Bank financial distress and restructuring in Europe

PROF. MAŁGORZATA IWANICZ-DROZDOWSKA, PH.D.

WARSAW SCHOOL OF ECONOMICS, POLAND

Agenda

- **Why did banks get into trouble?**

Iwanicz-Drozdowska M., Laitinen E., Suvas A., (2018). Paths of glory or paths of shame? An analysis of distress events in European banking, *Bank i Kredyt,* 49(2), pp. 115-144

- **How costly was bank restructuring?**

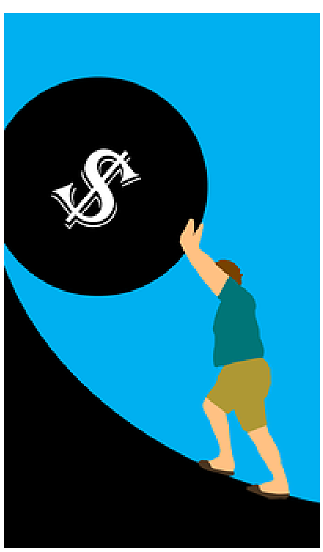
Iwanicz-Drozdowska M., Smaga P., Witkowski B. (2016). Bank restructuring in the EU. Which way to go?, *Journal of Policy Modeling*, 38 (3), pp. 572-586

Motivation

During the global financial crisis (GFC), many banks, both in Europe and in the US, faced significant financial troubles and were bailed out by their governments.

Much research has been carried out for the US banking sector, but for Europe the research is much more limited.

Our studies expand research on banks' distress and restructuring in Europe



Bank financial distress

Goal

Our goal is to identify "distress" and "non-distress" paths of banks, from 1 to 4 years prior to the distress event, in order to show whether and how different they are.

What has been done before? (1)

- **Only two studies deal somehow with banks' distress processes.**
- **Kolari et al. (2002) analysed the models' performance one and two years prior to failures. They found that logit model performance deteriorated over time, while trait recognition results were quite stable.**
- **Hambusch and Shaffer (2016) indicated that prediction performance deteriorates over longer forecast horizons. They attempted to tackle the problem of bank failures by using the leverage ratio (equity to assets ratio) as a continuous variable to predict US banks' problems. For 2000-2011 they registered 441 bank failures.**

What has been done before? (2)

- **Their model presented a reasonable forecasting ability and was capable of using different regressors, estimation techniques and macroeconomic data. However, forecasts for larger banks were less accurate than those for smaller ones. Moreover, the prediction accuracy for the crisis year was lower than in other years.**
- **However, there is a long list of research on failure processes for non-financial companies. E.g., Argenti (1976), D'Aveni (1989), Laitinen (1991), Richardson et al. (1994), Ooghe and de Prijcker (2008), Jardin and Severin (2011, 2012), Du Jardin (2015).**

Methodology and data (1)

- **12 CAMEL-like variables**
- **Bankscope data on European banks (1992-2014)**
- **Similar approach as Arena (2008), Betz et al. (2014) and Altman et al. (2014) to define the bank's distress, but extended by adding the event of bank's negative equity without any bailout or state aid**
- **The distress status and the year of distress were determined using the database from Iwanicz-Drozdowska et al. (2016) supplemented by new distress events identified in the European Commission's communication and the press.**

Methodology and data (2)

Differentiation between commercial vs. cooperative and savings banks and additionally clusters of banks

The initial data set contained 163 distressed and 3,566 non-distressed banks.

Four years of data are appropriate for revealing possible main different processes leading to the bank distress -> 132 banks fulfilled this criterion

Due to missing data our final data set contains 99 distressed banks

Methodology and data (3)

Paired sampling - 99 healthy (non-distressed) banks were selected that matched their distressed peers by country, years of the series, bank type (COM - commercial, or CS - from the savings or co-operative sector), and as closely as possible by size

Factor and cluster analyses (k-means) for extraction of bank distress processes

Estimation technique for distress prediction - binary logistic regression

Methodology and data (4)

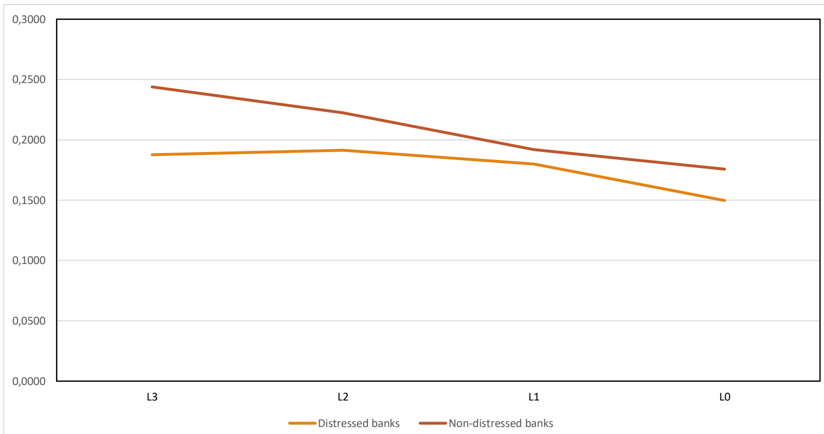
Distribution of banks by distress years and countries in the data.

