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Exploring the Systemic Risk of Domestic Banks with ΔCoVaR and Elastic-Net

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Abstract
We analyze the systemic risk of Italian banks with the ΔCoVaR from a bivariate normal GARCH model. The results show that it is a good measure of systemic risk and is applicable to the ranking of Italian other systemically important institutions. Using an elastic-net approach, we identify the balance sheet and market variables that explain the ΔCoVaR of Italian banks. The analysis confirms that these variables are key determinants of systemic importance and highlights how higher capitalization is beneficial to tackling systemic risk. And, we detect a connection between ΔCoVaR and some variables for trading and investment banking.

Keywords Financial crisis · Capital regulation · Banking supervision · Internal risk models · Systemic risk · Value-at-risk

JEL Classification G01 · G18 · G21 · G32 · G28 · E58

1 Introduction

Before 2007, Basel 1 had designed the banking regulatory framework to limit only the micro-prudential risk of individual institutions by focusing mainly on credit risk. After 2007, Basel II has introduced some novelties but is still firm-specific. Acharya (2009) criticized the regulatory framework in force at that time because it ignored the externalities of banks. Conversely, Resti and Sironi (2010) supported that framework by arguing that it could not be singled out as the main reason for the 2008 financial crisis. Even if systemic risk has received a lot of attention by academics, only its concrete realization in 2008 placed

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financial authorities in a position to see its effect on the overall financial system and on the real economy. Since then, financial authorities have set the stage for macro-prudential regulation (i.e., Basel III); and in 2011, the Financial Stability Board asked for the introduction of ad-hoc capital requirements for the largest financial institutions that are commensurate with the risks they pose to the financial system. For a critical discussion on the evolution of capital regulation, readers are referred to Herring (2018) and Hughes (2018).

Nowadays, the Basel Committee on Banking Supervision (2018) and the European Banking Authority (2020a) have specific capital surcharges in force for global systemically important banks (G-SIBs); their regulations prescribe in detail both identification and buffer calibration. The European Union also requires specific buffers for other systemically important institutions (O-SIIs), that is those banks that it considers to be systemically important at the national level. The identification of O-SIIs reflects the principles in the global framework provided by the Basel Committee to deal with domestic systemically important banks. For O-SIIs, while the EBA defines identification with specific criteria (see European Banking Authority (2014)), there are not yet guidelines for the buffer calibration. The O-SII buffers are set by the designated authorities on a yearly basis, usually for a small number of banks. In this paper, we assume as given the identification and buffer calibration that are related to systemically important institutions. The domestic system analyzed in this study is represented by the sample of listed Italian banks.

There is a need for a market-based indicator that can give further insight into the monitoring of systemic risk and into the identification of areas subject to possible additional supervisory scrutiny. For this reason, we base our analysis on an indicator that can be estimated in real time that we can use as an early warning tool at the country level for an international comparison or in stress periods like the current Covid-19 outbreak. Among the possible market-based systemic risk measures, we select the delta conditional value-at-risk (ΔCoVaR) as proposed by Adrian and Brunnermeier (2016) (see Löffler and Raupach (2018), for a discussion of possible shortcomings of this indicator).

Assuming that the ΔCoVaR is possibly a good candidate to measure systemic risk, the aim of this paper is threefold. First, we want to analyze the performance of this measure during the recent financial turmoil. Second, we want to verify if it is applicable to the ranking of Italian O-SIIs. Third, by leveraging the statistical and supervisory data that banks in Italy report to the Bank of Italy, we want to analyze what the main determinants of the ΔCoVaR are for listed Italian banks.

Most of the literature on systemic risk measures focuses on global or international banks and pays less attention to smaller banking systems or to domestic systemically important banks. As observed above, the analysis of O-SIIs has a practical interest for a supervisory authority. Furthermore, central banks and supervisory authorities collect granular balance sheet and supervisory data that are useful for conducting a robust econometric analysis. Empirical studies usually use quarterly data because banks primarily release balance sheet information on such basis. Conversely, the frequency of the information in our analysis is monthly. For these reasons we are in the position to explore the key determinants of systemic risk by applying an elastic-net regression with a time-varying approach to a relatively large number of factors.

Therefore, we build a dataset that comprises the market-based information (i.e., equity prices, price-to-book ratios, Italian sovereign spreads, and market implied volatilities) for a sample of listed Italian banks and statistical and supervisory data from the Bank of Italy. From this last source, we extract the balance sheet and prudential information of banks. In particular, we define a proxy for the risk profile of each bank, compute the size of each bank on the basis of total assets, and we detect the banks allowed to choose between standard or validated internal models (i.e., an indicator of sophistication). Thus, we consider the variables for assets and liabilities that highlight bank-specific characteristics and business models. We confirm that size is a key determinant of systemic importance. Bigger banks contribute more to systemic risk than smaller ones. Similarly to the studies of Moore and Zhou (2014), Bostandzic and Weiss (2018), and Brunnermeier et al. (2020) who support the idea that business models are relevant for systemic risk, we find a relation between ΔCoVaR and some factors that identify trading and investment banking. Further, the analysis confirms that higher capitalization is beneficial in tackling systemic risk (see Zedda and Cannas (2020)).

