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A sensitivities based CoVaR approach
to asset commonality and
its application to SSM banks

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Abstract

One important source of systemic risk can arise from asset commonality among financial institutions. This indirect interconnection may occur when financial institutions invest in similar or correlated assets and it is also described as overlapping portfolios. In this paper, we propose a new methodology for identifying and assessing banking sector systemic risk stemming from asset commonality in the spirit of CoVaR as defined by Adrian and Brunnermeier (2016). Based on granular information, we compute bank portfolio sensitivities to a large number of risk factors (e.g. interest rates, equity prices, credit spreads, exchange rates) and then compute the gains and losses under a large number of historical scenarios and the associated Δ CoVaR. The novel indicator proves to be consistent with other indicators of systemic importance, yet it has a more transparent foundation in terms of the source of systemic risk, which can contribute to effective micro and macroprudential supervision.

Keywords: Systemic risk, Overlapping portfolios, Financial networks, Financial regulation, CoVaR

JEL Codes: C58, E32, G01, G12, G18, G20, G32

Non-Technical Summary

An important source of financial linkages arises by “indirect” links between financial institutions through common financial asset holdings. When financial institutions invest in the same assets, their portfolios show a certain degree of overlapping (Poledna et al., 2021). Systemic risk can materialize because exogenous shocks can lead to portfolio devaluation across banks (even if they are not directly connected). The relevance of this source of systemic risk has gained importance since “the Great Moderation”, a period starting in the mid-1980s until 2007, over which portfolios of financial institutions have become more similar (Haldane, 2013).

In the literature, Acharya (2009), Acharya and Yorulmazer (2008, 2007) and Farhi and Tirole (2012) describe some theoretical motives for banks’ herding behavior in their investments. Regulation and the possibility of being bailout may generate incentives for herding behavior in banks’ investments. When banks fail together, the liquidation of their assets could have a large impact on the economy, which might lead to bailouts. This externality can be a relevant source of financial contagion arising from “indirect” links between financial institutions mediated by financial markets or any correlation across banks’ income or cost sources.

In this paper, we propose a new methodology for identifying and assessing banking sector systemic risk stemming from asset commonality in the spirit of CoVaR as defined by Adrian and Brunnermeier (2016).⁵ We derive a sensitivity based Δ CoVaR index and we apply it to banks’ securities portfolios as reported in the ECB database Security Holding Statistics.⁶ In more detail, based on granular information, we compute banks’ portfolio sensitivities to a large number of risk factors (e.g. interest rates, equity prices, credit spreads, exchange rates) and then compute the gains and losses under a large number of historical scenarios. Based on these realized gains and losses, we compute the associated Δ CoVaR.

⁵Adrian and Brunnermeier rely on equity prices of listed financial companies to measure the variation of systemic risk conditional on a firm being under distress relative to its median state. This effect is measured by Δ CoVaR, which they show to be a significant variable in the prediction of financial crisis.

⁶This database provides information, at the single ISIN level, on securities held by significant banks belonging to the Single Supervisory Mechanism (SSM) ECB (2020).

1. Introduction

An important source of financial linkages arises from “indirect” links between financial institutions mediated by financial asset holdings. When financial institutions invest in the same assets, their portfolios show a certain degree of overlapping (Poledna et al., 2021) and systemic risk can materialize because exogenous shocks can lead to portfolio devaluation across banks (even if they are not directly connected). The relevance of this source of systemic risk has gained importance since “the Great Moderation”, a period starting in the mid-1980s until 2007, over which portfolios of financial institutions have become more similar (Haldane, 2013).

In this paper, we propose a new methodology for identifying and assessing systemic risk stemming from the commonality of banks’ exposures. We leverage on the possibility to compute exposure’s sensitivities to a complete set of risk factors and on the concept of Δ CoVaR as defined by Adrian and Brunnermeier (2016) in order to capture tail interdependence.⁷ Hence, we propose a sensitivity based Δ CoVaR index. Our approach focuses on a specific source of systemic risk transmitted through an indirect channel of contagion related to overlapping of exposures across intermediaries. It is based on actual exposures (and the implied sensitivities to a complete set of relevant risk factors) in order to compute potential vulnerabilities of each bank and of the entire banking system.

It is worth highlighting that our methodology does not rely on the banks’ market price of equity. Therefore, it applies both to listed and unlisted institutions. This feature is particularly desirable as unlisted banks represent a significant amount of the total assets of the Euro Area significant institutions.⁸

We apply the proposed approach to assess the risk stemming from the commonality of banks’ financial securities portfolios, as reported in the ECB Security Holding Statistics (SHS) database.⁹ In more detail, based on this granular information, we first compute bank portfolio sensitivities to a large number of risk factors (e.g. interest rates, equity prices, credit spreads, exchange rates) and then compute the gains and losses under a large number of historical

⁷Adrian and Brunnermeier (2016) rely on equity prices of listed financial companies to measure the variation of systemic risk conditional to a firm being under distress relative to its median state. This effect is measured by Δ CoVaR, which they show to be a significant variable in the prediction of financial crisis.

⁸As such, other regulators might use this indicator when quantifying the systemic footprint of the supervised institutions. It is relevant to mention that it is equally or more common for non-banking financial institutions to be not listed.

⁹SHS database provides information, at the single ISIN level, on securities held by significant banks belonging to the Single Supervisory Mechanism (SSM) ECB (2020).

scenarios. Based on these derived gains and losses, we compute the implied Δ CoVaR as a measure of the systemic footprint of each bank and of the relevance of assets commonality as source of systemic risk. Instead of using network techniques as in Poledna et al. (2021) we efficiently summarize this information focusing on tail interdependence across banks and between each bank and the overall banking system.

While the implementation of Δ CoVaR proposed by Adrian and Brunnermeier (2016) is a reduced-form measure of systemic risk based on the equity price of banks, our approach identifies a source of systemic vulnerability originated by banks' asset commonality, allowing us to tailor appropriate macroprudential policies.

Conditional on data availability, this approach can be extended to derivative portfolios, loans and credit exposures. Moreover, the approach can take into consideration changes in banks' portfolio composition over time and provide a tool to track the resilience of the banking sector as a whole. This sensitivity based Δ CoVaR can also be fruitfully used for stress testing purposes in order to consider, in a transparent and efficient manner, the risks connected to banks' inter-linkages. (Vodenska et al., 2021).¹⁰

Systemic risk has become a prolific research field from both an academic and financial regulation perspective (see Benoit et al. 2016). Among the global measures of systemic risk, the Conditional Risk indicator from Chan-Lau et al.(2009) is a quantile regression based systemic indicator, and it is a measure of risk interdependence across financial institutions that accounts for common risk factors and potential nonlinear effects. The original indicator is calibrated on CDS data, but the methodology can work with different data. Systemic Expected Shortfall (SES) from Acharya et al. (2017) and the SRISK indicator from Brownlees and Engle (2017) rely on banks' balance sheet and stock market data to quantify the undercapitalization of a given financial institution given that the whole financial system is undercapitalized. The distress insurance premium (DIP) indicator of Huang et al. (2009) uses banks' single name CDS and their equity price correlation matrix to build a systemic risk indicator that should be equivalent to the risk premium that an insurance company would ask to guarantee a severe loss of the banking system. The Option-IPoD indicator proposed by Capuano (2008) estimates banks' probability of default from the price of their equity options. Segoviano Basurto and Goodhart

¹⁰The current stress test conducted by the European Banking Authority does not take into consideration connectivity between banks and the potential of one banks vulnerability spilling over to the rest of the system.

