated responses (outcomes) in longitudinal data (see for example Arellano & Bo, 2001). For modelling the time dependence in longitudinal data, in this paper we choose a copula approach, analogously to Smith et al. (2010) and Meade & Islam (2010), because it is a simple method to estimate multivariate models when the marginal responses are given. Furthermore, the copula approach is particularly suitable to model different kinds of dependence structures. In addition, the copula approach has been used in the regression framework for continuous and discrete data. For example Koleva & Paivab (2009) use a bivariate copula to model the dependence between errors. Radice et al. (2015) suggest a copula-based regression model for binary outcomes using a parametric copula, such as Clayton, Gumbel, Frank, Joe and

Student-t. Furthermore, Kraemer et al. (2013) propose a bivariate regression model for total loss estimation by combining marginal generalised linear models for continuous and discrete variables with a copula approach.

In this paper we consider a drawable vine (D-vine) copula as it is an extremely flexible representation of a multivariate distribution that uses bivariate copula densities (pair-copula) in a hierarchical approach as in Smith et al. (2010) and Smith (2015). In the D-vine copula approach, the multivariate probability density function is decomposed into pair-copulae that can be chosen independently from each other, generating a less flexible multivariate dependence structure. On the contrary, the multivariate copula models largely used in the literature, such as multivariate Archimedian, Gaussian, Gumbel, Clayton and Joe, have the same dependence structure for each pair-copulae. Moreover, the D-vine copula approach is suitable for modelling longitudinal data and to represent the dependence structure over time (Smith et al., 2010; Smith, 2015). For all these reasons, we use a D-vine copula approach to model the time series of the failure probabilities, previously estimated by using the GEV model. We define this method as LOBGEV model.

We apply the proposed methodology to the US banking market, which is a suitable case for our analysis for several reasons. Starting from October 2008, the US Treasury utilized several initiatives under the Troubled Asset Relief Program (TARP) to stabilise the US financial system, to spur economic growth, and to prevent unnecessary foreclosures. In line with recent studies (see for example Bayazitova & Shivdasani, 2012; Berger & Roman, 2015; Duchin & Sosyura, 2014), we focus on the Capital Purchase Program (CPP), the largest bank bailout programme under TARP launched by the Treasury.

Under the TARP-CPP, the Treasury provided capital to 707 financial institutions in 48 states, a total investment of approximately \$205 billion between October 2008 and December 2009. 174 of these financial institutions missed one or more TARP-CPP dividends, and 29 of them went bankrupt. Moreover, many of the small banks that received capital injections (372 out of 656 banks benefiting from preferred stocks investments) were hesitant to exit the programme (Wilson, 2013), raising doubts about their long-term viability. This means that there were banks that failed despite the fact that they received capital injections. In addition, from September 2008 to September 2014 more than 500 banks were resolved by the Federal Deposit Insurance Corporation (FDIC)[1]. We consider this resolution process as a default event.

From an empirical viewpoint, this is, to the best of our knowledge, the first paper that examines the effectiveness of the TARP-CPP programme on the temporal structure of banks' default probabilities. Previous papers mainly focus on the effects of the TARP-CPP on the risk-taking and moral hazard behaviour of banks (Dam & Koetter, 2012; Black & Hazelwood, 2013; Duchin & Sosyura, 2014), the performance of banks (Croci et al., 2015), the distortion of competition in the US banking market (Berger & Roman, 2015), and financial and stock price recovery (Liu et al., 2013). So far, Croci et al. (2015) is the only study that compares the probabilities of failure for banks that received capital injections under TARP-CPP and for those that did not. We extend this literature by proposing a new model to assess the temporal structure of the effects generated by capital injection. In this analysis, we find evidence that the TARP-CPP programme helped banks to reduce their default probabilities in the short term.

We organise the rest of the paper as follows. The next section reviews the literature on the probability of bank failures and capital injections. Following this, we propose a longitudinal model for binary rare events. The fourth section describes the data and the empirical results, with the fifth and final section stating and describing our conclusions.

2 An overview of recent studies on banks' bailout and failure

There is a growing amount of literature on the 2008 financial crisis, specifically its effects on the US banking system. A number of these studies have investigated the likelihood of bank failures in the US during and after the financial crisis (e.g. Cole & White, 2012; Berger & Bouwman, 2013; DeYoung & Torna, 2013; Croci et al., 2015).

[1]Retrieved from `https://www.fdic.gov/bank/individual/failed/banklist.html`, September 2014.

These authors evaluate a bank's performance using the CAMEL (the acronyms stands for Capital, Asset quality, Management, Earnings, and Liquidity) model that is widely utilized by credit rating agencies and regulators. Their findings suggest that low asset quality (non-performing loans), high concentration of business or commercial real estate loans, illiquidity, cost inefficiency, rapid asset growth, dependence on non-core deposit funding and both low profitability and capitalisation are key variables in predicting the probability of the failure of a bank.

More recent studies have focused on the probability of receiving capital injections in the US banking sector during the financial crisis. For example, Bayazitova & Shivdasani (2012) analyse the likelihood of a bank receiving CPP capital injections. The authors show that wholesale debt, Tier 1 ratio capital and commercial loans are all factors that can predict if a bank participates in the programme. They also point out that large banks are more likely to receive capital under the TARP-CPP. Croci et al. (2015) find that commercial and industrial loans, credit risk, non-performing loans, cost inefficiencies, goodwill and size can enhance the probability of receiving capital under the TARP-CPP.