While our analysis only focuses on Italian intermediaries, future studies can easily extend it to other banking systems, if detailed information on banks at an individual level is available. Applying the same approach to a different set of banks may highlight the importance of accounting for country-specific characteristics of the banking sector in monitoring systemic risk.

The rest of the paper is organized as follows. In Section 2, we estimate the ΔCoVaR, and we conduct the analysis to show that the proposed method leads to a proper measure for systemic risk (see Bianchi and Sorrentino (2020)). Then, we compare this measure with the O-SIIs buffers. In Section 3, we provide the time-varying estimates of the key determinants of the ΔCoVaR by following an elastic-net approach. Section 4 concludes.

2 ΔCoVaR

The ΔCoVaR measures the tail dependence between two random variables and comes from the value-at-risk (VaR) concept. Studies have defined the CoVaR as the VaR of the financial system conditional on individual institutions being under distress. In this paper, we define the system as the capitalization-weighted portfolio of all banks in the selected sample. Then, we define the ΔCoVaR as the difference between the CoVaR in the median state conditional on the institution being under distress. This definition represents the contribution of a bank to systemic risk. We define the distress (the median) as the event in which the bank's stock return is exactly equal to VaR (its median). As suggested by Adrian and Brunnermeier (2011), we estimate a bivariate GARCH model and evaluate the CoVaR by considering the time-varying covariance between each institution i and the financial system. As observed by Löffler and Raupach (2018), the GARCH model avoids possible estimation problems that arise in a quantile regression.

For each institution i, the random variable X_t^i represents the log returns of the market value of equity. Superscript *sys* denotes the entire financial system, that is, the capitalization-weighted portfolio of all financial institutions in the selected sample. The random variable X_t^{sys} represents the log returns of the financial system. We assume that the dynamics of the pair X_t^i and X_t^{sys} follow a bivariate normal GARCH model with Glosten-Jagannathan-Runkle (GJR) volatility (see Glosten et al. (1993)) and constant conditional correlation (CCC) that provides a closed-form expression for the ΔCoVaR (see Bianchi and Sorrentino (2020)), that is,

$$\Delta\text{CoVaR}^i_{q,t} = \phi^{-1}(q)\rho^i_t\sigma^{sys}_t, \tag{1}$$

where q is the tail level equal to 0.05, ϕ^{-1} is the inverse of the cumulative distribution function of a standardized normal random variable, ρ^i_t is the correlation between the residuals of institution i and those of the system, and σ^{sys}_t is one-day ahead forecast at day t of

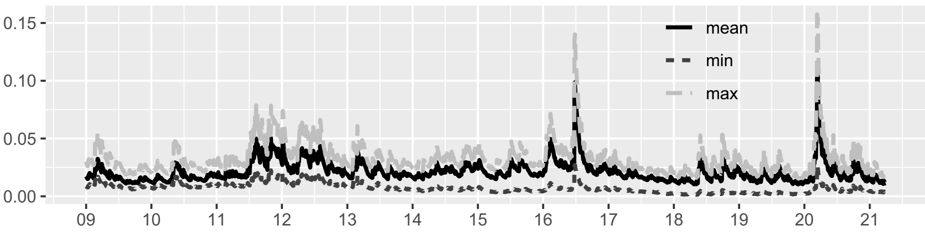

Fig. 1 Estimated time series from December 31, 2008, to March 31, 2021, of the ΔCoVaR based on the multivariate normal GJR-GARCH model with constant conditional correlation and changed in sign. The figure displays the mean, minimum, and maximum values over the bank sample

the volatility in the financial system. As observed in Adrian and Brunnermeier (2016), for jointly and normally distributed random variables, the ΔCoVaR estimate strictly depends on the correlation between institution i and the system. At a given point in time, systemic banks are those with the highest correlation with the system.

Recall that under this setting the VaR is given by the following formula:

$$\mathrm{VaR}^i_{q,t} = \phi^{-1}(q)\sigma^i_t, \tag{2}$$

where q is the tail level equal to 0.05, ϕ^{-1} is the inverse of the cumulative distribution function of a standardized normal random variable, and σ^i_t is the one-day ahead forecast at day t of the volatility in bank i.

We estimate the ΔCoVaR with daily data from December 31, 2008, to March 31, 2021, by considering rolling windows with a 5-year length. The dividend-adjusted closing stock prices for listed Italian banks are obtained from Refinitiv.[1] Then, we test for properties of persistence (banks tend to maintain the same level of ΔCoVaR over time) and ranking stability. Both features contribute to identifying a good risk measure. In particular, delivering stable rankings is considered as a useful property for a risk measure. As argued by Benoit et al. (2017), it would make little sense for a measure to classify a bank today as systemic and tomorrow as non-systemic. While ranking stability is potentially suitable for both banking regulators and supervisors because their policy decisions and supervisory actions have a long-term perspective, ranking volatility can be problematic if they want to include these measures in their toolbox to investigate the contribution of a bank to systemic risk (see Nucera et al. (2016)).