(2009) estimate the banking system joint multivariate probability distribution. Inter-linkages between financial institutions have also been analysed by Espinosa-Vega and Solé (2011) with a network analysis approach and by Giesecke and Kim (2011) in a reduced form model.

Acharya (2009), Acharya and Yorulmazer (2008, 2007) and Farhi and Tirole (2012) describe some theoretical motives for banks herding behavior in their investments. In order to minimize the externality related to “recessionary spillover”, banks have incentives to invest in the same assets and thus fail or survive together. Regulation and incentive for a bailout can generate a herding behavior too. When banks fail together, the liquidation of their assets may have a large impact on the economy. Bailouts could prevent this negative effect. Elsinger et al. (2006) consider asset commonalities between banks and show how losses stemming from common exposures dominate those due to direct contagion. Cifuentes et al. (2005) consider a dynamic model of losses due to indirect contagion. They study a model where banks interact through mutual exposures, modeling contagion through the Eisenberg-Noe algorithm, and indirectly due to the presence of an illiquid asset common to all banks. We contribute to this literature by defining a tractable systemic risk measure and by providing an application based on a granular dataset. More recently, Cont and Schaanning (2019) quantify indirect exposures due to deleveraging, and they show how these can be computed from the matrix of liquidity-weighted overlaps between portfolios of banks. Our work is organized as follows. We first detail the methodology that we use to compute a Δ CoVaR based on a set of sensitivities. Then, we apply this methodology to the sensitivities derived from the Security Holding Statistics and we propose some applications of the new measure to assess and identify possible threats to financial stability originating from overlapping portfolios.

The rest of the paper is organized as follows. Section 2 discusses the methodology. Section 3 describes an application of the proposed methodology to Euro area banks based on granular information on their financial holdings. Finally, section 4 concludes.

2. A sensitivity based Δ CoVaR

This section describes the methodology used to compute banks’ Δ CoVaR starting from banks’ sensitivities in full generality. Given a set B of institutions (in the rest of the analysis we will refer to banks) and a set $R = (1, \dots, R)$ of risk factors (e.g., financial shocks), $s_{i,r}$ denotes

the sensitivity of the value of institution $i \in B$ towards the risk factor r .¹¹ A complete profile of shocks or scenario is the collection of shocks $z = (z_1, z_2, \dots, z_R)$, and a set of scenarios of risk factors shocks is denoted as $Z = \{(z_{1,t}, \dots, z_{R,t})\}_{t \in (1 \dots T)}$, where T is the set of scenarios or shock profiles included in the analysis. For each shock and for each bank, we can compute the associated impact in terms of the change in the portfolio value (i.e. gains and losses) as:

$$l_{i,r,t} = s_{i,r} z_{r,t} \quad (1)$$

and the overall impact of a scenario t for bank i as $l_{i,t} = \sum_{r \in R} l_{i,r,t}$. Therefore, for each scenario t , we can compute a vector $l_{i,t}$ which describes the profit and loss for each bank. Based on this preliminary calculation, we are able to define banks' CoVaR along the same line as Adrian and Brunnermeier (2016) but instead of considering changes in banks equity prices we can compute tail comovements in banks' profit and loss. In our framework, bank i Value at Risk ($\text{VaR}_q(i)$) is defined as the solution to the equation:

$$\mathbb{P}(l_i \leq \text{VaR}_q^i) = q. \quad (2)$$

The $\text{CoVaR}_q^{j|C(l_i)}$ of the bank j is the VaR_q of the bank j at the q -percentile conditional on bank i suffering losses l_i greater or equal to its VaR_q^i . Therefore, the $\text{CoVaR}_q^{j|(i,q)}$ is defined implicitly as the solution of the equation¹²

$$\mathbb{P}(l_j \leq \text{CoVaR}_q^{j|(i,q)} \mid l_i \leq \text{VaR}_q^i) = \mathbb{P}(l_j \leq \text{CoVaR}_q^{j|\text{VaR}_q^i} \mid l_i \leq \text{VaR}_q^i) = q. \quad (3)$$

While the CoVaR is an indicator of the riskiness of bank j given a certain event, we are interested in measuring the impact that a shock on bank i has on bank j . Therefore, in the rest of the paper, we will mostly refer to the Δ CoVaR, defined as

$$\Delta \text{CoVaR}_q^{j|i} = \text{CoVaR}_q^{j|(i,0.99)} - \text{CoVaR}_q^{j|(i,0.5)} \quad (4)$$

The Δ CoVaR represents the additional amount of risk for bank j given that bank i is under

¹¹For illustrative purposes, we will consider only first-order sensitivities. This is not a limitation as higher order sensitivities can be easily added.

¹²For simplicity, the probability threshold is set equal to q for VaR of bank i and for CoVaR of bank j .

stress. Thus, it can be interpreted as a measure of commonality between the two banks.

Similarly, it is possible to define the CoVaR of bank i towards the system and the relative Δ CoVaR as

$$\mathbb{P}\left(l_{\text{system}} \leq \text{CoVaR}_q^{\text{system}|\text{VaR}_{q_i}^i} \mid l_i \leq \text{VaR}_{q_i}\right) = q$$

where

$$l_{\text{system},t} = \sum_{i \in (\text{SetBanks})} l_{i,t} \quad (5)$$

$$\begin{aligned} \Delta \text{CoVaR}_q^{\text{system}|i} &= \\ &= \text{CoVaR}_q^{\text{system}|\text{VaR}_{0.99}^i} - \text{CoVaR}_q^{\text{system}|\text{VaR}_{0.5}^i}. \end{aligned}$$

In the rest of the paper, we will refer to the Δ CoVaR of the system, unless stated differently. The bank specific Δ CoVaR expressed in Euro is defined as

$$\Delta^{\text{€}} \text{CoVaR}^{j|i} = \text{Size}_i^{\text{€}} \cdot \Delta \text{CoVaR}^{j|i} \quad (6)$$

3. An application to SSM banks security holdings

3.1. Data and first evidence

This section develops an application of the described methodology on a sample of Euro Area banks using data on their financial asset holdings.¹³ Our sample includes 100 banks domiciled in the Euro area and under the direct supervision of the Single Supervisory Mechanism (SSM). The majority of the sample (71 banks) comprises non-specialized lender banks; these include retail, wholesale, and commercial lenders. The sample also contains 13 universal banks, 8 globally systemically important banks (G-SIBs) and a small number of asset managers (3 banks), custodians (4 banks) and other type of banks. G-SIB banks are by definition larger, more complex and more interconnected, which makes them more systemically risky. The average market value of securities held by G-SIBs at the end of the first quarter of 2020 was around 140 billion EUR, while the average market value of securities across the other business model classifications was 17 billion EUR.

