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Evidence from the Euro Area

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Modelling country and group levels corporate default dependence: Evidence from the Euro area

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Abstract

This paper employs a mixed effects Cox model to estimate the failure dependence caused by firms' exposure to unobserved factors at both country and group level. We use a quarterly panel data set of 1,422 public listed firms across the Euro area over the period 1994Q1-2014Q4. The empirical analysis delivers three main results. First, when countries are grouped together, with economic and financial similar conditions, failure clustering tend to be larger, as firms are subject to an extra risk due to the impact of unobserved factors at the group level. Second, there is significant evidence of failure dependence caused by firms' exposure to country level unobserved factors. Third, models that do not account for the distance to default probability tend to perform poorly as compared with their counterparts.

Keywords: Hazard rates; mixed effects model; country and group level dependence; Eurozone

JEL Classification: G33, C51, C41.

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1 Introduction

The financial crisis and the sovereign debt crisis hit the Euro area significantly. Not only the PIIGS contries, but also Belgium and France were affected (Metiu, 2012; Arghyrou and Kontonikas, 2012; Ludwig, 2014), even though to a lesser extent.[1] As a result, banks were more conservative with their lending activities, and a large reduction in loan supply was observed, with an impact on investment activities, job creation, and sale growth (Acharya et al., 2016). Since then, business entities within the Euro have struggled to survive, and the hazard rates of these businesses have been severely affected, due to their exposure to risk factors at country and group level.

Das et al. (2007) observed excess default correlation induced by unobserved factors (or frailty factors), and showed that models based on the assumption that corporate defaults are conditionally independent after adjusting for observable factors tend to underestimate default clustering. Against this background, several studies have considered failure dependence induced by unobserved risk factors at country or industry levels using frailty factors (see e.g. Duffie et al., 2009; Chava et al., 2011; Koopman et al., 2011, 2012; Qi et al., 2014) so to yield more accurate estimates of hazard rates.

In this paper, we estimate the failure dependence of 1,422 public listed firms in 11 Eurozone countries over the period 1994Q1-2014Q4. The analysis is conducted at country and group level. As for the group level, we consider PIIGS and non-PIIGS countries, since the strong linkage between economic conditions and firm performance (see e.g Bhattacharjee et al., 2009; Bonfim, 2009; Chen, 2010; Tang and Yan, 2010; Jacobson et al., 2013). In addition, we consider three extra groups that are formed by including: only Belgium in the PIIGS (PIIGSB); only France in the PIIGS (PIIGSF); both Belgium and France in the PIIGS (PIIGSBF) (see also Giordano et al., 2013). This allows us to establish to what extent the crisis in the Euro area and Janssen, 2008; Wienke, 2011) within a multivariate framework of mixed effects Cox model (see Ripatti and Palmgren, 2000; Therneau and Grambsch, 2000; Therneau et al., 2003). A cluster level-specific random effect, which is assumed to follow a Gaussian distribution, is considered for country and group level clustering, and firms in each country are exposed to country (internal) and group level (external) risk (unobserved) factors. We also consider a non-nested frailty model, which accounts only for country level (internal) unobserved factors (firms are not exposed to any potential external risk factors). This model is considered for comparison purposes. It is expected that the estimates of the nested frailty model will likely be more accurate than those by the non-nested frailty model, due to the fact that the latter ignores the potential impact of externals factors. This may suggest that the total risk exposure of a firm is not only limited to country level factors, but also to bloc level factors. Therefore, the Euro area. Third, models that account for the distance to default probability covariate

2.1 Non-nested frailty models

Let T_{ij} and δ_{ij} respectively be the event time and event indicator (censoring indicator) of firm i listed in country j among q countries. The indicator δ_{ij} takes the value 1 if T_{ij} is a failure time and 0 otherwise. Suppose that the data set of firm i follows a shared frailty model. The hazard rate of the firm is defined as follows (see Ripatti and Palmgren, 2000; Therneau et al., 2003; Duchateau and Janssen, 2008, among others):

$$\lambda_{ij}(t) = \lambda_0(t) u_j exp(X_{ij}(t)\beta); \tag{1}$$

where $\lambda_{ij}(t)$ is the hazard rate of firm i listed in country j, and $X_{ij}(t)$ and β are vectors of