Year	AT	BE	CY	DE	DK	ES	FR	GR	IE	IS	IT	LV	NL	PT	SE	SI	UK	Total
1992	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2
1993	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	3
1996	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	4
1998	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
2001	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2003	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
2004	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
2007	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	2
2008	3	0	1	2	0	1	1	0	0	1	0	0	2	0	1	0	1	13
2009	3	0	0	2	0	2	0	6	3	0	4	2	0	0	1	0	0	23
2010	0	0	0	0	2	14	0	0	0	0	0	0	0	0	0	0	0	16
2011	0	2	0	1	2	6	1	0	1	0	0	1	0	0	0	1	0	15
2012	1	0	2	0	1	2	0	0	0	0	0	0	0	3	0	1	0	10
2013	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	3	0	6
2014	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Total	7	3	4	6	6	26	12	7	4	2	4	3	3	4	2	5	1	99

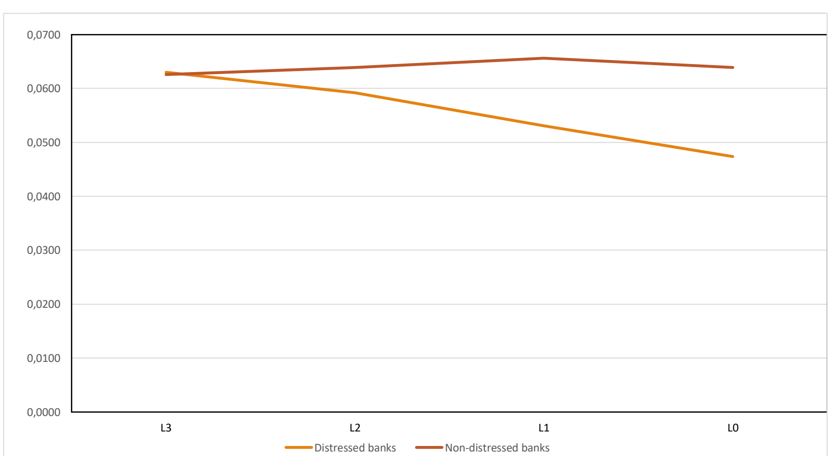
Descriptive statistics

	Distressed banks			Non-distressed banks			Paired t-test		
Variable	Median	Mean	Std dev.	Median	Mean	Std dev.	t-value	Pr > |t|	Signif.
Growth_TA	0,0137	0,0531	0,1979	0,0594	0,0803	0,1684	1,12	0,2649	
Growth_TA_L1	0,0771	0,1173	0,1800	0,0713	0,1254	0,2115	0,26	0,7968	
Growth_TA_L2	0,1151	0,1538	0,1864	0,0792	0,1203	0,2217	-1,35	0,1786	
Growth_EQ	-0,0005	-0,0316	0,3903	0,0357	0,0223	0,2428	1,22	0,2264	
Growth_EQ_L1	0,0419	0,0775	0,2674	0,0663	0,1551	0,3048	1,93	0,0569	*
Growth_EQ_L2	0,0895	0,1822	0,4203	0,0785	0,2126	0,5126	0,43	0,6656	
Growth_G_Loans	0,0130	0,0815	0,2041	0,0412	0,1031	0,2367	0,70	0,4854	
Growth_G_Loans_L1	0,0746	0,1329	0,2368	0,0571	0,1300	0,3006	-0,16	0,8755	
Growth_G_Loans_L2	0,1324	0,1742	0,2059	0,1075	0,1426	0,2555	-1,08	0,2813	
ROA	0,0013	-0,0011	0,0102	0,0027	0,0030	0,0092	3,15	0,0022	***
ROA_L1	0,0035	0,0036	0,0102	0,0045	0,0057	0,0088	1,90	0,0599	*
ROA_L2	0,0058	0,0057	0,0090	0,0050	0,0062	0,0080	0,51	0,6087	
ROA_L3	0,0063	0,0070	0,0071	0,0060	0,0073	0,0080	0,37	0,7106	
EQ_to_TA	0,0474	0,0506	0,0287	0,0639	0,0700	0,0434	4,18	<0,0001	***
EQ_to_TA_L1	0,0531	0,0590	0,0304	0,0656	0,0725	0,0397	3,35	0,0011	***
EQ_to_TA_L2	0,0592	0,0619	0,0312	0,0639	0,0725	0,0439	2,54	0,0127	**
