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Abstract

Systemic risk is the risk of a collapse of the entire financial system, typically triggered by the default of one, or more, interconnected financial institutions. In this paper we estimate the systemic risk contribution of each financial institution in a large sample of European banks. We follow a recent methodology first proposed by Adrian and Brunnermeier (2011) based on the *CoVaR* and find that size is a predictor of a bank's contribution to systemic risk, but it is not the only one. Also, banks that have their headquarters in countries with a more concentrated banking system tend to contribute more to European wide systemic risk, even after controlling for their size. Therefore, any financial regulation designed only to curb banks' size would not completely eliminate systemic risk. On average, balance sheet variables are very weak predictors of bank's contribution to systemic risk, if compared to market based variables. Accounting rules provide enough degrees of freedom to make balance sheet less informative than market prices. As a result, measures of risk based on higher frequency market prices are more likely to anticipate systemic risk.

Keywords: Systemic Risk, SIFIs, European Banking System, CoVaR.
JEL classification: G01; G18; G21; G32

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Section 1: Introduction

Systemic risk is the risk of a collapse of the entire financial system, typically triggered by the default of one, or more, interconnected financial institutions. Systemic risk can be characterized by three factors: (a) it affects a substantial portion of the financial system; (b) it involves negative externalities; (c) it requires intervention of public authorities for prevention and, eventually, management of the risky environment. Since the failure of Lehman Brothers, systemic risk gained great attention in policy circles; financial authorities and researchers have been looking for tools to evaluate and forecast the contribution to systemic risk posed by individual financial institutions. Those institutions considered to be a potential threat to the financial system are now usually referred to as SIFIs, or Systemically Important Financial Institutions.

Before 2007, the banking regulatory framework of Basel II had been developed around the concept of idiosyncratic, rather than systemic, risk. Idiosyncratic risk is bank, rather than industry wide, specific. In fact, Basel II was based on capital cushions against unexpected losses and internal models based on value-at-risk (VaR). Such models do not generally take into account feedback effects on single institutions from losses suffered by other financial intermediaries. Since 2007, many things have changed in the perception of risk in financial markets. The Financial Stability Board recently stated that "financial institutions should be subjected to requirements commensurate with the risks they pose to the financial system" (June, 2011). How can a regulator measure this type of risk? Is it possible to predict which bank is systemically important? What is the consequence of regulatory actions being driven only by standard measures of risk, like value-at-risk or market betas? These are some of the questions this paper tries to address.

In this paper we estimate the systemic risk contribution of each financial institution in a large sample of European banks. The issue is topical for the policy debate after the burst of the Eurozone sovereign debt crisis. Turbulence in the market for sovereign debt was rapidly passed to the financial institutions given their relevant holdings of government bonds and additional stringent regulatory rules from the newborn European Banking Authority (EBA), asking to apply haircuts to risky assets in banks' balance sheets.

In order to try to measure single institutions' contribution to systemic risk, we follow a recent methodology first proposed by Adrian and Brunnermeier (2011) which is based on the CoVaR metrics. CoVaR is the value at risk (VaR) of the financial system *conditional* on institution *i* being under distress. Institution's *i* contribution to systemic risk, its *ΔCoVaR,* is defined as the difference between the CoVaR conditional on institution *i* being under distress and the CoVaR in the "median" state of the same institution.

While Adrian and Brunnermeier (2011) applied this metrics to US banks, our sample covers European listed banks in the period 2000-2010. Our results are broadly consistent with those fund for US financial institutions: *ΔCoVaR* provides additional, and sometimes different, information on the systemic risk of a given financial institution with respect to VaR. Systemic risk is time-varying and is a function of different measures of aggregate risk, like market returns and volatility, term spread, credit spreads and liquidity. Only conditional measures of risk can capture these effects. We compute conditional $\Delta CoVaR$ and VaR in the full sample and use an expanding window in order to mimic the set of information available to the regulator. We show that these two measures are highly correlated, even though using an expanding window would have led the regulator to underestimate the first signs of the current financial crisis.

$\Delta CoVaR$ may be a very useful policy tool for regulators. It can help evaluating which bank characteristics are more relevant in terms of contribution to systemic risk. First, we find that $\Delta CoVaR$ is highly persistent: risky banks tend to stay risky. Second, recent policy debate has focused on the danger posed by large banks and on the need to curb their size. We find that size is indeed a predictor of a bank contribution to systemic risk, but it is not the only one. Also, banks that have their headquarters in countries with a more concentrated banking system, tend to contribute more to European wide systemic risk even after controlling for their size. Therefore, any financial regulation designed only to curb banks' size would not completely eliminate systemic risk. On average, balance sheet variables are very weak predictor of bank's contribution to systemic risk, if compared to market based variables. Probably, accounting rules provide enough degrees of freedom to make balance sheet less informative than market prices. As a result, measures of risk based on higher frequency market prices are more likely to anticipate systemic risk.

The existing literature on the topic can be divided in two strands.

The first, usually referred to as *network analysis*, looks at the joint distribution of losses by all market players and evaluates the extent to which the failure of an institution threatens the viability of its creditors (rather than examining the co-movement of extreme asset returns). Markose, Giansante, Gatkowski and Shaghaghi (2010) apply an agent-based modeling to a financial network by using CDS data of the top 25 US banks and use simulation results to devise an operational measure of systemic risk. Martinez-Jaramillo, Perez, Avila and Lopez (2010) use data from Mexican banks during the period 2007-2009 and apply the systemic risk network model to estimate the distribution of losses in order to perform stress tests and to investigate the effect that different levels of correlation have on the distribution of losses. The use of CDS market prices has become very common in the assessment of the risk of a financial institution. However, CDS market prices exist only for a limited number of listed banks. The advantage of $\Delta CoVaR$ depends on the fact that it can be easily computed for all listed banks.