¹³This application is meant to show how the proposed transparent and intuitive approach can be used to assess the systemic risk stemming from asset commonality.

For banks' financial holdings, we rely on the granular information of the *Securities Holdings Statistics* (SHS-G)¹⁴ database that covers all the Systemic Institutions (SIs) in the SSM.¹⁵ SHS-G is a security (ISIN) level dataset collected quarterly by the ECB and includes debt securities, listed equities, and investment fund shares or units held either in the banking or trading book.¹⁶ The data is enriched with detailed information on instruments, issuers, and prices from the central securities database (CSDB). Banks' holdings, as reported at the end of each quarter, are used to compute sensitivities to financial risk factors. The set of risk factors resembles the one used in the market risk scenario in the EBA Stress Test, where the main risk factors categories are: equity, interest rate, exchange rate and credit spread.¹⁷ Since the SHS-G dataset only covers financial asset holdings, excluding derivatives, the impact of shocks and scenarios is essentially linear. Therefore, first-order sensitivities are sufficient to compute the implied impact on banks' portfolio value.

In the analysis, we consider the set of risk factors included in the EBA biennial stress test (see EBA 2021). The scenarios are built considering the daily returns of risk factors in percentage changes for equity, exchange rate, and funds, in absolute terms for interest rate and credit spread.¹⁸

The scenarios considered are constituted by the daily returns of the whole set of relevant risk factors, as historically observed between the beginning of 2015 and the last quarter of 2020. Table 1 provides summary statistics of the return distribution given the gains and losses simulated using the daily risk factor changes. Over the sample period, the returns for each business model category are centered around zero, with a standard deviation close to 1%. Distributions are characterized by negative skewness, suggesting a fatter left tail.

In order to compute the profit or loss impact under a certain scenario, we perform a partial revaluation of banks' portfolio based on the computed first order sensitivities and the complete profile of shocks or scenario. Let K_i be the set of securities held by bank i and $s_{i,k,r}$ be the

¹⁴More information is available at the ECB Statistical Data Warehouse.

¹⁵The database includes information on the financial holdings of all domestic and foreign financial group entities that are captured by the prudential scope.

¹⁶In the analysis, all intra-group exposures have been identified and excluded; this covers securities that are both issued and held by the entity itself.

¹⁷Commodities are not included as they are less relevant for our sample of banks.

¹⁸We check for outliers in risk factor realizations and we winsorize the data based on the interquartile range. The Lower bound (lb) and upper bound (ub) for each risk factor were computed as follows: $lw = Q1 - (3 * IQR)$; $ub = Q3 + (3 * IQR)$ where IQR is the interquartile range and Q1 and Q3 are the first and the third quartile, respectively.

sensitivity for a given security k to the risk factor r . Given a shock $z_{r,t} \in Z$ we calculate the impact as

$$l_{i,r,t} = \sum_{k \in K_i} s_{i,k,r} z_{r,t} \quad (7)$$

As described in the previous section, the impact associated with a scenario or set of shocks t for bank i is defined as:

$$l_{i,t} = \sum_{r \in R} l_{i,r,t} \quad (8)$$

Let $L = \{l_{i,t}\}_{i \in B}$ be the set of banks' impacts for each scenario t and $l_{system,t}$ be the net impact on the whole system, i.e. $l_{system,t} = \sum_{i \in B} l_{i,t}$.¹⁹

Table 1: Summary statistics losses under historical scenarios (daily % variations)

Business model	N. banks	Daily obs	Mean	SD	Min	Max	Skew	Kurt
Asset Manager	3	4701	0.04	0.92	-4.42	3.72	-0.40	2.79
Custodian	4	6268	0.04	0.88	-4.42	4.23	-0.35	2.89
G-SIB	8	12536	0.08	0.87	-5.02	4.38	-0.39	2.96
Lender	71	111257	0.04	1.05	-10.17	9.63	-0.31	5.19
Universal Bank	13	20371	0.05	0.94	-5.34	4.51	-0.37	3.08

Source: SHS-G database.

Note: Implied daily losses as percentage changes of portfolio valuation under the given scenarios. Each bank portfolio and the associated sensitivities are considered as of the end of first quarter 2020.

To compute the CoVaR of the system with respect bank i we estimate the quantile regression on the implied losses given a scenario over a set of scenario:

$$l_{system,t} = \alpha_q + \beta_q l_{i,t} + \varepsilon. \quad (9)$$

Bank i 's VaR can be defined as the empirical 99-percentile of the full distribution of the losses $\{l_{i,t}\}_{t \in T}$. $\hat{\alpha}_{i,q}$ and $\hat{\beta}_{i,q}$ are the coefficients via quantile regression and, as in Adrian and

¹⁹In the definition it is implicitly assumed that transfers across banks are possible.

Brunnermeier (2016), the CoVaR and Δ CoVaR can be written as²⁰:

$$\begin{aligned}
\text{CoVaR}_q^{j|(i,q_i)} &= \hat{\alpha}_{i,j,q} + \hat{\beta}_{i,j,q} \text{VaR}_{q_i}^i \\
\text{CoVaR}_q^{j|(i,0.50)} &= \hat{\alpha}_{i,j,q} + \hat{\beta}_{i,j,q} \text{VaR}_{0.50}^i \\
\text{CoVaR}_q^{j|(i,0.99)} &= \hat{\alpha}_{i,j,q} + \hat{\beta}_{i,j,q} \text{VaR}_{0.99}^i \\
\Delta \text{CoVaR}_q^{j|(i,0.99)} &= \hat{\beta}_{i,j,q} (\text{VaR}_{0.99}^i - \text{VaR}_{0.50}^i)
\end{aligned} \tag{10}$$

3.2. Sensitivity based Δ CoVaR and other systemic risk indicators

We consider the entire sample of around 100 banks domiciled in the Euro Area and their financial holdings at the end of the first quarter of 2020. We take the 1490 different scenarios obtained considering the daily changes from the beginning of 2015 until the end of 2020 and inspect the summary statics of basic systemic risk measures. Table 2 contains summary statistics for the risk measures VaR, CoVaR and Δ CoVaR all of which are evaluated at the 99th percentile. We also include VaR at the 50th percentile, which reflects the bank’s median state. CoVaR and Δ CoVaR are estimated using quantile regressions following the methodology described in the previous section.

