"RoME Master in Economics"

Master of Science Thesis

Measuring Systemic Risk in the Italian Banking Ecosystem

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What we know about the global financial crisis is that we don't know very much.

Paul Samuelson, Nobel Prize for Economics in 1970

LUISS "GUIDO CARLI" & EIEF

Abstract

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Measuring Systemic Risk in the Italian Banking Ecosystem

by Andrea BO

During the last decade we have witnessed how distress can spread quickly through the financial system and threaten financial stability. Hence there has been increased focus on developing systemic risk indicators that can be used as policy tools. Adrian and Brunnermeier (2016) have introduced a new methodology in measuring spillover effects and sistemic risk contributions of institutions through the measure of Conditional Value at Risk ($CoVaR$), the value at risk of the financial system conditional on institutions being in distress. The purpose of this thesis is to apply the $CoVaR$ model to the Italian financial market to identify which are the institutions that contribute the most to the build-up of systemic risk and its best predictors. We provide forecast of a forward looking measure of sistemic risk contribution showing that it is able to predict half of realized covariances during the financial crisis.

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1 Introduction

Technological progress has gifted us with an interconnected and globalised world, a sprawling network of agents that are able to interact directly or indirectly with each other: nowadays, it is very hard to find a situation in which one exceptional event happens for some economic agents without having any impact on other economic agents. This happens also in financial markets, where in the recent years we have witnessed how during times of financial crisis distress can spread quickly through institutions threatening financial stability. The subprime crisis, the collapse of Lehman Brothers and the Greece's sovereign debt crisis are the most notable examples of such events, which happened in the financial world and have made disastrous repercussions on a number of economies.

The spreading of distress gives rise to systemic risk - the risk that the intermediation capacity of the entire financial system is impaired, with severe consequences for the supply of credit in the real economy. These systemic effects are generated from spillovers across institutions that arise due to contractual links between counterparties, exposures or more general macro-factors such as price effects and liquidity spirals. These facts made crucial for regulators to take adequate measures in order to prevent the collapse of the financial system. To do so, regulators need sustainable systemic risk indicators that also monitor the level of contagion among financial institutions.

One of these measures, that has been used for a long time, is the **Value at Risk (*VaR*)**, which focuses on the risk of a single financial institution in *isolation*. It is defined as the maximum loss of institution i for some confidence level q. The main issue with this approach is that a single institution's risk does not necessarily reflects its contribution to systemic risk. Indeed, an institution may be *individually systemic* because large and interconnected, or could be relatively small in term of size but still be *systemic as a part of a herd*. Moreover, systemic risk shows a time-series dimension by its very nature, where it typically builds up in time of low volatility in terms of bubbles and imbalances and materializes in time of crisis. A proper systemic risk measure should capture this build-up.

In this context, *Adrian and Brunnermeier* (2016) have developed a new measure of risk which can be applied to quantify systemic risk. It is the **Conditional Value at Risk (*CoVaR*)** which represents the *VaR* of a financial system (or of a single institution) conditionally on the fact that a financial institution is in distress. By defining the $\Delta CoVaR$ as the difference between the above mentioned *CoVaR* and the *CoVaR* when the institution is in a normal financial situation, we are able to capture the marginal contribution of a particular institution on the systemic risk as a whole. Projecting the obtained measures of $\Delta CoVaR$ on robust and reliable lagged characteristics of institutions - such as balance sheet items - we will estimate the *Forward-*$\Delta CoVaR$, a forward looking measure of risk that can be used as a monitoring tool for the prediction of systemic risk. Being tied to frequent and robust characteristics, the *Forward-*$\Delta CoVaR$ tries to address the problem that empirical risk measures suffer from the rarity of tail event, leading to inaccuracies in capturing systemic risk.

The objective of this thesis is to use the mentioned methodology to estimate systemic risk contribution in the Italian banking system analyzing listed financial institutions in the Italian Stock Exchange. Doing so, we will try to answer the following questions:

- Which are the the institutions who contribute the most (and the less) to the systemic risk in Italy, and which are the most exposed in the case of a crisis?

- What are the best predictors of systemic risk contribution and how such characteristics could be addressed in a regulatory framework and used to construct a predictive measure of systemic risk?

This thesis tries to provide an original contribution to the *CoVaR* and systemic risk literature by applying the presented methodology to the Italian case, analyzing a relevant topic in the banking sector debate given the high level of sovereign local debt held by Italian banks, highly exposed to non-performing positions and risks.

Unconditional and conditional $\Delta CoVaR$ are calculated using weekly data from 1999Q1 to 2019Q1 for all listed Italian banks plus the two biggest insurance company by market capitalization. The conditional $\Delta CoVaR$ is modelled as a function of state variables that captures the evolution of tail risk dependence over time, such as the implied market volatility from the *FTSE IVI*, credit and liquidity spread, market returns. We are able to capture and understand which are the Italian banks that contribute the most to systemic risk, and the most exposed one to financial crisis by reversing the directionality in the computation of the $\Delta CoVaR$.

In a successive step, we relate those $\Delta CoVaR$ - in a predictive sense - to institution's balance sheet characteristics using panel regressions. We show not only that size, leverage, maturity mismatch and other characteristics are good predictors of systemic risk, but the predicted values of those regressions have out of sample predictive power, being able to capture half of the realized covariance between institutions and the system during the financial crisis of 2008.

Outline. The remainder of the thesis is divided in 6 sections. The following paragraph will review the literature on systemic risk measures. Section 3 covers the theoretical background and the methodology used to apply the *CoVaR* model. Section 4 describes the data used as an input to model. The results are presented in Section 5. Finally in Section 6 conclusions are drawn.

2 Literature Review

The literature on systemic risk can be divided into two strands: one that looks at specific sources of systemic risk - called the **source-specific approach** - and the other that aims to derive global measures of systemic risk, more statistical in nature and does not take a particular stand on the causes of systemic risk - called the **global approach**.

The first one, very rich in contributes, studies distress-spreading mechanism such as liquidity spirals *(Shleifer and Vishny (1992), Duarte and Eisenbach (2015))*, balance sheet contagion *(Allen and Gale (2000))*, informational panic *(Chen (1999))*.

The ΔCoVaR model belongs to the latter approach, together with other measures such as the **Marginal Expected Shortfall (MES)** and its expansion **Systemic Expected Shortfall (SES)** of *Acharya et al. (2010)* and **Systemic Risk Measure (SRISK)** of *Acharya, Engle, and Richardson (2012)* and *Brownlees and Engle (2015)*. By defining the Expected Shortfall of the system as the expected average returns of the institutions in the system weighted by their market capitalization, the *MES* measures the increase in the risk of the system induced by a marginal increase in the weight of a single firm in the system. The *SES* and *SRISK* are extensions that take into account the sizes and liabilities of financial institutions. Those multiple measures of systemic risk when used in analysis provide different results as showed in *Benoit, Colliard et al. (2015)*, due to the basic different approach used to study systemic risk:

- The MES/SES/SRISK are *marginal* risk measures, as they are defined with the **first derivative** of the ES of the system with respect to the market value of an institution, while the $\Delta CoVaR$ is an *incremental* risk measure, since it is the **difference between two conditional** VaR

- They are based on two different **conditioning** events: the MES/SES/SRISK are fundamentally tied to the sensitivity of institutions returns to the one of the system while the $\Delta CoVaR$ capture the sensitivity of market returns to variation of the returns of a single institution

Hence, it is difficult to understand what is the "best" measure: we prefer $\Delta CoVaR$ as it is more broad in capturing determinants of tail risk, since we condition on all the available information summarized in a **large set of financial variables** - mixing **high-frequencies quantitative market indicator** with more **qualitative and robust items** such as leverage or balance sheet reports.

3 Theoretical Framework

3.1 Quantile

Define Y as a real valued random variable with cumulative distribution function $F_Y(y) = P(Y \leq y)$. The τth **quantile** of Y is given by

$$Q_Y(\tau) = F_Y^{-1}(\tau) = \inf\{y : F_Y(y) \geq \tau\} \tag{1}$$

where $\tau \in (0,1)$. Define the **loss function**[1] as $\rho_\tau(y) = y\left(\tau - \mathbb{I}_{y<0}\right)$ where $\mathbb{I}$ is an indicator function. Just as we can define the sample mean as the solution to the problem of minimizing a sum of squared residuals - which can be viewed as a specific version of a loss function - we can define the median as the solution to the problem of minimizing

[1] In mathematical optimization and decision theory, a loss function or cost function is a function that maps an event or values of one or more variables onto a real number intuitively representing some "cost" associated with the event. An optimization problem seeks to minimize a loss function.

a sum of absolute residuals. If the symmetric loss function yields the median, a specific quantile can then be found just by minimizing the *tilted* expected loss/absolute residuals $Y-u$ with respect to u - a scalar:

$$\min_u \mathbb{E}\left(\rho_\tau(Y-u)\right) = \min_u \left\{(\tau-1)\int_{-\infty}^{u}(y-u)dF_Y(y) + \tau\int_{u}^{\infty}(y-u)dF_Y(y)\right\} \tag{2}$$

This can be shown by setting the derivative of the expected loss function to equal to 0 and imposing q_τ to be the solution of

$$0 = (1-\tau)\int_{-\infty}^{q_\tau} dF_Y(y) - \tau\int_{q_\tau}^{\infty} dF_Y(y)$$

This equation can be reduced to

$$0 = F_Y(q_\tau) - \tau \rightarrow F_Y(q_\tau) = \tau \rightarrow q_\tau = F_Y^{-1}(\tau)$$

Hence q_τ is the τth **unconditional quantile** of the random variable Y and can be defined as

$$q_\tau = \arg\min_{q\in\mathbb{R}} \mathbb{E}\left(\rho_\tau(Y-u)\right) \tag{3}$$

3.2 Conditional quantile and quantile regression

Given the definition of unconditional quantiles as an optimization problem, it is easy to define conditional quantiles in an analogous fashion. To understand why, consider the least square regression that offers a model for how to proceed. Again, if we are presented with a random sample $\{y_1, y_2, \dots, y_n\}$, we solve

$$\min_{\mu\in\mathbb{R}} \sum_{i=1}^{n}(y_i-\mu)^2$$

and obtain the sample mean, an estimate of the unconditional population mean, $\mathbb{E}(Y)$.

If we now replace the scalar μ by a parametric function $\mu(x,\beta)$ and solve

$$\min_{\beta\in\mathbb{R}^k} \sum_{i=1}^{n}\left(y_i-\mu(x_i,\beta)\right)^2$$

we obtain an estimate of the conditional expectation *function* $\mathbb{E}(Y|x)$.

In quantile regression we proceed exactly in the same way. To obtain an estimate of the conditional quantile function, we simply replace the scalar μ in 2 by the parametric function $u(x_i, \beta)$ and then set the desired τth quantile.

For the familiar framework of linear functions of parameters as in a regression, suppose that the τth conditional quantile function is $Q_{Y|X}(\tau) = X\beta_\tau$ where X is a vector of predictor variables and β the vector of coefficients. Given the distribution function of Y, then β_τ can be obtained by solving - equivalently as 3 -

$$\beta_\tau = \underset{\beta \in \mathbb{R}^k}{\arg\min}\, \mathbb{E}\left(\rho_\tau(Y - X\beta)\right) \tag{4}$$

which is the *conditional* quantile of the random variable Y.

The regression coefficients vector β_τ describes how much $Q_{Y|X}(\tau)$ changes due to an unit change in one of the predictor variables contained in the vector X.

Sample quantile. In a similar fashion of the unconditional case, solving the sample analog of 4 gives the estimator of β:

$$\hat{\beta}_\tau = \underset{\beta \in \mathbb{R}^k}{\arg\min}\, \mathbb{E}\left(\rho_\tau(Y_i - X_i\beta)\right)$$

This last equation can be solved very efficiently by linear programming methods by using $2n$ slack variables (u^+, u^-) to represent positive and negative vectors of residuals and minimizing

$$\min_{(\beta, u^+, u^-) \in \mathbb{R}^k \times \mathbb{R}^{2n}_+} \left\{\tau 1_n' u^+ + (1-\tau) 1_n' u^- | X\beta + u^+ - u^- = Y\right\}$$

where X is the $n \times k$ regression matrix of p predictive variables and the solution $\hat{\beta}_\tau$ is a vector of the τ-quantile regression parameter estimates. This linear program can be solved using the simplex method or interior point methods.

