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Systemic Risk and the COVID Challenge in the European Banking Sector *

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Abstract

This paper studies the systemic risk contribution of a set of large publicly traded European banks. Over a sample covering the last twenty years and three different crises, we find that all banks in our sample significantly contribute to systemic risk. Moreover, larger banks and banks with a business model more exposed to trading and financial market volatility, contribute more. In the shorter sample characterized by the Covid-19 shock, sovereign default risks significantly affected the systemic risk contribution of all banks. However, the ECB announcement of the Pandemic Emergency Purchasing Programme restored calm in the European banking sector.

Keywords: CoVaR, systemic risk, Covid-19, banking regulation

JEL Classification: G01, G18, G21, G38

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1 Introduction

European banks are again in turmoil. The large and unexpected common shock related to the Covid-19 pandemic is severely affecting the functioning of the economy everywhere. The forecasted reductions in GDP and the likely emergence of many firm bankruptcies, notwithstanding the relevant amount of fiscal and monetary policy responses undertaken by the European Central Bank (ECB) and the single member states, are obviously worrying.

In this paper, we try to measure the systemic risk contribution of the most important European banks, where we denote the “system” as the European banking sector. This exercise is particularly relevant as Covid-19 represents the first extraordinary event, negatively affecting the global economy, after the pervasive reorganisation of the institutional architecture for financial regulation and supervision that followed the Great Financial Crisis and the European sovereign debt crisis. We also try to establish the factors responsible for a higher than average potential contribution of a single institution. Over a sample covering the last twenty years, we find that all our banks significantly contribute to systemic risk, but larger banks, and banks with a business model more exposed to securities and derivatives trading in financial markets, contribute more. In the shorter sample around the Covid-19 shock, we find that sovereign default risks significantly affected the systemic risk contribution of all banks, and particularly so for banks more exposed to financial markets volatility. The ECB announcement of the Pandemic Emergency Purchase Programme (PEPP) was indeed successful to restore calm in the European banking sector, as we document in the paper.

Banks are the primary source of funding for firms and households in Europe and the wide adoption of the traditional banking model in continental Europe makes them exposed to the combined negative effect of very low interest rate margins and the likely increase of non performing loans and assets as a result of the Covid-19 shock. In addition, the Banking Union has not been fully completed thus far and the vicious circle between fiscal and banking crises remains more than a mere possibility. We focus on the systemic risk contribution of the largest European banks, where we define “systemic risk” as the risk of a collapse of the entire European banking system, typically triggered by the default of one, or more, large and interconnected institutions. The importance of systemic risk is exemplified by three observations: first, it affects a substantial portion of the financial system; second, it involves negative externalities; third, it requires intervention of public authorities for prevention and, eventually, management of the risky environment. These considerations led the ECB to state that "large and complex financial institutions [should be] subject to regulatory and supervisory requirements commensurate to the risks they pose to the financial system and the real economy" (ECB Financial Stability Review June 2010). Indeed, following the global financial crisis, financial regulation and supervision have gradually given more weight to measuring, monitoring, and preventing systemic risk[1].

In this paper we estimate the systemic risk contribution of large European banks by using the ΔCoVaR, a simple yet informative risk measure first developed by Adrian and Brunnermeier (2016). Such tool is based on quantile regression methods (Koenker and Bassett Jr, 1978) and takes into account the role of asset prices and returns[2]. $CoVaR$ is a measure of risk conditional upon an adverse shock, where risk is defined as the standard value-at-risk (VaR). It is well known that VaR measures risk in terms of returns at a given probability: for example, a VaR of -10% at the 5% confidence level indicates that there is a probability of 5% of a return lower or equal to -10%. Given any two variables Y and X, ΔCoVaR is defined as the contemporaneous change in the VaR of Y conditional on X being at its VaR relative to its median state, and measures the conditional tail-dependency in a non-causal sense. In our framework, we let Y be the entire European banking sector, while Xs denote individual banks. Therefore, ΔCoVaR captures the marginal contribution of each institution to the systemic risk of the entire banking sector.

We first consider an extended period spanning twenty years that includes three major

[1] In the U.S., a new body, the Financial Stability Oversight Council was established at the Treasury Department, while a European Systemic Risk Board was created at the EU level in 2011. With the start of the Banking Union in the Eurozone, in 2014, a specialized macro-prudential division has been set up and empowered at the ECB.

[2] There exist several alternative measures of systemic risk and exposure to tail-risk. Many of them rely on CDS data, although CDS market prices exist only for a limited number of listed banks (Segoviano Basurto and Goodhart, 2009), while the ΔCoVaR can be computed easily for all listed banks. For example, Acharya, Engle, and Richardson (2012) focus on high-frequency marginal expected shortfall; Acharya, Pedersen, Philippon, and Richardson (2017) and Brownlees and Engle (2016) develop SRISK, which measures capital shortfall conditional on market stress; Billio, Getmansky, Lo, and Pelizzon (2012) builds a risk-measure based on Granger causality across institutions; Nucera, Schwaab, Koopman, and Lucas (2016) construct a systemic risk measures that summarize the information provided by alternative risk rankings using principal components.

shocks: the Great Financial Crisis (2007-2009), the European sovereign debt crisis (2012-2015), and the Covid-19 shock (2020); as well as important changes in the regulation of the banking sector. Over this period, we estimate the systemic risk contribution of the European banks in our sample by their ΔCoVaR, and we find that they all significantly contribute to the systemic risk of the banking sector. We also document the different intensities of such individual contributions. We then consider a large set of market-based and balance-sheet indicators and study whether they are useful in predicting contribution to systemic risk. In order to do so, we estimate a time-varying version of the ΔCoVaR using non-overlapping quarters. We use this time-varying measure to estimate predictive panel regressions that do not suffer from look-ahead bias. Our empirical strategy uses only information available to investors, or regulators, to study which indicators are associated with a larger systemic risk contribution in the following quarter. We find that larger banks have a higher systemic risk contribution, even after controlling for bank fixed effects, a result which is consistent with the literature (Adrian and Brunnermeier, 2016, Borri, Caccavaio, Di Giorgio, and Sorrentino, 2014). In addition, we find that a bank systemic risk contribution is persistent and higher for banks with a business model more exposed to financial markets: i.e., banks more involved with securities and derivatives trading seem to contribute more to systemic risk. Finally, we find that leverage is an important predictor of systemic risk contribution mostly for larger banks. This finding might support a revision of the current framework that assigns relative more weight to credit rather than market risk in the computation of the mandatory capital requirements.

We then focus on the shorter sample that starts in January 2020 and study the novel Covid-19 challenge to European banks. We observe that the large increase, in absolute value, of the mean ΔCoVaR is only matched by the increase observed during the Great Financial Crisis. We then use the daily CoVaR estimates for each bank in our sample, to study the evolution of their systemic risk contribution around the Covid-19 shock. We find that the ECB announcement of the Pandemic Emergency Purchasing Programme, on March 18, was a real turning point. Before this announcement, we find a significant systemic risk contributions for all banks. We also show evidence that sovereign default risks, which we proxy with the changes in the yield spread between the Italian and German benchmark government bonds, significantly predict higher systemic risk contributions of all banks, and not only of banks located in riskier countries, like Italy, Spain or Portugal. Since the ECB announcement of PEPP, however, only banks in Spain, France and the U.K. seem to be still characterized by a significant systemic risk contribution, while the sovereign default risk becomes less important. Finally, and interestingly, we also document that in the period before the ECB announcement of the PEPP, the evolution of sovereign risks affected particularly banks more exposed to financial markets volatility.

We evaluate the robustness of our results with respect to different dimensions. First, we consider different proxies for the banking "system". In the baseline analysis we consider the returns of a broad equity index for the European banking sector. We show that our results are unchanged when, instead, we consider either an equity index for only the largest banks in the Eurozone, or the average returns of the banks in our sample[3]. Second, we study the stability of the parameters of the quantile regressions used to estimate the ΔCoVaR and show that for more than half of the banks in the sample we observe "shift-contagion" (Caporin, Pelizzon, Ravazzolo, and Rigobon, 2018), i.e., a change in the intensity of the contribution across different quantiles. This result supports the argument that ΔCoVaR properly measures risk of contagion, and not simply exposure to a common shock. Finally, we show that our results are robust to using asset returns with a lower, and weekly, frequency.

This paper contributes to two strands of the literature. The first strand studies systemic risk in financial markets and the effectiveness of macroprudential policy, like credit growth tools or exposure limits (see, for example, Chu, Deng, and Xia (2020), Meuleman and Vander Vennet (2020), Brownlees, Chabot, Ghysels, and Kurz (2020), Brunnermeier, Rother, and Schnabel (2020), Giglio (2016), Laeven, Ratnovski, and Tong (2016), Engle, Jondeau, and Rockinger (2015), Acharya and Steffen (2012), Huang, Zhou, and Zhu (2009), Borri et al. (2014)). Although the literature relies on a set of different measures of systemic risk, and sometimes cover non-bank financial institutions, common findings are that market-based measures of systemic risk tend to be more reliable than balance sheet indicators; that size is a useful predictor of systemic risk contribution; and that leverage matters in periods of stress. With respect to this literature, we consider a sample of large publicly traded European banks and focus on a period which

[3]In the latter specification, we are able to exclude bank i from the "system" when estimating its systemic risk contribution.

includes the recent violent Covid-19 shock and new important changes in banking regulation, like the assignment of supervisory powers to the ECB or the implementation of higher capital requirements.

The second strand is the recent literature on the effects of the Covid-19 shock on financial markets. Bretscher, Hsu, Simasek, and Tamoni (2020), Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020) and Carletti, Oliviero, Pagano, Pelizzon, and Subrahmanyam (2020) analyze the effects of the Covid-19 shock on equity prices and on firms' profitability and equity shortfall. Li, Strahan, and Zhang (2020) analyze the unprecedented increase in liquidity demands that banks faced since the Covid-19 crisis, while Acharya and Steffen (2020) consider stress test scenarios for banks at the time of Covid-19. With respect to these papers, to the best of our knowledge, our study is the first investigating the systemic risk contribution of European banks during the Covid-19 challenge.

The rest of the paper is organized as follows: section 2 presents the model used to estimate the systemic risk contribution of individual institutions; section 3 presents the sample, while in section 4 we discuss our main empirical findings. Finally, section 5 presents our conclusions.

2 Model

In this section we describe the methodology we use to analyze the systemic risk contribution of individual banks with respect to the entire banking sector. We adopt the ΔCoVaR measure of systemic risk developed by Adrian and Brunnermeier (2016), which measures the conditional tail-dependency in a non causal sense and captures both spillovers and common exposure effects[4]. Our definition of systemic risk contribution is related to Forbes and Rigobon (2002), which defines it in terms of increase in cross-market linkages after a shock to one country. However, we specifically focus on the marginal effect of a tail-shock with respect to the normal state induced by a shock to a single institution. Note that there is a large literature on the

[4]Note that while $CoVaR$ is widely used, its simplicity comes at a cost. Mainik and Schaanning (2014) show that $CoVaR$, as well as other systemic risk measures like the Marginal Expected Shortfall (MES) and the Systemic Impact Index (SII), is not "dependent consistent" under very general distributional assumptions for the pair of variables. On the contrary, Mainik and Schaanning and Girardi and Ergun (2013) show that conditioning on a variable being "greater or equal", rather than just "equal", to its value-at-risk gives a better response to the dependence between two variables.

definition of contagion and spillovers (see, for example, the excellent reviews by Forbes (2012) and Rigobon (2019)). While spillovers are always present, in good and bad times, contagion is more important in periods of stress. As such, ΔCoVaR is similar in spirit to the definition of "shift-contagion" (Rigobon, 2019), which occurs when the propagation of shocks intensifies during crises.

2.1 Conditional Value-at-Risk

Let Y and X be two real-valued random variables. We denote the realizations of Y and X at time t as y_t and x_t, respectively, for $t = 1, \cdots, T$, and focus on $Q_\theta(y_t|\mathbf{I}_{t-1}, x_t)$; that is, the θ-th quantile of y_t conditional on the information set available at $t-1$ as well as on x_t, for $\theta \in (0,1)$. For the sake of simplicity, we set $Q_\theta(y_t|\mathbf{I}_{t-1}, x_{i,t}) \equiv Q_\theta(y_t)$. In our study, Y and X are, respectively, the value-weighted equity return of the entire European banking sector and the equity return of an individual institution in the sample. As a result, $Q_\theta(y_t)$ represents a measure of tail risk (i.e., the VaR) when θ takes small values in the interval $(0,1)$; that is, when focusing on the left tail of the conditional distribution of y_t. We aim at measuring the relationships between y_t and x_t in the occurrence of tail events and, for this purpose, focus on $\theta \in (0, 0.05]$.

The ΔCoVaR measure of systemic risk, introduced by Adrian and Brunnermeier (2016), builds on the following (linear) conditional quantile model:

$$Q_\theta(y_t) = \delta_\theta + \lambda_\theta x_t + \boldsymbol{\gamma}_\theta \mathbf{M}'_{t-1}, \tag{1}$$

where $\mathbf{M}_{t-1}$ is a $1 \times K$ vector of control variables observed at time $t-1$.

We estimate the parameters in (1) using the quantile regression method introduced by Koenker and Bassett (1978) and denote the resulting coefficients as $\widehat{\delta}_\theta$, $\widehat{\lambda}_\theta$ and $\widehat{\boldsymbol{\gamma}}_\theta$. We then compute the CoVaR as:

$$CoVaR_{t,\theta,\tau}^{y_t|x_t=\widehat{q}_\tau(x_t)} = \widehat{\delta}_\theta + \widehat{\lambda}_\theta \widehat{q}_\tau(x_t) + \widehat{\boldsymbol{\gamma}}_\theta \mathbf{M}'_{t-1}, \tag{2}$$

where $\widehat{q}_\tau(x_t)$ is the τ-th sample quantile of x_t; we focus on $\tau \in (0, 0.05]$ such that $q_\tau(x_t)$ reflects the VaR of x_t at the level τ[5].

We can also compute the CoVaR of y_t conditional on the normal (or median) state of x_t:

$$CoVaR_{t,\theta,1/2}^{y_t|x_t=\widehat{q}_{1/2}(x_t)} = \widehat{\delta}_\theta + \widehat{\lambda}_\theta \widehat{q}_{1/2}(x_t) + \widehat{\boldsymbol{\gamma}}_\theta \mathbf{M}'_{t-1}. \tag{3}$$

In what follows, we save on notation and do not use t, θ and τ as subscripts, or $y_t|x_t = \widehat{q}_\tau(x_t)$ as superscript, when we refer to the CoVaR. By subtracting (3) from (2), we obtain the ΔCoVaR, which takes the following form:

$$\Delta CoVaR_{\theta,\tau}^{Y|X} = \widehat{\lambda}_\theta \left[\widehat{q}_\tau(x_t) - \widehat{q}_{1/2}(x_t)\right]. \tag{4}$$

The ΔCoVaR quantifies the marginal impact of x_t on the VaR of y_t, i.e., when x_t moves from its median, or normal state, to its VaR, or distress state. As a result, the larger, in absolute value, the ΔCoVaR is, the higher the vulnerability of the entire system Y to shocks to individual institution X. We estimate the quantiles of y_t and x_t at the same level; that is, we set $\theta = \tau$. Hence, we further simplify the notation by setting $\Delta CoVaR_{\theta,\tau}^{Y|X} = \Delta CoVaR_\theta^{Y|X}$. In order to evaluate the standard errors of the estimated parameters, we employ a bootstrap method (see, among others, Davidson and Flachaire, 2008, Davino, Furno, and Vistocco, 2014).