The 99-percentile VaR across banks is 2.92% on average, ranging from 1.15% to 7.15%. The mean 50-percentile VaR is -0.06% which suggests that the median expected return given the distribution is positive on average. Across our sample of banks, the portfolios of all the institutions are increasing in the median scenario, with bank VaR 50% ranging from -0.02% to -0.2% . The difference in the standard deviation between the median and 99-percentile VaR suggests bank returns at the median show little variation across the sample however, they vary widely at the tail. The CoVaR of a bank measures system losses conditional on the bank being under stress, where stress is defined as a 99-percentile loss. The mean CoVaR is 3.28% or 0.91 bn EUR. Comparatively, the mean Δ CoVaR is 2.46% or 0.72 bn EUR. The latter measures the additional amount of losses suffered by the system when the bank moves from the median to a 99th percentile adverse event and measures the tail dependency between the bank and the system.

Figures 1 and 2 illustrate the distribution of Δ CoVaR across business model classifications in both percentage points, relative to the market value of their holdings, and EUR-valued,

²⁰Equations in (10) refer to the general case studying the evolution of bank j ’s risk conditional on an increase in losses for bank i . In our analysis, j is the system, as stated before.

Table 2: Descriptive statistics for: CoVar, Delta CoVaR and VaR

	Banks	Mean	SD	Median	Max	Min
Returns (%)						
VaR 99%	100	2.92	0.85	2.95	7.15	1.15
VaR 50%	100	-0.06	0.03	-0.06	-0.02	-0.2
CoVar 99%	100	3.28	0.16	3.3	3.76	2.89
Delta CoVar 99%	100	2.46	0.47	2.6	2.96	0.55
Billions of Euro						
VaR 99%	100	0.78	1.05	0.37	4.93	0
VaR 50%	100	-0.02	0.05	-0.01	0	-0.34
CoVar 99%	100	0.91	1.39	0.32	8.55	0
Delta CoVar 99%	100	0.72	1.07	0.25	5.89	0

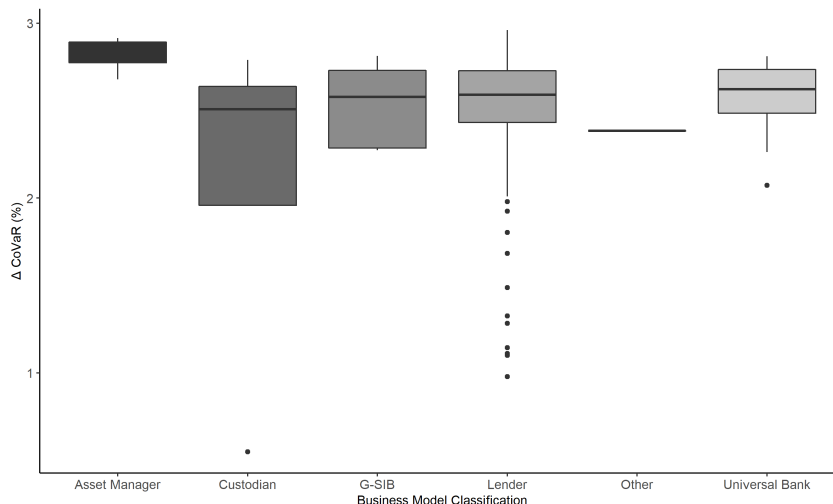
Source: SHS-G database.

Note: The sample includes the 100 reporting entities in the SHS-G statistics. The set of scenarios is built on the daily returns of risk factors as realized between the beginning of 2015 and the end of 2020. The banks' portfolio is the one observed at the of the first quarter of 2020.

respectively. Figure 1 shows that the median ΔCoVaR for asset managers is around 2.7% and, for example, only 2.4% for G-SIBs. This suggests that in relative (% of bank market value) terms, when asset managers are experiencing a stress event, the system will experience the greatest increase in its VaR. However, this does not show the full picture and, as explained in the previous section, there is a large difference in the size of bank securities portfolios across business models. Figure 2 shows the size-weighted ΔCoVaR measured in EUR. In this figure the GSIBs clearly stand out as having the largest ΔCoVaR and therefore, the greatest contribution to system losses when they experience a tail event. Universal banks also have a larger $\Delta^{\text{€}}\text{CoVaR}$ than the other business model groups. Conversely, asset managers have a very small size-weighted ΔCoVaR due to their smaller securities portfolios.

As mentioned, banks' financial holdings are used to compute the sensitivities to the financial risk factors. The sensitivity of each bank to each risk factor can be computed and the correlation between bank-specific vulnerabilities can be derived. The information from SHS-G data used throughout the exercise refers to the end of the first quarter of 2020, but a wider time frame can be considered when examining commonalities and their potential changes over time. Figure 3 shows the distribution of cross-bank correlations in different sets of sensitivities; most bank pairs have positive correlations above 0.5, and very few pairs display negative correlations, confirming strong portfolio commonalities. The distribution of correlations across bank pairs seems very stable over time, with similar statistics from the end of 2018 on.

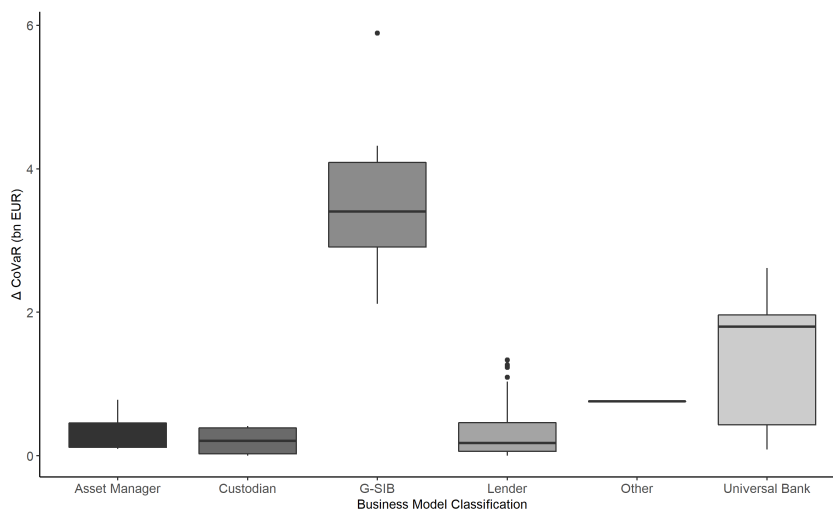
Figure 1: Distribution of ΔCoVaR (percentage points) across business model classification



Source: SHS-G database.