3.3 Value at Risk (VaR)

Value at Risk is a well-known and widely used risk measure by financial institutions. Value at Risk *measures the potential loss in the value of a risky asset or portfolio over a defined period for a given confidence interval*.

More formally, p-VaR is defined such that the probability of a loss greater than VaR is (at most) p while the probability of a loss less than VaR is (at least) $1-p$. For example, if a portfolio of stocks has a one-day 5%-VaR of €1 million, that means that there is a 0.05 probability that the portfolio will fall in value by more than €1 million over a one-day period. Informally, a loss of €1 million or more on this portfolio is expected on 1 day out of 20 days, because of 5% probability (*Jorion (2006)).*

Definition 1 *If X^i represents a variable of interest of institution i - for example, a profit and losses distribution or portfolio return - with a generic distribution $F_{X^i}(x_i)$, then given a confidence level $(1-q)$, VaR_q^i can be defined as:*

$$VaR_q^i = \inf\{x : F_{X^i}(x_i) \geq q\} \tag{5}$$

VaR is essentially the q-quantile of the return distribution $F_{X^i}(x_i)$ as defined by equation (1).

VaR can also be implicitly defined by:

$$Pr\left(X^i \leq VaR_q^i\right) = q \tag{6}$$

meaning that there is a $(100 \times q\%)$ chance of the variable X^i to become less than VaR_q^i over a defined period or in other words, with confidence level $(1-q)$, X^i will not be less than VaR_q^i.

There are different models to estimate the VaR of a portfolio or return distribution, either parametrically [2] (for example, variance-covariance VaR or delta-gamma VaR)

[2] As showed in Mabrouk S. and Saadi S. (2012): *Parametric Value-at-Risk analysis: Evidence from stock indices* (The Quarterly Review of Economics and Finance, 52(3), pp. 305-321)

or nonparametrically[3] (for examples, historical simulation VaR or resampled VaR) that are briefly discussed below.

Variance-Covariance Method: Made popular by JP Morgan at the start of the '90s, it is one of the fastest and easiest method to estimate the VaR. It relies on the fact that the only risk factor of a portfolio is the value of the factors contained in the portfolio itself. It it based on two fundamental assumptions:

- The distribution of returns of the risk factors (for example, securities in a portfolio) is a normal distribution.
- The movements in the portfolio's value is a linear combination of the movements of the securities that make it up. This implies that the movements in the value of the portfolio are also distributed according to a normal distribution.

Hence, once estimated the correlation matrix of returns between the securities from the historical series of the risk factors, given the properties of the normal distribution it is easy to obtain the desired percentile of the distribution of the movements of the expected values of the portfolio. This approach presents a variety of issues, mainly the fact that the hypothesis of normality of returns is irrealistic - usually returns distribution is leptokurtic[4] - and the hypothesis of linearity that automatically excludes all those instruments with non-linear payoffs.

Monte Carlo Method: A simulation technique that, given some assumptions on the

[3] As showed in Markovich N. (2007): *Nonparametric analysis of univariate heavy-tailed data* (Wiley Series in Probability and Statistics)

[4] Leptokurtic distributions are statistical distributions where there is a relevant presence of extreme points resulting in a higher kurtosis than found in a normal distribution. These extreme values evidence of "fat tails" relative to the normal distribution's tail. A distribution is leptokurtic when the kurtosis value is a large positive number (a "rule of thumb" is a kurtosis coefficient higher than 3).

distribution of returns and their correlation, forecasts a series of different sets of possible future values of the securities in a portfolio. For each set of values, the portfolio is then re-evaluated and from the vector of expected returns the desired percentile is extracted.

Historical Simulation Method: This approach uses historical data of returns to generate an empirical distribution. It then assumes that the empirical distribution can be used as a prediction for future returns. It is considered one of the best approach both because it does not involve any *a priori* hypothesis on the distribution of returns and because the correlation between risk factors is implicitly captured without the need of an *ad hoc* estimation.

A report made by McKinsey published in 2012 estimated that almost 85% of large banks in the world were using historical simulation while the remaining part Monte Carlo simulations. Therefore, for its properties, in this thesis we will use the Historical Simulation Method.

3.4 CoVaR

CoVaR stands for Conditional Value at Risk; the *CoVaR* of the financial system (or a particular bank, portfolio of asset, etc.) is defined as the *VaR* of the financial system, conditional on some scenario at a particular bank or a set of banks.

Definition 2 *We denote by $CoVaR_q^{j|i}$ the VaR of institution j (or the financial system) conditional on some particular event $\mathbb{C}(\mathbb{X})$ of institution i. That is, $CoVaR_q^{j|i}$ is implicitely defined by the q-quantile of the conditional probability distribution:*

$$Pr\left(X^j \leq CoVaR_q^{j|\mathbb{C}(\mathbb{X})} | \mathbb{C}(\mathbb{X})\right) = q$$

For the most of this thesis, we will focuse on the conditioning event $\left\{\mathbb{C}(\mathbb{X}) = VaR_q^i\right\}$ simplifying the notation to $CoVaR_q^{j|i}$. Moreover, we mainly study the case of j = *system*, i.e. when the return of the portfolio of all financial institutions is at its VaR level. In this case, we drop the superscript j. Informally, we could say that there is a q% chance of the system returns X^j becoming less than $CoVaR_q^{j|i}$ within a specified time period given that returns of bank i are at its q%-VaR level. Finally, we define a state of distress for an institution or financial system when its returns X^i hits their 1%-VaR level[5] while its normal situation is where returns are at their **median** level (the 50%-quantile). Therefore, to measure how much institution i contributes to the financial system (or bank j) VaR during stressful times we will look at the difference between the system VaR conditional on bank i being at its 1%-VaR level minus the system VaR conditional on bank i being at its median level.

Definition 3 *We denote institution i's contribution to j by*

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i}$$

The directionality of the $\Delta CoVaR$ model could be reversed, i.e. by studying the $\Delta CoVaR_q^{i|j}$ with $j = system$ we are able to understand which institution are most at risk if a financial crisis occur - we call this the *Exposure*-$\Delta CoVaR$.

4 Estimation Methodology

Quantile regression is an efficient way to estimate $CoVaR$ and is used here. It is not the only way, as GARCH models could be implemented to estimate the $CoVaR$, but it is one of the most feasible and it is proved to provide results strongly correlated with

[5] It could be done also by taking the 5%-VaR level; the lower the desired quantile, the more *severe* the state of distress.

the GARCH method. As showed in the previous section, quantile regression models the relationship between a a set of predictor variables and specific quantiles of the response variable. The difference with the more standard Ordinary Least Squares (OLS) regression is that its coefficients estimates the change in the mean of the response variable produced by a one-unit change in the predictor variable, keeping other predictor variables fixed. However, a quantile regression coefficient estimates the change in a specified quantile of the response variable produced by a one unit change in the predictor variable. This enables comparison of how different quantiles of the response variable may be affected by the predictor variable. As we will show later, when estimating *CoVaR* the focus is on a specific low quantile of a distribution and hence it is automatic to use quantile regression here.

4.1 Unconditional $\Delta CoVaR$

Consider a quantile regression of the financial sector returns X^{sys} on a particular institution i's returns for the $q^{th}-$ quantile

$$X_q^{sys} = \alpha_q^i + \beta_q^i X^i$$

The quantile regression coefficient β_q^i estimates the change in a specified quantile q of X_q^{sys} produced by a one unit change in X^i, i.e.

$$\hat{X}_q^{sys} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{7}$$

where by $\hat{X}^{sys}$ we denoted the predicted value of such regression for a particular quantile conditional on institution i. From the definition of *VaR* - which is a quantile - it follows that

$$\hat{X}_q^{sys} = VaR_q^{sys} | X^i \tag{8}$$

which means that the predicted value from the regression is the $q\%$-VaR of the financial system conditional on X^i.

By conditioning with $X^i = VaR^i_q$ we obtain the unconditional $CoVaR$ measure

$$CoVaR_q^{sys|X^i=VaR^i_q} := VaR_q^{sys}|VaR^i_q = \hat{\alpha}^i_q + \hat{\beta}^i_q VaR^i_q \tag{9}$$

$$\implies \Delta CoVaR_q^{sys|i} = \hat{\beta}^i_q (VaR^i_q - VaR^i_{50\%}) \tag{10}$$

4.2 Conditional $\Delta CoVaR$

In order to capture time variation in the joint distributions of X^i, X^{sys} (i.e. time-varying risk) we estimate the conditional distribution as a function of **state variables that replicate the information set available to the regulator**. We separately regress asset returns for each bank i and for the system on a number of lagged state variable included in the matrix M as follows

$$X^i_t = \alpha^i + \gamma^i M_{t-1} + \epsilon^i_t \tag{11}$$

$$X^{sys}_t = \alpha^{sys|i} + \beta^{sys|i} X^i_t + \gamma^{sys|i} M_{t-1} + \epsilon^{sys|i}_t \tag{12}$$

The predicted values from the quantile regression correspond to the VaR and $CoVaR$ of bank i at time t as follows:

$$VaR^i_t(q) = \hat{\alpha}^i_q + \hat{\gamma}^i_q M_{t-1} \tag{13}$$

$$CoVaR^i_t(q) = \hat{\alpha}^{sys|i} + \hat{\beta}^{sys|i} VaR^i_t(q) + \hat{\gamma}^{sys|i} M_{t-1} \tag{14}$$

$$\implies \Delta CoVaR^i_t(q) = CoVaR^i_t(q) - CoVaR^i_t(50\%) \tag{15}$$

$$= \hat{\beta}^{sys|i} (VaR^i_t(q) - VaR^i_t(50\%)) \tag{16}$$

The systematic state variables are conditioning variables that shift the conditional mean and volatility of the risk measure, where different firms loads on them in different directions.

5 Dataset

The dataset is composed by quarterly observation of balance sheet characteristics on all **listed** Italian banks as 2019Q1, for a total of **18 institutions (16 banks + 2 insurance company)**, ranging from **1998Q1 to 2019Q1**, taken from *Thomson Reuters Datastream* software. By focusing only on listed banks we are still able to capture the entire system since they are the biggest by market capitalization and represent 85% of the domestic bank market[6]. In particular, the balance sheet characteristics include total assets, liabilities and shareholders equity for each institutions including some particular assets/liabilities-class such as loans, intangibles, long and short term debt, that will be used to construct several characteristics indicator.

Our variable of interest for institutions returns is the growth rate of weekly share price, since it is closely related to the market value of assets which is in turn related to the supply of credit of the real economy. The growth rate of share price X_t^i for bank i at time t is defined by:

$$X_t^i = \frac{\text{Share Price}_t^i - \text{Share Price}_{t-1}^i}{\text{Share Price}_{t-1}^i} \tag{17}$$

where each time period (time t) – (time $t-1$) is one week.