Our sample period has at least five high volatility episodes: 1) the bankruptcy of Lehman Brothers in 2008, 2) the Italian sovereign debt crisis in 2011, 3) the Italian and the Brexit referendum in 2016, 4) the turmoil after the Italian political elections in 2018, and 5) the recent Covid-19 pandemic event. We aim to verify whether the results discussed in Bianchi and Sorrentino (2020) still hold true during the later event when the ΔCoVaR of Italian banks surged to its highest level in over 12 years (see Fig. 1).

The Kendall test between the systemic risk ranking obtained at day t and the one obtained six months earlier confirms that the ranking is stable over time. The Kendall test is used to measure the association between two measured quantities. In particular, the Kendall rank-order correlation coefficient (hereafter referred to as the Kendall correlation) is a measure

[1] Banca Finnat, Banca Ifis, Banca Intemobiliare, Banca Generali, Banca Mediolanum, Banca MPS, Banca Popolare di Sondrio, Banca Profilo, Banco BPM, Banco Desio, Bper Banca, Credito Emiliano, Credito Valtellinese, Finecobank, Intesa Sanpaolo, Mediobanca, Unicredit, and Ubi Banca. We consider all banks with at least five years of daily observations.

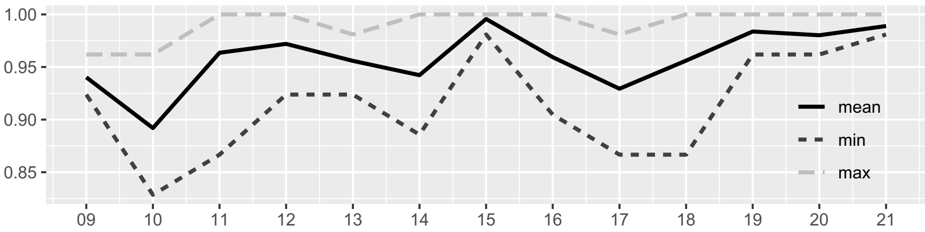

Fig. 2 Estimated Kendall correlation between the systemic risk ranking obtained at day t from the $\Delta\mathrm{CoVaR}_{q,t}$ and the one obtained six months earlier on each year from 2009 to 2021. Mean, minimum and maximum of daily values

of correlation between two ranking lists. Its values go from -1 to 1. From 0 to 1, the higher the Kendall correlation, the higher the similarity of the orderings of the data when ranked by each of the quantities (vice versa from 0 to -1, in the sense of divergence). If the p value of the test is small, say less than 0.05, then the correlation is significantly different from zero. Over the entire observation window, the Kendall correlation is on average 0.96 and the corresponding p value is zero.[2] This result remains true by testing the Kendall correlation on each year from 2009 to 2021. As shown in Fig. 2, the yearly minimum of the daily estimates of the Kendall correlation ranges from 0.83 to 0.98 and it is, on average, 0.91 (p values are always zero).

Furthermore, in order to assess the stability of the estimation method over time we estimate the daily lag-5 autocorrelation of the ΔCoVaR. It is on average equal to 0.86. Therefore, we empirically assess that our estimation method of ΔCoVaR is a good measure of risk that is useful in the overall assessment of risk in the Italian economy (Venditti et al. 2018).

As mentioned earlier, the designated authorities set the O-SIIs buffers on a yearly basis and the calibration of O-SIIs buffers is in the remit of the national authorities. By reflecting the need to retain flexibility and national specificities, buffer calibration approaches across European Union member states show a high level of diversity in both economic indicators and supervisory practices (see European Banking Authority (2020b)). The European Union deems flexibility as necessary to avoid potential overlaps between micro-and macro-prudential measures by balancing the need to strengthen the stability of systemic institutions with that of avoiding adverse effects on the economic recovery, or to account for country-specific characteristics of the banking sector.

To verify whether the estimates of the ΔCoVaR are applicable to the ranking of Italian O-SIIs, we report the estimated average ΔCoVaR of these banks for each year from 2009 to 2021, which is the entire time span of the empirical study. Figure 3 shows that the estimates are in line with the buffer calibration conducted by the Bank of Italy in recent years (see the Bank of Italy (2021) website). Based on the year-end data from 2015 to 2019, the Bank of Italy identified four banks for which it had requested O-SII buffers for the years from 2017 to 2021 (BMPS: Banca MPS; BP: Banco BPM; ISP: Intesa Sanpaolo; UCG: Unicredit). It carried out the identification on a yearly basis and made its decision on the specific capital buffer by following the indications contained in the guidelines of the European Banking Authority (2014). The Bank of Italy analyzed four dimensions: size, importance for the

[2] Banca Generali and Finecobank are not considered here because their ΔCoVaR is not available over the entire observation window.