Note: ΔCoVaR is measured in percentage of portfolio market value at the end of the first quarter of 2020. The box plot for each business model classification shows the median, the hinges (25th and 75th percentiles) and whiskers. The upper (lower) whisker extends from the hinge (the median value) to the largest (smallest) value no further than $1.5 \times IQR$ (Inter-Quantile Range) from the hinge and any outliers are plotted separately.

Figure 2: Distribution of $\Delta^\epsilon\text{CoVaR}$ (billions Euro) across business model classification



Source: SHS-G database.

Note: ΔCoVaR is measured in billions of Euro using bank portfolio market value at the end of the first quarter of 2020. The box plot for each business model classification shows the median, the hinges (25th and 75th percentiles) and whiskers. The upper (lower) whisker extends from the hinge (the median value) to the largest (smallest) value no further than $1.5 \times IQR$ (InterQuantile Range) from the hinge and any outliers are plotted separately.

Considering the business model classification, Table 3 lists the median correlation of each set of banks with the system: each group displays median correlations above 0.5, with the exception of G-SIBs, which appear to be less correlated to systemic sensitivities.

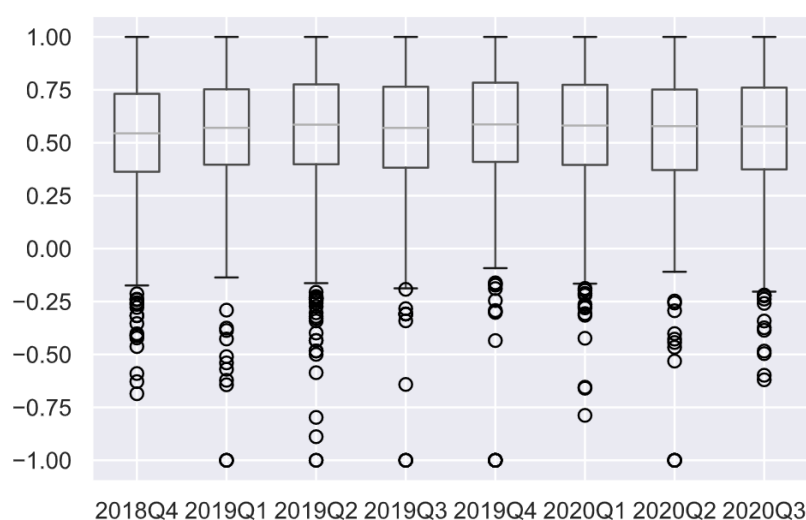
Table 3: Correlations in sensitivities by business model with respect to the system

	2018Q4	2019Q1	2019Q2	2019Q3	2019Q4	2020Q1	2020Q2	2020Q3
Asset Manager	0.62	0.65	0.65	0.64	0.64	0.64	0.57	0.57
Custodian	0.77	0.8	0.84	0.84	0.86	0.86	0.86	0.81
G-SIB	0.47	0.4	0.42	0.52	0.55	0.47	0.43	0.45
Lender	0.68	0.71	0.69	0.7	0.68	0.68	0.67	0.69
Universal bank	0.63	0.69	0.7	0.68	0.65	0.67	0.68	0.65

Source: SHS-G database.

Note: The sample includes the 100 reporting information of the SHS-G statistics. The set of scenarios is built on the daily returns of risk factors as realized between the beginning of 2015 and the end of 2020. The banks' portfolio is the one observed at the of the first quarter of 2020.

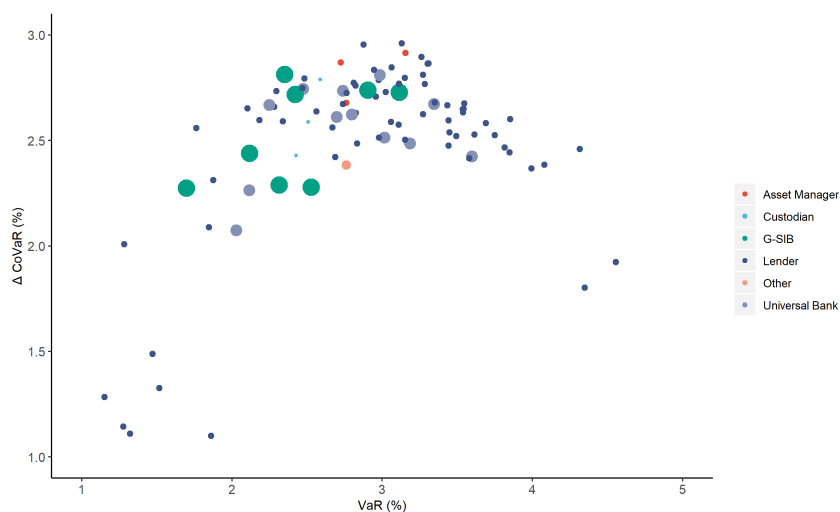
Figure 3: Correlations in sensitivities across banks over time



Source: SHS-G database.

An important characteristic of a systemic risk measure is that it captures more than just the idiosyncratic risk of the bank, that is, the risk of a bank to the system as a whole and not just to itself. Figure 4 shows the relationship between the 99-percentile VaR and ΔCoVaR , both measured in percent. Interestingly, there is no clear linear relationship between the two measures, such that banks with lower % VaR than others are not necessarily less systemic and vice versa. Naturally, when weighted by market value, a linear relationship emerges in the $\Delta^\epsilon\text{CoVaR}$. Similar to the box plots above, where GSIBs have the largest $\Delta^\epsilon\text{CoVaR}$ in general, they also have a larger VaR in Euro. From a macroprudential perspective, this highlights the importance of taking systemic risk measures into account, as VaR measures the potential losses at the bank level and may not capture the potential losses to the system.

Figure 4: VaR and ΔCoVaR relation



Source: SHS-G database.

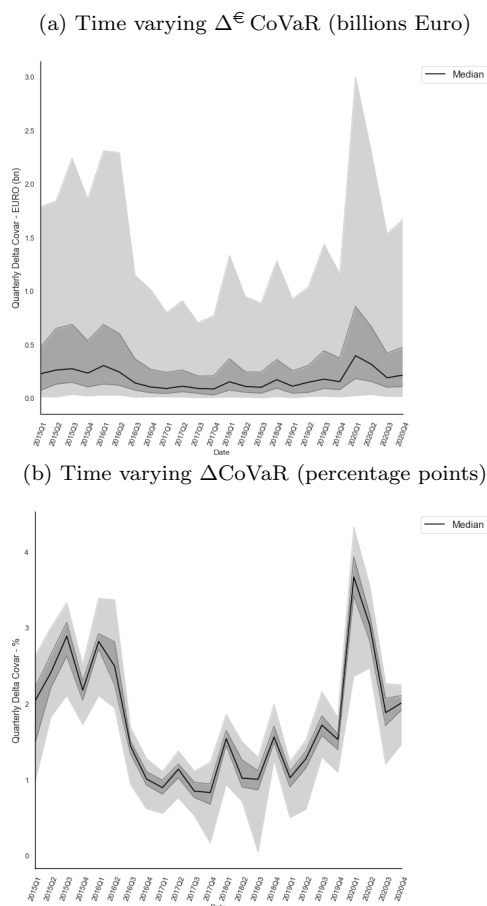
Note: ΔCoVaR and VaR in percent of portfolio market value at the end of the first quarter of 2020. Points' size is weighted according to the average market value for each business model classification.