3 Data

We consider a sample of 35 large publicly traded European banks located in 12 countries: Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Portugal, Spain, Switzerland, and the U.K. We construct the sample starting from the one used in White, Kim, and Manganelli (2015), and focus on the subset of all the banks whose headquarters are in European countries. Our sample contains the – two or three – largest banks in terms of market capitalization for each country. Our data start on 1/3/2000 and ends on 9/30/2020, and thus include the Great Financial Crisis (2007-09), the European sovereign debt crisis (2010-12), as well as the Covid-19

[5]Note that we could also use $\widehat{Q}_\tau(x_t)$ in (2) in place of $\widehat{q}_\tau(x_t)$, where $\widehat{Q}_\tau(x_t)$ is dynamically estimated from the following quantile regression model: $Q_\tau(x_t) = \alpha_\tau + \boldsymbol{\beta}_\tau \mathbf{M}'_{t-1}$, for $t = 2, ..., T$.

pandemic shock (2020)[6]. We obtain daily market equity data and quarterly balance sheet data from Bloomberg, and we convert non-euro stock prices into euros using the spot exchange rates. To capture returns of the entire European banking system we also collect data on two value-weighted equity indices of the banking sector: the Euro Stoxx Banks and the Stoxx Europe 600 Banks indices[7]. To allow for time-variation in the systemic risk measure, we include a set of state variables which capture time variation in the conditional moments. The state variables are lagged, and thus should be interpreted as variables that condition the mean and volatility of the risk measures. We focus on the following small set of state variables and collect their data also from Bloomberg: the Euro Stoxx index, the Barclays Pan-European High Yield index, the VDAX index, the yield spread between the 10-year Italian and German government bonds and the slope of the yield curve, measured by the spread between the German long-term bond yield (10-year) and the three-month German bill rate. Table A1 in the Online Appendix provides summary statistics for these state variables, while Figures A1 and A2 illustrate the evolution of the equity indices and the bank daily returns.

Table 1 presents some descriptive statistics regarding the daily returns of the banks in our sample and the two stock indices representative of the European banking sector. We observe that the mean daily return is negative for most banks, as well as for the two bank indices, highlighting the difficulties faced by the banking sector in the last 20 years. Daily returns are volatile (the mean standard deviation is equal to 2.75%, almost twice as large as the corresponding volatility for the broad European equity index), negatively skewed, and have large kurtosis. In fact, the mean daily 5% VaR is large (in absolute value) and approximately equal to -4.12%. Finally, we observe minimum and maximum daily returns ranging from -40% to 35%.

Table 2 presents additional descriptive statistics regarding our sample. Panel A reports the

[6]Notice that for some of the banks we have a shorter sample because they exited early. Refer to the last column of Table 1 for information on the number of available observations for each bank. Notice also that the ECB begun its supervisory role in November 2014. Hence, most of the banks in our sample are then currently under its supervision, with the exception of Credit Suisse, Danske Bank, Jyske Bank, Lloyds, Natwest, Standard Charter, Svenzka, Swedbank, UBS.

[7]The Euro Stoxx Banks (Bloomberg ticker: SX7E) is a value-weighted index containing 22 financial institutions from Eurozone countries and is a subset of the Euro Stoxx Index (Bloomberg ticker: SXXE). The Stoxx Europe 600 Banks (Bloomberg ticker: SX7P) is a value-weighted index containing 38 financial institutions from countries in the European regions and is a subset of the Stoxx Europe 600 (Bloomberg ticker: SXXP).

Table 1: Bank Returns. Descriptive Statistics

Name	Mean	Std	Min	Max	Skew	Kurt	VaR	T
ALPHA BANK AE	-0.14	4.25	-35.16	25.59	-0.25	12.48	-6.45	4932
BANK OF IRELAND	-0.08	4.02	-33.57	34.56	0.07	18.67	-5.33	4982
BANKINTER	-0.01	2.12	-10.99	12.76	0.30	6.63	-3.42	5201
BARCLAYS PLC	-0.04	2.79	-21.60	20.65	-0.28	13.34	-3.91	5407
BANCA CARIGE	-0.14	2.65	-20.76	26.19	0.15	17.50	-4.13	4592
BANCA MONTE DEI	-0.15	3.12	-24.21	20.03	-0.29	12.53	-4.66	4989
BANCA POP SONDRI	-0.02	1.92	-11.03	11.68	0.31	7.53	-3.04	4462
BPER BANCA	-0.04	2.50	-14.75	14.48	0.18	7.85	-3.99	4526
BBVA	-0.04	2.17	-14.16	11.00	-0.06	7.20	-3.41	5189
BANCO COM PORT-R	-0.11	2.71	-16.34	17.67	0.05	8.14	-4.28	4780
BANCO SANTANDER	-0.03	2.22	-12.75	12.19	-0.08	7.08	-3.54	5169
BNP PARIBAS	-0.01	2.35	-14.30	16.13	0.03	9.78	-3.53	5251
COMMERZBANK	-0.07	2.84	-15.81	16.57	0.08	8.16	-4.42	5205
CREDIT SUISS-REG	-0.03	2.34	-15.02	14.40	-0.08	9.69	-3.51	5405
DANSKE BANK A/S	0.00	1.96	-11.62	10.82	-0.13	7.81	-2.99	5386
DEUTSCHE BANK-RG	-0.04	2.52	-15.51	14.25	-0.07	8.05	-4.04	5244
EUROBANK ERGASIA	-0.23	5.48	-40.60	35.41	-0.41	12.98	-8.17	4781
ERSTE GROUP BANK	0.01	2.59	-17.34	14.06	-0.29	9.62	-3.76	5057
SOC GENERALE SA	-0.03	2.68	-17.71	15.54	-0.29	8.90	-4.07	5228
INTESA SANPAOLO	-0.01	2.51	-17.20	14.60	-0.24	8.55	-3.82	5179
JYSKE BANK-REG	0.02	1.76	-9.44	10.01	-0.05	7.75	-2.69	5382
KBC GROUP	-0.01	2.87	-24.29	20.28	-0.51	16.43	-4.09	5230
LLOYDS BANKING	-0.06	2.75	-29.58	18.42	-1.01	19.85	-3.93	5404
MEDIOBANCA	-0.00	2.08	-13.66	9.47	-0.20	6.82	-3.29	5210
NATL BANK GREECE	-0.20	4.49	-35.67	24.17	-1.12	15.34	-6.53	4956
NATIXIS	-0.02	2.76	-19.22	20.81	0.04	14.94	-3.98	5065
NORDEA BANK ABP	0.01	2.16	-11.87	13.64	0.10	8.55	-3.28	5407
NATWEST GROUP PL	-0.05	2.88	-25.91	20.62	-0.52	15.13	-4.21	5407
SEB AB-A	0.01	2.41	-16.63	16.08	-0.07	11.64	-3.51	5406
STANDARD CHARTER	-0.02	2.38	-16.68	15.60	-0.13	10.09	-3.42	5407
SVENSKA HAN-A	0.01	1.91	-12.07	11.90	-0.12	8.78	-2.89	5407
SWEDBANK AB-A	0.00	2.30	-16.74	14.54	-0.40	11.12	-3.46	5407
UBS GROUP AG	-0.02	2.15	-13.96	14.66	-0.10	10.77	-3.23	5406
UNICREDIT SPA	-0.05	2.68	-15.61	14.78	-0.09	8.34	-4.17	5215
DEXIA SA	-0.23	4.91	-54.16	38.57	-0.67	23.73	-6.90	4597
Euro Stoxx Banks	-0.03	1.90	-12.04	10.81	-0.15	7.93	-2.99	5407
Stoxx Europe 600 Banks	-0.03	1.71	-10.97	11.16	-0.16	9.42	-2.63	5407
Mean (banks)	-0.05	2.75	-19.88	17.78	-0.18	11.19	-4.12	

Notes: The Table reports the following descriptive statistics for the daily returns of the sample financial institutions: mean, standard deviation, minimum, maximum, skewness, kurtosis, VaR, and total number of observations. All moments are multiplied by 100 except skewness and kurtosis and are reported in euros. All returns are computed in levels. The VaR is for the 5% quantile. We additionally report the same statistics for the Euro Stoxx and Stoxx Europe 600 Bank indices. "Mean (banks)" denotes the simple average of the financial institutions in our sample. Data are from Bloomberg for the period 1/3/2000 to 9/30/2020.

sample averages of a series of balance sheet indicators (using for each institution the longest available sample). Specifically, market capitalization; size (measured as total assets as a fraction of the aggregate assets of the entire sample); loans to deposit ratio; bad loans as a fraction of total loans; tier-1 ratio; leverage ratio, measured as total assets to equity; return on equity (roe); level 2 and level 3 assets as a fraction of total assets. We summarize the main stylized facts as follows. First, the average bank in our sample has a market capitalization of euro 21 billions and a "size" of about 3.5% of the aggregate assets. The largest ones in terms of average market capitalization are Banco Santander, BNP Paribas, UBS, Barclays and BBVA. These five financial institutions are also the largest in terms of size, although the two indicators provide somewhat different information. As an example, Banco Santander has a market capitalization of euro 63 billions and accounts for approximately 7% of the total assets of the sample. The largest bank in terms of size is instead Barclays, with 13% of the total assets and a market capitalization of euro 44 billions. These figure may reflect underlying differences in the business models: in continental Europe, on average, banks are traditionally more focusing on traditional banking activities, however there are clear example in the sample of large institutions that are strongly active in securities and derivatives trading. We prefer measuring size in terms of assets, as market capitalization is more volatile. Second, we document differences in the business model, used by banks, by reporting the loans to deposit ratios and the level 2 and 3 assets as a fraction of the total. The average bank has a loans to deposit ratio of about 1.5, but institutions particularly active on financial markets, like Deutsche Bank, have ratios smaller than one (specifically, equal to 0.64). The last two columns of Panel A report the mean level 2 and level 3 assets as fraction of total assets. Level 2 assets are financial assets and liabilities that do not have a regular market pricing, but whose value can be determined based on market prices. Level 3 assets are financial assets and liabilities that are considered as the most illiquid and hardest to value. With respect to these two categories, the banks in our sample, on average, have almost 20% of their assets in the form of level 2 assets, and 1.5% in the form of level 3 assets. The fraction of the riskiest and most illiquid level 3 assets ranges from close to zero for more than one bank, to more than 4% for Credit Suisse. Third, while bad loans are about 4% of the total for the average bank, we observe figures ranging from almost 13% for the National Bank of Greece to only 0.5% for

Deutsche Bank. Such strong heterogeneity in the share of bad loans is a legacy of the Great Financial Crisis and of the subsequent European sovereign debt crisis, particularly affecting banks in countries more severely hit, like Italy, Greece, Portugal and Spain. Fourth, the average bank has a mean tier-1 ratio of almost 12% (ranging from about 9% for Banca Monte dei Paschi to almost 16% for Standard Charter); a mean leverage ratio of approximately 22 (ranging from about 8 for Credit Suisse to almost 50 for Dexia); and a positive average return on equity of approximately 5.5% with Swedbank being the most profitable one with a roe of 15%.

Panel B reports the values of three market indicators: "risk" denotes the realized volatility estimated from daily returns; β-CAPM denotes the OLS slope of a regression of each bank return on the Eurozone broader equity market return; and P/B denotes the mean price-to-book ratio. The average institution has a realized volatility of 2.32%; a β-CAPM slightly above one (1.15); and a price-to-book ratio also just above one (1.17), although recently it collapsed to about one-half of this value[8].

4 Empirical Results

In this section we present the main findings of our empirical analysis. First, we present the estimates of the systemic risk contribution of each bank, with respect to the entire banking sector, over the full sample. Second, we present the results of panel predictive regressions to identify which individual characteristics of banks in the sample are associated with a higher systemic risk contribution. Finally, we provide a snapshot of the value at risk of the banking system conditional on the different individual institutions being in distress during the recent Covid-19 shock.

[8]Since the beginning of 2019, the average price-to-book ratio in the sample is 0.62. Also for financial market indicators, we observe large heterogeneity across the sample: the β-CAPM can be as large as 1.4 (BNP Paribas or Deutsche Bank), and as low as 0.68 (JYSKE Bank). Similarly, the price-to-book ratio ranges from 1.8 (UBS) to 0.61 (Standard Charter). Finally, Panel C reports information relative to the country of domicile and currency of trading for each financial institution.

Table 2: Banks. Descriptive Statistics

	Panel A: balance sheet indicators									Panel B: market indicators			Panel C: institutional indicators	
Name	Mkt Cap	Size	Loans	Bad Loans	Tier-1	Leverage	ROE	LEV2	LEV3	Risk	β-CAPM	P/B	Country	Currency
ALPHA BANK AE	4.28	0.40	134.37	18.64	12.74	14.04	4.56	13.52	0.24	3.49	1.07	1.35	GR	EUR
BANK OF IRELAND										3.06	1.29		IR	EUR
BANKINTER	3.96	0.37	176.70	1.80	9.41	21.52	11.38	1.52	0.00	1.93	1.06	1.89	SP	EUR
BARCLAYS PLC	44.51	13.48	108.42	0.88	12.03	23.86	3.60	40.25	2.11	2.39	1.44	1.20	GB	GBP
BANCA CARIGE	2.34	0.22	164.28	8.13	9.14	12.17	-4.07	2.18	1.58	1.97	0.66	0.98	IT	EUR
BANCA MONTE DEI	6.34	1.36	160.36	11.09	8.82	20.42	-6.56	7.32	0.29	2.60	1.17	0.86	IT	EUR
BANCA POP SONDRI	1.58	0.19	113.73	7.61	10.29	14.91	4.92	1.12	0.46	1.55	0.66	0.77	IT	EUR
BPER BANCA	2.60	0.40	143.52	8.75	9.22	18.24	6.92	1.56	0.86	1.93	0.93	1.05	IT	EUR
BBVA	42.02	4.03	125.02	2.17	9.98	17.50	12.91	9.40	0.26	1.94	1.33	1.68	SP	EUR
BANCO COM PORT-R	5.15	0.68	142.19	4.24	9.56	22.28	6.53	2.84	1.31	2.30	0.93	1.70	PO	EUR
BANCO SANTANDER	63.48	7.07	132.21	1.90	10.02	16.58	10.43	11.50	0.22	1.98	1.37	1.27	SP	EUR
BNP PARIBAS	58.86	11.65	114.69	1.59	11.18	23.55	7.64	19.21	1.10	2.06	1.43	0.76	FR	EUR
COMMERZBANK	10.98	4.81	138.28	1.79	10.18	32.21	0.04	24.63	1.04	2.51	1.37	0.71	GE	EUR
CREDIT SUISS-REG	34.84	6.10	77.32	0.32	14.49	27.38	4.81	73.94	4.31	2.07	1.28	1.28	SZ	CHF
DANSKE BANK A/S	15.82	2.92	210.80	1.35	12.85	27.13	8.33	32.62	0.38	1.79	0.82	1.20	DE	DKK
DEUTSCHE BANK-RG	31.44	10.40	64.07	0.51	12.47	34.69	3.25	48.03	2.29	2.24	1.37	0.86	GE	EUR
EUROBANK ERGASIA		0.40	125.60	16.17	12.50	19.92	1.25	2.82	0.13	4.35	0.89		GR	EUR
ERSTE GROUP BANK	9.45	1.40	106.21	4.83	9.71	26.99	8.54	6.60	0.37	2.22	1.13	1.31	AS	EUR
SOC GENERALE SA	29.08	7.04	117.87	1.66	11.96	23.74	4.82	26.60	1.05	2.34	1.55	0.62	FR	EUR
INTESA SANPAOLO	33.43	4.18	151.85	5.39	10.32	15.90	6.50	7.81	0.75	2.24	1.33	1.05	IT	EUR
JYSKE BANK-REG	2.66	0.31	178.33	0.62	13.04	18.50	13.44	42.45	0.34	1.62	0.68	0.97	DE	DKK
KBC GROUP	19.14	2.02	93.04	2.41	13.22	22.59	10.07	6.23	1.47	2.33	1.30	1.34	BE	EUR
LLOYDS BANKING	48.00	5.56	123.29	2.91	14.21	20.03	2.07	10.40	0.99	2.28	1.26	1.09	GB	GBP
MEDIOBANCA	7.54	0.43	344.96	1.93	13.34	8.50	5.62	8.00	1.71	1.91	1.12	1.15	IT	EUR
NATL BANK GREECE	6.63	0.60	97.75	12.91	12.73	16.92	0.64	8.66	0.20	3.65	1.24	1.31	GR	EUR
NATIXIS	15.76	3.03	268.96	0.65	12.61	28.36	7.75	29.43	1.80	2.26	1.20	0.86	FR	EUR
NORDEA BANK ABP	2.95	0.38	173.00	0.74	12.27	22.26	13.11	32.71	1.07	1.95	1.12	1.36	FI	SEK
NATWEST GROUP PL	36.78	7.96	108.20	1.86	14.30	20.22	-7.42	41.31	0.72	2.47	1.36	0.61	GB	GBP
SEB AB-A	13.54	1.82	143.81	0.53	13.83	24.27	12.33	15.14	0.80	2.10	1.25	1.43	SW	SEK
STANDARD CHARTER	32.26	4.72	68.21	1.16	15.99	15.18	2.65	22.74	0.29	2.12	1.26	0.61	GB	GBP
SVENSKA HAN-A	15.53	1.77	235.25	0.28	14.95	24.24	15.17	3.18	0.04	1.73	0.99	1.67	SW	SEK
SWEDBANK AB-A	12.96	1.43	222.17	0.55	14.43	21.74	14.89	24.04	0.03	1.99	1.10	1.53	SW	SEK
UBS GROUP AG	49.62	7.35	72.15	0.22	15.53	31.42	6.94	29.96	1.57	1.88	1.19	1.81	SZ	CHF
UNICREDIT SPA	32.16	4.88	129.21	5.36	9.57	18.00	4.82	11.63	0.88	2.34	1.42	1.15	IT	EUR
DEXIA SA		3.27	547.72	0.47	9.47	48.73	-8.51	22.30	17.23	3.57	0.69		BE	EUR
Average	21.74	3.61	156.28	3.87	11.95	22.18	5.57	18.87	1.41	2.32	1.15	1.17	BE	EUR