(2) is normally distributed on the log-scale, and the parameters β and w are estimated by maximizing the penalised partial likelihood (PPL):

$$PPL = PL(\beta; w; data) - g(w; \theta); \tag{3}$$

where PL is defined as the log of the classical Cox partial likelihood conditioned on the data set:

$$PL(\beta; w) = \sum_{i=1}^{n} \int_0^{\infty} \Big[Y_i(t)(exp(X_i \beta + Z_i w)) - log \Big(\sum_k Y_k(t)(exp(X_k \beta + Z_k w)) \Big) \Big] dN_i(t); \tag{4}$$

and the penalty term is defined by

$$g(w; \theta) = \frac{1}{2\theta} \sum_{j=1}^{q} w_i^2; \tag{5}$$

where θ is the variance of the log-frailty or random effect.[3] For a given value of the variance estimate θ, we use the expansion and approximation of Ripatti and Palmgren (2000) to derive a modified likelihood defined as:

$$
\begin{aligned}
l_m(\beta; \theta) = & -\frac{1}{2}\log(|D|) + \log \int exp \Big[PL(\beta; w) - \frac{1}{2} w' D^{-1/2} w \Big] dw \\
\approx & \; PL(\beta; \tilde{w}) - \frac{1}{2}\log\Big(\tilde{w}' D^{-1/2} \tilde{w} + log|D|\Big) + \log(|H_{22}(\beta; \tilde{w})|); \qquad (6)
\end{aligned}
$$

where $D = \theta I$ is a diagonal matrix and I is an identity matrix of order $q \times q$; q is the number of countries in the sample, and $g(w; \theta) = \tilde{w}' D^{-1}(\theta) \tilde{w}$. The term $\tilde{w} = \tilde{w}(\beta; \theta)$ solves the following equation

$$\sum_{i=1}^{n} \int_0^{\infty} (Z_{ij} - \bar{Z}_j(t)) dN_i(t) - D^{-1}(\theta) \tilde{w} = 0 \tag{7}$$

[3] For details on penalised partial likelihood of a shared frailty model, see Ripatti and Palmgren (2000) and Therneau et al. (2003).

The coefficients of equation (9) can still be estimated without knowing the shape of λ_0. The random effects distribution G is a multivariate Gaussian distribution with zero mean and variance matrix Σ, which is a function of a vector of the parameters θ. Following Therneau and Grambsch (2000) and Therneau et al. (2003), we define the log penalised partial likelihood function as follows:

$$PPL(\beta, b; \theta) = l(\beta, b) - g(b; \theta), \tag{10}$$

where the penalty function $g(b; \theta) = b' \Sigma^{-1}(\theta) b/2$. The term $l(\beta, b)$ is called the partial likelihood (PL) (see Therneau, 2015) for any given value of β and b, and is defined as:

$$l(\beta, b) = \sum_{k=1}^{n_j} \int_0^{\infty} \left[Y_k(t)\eta_k(t) - \log \left(\sum_j Y_j(t)\eta_j(t) \right) \right] dN_k(t), \tag{11}$$

where $\eta_k(t) = X_k(t)\beta + Z_k(t)b$ is the linear score for firm k at time t, $X_k(t)$ and $Z_k(t)$ are the k^{th} rows of the covariate matrices X and Z, respectively. In other words, the above row matrices are the data set for firm k in country j. The term $Y_k(t)$ describes the surviving firms (or firms still at risk of default), which takes value 1 when firm k is active at time t, and 0 otherwise. Equation (10) can then be re-written as:[4]

$$PPL(\beta, b; \theta) = \sum_{k=1}^{n_j} \int_0^{\infty} \left[Y_k(t)\eta_k(t) - \log \left(\sum_j Y_j(t)\eta_j(t) \right) \right] dN_k(t) - \frac{b' \Sigma^{-1}(\theta) b}{2}. \tag{12}$$

The estimates of β and b, $\hat{\beta}$ and $\hat{b}$, are obtained by solving the following score equations (see Therneau et al., 2003):

$$\frac{\partial PPL}{\partial b_j} = \sum_{i=1}^{n} \int_0^{\infty} (Z_{ij} - \bar{Z}_j(t)) dN_i(t) - \frac{\partial g(b; \theta)}{\partial b_j}, \tag{13}$$

[4] For detailed treatment, refer to Therneau et al. (2003).

