SAFETY-NET BENEFITS CONFERRED ON DIFFICULT-TO-FAIL-AND-UNWIND BANKS IN THE US AND EU BEFORE AND DURING THE GREAT RECESSION

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1. Safety-net management

- **Alan Greenspan**:

  "Managers of financial institutions, the Federal Reserve, and other **regulators failed to fully comprehend the underlying size, length, and impact of the negative tail of the distribution of risk** outcomes" (Bloomberg Businessweek, Feb. 18., 2011).

- In our paper we wonder whether **adopting a contingent-claims perspective on the evolving distribution of tail risk might have improved their comprehension**.

- A nation’s financial **safety net is a set of programs aimed at protecting unsophisticated depositors and keeping systemically important markets and institutions from breaking down in difficult circumstances**.

- The principal goal of safety-net management is to **monitor, contain, and finance systemic risk.**

- Its governance procedures are complicated by differences in the capacities of different stakeholders to understand and promote their interests and these differences **vary widely across countries.**

- Both in Europe and the US, **safety-net managers seek to contain risk-taking** by protected institutions by:
    - Restricting their activities.
    - Prescribing risk-based capital requirements and insurance premia.

- This paper seeks to benchmark differences in **how well, both before and during the current crisis, safety-net managers in the US and 14 European countries managed the tradeoff** in their systems of institutional support **between the interests of bankers and taxpayers.**

SYSTEMIC RISK RESEMBLES A DISEASE THAT HAS TWO SYMPTOMS.

1. Official definitions focus only on the primary symptom: the extent to which authorities and industry sense a potential for substantial "spillovers" of defaults across leveraged financial counterparties and from these defaults to the real economy. Sources are: a) exposure to common risk factors(e.g., bad loans) and b) debts that institutions owe to one another.

2. Important 2nd **Symptom: Ability of Difficult-to-Fail (DFU institutions to receive subsidies from national safety nets give some firms and sectors a subsidized "Taxpayer** Put."

WE PROPOSE A WAY TO UNDERMINE THESE DEFENSES

- The costs and benefits a country generates through its safety net depend on:
  - **How much market discipline the net displaces.**
  - **How successfully safety-net managers substitute oversight for the market discipline they displace.**

- By engaging in regulation-induced innovation, building clout and exerting lobbying pressure, a country's **systemically-important-financial institutions (SIFIs) can keep tail risk from being adequately disciplined.**

•**Our methods and models generate a metric that can be used to estimate variation in the size of the safety-net benefits that lie at the heart of the taxpayer put. Changes in information collected from covered institutions can improve the precision of the metric and the accountability of regulatory and supervisory performance in individual countries.**

•No reason to expect industry clout or safety-net benefits to be the same in all countries. Safety nets differ in two ways:

a. Extent of regulatory capture (regulations, rule of law, enforcement,…)

b. Identity of powerful sectors and precise carriers of the subsidy flow.

PREVIEW OF RESULTS:

- We use the Bankscope database and contingent-claims models of safety-net benefits to estimate and compare the value of leverage ratios and ex ante safety-net benefits at firms thought or revealed to be DFU in the US and Europe during 2003-2008.

- **We find that during both 2003-2006 and 2007-2008 DFU banks in the US and Europe enjoyed substantially higher ex ante benefits than other institutions in the sample**. Safety-net benefits were significantly larger for DFU firms in Europe, but bailout decisions appear less driven by asset size and more by regulatory capture than in the United States.

2. Modeling the Determinants of Systemic Risk

- **How to measure systemic risk?** There is a considerable disagreement on this.
- There is **some agreement that systemic risk arises as a mixture of leverage and the volatility of financial-institution returns.**
- This paper employs **a two-equation model** developed by Duan, Moreau, and Sealey (DMS, 1992).
- Adding ideas from Ronn and Verma (1986) and Hovakimian and Kane (2000), two other studies [Carbo, Kane, and Rodriguez (2008, 2011)] **use this model to undertake cross-country comparisons of regulatory and merger policies**.

INPUT DATA

1. The insurance premium percentage (IPP), the market value of the asset (V) and bank assets' risk ($\boldsymbol{\sigma}_V$) are constructed from four <u>observable</u> variables using the Merton-Ronn Verma Model:

   B : total debt: computed as the difference between the book values of total assets and common equity.

   E : the market value of a bank's equity: computed as the end-of-period stock-market capitalization.