Notes: The Table reports additional descriptive statistics of the financial institutions in the sample. Panel A reports the mean values for the following set of balance sheet indicators: the market capitalization; the size (measured as total assets as a fraction of the aggregate assets in the sample); loans to deposit ratio; bad loans as a fraction of total loans; tier-1 ratio; leverage ratio, measured as total assets to equity; return on equity (roe); level 2 and level 3 assets as a fraction of total assets. Panel B reports the mean price to book ratio, realized daily volatility (Risk) and slope coefficient sfrom univariate CAPM regressions (β-CAPM) using the returns for the Euro Stoxx 50 as proxy for the market return. Panel C reports information on the country of domicile and the original trading currency for stock prices. Data are from Bloomberg and correspond to averages over the sample 2000:Q1 – 2020:Q3.

4.1 Contribution to Systemic Risk

We start by presenting the estimates for the ΔCoVaR of each institution following the model sketched in Section 2. We focus on the entire sample, from 1/3/2000 to 9/30/2020, and thus include in the analysis three major shocks to financial markets: the Great Financial Crisis; the European sovereign debt crisis; and the Covid-19 pandemic shock. In the estimation of equation (1), we include a set of (lagged) state variables, which capture time-variation in the market conditions that could influence the systemic risk contribution of each institution. Specifically, we use the returns of the Eurozone equity market (Euro Stoxx 600 Index) and VDAX volatility indices to capture time-variation in market conditions and risk premia; we use the returns on the European corporate bond market (Barclays Pan-Europe Corporate High-Yield Index) and the excess returns between the Italian and German 10-year government bonds to capture, respectively, corporate and sovereign default risks; we use the excess returns between long-term and short-term German government bonds to capture changes in the slope of the yield curve and, thus, expectations about changes in interest rates and economic conditions (see, for example, Rudebusch and Williams (2009)). In addition, to capture common variations in the banking sector, we also include the first principal component extracted from the daily returns of all institutions in the sample[9].

Table 3 presents the estimation results of the ΔCoVaRs as defined in equation (4). Specifically, Panel A presents, for each bank, its systemic risk contribution when we proxy the entire system with the Stoxx Europe 600 Banks index, a broad value-weighted index for the European banking sector[10]. We summarize our results as follows. First, the estimates for the ΔCoVaR are negative and significantly different from zero for each of the banks in the sample. The precision of the estimates, exemplified by the fact that standard errors are more than one order of magnitude smaller than the corresponding point estimates, in part depends on the large

[9]In our empirical analysis, rather than directly using changes in yields, we consider bond returns by backing out the implicit prices using the standard formula $\log P^{(n)} = -n \log Y^{(n)}$ relating bond prices and gross yields for zero-coupon bonds where n denotes maturity. For example, an unexpected increase in the Italian government default risk will determine a drop in the excess return between the Italian and German 10-year government zero-coupon bonds. Finally, in the estimation of the systemic risk contribution of financial institution i, we extract the first principal component using all financial institutions in the sample but the institution i.

[10]We report in Table A3 in the Online Appendix the coefficient estimates for both the marginal systemic risk contribution and state variables from equation (1).

sample size (for each financial institution we have approximately 5,500 daily returns) and in part on the fact that we consider a sample of the *largest* European banks. For robustness, we also estimate the ΔCoVaR using weekly frequency returns (see Table 7). Also in this case, the estimates are significant for all banks at standard confidence levels, although the standard errors are one order of magnitude larger than for the case of daily returns. Second, we document a large heterogeneity in the systemic risk contribution. For example, a relatively smaller bank like Eurobank Ergasia has a modest systemic risk contribution of approximately -0.6%, while larger banks like Banco Santander or BNP Paribas have a larger systemic risk contribution of approximately -2.2%. As a reference, it is useful to consider that the unconditional 5% VaR for the entire sample is equal to -2.63%. Therefore, our results indicate that, conditional on banks like Banco Santander or BNP being in a situation of distress, the value of the entire system drops almost as much as the unconditional VaR. Such evidence illustrates the strong interlinkages existing among large players in financial markets. Table 6 in the section on robustness (4.4) reports the estimates for the coefficients $\hat{\lambda}_\theta$ in equation (2) for different values of $\theta = 1\%, 5\%, 10\%, 50\%$. Caporin et al. (2018) argue that we observe "shift-contagion", defined as a shift in the intensity of propagation when large positive shocks to individual banks occur compared to normal shocks (see also Forbes and Rigobon (2002), Rigobon (2019)). In our sample, we find evidence of shift contagion for about half of the banks in the sample at standard significance levels. This provides evidence that ΔCoVaR is a good measure of contribution systemic risk.

Panel B and Panel C provide some robustness checks about the previous findings. Specifically, in Panel B we proxy the entire banking sector with the Euro Stoxx Banks index, while in Panel C we use the equally weighted return obtained using all banks in our sample. The reported results in the two panels are substantially consistent with those presented in Panel A, with the systemic risk contribution being larger when we proxy the entire system with the Euro Stoxx Banks index. Note that the latter index groups the largest institutions of the Eurozone only and, thus, excludes banks from countries like the U.K. or Switzerland. The higher reported risk contribution of individual banks, in this case, may reflect the impact of their stress on a more concentrated and interconnected banking sector. In the estimates of the systemic risk contribution of bank i from Panel A and B, it is obvious that bank i is also part of the entire system. To address this possible bias, in the construction of the equally weighted returns used in the estimates for Panel C, we remove institution i when estimating its systemic risk contribution. The estimation results are confirmed also in this specification.

Table 3: Contributions to $\Delta CoVaR$

Bank^i	Panel A: Stoxx Europe 600 Banks		Panel B: Euro Stoxx Banks		Panel C: equally weighted returns	
	$\Delta CoVaR$	s.e.	$\Delta CoVaR$	s.e.	$\Delta CoVaR$	s.e.
ALPHA BANK AE	**-0.868**	0.040	**-1.050**	0.048	**-1.101**	0.047
BANK OF IRELAND	**-1.329**	0.047	**-1.469**	0.051	**-1.287**	0.045
BANKINTER	**-1.703**	0.057	**-2.105**	0.068	**-1.677**	0.055
BARCLAYS PLC	**-2.080**	0.068	**-2.040**	0.068	**-1.826**	0.060
BANCA CARIGE	**-1.176**	0.061	**-1.444**	0.072	**-1.345**	0.065
BANCA MONTE DEI	**-1.451**	0.049	**-1.882**	0.060	**-1.528**	0.051
BANCA POP SONDRI	**-1.334**	0.053	**-1.773**	0.069	**-1.525**	0.061
BPER BANCA	**-1.475**	0.053	**-1.926**	0.067	**-1.621**	0.057
BBVA	**-2.243**	0.062	**-2.695**	0.073	**-2.090**	0.058
BANCO COM PORT-R	**-1.303**	0.055	**-1.590**	0.065	**-1.416**	0.057
BANCO SANTANDER	**-2.360**	0.066	**-2.830**	0.078	**-2.202**	0.063
BNP PARIBAS	**-2.270**	0.073	**-2.716**	0.087	**-2.127**	0.069
COMMERZBANK	**-1.879**	0.077	**-2.171**	0.089	**-1.826**	0.074
CREDIT SUISS-REG	**-2.067**	0.069	**-2.144**	0.072	**-1.780**	0.060
DANSKE BANK A/S	**-1.524**	0.056	**-1.623**	0.060	**-1.551**	0.057
DEUTSCHE BANK-RG	**-2.153**	0.073	**-2.449**	0.083	**-1.973**	0.067
EUROBANK ERGASIA	**-0.598**	0.039	**-0.782**	0.045	**-0.839**	0.045
ERSTE GROUP BANK	**-1.594**	0.057	**-1.820**	0.063	**-1.660**	0.057
SOC GENERALE SA	**-2.292**	0.067	**-2.729**	0.078	**-2.159**	0.063
INTESA SANPAOLO	**-1.911**	0.058	**-2.378**	0.071	**-1.889**	0.058
JYSKE BANK-REG	**-1.194**	0.043	**-1.310**	0.047	**-1.259**	0.045
KBC GROUP	**-1.865**	0.083	**-2.218**	0.098	**-1.882**	0.083
LLOYDS BANKING	**-1.909**	0.065	**-1.859**	0.064	**-1.692**	0.058
MEDIOBANCA	**-1.665**	0.056	**-2.102**	0.068	**-1.718**	0.057
NATL BANK GREECE	**-0.966**	0.048	**-1.195**	0.059	**-1.228**	0.057
NATIXIS	**-1.935**	0.066	**-2.188**	0.075	**-1.954**	0.068
NORDEA BANK ABP	**-1.870**	0.055	**-1.868**	0.056	**-1.721**	0.052
NATWEST GROUP PL	**-1.963**	0.069	**-1.912**	0.069	**-1.731**	0.062
SEB AB-A	**-1.800**	0.071	**-1.867**	0.071	**-1.699**	0.066
STANDARD CHARTER	**-1.770**	0.046	**-1.664**	0.045	**-1.456**	0.040
SVENSKA HAN-A	**-1.675**	0.055	**-1.720**	0.057	**-1.606**	0.053
SWEDBANK AB-A	**-1.748**	0.051	**-1.817**	0.054	**-1.680**	0.048
UBS GROUP AG	**-2.095**	0.085	**-2.101**	0.085	**-1.861**	0.076
UNICREDIT SPA	**-2.055**	0.066	**-2.589**	0.082	**-2.079**	0.067
DEXIA SA	**-0.773**	0.047	**-1.005**	0.056	**-0.917**	0.050

Notes: The Table reports the systemic risk contribution for each financial institution (i.e., its ΔCoVaR). The dependent variable is the return on the Stoxx Europe 600 Bank Index (Panel A); the Euro Stoxx Banks (Panel B); the equally weighted returns of the banks in our sample (Panel C). All regressions are based on daily returns and include the following set of (lagged) state variables: the returns on the Eurozone equity market (EZ equity); the returns on the European corporate bond market (Pan-Europe Corp); the returns on the VDAX volatility index (Vdax); the return spread between a 10-year Italian and German government bond (It Sov-Risk); the return spread between a long-term and a short-term German government bond (Yield Curve Slope); the first principal component extracted from the financial institutions in the sample ($Bank^m$). The state variables are lagged. All standard errors are obtained using a bootstrap procedure. Data are daily for the period 1/3/2000 to 9/30/2020 from Bloomberg.

4.2 Determinants of Systemic Risk Contribution

In this section we study which characteristics of banks are responsible for a larger contribution to systemic risk. We first estimate the model of section 2 using daily data for non overlapping quarters. Therefore, for each bank i we obtain a time-series, at the quarterly frequency, for its ΔCoVaR. Then, we estimate the following predictive panel regressions:

$$\Delta CoVaR_{it} = \alpha_i + \beta_y + \sum_{j=1}^{J} \gamma_{ij} F_{ijt-1} + \epsilon_{i,t} \tag{5}$$

where α_i denote bank fixed effects, β_y year-fixed effects, and γ_{ij} are the coefficients attached to (one quarter) lagged explanatory variables. In the regressions we consider both balance sheet and market based explanatory variables. As for balance sheet variables, we include "size"; "tier-1" capital ratio; "loans" to deposit ratio; the fraction of "level 3" assets to total assets; "leverage" ratio; "roe"; "price/book" ratio; and the "β-CAPM", measured as the slope coefficient in a regression of bank returns on the equity market returns using daily frequency data for each quarter. Table 4 reports the panel estimation results for different specifications of equation (5), where we include the year fixed effects in all specifications. First, we find that size is an important determinant of an individual institution's contribution to systemic risk, coherently with the exercise performed in the previous section and with most of the previous literature: largest banks contribute more to systemic risk. The effect of size remains significant and of a similar magnitude when we include one lag of the dependent variable (column 2); the tier-1 ratio (column 3); the β-CAPM and the loans to deposit ratio (column 4). When we include bank fixed effects, and then leverage, the coefficient of size remains significant, but its absolute value is reduced with respect to the first specification (columnn 6-7). A reason might be that size is relatively stable over the sample, and thus gets partly captured by the bank fixed effects and by some of the additional predictors we consider. The effect of size disappears only when we additionally include in the regression specification the ratio of level 3 assets as fraction of total assets (column 6); leverage interacted with size (column 8); the price-to-book ratio (columns 9); and roe (column 10), although the point estimates remain negative. Second, specification (4) shows that banks that are more sensitive to changes in the equity market values, as proxied by the β-CAPM, also have a higher systemic risk contribution, although the effect is quantitatively small and absorbed by bank fixed effects (columns 4 and 5). These institutions are likely to have a business model more exposed to financial markets, for example because they are active in securities and derivatives trading. In contrast, banks with a higher loans-to-deposit ratio, i.e., institutions with a more traditional business model, have a lower systemic risk contribution (see column (5), which additionally include bank fixed effects): a ten percentage points increase in the loans-to-deposit ratio is associated to a 0.6% percentage points lower ΔCoVaR. In addition, we find that the fraction of the (risky) level 3 assets is statistically significantly associated with a higher systemic risk contribution: a one percentage point increase in level 3 assets is associated to an increase by approximately 1.5 percentage points of the systemic risk contribution. However, the latter result is based on a smaller number of observations (approximately 1,500 out of almost 2,400 observations for specification in column 1) because of the incomplete data coverage for the level 3 assets of the banks in our sample. For this reason, in all other specifications we do not include this predictor in the panel regressions[11]. These results seem to suggest that banks particularly active in financial markets and relatively less in traditional lending may be responsible for more systemic risk. Regulatory supervisory revision of the capital requirements might consider these findings, given that the current Basel accord seems to penalize credit with respect to market risk. In column 7 to 10 we additionally investigate the role of leverage, and we find that it is associated with *lower* systemic risk contribution (column 7). Such finding, although very small in magnitude, is different from the one in Adrian and Brunnermeier (2016), which measures leverage not only with balance sheet data, but as the *market value* of total assets to equity.[12]

[11]Consistent with our findings, De Bruyckere, Gerhardt, Schepens, and Vander Vennet (2013) find that banks with less traditional banking activities in Europe are more exposed to sovereign default risks over the period 2007-2012. In contrast, Meuleman and Vander Vennet (2020) find evidence of risk-shifting behavior of some retail banks, in response to lending-oriented tools of macroprudential policy, which increase their exposure to business cycle or financial market shocks and, thus, increase their systemic risk contribution. Nucera, Lucas, Schaumburg, and Schwaab (2017) argue that smaller and traditional banks have a higher propensity to become undercapitalized in financial crisis when policy rates are extremely low, or negative.