$$Z_j(t) = Z_j(\;;b;t) = \frac{\sum Z_k j Y_k [X_k \; + Z_k b]}{\sum Y_k [X_k \; + Z_k b]}: \qquad (14)$$

We also obtain the integrated partial likelihood (IPL) by integrating out the random effects as obtained below (Therneau, 2015):

$$IPL = \frac{1}{(2\;)^{q/2} | \sum(\;) |^{1/2}} \int PPL(\;;\;) exp \left(b' \sum{}^{-1}(\;) b/2 \right) db; \qquad (15)$$

where q is the number of random effects. We estimate the parameters using the “*coxme*” package in *R* by (Therneau, 2015).

2.3 Data

Our data are drawn from DataStream and Worldscope for public listed firms in 11 member states of the Eurozone for the period 1994Q1-2014Q4. The sample is comprised of 1,422 firms: 905 active firms, 398 failed firms and 119 acquired or merged firms, and this translates into 71,680 quarterly firm observations. The countries are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The choice of these countries is based on data availability.[5] Table 1 presents firms' status at country level across the 11 selected members of the Eurozone.

The definition of firm failure may differ across all the member states of the Euro area. For the sake of uniformity, we follow Altman and Narayanan (1997), who provide a definition of failure: (i) filing by a company; (ii) bond default; (iii) bank loan default; (iv) delisting of a company; (v) government intervention via special financing; and (vi) liquidation.[6] We select failed, and acquired or merged firms from the DataStream “DEAD” category for each country in conjunction with other sources (e.g. Bloomberg bankruptcy segment). For instance, DataStream items “DEADGR”, “DEADBD” and “DEADFR” are the categories for dead

[5] These countries may have some accounting information disclosure differences, but Worldscope adjusts the variables for these differences.

[6] For delisting of a company, we cross check the reasons for delisting at other sources. These reasons include mergers, acquisitions and some of the reasons already stated.

Table 1: Active, failed and merged or acquired rms within the Eurozone

since the firm is censored as a result of a non-failure event.[7]

We employ some widely used covariates in the empirical literature of corporate failure, given their explanatory power (see Shumway, 2001; Duffie et al., 2007, 2009; Duan et al., 2012; Qi et al., 2014, among others). First, we use the 3 month T-bill rate, which is a measure of short-term interest rates. Second, we consider the one year trailing stock return, which is a good predictor of firm failure (see Shumway, 2001), and is constructed by cumulating monthly stock returns. Third, we use the one year trailing market return, which is a measure of the overall market performance, and is constructed by cumulating monthly market returns. Fourth, the distance to default probability is used as a probabilistic measure of volatility adjusted leverage. In constructing this measure, we follow Bharath and Shumway (2008): firms with higher probabilities are close to default, whilst firms with lower probabilities are far from default. Lastly, we consider the age of a firm to test whether older firms are less the mean than the latter. Additionally, the natural log of firm age is bounded by (0.000, 2.996) since the firm age falls within the interval [1, 21]. The 3 month T-bill rate ranges from 1.123% to 12.144%.

3 Empirical analysis

This section presents the empirical results obtained using non-nested and nested frailty models. More specifically, we first estimate the parameters of the non-nested frailty model, which serves as benchmark model. Then the parameters of the nested frailty model are estimated, and its performance is compared to that of the non-nested model. Lastly, we compute the total riskiness of firms in order to evaluate how firms are affected by country and group level unobserved factors.

In our analysis, we consider PIIGS countries against non-PIIGS ones along with three extra groups that are formed by including: only Belgium in the PIIGS (PIIGSB); only France in the PIIGS (PIIGSF); and both Belgium and France (PIIGSBF). In other words, we extract the country and group level frailty factors that affect listed firms for following pair of groups: (i) PIIGS versus non-PIIGS; (ii) PIIGSB versus non-PIIGSB; (iii) PIIGSF versus non-PIIGSF; and (iv) PIIGSBF versus non-PIIGSBF.

In the regression analysis, we employ distance to default probability, one year trailing stock return, one year trailing market return, ln(age), and 3 month T-bill rate as covariates. Table 3 reports the estimates for non-nested frailty models. For model 1, the hazard rate and Shumway, 2008). This implies that, for an appropriate default model specification, the distance to default probability should be augmented with suitable covariates. Model 3, which we consider to perform a confirmatory test on the distance to default probability, also shows the insignificance of the 3 month T-bill rate, while the other covariates are significant.

