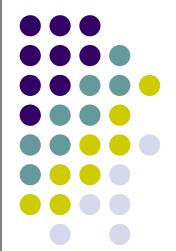
# Spatial dimension of the credit risk: Spatial filtering approach

### **Aleksandar PETRESKI**

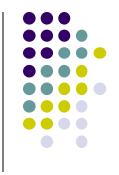
Jönköping International Business School, Sweden

Discussant Yannick LUCOTTE

Laboratoire d'Economie d'Orléans & PSB Paris School of Business



# Objectives and results of the paper



- Paper in line with previous empirical literature on credit scoring having:
  - investigated the main determinants of the probability of default
  - assessed the prediction accuracy and interpretability of scoring models
- In particular, this paper investigates whether the predictive power of a credit risk model increases with spatial filtering
- Analysis conducted for a large sample of companies from the Republic of Macedonia: data taken from different sources (credit registry, cadastre, NBRM)
- Main result of the paper: the prediction of defaults increases with spatial filtering and outperforms the base model
- → confirms the existence of clusters of defaults within geographical area



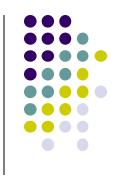
### 1) Theoretical foundations:

- Beyond econometric results, what could explain theoretically the importance of taking into account spatial proximity between firms to assess their probability of default?
- In other words, what could explain the existence of clusters of default within geographical area? Spatial links between firms or cross-regional differences in terms of economic conditions (household revenue, unemployment rate, remittances,...)
- Would be interesting to investigate whether the "spatial filtering approach" still outperforms the base model when including in the base model regional dummy variables



#### Data: 2)

- Presentation and discussion of data used should be more developed: preliminary descriptive statistics, sectoral and regional dispersion of firms, size heterogeneity of firms, ...
- In particular, it should be interesting to provide more details about the defaults of firms: how many firms defaulted over the period considered? In which sector(s) principally?
- Important information when estimating a logit (or probit model): a large number of 1 for the dependent variable could bias the results
- See, e.g., Maalouf, M., & Trafalis, T.B. (2011). Robust weighted kernel logistic regression in imbalanced and rare events data. Computational *Statistics & Data Analysis*, 55(1), 168-183.



### 3) Comparison of models:

- The main objective of the paper is to compare 3 different models of credit risk:
  - "base" model
  - model with the distance to capital or a geographical dummy as additional right-hand side variable
  - model using the "spatial filtering approach"
- However, due to constraints with the weight matrix, the size of the sample seems to not be the same for the "spatial filtering approach": 1106 companies.
- Is it the same sample for the "in-sample" and "out-of-sample" exercise?



### 4) Control variables:

- The literature on credit scoring discusses a number of potential credit risk drivers: see, e.g., recent papers on this issue using Bayesian model averaging (BMA) techniques
- In the paper, a small number of variables are considered: what justifies this choice? Certainly necessary to select more carefully the right-hand variables.
- This is justified in the paper by a potential collinearity issue:
  - however, how justify that the ROE and ROE are both considered, but also two similar measures of sales revenue
  - this could explain why a small number of variables are statistically significant
- Certainly important to consider the age of firms



### 5) Econometric approach:

- Why do not present the "traditional" ROC curve to present and discuss the accuracy of the different logit models considered?
- For robustness purpose, certainly important to consider an alternative weight matrix when using the "spatial filtering approach": for instance, why do not consider sector-by-sector weight matrix? By this way, only spatial links of firms in the same sector are considered.
- Would be interesting to extend the approach developed in the paper by considering Bayesian model averaging (BMA) techniques or a LASSO approach: a large set of credit risk drivers can be considered.
- → no doubt about the choice of covariates

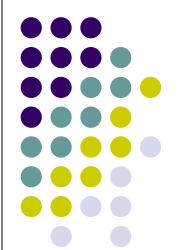
# Optimal bank capital requirements: An asymmetric information perspective

### Alessandra MARCELLETTI

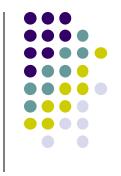
LUISS School of European Political Economy, Italy

Discussant Yannick LUCOTTE

Laboratoire d'Economie d'Orléans & PSB Paris School of Business



# Objectives and results of the paper



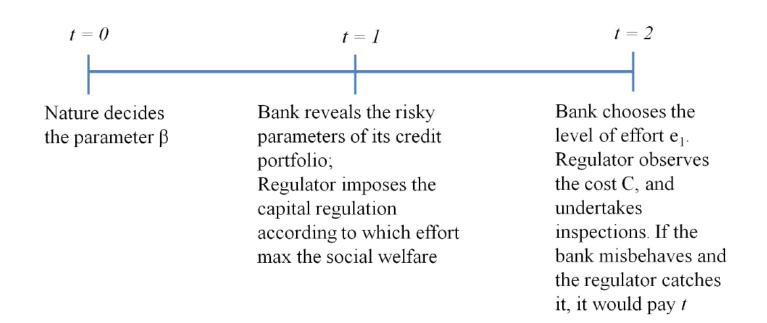
- Theoretical paper studying how to implement a socially optimal regulation scheme that simultaneously deals with both sources of asymmetric information: moral hazard and adverse selection
- Model with two agents: a "lying" bank and the regulator
- The main objective of the regulator is to maximize social welfare, balancing the benefit of offsetting risk and the opportunity cost of devoting public funds to maintain financial stability
- Main result of the paper: under incomplete and imperfect information, the risk-weighted asset scheme is the best prudential instrument to ensure financial stability
- → it implies the lowest marginal disutility for the bank and it ensures the maximization of the social welfare

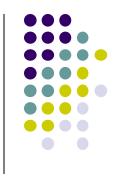
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### 1) Timing of the model:

• Timing of the model is certainly not sufficiently clear: in particular, does the level of effort of the bank  $e_1$  drives the portfolio risk at the period t=1?





### 2) Social welfare:

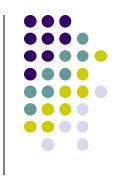
- How justify the inclusion of the bank's utility in the social welfare? Is it really an objective for the regulator?
- → would it be possible to weight the bank's utility in the social welfare function?

$$V = S - (1 - \theta_{e_2})B - (1 + \lambda)\left(C - t(1 - \theta_{e_2})(1 - e_1) + \frac{(1 - e_1)^2}{2}\right) + U_b$$



### 3) Size of the bank and level of effort:

- Hypothesis of the model: the bank asset quality and its composition depends on the screening effort  $e_1$  undertaken by the bank. The cost of screening is increasing and convex for the volume of safe assets that the banks screens.
- However this screening effort is completely independent of the size of the bank, as the volume of assets for instance.
- Would be interesting to take into account a "too big to fail" behavior in the model: one would expect that the screening effort  $e_1$  decreases with the size of the bank.



### 4) Preferences of the regulator:

- In the social welfare function, the model assumes that the regulator pays a social cost for using public funds to improve the stability of the financial system
- $\rightarrow$  the parameter  $\lambda$  captures the opportunity cost of devoting public funds to the banking sector instead of the real economy
- However, one would expect that the "risk-taking" behavior of the "lying" bank can also depend on the preferences of the regulator, i.e. the parameter  $\lambda$
- If the bank knows ex ante the preferences of the regulator, it will certainly induces a different behavior, and then conclusions of the model could be different