   $\boldsymbol{\sigma}_E$; standard deviation of the return on equity: computed as the standard deviation of deleveraged quarterly holding-period returns on stock for commercial banks.

   δ: fraction of bank assets distributed yearly as dividends to stockholders.

Data are taken directly from the Bankscope database, provided by Bureau Van Dijk.

- Throughout the paper, regression inputs are calculated in two different ways:
  - By the Ronn and Verma (RV) procedure
  - By a maximum-likelihood (ML) method developed by Duan (1994).

- The main difference is that the Duan model estimated the market value of assets using maximum-likelihood.

The two-equation model

$$B/V = \alpha_0 + \alpha_1 \sigma_V + \varepsilon_2 \qquad \textbf{(1)}$$

$$IPP = \beta_0 + \beta_1 \sigma_V + \varepsilon_3 \qquad \textbf{(2)}$$

- Regressions focus on regulator and market disciplinary responses to bank changes in σ_V. To the extent that leverage and volatility can be hidden with impunity, increasing a **bank's exposure to deep tail risk can almost always increase the value of its safety-net benefits.**

- For market and regulatory pressure to discipline and potentially to neutralize incremental risk-shifting incentives, two conditions must be met:

  - Bank capital increases with volatility: $\alpha_1 < 0$

  - Guarantee values do not rise with volatility: $\beta_1 \leq 0$

3. Preliminary Look at Mean Sample Experience

- **Table I lists the number of observations in our sample by country.** Over a third of the observations come from the US and Germany and roughly 80 percent come from the last six countries listed in the table.

- **Table II lists the sources from which we obtain the data we analyze.** It also introduces and defines some control variables that we incorporate into our regression experiments.

TABLE I
SAMPLE SIZE (NUMBER OF OBSERVATIONS)
Frequency: annual (2003-2008)

Austria	*476*
Belgium	*627*
Denmark	*206*
Finland	*78*
Luxembourg	*426*
Netherlands	*203*
Portugal	*158*
Sweden	*263*
Ireland	*157*
United Kingdom	*864*
Spain	*531*
France	*1112*
Italy	*1236*
Germany	*2227*
United States	*2153*
TOTAL	***11117***

TABLE II
DEFINITIONS AND SOURCES FOR VARIABLES

Variable	***Definition***	***Source***
B/V (%)	Leverage, measured as the ratio of the book value (*B*) of deposits and other debt to the market value of a bank's assets (*V*).	Bank-level data to compute this variable are obtained from the Bureau-Van Dijk Bankscope database.
IPP (%)	"Fair" insurance premium percentage, defined as the per-period flow of safety-net benefits that bank stockholders enjoy.	Bank-level data to compute this variable are obtained from the Bureau-Van Dijk Bankscope database.
σ_V (%)	Volatility, defined as the standard deviation of the return on bank assets	Bank-level data to compute this variable are obtained from the Bureau-Van Dijk Bankscope database.
Size (log total assets) (Eur mill)	Size of the banks measured by total book value of assets.	Bank-level data to compute this variable are obtained from the Bureau-Van Dijk Bankscope database.
Corruption perception index (10-CPI)	Transparency International's Corruptions Perceptions Index (CPI) is an aggregate indicator that ranks countries in terms of the degree to which corruption is perceived to exist among public officials and politicians. It is a composite index drawing on corruption-related data by a variety of independent and reputable institutions. The main reason for using an aggregated index of individual sources is that a combination of sources measuring the same phenomenon is more reliable than each source taken separately. The CPI ranges 1 to 10. Higher values of the index show less corruption. In order to normalize the values we have redefined the indicator as 10-CPI so that higher values show more corruption.	Transparency international (www.transparency.org)
Market volatility (VIX)	The VIX is calculated and disseminated in real-time by the Chicago Board Options Exchange. It is a weighted blend of prices for a range of options on the S&P 500 index. On March 26, 2004, the first-ever trading in futures on the VIX Index began on CBOE Futures Exchange (CFE). The formula uses a kernel-smoothed estimator that takes as inputs the current market prices for all out-of-the-money calls and puts for the front month and second month expirations.[1] The goal is to estimate the implied volatility of the S&P 500 index over the next 30 days. The VIX is the square root of the par variance swap rate for a 30 day term initiated today. Note that the VIX is the volatility of a variance swap and not that of a volatility swap (volatility being the square root of variance).	Chicago Board of Exchange (http://www.cboe.com/ micro/vix/introduction.aspx)
DFU Status	A binary variable that takes on the value of unity for banks that alternately either received open-bank assistance (DFUxp) or fell in the first decile of average 2003-2008 asset size for US and European banks in the Bankscope database (DFUxa).	Deciles are calculated by the authors. Identity of banks receiving equity injections is hand-collected.