EQ_to_TA_L3	0,0630	0,0655	0,0352	0,0626	0,0755	0,0620	1,71	0,0910	*
Deposits_to_G_Loans	0,7102	0,8514	1,0199	0,7742	1,0320	1,2540	1,12	0,2494	
Deposits_to_G_Loans_L1	0,7071	0,8484	1,0371	0,7697	1,0286	1,3338	1,05	0,2967	
Deposits_to_G_Loans_L2	0,6944	0,8436	0,9899	0,7769	1,0126	1,2127	1,08	0,2844	
Deposits_to_G_Loans_L3	0,7185	0,8741	0,9999	0,7837	1,0298	1,3496	0,90	0,3703	
L_Imp_to_G_Loans	0,0105	0,0141	0,0151	0,0067	0,0106	0,0142	-1,94	0,0555	*
L_Imp_to_G_Loans_L1	0,0066	0,0122	0,0148	0,0057	0,0095	0,0125	-1,56	0,1211	
L_Imp_to_G_Loans_L2	0,0050	0,0091	0,0135	0,0045	0,0079	0,0114	-0,84	0,4030	
L_Imp_to_G_Loans_L3	0,0042	0,0071	0,0110	0,0034	0,0062	0,0114	-0,62	0,5353	
NIM	0,0186	0,0207	0,0115	0,0193	0,0216	0,0150	0,55	0,5853	
NIM_L1	0,0202	0,0215	0,0112	0,0204	0,0229	0,0160	0,84	0,4035	
NIM_L2	0,0203	0,0215	0,0113	0,0197	0,0232	0,0161	0,98	0,3302	
NIM_L3	0,0215	0,0223	0,0120	0,0203	0,0235	0,0163	0,69	0,4930	
CI	0,6418	0,6526	0,2070	0,6056	0,6264	0,1847	1,01	0,3135	
CI_L1	0,5978	0,5944	0,1721	0,5786	0,5989	0,1756	0,38	0,7019	
CI_L2	0,5657	0,5867	0,1831	0,5787	0,5944	0,1848	0,26	0,7953	
CI_L3	0,5866	0,5963	0,1847	0,5953	0,6161	0,1979	0,83	0,4076	
Loans_to_TA	0,6541	0,6082	0,1685	0,6773	0,5998	0,2317	-0,40	0,6887	
Loans_to_TA_L1	0,6482	0,6041	0,1712	0,6668	0,6006	0,2338	-0,23	0,8223	
Loans_to_TA_L2	0,6551	0,6088	0,1812	0,6712	0,6060	0,2330	-0,17	0,8619	
Loans_to_TA_L3	0,6521	0,6088	0,1827	0,6643	0,5980	0,2297	-0,49	0,6741	
Loans_to_Funding	0,8925	0,9335	0,3726	0,8423	0,8798	0,4394	-1,08	0,2812	
Loans_to_Funding_L1	0,9039	0,9757	0,4271	0,8617	0,8971	0,4439	-1,41	0,1618	
Loans_to_Funding_L2	0,9284	0,9534	0,4268	0,8563	0,9064	0,4545	-0,83	0,4110	
Loans_to_Funding_L3	0,9208	0,9527	0,4243	0,8884	0,8997	0,4714	-0,92	0,3614	
Liquid_A_to_Funding	0,1498	0,2257	0,2494	0,1757	0,3244	0,3470	2,71	0,0079	***
Liquid_A_to_Funding_L1	0,1800	0,2632	0,2641	0,1918	0,3530	0,3658	2,46	0,0157	**
Liquid_A_to_Funding_L2	0,1913	0,2380	0,2092	0,2223	0,3464	0,3582	3,17	0,0021	***
Liquid_A_to_Funding_L3	0,1877	0,2520	0,2050	0,2439	0,3735	0,3648	3,59	0,0005	***
Legend:									
Significance: *= < 0,10 , **= < 0,05,*** = < 0,01.									