[12]Most of the literature finds that leverage is an important contributor of systemic risk in period of crisis. When we interact size with leverage, we obtain a negative coefficient coefficient, that is statistically significant at the 10% level in specification (10) (which additionally include the price-to-book market and roe).

Table 4: Determinants of $\Delta CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
size	-0.0593 ***	-0.0486 ***	-0.0467 ***	-0.0415 ***	-0.0219 **	-0.0004	-0.0491 ***	-0.0328	-0.0310	-0.0213
	(0.0118)	(0.0097)	(0.0096)	(0.0095)	(0.0093)	(0.0145)	(0.0148)	(0.0148)	(0.0201)	(0.0232)
tier-1			-0.0082	-0.0051	-0.0015	-0.0181	0.0049	0.0055	0.0108	0.0112
			(0.0069)	(0.0050)	(0.0080)	(0.0124)	(0.0072)	(0.0072)	(0.0083)	(0.0095)
β-CAPM				-0.0009 **	-0.0004	-0.0003	-0.0002 *	-0.0002	-0.0001	-0.0001
				(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
loans				0.0004	0.0006 ***	0.0008 *	0.0003 *	0.0003 *	-0.0002	-0.0001
				(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0006)	(0.0006)
level 3						-0.0155 ***				
						(0.0053)				
leverage							0.0001 ***	0.0001 ***	0.0001 **	0.0001 **
							(0.0000)	(0.0000)	(0.0000)	(0.0000)
size x leverage								-0.0004	-0.0006	-0.0007 *
								(0.0003)	(0.0005)	(0.0004)
roe										0.0008
										(0.0020)
price/book									-0.0007	-0.0006
									(0.0004)	(0.0004)
lag ΔCoVaR		0.1817 ***	0.1884 ***	0.1732 ***	0.1301 ***	0.1157 ***	0.1136 ***	0.1134 ***	0.1172 ***	0.1137 ***
		(0.0211)	(0.0221)	(0.0232)	(0.0194)	(0.0267)	(0.0203)	(0.0204)	(0.0201)	(0.0201)
observations	2370	2370	2293	2282	2282	1515	2157	2157	2059	2020
R-square	0.4697	0.4854	0.4832	0.4847	0.4758	0.4168	0.4663	0.4664	0.4664	0.4628
year fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
bank fixed effect	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES

Notes: The Table reports the results of the estimation of the panel regressions described in equation (5). The dependent variables are the financial institution ΔCoVaRs estimated using daily returns for different quarters. The explanatory variables are (one quarter) lagged. We consider the following explanatory variables: "size", measured as assets as a fraction of the total assets in our sample; the "tier-1" capital ratio; the "loans" to deposit ratio, measured as total loans as a fraction of total deposits; the level 3 assets as fraction of total assets; the "leverage" ratio, measured as total assets to equity; the "roe", measured as return on common equity; the "price/book" ratio; and the "β-CAPM", measured as the slope coefficient in a regression of bank returns on the equity market returns using daily frequency data for each quarter. All specifications include year fixed effects. Robust standard errors clustered at the financial institution level in brackets. Stars denote significance at the 1% (***), 5% (**) and 10% (*). Data are quarterly from Bloomberg for the period 2000-Q1 to 2020-Q2.

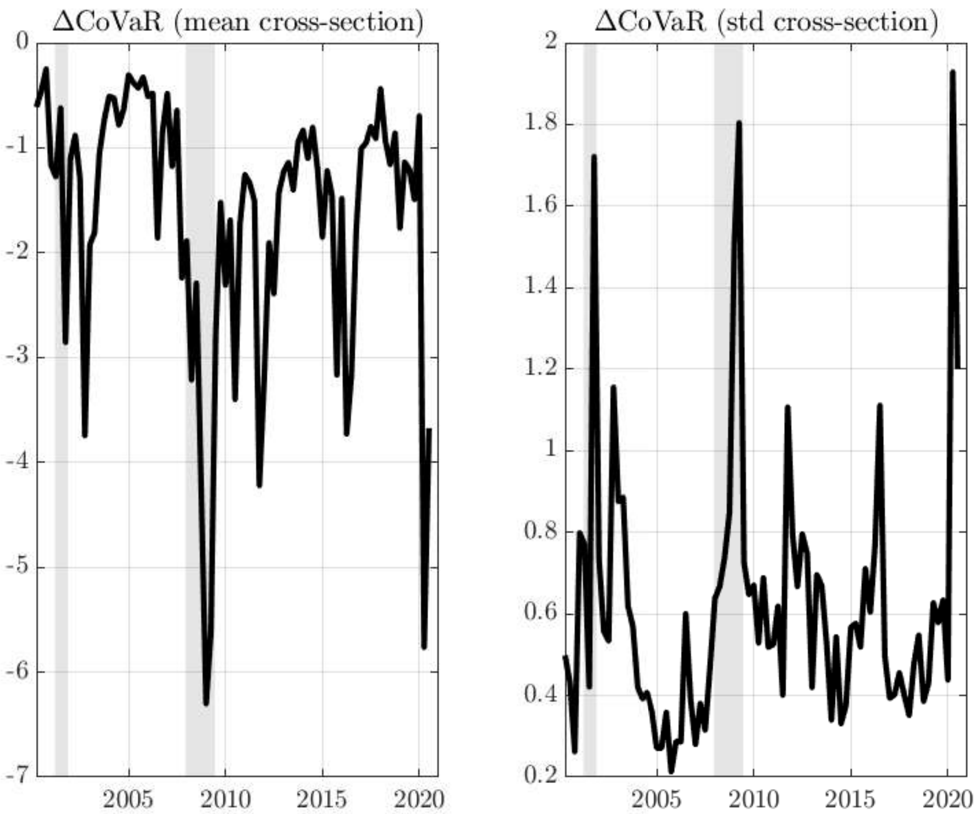
4.3 Systemic Risk and the Covid-19 Shock

The recent Covid-19 shock, associated with the diffusion of the pandemic and the induced lockdowns that were approved by governments all over the world, had a strong negative impact on economic and banking activity. Banks were particularly hit because of both the increased likelihood of defaults on loans to households and the business sector, and the drop in the value of government bonds, held in their balance sheets. We plot in Figure 1 the cross-sectional mean and volatility of the quarterly ΔCoVaR, estimated according to our model, using daily returns for non-overlapping quarters. The figure shows that both the ΔCoVaR cross-sectional mean and volatility substantially increased, in absolute value, during the Covid-19 shock with a magnitude only matched by the one in the Great Financial Crisis. In this section, we focus on the shorter sample characterized by the diffusion of the pandemic, from January 1, 2020 to the end of September 2020, and analyze the evolution of European banks' contributions to systemic risk and their determinants. We first estimate the time-varying CoVaR, for each bank, using daily data for the entire sample, and then estimate panel regressions for the sub-sample including only the predicted values starting from 1/1/2020. Because of the daily frequency and the shorter sample, we cannot consider balance sheet indicators. On the contrary, we focus on whether individual institutions in some countries had a larger systemic risk contribution, possibly because of the heterogenous intensity of the lockdowns or the timing of the diffusion of the pandemic in different European countries. In addition, we evaluate the effect on systemic risk contribution of the ECB non conventional measures, as well as of the dynamics of sovereign default risk (which Black, Correa, Huang, and Zhou (2016) and Pagano and Sedunov (2016) identify as an important risk factor). In our analysis we proxy the sovereign default risk with the changes in the yield spread on the benchmark 10-year Italian government bond with respect to the German bond with same maturity[13].

We report our main findings in Table 5. We use an empirical specification similar to that in equation (5). However, the dependent variable is the daily CoVaR of each institution; we include country dummies; and consider weekly fixed effects to control for the common dynamic of the

[13]We obtain similar results when we proxy sovereign default with the yield spread of other risky sovereigns). These results are available upon request.

Figure 1: Time-varying Δ CoVaR



Notes: This figure plots the evolution of the the cross-sectional mean and volatility of the quarterly ΔCoVaR. The shaded area denotes the last two NBER U.S. recession periods. Data are quarterly from Bloomberg for the period 2000-Q1 to 2020-Q2.

evolution of the pandemic emergency across European countries and for the policy measures decided by the ECB. We summarize the results reported in Table 5 as follows. First, banks located in Spain, France, and the U.K. are associated to a significant systemic risk contribution over the Covid-19 sample (see column 1). This result is related to the fact that banks located in these countries are the largest in our sample, and thus is consistent with the significant effect of size highlighted in Table 4. Second, when we interact the country dummies with an indicator variable that takes value one in the days prior to the announcement of the PEPP program by the ECB (March 18, 2020), then all institutions have a significant contribution to systemic risk (see column 2). The PEPP is a temporary asset purchase program of private and public sector securities. Initially endowed with a value of euro 750 billions, then it was extended by additionally euro 600 billion at the beginning of June, and it is not necessarily linked to the so called “capital key” rule[14]. While figure A3 and Figure A7 highlight how the PEPP announcement acted as a turning point in European equity and sovereign debt markets, section C in the Online Appendix provide additional econometric evidence of its role as a structural break. The contribution to systemic risk of banks in all countries remain significant also when we include bank fixed effects (see column 3). In column 4 we find a strong negative and significant effect of an increase in sovereign default risk, measured as an increase in the Italian sovereign spread. This effect is particularly large before the announcement of the PEPP program (see column 5). This points to the effectiveness of the ECB actions in curbing sovereign default risk and restoring the monetary policy transmission mechanism. When we interact the country dummies with the proxy for sovereign default risk and the PEPP indicator function (see column 6), we find that an increase in sovereign default risk is associated to an increase in the systemic risk contribution for all banks. Surprisingly, the effect is stronger for banks in countries like Germany and France, and smaller for Italian banks, even though we proxy the sovereign default risk exactly with the Italian government bond spread. One interpretation may be that investors anticipate that Italian banks would be bailed out in case of a default of Italy, while this would not apply to non-Italian banks as their exposure to the Italian sovereign debt could have been more easily avoided. The inclusion of week time effects, which capture time-varying factors common to all banks in the sample, reduce the magnitude, but not the significance, of the coefficients attached to the country dummies interacted with the sovereign default risk measure and the PEPP indicator function (see column (7)). Finally, we consider a specification with the country dummies, the sovereign default risk measure before the PEPP announcement, and the sovereign default risk measure before the PEPP announcement interacted with the β-CAPM (column (8)): the latter are estimated using data before the Covid-19 shock, and specifically up to 12/31/2019, and may be considered a proxy for the institutional business model, with higher β-CAPM corresponding to banks more active in securities and derivatives trading. We find a significant negative coefficient

[14]For details on the ECB PEPP program see Grund (2020) or the ECB press release. Note that on the same day ECB announced the PEPP program, it also announced a set of new expansionary measures, and in particular new weekly Longer Term Refinancing Operations with full allotment and negative interest rates as a bridge to the next TLTRO auction scheduled for June 24, and it added 120 billion euro to the existing asset purchase program. Finally, on the same day, the Federal Reserve board announced an extraordinary injection of liquidity for additional 1,500 billions of dollars, and authorized a 700 billions of dollars quantitative easing program.

attached to this variable. The evidence presented in column (8), thus, provides additional evidence to support the argument that the increase in sovereign default risk affected systemic risk particularly through the contribution of banks more exposed to the volatility of financial markets.

Table 5: Determinants of $CoVaR$ around Covid-19

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IT	-0.0000							-0.0000
	(0.0003)							(0.0003)
DE	0.0004 **							0.0006 **
	(0.0002)							(0.0002)
ES	-0.0015 ***							-0.0016 ***
	(0.0005)							(0.0005)
FR	-0.0012 ***							-0.0013 ***
	(0.0003)							(0.0003)
GB	-0.0015 ***							-0.0016 ***
	(0.0002)							(0.0002)
CH	0.0001							0.0001
	(0.0002)							(0.0002)
IT x pre-PEPP		-0.0033 ***	-0.0041 ***					
		(0.0008)	(0.0009)					
DE x pre-PEPP		-0.0029 ***	-0.0041 ***					
		(0.0002)	(0.0001)					
ES x pre-PEPP		-0.0054 ***	-0.0051 ***					
		(0.0005)	(0.0002)					
FR x pre-PEPP		-0.0063 ***	-0.0067 ***					
		(0.0008)	(0.0009)					
GB x pre-PEPP		-0.0058 ***	-0.0054 ***					
		(0.0006)	(0.0008)					
CH x pre-PEPP		-0.0036 ***	-0.0047 ***					
		(0.0004)	(0.0004)					
DEFAULT RISK				-0.6653 ***	1.0746 ***			
				(0.2246)	(0.2673)			
DEFAULT RISK x pre-PEPP					-3.8990 ***			2.1631 **
					(0.3747)			(1.0357)
IT x DEFAULT RISK x pre-PEPP						-2.4062 ***	-1.2948 ***	
						(0.4112)	(0.4389)	
DE x DEFAULT RISK x pre-PEPP						-5.0723 ***	-3.4889 ***	
						(0.9755)	(0.9567)	
ES x DEFAULT RISK x pre-PEPP						-3.5158 ***	-2.6884 ***	
						(0.8804)	(0.8858)	
FR x DEFAULT RISK x pre-PEPP						-6.0235 ***	-4.7610 ***	
						(0.9968)	(0.8565)	
GB x DEFAULT RISK x pre-PEPP						-2.4491 **	-1.5629	
						(1.0088)	(0.9655)	
CH x DEFAULT RISK x pre-PEPP						-1.7030 ***	-0.4288 *	
						(0.2876)	(0.3801)	
β-CAPM pre-Covid x DEFAULT RISK								-3.3305 ***
								(0.9611)
lag CoVaR	-0.0041	-0.0142	-0.0160	-0.0041	0.0189	0.0107	-0.1132 ***	-0.1140 ***
	(0.0183)	(0.0187)	(0.0188)	(0.0181)	(0.0180)	(0.0171)	(0.0214)	(0.0208)
observations	6187	6187	6187	6154	6154	6154	6154	6154
R-square	0.0016	0.0111	0.0106	0.0017	0.0151	0.0130	0.1392	0.1404
time effect	NO	NO	NO	NO	NO	NO	YES	YES
bank fixed effect	NO	NO	YES	YES	YES	YES	NO	NO

Notes: The Table reports the estimates of panel regressions. The dependent variable is the CoVaR of the European banking system conditional on individual institutions being at their 5% VaR and on a set of lag risk factors. Stars denote significance at the 1% (***), 5% (**) and 10% (*). Data are daily for the period 1/3/2000 to 9/30/2020 from Bloomberg.

4.4 Robustness

In this section, we study the stability of the marginal systemic risk contribution of the banks in our sample to different threshold levels for the quantile regressions, and the robustness of our main results with respect to weekly frequency returns.