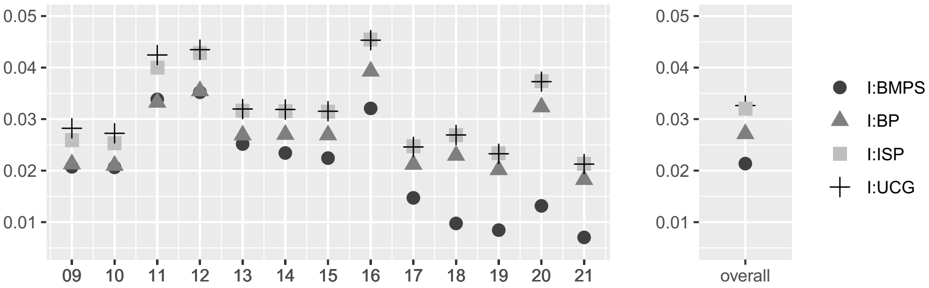

Fig. 3 Estimated average ΔCoVaR for each year from 2009 to 2021 for the four Italian O-SIIs (BMPS: Banca MPS; BP: Banco BPM; ISP: Intesa Sanpaolo; and UCG: Unicredit). The average over the entire time span is also displayed. Mean of daily values

national economy, complexity, and interconnection with the financial system. Table 1 shows the score and the corresponding capital buffer for each bank. To calibrate the buffer, the Bank of Italy defined six buckets of systemic importance that were based on the results of a cluster analysis. A buffer equal to 0% is assigned to the first bucket. The buffer then increases by 0.25 percentage points for each subsequent bucket (see Table 2). The Bank of Italy considered a transitional period; and for this reason, the requested buffer reported in Table 1 does not correspond to the buffer assigned to the bucket shown in Table 2.

The order defined by the ΔCoVaR does not differ from that provided by the method that relies on criteria implemented by the Bank of Italy. This empirical finding facilitates the use the ΔCoVaR for the timely monitoring of systemic risk, since this risk measure is available in real time at high frequency and over a long time horizon. Additionally, since it relies only on market data, it can be viewed as a useful tool to support the supervisory analysis of systemic risk.

3 Determinants of ΔCoVaR

After having estimated the ΔCoVaR, we explore the time-varying determinants of the contribution of banks to systemic risk by using balance sheet and market-based variables. We update and extend the analysis of Borri et al. (2014) in which they investigate several possible predictors of banks' contribution to systemic risk.

Table 1 Overall score for Italian O-SIIs (BMPS: Banca MPS; BP: Banco BPM; ISP: Intesa Sanpaolo; and UCG: Unicredit), and corresponding buffer in square brackets

	2017	2018	2019	2020	2021
UCG	3,844 (0)	3,454 (0.25)	3,429 (0.50)	3,053 (0.75)	3,199 (1.00)
ISP	2,215 (0)	2,518 (0.19)	2,631 (0.38)	2,633 (0.56)	2,557 (0.75)
BP	(-)	397 (0)	373 (0.06)	469 (0.13)	457 (0.19)
BMPS	512 (0)	375 (0.06)	322 (0)	386 (0.13)	383 (0.19)

Bank of Italy computed the O-SII buffer for a given year at the end of the previous year on the basis of the year-end data from two years earlier

Table 2 Categories of systemic importance from the Bank of Italy

bucket	O-SII overall score interval	O-SII buffer
6	$\geq 4,000$	1.25%
5	$[3,000, 3,999]$	1.00%
4	$[2,000, 2,999]$	0.75%
3	$[1,000, 1,999]$	0.50%
2	$[350, 999]$	0.25%
1	$[0, 349]$	0%

3.1 Data

The assumption that the composition of the balance sheet can explain the accumulation of systemic risk over time is a reasonable one. As observed by Wosser (2017), the analysis of the determinants of systemic risk can direct macro-prudential policy instruments toward those factors most closely associated with systemic risk. To this aim, we use granular information extracted from the statistical and supervisory data reported to the Bank of Italy by each bank located in Italy and market data from Refinitiv.

We refer to the ratio of risk weighted assets (RWAs) to total assets as *risk density* and use it as a proxy for the risk profile of each bank. Even if the reliability of the banks' calculations of RWAs is always under scrutiny (see Behn et al. (2016), and Bastos e Santos et al. (2020)), the risk density is a natural measure of bank risk-taking as pointed out by Dautović (2020), and it accounts for the deterioration in the quality of a credit portfolio (e.g., low-rated assets have a higher risk weight in comparison with less risky ones). Bastos e Santos et al. (2020) observe that the direct use of nonperforming loans might be more challenging from an econometric perspective due to the lags in their accounting rules. Additionally, the risk density provides a full picture of the entire credit portfolio not only for the more risky part. As observed by Bonaccorsi di Patti et al. (2016), differences in risk density are driven by a number of factors such as the composition of exposure and the methods used to compute the risk weights of each intermediary. To compute these risk weights, the prudential regulation allows banks to choose between standard or validated internal models. It could be the case that a bank with validated internal models computes the risk weights with internal models for some portfolios and with standard approaches for all other portfolios. To include this option, we compute the share of RWAs that banks evaluate with internal models with respect to the overall RWAs that they evaluate with both standard approaches and internal models. We refer to this share as the *internal model* factor. However, while regulations prescribe the standard approaches for computing risk weights, the supervisory authority validates all internal models applied for prudential purposes.