To find the best model in terms of goodness of fit across all the specifications, we use both the pseudo-deviance and the information criteria measures. For the former criterion, we have:

$$Pseudo\text{-}deviance = -2loglik_A + 2loglik_B; \tag{16}$$

where $-2loglik_A$ and $-2loglik_B$ are the deviance statistics for generic models A and B, respectively. The statistic in (16) says how model A performs worse than the supposed best model B, and it can be used in case of nested models. The statistic follows a chi-square distribution (χ^2), with the degrees of freedom being the difference between the number of parameters in model A and that in model B.

As for the information criteria, we consider the Akaike information criterion (AIC), the corrected Akaike information criterion (AICC), and the Bayesian information criterion (BIC):

$$AIC = -2logL + 2k; \tag{17}$$

$$AICC = AIC + \frac{2k(k+1)}{n-k-1}; \tag{18}$$

$$BIC = -2logL + klogn; \tag{19}$$

where $-2LogL$ is the partial likelihood, which is obtained by using the rank of events (Singer and Willett, 2003), k and n denote the number of parameters and events, respectively (see Raftery, 1995). As a rule of thumb, the lower the values of these information criteria, the better the fit. The information criteria are suitable for both non-nested and nested models.

Since model 2 nests model 1, and model 4 nests model 2, we use the pseudo-deviance to compare the performance of these models. In case of models 1 and 2 (the latter nests the former), the pseudo-deviance statistic is equal to $31.480(5173.580 - 5142.100)$, with 3 degrees of freedom. Since the value of the statistic is greater than the critical value, $\chi^2_{0.01(3)} = 16.266$, the null hypothesis that the coefficients of stock return, market return and ln(age) are all equal zero can be rejected. This implies an improvement of the fit due to the inclusion of these covariates, which makes model 2 the best candidate. Similarly, the values of this statistic for models 1 and 4 is 31.876, which is larger than the critical value $\chi^2_{0.01(4)} = 18.467$. Therefore, model 4 fits the data better than Model 1. Instead, a different result is found for models 2 and 4. Here, the value of the pseudo-deviance statistic, 0.396, is smaller than the critical value, $\chi^2_{0.01(1)} = 10.828$. Therefore, there is no improvement in terms of fit if one adds 3 month T-bill rate to model 4. Likewise, for models 3 and 4, the test statistic is 63.296 with $\chi^2_{0.01(1)} = 10$ 0for 32

Table 3: Non-nested frailty model speci cations with random e ects

	Dependent variable: Time to event			
	Model 1	Model 2	Model 3	Model 4
Distance to default prob.	1.221	0.929		0.925
	(0.231)	(0.255)		(0.255)
Stock return		-0.298	-0.490	-0.291
		(0.143)	(0.140)	(0.144)
Market return		-0.559	-0.482	-0.501
		(0.276)	(0.290)	(0.290)
ln(age)		-0.384	-0.375	-0.386
		(0.082)	(0.081)	(0.082)
3 month T-bill rate			-3.814	-3.125
			(4.960)	(4.968)
LogLik.(Fitted)	-2572.592	-2557.045	-2588.069	-2556.648
LogLik.(Integrated)	-2586.790	-2571.050	-2602.738	-2570.852
Integrated LR test	80.140	111.620	103.110	112.020
	[0.000]	[0.000]	[0.000]	[0.000]
Penalized LR test	108.540	139.630	132.450	140.430
	[0.000]	[0.000]	[0.000]	[0.000]
Pseudo-deviance	5173.580	5142.100	5205.476	5141.704
AIC	5175.580	5150.100	5213.476	5151.704
AICC	5175.601	5150.315	5213.691	5152.028
BIC	5175.861	5151.224	5214.600	5153.109
Dependence	0.185	0.179	0.203	0.186

Notes: The efron approximation is used to control for ties in the event times of rms. Standard errors and p-values are in round and square brackets, respectively. , denote signi cance at the 1%, 5%, and 10% level, respectively. LogLik.(Fitted) and LogLik.(Integrated) are the tted and integrated likelihoods due to unobserved factors, respectively. The terms Integrated LR and Penalized LR denote the unobserved factors-adjusted integrated and penalized likelihood ratio tests, respectively. The pseudo-deviance is used to compare the overall model t of nested models, while the Akaike information criterion (AIC), corrected Akaike information criterion (AICC), and Bayesian information criterion (BIC) measures are used to compare either nested or non-nested models.