The second strand in the literature is usually referred to as *micro-evidence approach*. It moves from bank specific variables and tries to quantify the contribution of each financial institution to systemic risk. Huang, Zhou and Zhu (2009) consider twelve major US banks during the sample period 2001-2008. They use data on CDS and time-varying correlations in stock returns across these firms to estimate expected credit losses above a given share of the financial sector's total liabilities. De Jonghe (2010) generates a market-based measure of banks' systemic risk exposure by using extreme value analysis. Systemic banking risk is measured by the *Tail Beta*, which equals the probability of a sharp decline in a bank's stock price conditional on a crash in a banking index. For all listed European banks over different time periods, over the sample period 1992-2007, the author documents the presence of substantial cross-sectional heterogeneity and time variations in the Tail Betas of banks. Segoviano and Goodhart (2009) look at how individual firms contribute to the potential distress of the system by using CDS of these firms within a multivariate copula setting. In particular, they quantify the probability of sequential bank failures and measure the systemic risk and financial linkages through distress or failure dependent matrices. Giglio (2010) measures the joint default risk of large financial institutions (systemic default risk) by using information in bond and CDS prices. Acharya, Pedersen, Philippon and Richardson (2010), build a systemic risk measure named *SES* (i.e., systemic expected shortfall), which equals the expected bank's undercapitalization in a future systemic event in which the overall financial system is undercapitalized. They show that this measure is empirically related to a financial firm's marginal expected shortfall, or *MES*.

We follow Adrian and Brunnermeier (2011) and compute conditional VaR and *ΔCoVaR* on market-valued asset returns. These measures are close to *SES* (or to *MES*), since they provide an indirect quantification of the expected recapitalization needs in the event of a financial crisis. The advantage of using *ΔCoVaR* with respect to *SES* (or to *MES*) is that we can build a measure of risk conditioning on several available information summarized in a large set of financial variables. Our analysis provides a back test of Adrian and Brunnermeier's (2011) results on US financial institutions and policy insights with respect to European banking regulation and risk control.

The remainder of the paper is organized as follows: section 2 introduces our measure of systemic risk; section 3 presents the data; section 4 contains the estimates for VaR and *ΔCoVaR* and a regression analysis that tries to find variables and indicators that can help predict systemic risk; section 5 concludes.

Section 2: Measuring Systemic Risk

We measure systemic risk using the *ΔCoVaR* metrics, first developed by Adrian and Brunnermeier (2011). *ΔCoVaR* evaluates the contribution to systemic risk of each single financial institution by measuring the system's minimum loss in market-valued assets when the financial institution is suffering losses equal to its VaR and when the same financial institution is in its median state. Since *ΔCoVaR* looks at conditional system's losses in market-valued assets, it can provide useful information about the recapitalization needs of the financial system in a tail event. In this respect, *ΔCoVaR* is close to other recently proposed measures of risk as the marginal expected shortfall (Acharya, Pedersen, Philippon and Richardson (2010)).

Adrian and Brunnermeier (2011) develop a measure of downside risk and name it *ΔCoVaR*, where "Co" stands for "conditional, contagion or co-movement." While VaR should capture the underlying downside risk of a bank, it does not necessarily reflect systemic risk. The *ΔCoVaR* of a given bank represents instead the systemic risk contribution posed by a given bank. In fact, the bank *i*'s CoVaR with respect to the system is defined as the VaR of the whole financial system, conditional on bank *i* being in distress. The difference between the resultant CoVaR and the CoVaR conditional on the median state of bank *i* captures its marginal contribution to systemic risk.

Following Adrian and Brunnermeier (2011), we define with $A_t^i = ME_t^i L_t^i$ the market value of bank i's total assets at time t, where ME is the bank's market capitalization and L_t^i the bank's asset-to-equity ratio (the leverage ratio). We define the growth rate of market valued total assets of bank i with $X_t^i = A_t^i / A_{t-1}^i - 1$. Superscript "sys" denotes the entire financial system, i.e. the set of all the banks in our sample. The growth rate of market valued total assets of the financial system X_t^{sys} is computed as the average market valued asset returns weighted by lagged market valued total assets.

We define the VaR of bank i as the threshold value below which the historical market values fall by some pre-specified frequency or level of confidence q. The VaR with level of confidence q is equal to:

$$\Pr\left(X^i \leq VaR_q^i\right) = q.$$

The system CoVaR, for a given level of confidence q, of bank i, is the VaR of the financial system, conditional on bank i being in distress. Bank i is in distress when its market returns are equal, or below, its VaR with confidence level q. As a result, we can write:

$$\Pr\left(X^{sys} \leq CoVaR_q^{sys|X^i = VaR_q^i}\right) = q.$$

In our simulations, a level of q equal to one percent denotes a distress state of the world, while a level equal to fifty percent denotes a normal, or median, state. When a bank poses a risk to the entire financial system, its CoVaR is a very low and negative number. We define bank's i contribution to systemic risk by:

$$\Delta CoVaR_q^{sys|i} = CoVaR_q^{sys|X^i = VaR_q^i} - CoVaR_q^{sys|X^i = VaR_{50\%}^i}.$$

$\Delta CoVaR_q^{sys|i}$ captures the negative externality that bank i imposes on the banking system in the event of distress.