Figure 4 shows that the weights of internal models increased over time, because either more banks concluded the validation process or already validated banks asked for validation of a larger number of portfolios. The weighted average in Fig. 4 is computed on the basis of banks' total assets. The internal model factor can also be viewed as an indicator of sophistication (eight listed Italian banks do not have any validated internal model for the computation of capital requirements). As recently observed by the European Central Bank (2021), large and more complex banks typically use internal models that serve as a basis to calculate their capital requirements.

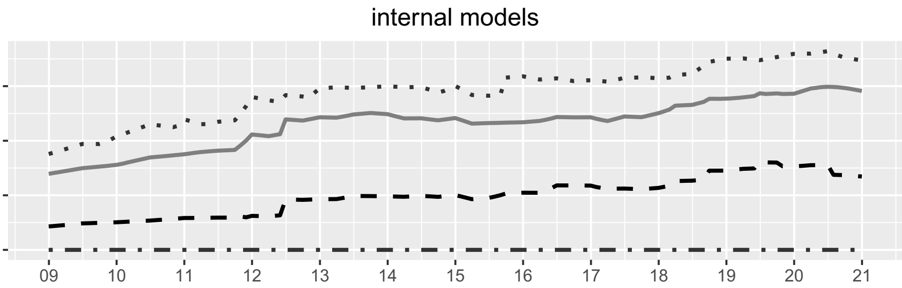

Fig. 4 Factor dynamics of internal models from December 31, 2008, to December 31, 2020: minimum (dotted dashed), mean (dashed), weighted average (solid), and maximum (dotted) values across all banks in the sample. A factor is defined as the ratio between risk weighted assets (RWAs) that are computed with internal models and the overall RWA that is computed with both standardized approaches and internal models

To account for the various sources of risk, we separately consider the exposure for credit risk, market risk, and for other risks (a study on the systemic risk implications of credit risk was recently conducted by Löffler (2020)). Thus, we have three different ratios defined as the RWAs (credit, market, and other) over total assets.

As a measure of financial strength, we consider the ratio between Tier 1 capital and RWAs of banks. The size variable is defined as the ratio between total assets and aggregate total assets across all banks in the sample. Further, this variable resembles the size indicator needed to compute the score under the O-SII framework. These factors (e.g., risk densities, Tier 1 ratio, and size) are extracted from the prudential reporting. Since banks report prudential information on a quarterly basis, we linearly interpolate quarterly data to extract monthly observations. This procedure is reasonable because the dynamics of these factors are quite smooth.

Next, we consider various balance sheet variables that we extract from the monthly statistical reporting of banks. However, while banks report prudential data on a consolidated basis with a quarterly frequency, they report the statistical data on an individual basis with a monthly frequency. After having removed intra-group exposures, we aggregate data by group to obtain consolidated data from monthly statistical reporting. Thus, we compute the total assets based only on statistical data and consider them as a reference amount for these balance sheet variables. To account for both the characteristics and the business models of banks, we look at asset composition (i.e., Italian sovereign bonds holdings, total securities holdings, and retail loans), intra-bank exposures, activity in the derivative market, and the liability structure (i.e., securities, deposits, and euro-system credit operations). All these variables are in percentage of total assets and were extracted from the statistical data. In our setting, the banks' sophistication is captured not only by the internal model factor but also by the factors related to security issues and derivative trading.

Additionally, we analyze two different risk measures. The first is the VaR given in Eq. 2 that represents the risk of the equity of a given bank and to which we refer to as *equity VaR*. The second risk measure is the VaR that is computed with granular information on security holdings by following the historical simulation approach proposed in Bianchi (2021) that we refer to as *security holdings VaR*. While the first VaR represents the risk of the bank equity as perceived by the market, the second VaR represents the risk of the portfolios with securities. These two risk measures can be different, because they are estimated with different assets, and they reflect different sources of risk. Further, while the factor for total security holdings represents the amount of the securities in a portfolio in relation to total assets, the VaR for security holdings represents the risk of this portfolio. Del Vecchio et al. (2021) recently implemented an approach similar to that proposed by Bianchi (2021) to estimate the ΔCoVaR implied for the security portfolios held by significant banks belonging to the Single Supervisory Mechanism (SSM).

Market-based information, such as the price-to-book ratio, the Italian sovereign spread with respect to German government bonds, and the market implied volatility (VSTOXX) are also account for.

Table 3 and Fig. 5 give the summary statistics for the balance sheet and market factors analyzed in the empirical study. They show that the balance sheet composition varies over time and that at least for some factors, there are large differences between banks (mean and median values differ). Therefore, the dynamics of the capital and risk density ratios are also influenced by the evolution of the regulatory framework over time. On the basis of these considerations and on the fact that in the time span studied in this study there were at least five high volatility episodes, an estimation with time-varying parameters seems more appropriate for this type of data.