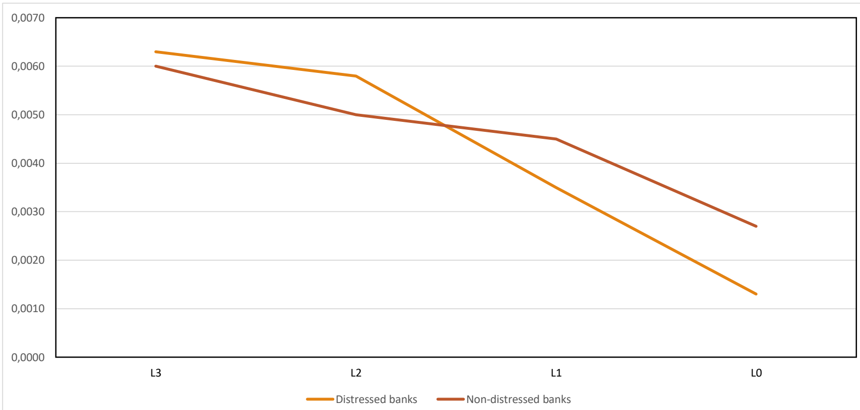
Significant differences – liquid assets to funding



Significant differences – equity to assets



Significant differences - ROA



Stepwise logistic regression (1)

Panel 1. Estimated Year -1 Model.				
Variable	Estimate	Std. Error	Wald Chi-Square	Pr > ChiSq
Intercept	5,3422	1,3893	14,79	0,0001
EQ_to_TA	-22,5017	5,7128	15,51	<.0001
Deposits_to_G_Loans	-0,3709	0,1933	3,68	0,0549
L_Imp_to_G_Loans	28,3772	12,1465	5,46	0,0195
Loans_to_TA	-4,8094	1,6092	8,93	0,0028
Liquid_A_to_Funding	-4,1037	1,0730	14,63	0,0001

Panel 2. Estimated Year -2 Model.				
Variable	Estimate	Std. Error	Wald Chi-Square	Pr > ChiSq
Intercept	4,2347	1,2491	11,49	0,0007
Growth_EQ	-1,1094	0,6161	3,24	0,0718
Growth_G_Loans	1,6375	0,7525	4,74	0,0295
EQ_to_TA	18,2335	5,6075	10,57	0,0011
L_Imp_to_G_Loans	33,8642	12,5405	7,29	0,0069
Loans_to_TA	-6,1087	1,8633	10,75	0,0010
Loans_to_Funding	1,5977	0,5434	8,65	0,0033
Liquid_A_to_Funding	-4,2888	1,1377	14,21	0,0002

Stepwise logistic regression (2)

Panel 3. Estimated Year -3 Model.				
Variable	Estimate	Std. Error	Wald Chi-Square	Pr > ChiSq
Intercept	4,6988	1,2133	15,00	0,0001
EQ_to_TA	10,7103	4,8260	4,93	0,0265
Loans_to_TA	-5,6987	1,6454	11,99	0,0005
Loans_to_Funding	0,9085	0,4974	3,34	0,0678
Liquid_A_to_Funding	-4,7904	1,2007	15,92	<.0001

Panel 4. Estimated Year -4 Model.				
Variable	Estimate	Std. Error	Wald Chi-Square	Pr > ChiSq
Intercept	3,6193	1,0451	11,99	0,0005
Loans_to_TA	-5,7880	1,6316	12,58	0,0004
Loans_to_Funding	1,2945	0,5141	6,34	0,0118
Liquid_A_to_Funding	-4,2972	1,0733	16,03	<.0001

Performance

Panel 1. General performance measures.				
	Estimation year			
Performance measure	Year -1	Year -2	Year -3	Year -4
Aikaike Information Criterion (AIC)	246,1	251,9	257,3	259,4
Schwarz Criterion (SC)	265,8	278,2	273,8	272,5
R-Square	0,185	0,177	0,128	0,110
Max-rescaled R-Square	0,246	0,236	0,171	0,147

Panel 2. Areas under the ROC curve (AUCs).				
	Estimation year			
Model type	Year -1	Year -2	Year -3	Year -4
Estimated model	0,768	0,768	0,714	0,690
Jack-knife cross-validated model	0,734	0,719	0,677	0,659

Panel 4. Estimation year correct classifications (%).				
	Estimation year			
Classified banks	Year -1	Year -2	Year -3	Year -4
Percent of correctly classified distressed banks	77,78	67,68	64,65	59,60
Percent of correctly classified non-distressed banks	65,66	69,70	64,65	64,65
Percent of correctly classified (overall)	71,72	68,69	64,65	62,13

Clusters for distressed banks

Cluster # 1 – 2 outliers -> (very) acute failure

Cluster # 2 – 60 banks –> “low margin-decliners” (large banks)

Cluster # 3 – 10 banks –> “high margin-lingerers” (small banks)

Cluster # 4 – 27 banks –> “high costs-decliners” (medium-sized banks)

Clusters for non-distressed banks

Three small clusters with different characteristics

Cluster # 4 – 68 banks –> “solid-decliners”

Cluster # 5 – 11 banks –> “solid-steady growth”

Cluster # 6 – 16 banks –> “solid-slow growth”

Performance of models for clusters (1)

Panel 1. Estimation data results.