Additionally, a number of studies have focused on the effects of policy interventions for banks. However, despite this research, it is not still entirely clear how and to what extent policy interventions are effective in ensuring the stability of the banking system. Interventions may reduce the probability of insolvency in the short-term, but they may also create a distortion of competition and provide incentives for misleading behaviour. In this regards, recent papers (e.g. Gropp et al., 2011; Black & Hazelwood, 2013; Calderon & Schaeck, 2015) have shown that bailouts can increase the moral hazard behaviour of banks when monitoring incentives are distorted. In addition, Berger et al. (2014)) demonstrate that bailouts can lead to inappropriate loan pricing and the granting of loans to riskier borrowers. Furthermore, Duchin & Sosyura (2014) point out that banks increased the risk profile of both their lending activities and their portfolio investments after being enrolled in the TARP-CPP programme. In contrast, Koetter & Noth (2015) find that higher bailout probabilities are not associated with moral hazard of banks, but that instead, banks with a higher likelihood of being bailed-out engaged in less risky behaviour. Berger & Roman (2015) provides evidence of TARP-banks increasing their market share and market power relative to non-TARP banks. More recently, Croci et al. (2015) has shown that bailing-out more banks would have been cost-efficient and would have reduced the number of banks that went through the FDIC resolution process. So far, this is the only paper that we aware of that has analysed the probability of default of banks that received a bailout. The authors however still make use of the probit model that, as mentioned earlier, has some fundamental drawbacks. Given this evidence, it is clear that the debate on the effects of bailouts on the risk profile of banks is still on going. So far, the impact of policy interventions on the dependence structure of the distress probabilities of banks over time has been overlooked. We therefore bridge this gap by proposing a new model that estimates the influence of the capital injections over time on the dependence structure of the distress probabilities.

3 Methodology

In this paper we propose a longitudinal model in order to evaluate the changes in the probabilities of failure over a period of time. Specifically, we propose a GEV longitudinal model (LOBGEV) by combining the GEV model and the D-vine copula. The proposed model has two levels of analysis. First, we make use of the GEV model because it has been proposed for improving the classification accuracy of the commonly used logistic and probit models for strongly unbalanced samples. The GEV model, described in the following section, is used to estimate the probability of bank distress and the probability of being bailed out at each time t. Second, the dependence across the probabilities of failure over time is modelled by a multivariate copula. Given its flexibility, we choose a D-vine copula approach, described in Section 3.2.

3.1 GEV model

Let Y_t be a response variable that describes at time t a binary rare event, i.e. binary dependent variable with a very small number of one than zero. We will be interested in predicting the probability $\pi_t = P(Y_t = 1|\mathbf{x}_{t-1})$ given values of covariate vector $\mathbf{x}$ at time $t-1$.

The usually statistical models for binary response variable, like the logistic regression model, present several drawbacks in rare event studies. In particular, rare events have proven difficult to predict. When the data is in fact unbalanced, the estimate of the dependent variable tends to be biased towards the majority class, which is usually the less important class to correctly predict (King & Zeng, 2001). Specifically, the use of a symmetric link function, such as the logit or probit function, may underestimate π_t for the rare events $\{Y_t = 1\}$, as the response curve π_t approaches zero at the same rate as it approaches one (King & Zeng, 2001; Wang & Dey, 2010; Marra et al., 2014; Calabrese & Osmetti, 2013).

To overcome these drawbacks Calabrese & Osmetti (2013) propose a new flexible GLM for predicting binary rare events. If we assume that the rare events are the outcomes $\{Y_t = 1\}$[2], their features are represented by the tail of the response curve for values close to one. As the GEV random variable is used in the literature (Falk et al., 2010) to model the tail of a distribution, Calabrese & Osmetti (2013) consider a flexible skewed link function based on the GEV distribution. The proposed model is a very flexible parametric model, particularly suitable to model binary rare event data:

$$\frac{[-\ln(\pi_t)]^{-\tau} - 1}{\tau} = \alpha + \sum_{k=1}^{p} \beta_k x_{t-1,k}, \tag{3.1}$$

where $\pi_t = P(Y_t = 1|\mathbf{x}_{t-1})$ is the probability of the event $(Y_t = 1)$ at time t and where $\mathbf{x}_{t-1} = (x_1, x_2, ..., x_p)$ is the vector of p covariates observed at time $t-1$. Calabrese & Osmetti (2015) propose the BGEVA model by including an additive component to the GEV model. The BGEVA model has been then improved by Calabrese et al. (2016).

[2]The GEV model is suitable also if the rare events are the outcomes $\{Y_t = 0\}$ as the GEV link function can be left or right skewed.

Several studies (Andreeva et al., 2016; Calabrese et al., 2016; Calabrese & Osmetti, 2015, 2013) have shown that the GEV model outperforms the logistic and the probit models even if the percentage of ones in the sample is one percent.