- In our estimation we indentify the DFU status which is proxied **ex ante by a size criterion (DFUxa) –the highest decile of the distribution- and ex post by the receipt of open-bank assistance (DFUxp).**

- As for the selection of DFUxp banks**, we rely on two main sources:**
  - In the case of European Union banks, we consider what the European Commission (EC) has considered as State aid including capital injections/recapitalization and debt guarantees.
  - As for the US DFUxp banks, we rely on the data provided by the US Department of Treasury on banks joining the Asset Guarantee Program, the Capital Assistance Program and the Capital Purchase Program.

- **Table III** describes the mean behavior of leverage, volatility, and the fair insurance premium percentage for different groupings of banks. [regression inputs are calculated in two different ways: by the Ronn and Verma (RV) procedure and by a maximum-likelihood (ML) method developed by Duan (1994)]

- **Mean safety-net benefits range between 10 and 22 basis points**. Mean leverage proves uniformly higher under the ML procedure, while volatility and IPP are often lower.

- **Both kinds of DFU banks show higher safety-net benefits than other banks in both regions and time frames**. In most cases, DFU institutions show more leverage, too.

- Both before and during the crisis, **DFU banks in Europe show more leverage and safety-net benefits than DFU banks in the US** and DFUxp banks extracted more benefits than DFUxa firms.

- **During the crisis, DFU banks in Europe and the US decreased volatility, reduced their leverage and did suffer procyclical cuts in the mean size of ex ante safety net benefits.**

TABLE III (SELECTION)

MEAN LEVERAGE RATIO (B/V), MEAN FAIR PREMIUM (IPP), AND VOLATILITY OF RETURN ON ASSETS (σ_V): ALL BANKS, DFUxa and DFUxp BANKS IN EUROPE AND IN THE US

Country	B/V (%)		IPP (%)		σ_V (%)	
	RV	ML	RV	ML	RV	ML
ALL BANKS (FULL SAMPLE)	84.8	87.1	0.143	0.119	1.815	1.582
ALL BANKS IN EUROPE	85.3	86.0	0.153	0.134	1.988	1.727
ALL BANKS IN THE US	82.5	83.9	0.139	0.127	1.490	1.368
DFUxa BANKS (FULL SAMPLE)	86.9	89.8	0.167	0.145	1.593	1.597
DFUxp BANKS (FULL SAMPLE)	88.0	90.9	0.174	0.156	1.669	1.490
DFUxa BANKS IN EUROPE	88.1	90.0	0.179	0.164	1.696	1.487
DFUxp BANKS IN EUROPE	89.3	91.6	0.189	0.180	1.792	1.594
DFUxa BANKS IN THE US	80.5	82.2	0.127	0.116	1.396	1.284
DFUxp BANKS IN THE US	83.4	84.2	0.140	0.134	1.503	1.411
ALL BANKS IN EUROPE (PRE 2007)	86.7	88.0	0.157	0.163	2.134	2.166
ALL BANKS IN THE US (PRE 2007)	83.2	84.3	0.149	0.156	1.529	1.632
ALL BANKS IN EUROPE (2007-2008)	83.9	84.3	0.132	0.138	1.842	1.931
ALL BANKS IN THE US (2007-2008)	81.1	81.5	0.128	0.137	1.344	1.388
DFUxa BANKS IN EUROPE (PRE 2007)	90.4	92.6	0.198	0.185	1.591	1.403
DFUxa BANKS IN THE US (PRE 2007)	81.5	82.4	0.158	0.146	1.343	1.211
DFUxa BANKS IN EUROPE (2007-2008)	85.7	88.6	0.165	0.150	1.967	1.663
DFUxa BANKS IN THE US (2007-2008)	78.2	80.1	0.119	0.102	1.491	1.396
DFUxp BANKS IN EUROPE (PRE 2007)	92.3	93.4	0.215	0.220	1.635	1.523
DFUxp BANKS IN THE US (PRE 2007)	83.8	84.1	0.176	0.160	1.428	1.323
DFUxp BANKS IN EUROPE (2007-2008)	89.9	90.1	0.179	0.162	2.123	1.815
DFUxp BANKS IN THE US (2007-2008)	82.3	83.1	0.129	0.118	1.538	1.493