Table 3 Summary statistics: 0.1-quantile (q_{10}), 0.25-quantile (q_{25}), mean, median, 0.75-quantile (q_{25}), 0.9-quantile (q_{10}), and standard deviation (sd) between December 31, 2008, and December 31, 2020, for the variables considered in the empirical study

	q10	q25	mean	median	q75	q90	sd
ΔCoVaR	1.09	1.49	2.26	2.07	2.74	3.60	1.11
internal models	0.00	0.00	20.00	0.00	48.22	58.16	25.46
risk density (credit)	20.76	30.94	44.34	42.22	58.66	68.86	17.99
risk density (market)	0.20	0.67	2.51	1.29	2.83	6.44	3.63
risk density (other)	3.63	4.32	5.65	5.00	6.40	8.07	2.51
Italian sovereign bonds	4.13	6.77	18.57	11.03	19.00	55.22	18.53
securities holdings	11.33	14.55	28.56	20.14	38.13	64.33	19.53
retail loans	20.09	38.56	53.47	59.93	68.38	75.72	20.22
infra banks exposures	2.61	4.20	9.93	6.73	13.39	21.33	8.58
derivatives fair value	0.06	0.42	7.72	1.36	11.17	23.34	12.11
issues	0.00	2.00	13.16	11.04	21.58	28.35	11.65
deposits	33.85	42.67	54.00	54.37	64.73	78.68	17.21
eurosystem	0.00	1.65	6.81	6.16	9.88	13.59	6.05
Tier1 ratio	7.92	10.30	13.85	12.04	14.90	22.98	6.18
size	0.09	0.43	6.29	1.48	5.63	27.67	10.92
price-to-book	28.46	41.70	95.26	64.18	97.21	218.07	94.67
equity VaR	2.57	2.98	4.08	3.62	4.65	6.23	1.70
securities holdings VaR	0.31	0.42	0.71	0.58	0.84	1.15	0.54
sovereign spread	1.06	1.33	1.94	1.62	2.47	3.26	0.94
implied volatility	14.35	16.88	22.92	21.85	26.41	33.05	8.31

All variables are expressed in percentages or percentage points. ΔCoVaR is based on the multivariate normal GJR-GARCH model with constant conditional correlation. Balance sheet and prudential information are extracted from the statistical and supervisory reporting collected by the Bank of Italy. Market-based information are obtained from Refinitiv