In this paper, we use the GEV model for different purposes. First, we estimate the banks' failure probability in 2008 to analyse the characteristics relevant to explain banks' distress in the pre-intervention period. Second, we apply the GEV model to evaluate the probability of receiving capital injections in 2008 and 2009. Third, we estimate the probability of failure conditionally to the event "a bank receives a capital injection" ($I = 1$) and "a bank does not receive any capital injection" ($I = 0$) during the post-intervention period (2010-2013). Therefore, let Y_t be the binary r.v.such that ($Y_t = 1$) is a banks failed at time t. We apply the model in equation (3.1) at each time (from 2010 to 2013) to estimate both conditional probabilities of failure $P(Y_t = 1|I = 1)$ and $P(Y_t = 1|I = 0)$. In this way we are able to analyse how and to what extent the impact of the covariates changes over the time.

3.2 The D-vine copula

Definition 3.1 (Multivariate copula)**.** The copula is a multivariate cumulative distribution function (cdf) with $U_1, U_2, ..., U_d$ uniformly distributed marginals random variables on $I = [0, 1]$:

$$C(u_1, u_2, ..., u_d) = P(U_1 \leq u_1, U_2 \leq u_2, ..., U_d \leq u_d)$$

The importance of copulae in statistical modelling stems from Sklar's theorem which shows that every multivariate distribution can be represented via the choice of an appropriate copula and it provides a general mechanism to construct multivariate models in a straightforward manner.

Theorem 3.1 (Sklar)**.** *Let $X_1, ..., X_d$ be a set of random variables with joint cdf $F(\cdot)$ and marginals cumulative distribution functions (cdfs) $F_1(\cdot), F_2(\cdot), .., F_d(\cdot)$. It exists a* *copula function* $C : I^d \to I$ *such that* $\forall x_1, x_2, ..., x_d \in \mathcal{R}^d$

$$F(x_1, ..., x_d) = C(F_1(x_1), ..., F_d(x_d)). \tag{3.2}$$

If $F_1(\cdot), F_2(\cdot), .., F_d(\cdot)$ *are continuous functions then the copula* $C(\cdot)$ *is unique. Conversely, if* $C(\cdot)$ *is a copula function and* $F_1(\cdot), F_2(\cdot), .., F_d(\cdot)$ *are marginal cdfs, then the* $F(x_1, ..., x_d)$ *in* (3.2) *is a multivariate cdf.*

The principal advantage to use a copula approach follows from the Sklar theorem. This theorem states that each joint distribution can be expressed in terms of marginal distributions and a copula function that captures the dependence structure between the marginal probabilities. The main advantages of the copula approach are that it is a simple method to estimate multivariate models for given marginal distribution functions and it can represent different kinds of dependence structures. Simpler models usually assume a linear dependence, such as the multivariate normal distribution, or linear tail dependence, such as the multivariate Student-t. On the contrary, the copula model can account for non-linear dependence or non-linear upper/lower tail dependence.

In high dimensions, multivariate copula-based models have been employed largely to account for complex dependence structure in order to consider non-normality assumption (Joe, 1997; Whelan, 2004; Savu & Trede, 2010). In the recent literature, the multivariate probability density function has been composed into the product of bivariate copulae, also known as pair-copulae, that can be chosen independently from each other from a wide class of bivariate copulae. In order to represent the dependence structure between the pair-copulae, a graphical model is used. The resulting approach is known as vine copulae (Czado, 2010). A goodness of fit test can be performed to choose the combination of the pair-copulae that best fits to data. Smith et al. (2010); Smith (2015) and Panagiotelis et al. (2012) use a vine-copula approach to model the dependence structure for longitudinal data and have shown encouraging results on the goodness of fit achieved in an empirical analysis on headache severity. Different vine decomposition, such as regular-vine (R-vine), canonical-vine (C-vine) and drawable vine (D-vine), have been proposed to describe specific dependence between the variables. Aas et al. (2009) and Czado (2010) extensively explain the main differences among R-vines, C-vines and D-vines. Bedford & Cooke (2002) propose the D-vine copula for modelling time series. As the aim of this paper is to model the failure probability of banks over time, we use the D-vine copula approach for their flexibility and parsimony. We do not use multivariate copula families, such as multivariate Clayton, Gumbel, Frank, Gaussian and Student-t copula, because, if we decompose these families in pair-copulae, they all need to belong to the same copula family, showing the same dependence structure. The condition that the dependence structure is invariant over time is seldom satisfied by longitudinal data. This assumption is instead removed in the D-vine copula approach (Smith et al. (2010) and Smith (2015)). Coherently, several simulation and empirical studies for continuous and discrete data (e.g. Aas & Berg, 2009; Smith et al., 2010; Smith & Khaled, 2012; Kraemer et al., 2013; Panagiotelis et al., 2012) have shown that the D-vine copula can achieve a higher goodness of fit than the multivariate copulae, such as Clayton, Gumbel and Gaussian.

The D-vine copula approach has previously been applied in several fields. For example, D-vine has been used to forecast electricity load (see Smith et al., 2010) and to model the dependence structure between the amounts of precipitation over time in several geographic areas (see Daeyoung et al., 2013). In finance, Aas & Berg (2009) use them to model the time series of financial log-returns.