To study the stability of the estimates of systemic risk contribution, we follow Caporin et al. (2018) which argues that we observe "shift-contagion" when the intensity of the contribution changes across the different quantiles, and specifically is higher for lower quantiles. Table 6 reports the estimates for the marginal systemic risk contribution for the quantiles 1%, 5%, 10% and 50%, and the p-values of tests whether the coefficients for the quantiles 1%, 5%, 10% are statistically different from the ones of the median quantile. In our sample, we find that for 17 out of 35 banks, the marginal systemic risk contribution for the 1% and 5% quantile is statistically different from the median quantile (and for 13 out 35 banks for the 10% quantile). Therefore, our results support the evidence of significant systemic risk contribution for a large number of banks in our sample. Interestingly, these tests reject the null of increasing intensity in the contribution for some large banks, like BBVA, BNP Paribas, or UBS. While this is evidence against a significant systemic risk contribution for these banks under the stricter definition of "shift-contagion", it does not support the conclusion that these banks are not systemically important. In fact, in terms of the point estimates of the marginal contribution to systemic risk, these banks are also those with the largest effects: BBVA (0.670); BNP Paribas (0.6.39); UBS (0.653)[15].

Table 7 reports the estimates for the ΔCoVaR for each bank using weekly frequency returns. As for the case of daily returns, also for weekly returns the ΔCoVaR are significant for all banks, although the standard errors are larger by one order of magnitude. These results support the fact that the baseline results illustrated in Table 3 are not only driven by the large number of observations, but also by the fact that all banks in the sample are relatively large, and thus have a significant, although heterogenous, contribution to systemic risk.

[15] Caporin et al. (2018) also argue that the increasing intensity in the estimates for risk contribution might depend on heteroskedasticity effects or endogeneity issues. The former can be addressed by GARCH filtering the return series, the latter by estimating a multiple regression version of the ΔCoVaR (see, for example, Bonaccolto, Borri, and Consiglio (2020)).

Table 6: $CoVaR$: Stability of Estimated Coefficients

	$\hat{\lambda}_{1\%}$	s.e.	$\hat{\lambda}_{5\%}$	s.e.	$\hat{\lambda}_{10\%}$	s.e.	$\hat{\lambda}_{50\%}$	s.e.	$p(\hat{\lambda}_{1\%} - \hat{\lambda}_{50\%})$	$p(\hat{\lambda}_{5\%} - \hat{\lambda}_{50\%})$	$p(\hat{\lambda}_{10\%} - \hat{\lambda}_{50\%})$
ALPHA BANK AE	**0.140**	0.004	**0.138**	0.004	**0.137**	0.004	**0.122**	0.004	0.001	0.002	0.004
BANK OF IRELAND	**0.257**	0.004	**0.256**	0.004	**0.254**	0.004	**0.239**	0.004	0.001	0.002	0.005
BANKINTER	**0.507**	0.007	**0.503**	0.007	**0.507**	0.007	**0.506**	0.007	0.450	0.388	0.457
BARCLAYS PLC	**0.536**	0.004	**0.536**	0.005	**0.534**	0.005	**0.525**	0.004	0.032	0.041	0.059
BANCA CARIGE	**0.298**	0.007	**0.289**	0.007	**0.285**	0.007	**0.241**	0.007	0.000	0.000	0.000
BANCA MONTE DEI	**0.325**	0.005	**0.321**	0.006	**0.318**	0.005	**0.285**	0.005	0.000	0.000	0.000
BANCA POP SONDRI	**0.436**	0.009	**0.433**	0.009	**0.434**	0.009	**0.430**	0.008	0.337	0.425	0.399
BPER BANCA	**0.365**	0.007	**0.365**	0.007	**0.363**	0.006	**0.358**	0.006	0.214	0.211	0.276
BBVA	**0.671**	0.005	**0.670**	0.005	**0.671**	0.005	**0.663**	0.004	0.125	0.154	0.114
BANCO COM PORT-R	**0.324**	0.007	**0.320**	0.007	**0.317**	0.006	**0.288**	0.006	0.000	0.000	0.000
BANCO SANTANDER	**0.658**	0.004	**0.658**	0.004	**0.658**	0.004	**0.649**	0.004	0.069	0.074	0.074
BNP PARIBAS	**0.639**	0.004	**0.639**	0.004	**0.641**	0.004	**0.642**	0.004	0.325	0.332	0.464
COMMERZBANK	**0.437**	0.005	**0.435**	0.005	**0.431**	0.005	**0.418**	0.004	0.002	0.004	0.018
CREDIT SUISS-REG	**0.593**	0.005	**0.593**	0.005	**0.591**	0.005	**0.583**	0.005	0.071	0.077	0.128
DANSKE BANK A/S	**0.511**	0.007	**0.509**	0.007	**0.511**	0.007	**0.511**	0.007	0.484	0.390	0.477
DEUTSCHE BANK-RG	**0.535**	0.004	**0.535**	0.004	**0.531**	0.004	**0.524**	0.004	0.031	0.031	0.110
EUROBANK ERGASIA	**0.075**	0.003	**0.074**	0.003	**0.073**	0.003	**0.060**	0.003	0.001	0.001	0.002
ERSTE GROUP BANK	**0.421**	0.006	**0.420**	0.006	**0.423**	0.006	**0.428**	0.005	0.187	0.180	0.278
SOC GENERALE SA	**0.564**	0.003	**0.564**	0.003	**0.563**	0.003	**0.558**	0.003	0.080	0.100	0.118
INTESA SANPAOLO	**0.507**	0.005	**0.505**	0.005	**0.507**	0.005	**0.503**	0.005	0.284	0.374	0.249
JYSKE BANK-REG	**0.443**	0.009	**0.443**	0.009	**0.444**	0.009	**0.454**	0.008	0.190	0.200	0.222
KBC GROUP	**0.455**	0.005	**0.452**	0.005	**0.454**	0.005	**0.453**	0.004	0.370	0.449	0.422
LLOYDS BANKING	**0.494**	0.005	**0.492**	0.005	**0.491**	0.005	**0.480**	0.005	0.020	0.043	0.055
MEDIOBANCA	**0.509**	0.007	**0.510**	0.007	**0.511**	0.007	**0.513**	0.006	0.354	0.376	0.432
NATL BANK GREECE	**0.154**	0.004	**0.151**	0.004	**0.147**	0.004	**0.131**	0.004	0.000	0.000	0.001
NATIXIS	**0.488**	0.005	**0.490**	0.005	**0.488**	0.005	**0.484**	0.004	0.267	0.157	0.244
NORDEA BANK ABP	**0.564**	0.007	**0.571**	0.006	**0.560**	0.007	**0.565**	0.006	0.458	0.230	0.304
NATWEST GROUP PL	**0.471**	0.004	**0.472**	0.004	**0.471**	0.004	**0.460**	0.004	0.028	0.022	0.035
SEB AB-A	**0.519**	0.006	**0.514**	0.006	**0.517**	0.006	**0.521**	0.006	0.409	0.211	0.330
STANDARD CHARTER	**0.522**	0.006	**0.522**	0.006	**0.519**	0.006	**0.513**	0.005	0.120	0.113	0.207
SVENSKA HAN-A	**0.577**	0.008	**0.579**	0.008	**0.579**	0.008	**0.587**	0.007	0.171	0.242	0.236
SWEDBANK AB-A	**0.503**	0.006	**0.500**	0.006	**0.501**	0.006	**0.503**	0.006	0.475	0.355	0.362
UBS GROUP AG	**0.653**	0.005	**0.650**	0.005	**0.650**	0.005	**0.645**	0.005	0.151	0.237	0.223
UNICREDIT SPA	**0.497**	0.005	**0.496**	0.005	**0.494**	0.005	**0.488**	0.004	0.061	0.092	0.145
DEXIA SA	**0.120**	0.004	**0.115**	0.004	**0.113**	0.004	**0.086**	0.004	0.000	0.000	0.000

Notes: The Table reports the coefficient estimates for the marginal systemic risk contribution for the quantiles 1%, 5%, 10% and 50%. All standard errors are obtained using a bootstrap procedure. The last three columns report the p-values for the test that the coefficients $\hat{\lambda}_j$ with j = 1%, 5%, 10% are statistically different from $\hat{\lambda}_{50\%}$. The p-values are based on standard z-tests (z =). Data are daily for the period 1/3/2000 to 9/30/2020 from Bloomberg.

Table 7: Contributions to $\Delta CoVaR$ (Weekly Frequency)

$Bank^i$	Panel A: Stoxx Europe 600 Banks		Panel B: Euro Stoxx Banks		Panel C: equally weighted returns	
	$\Delta CoVaR$	s.e.	$\Delta CoVaR$	s.e.	$\Delta CoVaR$	s.e.
ALPHA BANK AE	**-2.847**	0.274	**-3.327**	0.317	**-3.401**	0.302
BANK OF IRELAND	**-3.930**	0.313	**-4.684**	0.365	**-4.170**	0.326
BANKINTER	**-3.685**	0.239	**-4.954**	0.312	**-3.888**	0.251
BARCLAYS PLC	**-4.408**	0.290	**-4.329**	0.296	**-4.159**	0.279
BANCA CARIGE	**-3.524**	0.317	**-4.341**	0.383	**-4.035**	0.351
BANCA MONTE DEI	**-4.373**	0.293	**-5.399**	0.342	**-4.775**	0.312
BANCA POP SONDRI	**-3.354**	0.297	**-4.131**	0.352	**-3.738**	0.318
BPER BANCA	**-3.710**	0.301	**-4.888**	0.386	**-4.373**	0.345
BBVA	**-5.161**	0.326	**-6.164**	0.388	**-4.910**	0.315
BANCO COM PORT-R	**-4.189**	0.294	**-5.094**	0.353	**-4.697**	0.319
BANCO SANTANDER	**-5.329**	0.316	**-6.324**	0.369	**-4.922**	0.302
BNP PARIBAS	**-5.182**	0.403	**-6.186**	0.477	**-5.033**	0.391
COMMERZBANK	**-4.521**	0.381	**-5.273**	0.436	**-4.691**	0.401
CREDIT SUISS-REG	**-4.490**	0.254	**-4.894**	0.282	**-4.309**	0.251
DANSKE BANK A/S	**-3.799**	0.247	**-4.252**	0.285	**-4.192**	0.273
DEUTSCHE BANK-RG	**-4.536**	0.259	**-5.261**	0.298	**-4.450**	0.261
EUROBANK ERGASIA	**-2.390**	0.323	**-2.777**	0.370	**-2.923**	0.362
ERSTE GROUP BANK	**-3.854**	0.250	**-4.319**	0.285	**-3.983**	0.265
SOC GENERALE SA	**-5.173**	0.312	**-6.196**	0.371	**-5.043**	0.307
INTESA SANPAOLO	**-4.642**	0.272	**-5.715**	0.319	**-4.679**	0.265
JYSKE BANK-REG	**-3.120**	0.241	**-3.583**	0.281	**-3.174**	0.248
KBC GROUP	**-4.087**	0.255	**-4.527**	0.287	**-4.005**	0.255
LLOYDS BANKING	**-4.303**	0.383	**-4.218**	0.401	**-4.051**	0.370
MEDIOBANCA	**-4.187**	0.264	**-5.178**	0.319	**-4.487**	0.281
NATL BANK GREECE	**-3.024**	0.303	**-3.932**	0.388	**-3.787**	0.354
NATIXIS	**-4.372**	0.402	**-5.058**	0.468	**-4.476**	0.415
NORDEA BANK ABP	**-3.841**	0.353	**-4.359**	0.411	**-3.904**	0.365
NATWEST GROUP PL	**-4.752**	0.405	**-4.895**	0.421	**-4.429**	0.383
SEB AB-A	**-3.797**	0.257	**-4.069**	0.288	**-3.938**	0.267
STANDARD CHARTER	**-4.349**	0.263	**-4.211**	0.266	**-4.131**	0.255
SVENSKA HAN-A	**-3.672**	0.234	**-3.912**	0.262	**-3.661**	0.238
SWEDBANK AB-A	**-3.722**	0.263	**-4.032**	0.297	**-3.927**	0.279
UBS GROUP AG	**-4.493**	0.365	**-4.773**	0.397	**-4.289**	0.356
UNICREDIT SPA	**-5.053**	0.343	**-6.001**	0.402	**-5.244**	0.357
DEXIA SA	**-3.850**	0.364	**-4.671**	0.437	**-4.140**	0.385

Notes: The Table reports the systemic risk contribution for each financial institution (i.e., its ΔCoVaR). The dependent variable is the return on the Stoxx Europe 600 Bank Index (Panel A); the Euro Stoxx Banks (Panel B); the equally weighted returns of the banks in our sample (Panel C). All regressions are based on weekly returns and include the following set of (lagged) state variables: the returns on the Eurozone equity market (EZ equity); the returns on the European corporate bond market (Pan-Europe Corp); the returns on the VDAX volatility index (Vdax); the return spread between a 10-year Italian and German government bond (It Sov-Risk); the return spread between a long-term and a short-term German government bond (Yield Curve Slope); the first principal component extracted from the financial institutions in the sample ($Bank^m$). The state variables are lagged. All standard errors are obtained using a bootstrap procedure. Data are weekly for the period 1/3/2000 to 9/30/2020 from Bloomberg.

5 Conclusions

In this paper we study the systemic risk contribution of large European banks over a long period which includes three large financial crisis: the Great Financial Crisis, the European sovereign debt crisis, and the recent crisis related to the Covid-19 pandemic. The sample also covers important changes that occurred in the regulation of the banking sector, like the assignment to the ECB of a new supervisory role in the Eurozone, or the introduction of more stringent capital and leverage requirements with Basel III. As a measure of systemic risk contribution we focus on ΔCoVaR, which is based on quantile regressions and asset prices.

Over this period, spanning twenty years, we find that all banks in our sample significantly contribute to systemic risk, but larger banks, and banks with a business model more exposed to financial markets, contribute more. In the shorter sample, around the Covid-19 shock, we find that sovereign default risks significantly affected the systemic risk contribution of all banks up to the ECB announcement of the PEPP (and of other additional actions undertaken in support of banks such as new and more convenient conditions extended through the targeted long-term refinancing operations): we find that the ECB was successful in restoring calm in the European banking sector.

The recent Covid-19 shock caused the equity prices of most banks to collapse by a magnitude we did not observe since the Great Financial Crisis. Importantly, *this time was different*: we did not enter into a financial crisis and banks seem – for the time being – to have been able to weather the storm. This might in part depend on the extraordinary (although likely temporary) supportive measures undertaken by the ECB, by European governments, and the European Union. However, it is reasonable to conclude that the new regulation after the Great Financial Crisis, which set higher capital requirements for banks and more stringent stress tests has proved successful at avoiding a new large financial crisis[16]. At the same time, our results show that large banks particularly active in financial markets may be responsible for more systemic risk with respect to those more involved with traditional lending activities. The current Basel accord seems to penalize credit with respect to market risk in the computation

[16]For an introduction on the role of capital in financial institutions see Berger, Herring, and Szegö (1995).

of the overall capital requirements. It could therefore be wise to investigate a partial revision of the banking regulation framework increasing the weight on market risk.

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Online Appendix (not for pubblication)

This Online Appendix for Borri, N. and G. Di Giorgio, "Systemic Risk an the COVID Challenge in the European Banking Sector" is available on the authors' websites and is organized as follows:

- Section 3 presents additional evidence on the data used in this paper.
- Section B presents additional results and robustness checks for the ΔCoVaR estimation.
- Section C presents additional results and robustness checks on the short sample containing the Covid-19 shock.