Following Adrian and Brunnermeier (2011), we estimate unconditional and conditional VaR and *CoVaR* via quantile regressions on weekly data. The unconditional estimates are constant over time, while the conditional estimates are function of state variables that, at each point in time, summarize the information set available to the representative investor, or the regulator. In order to compute the conditional estimates, we separately regress asset returns for each bank i and for the system on a number of state variables included in the matrix M for the 1% quantile. By running quantile regressions on state variable we capture time-varying risk. For bank's i we use:

$$X_t^i = \alpha^i + \gamma^i M_{t-1}^i + \epsilon_t^i$$

For the entire financial system, we have:

$$X_t^{sys} = \alpha^{sys|i} + \beta^{sys|i} X_t^i + \gamma^{sys|i} M_{t-1} + \epsilon_t^{sys|i}$$

The predicted values from the quantile regressions correspond to the VaR and the CoVaR of bank *i* as follows:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1},$$

$$CoVaR_t^i(q) = \hat{\alpha}^{sys|i} + \hat{\beta}^{sys|i} VaR_t^i(q) + \hat{\gamma}^{sys|i} M_{t-1}$$

The $\Delta CoVaR_t^i(q)$ for each bank is simply equal to:

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(q = 50\%).$$

Section 3: The data

We collect market data for 233 banks listed in a large sample of Eurozone countries from 2000 to March 2012 from DataStream. The banks in the sample are listed in: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The sample does not suffer from survivorship bias since it includes banks that went out of business, merged with other banks or were bought by other banks. For each bank, we also collect balance sheet data for the period 2000 to 2011. In particular, we were able to find data on total assets and liabilities, long and short term debt and common equity for 154 of the 233 banks in the sample. Balance sheet data for 2011 are available only for a few banks, thus we restrict our analysis to the period 2000-2010. The complete list of banks in the sample is available in the appendix.

In order to estimate the conditional *ΔCoVaR* we include a set of state variables that summarize available information at each time period. The state variables are: 1) the change in the option implied volatility on the DAX, which capture the implied volatility in the stock market (*ΔVDAX*); 2) the short term liquidity spread: the difference between the 3m Euribor rate and the short-term German government bond yield (*liquidity spread*); 3) the change in the slope of the yield curve: the yield spread between the 10y and the 3m German government bond yields (*long term spread*); 4) the equity market return (*DAX return*); 5) the change in the 3m German government bond yield (*3-month Treasury change*). Note that we are implicitly assuming that market prices of the German financial market contains useful information on the entire Eurozone[1]. While this would have been an innocuous assumption before the sovereign crisis in Europe, it is more controversial for analyses that take into account data from 2011 onwards, given the outburst of financial turbulence in peripheral European countries.

[1] While our sample of banks is international (indeed the banks are listed in eleven European countries) we use the German state variables as key determinants of banks valuations around Europe. We believe that this is a reasonable assumption for two reasons. First, given the evidence of German spillovers on the rest of Europe. Second, due to the proven high correlations among the non-German state variables' time series and the German ones: they span from a value equal to 0,758, *ΔVCAC40* with respect to *ΔVDAX,* to 0,999, the change in the 3m Italian government bond yield with respect to the correspondent German values.

Table 1 contains summary statistics relative to the state variables we use. We also report the 1% stress level. Following Adrian and Brunnermeier (2011), we define the 1% stress level as the average value conditional on the financial system being at, or below, its VaR 1%. In our sample, when the financial system is in distress, the VDAX, the liquidity spread, and the long term spread tend to increase; while the stock market and the yield on short-term safe assets drop.

Table 1: State variables summary statistics.

Variable (x 100)	mean	std	min	max	1% Stress
ΔVDAX	0.11	5.18	-19.08	40.02	13.74
Liquidity spread	2.36	4.22	-32.09	31.1	0.55
Long term spread	113.29	92.84	-158.8	285.65	14.5
DAX return	0.02	1.6	-8.49	11.4	-3.84
3-month Treasury change	-0.07	4.17	-35.94	42.18	-1.55

Notes: The table reports mean, standard deviation, minimum, maximum and 1% stress level of the state variables used in the construction of the *ΔCoVaR*. The state variables are the change in the implied volatility index on the DAX (ΔVDAX), the spread between the short-term EURIBOR and the short-term German government bond yield (Liquidity spread), the spread between a 10-year and a 3-month German government bond yield (Long term spread), the return on the DAX (DAX return) and the change in the 3-month German government bond yield (3-month Treasury change). The stress level corresponds to the variable's mean conditional on the financial system being in distress. Data are weekly, and in percentage from DataStream. The sample is 31/12/1999 - 31/12/2010.

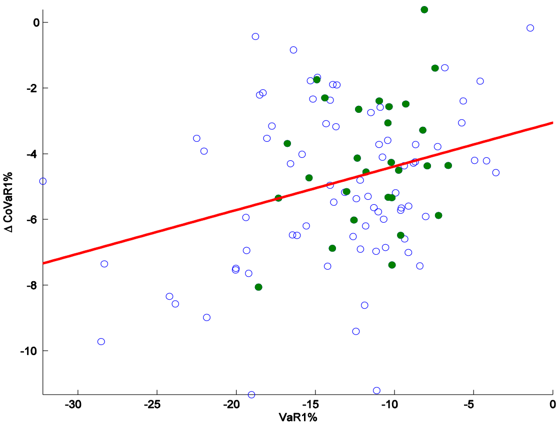
Section 4: Results

In this section, first we estimate unconditional and conditional VaR and *ΔCoVaR* for the full sample of European banks, and for a subsample containing the Italian banks only. Then, we investigate what variables are good predictors of systemic risk at the bank level.

Section 4.1: Estimating VaR and *ΔCoVaR*

For a regulator not only is important to know the probability of a bank failure, but also to estimate the negative effect that distress in one financial institution has on the entire financial system. We start by computing the unconditional VaR and *ΔCoVaR* of each bank using the full sample of banks. Figure 1 plots the unconditional VaR and *ΔCoVaR* for the period 2000-2010. The green dots represent the Italian banks. The scatter plot shows the weak, even though positive, relationship between the two measures of risk. This is the same result that Adrian and Brunnermeier (2011) find in the sample of US financial institutions. For example, the figure shows how banks with unconditional VaR 1% equal to -20 percent have the *ΔCoVaR* in the range that goes from 0 to almost -10 percent. As a result, a regulator that uses only VaR to measure systemic risk can potentially highly over or under estimate it.