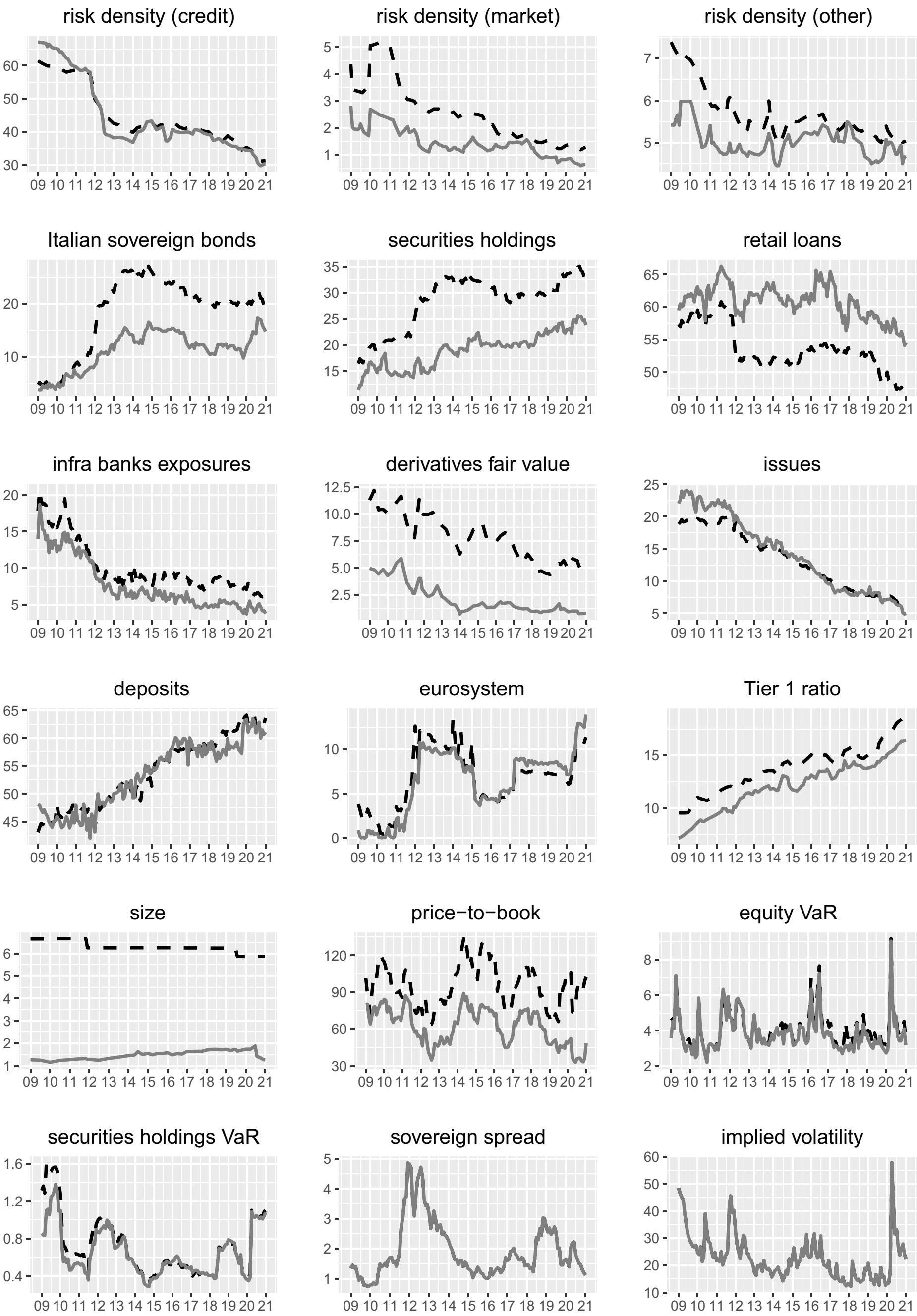

Fig. 5 Factor dynamics from December 31, 2008, to December, 31, 2020: mean (dashed) and median (solid) values across all banks in the sample. All numbers are in percentages or percentage points. The internal model factor is reported in Fig. 4

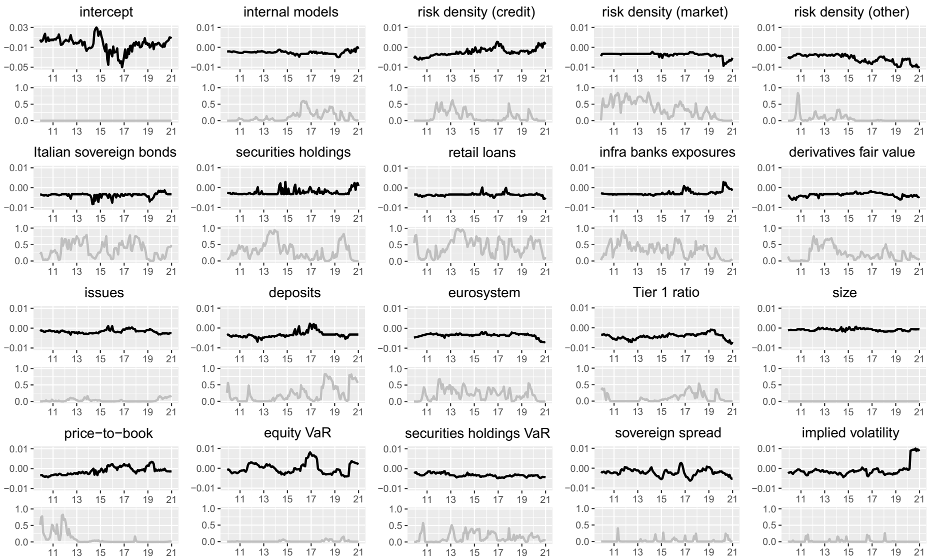

Fig. 6 Rolling window elastic-net estimates (coefficeints, black lines, and p-values, gray lines) from December 31, 2008, to December 31, 2020. All estimates, with the exception of the intercept, are rescaled by the standard deviation of the corresponding factor

3.2 Model estimates

As observed above, the empirical analysis is conducted on monthly data. Thus, we estimate the following pooled linear model:

$$\Delta \mathrm{CoVaR}_t^i = \alpha_k + \beta_k X_t^i + \varepsilon_t^i, \tag{3}$$

where the vector X_t^i represents the factors described above in month t; i ranges from 1 to 18 that is the number of banks in the sample; and k ranges from 1 to 134 that is the number of rolling window estimations in the period from December 31, 2008, to December 31, 2020. The rolling windows are 12 months long. For each estimation step k, we consider 190 month-bank observations (the number of banks varies over time) on average. Similarly to (Alessi et al. 2020), the parameters of the model in Eq. 3 are obtained through an elastic-net approach[3] (Hastie et al. 2015). This approach facilitates the consideration of a large number of factors in the regression (3) and to obtain robust estimates even if the factors are correlated. The elastic-net method is an extension of the lasso method. This latter method sometimes does not perform well with highly correlated variables. The elastic-net deals better with correlated groups, and tends to select (or not) the correlated features together.[4] The p values are computed by generating 5,000 bootstrap samples.[5] The estimated coefficients and the corresponding p values are reported in Fig. 6 (as usual, the null hypothesis is that

[3] We select $\alpha = 0.2$ in the *cv.glmnet* function of the *glmnet* package of R.

[4] Instead of considering estimates with rolling windows, we could have used the recently studied *fused elastic-net* approach that would have allowed us to estimate all time-varying parameters in a single step. We did not consider this more complex estimation approach, mainly because it was not yet standard in the literature and there were not specific R packages to deal with this type of problem.

[5] The computing time is around six minutes for each step k.

the coefficient is zero). To have a better visualization, all estimates, with the exception of the intercept, are rescaled by the standard deviation of the corresponding factor. The coefficients and their significance levels clearly vary over time. The R^2 is, on average, 0.81. Even if the R^2 remains a measure of calibration error under the elastic-net approach, the importance of this statistic is not the same as in a least squares estimation mainly because that approach should be evaluated not only by looking at the calibration performance but also by assessing its prediction accuracy.