In order to assess the information provided by our new systemic risk indicator based on banks' financial holdings and the implied sensitivities, we compute the ΔCoVaR on a quarterly basis from the first quarter of 2015 until the last quarter of 2020, using the preceding three months' daily changes as a time window for the risk factor scenarios but keeping the sensitivities fixed ²¹. Figures 5a and 5b show that the systemic risk stemming from the commonality of financial holdings is clearly pro-cyclical and tends to anticipate systemic events. Interestingly, the relative systemic importance of banks seems to change over time. This reflects both the relative importance of shocks and the banks' portfolio composition (see Appendix). This evidence seems to support the potential use of this indicator for financial stability purposes. The sensitivity-based ΔCoVaR can be used to assess vulnerabilities and predict the impact of financial market turmoil.

We summarize the quarterly time-varying distributions displayed in Figures 5a and 5b by their quarterly median values, the solid lines, to obtain a time-series indicator of systemic risk. To assess the information it provides, we compare it with other indicators coming from the existing literature. We focus on those more commonly used for financial stability purposes, namely: the Financial Conditions Indicator (FCI) initially presented by the IMF using the

²¹We considered banks' portfolio as reported at the end of the first quarter of 2020.

Figure 5: Distribution over time variation of Δ CoVaR for SSM banks



Source: SHS-G database.

Note: Time series of Δ CoVaR in both percentages and EUR billions. The solid line is the median Δ CoVaR across the banks' sample for each quarter, while the shaded gray areas represent percentiles 10 and 30 of the same distribution.

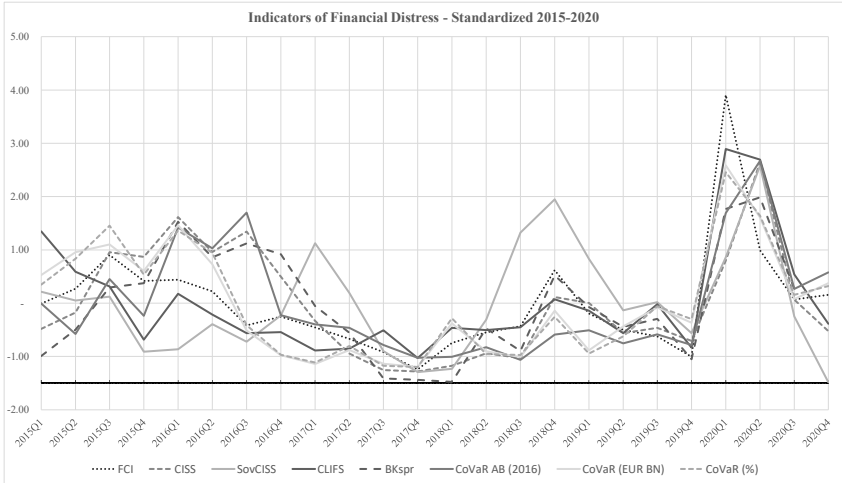
methodology of Koop and Korobilis (2013), the Composite Indicator of Systemic Stress (CISS) of Kremer et al. (2012) and its sovereign risk-focused (sovCISS) version presented in Garcia-de Andoain and Kremer (2017), the Country-Level Index of Financial Stress based on Duprey et al. (2017) and the synthetic measure of bank bond spreads of Gilchrist and Mojon (2018). Since all these measures refer to the financial stability of the system as whole, we need to aggregate our index by taking the median Δ CoVaR within the sample of banks for each quarter, and perform the same aggregation on the original stock price-based Δ CoVaR by Adrian and Brunnermeier. From the beginning of 2015 until the end of 2020 the sensitivity-based Δ CoVaR appears to move in line with the other indicators over time (Figure 6) and its correlation with them is positive, though still far from being equal to one (Table 4). Since some of the systemic risk

indicators reflect at least partially the development in financial markets within the quarter, the correlation among the indicators does not come as a surprise. The variance over time of the sensitivity-based Δ CoVaR is lower than the one of FCI, CISS and the Δ CoVaR by Adrian and Brunnermeier (2016).²² The autocorrelation over the time of all the considered indicators are below one and it does not differ significantly.²³

Between 2015 and 2020 there was no purely banking crisis (see Nguyen et al., 2022 and Laeven and Valencia, 2020) yet we observed a surge in sovereign spreads in 2018 and the outbreak of the pandemic at the beginning of 2020. Unsurprisingly, the latter crisis was not anticipated by any of the indicators, while the former seems to be anticipated by an increase in the sensitivity-based Δ CoVaR. Despite this evidence, we would like to stress that our indicator should not anticipate the happening of a crisis but rather flag whether banks’ portfolios and exposures can be, in principle, exposed to the same sources of risks.

This first evidence suggests that asset commonality among banks can be one of the channels for systemic risk to materialize and, differently from other indicators, the sensitivity-based Δ CoVaR can be used to identify the risk factors that contribute most to the building-up of systemic risk and which banks are more exposed and potentially impacted.

Figure 6: Indicators of Financial Distress



Note: Each indicator has been standardized considering observations in the displayed period.

²²The variance of $\Delta^{\text{€}}$ CoVaR and Δ CoVaR are respectively equal to 0.14 and 0.15

²³The autocorrelation of $\Delta^{\text{€}}$ CoVaR and Δ CoVaR are respectively equal to 0.62 and 0.61

We also perform a Growth-at-Risk exercise as in Adrian et al. (2019) to understand the potential of this indicator in predicting macroeconomic downturns measured as the lower quantiles of GDP growth. This assessment has been performed by Figueres and Jarociński (2020) using several indicators like the CISS, which displays strong predictive accuracy in the Euro Area. Table 5 lists the Pseudo- R^2 of Koenker and Machado (1999) for different quantile regression models, each including a constant, lagged GDP and the financial indicator. The goodness of fit appears high for Δ CoVaR on the left tail of GDP growth. Despite the fact that the test is performed using a very short time series (2015Q1-2020Q4), this first evidence supports the hypothesis that Δ CoVaR can be a good leading indicator of the contraction of economic activity in the Euro Area.