The state variables added to the model are:

- **FTSE MIB IVI**: the implied volatility of the FTSE MIB index anticipated on the derivative sector to account for the volatility in financial markets[7]

- **Liquidity Spread:** represent the short-term risk generated by a run to rise liquidity and is computed as the difference between the 3m Euribor rate and the 3m Italian Government bond yield

[6]"The Italian Banking Sector", *Banca Intesa Report, 2014*

[7]The 30-days IVI is available only from 2010; therefore we use estimated values for the period before by regressing it on the VDAX, the IVI for the DAX index - in which both shows strong correlations

- **3m Bond change:** the change in the 3m Italian Government bond yield
- **Term spread:** computed as the yield spread between the 10y and 3m Italian Government bond yield to account for possible business cycles
- **ITA-DEU Spread:** the spread between the yield of the 10y German Government bond and 10y Italian Government bond, a "default-risk" indicator that became popular in the last years for agents of financial markets
- **Credit Spread:** the change in the 10y BAA-rated European Corporate Bond and the 10y Italian Government bond - captures the extent to which a risk premium could be generated by investing in the private sector rather than the public one
- **Market Return**: computed as the weekly percentage returns on the FTSE MIB index
- **Real Estate Excess Returns:** computed as the excess return of the FTSE MIB Real Estate index over the FTSE MIB index[8], to account for possible effects on the housing market, given that institutions are exposed directly to it either through investments or indirectly with collaterals

6 Results

6.1 Unconditional estimation

We start by computing the **unconditional** VaR and $\Delta CoVaR$ of each bank using the full sample. We drop institutions with less than 250 observation for the variable X^i (around

[8]The FTSE RE is available only from the 2010 - hence a regression of it over the FTSE MIB was performed, showing strong correlaction, to predict the values over the entire time range

Table 1: **Summary statistics for the state variables**

Variable	Mean	Std. Dev.	Min	Max
FTSE IVI	26.89	5.49	12.52	54.14
Liquidity Spread	-3.5	84.9	-675.1	220.1
3m Bond change	-0.57	23.2	-313.6	283.2
Term spread	205.8	117.9	-91.5	547.7
ITA-DEU Spread	110.7	109.9	6.3	528
Credit Spread	8.79	115.6	-217.6	459
Market return	0.04	3.23	-21.7	21.6
Real Estate Excess	0.009	2.62	19.01	45.98

The spreads and spread changes are expressed in weekly basis points (highlighted in grey), and returns are in weekly percent

5 years). Figure (1) plots them for the full period of interest. While the reported measures **do not take into account information that comes from other financial variables** and assume each bank risk's contribution is constant over time, they are informative on the relationship between VaR and $\Delta CoVaR$. The scatter plot shows the positive but **highly weak relationship** between the two: hence a regulator that relies only on the VaR measure might **over/under estimates systemic risk contribution**

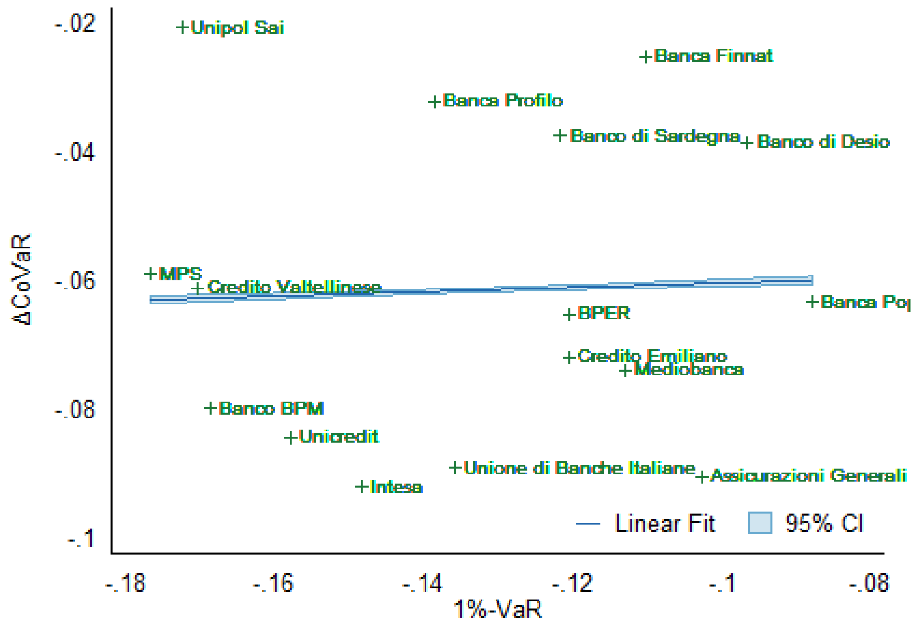


Figure 1: **Scatter plot between the 1%-$\boldsymbol{VaR^i}$ and $\Delta CoVaR^i$ of institution i reported in weekly percent returns**. 1%-VaR^i is the 1% quantile of firm returns, and $\Delta CoVaR^i$ gives the percentage point change in the financial 1%-VaR when a particular institution realizes its own 1%-VaR^i

6.2 Time-varying estimation

We proceed to the next step by computing the time-varying VaR and $\Delta CoVaR$ estimating the predicted value for the 1% and 5% quantile of the regressions (13), (14). The complete output of those regression are reported in Appendix[9]; Table (2) shows the average significance of the coefficients for the 1%-VaR and 1%-$CoVaR$ regressions, computed as the fraction of the banks in the sample, over the total, on which the explanatory variable is statistically significant at least at the 10% level. At the bank level, most of the VaR_t^i variation is driven on average by the spread between Italian and German government bonds, the credit spread and the market return in the FTSE MIB,

[9]The output of the quantile regressions are reported in the Appendix in Table (11)-(14)

while at the system level most of the $CoVaR_t^i$ variation is driven by the volatility in the FTSE MIB, the market return, the liquidity and credit spread, and the excess returns on the housing market. As expected, a strong determinant of the system VaR is also the event of one bank being in distress.

Table 2: **Average significance of state variables expsosure and effect for the 1%-VaR and 1%-$CoVaR$ regressions**

Variables	Relevance (%)		
	VaR_t^i	$CoVaR_t^i$	Effect on risk
FTSE IVI	25	88	Increase
Liquidity Spread	13	81	Increase
3m Bond Change	25	13	Not defined
Term Spread	25	25	Decrease
ITA-DEU Spread	88	25	Increase
Credit Spread	63	88	Increase
Market return	56	81	Decrease
Real Estate Return	19	75	Decrease
Bank Return	-	63	Decrease
Constant	25	31	

Relevance stands for the overall significance of the coefficients of the model: it is computed as the fraction of the banks in the sample, over the total, on which the explanatory variable is statistically significant at least at the 10% level

A higher FTSE IVI, liquidity spread, Italian-German government bond yield spread, credit spread tend to be associated with more negative risk measure. In addition, lower term spread, market returns, real estate and bank returns are associated with larger risk. Interestingly, the 3m Italian bond change seems not to be relevant for measure of risk and its effect on risk varies differently with respect to the bank considered. Overall, the average significance of the conditioning variables shows that they proxy for time variation in quantiles and particularly in $CoVaR$.

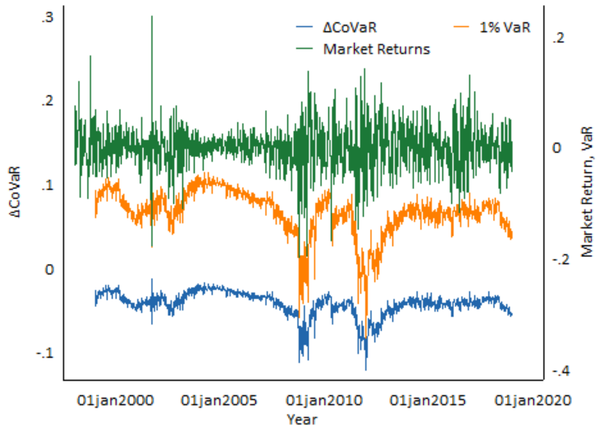


Figure 2: **Time-series evolution of the average returns of institutions of the sample (in green), the average** 1%-VaR **(in orange), the average** 1%-$\Delta CoVaR$**.** All risk measures are in percent weekly returns.

As visible from Figure (2), in the time series dimension, the average 1%-VaR and its related $\Delta CoVaR$ shows a strict relation in their evolution: a way to interpret $\Delta CoVaRs$ is by viewing them as **cross sectional allocation of system wide risk to the various institutions**. On average, $\Delta CoVaR$ is lower in magnitude than the VaR counterpart and less volatile: it is a first possible signal of the over/under estimation of isolated risk taking into account the VaR. Summary statistics for the estimated risk measure at the 1%-quantile are reported in Table (3).

Table 3: **Summary statistics for the estimated risk measures.**

Variable ($\times$100)	Obs.	Mean	Std. Dev.	Min	Max
Bank returns X^i	17,340	0,03	5,63	-68,59	233,70
1%-Var_t^i	16,976	-11,84	6,39	-79,78	2,65
1%-Var_t^{system}	1,061	-9,29	3,93	-31,66	-2,21
1%-$\Delta CoVaR_t^i$	16,976	-4,21	2,89	-25,97	1,93

All quantities are expressed in units of weekly percent returns

In Table (4) we report the estimated risk contribution for each individual institution. The $q\%$-$\Delta CoVaR$ measure indeed how much bank i adds to the system VaR when that bank i moves from its median state to its $q\%$-VaR level. As an example, the 1%-$\Delta CoVaR^{sys|BPER} = -5,12\%$ indicates that BPER adds $5,12\%$ to the system 1%-VaR when its moves from the median state to a distress situation.

Table 4: **Contribution to systemic risk by Italian banks when in distress situation.**

	$1\% - \Delta CoVaR^{sys\|Bank}$				$5\% - \Delta CoVaR^{sys\|Bank}$				
Banks	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	SIFI
Assicurazioni Gen.	-5,80	2,08	-18,43	0,79	-4,78	1,96	-16,02	-0,11	
BPER	-5,26	2,22	-16,20	0,28	-3,49	1,69	-13,14	0,01	
Banca Finnat	-1,39	0,40	-3,75	0,08	-0,94	0,21	-2,14	-0,53	
Banca Popolare	-5,14	1,70	-16,21	-0,25	-3,20	1,05	-8,69	-1,80	
Banca Profilo	-1,06	0,43	-3,35	-0,23	-0,46	0,14	-1,26	0,04	
Banco BPM	-5,09	2,17	-15,11	-1,24	-3,80	1,43	-11,01	-1,22	
Banco di Desio	-1,93	0,59	-6,56	-0,22	-2,24	0,48	-5,59	-0,79	
Banco di Sardeg.	-3,54	1,46	-11,48	-0,60	-1,50	0,60	-4,83	-0,17	
Credito Emiliano	-5,26	2,25	-20,72	1,93	-3,62	1,58	-13,58	-0,77	
Credito Valtell.	-1,64	1,01	-7,88	0,39	-2,42	1,13	-7,06	-0,35	
Intesa	-6,68	3,05	-23,15	1,40	-5,01	2,38	-17,80	-0,31	✓
MPS	-3,87	1,84	-16,83	-1,01	-3,32	0,83	-7,53	-0,36	✓
Mediobanca	-5,59	1,60	-15,36	-0,25	-4,81	1,25	-11,00	-1,71	
Unicredit	-5,43	2,54	-25,97	-1,09	-4,54	1,84	-16,10	-1,89	✓
Unione di Banche	-7,06	2,47	-18,08	0,62	-4,80	1,73	-13,31	-1,80	
Unipol Sai	-0,60	0,25	-1,29	-0,11	-1,59	0,48	-3,60	-0,62	

All quantities are expressed in units of weekly percent returns

The relative most systemic risk contributors banks are, on average, **Generali, BPM, Credito Emiliano, Intesa, Unicredit, Mediobanca, UBI**. It is interesting to notice that only 2 of them - Intesa and Unicredit - are reported as systemic by the *Financial Stability Board's* **SIFI** as of 2018[10]. By the same reasoning, banks such Mediobanca, UBI, BPER should be indexed as SIFI as well.

[10]The *Systemically Important Financial Institutions* index elaborated by the FBS is a regulatory response to the financial crisis of the 2008 that require the indexed banks to respect stricter capital and liquidity requirements

By reversing the directionality of the study, i.e. computing the 1%-$\Delta CoVaR^{Bank|sys}$, we are able to compute the so called *Exposure*-$\Delta CoVaR$, which capture the extent to which institutions are most at risk in the case of a systemic financial crisis. Infact, it reports the increase in the VaR of institution i conditional on the system being at its VaR level, i.e. in a distress situation. Such measures are reported in Table (5).