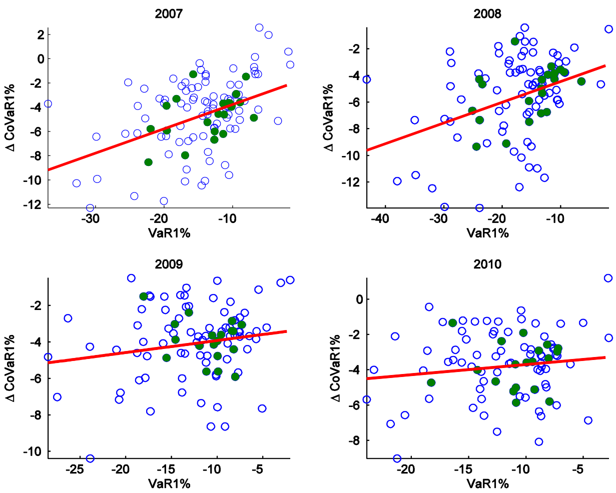
Figure1: Unconditional VaR vs ΔCoVaR (Full sample)



Notes: The scatter plot shows the relationship between unconditional VaR 1% and *ΔCoVaR* 1% in the full sample of Eurozone banks. VaR and *ΔCoVaR* are in units of weekly market valued asset returns in percentage. Green dots correspond to Italian banks. Data are from DataStream for the period 12/1999-12/2010.

The unconditional Var and *ΔCoVaR* do not take into account information that comes from other financial variables and assume each bank risk's contribution is constant over time. We use a set of state variables to compute conditional measure of risks. The state variables expand the information set of the regulator, or of any investor, when computing Var and *ΔCoVaR*. We estimate conditional Var and *ΔCoVaR* at weekly frequency for the period 2000-2010. In Figure 2 we plot the yearly averages of the two measures of risk around the financial crisis (2007-2010). The positive relationship between Var and *ΔCoVaR* weakness over time and is close to zero in 2010 when the sovereign crisis hit the Eurozone more deeply.

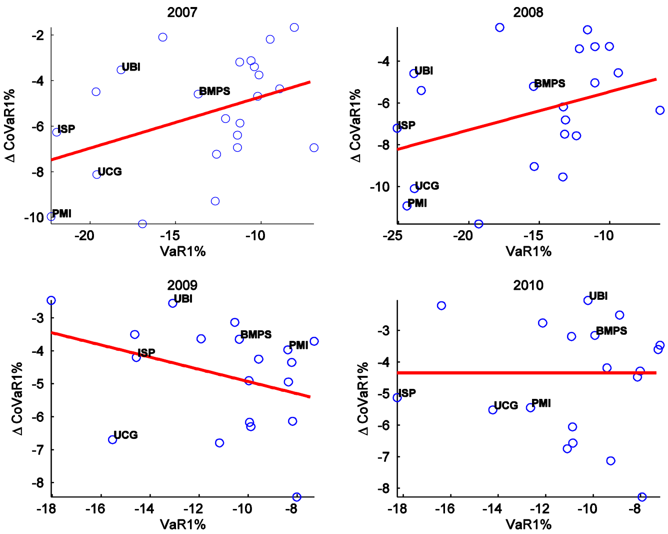
Figure 2: VaR vs ΔCoVaR around the Financial Crisis (Full Sample)



Notes: The scatter plots show the relationship between average annual VaR 1% and ΔCoVaR 1% in the full sample of European banks in the period 2007-2010. VaR and ΔCoVaR are in units of weekly market valued asset returns in percentage. Green dots correspond to Italian banks.

Figure 3 reports the same scatter plots for the subsample of Italian banks and shows that these banks behave like the banks in the rest of the Eurozone.

Figure 3: VaR vs ΔCoVaR around the Financial Crisis (Subsample: Italy)



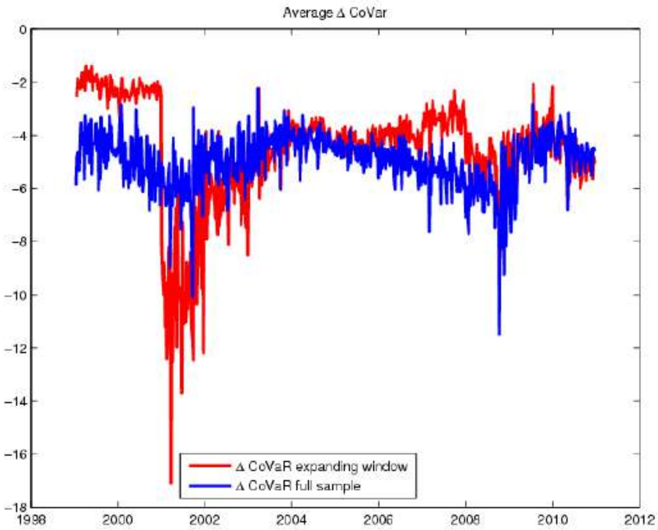
Notes: The scatter plots show the relationship between average annual VaR 1% and ΔCoVaR 1% for a sample of Italian banks in the period 2007-2010. VaR and ΔCoVaR are in units of weekly market valued asset returns in percentage. For the five largest banks we also report their ticker symbol: Unicredit Group (UCG), IntesaSanPaolo (ISP), Banca Monte dei Paschi (BMPS), Banca Popolare di Milano (PMI) and UBI Banca (UBI).