The internal model factor is statistically significant and positive in more than the half of the cases, particularly in more recent years that indicates more sophisticated banks have a higher ΔCoVaR.[6] With regard to balance sheet variables, size is a good predictor of the bank's contribution to systemic risk but it is not the only one. Size is without a doubt a major driver of systemic risk, and therefore, it should be reflected in the risk measure. In the definition of ΔCoVaR, we assume that the system is defined as the capitalization-weighted portfolio of all banks in the selected sample. Since portfolio weights depend on market capitalizations, our ΔCoVaR estimates (i.e., the dependent variable) account for bank dimension.

We find that the different components of the risk density do not contribute equally to explain the behavior of the systemic risk measured by the ΔCoVaR, and the contribution varies over time. Starting after 2015, banks that had more exposure to credit risk had a higher systemic risk. After the same year, while the market risk component is not significant, the other risks have a slightly negative impact on the systemic risk. However, by looking at the unscaled coefficients, the weight of the risk density that is related to credit exposures is higher in comparison with the weight of the risk density that is related to other exposures. Over the entire observation period, the higher the risk density on average, the higher the systemic risk as measured by the ΔCoVaR. As discussed in the study of the European Systemic Risk Board (2019), a significant exposure to credit risk may by associated with increasing systemic risk. This increase could also be the result of negative market sentiment toward these types of exposures, which is information that is nowadays widespread and strongly monitored by market operators. While in Borri and Di Giorgio (2021) the relation between ΔCoVaR and the Tier 1 ratio was not significant, we find a negative correlation between the two measures. As observed by Zedda and Cannas (2020), size matters but capital also plays a crucial role. In particular, capital is not only a presidium facing the stand-alone risk of default, but it also has a role in the reduction of systemic risk.

The amount of Italian sovereign bonds in bank portfolios and euro-system credit operations does not affect the contribution of banks to systemic risk. Traditional banking activities do not contribute to the systemic risk. As in the studies of Bostandzic and Weiss (2018) and Brunnermeier et al. (2020) that study the relations between systemic risk and business models, we find a connection between the ΔCoVaR and some factors that identify trading or investment banking, that is, derivative trading and issues of securities as funding sources. Conversely, even if with a low significance level, in some cases traditional lending and deposits have a decreasing effect on the exposure of banks to systemic risk. However, security holdings and the risk of this portfolio (i.e., its VaR) are not statistically significant. Similarly to Bianchi (2021), this empirical finding can be explained by the fact that the market risk of the security portfolios is not the main risk driver of the bank, there are other risk factors not related to those portfolios (e.g., credit risk), and the market does not know

[6] As a robustness check, we replaced the internal model factor with a dummy variable that identifies the banks with validated internal models. This alternative model specification gives similar results.

the exact composition of them. This evidence is also supported by the results related to the market risk density.

As showed in Section 2, in the time span considered in this study several high volatility episodes occurred during which the ΔCoVaR peaked to its highest levels. As expected, market-based information are important from a systemic perspective (see also Borri and Di Giorgio (2021)), particularly during the more recent financial turmoil. This is mainly due to the fact that we estimate the ΔCoVaR on equity log-returns, whose dynamics depend also on the credit spread and market volatilities.

The equity VaR is correlated with the ΔCoVaR, and this result depends on how we define and estimate the systemic risk in this study (see also Benoit et al. (2017)).

The main idea behind the model in Eq. 3 is to identify the determinants of systemic risk. The model looks at ΔCoVaR and several contemporaneous explanatory variables. A potentially useful application of the same model can be obtained by considering lagged explanatory variables. This application allows the model to be used for forecasting purposes. For this reason we estimate the model in Eq. 3 by considering the explanatory variables with a lag of one to three months. We do not observe remarkable differences in the sign of the estimated parameters and in their significance level.[7] However, the average R^2 decreases to 0.60 and 0.56 with these lags. Even in these cases the estimated parameters vary over time. Further, we do not consider the lagged dependent variable as an explanatory variable.

Our results show that both bank characteristics and market-based variables provide important information on the build-up of systemic risk to be monitored on a regular basis and to be accounted for when discussing follow-up actions. Without replacing a subjective assessment of financial stability risks or questioning the identification and buffer calibration process of O-SIIs, our findings indicate financial authorities should add this information to their toolbox to investigate the contribution of each bank to systemic risk.

4 Conclusions

In this study, we show that the ΔCoVaR obtained by means of a bivariate normal GARCH model is a good measure of systemic risk. We verify that ΔCoVaR estimates are applicable to the ranking of Italian O-SIIs, and that the proposed estimation provides valuable insights on the monitoring of systemic risk. Additionally, the supervisory authorities have information that are good predictors of systemic risk. Indeed, we find that both bank characteristics and market-based variables are relevant for the monitoring of systemic risk. In particular, the empirical study shows that size and capital influence the contribution of banks to systemic risk and that the factors identifying trading or investment-banking activities also play a role. As expected, the dynamics of the domestic financial market affect the behavior of the systemic risk measure analyzed in this study. Finally, the relations between the ΔCoVaR and its determinants are time-varying.

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[7] The results are available on request.

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