Table 5: **Increase in Italian bank's VaR in the case of a financial crisis**

	1%-$\Delta CoVaR^{Bank\|sys}$				5%-$\Delta CoVaR^{Bank\|sys}$			
Banks	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Assicurazioni Gen.	-5,65	2,78	-20,13	-1,53	-4,05	1,90	-17,56	-1,53
BPER	-5,57	2,44	-19,43	-0,39	-3,83	1,73	-13,51	-0,81
Banca Finnat	-5,58	2,46	-19,33	-0,56	-3,83	1,71	-13,36	-0,72
Banca Popolare	-4,52	1,99	-15,52	-0,40	-3,11	1,37	-11,00	-0,42
Banca Profilo	-6,80	2,98	-23,59	-0,47	-4,68	2,08	-15,86	-0,81
Banco BPM	-11,14	4,83	-39,10	0,07	-7,72	3,31	-25,61	-1,77
Banco di Desio	-3,06	1,34	-10,51	-0,31	-2,10	0,93	-7,45	-0,36
Banco di Sardeg.	-3,37	1,48	-11,59	-0,32	-2,31	1,03	-8,19	-0,41
Credito Emiliano	-9,78	4,22	-33,25	-0,84	-6,75	3,05	-22,99	-1,24
Credito Valtell.	-5,18	2,27	-17,84	-0,52	-3,55	1,57	-12,77	-0,52
Intesa	-8,69	3,16	-29,67	-0,73	-5,98	2,47	-20,04	-2,49
MPS	-8,68	3,98	-31,98	2,16	-5,87	2,73	-20,34	-1,02
Mediobanca	-8,92	3,91	-30,72	-0,65	-6,15	2,85	-23,87	-0,87
Unicredit	-10,89	4,78	-37,30	0,18	-7,44	3,38	-29,79	-0,84
Unione di Banche	-12,38	5,43	-43,41	-0,65	-8,38	3,77	-30,24	-1,27
Unipol Sai	-4,92	2,14	-16,91	-0,40	-3,32	1,50	-11,93	-0,50

All quantities are expressed in units of weekly percent returns

As an example, the 1%-$\Delta CoVaR^{BPER|sys} = -5,74\%$ indicates that the system adds $5,74\%$ to the BPER 1%-VaR when its moves from the median state to a distress situation.

As visible, the banks that might be relatively more vulnerable in the case of a financial crisis are **UBI, Unicredit, Credito Emiliano, MPS, Banco BPM**. This could be relevant in order to tailor policy tools to protect such banks in the case of potentially dangerous systemic events.

6.3 *Forward-Δ CoVaR*

In this section we will try to understand which are good predictors of systemic risk contribution at the bank level; we perform a pooled OLS regression of $\Delta CoVaR$ over several balance sheet characteristics and then present out of sample test. Moreover, doing so let us address a key issue of systemic risk regulation: measurament accuracy. Infact, risk measures analyse tail events of particular returns distribution that tend to be tend to be rarely observed at high frequencies. Hence, they might be imprecise by nature. By relating $\Delta CoVaR$ with more robust and easy-to-observe characteristics of institutions, such as balance sheet items, allows for a more precise inference of $\Delta CoVaR$. The predicted value of the regression with different lags will provide us the forward looking forecast of $\Delta CoVaR$ at different horizons; the so-called *Forward*-$\Delta CoVaR$.

We will use the following set of characteristics, measured at the quarterly-level - since it is the highest frequency available for balance sheet items:

- **Leverage:** measure the degree of debt recursion of an institution, defined as $\frac{\text{Total Asset}}{\text{Total Equity}}$
- **Maturity mismatch:** an indicator for the liquidity position of an institution[11], defined as $\frac{\text{Short-term debt}}{\text{Total debt}}$
- **Size:** defined as the log of total book equity
- **Market-to-book ratio:** defined as the ratio of the market to the book value of total equity, useful to capture the agents' valuation of a particular institution

[11] A maturity mismatch is a financial situation of an institution or firm in which assets held to meet future liabilities are not aligned in terms of maturity/expiration time. When there is a maturity mismatch, a liquidity squeeze could arise: for example, the mismatch between the maturities of banks' deposits and loans makes banks susceptible to bank runs where long-term loans are not available to repay debtors.

- **Equity return volatility:** computed as the variance of weekly equity return within each quarter for each bank

- **Market β:** computed as the covariance of the bank's return with the market returns over the variance of the market returns

Table 6: **Summary statistics for the quarterly balance sheet characteristics of Italian banks used in the** *Forward*-$\Delta CoVaR$ **regression**

Variable	Obs	Mean	Std. Dev.	Min	Max
Leverage (%)	17,300	15,58	0,07	1,08	80,00
Maturity Mismatch (%)	16,778	17,88	0,13	0,00	76,00
Log Equity	17,300	14,71	1,73	8,90	17,98
Volatility (%)	17,368	0,32	0,01	0,00	50,86
Market β	17,824	0,80	0,26	0,36	1,28
Market-to-book	17,018	1,28	0,94	0,07	9,83

We generate a quarterly measure of $\Delta CoVaR$ by summing its weekly measure inside each quarter (this is possible since $\Delta CoVaR$ is by construction a yield measure that can be capitalized) to relate it to the above quarterly-characteristics.

We regress the 1%-$\Delta CoVaR$ and the 5%-$\Delta CoVaR$ on the 1 quarter, 1 year and 2 year lagged bank characteristics in-sample until 2018. In the regression are added as independend variable also: the lagged VaR - given that there is a weak but still positive relation with $\Delta CoVaR$ both in a cross-sectional and time-series dimension; the lagged $\Delta CoVaR$ - to check for persistance. Results are presented in Table (7).

Almost all the explanatory variable are **significant at the** 1% **level**, showing **consistence in the sign** both in the different lagged periods and when changing the quantile of the $\Delta CoVaR$. The coefficients have to be interpreted as different sensitivities of $\Delta CoVaR$ with respect to the examined characteristics.

Table 7: $\Delta CoVaR^i$ **Forecasts for all Italian institutions in the dataset**. The table reports the coefficient from the forecasting regression of $\Delta CoVaR^i$ at the 1% and 5% quantile level. All regressions include time effects.

	Panel A: 1%-$\Delta CoVaR$			Panel B: 5%-$\Delta CoVaR$		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Variables	1 Quarter	1 Year	2 Years	1 Quarter	1 Year	2 Years
Leverage	0.01932*	-0.00530	-0.04840**	0.04227***	0.07430***	0.04179**
	(0.011)	(0.020)	(0.024)	(0.008)	(0.014)	(0.017)
Maturity Mismatch	-0.07800***	-0.29356***	-0.39909***	-0.03701***	-0.11666***	-0.13143***
	(0.006)	(0.012)	(0.015)	(0.005)	(0.008)	(0.010)
Log Book Equity	-0.00954***	-0.03662***	-0.05213***	-0.00720***	-0.02533***	-0.03334***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Market β	-0.01230**	-0.05806***	-0.12512***	-0.03733***	-0.15417***	-0.26949***
	(0.005)	(0.010)	(0.012)	(0.004)	(0.007)	(0.009)
Market-to-book	-0.00199**	-0.00492***	-0.00646***	-0.00386***	-0.01415***	-0.02273***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Volatility	0.50154***	1.81617***	2.70845***	0.52548***	2.07192***	3.18110***
	(0.056)	(0.105)	(0.129)	(0.050)	(0.090)	(0.107)
$\Delta CoVaR$	0.91336***	0.66005***	0.46943***	0.88271***	0.53282***	0.28052***
	(0.004)	(0.007)	(0.009)	(0.006)	(0.010)	(0.012)
VaR	-0.00756***	-0.03950***	-0.07145***	-0.01325***	-0.03810***	-0.06948***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.006)	(0.007)
Constant	0.08362***	0.31883***	0.43670***	0.05857***	0.20794***	0.25863***
	(0.012)	(0.023)	(0.028)	(0.009)	(0.017)	(0.019)
Observations	15,498	14,922	14,154	15,498	14,922	14,154
R-squared	0.933	0.775	0.686	0.929	0.784	0.722

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Institutions with higher maturity mismatch, larger size, market β, market-to-book ratio and VaR are associated with **larger** systemic risk contribution one quarter, one year and two year later both at the 1% and 5% level. Instead, **higher** market return, volatility and leverage **reduce** contribution to systemic risk. The size-only approach usually discussed, famouse for the debate on the *"too big too fail institutions"* fails to recognize all the other predictors of systemic risk contribution.

The $\Delta CoVaR$ coefficient is significantly different from zero, meaning that **risky**

banks tends to stay risky and the significant negative coefficient for VaR means that banks that increase their exposure tends to increase systemic risk contribution at different future lags.

As an example, an increase in the maturity mismatch forecast - from 10% to 11% - at the one-quarter horizon implies an increase of systemic risk contribution of 7.8%: for a bank with €1 billion of total asset this imply €4ì78 millions of risk contribution.

We expand the set of available characteristics to more typical balance sheet items of banks, both on the assets and liabilities side. By doing so we drop the two insurance companies of the dataset. The new characteristics are:

- **Loans:** all the active loans of the banks excluded the non-performing ones
- **Non-performing loans:** loans on which the repayment is considered to be unlikely - usually they are expired since 90 days and represent one of the main component of risk in the bank's business
- **Intangible assets:** assets that lack physical substance, such as patents, goodwill, trademark, franchises
- **Deposits (excl. DD):** deposits such as money market accounts, saving accounts, time and call deposits
- **Demand deposits:** The most common form of deposits, the standard checking accounts

Table 8: $\Delta CoVaR^i$ **Forecasts for all Italian banks with added bank characteristics**. The table reports the coefficient from the forecasting regression of $\Delta CoVaR^i$ at the 1% and 5% quantile level. All regressions include time effects.

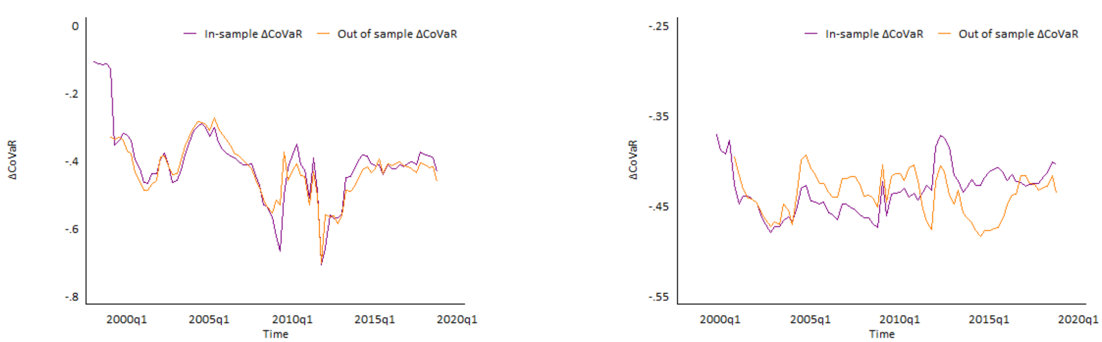
	Panel A: 1%-$\Delta CoVaR$			Panel B: 5%-$\Delta CoVaR$		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Variables	1 Quarter	1 Year	2 Years	1 Quarter	1 Year	2 Years
Leverage	0.00766	-0.12837***	-0.29087***	0.04548***	0.01465	-0.13183***
	(0.014)	(0.026)	(0.031)	(0.010)	(0.018)	(0.020)
Maturity Mismatch	-0.10216***	-0.40960***	-0.61265***	-0.03839***	-0.15713***	-0.21212***
	(0.011)	(0.020)	(0.024)	(0.008)	(0.013)	(0.015)
Log Book Equity	-0.00985***	-0.04233***	-0.06885***	-0.00548***	-0.02685***	-0.04437***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
Market β	-0.00780	-0.00103	0.02223	-0.04648***	-0.14935***	-0.19629***
	(0.007)	(0.013)	(0.016)	(0.005)	(0.009)	(0.011)
Market-to-book	-0.00194	-0.01445***	-0.03698***	0.00002	-0.00722***	-0.02974***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Volatility	0.67771***	2.81297***	3.50021***	0.98572***	4.66488***	6.52531***
	(0.095)	(0.174)	(0.206)	(0.095)	(0.165)	(0.185)
$\Delta CoVaR$	0.90956***	0.64082***	0.44233***	0.85489***	0.36608***	0.06683***
	(0.004)	(0.008)	(0.010)	(0.009)	(0.015)	(0.017)
VaR	-0.01073***	-0.06044***	-0.10810***	-0.00715	0.01074	-0.01884**
	(0.002)	(0.004)	(0.004)	(0.005)	(0.008)	(0.009)
Loans (excl. NPL)	-0.00639	0.00791	-0.12163***	0.01725*	0.11687***	0.10519***
	(0.013)	(0.024)	(0.029)	(0.010)	(0.017)	(0.019)
Non-performing loans	-0.12041***	-0.65102***	-0.95151***	-0.11205***	-0.41633***	-0.57359***
	(0.025)	(0.049)	(0.063)	(0.018)	(0.034)	(0.040)
Intangible Assets	-0.30361***	-2.08990***	-3.80145***	-0.15112**	-1.36236***	-2.87774***
	(0.100)	(0.185)	(0.221)	(0.072)	(0.127)	(0.144)
Deposits (excl. DD)	-0.01980	-0.04481	-0.01652	0.02090	0.12093***	0.28390***
	(0.018)	(0.033)	(0.039)	(0.013)	(0.023)	(0.026)
Demand Deposits	0.04746**	0.19142***	0.27909***	0.02394*	0.08198***	0.04967*
	(0.019)	(0.035)	(0.043)	(0.014)	(0.024)	(0.028)
Constant	0.08478***	0.34010***	0.66384***	-0.00595	0.00559	0.11360***
	(0.020)	(0.036)	(0.043)	(0.014)	(0.024)	(0.028)
Observations	12,698	12,266	11,690	12,698	12,266	11,690
R-squared	0.920	0.745	0.664	0.918	0.767	0.726