A Data

This section presents additional information and evidence on the data used in this paper. Figure A1 plots the evolution of the Stoxx Europe 600 Banks index, along the broad Stoxx Europe 600 market index, which includes stocks from all sectors of the economy. The figure shows the high correlation between the two indices at least up to the Great Financial Crisis (GFC) (i.e., the correlation coefficient is equal to 0.78). Since the GFC, the bank index did not really recover, while the broad stock index climbed back up (the correlation over the entire period is 0.05). Both indices dropped substantially as a result of the Covid-19 shock, and only the broad stock index has gained back some of the lost ground since this shock. Since the beginning of the sample, in January 2000, the Stoxx Europe 600 Banks index has lost approximately 80% of its market value, while the Stoxx Europe 600 is roughly flat. The strong negative performance of the Stoxx Europe 600 Banks index highlights the difficulties faced by European banks in the last twenty years. Figure A2 plots the daily equity returns for all the banks in the our sample (left panel), and for two proxies for the entire system: the Stoxx Europe 600 Banks index (orange line) and the equally weighted average of the daily returns of the banks in our sample (blue line). The figure highlights the time-varying and pro-cyclical volatility in daily returns, and the magnitude of idiosyncratic shocks: i.e., the mean volatility of the individual series (approximately 2.7%) is much larger than for the indices (approximately 1.74%). A principal component analysis of the daily bank returns over the entire period shows that the first principal component explains about 40% of the total variation, and the first three principal components approximately 60%.

Table A1 reports descriptive statistics for the state variables used in the estimation of the ΔCoVaR. Panel A refers to the long sample that starts in January 2000, while Panel B to the short Covid-19 sample, which starts in January 2020. While the daily means for all variables are all close to zero, state variables differ with respect to the remaining moments: equity indices are more volatile than the bond indices, and all variables are less volatile than the VDAX volatility index. Over both the full and the Covid-19 samples, returns for all variables are negatively skewed, and have large kurtosis, with the exception of the VDAX which is positively skewed. Recall that an increase in the VDAX denotes increased stress in financial markets. Comparing the two samples, as expected, daily returns during the short Covid-19 sample are smaller and more volatile. Table A2 additionally report the sample correlation matrix for the state variables. We note that all variables are positively correlated, and that the returns on the VDAX index are highly correlated (0.71) with the European broad equity market returns.

B ΔCoVaR Estimation

In this section we report additional results and evaluate the robustness of our baseline findings in the estimation of the systemic risk contribution of European banks.

B.I Coefficient Estimates

In Table 3 we present directly the estimates for the ΔCoVaR of each bank in the sample, according to the model defined in equation (4). In Table A3 we report instead the coefficient estimates for both the marginal systemic risk contribution and state variables from equation (1). We first note that the estimates for the marginal contribution of each institution ($Bank^i$) are all positive and statistically different from zero, and range from 0.670 for BBVA to 0.074 for EUROBANK ERGASIA. In terms of the coefficients attached to the state variables (which are

Table A1: Descriptive Statistics (state variables)

Name	Mean	Std	Min	Max	Skew	Kurt	VaR
	Panel A: full sample						
Stoxx Europe 600	-0.00	1.21	-7.73	8.01	-0.29	8.77	-1.94
Barclays Pan-European HY	0.02	0.38	-3.84	2.87	-1.96	29.47	-0.45
VDAX	-0.00	5.59	-22.01	30.57	0.71	6.05	9.68
IT10Y spread	-0.00	0.62	-5.31	5.20	-0.39	21.41	0.82
Yield curve slope	0.01	0.57	-4.40	4.10	-0.33	12.91	-0.84
	Panel B: Covid-19 sample						
Stoxx Europe 600	-0.05	1.82	-7.73	8.01	-0.67	7.37	-3.60
Barclays Pan-European HY	-0.02	0.67	-3.84	1.97	-2.50	15.71	-0.95
VDAX	0.36	8.33	-17.84	30.57	1.29	5.59	15.27
IT10Y spread	0.00	0.96	-5.31	5.20	-0.89	15.10	1.42
Yield curve slope	0.02	0.85	-4.40	4.10	-0.84	12.80	-1.08

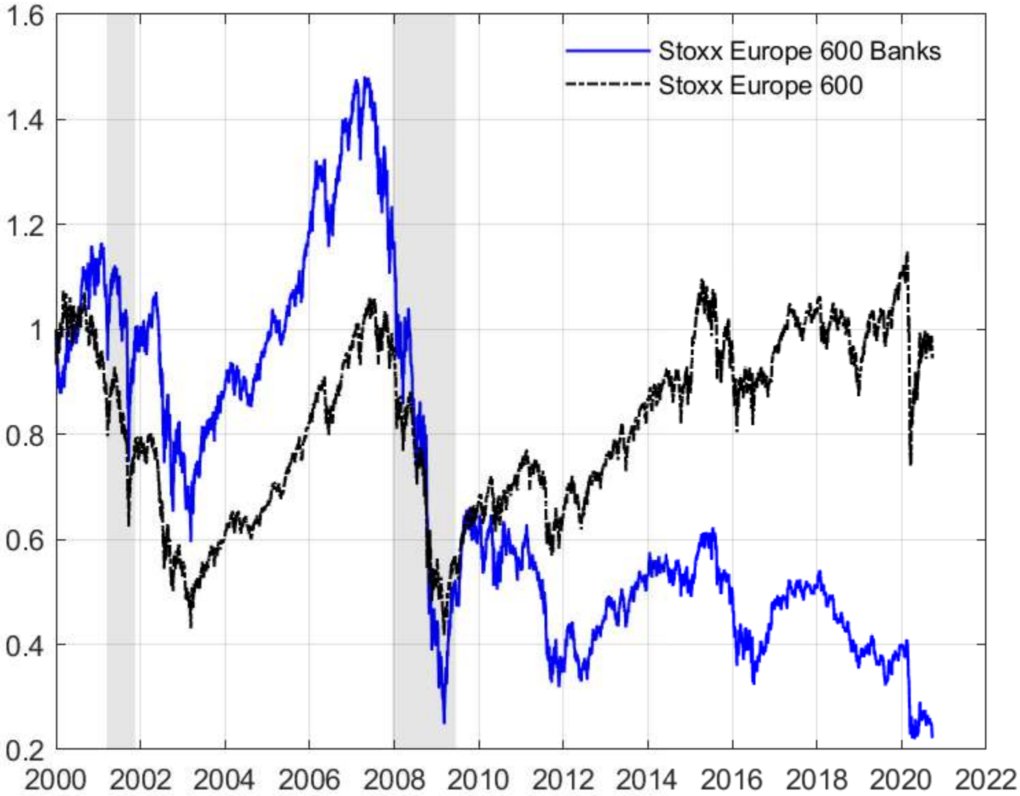
Notes: The Table reports the following descriptive statistics: mean, standard deviation, minimum, maximum, skewness, kurtosis, VaR, for the returns on the following variables: Euro Stoxx 600; Barclays Pan-European High Yield Index; VDAX; the Italian 10Y government bond spread with respect to the German Bund with same maturity; and the yield curve slope measures as spread between a long-term (10-year) and short-term (3-month) German bond. All statistics are multiplied by 100 except for skewness and kurtosis. The VaR is for the 5% quantile (and 95% quantile for the VDAX, as a higher value of the index denotes stress on financial markets). For the bond spread and the slope of the yield curve we consider the corresponding excess returns rather than the yield differences (i.e., we back out the implicit prices using the standard formula $\log P^{(n)} = -n \log Y^{(n)}$ relating bond prices and gross yields for zero-coupon bonds where n denotes maturity). Panel A refers to the full sample 1/1/2020 to 9/30/2020. Panel B refers to the Covid-19 sample: 1/1/2020 to 9/30/2020. Data are from Bloomberg for the period January 1, 2000 to September 30, 2020.

Table A2: Correlation Matrix (state variables)

asset	Eurostoxx 600	Barclays Pan-European HY	VDAX	IT10Y spread	Yield curve slope
Eurostoxx 600	1.00	0.33	0.71	0.31	0.07
Barclays Pan-European HY	0.33	1.00	0.23	0.15	0.13
VDAX	0.71	0.23	1.00	0.30	0.12
IT10Y spread	0.31	0.15	0.30	1.00	0.78
Yield curve slope	0.07	0.13	0.12	0.78	1.00

Notes: The Table reports the correlation matrix for the following state variables: Euro Stoxx 600; Barclays Pan-European High Yield Index; VDAX; the Italian 10Y government bond spread with respect to the German Bund with same maturity; and the yield curve slope measures as spread between a long-term (10-year) and short-term (3-month) German bond. For the bond spread and the slope of the yield curve we consider the corresponding excess returns rather than the yield differences (i.e., we back out the implicit prices using the standard formula $\log P^{(n)} = -n \log Y^{(n)}$ relating bond prices and gross yields for zero-coupon bonds where n denotes maturity). Data are from Bloomberg for the period January 1, 2000 to September 30, 2020.

Figure A1: Evolution of the Equity Indices



Notes: This figure plots the evolution of the Stoxx Europe 600 Banks (solid blue line) and Stoxx Europe 600 (black dashed line) indices. Both indices are set to 1 at the beginning of the sample. The dark shaded regions correspond to the two last NBER U.S. recession periods. Data are daily from Bloomberg for the period 1/3/2000 to 9/30/2020.

lagged by one period), we note that the coefficients corresponding to the common banking system factor ($Bank^m$), Eurozone equity market (EZ Equity), equity volatility (VDAX) and yield curve slopes are small and mostly not statistically different from zero. In contrast, we find that an increase in corporate default risk is associated with a *reduction* in the systemic risk contribution of the banks in our sample (i.e., the coefficients associated to the Pan-Europe Corp are all negative); while an increase in sovereign default risk is associated with an *increase* in the systemic risk contribution of the banks in our sample (i.e., the coefficients associated to the return spread between the Italian and German 10-year government bonds are mostly positive).

C The Covid-19 Sample

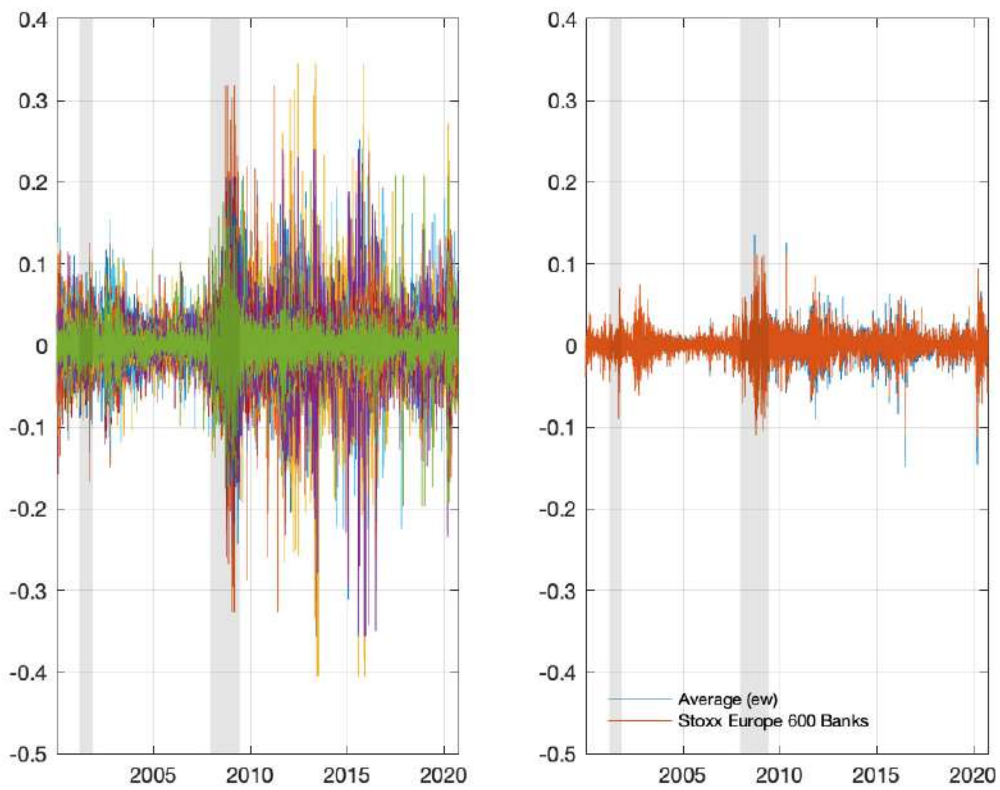
In this section we present additional results and evidence relative to the short sample which starts on January 1, 2020 and includes the large Covid-19 shock.