In the estimation of the conditional Var and *ΔCoVaR* we used several information available to a regulator, or investor, which has access to market data for the period 2000-2010. However, when a regulator estimates systemic risk at a given point in time, it has information only up to that day. Future information is unknown. We repeat the estimation using an expanding window: at each point of time *t*, we estimate the conditional Var and *ΔCoVaR* using only information up to *t*.

In Figure 4 we plot the time series of the average (across banks) *ΔCoVaR* in the two cases. At the beginning of the sample, the estimation with expanding window uses a small set of data (for example, *ΔCoVaR* at the end of 2000 is estimated with weekly data for the year 2000 only). Toward the end of the sample, the estimation with expanding window uses the same data as that of the full sample. Figure 4 shows that if data available to the regulator is limited, *ΔCoVaR* might lead to a strong over/under estimation of systemic risk. In fact, the estimation with an expanding window shows a large increase in the average contribution to systemic risk around 2001, which is not present in the estimation with the full size window. The intuition is simple: *ΔCoVaR* (as any tail risk measure) is based on events with very low probability; in a small sample, these events might not occur (leading to an underestimation of risk), or if they occur their probability is over-estimated.

An obvious policy implication follows from this finding: regulators should use enough backward information in order to properly estimate bank's systemic risk contribution.

Figure 4: Average ΔCoVaR: full sample vs. expanding window



Notes: The scatter plots show the difference of the average *ΔCoVaR* values obtained by using a distribution based on data from the full sample and on a distribution which increases year by year (expanding window). The sample is all the banks in the period 2000-2010.

Section 4.2: Predicting systemic risk

What variables are good predictors of systemic risk at the individual bank level? In this section, we estimate a pooled OLS panel in order to answer this question. Table 2 reports summary statistics of our dependent variable: the $\Delta CoVaR$ of each bank as estimated in section 4.1. Bank level data are grouped by country of origin and refer to the period 2000-2010. In addition, the table reports mean values before and after the current financial crisis. The table shows that $\Delta CoVaR$s are not uniformly distributed across countries. For example, in Austria, Belgium, France and Ireland we observe higher levels of systemic risk. Somewhat surprisingly, we do not observe large differences in the average bank's contribution to systemic risk before and after the financial crisis. The reason may be that only some institutions increased their contribution to systemic risk during the financial crisis and averages at the country level smooth out this effect.

Table 2: Δ*CoVaR*: summary statistics

Δ*CoVaR*	obs	mean	min	max	std	Financial crisis Pre	Financial crisis Post
Austria	44	-0.065	-0.131	-0.001	0.041	-0.065	-0.068
Belgium	45	-0.063	-0.140	-0.010	0.035	-0.065	-0.058
Finland	25	-0.036	-0.063	-0.016	0.015	-0.038	-0.033
France	254	-0.051	-0.226	0.000	0.031	-0.054	-0.044
Germany	124	-0.038	-0.170	0.000	0.029	-0.039	-0.034
Greece	131	-0.032	-0.106	-0.004	0.021	-0.033	-0.030
Ireland	35	-0.050	-0.129	0.000	0.027	-0.049	-0.051
Italy	299	-0.042	-0.122	-0.002	0.021	-0.042	-0.042
Netherland	21	-0.034	-0.047	-0.002	0.010	-0.034	-0.033
Portugal	56	-0.038	-0.081	-0.004	0.020	-0.039	-0.033
Spain	153	-0.041	-0.137	-0.005	0.026	-0.041	-0.045

Notes: The table reports, for each country in the sample, the summary statistics for *ΔCoVaR* 1%. Table reports the number of observations, the mean, the minimum, the maximum and the standard deviation for the period 2000-2010. The last two columns report the average values for the period before the financial crisis (2000-2007) and after the financial crisis (2008-2010).

We estimate a pooled regression where the dependent variable is the weekly *ΔCoVaR* for each bank at the end of each year in the sample 2000-2010. We consider a set of regressors that includes banks' characteristics and other market or industry factors. In particular, we collect variables to account for i) banks' balance sheet; ii) the structure of the banking system in the country of origin of each institution; iii) market-related characteristics; and iv) risk characteristics.

We use *Leverage* and *Long debt* to characterize the main features of banks' balance sheet. *Leverage* is defined as total asset over total equity in book values. *Long debt* is the ratio between long term debt and total debt. Both variables are constructed from balance sheet data obtained from DataStream. Adrian and Brunnermeier (2011) find that higher leverage tends to be associated with larger contributions to systemic risk in a sample of US financial institutions.

Concentration is a characteristic of the banking system in the country of origin of each bank in the sample and is defined as the share of total assets of the five largest credit institutions. The concentration variable is built by the ECB. De Nicolò et al. (2003) find that banking systems with higher degree of concentration tend to have higher systemic risk. We also include *Country dummies* to account for country-specific characteristics.

Adrian and Brunnermeier (2011) find that financial institutions with larger size, higher price to book ratio and returns' volatility tend to contribute more to systemic risk. As a result, we include in the panel several market related characteristics. *Market Value* is the log of the market capitalization (it is the proxy used for the size). *Price to book* is the ratio between stock price and book value. *Returns* are the total stock returns in the year. *Volume* is ratio between total volume and market value within each year. *Returns*, *Market Value*, *Price to book*, and *Volume* are computed as the average of daily data within each year obtained from DataStream.

We approximate risk characteristics' at the bank level by their market beta: *Beta* is the equity market beta calculated from weekly equity returns for the whole sample. Adrian and Brunnermeier (2011) find that banks with higher beta contribute more to systemic risk.

Since there is evidence that, during the recent financial crisis, the use of high leverage to boost returns contributed to financial instability (see for example, Alessandri and Haldane (2009)), we also include in the panel analysis an interaction term between *Returns* and *Leverage*. We name this factor *Instability factor* and our prior is that systemic risk should be larger for those banks who have obtained high returns through high leverage. We also include in the regression the banks *VaR*, since we know from our previous analysis that there exists a positive, but weak, relationship between *ΔCoVaR* and *VaR*.