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As showed in Table (8) the assets items of the balance sheet all are good predictors of systemic risk and tend to increase their contribution: this could be because, for example, an increase in loans volumes is equivalent to an increase in the exposures of a bank that might be subject to defaulting. Conditioning on non-performing loans, we see that they are the true driver of systemic risk in the loan asset-class, being the more prone to default thus generating risk: this is a significant results given the high levels of NPL in Italian banks. On the liabilities side, deposits decrease systemic risk contribution (expecially the demand deposits type) since they are more stable resource of funding with respect to debt.

Out-of-sample *Forward*-$\Delta CoVaR$

The above regression were run in-sample until 2018. We re-perform the regression now using the entire time span of the dataset and proceed to compare the in-sample and ou-of-sample predicted value of *Forward*-$\Delta CoVaR$ at different periods. As visible from Figure (3), the out of sample estimates replicates reasonably well the in sample one, with an expected decrease in accuracy when the time horizon of forecasting increase, showing the good predictive power of the *Forward*-$\Delta CoVaR$.



(a) **Average** 5%-$\Delta CoVaR$ **estimates in and out of sample for 1 quarter lag.**

(b) **Average** 5%-$\Delta CoVaR$ **estimates in and out of sample for 2 year lag.**

Figure 3: **Comparison between in-sample and out of sample predicted values of the** *Forward*-$\Delta CoVaR$ **regressions at different time horizons.** Measures are in quarterly percent returns.

Moreover, by comparing the realized quarterly average $\Delta CoVaR$ with the two-year average *Forward*-$\Delta CoVaR$ as in Figure (4), we notice that the two measures shows negative correlation, expecially from 2008. When the *contemporaneous* $\Delta CoVaR$ - is small - the realized systemic risk contribution is low - the *Forward*-$\Delta CoVaR$ is large (in absolute value) - the future systemic risk contribution is high. This result captures the idea that systemic risk build-up in the background during time of lower volatility; therefore policies based on that measure are countercyclical. This allows us to solve the procyclicality "issue" where regulation based in contemporaneous risk measures tends to be excessively tight after adverse events and loose in period of stability, amplifying the impact of a crisis and indirectly enhancing risk taking in normal conditions[12].

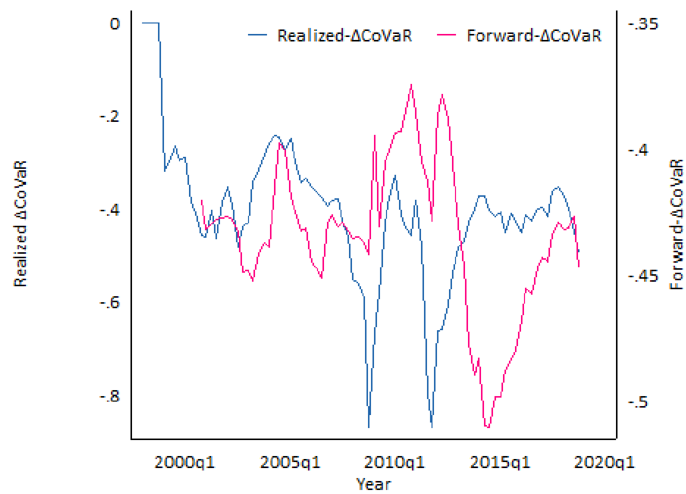


Figure 4: **Two year** 5% *Forward*-$\Delta CoVaR$ **comparison with contemporaneous** 5% $-\Delta CoVaR$**.** The graph shows the average 2-year forward and contemporaneous $\Delta CoVaR$ computed at the 5% quantile level. Measures are in quarterly percent returns. The *Forward*-$\Delta CoVaR$ at any given date uses the data available at that time to predict $\Delta CoVaR$ two years in the future.

In another test to evalute the performance of the *Forward*-$\Delta CoVaR$, we use it to

[12]Studies on the procyclicality of capital regulation can be found in *Estrella (2004), Kashyap and Stein (2004)*

forecast the cross section of a measure of realized systemic risk contribution: as a proxy, we compute covariances of financial institutions returns with the system return during the financial crisis (2007Q1-2009Q1). We regress the *Forward*-$\Delta CoVaR$ with data as of 2006Q4 at different time horizons over the crisis covariance: as a result, the 2-year *Forward*-$\Delta CoVaR$ is able to explain over 50% of the cross sectional covariance in the next two years, during the crisis, proving strong predictive power. By changing the horizon of prediction, with the 1-year or 1-quarter *Forward*-$\Delta CoVaR$, coefficients slightly change as well as the R-squared, but still showing robust results; the 2-year *Forward*-$\Delta CoVaR$ seems to be the strongest predictor of the future crisis covariance. Morover, by adding to the 2-year *Forward*-$\Delta CoVaR$ regressions lagged balance sheet characteristics the R-squared does not change (and two out of three coefficients are not significant), meaning that the *Forward*-$\Delta CoVaR$ is already able to capture balance sheet characteristics effects on systemic risk contribution.

Table 9: $\Delta CoVaR$ **forecasts during the financial crisis.** The table reports a regression of the realized crisis covariance during the 2007Q1-2009Q1 (estimated from weekly data) on the *Forward*-$\Delta CoVaR$ as of 2006Q4.

	(1)	(2)	(3)	(4)
Variables	Covariance during the crisis			
2Y Forward CoVaR	-0.214***			
1Y Forward CoVaR		-0.055***		
1Q Forward CoVaR			-0.054***	
Maturity Mismatch				-0.0002
Leverage				-0.0005***
Log Book Equity				-0.00002
Observation	1,443	1,443	1,443	1,443
R-squared	53,66%	42,75%	45,59%	53.89%

7 Conclusion

During financial crisis, tail events tend to **spill across institutions**. With the $\Delta CoVaR$ model, that is built to measure systemic risk, we are able to capture these effects. In this thesis we estimate the contribution to systemic risk of Italian listed banks for the period 1999-2019, identifying both the *riskier* banks and the most exposed to bad financial shocks. Moreover, we find that the informations contained in $\Delta CoVaR$ are different from those contained in the VaR, hence regulators should take it into account to monitor the systemic risk posed by banks.

Recent policy debate has been developed around the danger posed by large banks. By relating $\Delta CoVaR$ to institutions' characteristics we **identified what are good predictors of systemic risk** other than size: balance sheet items such as leverage, NPL, market β, maturity mismatch. Therefore any financial regulation aimed only at limiting banks' size could not completely eliminate systemic risk. The regression coefficients roughly identifies the effects on systemic risk contribution of curbing one institution's characteristics. This makes the $\Delta CoVaR$ a useful tool for policy making and regulation.

Moreover, given that the conditional measures of systemic risk are time varying and affected by market-based risk factors, macro prudential regulation should also monitor informations provided by financial markets.

An interesting way to expand this work would be to compute the $\Delta CoVaR$s between each possible couple of banks, i.e. to compute the VaR of institution i when institution j is in distress ($i \neq j$), and viceversa. This would let us obtain the pairwise connection between each banks and with some specific Granger-causality tests it could be possible to capture a *network effect* between each institution by understanding which banks push the risk profile of its counterparties.

Another avenue of research could be to add additional macro variables to the returns when estimating the $CoVaR$. As already suggested by *Adrian and Brunnermeier (2016)* it could be possible to take into account variables which are presumed to explain stock returns as business cycle or investor sentiment.

Finally, from the predicted value of the $\Delta CoVaR$ regressions we constructed a forward looking measure of systemic risk, called *Forward*-$\Delta CoVaR$, that provides reliable forecasts of future systemic risk contribution at different time horizons. To test its performance, we find that it is able to explain half of the realized crisis covariance during the financial crisis.

Hence, we conclude that $\Delta CoVaR$ is a very useful and relevant policy tool for regulators that can estimate which factors are more relevant in terms of contribution to systemic risk, being able to access wider and more granular information set.

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Appendix

Table 10: **Full list of Italian financial institutions in the sample with their average returns, average unconditional** 1%-VaR **and** 1%-$\Delta CoVaR$ **(constant in time) and average conditional/time-varying** 1%-VaR **and** 1%-$\Delta CoVaR$**.**

Banks	Returns	Uncond. 1%-VaR	Uncond. 1%-$\Delta CoVaR$	1%-VaR	1%-$\Delta CoVaR$
Assicurazioni Gen.	-0,01	-10,27	-9,03	-8,27	-5,80
BPER	0,04	-12,05	-6,52	-10,78	-5,26
Banca Finnat	0,01	-11,02	-2,52	-10,17	-1,39
Banca Popolare	0,06	-8,80	-6,33	-8,18	-5,14
Banca Profilo	-0,25	-13,86	-3,22	-11,79	-1,06
Banco BPM	0,14	-16,87	-7,98	-12,60	-5,09
Banco di Desio	0,06	-9,66	-3,86	-8,19	-1,93
Banco di Sardeg.	0,06	-12,17	-3,75	-8,85	-3,54
Credito Emiliano	0,15	-12,05	-7,19	-11,20	-5,26
Credito Valtell.	-0,05	-17,03	-6,11	-14,53	-1,64
Intesa	0,05	-14,84	-9,20	-11,94	-6,68
MPS	-0,40	-17,67	-5,90	-15,65	-3,87
Mediobanca	0,14	-11,29	-7,38	-10,83	-5,59
Unicredit	-0,07	-15,79	-8,43	-12,14	-5,43
Unione di Banche	0,00	-13,59	-8,90	-11,77	-7,06
Unipol Sai	0,25	-17,24	-2,07	-11,85	-0,60

All quantities are expressed in units of weekly percent returns

Table 11: 1%-VaR **quantile regression output.** The Table shows the coefficients from the quantile regression