We describe the D-vine model for continuous data. Let $(X_1, X_2, ..., X_T)$ be an univariate time series of continuously distributed data observed at T possibly unequally spaced points in time, the joint density function $f(x_1, x_2, ..., x_T)$ can be always decomposed in a product of the conditional (to the past) distributions:

$$f(x_1, x_2, ..., x_T) = \prod_{t=2}^{T} f(x_t|x_{t-1}, ..., x_1) f(x_1).$$

By using a pair-copula (bivariate copula) representation we have:

$$f(x_t|x_{t-1},...,x_1) = \prod_{j=1}^{t-1} c_{t,j}[F(x_t|x_{t-1},...,x_{j+1}), F(x_j|x_{t-1},...,x_{j+1}); \theta_{t,j}] f(x_t)$$

where $F(x_t|\cdot)$ is the cdf of X_t conditional to the past, $f(x_t)$ is the density function of the marginal X_t and $c_{t,j} = c_{t,j|t-1,t-2,...,j+1}$ is the pair-copula density with association parameters $\theta_{t,j}$ between the variables X_t and X_j conditional to the times from $j+1$ to $t-1$ (see Smith et al. (2010) for details).

Therefore, the joint distribution of the process becomes a D-vine copula model of order T, which is a product of T marginal densities and $T(T-1)/2$ pair-copula densities:

$$f(x_1, x_2, ..., x_T) = \prod_{t=2}^{T} \left[\prod_{j=1}^{t-1} c_{t,j}(u_{t|j+1}, u_{j|t-1}; \theta_{t,s}) f(x_t) \right] f(x_1), \tag{3.3}$$

where $u_{t|j+1} = F(x_t|x_{t-1},...,x_{j+1})$ and $u_{j|t-1} = F(x_j|x_{t-1},...,x_{j+1})$.

3.3 Longitudinal Binary Generalised Extreme Value (LOBGEV) model

Let $\pi_1, \pi_2, ..., \pi_T$ be the univariate series of failure probabilities modelled by the GEV model in equation (3.1). We define the joint probability of failures over the periods $t = 1, ..., T$ by a copula representation as in equation (3.2):

$$P(Y_1 = 1, Y_2 = 1, ..., Y_T = 1) = C(\pi_1, \pi_2, ..., \pi_t, ..., \pi_T).$$

This representation allows modelling the temporal dependence across the probabilities of failure. Let c be the copula density function of the copula C. Following a procedure similar to the one described for the D-vine model in the previous section, the copula density function $c(\pi_1, \pi_2, ..., \pi_T)$ can be decomposed in a product of the conditional (to the past) pair-copula density functions:

$$c(\pi_1, \pi_2, ..., \pi_T) = \prod_{t=2}^{T} \left[\prod_{j=1}^{t-1} c_{t,j}(u_{t|j+1}, u_{j|t-1}; \theta_{t,j}) \right] \tag{3.4}$$

where $c_{t,j} = c_{t,j|t-1,t-2,...,j+1}$ is the pair-copula with association parameters $\theta_{t,j}$ between π_t and π_j conditional to the times from $j+1$ to $t-1$ and $u_{t|j+1} = \pi_t|\pi_{t-1}, ..., \pi_{j+1}$ and $u_{j|t-1} = \pi_j|\pi_{t-1}, ..., \pi_{j+1}$.

Therefore, the joint distribution of the process becomes a D-vine copula model of order T, which is a product of T marginal densities and $T(T-1)/2$ pair-copula densities. We call this model Longitudinal Binary Generalised Extreme Value model (LOBGEV). Since the LOBGEV is based on copula function, it could be different from the longitudinal model usually based on normal distribution and its dependence structure could not be linear. In this way, a flexible, parsimonious and not necessary normal longitudinal model for banks' probabilities of failing is proposed.

4 Empirical evidence

4.1 Data

The data on TARP-CPP comes from the U.S. Department of the Treasury, while the data on FDIC auctions are retrieved from the FDIC website. The accounting data are retrieved from the Federal Reserves Reports of Condition and Income (Call Reports) for commercial banks on a quarterly basis from the first quarter in 2007 to the third quarter in 2013. Call reports data for commercial banks were downloaded from the Federal Reserve Bank of Chicago' s website[3] (starting from March 2011). Analogously to Croci et al. (2015), we focus our analysis on commercial banks. As concerns the macroeconomic variables, the data on gross domestic product per capita (GDP) and the personal income growth rate come from U.S. Bureau of Economic Analysis (BEA), while those on the unemployment rate from the Bureau of Labor Statistics, Local Area

[3] $https://cdr.ffiec.gov/public/$

Unemployment Statistics[4].

We consider as a distress event, the failure of a bank under the resolution of the FDIC. Specifically, a bank can be resolved by the FDIC under three different types of transaction: (i) assistance transactions where the failed / assisted institution remains open and its charter survives the resolution process; (ii) purchase and assumption transactions where the failed / assisted institution's insured deposits are transferred to a successor institution, and its charter is closed; and (iii) payoff transactions, the deposit insurer - the FDIC or the former Federal Savings and Loan Insurance Corporation - pays insured depositors, the failed / assisted institution's charter is closed, and there is no successor institution[5]. In this paper, we do not make a distinction between these three categories.