4. Regression Analysis

- **Difference-on-difference regression experiments estimate equations (1) and (2) including three control variables and three parameter-shift indicators (interaction terms) for DFU banks**:
  - **The log of asset size** is introduced as a hard-to-interpret proxy that aggregates the influence of political clout, complexity, and public awareness.
  - **Regulatory capture: Transparency International's Corruption Perception Index** (**10-CPI**) is used to represent cross-country differences in a government's susceptibility to regulatory forbearance and/or capture.
  - We include the **so-called "fear index" (VIX)** as a way to distinguish the impacts of marketwide and idiosyncratic volatility.

- **Table IV - Baseline results:**
  - **Pooling pre-crisis and crisis years (2003-2008), Table 4 applies our model separately to panels of US and European banks and bank holding companies.**
  - Except for VIX and the corruption index (which proves significant only in Europe where there is cross-section variation), **most differences between US and European leverage equations are statistically significant.**
  - The effects of asset size on safety-net benefits (i.e., on IPP) are similar across countries, **but at the margin DFU banks in the US extract slightly more benefits than their European counterparts.**

(note that the shift variable in the size effect for DFU banks is never significant and is dropped from subsequent runs)

TABLE IV (SELECTION)

European sample				
	Δ(B/V)		***ΔIPP***	
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.002** (-26.14)	-0.004** (-34.17)	0.007** (19.83)	0.008** (25.16)
Size (log total assets)	0.013** (14.31)	0.016** (17.90)	-0.015** (-14.51)	-0.011** (16.31)
$\Delta\sigma_V$ X DFUxa banks Europe	-0.020** (-6.53)	-0.025** (-8.83)	0.019** (6.50)	0.020** (7.28)
Size X DFUxa banks Europe	0.003 (1.23)	0.001 (1.01)	0.003 (1.23)	0.003 (1.23)
Corruption perception index (10-CPI)	0.008** (3.29)	0.011** (4.88)	0.016** (6.04)	0.008** (3.29)
Market volatility (VIX)	-0.001* (1.93)	-0.001* (2.16)	0.012 (0.27)	0.018 (0.14)
Observations	8,964	8,964	8,964	8,964
Number of banks	1,494	1,494	1,494	1,494
R^2	0.517	0.604	0.685	0.643
US sample				
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.006** (-18.07)	-0.007** (-31.20)	0.009** (18.51)	0.011** (25.14)
Size (log total assets)	0.029** (14.13)	0.024** (17.53)	-0.016** (-11.15)	-0.014** (22.23)
$\Delta\sigma_V$ X DFUxa banks US	-0.038** (-5.57)	-0.032** (-8.92)	0.024** (3.63)	0.029** (3.97)
Size X DFUxa banks US	0.002 (1.12)	0.004 (1.25)	0.007 (0.44)	0.003 (0.78)
Corruption perception index (10-CPI)	0.004 (1.18)	0.007 (0.96)	0.010 (0.85)	0.006 (0.72)
Market volatility (VIX)	-0.003** (2.85)	-0.004** (3.49)	0.010 (0.68)	0.012 (0.19)
Observations	2,153	2,153	2,153	2,153
Number of banks	358	358	358	358
R^2	0.693	0.618	0.688	0.715

US DFUxa banks extract slightly more benefits than their EU counter parts

- Table V.A shows the effect of limiting the DFU shift variable to banks that receive explicit State aid during the crisis (DFUxp):
  - Differences between Europe and the US in coefficients for idiosyncratic volatility, asset size, corruption, and the intensification of the role of volatility for DFUxp banks become sharper and uniformly more significant.

- Table V.B re-runs the Table 5A regression experiment using Heckman's (1976, 1978) procedure for **endogenizing the selection process for providing capital support to DFU banks.** This procedure adds the Heckman Lambda (i.e., the Mills Odds Ratio for selection) calculated from the selection model to the potential determinants of leverage and safety-net benefits.
  - **differences in the probit selection models for receiving State aid are markedly different.** In Europe, asset size has no significant effect. Idiosyncratic volatility and **the corruption index "dominate" government bailout decisions in Europe.**

TABLE V.A (SELECTION)