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

at the 1% level, i.e. the quantile regression of each financial institutions returns over the one-week lagged state variables. The predicted value of the quantile regression correspond to the 1%-VaR of institution i at time t as follows:

$$VaR_t^i(1\%) = \hat{\alpha}_{1\%}^i + \hat{\gamma}_{1\%}^i M_{t-1}$$

Lagged Variables	(1) Assicurazioni Gen.	(2) BPER	(3) Banca Finnat	(4) Banca Popolare	(5) Banca Profilo	(6) Banco BPM	(7) Banco di Desio	(8) Banco di Sardeg.	(9) Credito Emiliano	(10) Credito Valtell.	(11) Intesa	(12) MPS	(13) Mediobanca	(14) Unicredit	(15) Unione di Banche	(16) Unipol Sai
FTSE IVI	-0.00144***	-0.00045	-0.00085	-0.00036	-0.00202***	0.00160	-0.00090	-0.00053	-0.00195	-0.00055	-0.00361***	-0.00210	-0.00209	-0.00297**	0.00153	-0.00438
	(0.000)	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.007)	(0.001)	(0.005)	(0.002)	(0.001)	(0.001)	(0.003)
Liquidity Spread	-0.00126	-0.01167	-0.01801	-0.01064***	-0.02616**	-0.01080	-0.01435	-0.00871	0.00152	-0.01225	-0.00861	-0.02720	-0.00748	-0.00486	-0.01377	-0.02009
	(0.010)	(0.011)	(0.013)	(0.003)	(0.012)	(0.014)	(0.010)	(0.013)	(0.015)	(0.047)	(0.008)	(0.037)	(0.011)	(0.010)	(0.009)	(0.020)
3m Bond Change	0.02123	-0.03773	0.02299	-0.02045**	0.06057*	0.02217	0.04742	-0.01174	0.06381	0.11165	0.02752	0.08337	-0.01897	0.07338**	-0.03990*	-0.05449
	(0.028)	(0.033)	(0.037)	(0.009)	(0.036)	(0.042)	(0.030)	(0.037)	(0.045)	(0.136)	(0.023)	(0.108)	(0.031)	(0.029)	(0.024)	(0.059)
Term Spread	0.00417	0.00135	0.02428*	0.00780**	0.02592*	0.01935	0.01790	0.00102	-0.00299	0.02632	0.00338	0.03239	0.00398	0.01742	-0.01634*	0.01538
	(0.011)	(0.013)	(0.014)	(0.003)	(0.014)	(0.016)	(0.012)	(0.014)	(0.017)	(0.052)	(0.009)	(0.042)	(0.012)	(0.011)	(0.010)	(0.023)
ITA-DEU Spread	-0.02126*	-0.03871***	-0.01421	-0.03329***	-0.04105***	-0.09157***	-0.02960**	-0.03167**	-0.02011	-0.08828*	-0.03350***	-0.09536**	-0.02269*	-0.06959***	-0.01937*	-0.08971***
	(0.011)	(0.013)	(0.014)	(0.003)	(0.014)	(0.016)	(0.012)	(0.014)	(0.018)	(0.053)	(0.009)	(0.042)	(0.012)	(0.011)	(0.010)	(0.023)
Credit Spread	-0.01475*	0.00324	-0.00166	-0.00937***	-0.03260***	-0.04481***	-0.00651	-0.02795***	-0.03089**	0.01624	-0.03232***	0.01834	-0.01022	-0.03824***	-0.03177***	-0.03768**
	(0.008)	(0.009)	(0.010)	(0.002)	(0.010)	(0.012)	(0.008)	(0.010)	(0.013)	(0.038)	(0.006)	(0.031)	(0.009)	(0.008)	(0.007)	(0.017)
Market Return	0.47309**	0.44163*	0.47348*	0.19198***	0.58128**	0.15723	0.34855	0.49693*	0.80709**	0.36234	0.18226	0.06733	0.61088***	0.02702	0.41025**	0.25766
	(0.209)	(0.247)	(0.277)	(0.066)	(0.273)	(0.312)	(0.225)	(0.277)	(0.337)	(1.019)	(0.170)	(0.820)	(0.236)	(0.221)	(0.203)	(0.444)
Real Estate Return	0.18453	0.20189	0.32298	0.20901***	0.21811	-0.07988	0.02984	0.31579	0.34524	-0.43454	0.71028***	0.01443	0.20920	0.56984**	0.20962	-0.65729
	(0.243)	(0.288)	(0.322)	(0.077)	(0.315)	(0.363)	(0.261)	(0.322)	(0.392)	(1.186)	(0.198)	(0.945)	(0.275)	(0.257)	(0.203)	(0.517)
Constant	-0.02810	-0.05200	-0.11795**	-0.04983***	-0.07611	-0.11811**	-0.06214	-0.03896	-0.02913	-0.09305	0.01126	-0.08268	-0.03460	-0.00845	-0.09973***	0.04157
	(0.036)	(0.043)	(0.048)	(0.011)	(0.047)	(0.054)	(0.039)	(0.048)	(0.058)	(0.176)	(0.029)	(0.140)	(0.041)	(0.038)	(0.032)	(0.077)
Observations	1,061	1,061	1,061	1,061	1,032	1,061	1,061	1,061	1,061	1,061	1,061	1,036	1,061	1,061	826	1,061

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: 5%-VaR **quantile regression output.** The Table shows the coefficients from the quantile regression

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

at the 5% level, i.e. the quantile regression of each financial institutions returns over the one-week lagged state variables. The predicted value of the quantile regression correspond to the 5%-VaR of institution i at time t as follows:

$$VaR_t^i(5\%) = \hat{\alpha}_{1\%}^i + \hat{\gamma}_{1\%}^i M_{t-1}$$

Lagged Variables	(1) Assicurazioni Gen.	(2) BPER	(3) Banca Finnat	(4) Banca Popolare	(5) Banca Profilo	(6) Banco BPM	(7) Banco di Desio	(8) Banco di Sardeg.	(9) Credito Emiliano	(10) Credito Valtell.	(11) Intesa	(12) MPS	(13) Mediobanca	(14) Unicredit	(15) Unione di Banche	(16) Unipol Sai
FTSE IVI	-0.00152***	0.00041	-0.00113	-0.00014	-0.00096	0.00060	0.00042	-0.00113	-0.00185***	0.00166	-0.00302***	0.00002	-0.00043	-0.00090	-0.00001	-0.00197
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Liquidity Spread	0.00044	-0.01267***	-0.00175	-0.00386	-0.01443***	-0.01160	-0.00836**	-0.00541	-0.00878**	-0.01196	-0.00432	-0.01710**	-0.00352	-0.00710	-0.00902	0.00490
	(0.003)	(0.005)	(0.006)	(0.006)	(0.006)	(0.010)	(0.004)	(0.006)	(0.004)	(0.008)	(0.007)	(0.008)	(0.005)	(0.007)	(0.008)	(0.008)
3m Bond Change	0.00150	-0.01906	0.00103	-0.00550	0.00852	-0.03410	0.01872*	-0.03432**	0.01452	0.00384	0.02656	0.00221	-0.00973	-0.00351	-0.03151	0.01574
	(0.008)	(0.014)	(0.017)	(0.018)	(0.016)	(0.029)	(0.010)	(0.017)	(0.013)	(0.022)	(0.020)	(0.022)	(0.014)	(0.019)	(0.021)	(0.024)
Term Spread	0.00063	0.01129**	0.00903	0.00288	0.00023	0.01191	0.00859**	0.00810	0.00304	0.01193	0.00248	0.02086**	0.00385	0.01440*	0.00163	-0.00659
	(0.003)	(0.005)	(0.007)	(0.007)	(0.006)	(0.011)	(0.004)	(0.006)	(0.005)	(0.009)	(0.008)	(0.009)	(0.006)	(0.007)	(0.008)	(0.009)
ITA-DEU Spread	-0.01380***	-0.03955***	-0.00642	-0.02148***	-0.00802	-0.05234***	-0.01481***	-0.01903***	-0.01851***	-0.04255***	-0.02271***	-0.03776***	-0.01936***	-0.04226***	-0.03022***	-0.02714***
	(0.003)	(0.005)	(0.007)	(0.007)	(0.006)	(0.011)	(0.004)	(0.007)	(0.005)	(0.009)	(0.008)	(0.009)	(0.006)	(0.008)	(0.009)	(0.010)
Credit Spread	-0.01374***	-0.00328	-0.00180	-0.00462	-0.01449***	-0.02534***	-0.00548*	-0.01423***	-0.01950***	-0.00184	-0.01864***	-0.00363	-0.00794*	-0.02788***	-0.01172**	-0.02504***
	(0.002)	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.003)	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.007)
Market Return	0.32047***	0.16087	0.14917	0.06834	0.45485***	0.16686	0.23757***	0.31638**	0.29307***	0.14224	0.19058	0.39703**	0.27429**	0.11921	0.14566	0.33128*
	(0.064)	(0.102)	(0.130)	(0.134)	(0.122)	(0.218)	(0.077)	(0.125)	(0.096)	(0.169)	(0.149)	(0.167)	(0.108)	(0.145)	(0.176)	(0.183)
Real Estate Return	0.15904**	0.37571***	0.04474	-0.05306	0.19155	-0.03497	0.06861	0.14588	0.17931	0.02952	0.40857**	-0.01182	0.24936**	0.20256	0.00754	0.20623
	(0.074)	(0.119)	(0.151)	(0.156)	(0.140)	(0.254)	(0.089)	(0.146)	(0.112)	(0.196)	(0.173)	(0.192)	(0.126)	(0.169)	(0.176)	(0.213)
Constant	-0.00337	-0.05442***	-0.03997*	-0.03007	-0.04035*	-0.07384*	-0.07005***	-0.01684	-0.00322	-0.09756***	0.02233	-0.10499***	-0.04721**	-0.04445*	-0.04233	0.01960
	(0.011)	(0.018)	(0.022)	(0.023)	(0.021)	(0.038)	(0.013)	(0.022)	(0.017)	(0.029)	(0.026)	(0.029)	(0.019)	(0.025)	(0.028)	(0.032)
Observations	1,061	1,061	1,061	1,061	1,032	1,061	1,061	1,061	1,061	1,061	1,061	1,036	1,061	1,061	826	1,061

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: 1%-$CoVaR$ **quantile regression output.** The Table shows the coefficients from the quantile regression

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

at the 1% level, i.e. the quantile regression of the financial system returns over institution i asset return and the lagged state variables. To avoid endogeneity, we compute each time system returns without considering the bank onto which we condition. Thus we have n regression where n is the number of institution that compose the system[a]. The predicted value of the quantile regression correspond to the 1%-VaR of the financial system when institution i is in distress, the so-called $CoVaR_t^i$, as follows:

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Lagged Variables	Assicurazioni Gen.	BPER	Banca Finnat	Banca Popolare	Banca Profilo	Banco BPM	Banco di Desio	Banco di Sardeg.	Credito Emiliano	Credito Valtell.	Intesa	MPS	Mediobanca	Unicredit	Unione di Banche	Unipol Sai
Bank Return X^i	0.69254***	0.48814***	0.14047***	0.63636***	0.09425***	0.40558***	0.23831**	0.41079***	0.46902***	0.11611	0.54954***	0.24992***	0.50852***	0.44400***	0.60278***	0.05066
	(0.126)	(0.085)	(0.051)	(0.076)	(0.027)	(0.034)	(0.095)	(0.098)	(0.089)	(0.176)	(0.052)	(0.043)	(0.071)	(0.060)	(0.052)	(0.161)
FTSE IVI	-0.00149**	-0.00247***	-0.00221**	-0.00182***	-0.00140	-0.00203***	-0.00179	-0.00130*	-0.00196**	-0.00279***	-0.00148**	-0.00220**	-0.00048	-0.00100	-0.00100	-0.00204**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Liquidity Spread	-0.01242	0.00085	-0.00562	0.00847	0.00226	-0.00527	-0.00930	0.01072	0.00563	-0.00903	-0.00343	0.00053	-0.00643	-0.00296	0.00420*	-0.00794
	(0.008)	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)	(0.008)	(0.010)	(0.006)	(0.006)	(0.005)	(0.010)	(0.006)	(0.005)	(0.002)	(0.009)
3m Bond Change	0.03895*	-0.00958	0.02217	0.01069	0.00705	0.01545	0.00625	-0.00059	0.00376	0.02417	-0.02785	0.02768	0.00843	-0.00414	-0.01952**	0.05012
	(0.022)	(0.024)	(0.022)	(0.025)	(0.011)	(0.018)	(0.025)	(0.021)	(0.029)	(0.017)	(0.019)	(0.027)	(0.016)	(0.020)	(0.009)	(0.031)
Term Spread	0.01477*	0.00405	0.00772	0.00318	-0.00303	0.00815	0.01264***	0.00766*	0.01051	0.01450***	0.01209***	0.01146	-0.00112	0.00503	-0.00175	0.01237
	(0.008)	(0.008)	(0.006)	(0.009)	(0.008)	(0.008)	(0.004)	(0.005)	(0.007)	(0.005)	(0.003)	(0.012)	(0.007)	(0.005)	(0.004)	(0.011)
ITA-DEU Spread	-0.02818***	-0.02402***	-0.03255***	-0.01145	-0.01952***	-0.01401**	-0.03636***	-0.02119***	-0.00941	-0.03350***	-0.01294**	-0.02945***	-0.01862***	-0.00999**	-0.01296**	-0.03918***
	(0.008)	(0.008)	(0.007)	(0.009)	(0.007)	(0.006)	(0.005)	(0.006)	(0.010)	(0.006)	(0.006)	(0.009)	(0.006)	(0.004)	(0.005)	(0.011)
Credit Spread	-0.01225*	-0.02036***	-0.01968***	-0.01472***	-0.02186***	-0.00333	-0.02147***	-0.01814***	0.00028	-0.01678***	-0.00780**	-0.01662***	-0.02370***	-0.00687	-0.01126***	-0.02195***
	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.006)	(0.007)	(0.005)	(0.003)	(0.006)
Market Return	0.05871	0.25752***	0.33843***	0.15085	0.36549***	0.26741*	0.32567***	0.24355***	0.04858	0.38028***	-0.02664	0.27784**	0.00419	0.25919***	0.19638***	0.32765*
	(0.138)	(0.098)	(0.102)	(0.093)	(0.091)	(0.155)	(0.113)	(0.088)	(0.142)	(0.146)	(0.159)	(0.114)	(0.082)	(0.096)	(0.065)	(0.175)
Real Estate Return	0.26845	0.42471***	0.56887***	0.33407***	0.53428***	0.12965	0.55678***	0.37039***	0.21840	0.34641**	0.09527	0.38648***	0.08257	0.03910	0.33164*	0.61768***
	(0.164)	(0.150)	(0.160)	(0.083)	(0.113)	(0.147)	(0.187)	(0.096)	(0.201)	(0.149)	(0.131)	(0.140)	(0.126)	(0.076)	(0.172)	(0.202)
Constant	-0.03278**	0.01615	-0.00729	-0.01929	-0.02189	-0.00872	-0.01926	-0.04523***	-0.02864	-0.00433	-0.02908	-0.00925	-0.02540**	-0.02430**	-0.00408	-0.01951
	(0.016)	(0.018)	(0.019)	(0.017)	(0.023)	(0.015)	(0.033)	(0.009)	(0.025)	(0.018)	(0.019)	(0.022)	(0.011)	(0.011)	(0.018)	(0.017)
Observations	1,061	1,061	1,061	1,061	1,032	1,061	1,061	1,061	1,061	1,061	1,061	1,036	1,061	1,061	826	1,061

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] As an exaple, Column (1) represent the output of the regression of the system returns, without considering the contribution of *Assicurazioni Generali*, over *Assicurazioni Generali* returns and lagged state variables.

Table 14: 5%-$CoVaR$ **quantile regression output.** The Table shows the coefficients from the quantile regression

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

at the 5% level, i.e. the quantile regression of the financial system returns over institution i asset return and the lagged state variables. To avoid endogeneity, we compute each time system returns without considering the bank onto which we condition. Thus we have n regression where n is the number of institution that compose the system[a]. The predicted value of the quantile regression correspond to the 5%-VaR of the financial system when institution i is in distress, the so-called $CoVaR_t^i$, as follows:

$$CoVaR_t^i(5\%) = \hat{\alpha}_{5\%}^{sys|i} + \hat{\beta}_{5\%}^{sys|i} VaR_t^i(5\%) + \hat{\gamma}_{5\%}^{sys|i} M_{t-1}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Lagged Variables	Assicurazioni Gen.	BPER	Banca Finnat	Banca Popolare	Banca Profilo	Banco BPM	Banco di Desio	Banco di Sardeg.	Credito Emiliano	Credito Valtell.	Intesa	MPS	Mediobanca	Unicredit	Unione di Banche	Unipol Sai
Bank Return X^i	0.79546***	0.52307***	0.17123***	0.61928***	0.06819	0.44946***	0.39430***	0.30325***	0.53004***	0.34800***	0.60248***	0.34343***	0.64775***	0.54686***	0.62803***	0.23982*
	(0.069)	(0.032)	(0.040)	(0.043)	(0.084)	(0.024)	(0.073)	(0.045)	(0.045)	(0.068)	(0.030)	(0.081)	(0.031)	(0.042)	(0.039)	(0.133)
FTSE IVI	-0.00084	-0.00160***	-0.00167**	-0.00184***	-0.00198***	-0.00132***	-0.00116*	-0.00088***	-0.00128*	-0.00177***	-0.00038	-0.00103	-0.00100***	-0.00075*	-0.00068	-0.00091
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Liquidity Spread	-0.00577	0.00100	-0.00467	-0.00173	-0.00864	0.00017	-0.00285	-0.00087	-0.00307	0.00088	0.00203	-0.00304	-0.00291	0.00048	0.00084	-0.00040
	(0.005)	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.002)	(0.006)
3m Bond Change	0.00625	0.02953*	-0.00364	-0.00546	-0.01682	0.00745	-0.02538	-0.00487	-0.00832	-0.00148	-0.00267	0.01729	0.01534	-0.00258	-0.01283	0.02819
	(0.020)	(0.018)	(0.023)	(0.023)	(0.022)	(0.015)	(0.025)	(0.013)	(0.013)	(0.017)	(0.009)	(0.026)	(0.011)	(0.010)	(0.008)	(0.018)
Term Spread	0.00845***	0.00364	0.00416	0.00603	0.00496	0.00180	0.00787***	0.00559	0.00324	0.00401	0.00342	0.00371	0.00276	-0.00034	0.00228	0.00215
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
ITA-DEU Spread	-0.01654***	-0.01300***	-0.02587***	-0.01642***	-0.02227***	-0.00926***	-0.02759***	-0.02252***	-0.01169***	-0.01768***	-0.00282	-0.01811***	-0.01481***	-0.00569**	-0.01485***	-0.02006**
	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.006)	(0.004)	(0.003)	(0.003)	(0.008)
Credit Spread	-0.00696**	-0.01402**	-0.01595***	-0.01400***	-0.01264**	-0.00767**	-0.01760***	-0.01201**	-0.00471	-0.01322***	-0.00506*	-0.00990	-0.00958***	-0.00663***	-0.01240***	-0.01238*
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.006)	(0.003)	(0.004)	(0.003)	(0.006)	(0.003)	(0.002)	(0.002)	(0.007)
Market Return	-0.00146	0.13236**	0.17701**	0.13683	0.20252	0.14649*	0.21156***	0.10842	0.05921	0.12617	0.04230	0.19302**	-0.09003*	0.07164	0.07742	0.03718
	(0.059)	(0.062)	(0.073)	(0.105)	(0.154)	(0.079)	(0.062)	(0.067)	(0.077)	(0.080)	(0.054)	(0.096)	(0.049)	(0.059)	(0.056)	(0.110)
Real Estate Return	0.16042*	0.23516***	0.26327*	0.27834***	0.26926**	0.07486	0.36636***	0.10166	0.08188	0.18635	-0.05756	0.21656	-0.02648	0.05825	0.03983	0.12157
	(0.094)	(0.091)	(0.142)	(0.098)	(0.128)	(0.084)	(0.099)	(0.102)	(0.111)	(0.115)	(0.042)	(0.134)	(0.075)	(0.050)	(0.104)	(0.223)
Constant	-0.02180	0.00289	0.00575	0.00312	0.00901	-0.00037	-0.01433	-0.02003	-0.00505	0.00985	-0.03307***	-0.00588	-0.00270	-0.00524	-0.00611	-0.01082
	(0.014)	(0.011)	(0.019)	(0.011)	(0.021)	(0.012)	(0.018)	(0.012)	(0.019)	(0.012)	(0.010)	(0.016)	(0.008)	(0.011)	(0.010)	(0.019)
Observations	1,061	1,061	1,061	1,061	1,032	1,061	1,061	1,061	1,061	1,061	1,061	1,036	1,061	1,061	826	1,061

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] As an exaple, Column (1) represent the output of the regression of the system returns, without considering the contribution of *Assicurazioni Generali*, over *Assicurazioni Generali* returns and lagged state variables.

Master Thesis Summary

Measuring Systemic Risk in the Italian Banking Ecosystem

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During the last decade we have witnessed how distress can spread quickly through the financial system and threaten financial stability. Hence there has been increased focus on developing systemic risk indicators that can be used as policy tools. Adrian and Brunnermeier (2016) have introduced a new methodology in measuring spillover effects and sistemic risk contributions of institutions through the measure of Conditional Value at Risk (*$CoVaR$*), the value at risk of the financial system conditional on institutions being in distress. The purpose of this thesis is to apply the *$CoVaR$* model to the Italian financial market to identify which are the institutions that contribute the most to the build-up of systemic risk and its best predictors. We provide forecast of a forward looking measure of sistemic risk contribution showing that it is able to predict half of realized covariances during the financial crisis.

Introduction

Technological progress has gifted us with an interconnected and globalised world, a sprawling network of agents that are able to interact directly or indirectly with each other: nowadays, it is very hard to find a situation in which one exceptional event happens for some economic agents without having any impact on other economic agents. This happens also in financial markets, where in the recent years we have witnessed how during times of financial crisis distress can spread quickly through institutions threatening financial stability. The subprime crisis, the collapse of Lehman Brothers and the Greece's sovereign debt crisis are the most notable examples of such events, which happened in the financial world and have made disastrous repercussions on a number of economies.

The spreading of distress gives rise to systemic risk - the risk that the intermediation capacity of the entire financial system is impaired, with severe consequences for the supply of credit in the real economy. These systemic effects are generated from spillovers across institutions that arise due to contractual links between counterparties, exposures or more general macro-factors such as price effects and liquidity spirals. These facts made crucial for regulators to take adequate measures in order to prevent the collapse of the financial system. To do so, regulators need sustainable systemic risk indicators that also monitor the level of contagion among financial institutions.

One of these measures, that has been used for a long time, is the **Value at Risk (*VaR*)**, which focuses on the risk of a single financial institution in *isolation*. It is defined as the maximum loss of institution i for some confidence level q. The main issue with this approach is that a single institution's risk does not necessarily reflects its contribution to systemic risk. Indeed, an institution may be *individually systemic* because large and interconnected, or could be relatively small in term of size but still be *systemic as a part of a herd*. Moreover, systemic risk shows a time-series dimension by its very nature, where it typically builds up in time of low volatility in terms of bubbles and imbalances and materializes in time of crisis. A proper systemic risk measure should capture this build-up.

In this context, *Adrian and Brunnermeier* (2016) have developed a new measure of risk which can be applied to quantify systemic risk. It is the **Conditional Value at Risk (*CoVaR*)** which represents the *VaR* of a financial system (or of a single institution) conditionally on the fact that a financial institution is in distress. By defining the $\Delta CoVaR$ as the difference between the above mentioned *CoVaR* and the *CoVaR* when the institution is in a normal financial situation, we are able to capture the marginal contribution of a particular institution on the systemic risk as a whole. Projecting the obtained measures of $\Delta CoVaR$ on robust and reliable lagged characteristics of institutions - such as balance sheet items - we will estimate the *Forward*-$\Delta CoVaR$, a forward looking measure of risk that can be used as a monitoring tool for the prediction of systemic risk. Being tied to frequent and robust characteristics, the *Forward*-$\Delta CoVaR$ tries to address the problem that empirical risk measures suffer from the rarity of tail event, leading to inaccuracies in capturing systemic risk.

The objective of this thesis is to use the mentioned methodology to estimate systemic risk contribution in the Italian banking system analyzing listed financial institutions in the Italian Stock Exchange. Doing so, we will try to answer the following questions:

- Which are the the institutions who contribute the most (and the less) to the systemic risk in Italy, and which are the most exposed in the case of a crisis?