Table A3: $CoVaR$: Estimated Coefficients

	Bank^i	s.e.	*Bank*^{m}	s.e.	EZ Equity	s.e.	Pan-Europe Corp	s.e.	Vdax	s.e.	It Sov-Risk	s.e.	Yield Curve Slope	s.e.
ALPHA BANK AE	**0.138**	0.004	**0.011**	0.003	**-0.075**	0.027	**-0.419**	0.054	**-0.001**	0.002	**0.142**	0.050	**-0.063**	0.050
BANK OF IRELAND	**0.256**	0.004	**0.003**	0.003	**0.019**	0.027	**-0.453**	0.050	**-0.005**	0.004	**0.132**	0.047	**-0.019**	0.046
BANKINTER	**0.503**	0.007	**0.009**	0.003	**-0.011**	0.023	**-0.336**	0.044	**-0.002**	0.003	**0.025**	0.041	**-0.032**	0.040
BARCLAYS PLC	**0.536**	0.004	**0.002**	0.002	**-0.049**	0.018	**-0.295**	0.037	**0.002**	0.003	**0.101**	0.037	**-0.082**	0.036
BANCA CARIGE	**0.289**	0.007	**0.005**	0.003	**-0.020**	0.022	**-0.434**	0.054	**0.001**	0.003	**0.247**	0.051	**-0.144**	0.050
BANCA MONTE DEI	**0.321**	0.005	**0.004**	0.002	**-0.003**	0.009	**-0.375**	0.048	**0.001**	0.003	**0.138**	0.048	**-0.117**	0.047
BANCA POP SONDRI	**0.433**	0.009	**0.011**	0.003	**-0.059**	0.027	**-0.392**	0.053	**0.004**	0.004	**0.113**	0.049	**-0.070**	0.049
BPER BANCA	**0.365**	0.006	**0.008**	0.003	**-0.057**	0.026	**-0.004**	0.091	**0.004**	0.004	**0.072**	0.048	**-0.043**	0.049
BBVA	**0.670**	0.005	**0.006**	0.002	**-0.056**	0.018	**-0.201**	0.033	**0.008**	0.003	**0.024**	0.033	**-0.044**	0.032
BANCO COM PORT-R	**0.320**	0.006	**0.004**	0.003	**-0.017**	0.023	**-0.429**	0.051	**-0.002**	0.003	**0.148**	0.048	**-0.060**	0.047
BANCO SANTANDER	**0.658**	0.004	**0.007**	0.001	**-0.001**	0.007	**-0.270**	0.031	**0.000**	0.002	**0.021**	0.018	**-0.001**	0.007
BNP PARIBAS	**0.639**	0.004	**0.005**	0.002	**-0.007**	0.013	**-0.223**	0.029	**0.000**	0.000	**-0.026**	0.028	**0.016**	0.028
COMMERZBANK	**0.435**	0.005	**0.004**	0.002	**0.011**	0.021	**-0.322**	0.042	**-0.002**	0.003	**0.061**	0.033	**0.006**	0.025
CREDIT SUISS-REG	**0.593**	0.005	**0.005**	0.002	**-0.073**	0.020	**-0.252**	0.037	**-0.002**	0.003	**0.077**	0.035	**-0.063**	0.034
DANSKE BANK A/S	**0.509**	0.007	**0.005**	0.003	**-0.076**	0.021	**-0.311**	0.048	**-0.000**	0.000	**0.170**	0.044	**-0.132**	0.043
DEUTSCHE BANK-RG	**0.535**	0.004	**0.003**	0.002	**-0.018**	0.018	**-0.001**	0.038	**-0.001**	0.003	**0.155**	0.033	**-0.087**	0.032
EUROBANK ERGASIA	**0.074**	0.003	**0.008**	0.003	**-0.039**	0.028	**-0.450**	0.055	**-0.001**	0.002	**0.107**	0.050	**-0.026**	0.050
ERSTE GROUP BANK	**0.420**	0.006	**0.007**	0.003	**-0.070**	0.024	**-0.394**	0.048	**0.003**	0.004	**0.048**	0.043	**0.038**	0.042
SOC GENERALE SA	**0.564**	0.003	**-0.000**	0.001	**-0.002**	0.011	**-0.151**	0.029	**-0.001**	0.002	**0.000**	0.003	**0.008**	0.016
INTESA SANPAOLO	**0.505**	0.005	**0.009**	0.002	**-0.032**	0.021	**-0.337**	0.040	**0.004**	0.003	**0.064**	0.036	**-0.014**	0.034
JYSKE BANK-REG	**0.443**	0.009	**0.009**	0.003	**-0.053**	0.027	**-0.529**	0.053	**-0.005**	0.004	**0.130**	0.048	**-0.050**	0.048
KBC GROUP	**0.452**	0.005	**0.003**	0.002	**-0.037**	0.019	**-0.330**	0.042	**0.000**	0.001	**0.097**	0.040	**-0.053**	0.039
LLOYDS BANKING	**0.492**	0.005	**0.012**	0.002	**-0.071**	0.019	**-0.205**	0.039	**0.001**	0.002	**0.088**	0.037	**-0.071**	0.036
MEDIOBANCA	**0.510**	0.007	**0.009**	0.003	**-0.022**	0.022	**-0.398**	0.043	**-0.005**	0.003	**0.080**	0.041	**-0.064**	0.041
NATL BANK GREECE	**0.151**	0.004	**0.008**	0.003	**-0.087**	0.026	**-0.391**	0.053	**0.003**	0.003	**0.156**	0.049	**-0.089**	0.049
NATIXIS	**0.490**	0.005	**0.011**	0.002	**-0.050**	0.020	**-0.333**	0.041	**0.001**	0.002	**-0.057**	0.036	**0.028**	0.035
NORDEA BANK ABP	**0.571**	0.006	**0.014**	0.003	**-0.111**	0.022	**-0.026**	0.044	**0.001**	0.003	**0.205**	0.041	**-0.134**	0.040
NATWEST GROUP PL	**0.472**	0.004	**0.005**	0.002	**-0.016**	0.019	**-0.327**	0.038	**-0.003**	0.003	**0.074**	0.036	**-0.037**	0.034
SEB AB-A	**0.514**	0.006	**0.019**	0.003	**-0.138**	0.023	**-0.290**	0.043	**0.002**	0.003	**0.136**	0.041	**-0.091**	0.042
STANDARD CHARTER	**0.522**	0.005	**0.015**	0.002	**-0.083**	0.021	**-0.236**	0.041	**-0.003**	0.003	**0.057**	0.026	**-0.003**	0.013
SVENSKA HAN-A	**0.579**	0.007	**0.018**	0.003	**-0.147**	0.027	**-0.007**	0.079	**0.002**	0.005	**0.153**	0.044	**-0.153**	0.043
SWEDBANK AB-A	**0.500**	0.006	**0.015**	0.002	**-0.061**	0.023	**-0.384**	0.045	**-0.002**	0.003	**0.121**	0.041	**-0.050**	0.042
UBS GROUP AG	**0.650**	0.005	**0.003**	0.002	**-0.035**	0.018	**-0.164**	0.036	**-0.005**	0.003	**0.163**	0.033	**-0.121**	0.033
UNICREDIT SPA	**0.496**	0.005	**0.006**	0.002	**-0.042**	0.021	**-0.254**	0.037	**0.009**	0.003	**0.036**	0.033	**-0.012**	0.032
DEXIA SA	**0.115**	0.004	**0.015**	0.003	**-0.098**	0.027	**-0.371**	0.055	**-0.001**	0.003	**0.111**	0.050	**-0.029**	0.051

Notes: The Table reports the coefficient estimates for both the marginal systemic risk contribution and state variables from equation (1). The dependent variable is the return on the Euro Stoxx 600 Bank Index. The set of state variables include: the returns on the Eurozone equity market (EZ equity); the returns on the European corporate bond market (Pan-Europe Corp); the returns on the VDAX volatility index (Vdax); the return spread between a 10-year Italian and German government bond (It Sov-Risk); the return spread between a long-term and a short-term German government bond (Yield Curve Slope); the first principal component extracted from the banks in the sample ($Bank^m$). The state variables are lagged. All standard errors are obtained using a bootstrap procedure. Data are daily for the period 1/3/2000 to 9/30/2020 from Bloomberg.

Figure A2: Daily Returns

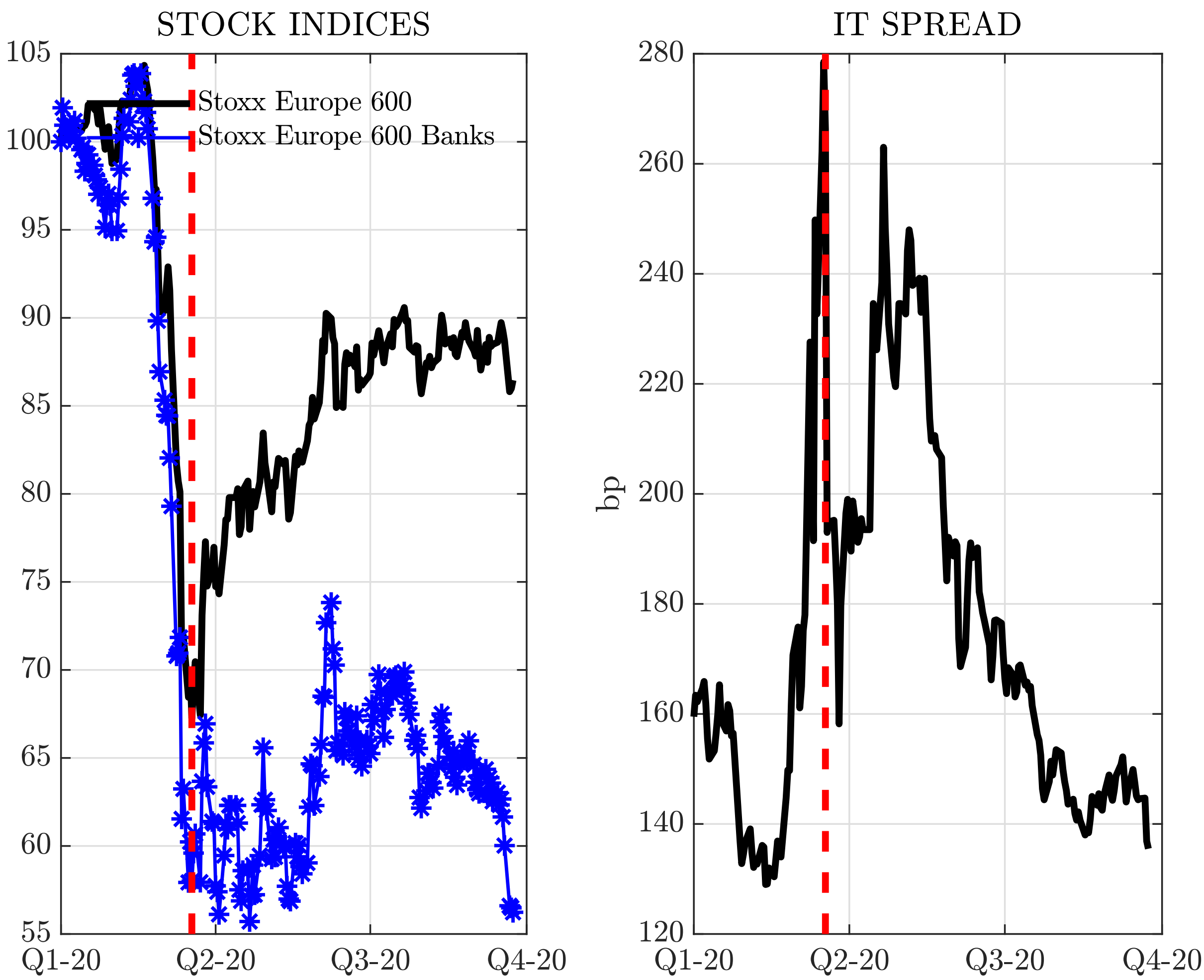


Notes: This figure plots the daily equity returns for all the banks in the our sample (left panel), and for two proxies for the entire system: the Stoxx Europe 600 Banks index (orange line) and the equally weighted average of the daily returns of the banks in our sample (blue line). The dark shaded regions correspond to the two last NBER U.S. recession periods. Data are daily from Bloomberg for the period 1/3/2000 to 9/30/2020.

C.I European Financial Markets during the Covid-19 sample

Figure A3 provides a quick snapshot about European financial markets during the Covid-19 pandemic. The left panel plots the evolution of two reference indices for the broad equity market (Stoxx Europe 600) and for the subset containing the financial institutions (Stoxx Europe 600 Banks). Both indices dropped substantially (approximately by 35 and 55% respectively) with the onset of the pandemic in Europe at the end of February. After the intervention by the ECB, with the introduction of the PEPP program, the equity market index rebounded, while the bank index first recovered part of the lost ground but then dropped again. The right panel plots the evolution of the yield spread on the Italian 10-year government bond with respect to the German government bond with same maturity. As for the equity indices, the yield spread, which measure the perceived risk of default of Italy on its government debt, started to increase substantially at the end of February. It reached a peak of approximately 280 bp on the announcement day, by the ECB, of the PEPP program. Since the peak, the yield spread has dropped substantially and currently hovers around 140 bp, although it reached a second high mark of around 260 bp at the end of April, when most countries in Europe were under lockdown. Note that on April 30, the ECB further eased the conditions for the TLTROs. It also provided a set of new monthly LTROs with full allotment, with maturity until September 2021, to allow its counterparts to receive funding at 25 basis points less then the main refinancing rate, establishing an abundant and convenient line of financing. We estimates Chows tests for structural breaks on both the equity indices and the yield spread, using a break date March 18, 2020, i.e., the announcement date for the PEPP program by the ECB. For all series, the tests reject the null that the series have the same mean before and after the break.

Figure A3: European Financial Markets around the Covid-19 Pandemic

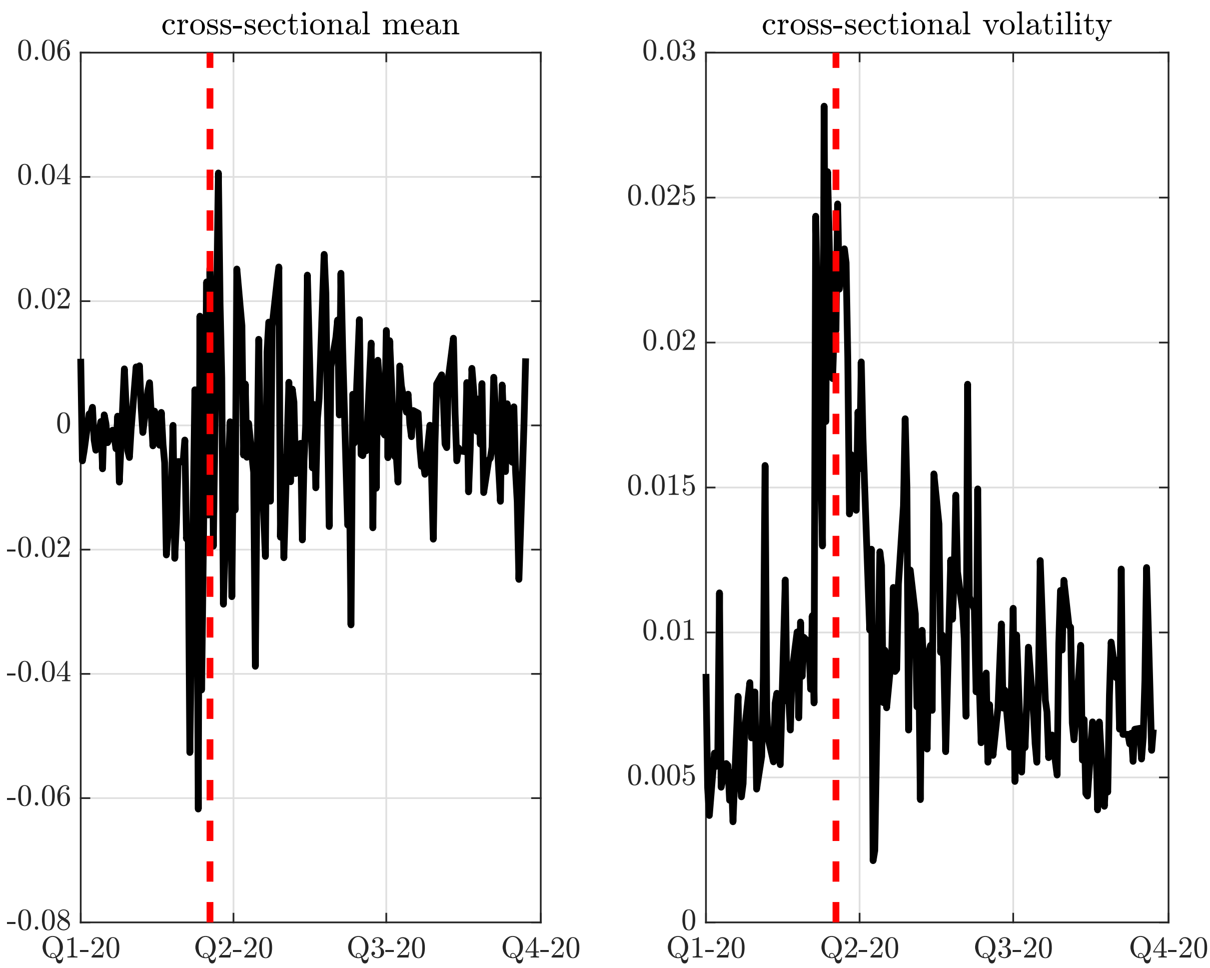


Notes: This figure plots in the left panel the evolution of the Stoxx Europe 600 (solid black line) and Stoxx Europe 600 Banks (blue line with star marker) indices (normalized to 100 at the beginning of the sample); and in the right panel the evolution of the yield spread for the Italian 10 year benchmark government bond with respect to the German government bond with same maturity (in basis points). The vertical dashed-red line corresponds to the ECB announcement of the PEPP program on March 18, 2020. Both indices are normalized to 1 on 1/3/2000. Data are from Bloomberg for the period 1/3/2000 to 9/30/2020.

C.II CoVaR during the Covid-19 sample

In Figure 1 we present the evolution of the cross-sectional mean and standard deviation of the quarterly ΔCoVaR estimated using daily data for non overlapping quarters. In Figure A4 we present, instead, the cross-sectional mean and standard deviation of the daily CoVaR, estimated using equation (3). The time-variation in the daily CoVaR depends on the presence of the state variables. Specifically, we use the entire period to estimate (3), and in Figure A4 we plot the two cross-sectional moments for the shorter Covid-19 sample, which starts on January 1, 2020. The CoVaR with respect to bank i measures the conditional VaR of the entire banking system, conditional on bank i being at its VaR (5%). We observe that the largest negative value for the mean CoVaR, as well as the largest value of the cross-sectional standard deviation, occur just before the ECB announcement of the PEPP program.