	Distressed banks				Non-distressed banks					
Period	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Year -1										
Number: correct/total	2/2	44/60	9/10	22/27	1/1	1/1	2/2	48/68	8/11	5/16
Percent correct	100,0	73,3	90,0	81,5	100,0	100,0	100,0	70,6	72,7	31,3
Year -2										
Number: correct/total	2/2	39/60	10/10	16/27	1/1	0/1	2/2	50/68	6/11	10/16
Percent correct	100,0	65,0	100,0	59,3	100,0	0,0	100,0	73,5	54,6	62,5
Year -3										
Number: correct/total	2/2	41/60	6/10	15/27	1/1	1/1	2/2	43/68	6/11	11/16
Percent correct	100,0	68,3	60,0	55,6	100,0	100,0	100,0	63,2	54,6	68,8
Year -4										
Number: correct/total	1/2	41/60	3/10	14/27	1/1	1/1	2/2	44/68	5/11	11/16
Percent correct	50,0	68,3	30,0	51,9	100,0	100,0	100,0	64,7	45,5	68,8

Performance of models for clusters (2)

Panel 2. Jack-knife cross-validation results.

	Distressed banks				Non-distressed banks					
Period	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Year -1										
Number: correct/total	1/2	42/60	9/10	22/27	1/1	1/1	2/2	46/68	8/11	5/16
Percent correct	50,0	70,0	90,0	81,5	100,0	100,0	100,0	67,7	72,7	31,3
Year -2										
Number: correct/total	1/2	36/60	10/10	15/27	1/1	0/1	2/2	46/68	5/11	8/16
Percent correct	50,0	60,0	100,0	55,6	100,0	0,0	100,0	67,7	45,5	50,0
Year -3										
Number: correct/total	2/2	40/60	5/10	14/27	1/1	1/1	2/2	42/68	6/11	11/16
Percent correct	100,0	66,7	50,0	51,9	100,0	100,0	100,0	61,8	65,6	68,8
Year -4										
Number: correct/total	1/2	40/60	3/10	14/27	1/1	1/1	2/2	44/68	5/11	11/16
Percent correct	50,0	66,7	30,0	51,9	100,0	100,0	100,0	64,7	45,5	68,8

Conclusions (1)

- The empirical results of the development paths of banks show that there are different processes banks follow before the distress event.
- Processes for the distressed banks: (1) “low margin-decliners”, (2) “high margin-lingerers” and (3) “high costs-decliners” banks.
- Processes for the non-distressed banks: (1) “solid-decliners”, (2) “solid-steady growth”, (3) “solid-slow growth”.
- Four or three years prior to the distress event, the differences between the distressed banks and their mates seem to be not palpable in most of the cases.

Conclusions (2)

- However, 1 or 2 years prior to the distress, they become more visible.
- Special attention should be paid to measures of liquidity (in our study liquid assets to funding ratio) and to business model (loans to assets ratio in our study)
- Also equity to total assets ratio and impairment charges provide some guidelines
- Higher performance of models based on clusters, especially for “growth” banks, calls for monitoring in homogenous groups based on a wide set of characteristics, not just looking at the banks’ legal forms or sizes.
- It is difficult to predict the distress events with the use of set of CAMEL-like variables, although they are widely used in academic literature and in practice.

How costly was bank restructuring?

Goal

Our goal was to model the determinants of restructuring costs and rank the cost of each tool applied.

- **What are the determinants of costs of bank restructuring methods?**
- **Which restructuring tools were most expensive?**

Restructuring tools (1)

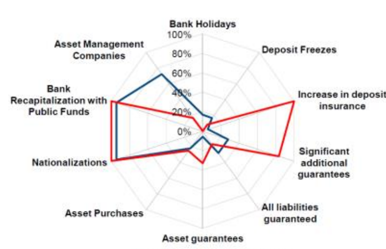
Laeven and Valencia (2008) provided the division of restructuring tools into:

1. **The ones used during containment of the crisis, such as: suspension of convertibility of deposits, regulatory forbearance, liquidity support, government guarantees for deposits**
2. **The ones used for crisis resolution, such as: conditional, government-supported workouts of distressed loans (decentralized), debt forgiveness, setting up asset management companies (AMCs), government-assisted sale, government-supported recapitalization.**

S.Claessens et. al. (2011) covered in the analysis of the GFC 12 countries up to 2009.

Restructuring tools (2)

Figure 2. Containment and Resolution Policies
(In percent of sample countries adopting)



S.Claessens, C. Pazarbasioglu, L. Laeven, M. Dobler, F. Valencia, O. Nedelescu, K. Seal, *Crisis Management and Resolution: Early Lessons from the Financial Crisis*, "IMF Staff Discussion Note", March 2011, p. 8.