European sample				
	Δ(B/V)		***ΔIPP***	
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.003** (-18.31)	-0.005** (-22.51)	0.006** (14.02)	0.007** (33.08)
Size (log total assets)	0.011** (12.24)	0.014** (18.88)	-0.013** (-17.29)	-0.010** (14.25)
$\Delta\sigma_V$ X DFUxp banks in Europe	-0.009** (-7.12)	-0.012** (-7.31)	0.027** (8.15)	0.029** (6.10)
Corruption perception index (10-CPI)	0.010** (2.98)	0.011** (4.88)	0.016** (6.04)	0.008** (3.29)
Market volatility (VIX)	-0.002* (2.20)	-0.007** (2.96)	0.013 (0.08)	0.011 (0.19)
Observations	8,964	8,964	8,964	8,964
Number of banks	1,494	1,494	1,494	1,494
R^2	0.616	0.594	0.702	0.625
US sample				
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.006** (-17.12)	-0.008** (-28.68)	0.010** (17.27)	0.013** (22.65)
Size (log total assets)	0.025** (16.77)	0.019** (14.31)	-0.018** (-12.72)	-0.017** (25.90)
$\Delta\sigma_V$ X DFUxp banks in the US	-0.022** (-6.19)	-0.028** (-6.84)	0.033* (2.14)	0.035** (4.42)
Corruption perception index (10-CPI)	0.003 (0.82)	0.005 (0.48)	0.014 (1.12)	0.010 (0.95)
Market volatility (VIX)	-0.006** (3.48)	-0.005** (3.89)	0.014 (0.71)	0.011 (0.28)
Observations	2,153	2,153	2,153	2,153
Number of banks	358	358	358	358
R^2	0.685	0.624	0.603	0.745

US DFUxp banks also extract more benefits than their EU counter parts

TABLE V.B (SELECTION EQUATIONS ONLY)

FIXED-EFFECTS PROBIT SELECTION MODELS FOR ZERO-ONE BINARY VARIABLES DISTINGUISHING DFU BANKS BENEFITING FROM STATE AID (1) FROM THE REST OF DFU BANKS (0)				
σ_V	0.963** (12.39)	0.815** (7.05)	0.963** (12.39)	0.815** (7.05)
Size (log total assets)	0.013 (1.16)	0.004 (0.96)	0.013 (1.16)	0.004 (0.96)
Corruption perception index (10-CPI)	0.823** (6.28)	0.916** (8.62)	0.823** (6.28)	0.916** (8.62)
Observations	826	826	826	826
Number of DFUxa banks	137	137	137	137
Number of DFUxp banks	43	43	43	43
Log-likelihood	-626.3	-458.5	-626.3	-458.5
Fraction of correct predictions	88.5	90.4	88.5	90.4
US sample				
$\Delta\sigma_V$	-0.007** (-14.06)	-0.24.06)	0.011** (13.08)	0.012** (21.04)
Lambda (Mills ratio)	-0.094** (4.41)	-0.078** (5.13)	-0.028** (6.40)	-0.034** (6.21)
Size (log total assets)	0.028** (15.93)	0.020** (11.10)	-0.016** (-12.13)	-0.013** (23.03)
$\Delta\sigma_V$ X DFUxp banks in the US	-0.021** (-7.05)	-0.031** (-7.13)	0.034* (2.10)	0.030** (5.06)
Corruption perception index (10-CPI)	0.005 (0.88)	0.006 (0.51)	0.013 (1.08)	0.009 (0.72)
Market volatility (VIX)	-0.006** (3.20)	-0.007** (4.13)	0.014 (0.62)	0.012 (0.33)
Observations	2,153	2,153	2,153	2,153
Number of banks	358	358	358	358
R^2	0.690	0.645	0.615	0.758
FIXED-EFFECTS PROBIT SELECTION MODELS FOR ZERO-ONE BINARY VARIABLES DISTINGUISHING DFU BANKS BENEFITING FROM STATE AID (1) FROM THE REST OF DFU BANKS (0)				
σ_V	0.703** (18.05)	0.626** (12.35)	0.703** (18.05)	0.626** (12.35)
Size (log total assets)	1.624** (6.51)	1.498** (7.18)	1.624** (6.51)	1.498** (7.18)
Corruption perception index (10-CPI)	0.621 (0.44)	0.521 (0.76)	0.621 (0.44)	0.521 (0.76)
Observations	203	203	203	203
Number of DFUxa banks	33	33	33	33
Number of DFUxp banks	22	22	22	22
Log-likelihood	-484.0	-507.2	-484.0	-507.2
Fraction of correct predictions	89.9	88.5	89.9	88.5

Size does not discriminate between DFU banks and other banks in Europe while the corruption perception does discriminate

Size discriminates between DFU banks and other banks in US while the corruption perception does not

- Tables VI.A and VI.B run the baseline model of Table IV separately for pre-crisis and crisis years: i.e., for 2003-2006 and 2007-2008:
  - The most interesting differences are those in which the subperiod coefficients both lie substantially above or below those for the pooled equation.
  - This phenomenon occurs for the effects on IPP of the DFU shift variable in both regions (+), for corruption (+) in Europe, for size (-) and volatility (+) in the US.