Some of the banks in the sample have been listed by the FSB as Systematically Important Financial Institutions[2] (*SIFIs*) and according to Basel's rules they might be subject to enhanced capital requirement. Therefore, we include a dummy for *SIFIs* and check if their contribution to systemic risk is larger than average after controlling for other characteristics.

Table 3 presents summary statistics for all the variables of the panel for the period 2000-2010. The average weekly *ΔCoVaR* is equal to -4.4 percent and does not differ in the period before and after the financial crisis. The share of long debt is about 44%, and increases substantially after the crisis. The average price to book is about 1.5, but drops sharply to below unity after 2007, reflecting decline in stock prices.

Table 3: All variables, summary statistics (2000-2010)

	obs	mean	min	max	std	Financial crisis Pre	Financial crisis Post
ΔCoVaR	1187	-0.044	-0.126	-0.003	0.027	-0.044	-0.041
Leverage	1187	18.8%	1.8%	64.7%	0.111	18.6%	19.1%
Long Debt	1118	44.3%	0.1%	99.4%	0.254	42.1%	51.0%
Concentr.	1187	45.3%	19.9%	87.0%	0.177	44.3%	48.8%
Returns	1163	5.9%	-79.0%	127.5%	0.362	11.3%	-11.3%
Market Value	1187	7.090	2.190	11.070	1.997	7.119	6.998
Price To Book	1185	1.48	0.18	4.43	0.846	1.627	0.99
Volume	1180	0.36	0.00	5.95	0.875	0.290	0.59
Beta	1187	0.023	-0.290	0.285	0.107	0.019	0.033
VaR	1187	-0.139	-0.352	-0.020	0.066	-0.142	-0.131

Notes: The table reports the summary statistics for the variables in the *ΔCoVaR* regressions. All variables are winsorized at the 1st and 99th percentiles. Table reports the number of observations, the mean, the minimum, the maximum and the standard deviation for the period 2000-2010. The last two columns report the average values for the period before the financial crisis (2000-2007) and after the financial crisis (2008-2010). Variables are described in 4.2.

[2] FSB (2011), Policy Measures to Address Systemically Important Financial Institutions. The list is based on the methodology set out in the BIS document Global systemically important banks: Assessment methodology and the additional loss absorbency requirement (2011b).

Table 4 reports the unconditional pairwise correlations of the variables in our panel. On average, correlations are weak. On average, the relationship between balance sheet variables and measure of systemic risk is weaker than with respect to market price variables.

Table 4: All variables, correlation matrix

	$\Delta CoVaR$	Leverage	Long Debt	Concentr.	Returns	Market Value	Price To Book	Volume	Beta	*VaR*
$\Delta CoVaR$	1									
Leverage	-0.05	1								
Long Debt	-0.04	0.00	1							
Concentr.	-0.02	-0.05	-0.28*	1						
Returns	0.08*	-0.07	0.02	-0.05	1					
Market Value	-0.26*	0.40*	-0.08*	0.02	-0.03	1				
Price To Book	0.00	0.21*	-0.14*	0.05	-0.02	0.31*	1			
Volume	0.07	-0.03	-0.03	-0.06	-0.03	0.11*	-0.10*	1		
Beta	0.20*	-0.05	0.05	-0.01	0.01	-0.42*	-0.13*	-0.05	1	
VaR	0.42*	-0.23*	0.07	-0.14*	0.16*	-0.28*	-0.16*	-0.13*	0.15*	1

Notes: The table reports correlation coefficients among the variables in the *ΔCoVaR* regressions. Significance levels are denoted by * for 1%. Variables are described in 4.2.

In the sample of European banks we consider are included 8 SIFIs: Banco Santander, BNP Paribas, Commerzbank, Credt Agricole, Deutsche Bank, Dexia, Societe Generale, Unicredit. In Table 5 we report average values for the variables in our panel for the 8 SIFIs and the remaining banks in the sample. The table also reports p-values of the t-test for the hypothesis that the values in the first and second group are significantly different: SIFIs are indeed different with respect to risk characteristics. In fact, SIFIs are on average bigger, more levered and have higher *ΔCoVaR* and *VaR*.

Table 5: All variables, average values for SIFIs and other banks in the sample

	SIFIs			Others Banks			P-value
	mean	Financial crisis Pre	Financial crisis Post	mean	Financial crisis Pre	Financial crisis Post	
$\Delta CoVaR$	-0.054	-0.056	-0.049	-0.041	-0.041	-0.042	0.042
Leverage	19.1%	20.2%	16.2%	14.9%	15.5%	12.8%	0.001
Long Debt	46.0%	36.5%	71.4%	52.3%	50.0%	61.3%	0.327
Returns	1.2%	7.3%	-15.3%	4.9%	10.6%	-18.0%	0.726
Market Value	10.433	10.383	10.567	7.286	7.299	7.233	0.000
Price To Book	1.64	2.00	0.67	1.40	1.53	0.85	0.329
Volume	0.53	0.28	1.21	0.74	0.69	0.93	0.249
Beta	-0.029	-0.029	-0.029	-0.006	-0.009	0.005	0.002
VaR	-0.176	-0.181	-0.162	-0.126	-0.128	-0.118	0.007

Notes: The table shows the mean values of the variables for two different groups of banks for the period 2000-2010, for the period before the financial crisis (2000-2007) and for the period after the financial crisis (2008-2010). The first group includes SIFIs. The second group includes all the others banks in the sample. The table also reports the p-value for the hypothesis that the values in the two group for the whole period are significantly different. Variables are described in 4.2.