Restructuring tools (3)

The literature devoted to the restructuring of banks is mostly focused on actions undertaken during the financial crisis (e.g. Hoelscher and Quintyn 2003; Honohan and Laeven 2005; Laeven and Valencia 2008; Claessens et al. 2011) such as the ones mentioned above and consequences of the financial support provided to banks either from moral hazard perspective (e.g. Claessens et al. 2011, Hryckiewicz 2014) or overall fiscal burden (e.g. Claessens et al. 2011).

Methodology and data (1)

Our study covers restructuring of banks in the EU countries for the period from 2008 to 2014. Not all EU countries had to recapitalize financial institutions. Such financial support was not used in *inter alia* the Czech Republic, Estonia, Poland and Malta. There were also some countries, such as Latvia and Lithuania, in which financial institutions were granted state aid only to a very limited extent. In total we examined 84 cases of banks' restructuring from 17 EU countries, as well as 3 'aid packages' targeting banks in Denmark. However, full set of financial data was available for 80 banks.

Methodology and data (2)

Financial data of banks were obtained from banks' financial statements for the period 2006-2014. Data on the amounts of financial support and repayments for each individual bank were collected from banks' financial statements, public institutions report, official communiqués and press releases. Bank-level data were aggregated on a country-level and compared with European Commission data as a benchmark.

The source of macroeconomic and banking sector data is ECB Statistical Data Warehouse, Eurostat database, IMF World Economic Outlook and reports of ECB and national central banks in EU countries (sometimes also banking supervisory authorities).

Methodology and data (3)

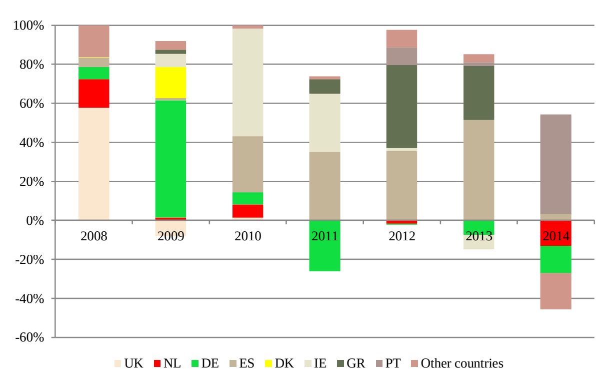
In more than three quarters of cases we analyzed, the restructured banks implemented, in 2006-2008, expansionary credit policies, which consequently led to the deterioration of asset quality and high credit loss provisions. Almost 40% of cases were linked to the exposure to the real estate market (e.g. Spain, Ireland and Portugal). On the other hand, in one sixth of the cases, the problems were largely the result of exposure to subprime market (e.g. Germany, France) and in the same proportion, the result of exposure to government bonds (case of Greece).

Macroeconomic costs – our data (1)

Based on case studies we estimate the size of net banks' recapitalization (called also net state aid) and support for asset management companies (their initial capital and additional capital used to cover losses) in total at EUR 536.1 billion from public sources between 2008-2014, the majority of which (66,1%) was used in the first two years. This amount was earmarked to recapitalize 84 banks, Danish banks participating in the credit package, and 4 AMCs.

Macroeconomic costs – our data (2)

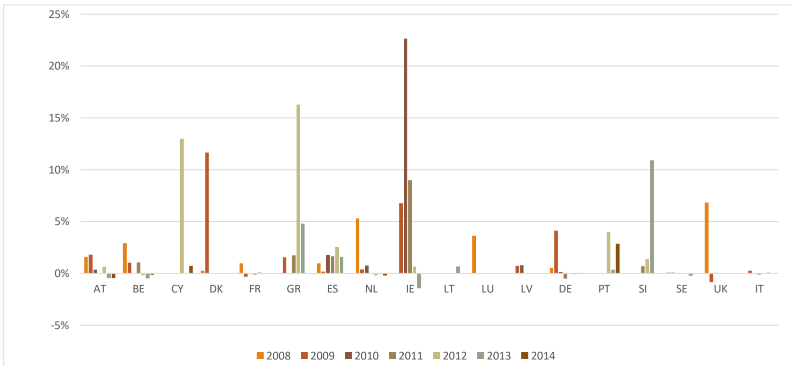
Figure 1. Structure of recapitalization between 2008-2014.