- What are the best predictors of systemic risk contribution and how such characteristics could be addressed in a regulatory framework and used to construct a predictive measure of systemic risk?

This thesis tries to provide an original contribution to the *CoVaR* and systemic risk literature by applying the presented methodology to the Italian case, analyzing a relevant topic in the banking sector debate given the high level of sovereign local debt held by Italian banks, highly exposed to non-performing positions and risks.

Theoretical Framework

Value at Risk (VaR)

Value at Risk is a well-known and widely used risk measure by financial institutions. Value at Risk *measures the potential loss in the value of a risky asset or portfolio over a defined period for a given confidence interval*.

More formally, p-VaR is defined such that the probability of a loss greater than VaR is (at most) p while the probability of a loss less than VaR is (at least) $1-p$.

Definition 1 *If X^i represents a variable of interest of institution i - for example, a profit and losses distribution or portfolio return - with a generic distribution $F_{X^i}(x_i)$, then given a confidence level $(1-q)$, VaR^i_q can be defined as:*

$$VaR^i_q = \inf\{x : F_{X^i}(x_i) \geq q\} \tag{1}$$

*VaR is essentially the q-quantile of the return distribution $F_{X^i}(x_i)$ as defined by equation (**??**).*

VaR can also be implicitly defined by:

$$Pr\left(X^i \leq VaR^i_q\right) = q \tag{2}$$

meaning that there is a $(100 \times q\%)$ *chance of the variable* X^i *to become less than* VaR^i_q *over a defined period or in other words, with confidence level* $(1-q)$, X^i *will not be less than* VaR^i_q.

CoVaR

$CoVaR$ stands for Conditional Value at Risk; the $CoVaR$ of the financial system (or a particular bank, portfolio of asset, etc.) is defined as the VaR of the financial system, conditional on some scenario at a particular bank or a set of banks.

Definition 2 *We denote by* $CoVaR^{j|i}_q$ *the VaR of institution j (or the financial system) conditional on some particular event* $\mathbb{C}(\mathbb{X})$ *of institution i. That is,* $CoVaR^{j|i}_q$ *is implicitely defined by the q-quantile of the conditional probability distribution:*

$$Pr\left(X^j \leq CoVaR^{j|\mathbb{C}(\mathbb{X})}_q | \mathbb{C}(\mathbb{X})\right) = q$$

For the most of this thesis, we will focuse on the conditioning event $\left\{\mathbb{C}(\mathbb{X}) = VaR^i_q\right\}$ simplifying the notation to $CoVaR^{j|i}_q$. Moreover, we mainly study the case of $j = system$, i.e. when the return of the portfolio of all financial institutions is at its VaR level. In this case, we drop the superscript j. Informally, we could say that there is a $q\%$ chance of the system returns X^j becoming less than $CoVaR^{j|i}_q$ within a specified time period given that returns of bank i are at its $q\%$-VaR level. Finally, we define a state of distress for an institution or financial system when its returns X^i hits their 1%-VaR level[1] while its normal situation is where returns are at their **median** level (the 50%-quantile). Therefore, to measure how much institution i contributes to the financial system (or bank j) VaR during stressful times we will look at the difference between the system VaR conditional on bank i being at its 1%-VaR level minus the system VaR conditional on bank i being at its median level.

[1]It could be done also by taking the 5%-VaR level; the lower the desired quantile, the more *severe* the state of distress.

Definition 3 *We denote institution i's contribution to j by*

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i}$$

The directionality of the $\Delta CoVaR$ model could be reversed, i.e. by studying the $\Delta CoVaR_q^{i|j}$ with $j = system$ we are able to understand which institution are most at risk if a financial crisis occur - we call this the *Exposure*-$\Delta CoVaR$.

Estimation Methodology and Results

Quantile regression is an efficient way to estimate $CoVaR$ and is used here: it models the relationship between a a set of predictor variables and specific quantiles of the response variable. The difference with the more standard Ordinary Least Squares (OLS) regression is that its coefficients estimates the change in the mean of the response variable produced by a one-unit change in the predictor variable, keeping other predictor variables fixed. However, a quantile regression coefficient estimates the change in a specified quantile of the response variable produced by a one unit change in the predictor variable. This enables comparison of how different quantiles of the response variable may be affected by the predictor variable. As we will show later, when estimating $CoVaR$ the focus is on a specific low quantile of a distribution and hence it is automatic to use quantile regression here.

Unconditional $\Delta CoVaR$

Consider a quantile regression of the financial sector returns X^{sys} on a particular institution i's returns for the $q^{th}-$ quantile

$$X_q^{sys} = \alpha_q^i + \beta_q^i X^i$$

The quantile regression coefficient β_q^i estimates the change in a specified quantile q of X_q^{sys} produced by a one unit change in X^i, i.e.

$$\hat{X}_q^{sys} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{3}$$

where by $\hat{X}^{sys}$ we denoted the predicted value of such regression for a particular quantile conditional on institution i. From the definition of *VaR* - which is a quantile - it follows that

$$\hat{X}_q^{sys} = VaR_q^{sys} | X^i \tag{4}$$

which means that the predicted value from the regression is the q%-*VaR* of the financial system conditional on X^i.

By conditioning with $X^i = VaR_q^i$ we obtain the unconditional $CoVaR$ measure

$$CoVaR_q^{sys|X^i=VaR_q^i} := VaR_q^{sys} | VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{5}$$

$$\implies \Delta CoVaR_q^{sys|i} = \hat{\beta}_q^i (VaR_q^i - VaR_{50\%}^i) \tag{6}$$

0.1 Conditional $\Delta CoVaR$

In order to capture time variation in the joint distributions of X^i, X^{sys} (i.e. time-varying risk) we estimate the conditional distribution as a function of **state variables that replicate the information set available to the regulator**. We separately regress asset returns for each bank i and for the system on a number of lagged state variable included in the matrix M as follows

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \epsilon_t^i \tag{7}$$

$$X_t^{sys} = \alpha^{sys|i} + \beta^{sys|i} X_t^i + \gamma^{sys|i} M_{t-1} + \epsilon_t^{sys|i} \tag{8}$$

The predicted values from the quantile regression correspond to the VaR and $CoVaR$ of bank i at time t as follows:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{9}$$

$$CoVaR_t^i(q) = \hat{\alpha}^{sys|i} + \hat{\beta}^{sys|i} VaR_t^i(q) + \hat{\gamma}^{sys|i} M_{t-1} \tag{10}$$

$$\implies \Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%) \tag{11}$$

$$= \hat{\beta}^{sys|i}(VaR_t^i(q) - VaR_t^i(50\%)) \tag{12}$$

The systematic state variables are conditioning variables that shift the conditional mean and volatility of the risk measure, where different firms loads on them in different directions.

Unconditional and conditional $\Delta CoVaR$ are calculated using weekly data from 1999Q1 to 2019Q1 for all listed Italian banks plus the two biggest insurance company by market capitalization. The conditional $\Delta CoVaR$ is modelled as a function of state variables that captures the evolution of tail risk dependence over time, such as the implied market volatility from the *FTSE IVI*, credit and liquidity spread, market returns. We are able to capture and understand which are the Italian banks that contribute the most to systemic risk (Table (1) is an example of the output of the analysis), and the most exposed one to financial crisis by reversing the directionality in the computation of the $\Delta CoVaR$.

Table 1: **Contribution to systemic risk by Italian banks when in distress situation.**

	$1\% - \Delta CoVaR^{sys\|Bank}$				$5\% - \Delta CoVaR^{sys\|Bank}$				
Banks	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	SIFI
Assicurazioni Gen.	-5,80	2,08	-18,43	0,79	-4,78	1,96	-16,02	-0,11	
BPER	-5,26	2,22	-16,20	0,28	-3,49	1,69	-13,14	0,01	
Banca Finnat	-1,39	0,40	-3,75	0,08	-0,94	0,21	-2,14	-0,53	
Banca Popolare	-5,14	1,70	-16,21	-0,25	-3,20	1,05	-8,69	-1,80	
Banca Profilo	-1,06	0,43	-3,35	-0,23	-0,46	0,14	-1,26	0,04	
Banco BPM	-5,09	2,17	-15,11	-1,24	-3,80	1,43	-11,01	-1,22	
Banco di Desio	-1,93	0,59	-6,56	-0,22	-2,24	0,48	-5,59	-0,79	
Banco di Sardeg.	-3,54	1,46	-11,48	-0,60	-1,50	0,60	-4,83	-0,17	
Credito Emiliano	-5,26	2,25	-20,72	1,93	-3,62	1,58	-13,58	-0,77	
Credito Valtell.	-1,64	1,01	-7,88	0,39	-2,42	1,13	-7,06	-0,35	
Intesa	-6,68	3,05	-23,15	1,40	-5,01	2,38	-17,80	-0,31	✓
MPS	-3,87	1,84	-16,83	-1,01	-3,32	0,83	-7,53	-0,36	✓
Mediobanca	-5,59	1,60	-15,36	-0,25	-4,81	1,25	-11,00	-1,71	
Unicredit	-5,43	2,54	-25,97	-1,09	-4,54	1,84	-16,10	-1,89	✓
Unione di Banche	-7,06	2,47	-18,08	0,62	-4,80	1,73	-13,31	-1,80	
Unipol Sai	-0,60	0,25	-1,29	-0,11	-1,59	0,48	-3,60	-0,62	

All quantities are expressed in units of weekly percent returns

In a successive step, we relate those $\Delta CoVaR$ - in a predictive sense - to institution's balance sheet characteristics using panel regressions. We show not only that size, leverage, maturity mismatch and other characteristics are good predictors of systemic risk, but the predicted values of those regressions have out of sample predictive power, being able to capture half of the realized covariance between institutions and the system during the financial crisis of 2008.

Conclusion

During financial crisis, tail events tend to **spill across institutions**. With the $\Delta CoVaR$ model, that is built to measure systemic risk, we are able to capture these effects. In this thesis we estimate the contribution to systemic risk of Italian listed banks for the period 1999-2019, identifying both the *riskier* banks and the most exposed to bad financial shocks. Moreover, we find that the informations contained in $\Delta CoVaR$ are different from those contained in the VaR, hence regulators should take it into account to monitor the systemic risk posed by banks.

Recent policy debate has been developed around the danger posed by large banks. By relating $\Delta CoVaR$ to institutions' characteristics we **identified what are good predictors of systemic risk** other than size: balance sheet items such as leverage, NPL, market β, maturity mismatch. Therefore any financial regulation aimed only at limiting banks' size could not completely eliminate systemic risk. The regression coefficients roughly identifies the effects on systemic risk contribution of curbing one institution's characteristics. This makes the $\Delta CoVaR$ a useful tool for policy making and regulation.

Moreover, given that the conditional measures of systemic risk are time varying and affected by market-based risk factors, macro prudential regulation should also monitor informations provided by financial markets.

An interesting way to expand this work would be to compute the $\Delta CoVaR$s between each possible couple of banks, i.e. to compute the VaR of institution i when institution j is in distress ($i \neq j$), and viceversa. This would let us obtain the pairwise connection between each banks and with some specific Granger-causality tests it could be possible to capture a *network effect* between each institution by understanding which banks push the risk profile of its counterparties.

Another avenue of research could be to add additional macro variables to the returns when estimating the $CoVaR$. As already suggested by *Adrian and Brunnermeier (2016)* it could be possible to take into account variables which are presumed to explain stock returns as business cycle or investor sentiment.

Finally, from the predicted value of the $\Delta CoVaR$ regressions we constructed a forward looking measure of systemic risk, called *Forward-*$\Delta CoVaR$, that provides reliable forecasts of future systemic risk contribution at different time horizons. To test its performance, we find that it is able to explain half of the realized crisis covariance during the financial crisis.

Hence, we conclude that $\Delta CoVaR$ is a very useful and relevant policy tool for regulators that can estimate which factors are more relevant in terms of contribution to systemic risk, being able to access wider and more granular information set.