<table>
<tr><th rowspan="2">Year</th><th colspan="2">TARP-CPP banks</th><th colspan="2">banks not included in TARP-CPP</th><th rowspan="2">Total</th></tr>
<tr><td>Failing</td><td>Non-failing</td><td>Failing</td><td>Non-failing</td></tr>
<tr><td>2008</td><td>0</td><td>272</td><td>12</td><td>6,831</td><td>7,115</td></tr>
<tr><td>2009</td><td>3</td><td>523</td><td>140</td><td>6,449</td><td>7,115</td></tr>
<tr><th>Year</th><td colspan="2">Failing</td><td colspan="2">Failing</td><th>Total</th></tr>
<tr><td>2010</td><td colspan="2">5</td><td colspan="2">157</td><td>6,790</td></tr>
<tr><td>2011</td><td colspan="2">9</td><td colspan="2">92</td><td>6,721</td></tr>
<tr><td>2012</td><td colspan="2">9</td><td colspan="2">49</td><td>6,329</td></tr>
<tr><td>2013</td><td colspan="2">3</td><td colspan="2">59</td><td>6,048</td></tr>
</table>

Table 1: Distribution of banks' failures from 2008 to 2013 in the US.

Table 1 shows the distribution of failures from 2008 to 2013 for the US banks in the data. The number of failings over time shows different patterns for banks that received capital injection and those that did not receive such support. In the first group, the banks in distress achieve their maximum in 2011 and 2012, in the second group earlier in 2010.

[4]The data are available on the following website: $http : //www.bea.gov/iTable/index_regional.cfm$ and $http : //www.bls.gov/lau/data.htm$

[5]See `https://www.fdic.gov/` for more details.

4.2 Determinants of capital injection and banks' failures

In this section we analyse the determinants of banks' failures and receiving capital injections for the years 2008 and 2009. Additionally, we compare the covariates of the probability of distress for both the banks that were enrolled in the TARP CPP programme and did not receive any capital injection. In order to identify the explanatory variables of the GEV model for each year from 2008 to 2013, we follow the CAMEL framework in the line with previous studies (e.g. Wheelock & Wilson, 2000; Rossi, 2010; Cole & White, 2012; Dam & Koetter, 2012; Berger & Bouwman, 2013; Calabrese & Giudici, 2015).

Our model consists of a combination of variables that previous and recent studies have identified to be relevant for the prediction of a bank failure or bailout during the 2008-2009 financial crisis. In particular, in accordance with Dam & Koetter (2012) and Cole & White (2012) we include equity-to-asset ratio, total loans/total assets, other real estate owned/total assets, cost inefficiency, liquidity, size and holding companies in our model. We expect cost inefficiency to have a direct influence on the likelihood of a bank's failing. Since other real estate owned/total assets have been extraordinarily risky for banks in the past, we expect this variable to impact directly on failure. In addition, consistent with Wheelock & Wilson (2000), a positive value for the liquidity variable could lead to the possibility of liquidity problems for a bank. Banks with a liquidity problem are more likely to fail. Therefore, we expect that liquidity has a direct effect on the probability of failure of a bank. In contract, the level of capitalization, size and being part of a holding company should show an inverse relationship on the likelihood of failure. As maintained by Berger & Bouwman (2013), membership of a bank holding company should reduce the probability of failure because it strengthens its competitive position as a consequence of the capital support provided by the holding company. Furthermore, as suggested by Calabrese & Giudici (2015), we also add Tier 1 capital ratio and performance as predictors of bank failure to our model. We explain that we expect these variables to have an inverse relationship with the likelihood of a bank failing.

Next, drawing on the US literature (e.g. Cole & White, 2012; Croci et al., 2015), we select commercial and industrial loans as a key variable to predict banks' failure during the recent financial crisis. We also take into account the brokered deposit over total and non-interest income over both operating income and total assets asset following Berger & Bouwman (2013) and DeYoung & Torna (2013). Both these variables appear to be important determinants of bank failure during the recent crisis as they are related either to high-risk activities or to trading positions that are easy to change but difficult to monitor. Finally, we acknowledge the importance of local and regional economic conditions. In this regard, we explain that in accordance with Koetter et al. (2007) and Arena (2008) we include gross domestic product per capita (GDP), the unemployment rate and the personal income growth rate in our model. In the same manner, a few recent studies have focused on probability of capital injections in the US banking sector during the recent 2007-2009 financial crisis. Specifically, Bayazitova & Shivdasani (2012) analyse the likelihood of banks' application for CPP capital injections. The authors show that that wholesale debt, Tier 1 ratio, commercial loans and the state macro index growth are all factors that predict a bank's participation decision to the programme. They also point out that large banks are more likely to be accepted into the TARP CCP. This is in line with Croci et al. (2015), who find that commercial and industrial loans, credit risk, non-performing loans, cost inefficiencies, goodwill and size enhance the probability of being accepted for TARP-CCP.

In order to have annual data, we compute a 4 quarter moving average. The dependent variable is forecasted one year ahead. Therefore, all explanatory variables are measured one year in advance, with respect to the year in which the dependent variable is observed. To avoid multicollinearity in the regression models, we remove the explanatory variables with the Variance Inflation Factor (VIF) higher than 5. We initially consider 37 variables; only 22 of them are significant at the level of 5% or low in at least one GEV model. The list of the variables included in the models is reported below:

- Holding: a dummy variable that equals one if the bank is part of a bank holding company, otherwise it is zero;

- EQTA: equity over total assets;
- Size: logarithm of total assets;
- Other RE: all other direct and indirect investments in real estate over total asset;
- C&I Loans: commercial and industrial loans over total assets;
- ROA: net income over total assets;
- Loans: loans and leases, net unearned income and allowance over total assets;
- ROE: net income over total equity;
- NIM: net interest income over total assets;
- Non Interest Income 1: non-interest income over operating income;
- Non Interest Income 2: non-interest income over total assets;
- Loan Loss Reserves: loan loss allowance over total assets;
- Tier 1 Ratio: Tier 1 over risky assets,
- Liquidity: federal funds purchased in domestic offices net of funds sold in domestic offices over total assets;
- Non Performing Loans: past due and nonaccrual loans over total assets;
- Brokered deposit: brokered deposit over total assets;
- Cost Inefficiency: noninterest expenses over non-interest income and interest income;
- Age: Difference between sample year and the year of opening;
- GDP: GDP growth rate at the state level;
- UR: unemployment rate at the state level;
- PI: personal income growth rate at the state level.