Note: negative figures correspond to the repayment of recapitalization measures; data collected from the case studies

Macroeconomic costs – our data (3)

Figure 2. The recapitalization of EU banks in 2008-2014 (as % of GDP in a given year)



Note: negative figures correspond to the repayment of recapitalization measures; data collected from the case studies

Restructuring tools (1)

Types of restructuring methods used in the analysis:

CAP – bank recapitalization (29 banks)

CAP_MERGER – recapitalization or temporary nationalization of the bank, and subsequent merger with another bank (16 banks)

CAP_RES –recapitalization and significant restructuring of the bank (13 banks)

LIQ – liquidation of the bank, preceded by capital support (10 bank)

NAT– nationalization of the bank (12 banks)

Restructuring tools (2)

The bail-in was used in a limited number of cases either within the scope of restructuring or nationalization programme (Bank of Cyprus in 2013, Nova Kreditna Banka Maribor and Nova Ljubljanska Banka - Slovenia in 2013 and Banco Gallego - Spain in 2013) or in order to support bank's liquidation (Laiki Bank – Cyprus in 2013, Factor Banka and Probanka – Slovenia in 2013).

Restructuring tools (3)

Resolution, as a broader concept, was used in several countries in a slightly different way:

- **In the UK, Ireland and Austria resolution companies were set up in order to manage bad assets of given banks (UK Asset Resolution from 2008 for Bradford & Bingley and Northern Rock; Irish Bank Resolution Corporation from 2011 for Anglo Irish and Irish Nationwide Building Society; Heta Asset Resolution AG from 2014 for Hypo Alpe-Adria-Bank International AG).**
- **In Denmark (Finansiel Stabilitet from 2008), Spain (Fondo de Reestructuración Ordenada Bancaria from 2009) and Portugal (Fundo de Resolução from 2012) institutions responsible for resolution of any bank were set-up.**
- **In Austria (1 bank), in Belgium (2), Cyprus (1), Greece (2), Latvia (1), Germany (1) banks were divided into "bad" and "good" ones in order to give the second chance to a "good" bank and orderly liquidate a "bad" bank.**

Restructuring tools (4)

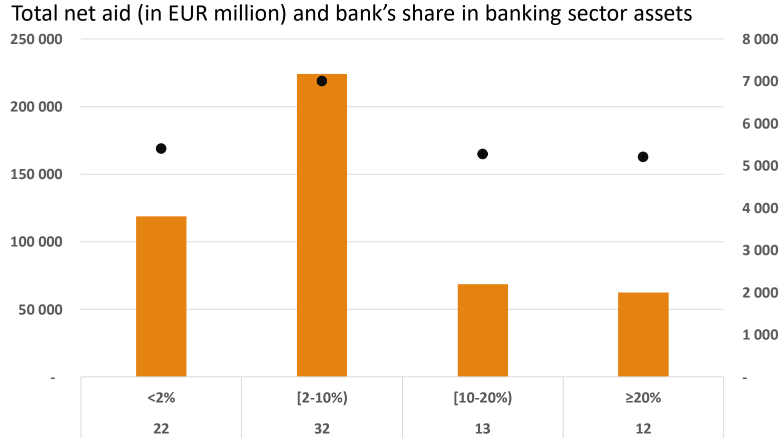
Restructuring methods depending on bank's size

<2%			[2-10%)		
CAP+	NAT	LIQ	CAP+	NAT	LIQ
ES	UK	DK, GR, LT	IT, AT, IE, LV, DE	AT, ES, IE, PT, NL, DE	DE, SI, IE
[10-20%)			≥20%		
CAP+	NAT	LIQ	CAP+	NAT	LIQ
CY, FR, GR, PT, UK	SI		BE, NL, SE		CY

Note: systemic banks are those banks whose average size of assets to country's GDP in 2009 was equal or more than 20%. large banks are banks with assets to country's GDP in the range of 10—20%. medium banks are banks with assets to country's GDP in the range of 2—10%. and small banks are banks with assets to country's GDP of less than 2% of GDP. Based on case studies.

Restructuring tools (5)

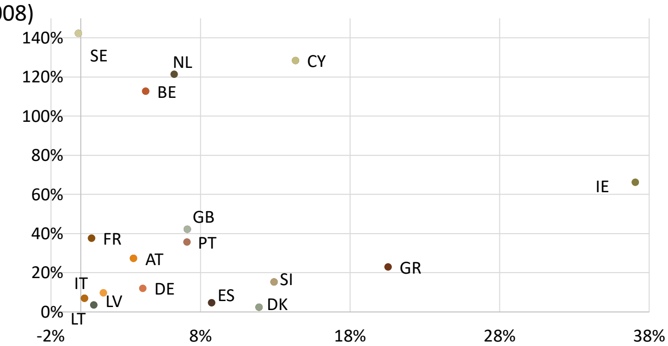
Total net aid (in EUR million) and bank's share in banking sector assets



Note: total net financial assistance granted – left scale (columns); average net financial assistance granted to a bank in a given size range – right scale (dots)

Restructuring tools (6)

Total financial aid (net) to GDP (2008) vs. average size of the rescued banks to GDP (2008)



Notes: total financial aid (net) to GDP (2008) – horizontal scale; average assets of the rescued banks to GDP (2008) – vertical scale. Based on case studies.