Table 6 reports our main results from a pooled OLS panel regression with weekly *ΔCoVaR* at yearly frequency as dependent variable. All the regressions include country fixed effects and robust standard errors. The explanatory variables have been winsorized at the 1st and 99th percentiles. *ΔCoVaR* is persistent, as the regression coefficient on its lagged values is always significantly different from zero.

We first include only variables related to the structure of balance sheets and to countries of origin banking systems as explanatory variables. *Concentration* is the only variable with an effect significantly different from zero. Banks that have their principal headquarters in countries with a more concentrated banking system contribute more to system wide systemic risk.

In the second column of Table 6 we report coefficients from a regression that included market related characteristics. Banks with larger size, higher price to book ratio and higher returns' volatility contribute more to systemic risk. These results are consistent with those found by Adrian and Brunnermeier (2011) in the sample of US banks.

The third column includes risk characteristics of a bank: *Beta* and the *Instability Factor*. The latter is strongly significant, consistent with the idea that contribution to systemic risk is larger for banks that had higher returns through higher leverage.

In the fourth and fifth column we add, respectively, the dummy *SIFIs* and the contemporaneous *VaR*: both coefficients are different from zero. Therefore, *SIFIs* contribute more to systemic risk even after controlling for other characteristics. This finding seems supporting Basel policies. In addition, *VaR* is informative about financial institution's contribution to systemic risk.

Table 6: Δ*CoVaR* regressions.

ΔCoVaR	(i)	(ii)	(iii)	(iv)	(v)
ΔCoVaR (t-1)	0.701***	0.667***	0.684***	0.691***	0.641***
	(0.033)	(0.031)	(0.030)	(0.030)	(0.025)
Leverage (t-1)	-0.007	0.012	0.009		
	(0.007)	(0.008)	(0.008)		
Long Debt (t-1)	-0.243	-0.367	-0.337	-0.375	-0.128
	(0.248)	(0.239)	(0.237)	(0.234)	(0.195)
Concentration	-0.039*	-0.036*	-0.036*	-0.038*	-0.036**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.017)
Returns		0.927***	0.883***	0.881***	0.396***
		(0.160)	(0.156)	(0.158)	(0.124)
Market Value		-0.152***	-0.122***		
		(0.036)	(0.038)		
Price To Book		-0.359***	-0.221**	-0.287***	-0.061
		(0.091)	(0.089)	(0.089)	(0.075)
Volume		0.165***	0.148**	0.112*	0.233***
		(0.063)	(0.064)	(0.064)	(0.050)
Beta			0.005	0.009	0.002
			(0.007)	(0.006)	(0.005)
Instability Factor (t-1)			-0.038***	-0.039***	-0.028***
			(0.008)	(0.008)	(0.008)
SIFIs				-0.006**	
				(0.003)	
VaR					0.169***
					(0.009)
Constant	0.024	0.036**	0.034*	0.029*	0.042***
	(0.017)	(0.018)	(0.018)	(0.018)	(0.015)
Observations	963	960	960	960	960
R-squared	0.565	0.60	0.61	0.61	0.73

Notes: The table presents the results of the *ΔCoVaR* regressions. All variables are defined in 4.2. All regressions include country fixed effects; robust standard errors are reported in parentheses; the explanatory variables have been winsorized at the 1st and 99th percentiles; significance levels are denoted by * for 10%, ** for 5% and *** for 1%.

Section 5: Conclusions

In this paper we estimated the contribution to systemic risk of European banks in a large sample of listed banks for the period 2000-2010. We measure banks' contribution to systemic risk by *ΔCoVaR*: each bank's contribution to system VaR when in a state of distress with respect to a normal (median) state. *ΔCoVaR* was first developed by Adrian and Brunnermeier (2011) and applied to US financial institutions. We define "the system" as the set of European banks in the sample. As a result, we abstract from the systemic risk spillovers from European banks to the rest of the world, and from the rest of the world to European banks, that are likely to be relevant. For example, in our current analysis the systemic event of Lehman Brothers' failure shows up only indirectly, through its negative effects on European banks. We leave to forthcoming work the study of the interactions between the European banking system and other financial system (especially the US).

In the sample of European banks, we find that *ΔCoVaR* may be a very useful policy tool for regulators. It can help evaluating which bank characteristics are more relevant in terms of contribution to systemic risk. First, we find that *ΔCoVaR* is highly persistent: risky banks tend to stay risky. Second, recent policy debate has focused on the danger posed by large banks and on the need to curb their size. We find that size is indeed a predictor of a bank contribution to systemic risk, but it is not the only one. Also, banks that have their headquarters in countries with a more concentrated banking system, tend to contribute more to European wide systemic risk even after controlling for their size. Therefore, any financial regulation designed only to curb banks' size would not completely eliminate systemic risk. On average, balance sheet variables are very weak predictor of bank's contribution to systemic risk, if compared to market based variables. This conclusion seems to support the thesis pointed out by Haldane (2011). Probably, accounting rules provide enough degrees of freedom to make balance sheets less informative than market prices. As a result, measures of risk based on higher frequency market prices are more likely to anticipate systemic risk.