We apply the GEV model by estimating the equation (3.1) using the maximum likelihood method. The estimation procedure is implemented in the R package BGEVA (Marra et al., 2014) available on CRAN. Table 2 reports the findings of the GEV model for the probability of failure and the probability of receiving capital injection in 2008 and 2009.

Variables	**2008**		**2009**
	failure	**TARP-CPP**	**TARP-CPP**
Holding		-0.23(***)	-2.89(***)
EQTA			
Size		0.17(***)	0.14(***)
Other RE		-6.21(*)	-5.44(*)
C&I Loans		1.11(***)	1.47(***)
ROA			
Loans			0.69(***)
ROE	-0.80(***)		
NIM			-17.60(***)
Non Interest Income 1	0.004 (***)		
Non Interest Income 2			
Cost Inefficiency			
Loan Loss Reserves	46.03 (***)		
Tier 1 ratio	-58.84 (***)	-2.84(***)	
Liquidity	-18.95(***)		
Nonperforming Loans	15.97(***)	-2.05(***)	
Brokered Deposit			
Age		-0.11(*)	
GDP			
UR		0.04(***)	
PI		20.89(**)	15.96(***)

Table 2: The estimates of the GEV model for the probability of failure and the probability of receiving capital injection in 2008 and 2009 in the US. The number of "*" denotes the significant level: (***) is $p \leq 0.000$, (**) is $p \leq 0.001$, (*) is $p \leq 0.01$.

In line with previous studies (e.g. Wheelock & Wilson, 2000; Cole & White, 2012; DeYoung & Torna, 2013) our results show that banks with less liquidity (Loan Loss Reserves over total loans), low asset quality (nonperforming loans), poor performance (ROE) and low capitalization (Tier 1 ratio) were more likely to fail in 2008. We also find that banks with high non-traditional income sources (Non -interest income 1) had a high probability of failing. In this regards, DeYoung & Torna (2013) point out that banks that engage in risky nontraditional activities are more likely to take risks in their traditional lines of business.

Columns 2 and 3 of Table 2 report the determinants for receiving the capital injection in 2008 or 2009. Banks with large commercial and industrial loans (C&I Loans) and low real estate (Other RE) were more likely to be bailed out in 2008 and 2009. This finding is unsurprising given that loans are typically the least liquid and riskiest assets. In line with the paradigm too big to fail, large banks were more likely to receive capital injection. In addition, we find that bank holding company membership reduced the probability of capital injection in 2008. As pointed out by Berger & Bouwman (2013), commercial banks can benefit from the financial support provided by the holding company and therefore there is less need to get further funds. In 2009, banks that invested more in a tradition portfolio of activities (high loans over total assets) and that suffered from an economic viewpoint (low net interest margin) had a high probability of receiving capital injection. Finally, concerning the macroeconomic variables, banks located in the States with high personal income growth rate (PI) and unemployment rate (UR) were more likely to be bailed out.

Table 3 displays the determinants of the probability of failure conditionally to the event intervention ($I_i = 1$) and non-intervention ($I_i = 0$) and the relative explicative variables for the period post-intervention 2010−2013. Capitalisation level (EQTA, equity over total assets) appears to be an important variable to reduce the probability of failing for the banks that received capital injection for all the years under investigation. Instead, Size was associated with a high probability of failing for all the banks in 2012, while only for the banks that did not receive TARP-CPP in 2011. As concerns the probability conditionally to the non-intervention ($I_i = 0$), low capitalisation (EQTA, Tier 1 ratio), and performance (ROA) were key variables for the occurrence of the failure in 2010-2011. Liquidity appears to diminish the probability of failing of the banks that received capital injection in 2012. Moreover, as in 2008, total non-interest income and nonperforming loans were both important predictive variables for bankruptcy in 2010. The excessive increase of non-interest expenses and the reduction of the interest income sources have then impacted negatively on the probability of failure (cost inefficiency) subsequently in 2011 and 2013. Finally, with regards to the macroeconomic variables, banks with high

Variables	2010		2011		2012		2013	
	TARP	**no TARP**	**TARP**	**no TARP**	**TARP**	**no TARP**	**TARP**	**no TARP**
Holding Dummy					-4.80(***)	-0.11		
EQTA	-53.72(**)	-35.67(**)	-46.82(***)	-93.45(***)	-4.85(*)	-2.27(**)	-20.11(**)	-198.65(***)
Size				0.37(***)	0.36(***)	0.32(***)		
Other RE								
C&I Loans								
ROA		-29.32(***)		-12.25(**)		-21.59(***)		-172.29(**)
Loans		-3.84(**)		5.03(**)		0.79(***)		
ROE						-0.32(***)		
NIM								
Non Interest Income 1								
Non Interest Income 2		32.52(**)						
Cost Inefficiency				0.71(**)				0.57(*)
Loan Loss Reserves								
Tier 1 ratio		-42.75(***)		-15.08(***)				
Liquidity					-2.81(*)			
Non Performing Loans		10.70(***)						
Brokered Deposit								
Age		0.34 (***)				-0.13(***)		
GDP						-2.54(*)		97.47(*)
UR								
PI		-175.77 (***)						-239.69(**)
Trading Assets								