Table 4: Correlations of sensitivity based Δ CoVaR with other of financial distress indicators

	FCI	CISS	Sov.	Bank	CLIFS	ΔCoVaR
			CISS	Spread		AB 2016
$\Delta^{\text{€}}\text{CoVaR}$	84%	67%	18%	64%	80%	72%
ΔCoVaR	82%	69%	17%	65%	77%	74%
<i>Variance</i>	1.0	1.04	0.11	0.07	0.5	1.04
<i>Autocorrelation</i>	0.22	0.60	0.42	0.47	0.56	0.53

In order to highlight the possible spill-over effects across banks and countries, figures 8a and 8b show the bilateral Δ CoVaR across the SSM banks grouped by their country of domicile in the form of a heat map. Each heat map shows the Δ CoVaR of bank j (on the y-axis) when bank i (on the x-axis) is under stress. For illustrative purposes, we consider the whole set of historical scenarios that occurred from the beginning of 2015 to the end of 2020. We can highlight a few relevant aspects for financial stability. Within country clusters, it is evident that banks belonging to the same jurisdiction show a high degree of commonality. Yet, international banks show commonality with banks across countries, even beyond the group of G-SIBs. These latter aspects point to the importance of a sovranational perspective for macroprudential policies.

Table 5: In-sample Growth-at-Risk predictive power of alternative systemic risk indicators

One quarter ahead Growth at Risk									
	GDP	FCI	CISS	Sov.	CLIFS	Bank	CoVaR	CoVaR	CoVaR
				CISS		Spread	AB		(%)
95%	0.13	0.44	0.30	0.31	0.43	0.36	0.39	0.49	0.50
90%	0.00	0.34	-0.03	-0.02	0.31	0.11	0.20	0.35	0.35

One year ahead Growth at Risk									
	GDP	FCI	CISS	Sov.	CLIFS	Bank	CoVaR	CoVaR	CoVaR
				CISS		Spread	AB		(%)
95%	0.36	0.48	0.40	0.42	0.40	0.37	0.49	0.46	0.50
90%	0.13	0.22	0.16	0.13	0.14	0.14	0.22	0.20	0.23

Note: In the first column (labelled as GDP) shows the Pseudo- R^2 for the quantile regression with Euro Area GDP growth as dependent variable and its lagged equivalent (either one quarter or one year) and a constant as independent variables. The following columns display the same statistic for the quantile regression where each systemic risk indicator named in the header is added to the initial specification. For example, the FCI model is a quantile regression adding the lagged FCI index as independent variable. The CISS model uses the lagged CISS instead of the FCI as a predictor of the lower quantiles of GDP growth conditional on lagged growth. The CoVaR table refers to the $\Delta CoVaR$ indexes, with AB indicating the index based on stock-prices by Adrian and Brunnermeier.

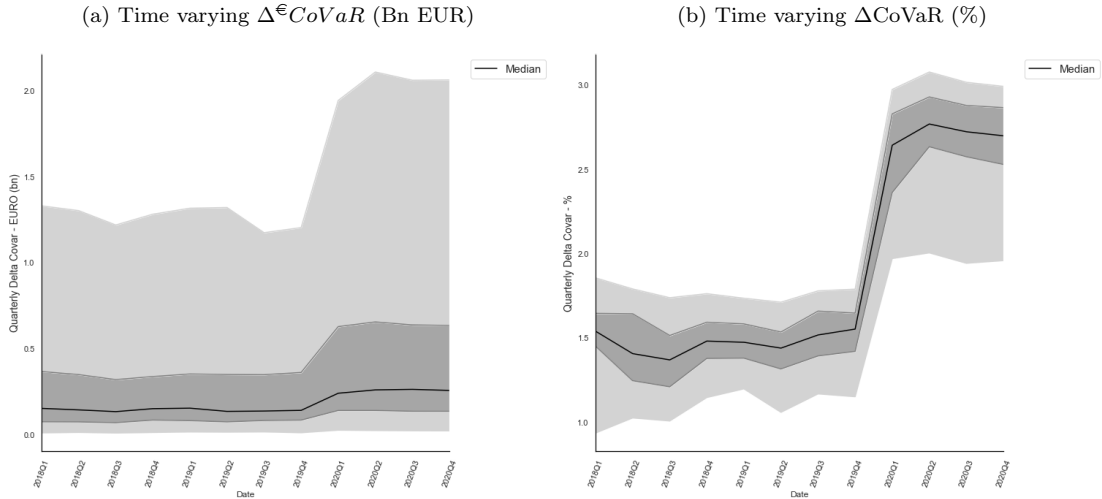
In order to show the use of the sensitivity-based Δ CoVaR in real-time, we compute it by taking scenarios over quarterly windows, using daily observations over three-month time windows. In order to consider a wider set of scenarios, we are interested in how the indicator would change with an increasingly larger set of scenarios. Figures 7a and 7b display the results of such an exercise, where starting from 2018, the daily data adds up each quarter to enrich the risk factors' distribution.

As in the previous section, systemic risk appeared to be pro-cyclical in the mentioned time series. The expanding window setting confirms such an interpretation (especially for the first quarter of 2020), but also highlights another interesting aspect: if risk goes up, it takes a long time for it to reduce again. The lower quantiles can be affected by one specific event that characterises the distribution for a long time horizon. The expanding information can also represent banks' perception of risk, which can, in fact, be influenced by crisis events for long

periods of time.

The way risks can easily increase in both agents' perception and eventually revert slowly to previous levels is an additional element for macroprudential policy-makers to consider. Preventing excessive commonalities in banks' vulnerabilities can avoid sizable systemic risk shocks that might affect the financial system for long periods.

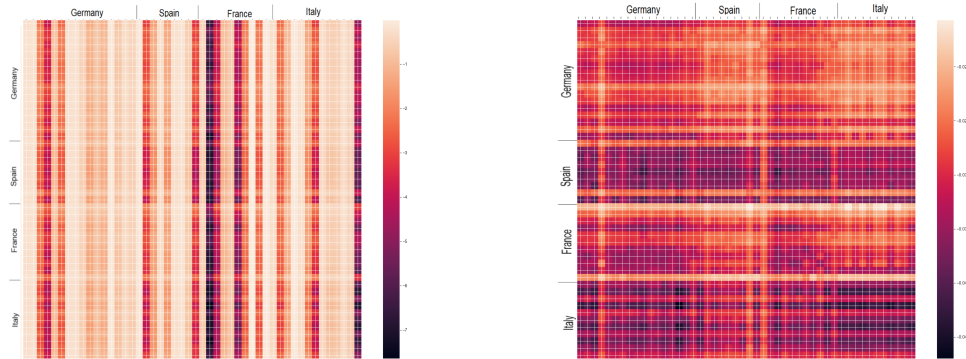
Figure 7: Distribution over time of Δ CoVaR for SSM banks



Note: Time series of Δ CoVaR in both percentages and EUR billions. The solid line is the median Δ CoVaR across the banks' sample for the expanding window at each quarter, while the shaded gray areas represent percentiles 10 and 30 of the same distribution.