- Table VII looks at differences between coefficients in precrisis and crisis years for US and European banks separately (not shown for simplicity).
  - **In Europe, crisis years show an intensification in impact in a few variables and equations: for idiosyncratic volatility on safety-net benefits**; for the DFU shift variable on leverage under the ML procedure and on IPP using the RV approach; and for corruption in the leverage equation and in the ML model for IPP.
  - **In the US, the effects of asset size and the DFU shift variable intensifies under both procedures.**

- Tables VIII.A and VIII.B (not shown) re-run the experiments of Tables VI.A and VI.B using the Heckman procedure. All the results hold.

- For European and US sample banks, Table IX shows the statistical differences between table VIII.A (pre-crisis) and table VIII.B. (crisis).The leverage and IPP equations underwent many statistically significant changes between precrisis and crisis periods.

- Economically, **the effects on IPP are the most interesting. In Europe, the shift in the volatility slope for DFU banks receiving State aid increased by roughly 50 percent under both procedures**. **In the US, this coefficient also increased but the effect is smaller and significant only under the RV procedure.**

5. Special Cases of Portugal, Ireland, Italy, and Spain

- Ireland, Portugal, Italy, and Spain have all seen substantial increases in the credit premium on their sovereign debt. Tables X.A and X.B apply the expanded DMS model to these countries.
  - Although idiosyncratic volatility ($\Delta\sigma_V$)is always significant in these four countries, market volatility (VIX index) is not.
  - Time-series variation in the index of perceived corruption almost always impacts leverage, IPP, and selection significantly. However, the **economic significance of this proxy for regulatory enforcement (10-CPI) is higher in Ireland (0.021 in the ML version of the IPP equation) than in Portugal (0.011), Spain (0.008) or Italy (0.006).**
  - Size impacts selection (differences between DFU banks and other banks) except in Portugal. **Idiosyncratic volatility** ($\Delta\sigma_V$) **affects safety-net benefits much more in Portugal (0.010) and Ireland (0.018) than in Spain (0.008) and Italy (0.006).**

SELECTION OF TABLES X.A AND X.B FOR PORTUGAL IRELAND, SPAIN AND ITALY

Portugal				
	Δ(B/V)		***ΔIPP***	
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.003** (-8.64)	-0.004** (-22.16)	0.011** (10.51)	0.010** (9.87)
Ireland				
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.002** (-11.01)	-0.002** (-16.50)	0.015** (13.08)	0.018** (14.82)
Spain				
	Δ(B/V)		***ΔIPP***	
	RV	ML	RV	ML
$\Delta\sigma_V$	-0.004** (-15.04)	-0.005** (-25.18)	0.006** (16.12)	0.008** (16.27)
Italy				
$\Delta\sigma_V$	-0.007** (-10.13)	-0.008** (-15.06)	0.008** (16.67)	0.006** (12.34)

Idiosyncratic volatility $(\Delta\sigma_V)$ **affects safety-net benefits much more in Portugal (0.010) and Ireland (0.018) than in Spain (0.008) and Italy (0.006).**

6. Lessons and Policy Implications

- **Two important lessons** from our results:
  - Despite being limited to annual data for key variables, changes in volatility and leverage consistently help to predict changes in the flow of safety-net benefits across different models, regions, and time periods.
  - The cross-country proxy for regulatory capture (the index of perceived corruption) helps to explain safety-net benefits and bailout decisions in Europe.

- **Policy implications:**
  - Authorities could do a better job of controlling safety-net benefits if they improved their information systems.
  - Bankers should report data on earnings and net worth more frequently and under civil penalties for fraud and negligent misrepresentation.
  - If the values of on-balance-sheet and off-balance-sheet positions were reported weekly or monthly to national authorities, rolling regression models could be used to estimate changes in the flow of safety-net benefits in ways that would allow regulators to observe and manage taxpayers' stake in the safety net in a more timely manner