rms that usually exhibit averagely higher distance to default probability are more prone to experience failure within the Eurozone. Second, a rise in stock return and market return increases the expected time to default. This outcome seems to suggest that rms listed within the Euro area with a consistent increase in their returns are less likely to move towards a failure point, and performing markets tend to enhance the survival rate of such rms, as compared to those of averagely decreasing stock returns. Third, the signi cance of age in our models reveals that older rms in Euro area are less likely to fail than the younger ones. This may be due to the liability of newness (see e.g Baum, 1996; Aldrich and Ruef, 2006; Wiklund et al., 2010), as older rms may have more business contacts, better understanding of the dynamics of the business environment and more robust organisational structure. Further, older rms as our benchmark model.

The empirical results are illustrated in Tables 4 and 5. In all models, almost all the regressors are significant with the expected signs. For example, in the D_{PG} model, the coefficient of distance to default probability is positive and significant, and those of the stock return, market return, and ln(age) are negative and significant. While these results do not differ from those in Table 3, measures of dependence have improved considerably, regardless of the specification of the model. This implies that when determining risk rates of listed firms in an economic bloc during unfavourable market and economic conditions, it is more appropriate to group countries according to similar macroeconomic structures. Failure to do so may lead to underestimation of risk rates, since non-nested models are based on the hypothesis that countries are independent to each other. As such, the economic and financial activities between member states have no significant impact on firms, and the macroeconomic conditions in one or more countries may be not transmitted to another. Therefore, the risk level of firms is restricted to only country level, and the potential group level exposure is ignored in the estimation parameters. On the contrary, nested models assume dependence among member states through the interaction of countries. Therefore, using these models more accurate estimates of the risk level can be gained.

We complete our analysis with an investigation of the impact of firms' membership to the diverse groups of the Euro area on riskiness. In Table 6, we report results related to the risk scores and the level of riskiness of firms within countries, and PIIGS and non PIIGS group of countries. In the event of failure clustering, the country (group) score shows how firms are likely to fail either faster or slower. As such, we use value 1 (expected value of frailty) as a threshold value for gauging riskiness. A risk-score large than 1 implies more riskiness, while a score lower than 1 is considered less riskiness. Examples of more risky countries are Austria, Finland, Greece, Ireland, Netherlands and Portugal, while the less risky countries are Belgium, France, Germany, Italy and Spain. For instance, the risk scores for Portugal and Belgium are 1.231 and 0.984 respectively, values that are shared by firms in these countries. The country

Table 5: Nested frailty models: PIIGSB and PIIGSF groups

Dependent variable: Time to event				
	PIIGSB		PIIGSF	
	D_B	S_B	D_F	S_F
Distance to default prob	1.331	0.847	1.349	0.876
	(0.277)	(0.258)	(0.277)	(0.258)
Stock return	-0.272	-0.320	-0.262	-0.317
	(0.145)	(0.147)	(0.145)	(0.149)
Market return	-0.712	-0.732	-0.757	-0.752
	(0.318)	(0.311)	(0.321)	(0.311)
ln(age)	-0.369	-0.356	-0.378	-0.391
	(0.084)	(0.096)	(0.084)	(0.097)
LogLik.(Fitted)	-1839.700	-2487.728	-1788.692	-2451.328
LogLik.(Integrated)	-2560.389	-2592.065	-2563.549	-2592.324
Integrated LR test	132.940	69.590	126.620	69.070
	[0.000]	[0.000]	[0.000]	[0.000]
Penalized LR test	1574.320	278.260	1676.340	351.060
	[0.000]	[0.000]	[0.000]	[0.000]
Psuedo-Deviance	5120.778	5184.130	5127.098	5184.648
AIC	5128.778	5192.130	5135.098	5192.648
AICC	5128.993	5192.345	5135.313	5192.863
BIC	5129.902	5193.254	5136.222	5193.772
Dependence	1.929	0.288	2.094	0.398

Notes: Standard errors and p-values are in round and square brackets, respectively. D_B and S_B indicate the models for PIIGSB with similar trends in terms of the distance to default and stock returns respectively, whereas D_F and S_F are the models for the PIIGSF. , denote signi cance at the 1%, 5%, and 10% level, respectively. For further details, see Table 3.