Table 3: The estimates of the GEV model for the probability of failure for the two groups of banks that are included and not in the TARP-CPP project for the period 2010 − 2013 in the US.The number of "*" denotes the significant level: (***) is $p \leq 0.000$, (**) is $p \leq 0.001$, (*) is $p \leq 0.01$.

personal income growth rate were more likely to fail in the States in 2010 and 2013.

4.3 Did the TARP CPP increase the stability of the banking system?

In this section we analyse the effectiveness of TARP-CPP in increasing banking stability. To achieve this aim, we apply the LOBGEV model proposed in this paper[6] This model allows us to estimate the type and the level of dependence between the distress probabilities over time.

Specifically, we apply the GEV model, presented in section 3.1, to all the banks in 2008 and to the two groups of banks - those that received capital injections and those that did not - for each year from 2009 to 2013. The dependent variable is bank failure or non-failure in a given year. Using the parameters estimates of the GEV model, we assess the distress probabilities $P(D_{2008} = 1)$, $P(D_t = 1|I = 0)$ and $P(D_t = 1|I = 1)$ for $t = 2009, 2010, 2011, 2012, 2013$. Afterwards, we measure the dependence between the distress probability in 2008 $P(D_{2008} = 1)$ and the conditional probability $P(D_t = 1|I = 0)$ or $P(D_t = 1|I = 1)$ after the intervention (2010-2013) using the D-vine copula described in section 3.2. The level of dependence is given by the association copula parameter $\theta_{t,j}$ defined in section 3.3. To evaluate the effectiveness of the capital injections, we analyse the temporal structure of the failure probabilities for the banks that benefit from TARP-CPP interventions $P(D_t = 1|I = 1)$ and for those that did not receive such funds $P(D_t = 1|I = 0)$.

The pair-copula families that maximise the Goodness of Fit Test or the Akaike information criterion are chosen in order to provide the best fit to the data. Gaussian copula achieves the best fit to data if we are interested in modelling the dependence structure between the failure probability in 2008 and the same probability in 2010, 2011, 2012 and 2013 for both non-TARP and TARP recipients. Since the estimated pair-copulae are Gaussian, the dependence between the failure probabilities is linear. Instead, we obtained that different pair-copula families, such as the Student-t and the Gumbel copulae,

[6] The LOGBEV model is implemented in R and the code is available upon request from the authors.

provide the best fit to data if we model the dependence between the failure probabilities after the beginning of the implementation of the TARP-CPP programme, i.e. from 2009 to 2013. It is interesting that both Student-t and the Gumbel copulae show a tail dependence, in the first framework the tail dependence is linear, in the latter it is an upper tail dependence. Table 4 reports the association parameter estimates of the Gaussian copula, that are the intensity of the dependence of the failures probabilities over time for the two groups of banks that were either included or not in the TARP-CPP programme. At the first glance, we note that in 2010 the TARP-CPP programme consistently decrease the default probability dependence with the default of probability in October 2008, when the programme was launched. Specifically, in 2010, the correlation between the $P(D_t = 1|I = 1)$ and $P(D_{2008} = 1)$ was 0.04 while those for the $P(D_t = 1|I = 0)$ and $P(D_{2008} = 1)$ was 0.4286. This result suggests that the TARP-CPP programme has provided an immediate relief to the banks enrolled in the programme through a decrease of their probability of failing. However, the correlation between the $P(D_t = 1|I = 1)$ in 2011 and $P(D_{2008} = 1)$ was 0.1330 and higher in 2012, 0.2254. In the same manner, the correlation between the $P(D_t = 0|I = 1)$ in 2012 and $P(D_{2008} = 1)$ has increased. In 2013, the correlation between both $P(D_t = 1|I = 1)$ and $P(D_t = 1|I = 0)$, and $P(D_{2008} = 1)$ have reached almost the same level (respectively, 0.0753 and 0.0923).

These results potentially have important and significant implications. In particular, capital injections helped banks to reduce their default probabilities in the short term. However, such an effect is less strong after 2010 until 2012, when banks that did not receive capital injections show similar patterns. This suggests that the TARP was effective in reducing the default probability especially during the peak of the global financial crisis. Our findings are in line with Berger & Bouwman (2013)'s paper, which shows that capital is an effective tool in enhancing banks performance (in terms also of survival as distance to default) especially during crises and economic downfall. The effectiveness of the TARP programme in the short term could be due to the competitive advantages and the increase of market shares and market power for the TARP banks, as shown by Berger & Roman (2015). From 2010, the dependences between the probabilities of defaults for banks that were either supported or not by the TARP-CPP programme are similar. We find two main reasons to explain these results. Firstly, typically large banks with high market power have appeared to have taken on more risk as a consequence of capital injections during the TARP programme, as pointed out by Berger & Roman (2015), Black & Hazelwood (2013) and Duchin & Sosyura (2014). Secondly, TARP banks could have struggled with the costs of TARP-funds which could have harmed their market power and soundness (Berger & Roman, 2015).