Figure 8: Heat-map of bilateral ΔCoVaR

(a) Heat-map of bilateral $\Delta^{\text{€CoVaR}}$ (Billions EUR) (b) Heat-map of bilateral ΔCoVaR (%)



Note: Bank cross-section of ΔCoVaR in both percentages and billions of Euro for the period 2015-2020.

4. Conclusions

In this paper, we illustrate a novel indicator of systemic risk aiming to identify and quantify a source of systemic risk stemming from the correlation in banks' losses due to the asset commonality in banks' exposures. Using a sensitivity-based approach, we are able to reduce a problem that is fundamentally multi-dimensional and complex to a synthetic and yet comprehensive indicator, which proved to be able to identify the build up of systemic risk by leveraging on the conceptual framework proposed by Adrian and Brunnermeier (2016). The sensitivity based ΔCoVaR indicator highlights the more systemic institutions and the more relevant risk factors for banks' exposures. Therefore, it can be used for the identification of possible threats to financial stability and to measure the systemic footprint of specific institutions.

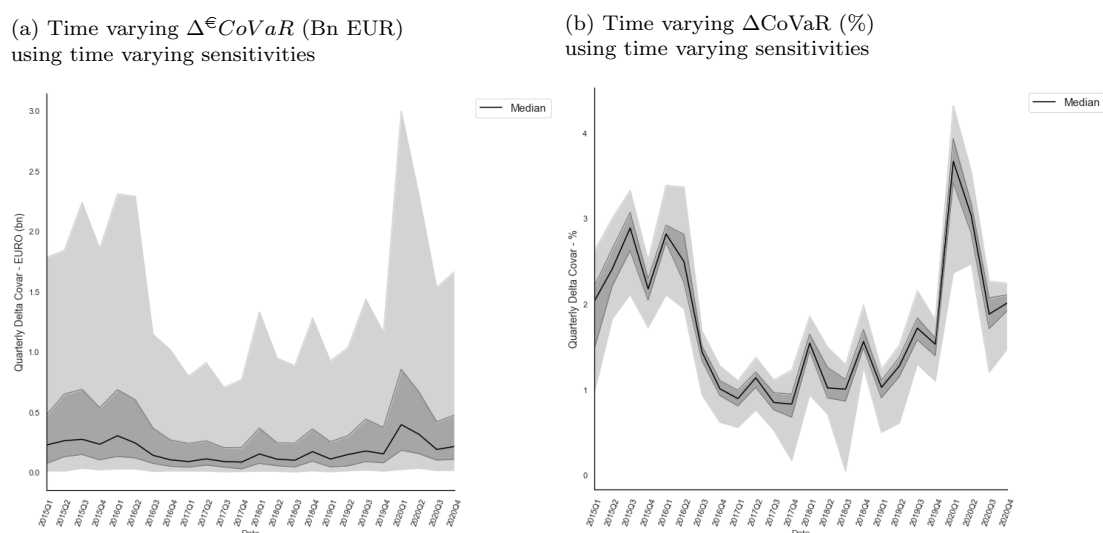
For illustrative purposes, we apply the novel indicator to the granular information on financial assets held by significant institutions in the SSM to compute the implied ΔCoVaR and show the possible use of the indicator for financial stability purposes.

5. Appendix

5.1. Time Varying Sensitivities

As mentioned in Section 3.1 portfolio commonalities appear to be persistent through time, as correlations among sensitivities maintain a very similar distribution from the last quarter of 2018 to third quarter of 2020. Therefore it is sufficient to simply use a representative set of sensitivities to built the time-varying Δ CoVaR, as done in Section 3 using information at the end of the first quarter of 2020. SHS-G data. Figure 9 shows the evolution of the Δ CoVaR built using time varying sensitivities from the of 2018 to the third quarter of 2020. The differences in the index's behaviour with respect to the one presented in Figure 5 are relatively small, which justifies the use of constant sensitivities (at the end of the first quarter of 2020).

Figure 9: Distribution over time of Δ CoVaR for SSM banks



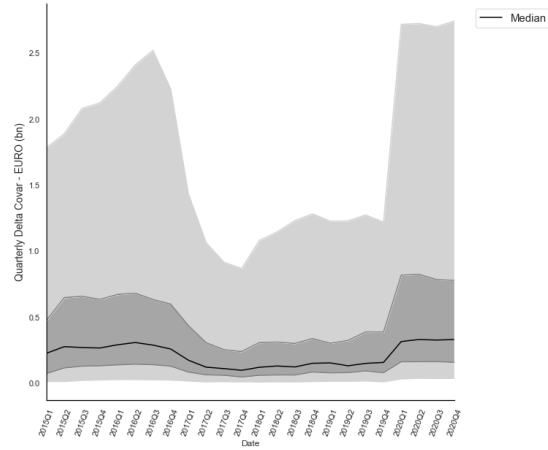
Source: SHS-G database.

Note: Time series of Δ CoVaR in both percentages and EUR billions. The solid line is the median Δ CoVaR across the banks' sample for the expanding window at each quarter, while the shaded gray areas represent percentiles 10 and 30 of the same distribution.

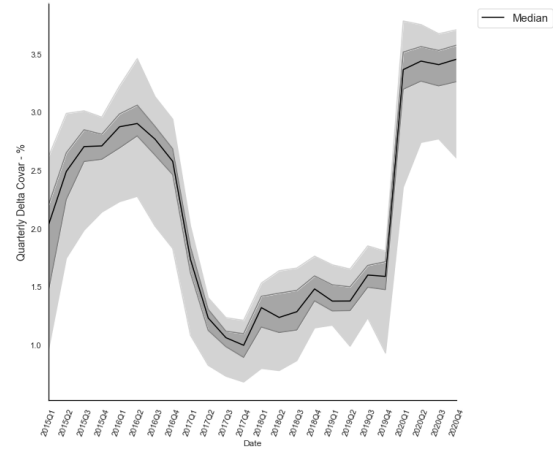
Section 3 presents the distribution of the CoVaR across banks over time in an expanding window setting, where the distribution of each risk factor increases its size each quarter. Coming close to banks' actual practices, it might be of use to consider a one-year horizon for the calculation of the CoVaR, keeping the risk-factors' window size fixed to one year, but performing the exercise for each available quarter from 2015 to 2020. Figure 10 shows the time-varying distribution, displaying once again how persistently negative shocks can be reflected through this risk measure.

Figure 10: Distribution over time variation of Δ CoVaR for SSM banks

(a) Time varying $\Delta^{\text{€}}\text{CoVaR}$ (Bn EUR) using a rolling one-year window



(b) Time varying Δ CoVaR (%) using a rolling one-year window



Source: SHS-G database.

Note: Time series of Δ CoVaR in both percentages and EUR billions. The solid line is the median Δ CoVaR across the banks' sample for each quarter, while the shaded gray areas represent percentiles 10 and 30 of the same distribution.

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