Table 6: Scores and riskiness for nested frailty models: PIIGS versus non-PIIGS

	County level		D_{PG}			S_{PG}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PIIGS	Country Score	Country Riskiness	Group Score	Group Riskiness	Total Riskiness	Group Score	Group Riskiness	Total Riskiness
Portugal	1.231	0.231	1.092	0.092	0.323	1.134	0.134	0.365
Ireland	1.423	0.423	1.092	0.092	0.515	1.134	0.134	0.557
Italy	0.729	-0.271	1.092	0.092	-0.179	1.134	0.134	-0.137
Greece	1.449	0.449	1.092	0.092	0.541	1.134	0.134	0.583
Spain	0.777	-0.223	1.092	0.092	-0.131	1.134	0.134	-0.089
non-PIIGS								
Austria	1.793	0.793	0.915	-0.085	0.708	0.882	-0.118	0.675
Belgium	0.984	-0.016	0.915	-0.085	-0.101	0.882	-0.118	-0.134
Finland	1.044	0.044	0.915	-0.085	-0.041	0.882	-0.118	-0.074
France	0.583	-0.417	0.915	-0.085	-0.502	0.882	-0.118	-0.535
Germany	0.536	-0.464	0.915	-0.085	-0.549	0.882	-0.118	-0.582
Netherlands	1.209	0.209	0.915	-0.085	0.124	0.882	-0.118	0.091

Notes: D_{PG} (columns 3 to 5) and S_{PG} (columns 6 through 8) refer to PIIGS countries which have similar behaviour of distance to default probability and stock return, respectively. Figures in columns (1) and (2) indicate country-level scores and riskiness, respectively. Figures in column (2) are obtained by subtracting value 1 (expected value of the unobserved factors) from numbers in column (1). Figures in columns (4) and (7) are obtained by subtracting value 1 from gures in columns (3) and (6). Total riskiness for D_{PG} and S_{PG} are constructed by adding gures in columns (2) to those in column (4), and numbers in column (2) to those in column (7), respectively.

followed by Ireland and Portugal, while France has the lowest risk level. For the non-PIIGSBF and PIIGSF groups. The following results are obtained. The risk score falls within the range (1.121, 1.153) and (1.000, 1.003) for PIIGSB and PIIGSF, respectively. Thus, the group riskiness, when Belgium is regarded as a member of the PIIGS, falls within the range 12.10%-15.30%, while that of France is bounded by -0.3% and 0.3%. This seems to suggest that Belgium behaved more like the PIIGS countries than France does, as a result of the crisis.

The above empirical results show that accounting for country level (internal) risk factors may add some explanatory power to default rate models within the Euro area for ranking individual countries in terms of riskiness. However, firms are externally exposed to extra risk induced by the economic and financial activities among the member states of the Euro area, and neglecting the potential impacts of group level (external) risk factors on firms' behaviour may likely lead to the underestimation of failure rates and related dependencies among firms. Further, firms listed within the periphery (weaker) group of countries experience higher risk level compared to those listed in the non-periphery (stronger) group in the Euro area.

4 Conclusion

The estimates of failure probability and its correlation play an important role in contemporary risk management for corporations, regulators, investors and academics (see Shumway, 2001; Duffie et al., 2007; Duan et al., 2012, among others).

In this paper we employ a mixed effects Cox model that accounts for nested unobserved factors to investigate the hazard rates and dependence structures of public listed firms of the stock exchanges in 11 Euro countries. The model embodies both country (internal) and group level (external) risk unobserved factors. For comparison purpose, we also consider a non-nested frailty model, which only incorporates unobserved factors at country level.

In the empirical analysis, we employ covariates largely used in the empirical literature, such as distance to default probability, one year trailing stock return, one year trailing market return, firm age, and 3 month T-bill rate, and consider four different groups of countries for the nested frailty model, namely PIIGS, PIIGSBF (Belgium and France are included in the

paper examines the impact of firms' membership to groups of the Euro area on riskiness.

Further research may consider a three level nested frailty model that accounts for sector level exposures in addition to country and group levels. This is because firms may be subjected to some industry level regulatory requirements and competition which may influence their risk levels.

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