In addition, we find a linear dependence structure between the probabilities of failure in 2008 and after that. This means that the likelihood of failure after 2008 depends on the level of distress of the bank at the peak of the financial crisis for non-TARP and TARP recipients, regardless of whether a bank is healthy or not. On the contrary, after 2008, the dependence between the probabilities of failure becomes a tail dependence for the two groups of bank. These results could be due to a distortion of the financial market caused by the government support. As shown by Black & Hazelwood (2013) and Duchin & Sosyura (2014), banks that receive government assistance tend to increase their risk taking for both lending and investment activities as a general attitude. For this reason, we find that the time series of the probabilities of failures after 2008 show dependence only for distressed TARP banks. Duchin & Sosyura (2014) also show that a higher risk attitude is associated more with a signal of government support rather than with the capital injection itself. In line with our results, they specifically find that a higher risk-taking attitude is more evident for banks that are closer to financial distress or that were allowed to skipped dividend payments required by the TARP programme. Furthermore, banks learned about the government forbearance attitude during the running of the TARP-CPP programme (over the period 2008-2009). Therefore, it is reasonable to find a different risk-attitude for a specific group of banks after the beginning of the TARP programme. As pointed out by Berger & Roman (2015), market power banks, which are typically the large ones, appear to have taken on more risk because of capital injection during the TARP programme. This means that banks with higher risk exposure tended to take on more risk after 2008. In addition, it is plausible to find a tail dependence

Time	Dependence between $P(D_t = 1 \mid I = 1)$ **and** $P(D_{2008} = 1)$	Dependence between $P(D_t = 1 \mid I = 0)$ **and** $P(D_{2008} = 1)$
2009-2008	0.6548	0.7858
2010-2008/2009	0.0443	0.4286
2011-2008/(2009-10)	0.1330	0.0691
2012-2008/(2009-10-11)	0.2254	0.1955
2013-2008/(2009-10-11-12)	0.0753	0.0923

Table 4: The level of dependence between the failure probability $P(D_{2008} = 1)$ and the conditional failure probabilities $P(D_t = 1|I = 0)$ or $P(D_t = 1|I = 1)$ for the two groups of banks that are included and not in the TARP-CPP project for the period 2009-2013.

for the non-TARP recipients after the peak of the financial crisis. These banks were not considered sufficiently healthy or systemically important to be integrated in the programme. Hence, the distressed and the healthy banks maintain their risk performance after the beginning of the implementation of the TARP-CPP programme, i.e. from 2009 to 2013.

5 Conclusion

The 2008 financial crisis has highlighted the importance of reliable and robust models to monitor and assess banks' stability in order to reduce the social costs of failures and rescue policies. This issue is of particular interest because the financial crisis has led to a vast amount of costly policy interventions to stabilize the financial system. While these initiatives have provided relief to the banking system, their effects on the stability of the banking system over a prolonged period of time is still controversial. Bailouts can favour moral hazard behaviour of banks and in turn increase their risk profile over time (Hakenes & Schnabel, 2010; Dam & Koetter, 2012; Black & Hazelwood, 2013; Duchin & Sosyura, 2014). Even though there is an increasing number of studies on capital injections to banks during the financial crisis, the effectiveness of bailouts in reducing the probability of failure over time is relatively unexplored.

This paper contributes to the operational research literature by covering this gap. In particular, we propose a new longitudinal model for binary rare events, the Longitudinal

Binary Generalised Extreme Value (LOBGEV) model. This model uses the GEV model (Calabrese & Osmetti, 2013) to represent the marginal distributions of the D-vine copula (Smith et al., 2010). We employ this new model to analyse the impact of the TARP-CPP capital injections on the probability of failure of US commercial banks from 2008 to 2013. Our results provide three important empirical contributions.

First, using the GEV model, we analyse the determinants of receiving capital injections under the TARP-CPP and of bank failures over the period 2008-2009. Our results show that low liquidity, low asset quality, poor performance and low capitalization, high non-traditional income sources increase the probability of bank distress. Moreover, we find that banks with high commercial and industrial loans, large size, and low real estate are more likely to be bailed-out.

Second, we apply the GEV model to identify the characteristics that are relevant to describe banks' failure after the TARP-CPP projects. Our findings show that higher levels of capitalisation reduce the probability of bankruptcy for banks that received TARP-CPP funds for all the years under investigation. Moreover, both capitalisation and performance of banks are pivotal variables for the distress probability conditionally to the non-intervention. As concerns the macroeconomic variables, US banks with high personal income growth rate were less likely to fail in 2010 and 2013.

Third, we propose the LOBGEV model to investigate the temporal dependence structure of the failure probabilities for banks that received TARP-CPP capital injections and for those that did not. This new model can be used by regulators and policy makers to assess the effectiveness of capital injections over time in improving banks performance. In particular, our investigation is driven by a simple but powerful question: did the TARP-CPP programme reduce banks default probabilities? Our results suggest that, after an initial relief, the correlation between the probabilities of failure for TARP-CPP recipients over a period of five years is almost the same as the correlation for banks that did not receive capital injections. Therefore, the TARP-CPP programme was effective in reducing banks default probabilities only in the short term, during the peak of the global financial crisis.

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