Model (1)

- **We model cost of bank restructuring on the microeconomic level: ASS_D, defined as the ratio of net state aid to deposits of the customers in the year of the first intervention or the year before.**
- **We identified 4 banks for which, the ASS_D was above 1 (Proton Bank – Greece, Anglo-Irish Bank – Ireland, Hypo Real Estate Holding AG – Germany and Bradford & Bingley – the UK).**

Model (2)

- **The model can be written as:**

$$ASS\_D\_CAT_i^* = x_i'\beta + \varepsilon_i$$

$$ASS\_D\_CAT_i = \begin{cases} 1 \;\; iff \; -\infty < ASS\_D_i^* \leq cut_1 \\ 2 \;\; iff \; cut_1 < ASS\_D_i^* \leq cut_2 \\ \vdots \\ k \;\; iff \; cut_{k-1} < ASS\_D_i^* \leq \infty, \end{cases}$$

for i=1,...,N where $ASS\_D\_CAT_i$ represents the number of group in which the i-th bank is classified on the basis of the value of ASS_D, $ASS\_D\_CAT_i^*$ is the unobserved (latent) variable that can be thought of an i-th bank 'propensity' to obtain a high ratio of net state aid to deposits of the customers, x_i' is a vector of explanatory variables, ε_i is the logistically distributed error term, while β, cut_1,..., cut_{k-1} are the estimable parameters of the model.

In this paper we present the results for the dependent variable divided into 4 categories (k=4), while emphasizing that conclusions (particularly of the qualitative nature) do not differ significantly from those with a different number of options considering the dependent variable.

Model (3)

Descriptive statistics

Quantitative variables				
Variable	Mean	Standard deviation	Minimum	Maximum
ASS_D	1.1155	7.7365	0	69.2596
B_SHARE	0.0922	0.1188	0.0012	0.6053
D_GDP	0.1575	0.2567	0.0002	1.6051
CAR	0.1007	0.0349	-0.0385	0.2170
LEV	34.3258	26.4290	9.1766	155.1250
DGS_D	0.2259	0.7104	0	5.3646
Qualitative variables				
DIAG	0: 41.25%. 1: 58.75%			
CR_EXP	0: 23.75%. 1: 76.25%			
RESCUE	CAP: 36.25%. CAP_MERGER: 20%. CAP_RES: 16.25%. LIQ: 12.5%. NAT: 15%			

Model (4)

Ordered logit model

Variable	$\hat{\beta}$	Standard error	p value
B_SHARE	-0.0911	3.3471	0.978
D_GDP	-4.7612	1.8019	0.008
CAR	-17.3671	8.1157	0.032
LEV	-0.0106	0.0091	0.246
DGS_D	-0.6555	0.3749	0.080
DIAG	-1.7680	0.5162	0.001
CR_EXP	-0.6436	0.6122	0.293
Binary variables for the RESCUE*			
CAP_MERGER	2.3382	0.7425	0.002
CAP_RES	2.0418	0.7081	0.004
LIQ	3.9234	0.9649	0.000
NAT	3.0063	0.7658	0.000

Note: *CAP is the reference category for the parameter estimates given in this group of variables

Conclusions (1)

- **Liquidation was applied (except Cyprus) to small and medium-sized banks. It was the most expensive restructuring tool, used when there was ‘no hope’ for bank recovery, even with the financial support. For three liquidated banks bail-in was applied.**
- **The least costly and the most common restructuring tool was ‘pure’ recapitalisation, which is a typical bailout measure. Therefore, we claim that the bailout should not be written off the political agenda, however, it should be used under very restrictive conditions.**
- **This conclusions are partly in line with Gong and Jones (2013) postulates to bailout banks with systemic importance and provide no bail-out options for small banks.**

Conclusions (2)

- Moreover, as Wilson (2011) and Philippon and Schnabl (2013) indicated, the recapitalization of banks was effective to deal with debt overhang and stimulate credit activity. Thus, we claim that the bail-out should not be written off the political agenda, however it should be used under strict conditions, such as the ones applied in the EU under state aid framework.
- Cost of bank restructuring is linked to the correct diagnosis of the problem. Out of 80 banks in 47 cases the amount of the first financial assistance was enough to allow for banks' recovery. The average ASS_D for properly diagnosed banks was 4 times lower than for the other ones. This calls for restrictive and uniformed assessment of banks' problems. Balance sheet assessment (AQR conducted by ECB before the start of the banking union) should be recognized as an example of such a methodology.

Thank you for your attention!

E-MAIL: MIWANI@SGH.WAW.PL