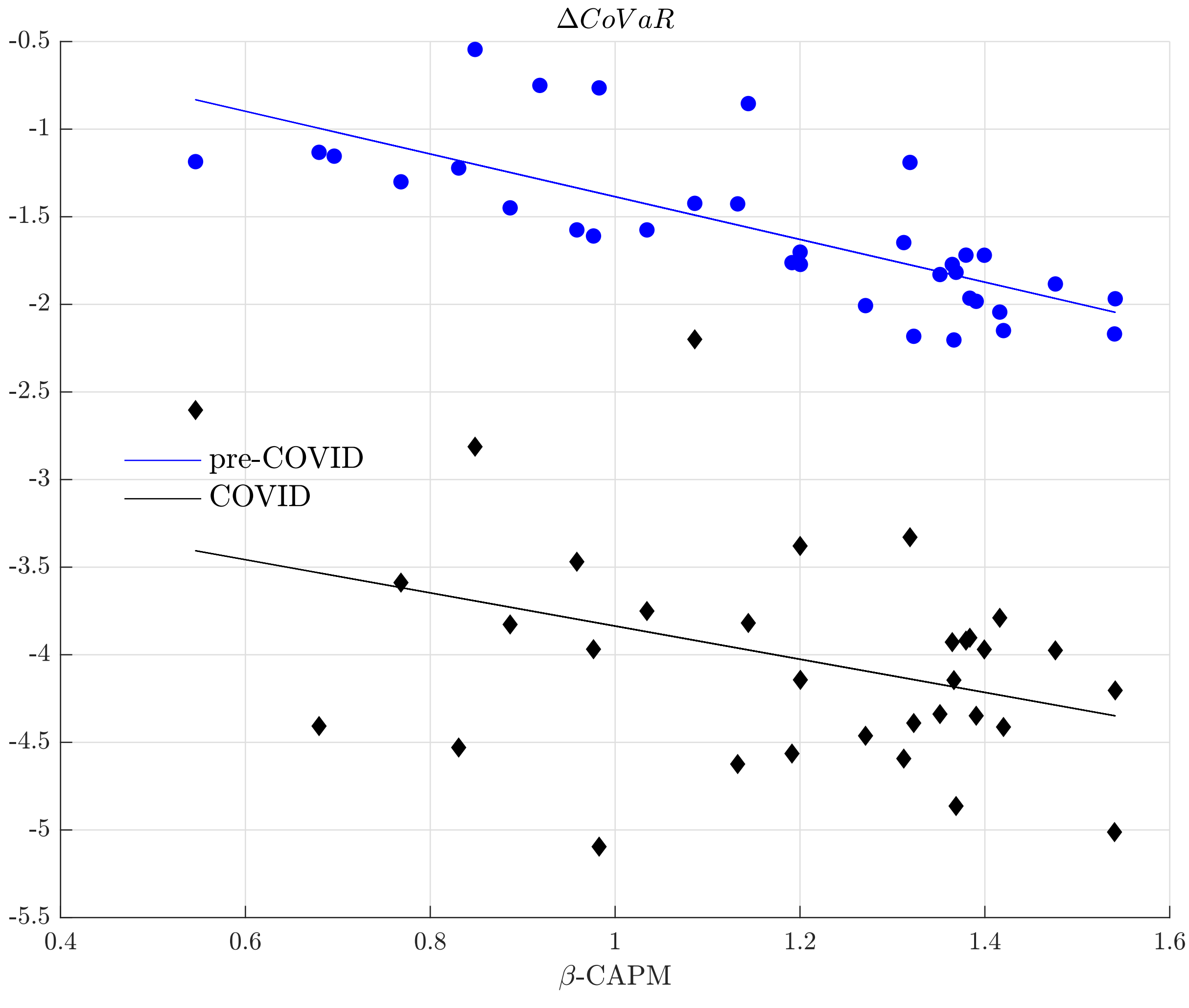
Figure A4: CoVaR during the Covid-19 Shock



Notes: This figure plots the evolution the number of Covid-19 cases (left panel) and deaths (right panel) in the set of European countries where the banks in our sample have their domicile. Both the number of cases and deaths are reported on a log scale. The set of countries are: Germany (DE); Italy (IT); Spain (ES); France (FR); the U.K. (GB); Ireland (IE); Denmark (DK); Greece (GR); Portugal (PT); Switzerland (CH); Finland (FI); and Belgium (BE). The vertical dashed-red line corresponds to the ECB announcement of the PEPP program on March 18, 2020. Data are from Bloomberg for the period 1/3/2000 to 9/30/2020.

In Figure A5 and Figure A6 we provide suggestive evidence that banks more exposed to financial markets are those with a larger increase (in absolute value) of the corresponding ΔCoVaR. Specifically, we first estimate, for each bank in the sample, the ΔCoVaR over two samples: the first starts on January 1, 2000 and ends on 12/31/2019 (pre-COVID sample); the second starts on January 1, 2020 and ends on 9/30/2020 (COVID sample). We then plot two scatter plots that relate the ΔCoVaR over the two samples with the β-CAPM estimated in the pre-COVID sample (Figure A5) and the median loans-to-deposit ratio measures in the pre-COVID sample (Figure A6). We estimate the β-CAPM as slope coefficients in regressions of bank returns on the European broad equity market returns. First, the two figures show the downward shift in the ΔCoVaR of most banks in the Covid-19 sample. Second, we find that in both samples, banks more exposed to financial markets (i.e., with a higher β-CAPM), or with a smaller loans-to-deposit ratio, have a higher systemic risk contribution. The latter is evidence consistent with the results of the predictive panel regressions presented in the paper which highlight the lower systemic risk contribution of more traditional banks with respect to banks more actively involved in securities and derivatives trading. Third, we find that in the two samples the relationship between the ΔCoVaR and both the β-CAPM and the loans-to-deposit ratio is stable (i.e., we cannot reject the nulls that the slope coefficients are equal).

Figure A5: ΔCoVaR and Bank β-CAPM

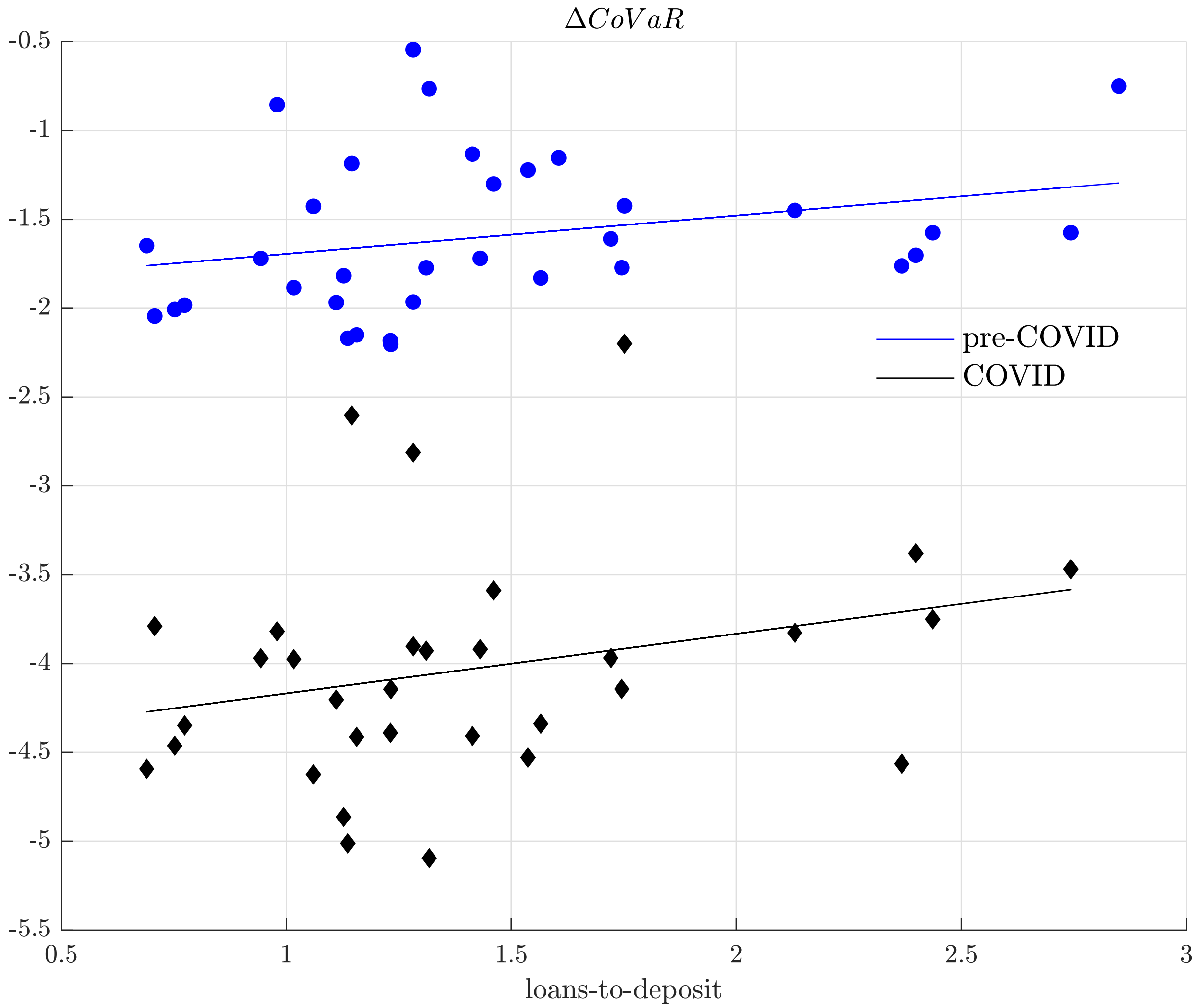


Notes: This figure reports the scatter plot of the ΔCoVaRs for each banks over the pre-COVID sample (1/1/2000 to 12/31/2019, blue dots) and the shorter Covid-19 sample (1/1/2020 to 9/30/2020, black diamonds) with respect to each institution's β-CAPM estimated over the pre-COVID sample. For each bank, we estimate the β-CAPM as the slope coefficient in a regression of daily bank returns on the returns of the broad European equity index. The straight blue and black lines denote OLS fit lines. Data are from Bloomberg for the period 1/3/2000 to 9/30/2020.

C.III Evolution of the Covid-19 Pandemic in European Countries

Figure A7 provides a snapshot of the evolution of the Covid-19 pandemic in the set of European countries where the banks in our sample have their headquarters. Specifically, the left panel

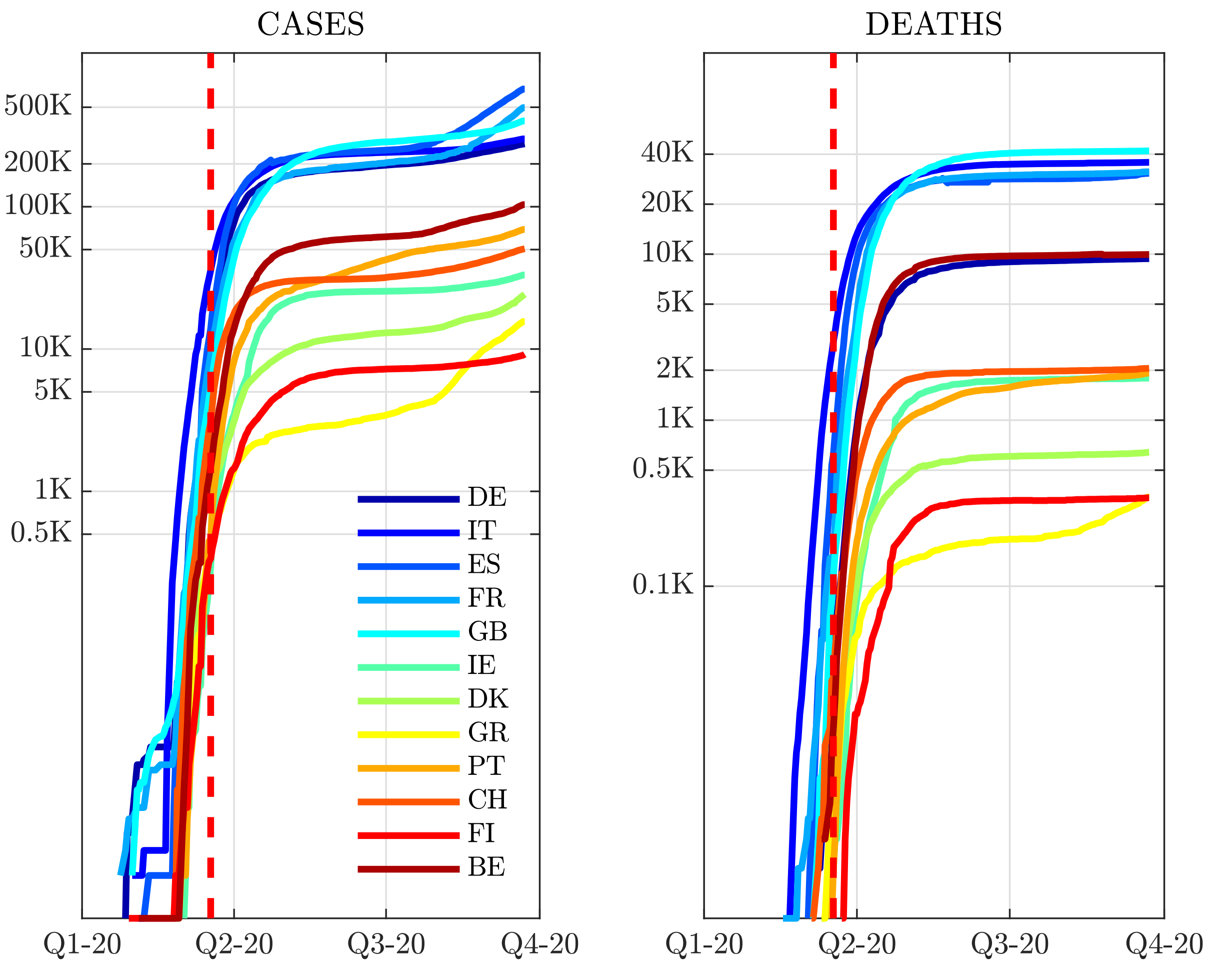
Figure A6: ΔCoVaR and Loans-to-Deposit



Notes: This figure reports the scatter plot of the ΔCoVaRs for each banks over the pre-COVID sample (1/1/2000 to 12/31/2019, blue dots) and the shorter Covid-19 sample (1/1/2020 to 9/30/2020, black diamonds) with respect to each institution's loans to deposit ratio in 2019. The straight blue and black lines denote OLS fit lines. Data are from Bloomberg for the period 1/3/2000 to 9/30/2020.

of the Figure plots the evolution of the Covid-19 cases, while the right panel of the Covid-19 (official) deaths. We note how the diffusion and evolution of the pandemic was not the same in all countries. In fact, the onset of the pandemic occurs in different dates of the Spring 2020 in different European countries, which also differ in the total number of cases and deaths, and in the timing of the flattening of the evolution of the pandemic. For example, Italy is the country first hit by the outbreak (in mid February) and also one of the countries with the largest number of cases and deaths. In contrast, Belgium and Finland are hit later (in mid March), and have a substantially lower number of cases and deaths than Italy, although these figures are not normalized by population size.

Figure A7: The Covid-19 Pandemic in Europe



Notes: This figure plots the evolution the number of Covid-19 cases (left panel) and deaths (right panel) in the set of European countries where the banks in our sample have their domicile. Both the number of cases and deaths are reported on a log scale. The set of countries are: Germany (DE); Italy (IT); Spain (ES); France (FR); the U.K. (GB); Ireland (IE); Denmark (DK); Greece (GR); Portugal (PT); Switzerland (CH); Finland (FI); and Belgium (BE). The vertical dashed-red line corresponds to the ECB announcement of the PEPP program on March 18, 2020. Data are from Bloomberg for the period 1/3/2000 to 9/30/2020.