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Appendix: List of banks in the sample

Name	Market	Name	Market	Name	Market
BANK AU.CREDITANSTALT	AT	EUROHYPO	DE	BCA.PPO.BERGAMO	IT
ERSTE GROUP BANK	AT	EUROHYPO	DE	BCA.PPO.COML.INDR.	IT
OBERBANK	AT	HVB REAL ESTATE BANK	DE	BCA.PPO.CREMA	IT
RAIFFEISEN BANK INTL.	AT	IKB DEUTSCHE INDSTRBK.	DE	BCA.PPO.LUINO E VARESE	IT
VOLKSBANK VBG.PC.	AT	ING BHF-BANK	DE	BCA.TOSCANA	IT
ALMANIJ	BG	KBC BANK DEUTSCHLAND	DE	BNC.DI DESIO E DELB.	IT
BANQUE NALE.DE BELGIQUE	BG	LANDESBANK BL.HLDG.	DE	CAPITALIA DEAD MERGED 92939	IT
DEXIA	BG	MERKUR BANK	DE	COMIT	IT
KBC ANCORA	BG	NUERNBERGHYP	DE	CREDITO ARTIGIANO	IT
KBC GROUP	BG	OLDENBURGISCHE LB.	DE	CREDITO BERGAMASCO	IT
AKTIA 'A'	FI	QUIRIN BANK	DE	CREDITO EMILIANO	IT
ALANDSBANKEN 'A'	FI	RHEIN.HYPBK.	DE	CREDITO VALTELLINES	IT
MANDATUM BANK B	FI	SUEDBODEN	DE	INTESA SANPAOLO	IT
POHJOLA PANKKI A	FI	UMWELTBANK	DE	IW BANK	IT
BANQUE REUNION	FR	AGRI.BANK OF GREECE	GR	MEDIOBANCA	IT
BANQUE TARNEAUD	FR	ALPHA BANK	GR	MELIORBANCA	IT
BNP PARIBAS	FR	ATTICA BANK	GR	ON BANCA	IT
CIC 'A'	FR	BANK OF GREECE	GR	RETI BANCARIE HOLDING	IT
CR.AGR.ALPES PROVENCES	FR	BANK OF PIRAEUS	GR	ROLO BANCA 1473	IT
CR.AGR.HAUTE NORM.	FR	EFG EUROBANK ERGASIAS	GR	SAN PAOLO IMI	IT
CR.AGR.L-ATLANTIQUE	FR	EMPORIKI BK.OF GREECE	GR	UBI BANCA	IT
CR.AGR.SUD RHONE ALPES	FR	ETBA BANK	GR	UNICREDIT	IT
CR.AGRICOLE MORBIHAN	FR	GENERAL BANK OF GREECE	GR	ABN AMRO HOLDING	NL
CRCAM AQUITAINE	FR	MARFIN EGNATIA BANK	GR	KEMPEN & CO	NL
CRCAM ATLANTIQUE VENDEE	FR	NATIONAL BK.OF GREECE	GR	VAN LANSCHOT	NL
CRCAM BRIE PIC2CCI	FR	NIBID	GR	BANCO BPI	PT
CRCAM ILLE-VIL.CCI	FR	PROTON BANK	GR	BANCO COMR.PORTUGUES 'R'	PT
CRCAM LANGUED CCI	FR	T BANK	GR	BANCO ESPIRITO SANTO	PT
CRCAM NORD DE FRANCE CCI	FR	TT HELLENIC POSTBANK	GR	BANCO TOTTA ACORES	PT
CRCAM NORMANDIE SEINE	FR	ALLIED IRISH BANKS	IR	BANIF-SGPS	PT
CREDIT AGR.CENTRE LOIRE	FR	ANG.IR.BK.	IR	FINIBANCO	PT
CREDIT AGR.GIRONDE	FR	BANK OF IRELAND	IR	BANCO ATLANTICO	ES
CREDIT AGR.ILE DE FRANCE	FR	FIRST ACTIVE	IR	BANCO DE ANDALUCIA	ES
CREDIT AGR.LOIRE-H-LOIRE	FR	BANCA ANTONVENETA	IT	BANCO DE CASTILLA	ES
CREDIT AGR.MIDI (3EME)	FR	BANCA CARIGE	IT	BANCO DE CREDITO BALEAR	ES
CREDIT AGR.TOULOUSE	FR	BANCA CR FIRENZE	IT	BANCO DE GALICIA	ES
CREDIT AGR.TOURAINE	FR	BANCA FINNAT	IT	BANCO DE SABADELL	ES
CREDIT AGRICOLE	FR	BANCA LOMBARDA	IT	BANCO DE VALENCIA	ES
CREDIT AGRICOLE OISE	FR	BANCA MONTE DEI PASCHI	IT	BANCO DE VASCONIA	ES
CREDIT AGRICOLE SOMME	FR	BANCA NAZ.LAVORO	IT	BANCO ESPANOL DE CREDITO	ES
CREDIT FONCIER DE MONACO	FR	BANCA POPOLARE DI MILANO	IT	BANCO FINANTIA SOFINLOC	ES
CREDIT LYONNAIS	FR	BANCA POPOLARE ETRURIA	IT	BANCO GUIPUZCOANO	ES
NATIXIS	FR	BANCA POPOLARE INTRA	IT	BANCO PASTOR	ES
SOCIETE GENERALE	FR	BANCA POPOLARE ITALIANA	IT	BANCO POPULAR ESPANOL	ES
VIA BANQUE	FR	BANCA PPO.DI SONDRIO	IT	BANCO SANTANDER	ES
ALLGEM.PRIVATKUNDENBANK	DE	BANCA PPO.DI SPOLETO	IT	BANCO ZARAGOZANO	ES
BANKVEREIN WERTHER	DE	BANCA PPO.EMILIA ROMAGNA	IT	BANKINTER 'R'	ES
COMMERZBANK	DE	BANCO DI SARDEGNA RSP	IT	BBV.ARGENTARIA	ES
DEPFA BANK	DE	BANCO POPOLARE	IT	CAIXABANK	ES
DEUTSCHE BANK	DE	BCA.AGRICOLA MANTOVANA	IT	CAJA DE AHORROS DEL MEDIT	ES
DEUTSCHE POSTBANK	DE	BCA.LEGNANO	IT		
ENTRIUM DIRECT BANKERS	DE	BCA.PPO.ADRIATICO	IT		