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MIDAS models in banking sector – systemic risk comparison

1. Introduction

With the elapse of time, financial markets have become more and more correlated. The respective literature presents different channels that have caused these interlinkages. Across financial markets, these mutual dependencies could reflect the similarities in industrial structure, monetary integration, bilateral trade, and geographical proximity. An empirical fact is that there is no unique economic determinant in supporting the integration of financial markets across different countries. However, from empirical observations, it follows that countries in close geographical proximity are more interlinked than countries in different regions

The empirical fact is that, after the introduction of the euro, the return correlations among the developed markets as well as European economic and monetary union (EMU) stock markets increased considerably. The empirical observations confirm that these higher dependencies have stabilized since the introduction of the euro.

During financial crises, losses tend to spread across financial institutions, thus affecting the financial system as a whole. Systemic risk measures capture the potential losses for the spreading of financial distress across institutions by capturing this increase in tail co-movement.

To present this concept, Adrian and Brunnermeier (2011) developed the CoVaR method. To emphasize the systemic nature of their risk measure, they add the measures the prefix Co to the existing risk (which stands for conditional, contagion, or co-movement).

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Dynamic factor models were developed in the eighties as a result of the needs by policy makers with respect to the forecasts of key macroeconomic variables; these models were based on small sets of time series, usually no more than ten enabled forecasts (especially in short-term situations). The quality of these forecasts was even better than the quality of forecasts by structural models or DSGE models. The most-important class of these models were those that allowed the processing of data exhibiting different frequency and time series with missing data. These models enabled us to reflect the dynamics and main dependencies among key macroeconomic variables.

Thus, these models were even used as reference models by central banks, international institutions, and state offices responsible for macro policies. In the current century, the researchers elaborated the new approach of modeling within one structure of time series collected with different frequency – the so-called regression models with mixed frequencies of sampling (MIDAS – Mixed Data Sampling Regressions). In the first step, these models were simple one-equation structures. However, further models captured multiple structures. They assured the modeling of unobservable components.

The main goal of this contribution is a comparison of the risk measures used in financial theory and practice and their applications to risk assessment in the banking sector.

The next section features an overview of the literature. The following chapter presents the methodology used in the empirical part of this contribution. In Section 4, the empirical results are reported. The last section concludes the paper.

2. Literature

In the financial literature, systemic risk measures are the subject of intensive research. Acharya et al. (2010) introduced the Systemic Expected Shortfall (SES) of a financial institution. This is its propensity to be undercapitalized when the system as a whole is undercapitalized. In the same paper, one of the most-widely-used systemic risk measures was introduced; i.e., Marginal Expected Shortfall (MES). This measure expected losses when a market declines beyond a given threshold. The application of this measure can be found in Banulescu and Dumitrescu (2015), Benoit et al. (2013), Popescu and Turcu (2014), and Brownless and Engle (2012), among others. CoVaR introduced by Adrian and Brunnermeier (2011) corresponds to the Value at Risk of the market return obtained conditionally on an event for a given institution. They defined the contribution of the institution to systemic risk as the difference of the two values of CoVaR. Benulescu and Dumitrescu (2015)

proposed CES, a forward-looking method that encompasses MES. The empirical applications show that CES is relatively stable over time.

Popescu and Turcu (2014) transposed s systemic-risk approach to the Eurozone members by adapting those measures initially developed for the market risk to sovereign debt risk.

The proper forecast of future volatility is one of the main problems with respect to risk management and asset allocation. In the economic literature, it is well documented that volatility depends strongly on time and the different factors causing this time variation.

The MIDAS regression model was developed by Anderou and Ghysels (2004) and Ghysels et al. (2006a, 2006b). It allows data from different frequencies to be introduced into the same model. This approach enables a combination of high-frequency returns with macro-finance data that are only observed at lower frequencies (such as monthly or quarterly).

Engle and Rangel (2008) applied this technique to the GARCH framework to form the spline GARCH model. The GARCH-MIDAS modelis a combination of the spline GARCH framework and the volatility decomposing approach (comp. Ding and Granger, 1996; Engle and Lee, 1999; Bauwens and Storti, 2009; Amado and Teräsvirta, 2013) It was introduced by Engle et al. (2012). The advantage of this model is that it allows us to incorporate information on the macroeconomic environment into the long-run component.

Baele et al. (2010) and Colacito et al. (2011) used the MIDAS technique to the DCC model of Engle (2002). They decomposed the co-movement of stocks and bonds into short-run and long-run components.

The GARCH-MIDAS model is used in Conrad and Loch (2011) to investigate the relationships between long-term market risk (for US data) and the macroeconomic environment. They show that macro variables carry information on stock market risk and have a predictive ability for long-term volatility forecasting.

Asgharian et al. (2013) examined the information contained in large group of macroeconomic data. They showed that including low frequency macroeconomic data in the GARCH-MIDAS model improves the forecasting ability for the long-term variance component.

In a more-recent contribution, Conrad et al. (2014) use the GARCH-MIDAS model in order to decompose the stock returns into short-run and long-run components. They examined the long-run volatility component using economic factors. The DCC-MIDAS model is extended by allowing macro-finance variables to enter the long-run component of the correlation of crude oil and stock returns. They found that the behavior of the long-term correlation is counter cyclical.

The novelty of our contribution is the application of MIDAS models in the assessment of risk measures. To model the secular component, we used

monthly realized volatility approximated as a sum of the squares of daily returns. Another possibility to model the long-run component is to use macroeconomic data; however, it was not available to the authors and may be a basis for future research.

In the next section, we describe the methodology used in risk measurement (MES and ΔCoVaR) and the GARCH-MIDAS and DCC-MIDAS models.

3. Methodology

MES and ΔCoVaR

We consider two popular measure of systemic risk. The first is defined in Acharya et al. (2010) and is based on the concept of Expected Shortfall. Consider the conditional Expected Shortfall computed at time t (given the information up to time $t - 1$):

$$ES_{m,t}\left(C\right) = E_{t-1}\left(r_{mt} \mid r_{mt} < C\right) = \sum_{i=1}^{N} w_{it} E_{t-1}(r_{it} \mid r_{mt} < C)$$

where r_{mt} and r_{it} are the returns of the market and asset (bank), respectively. Threshold C defines the distress event, while w_{it} is the weight of Firm i in the financial system. Given the risk of system measured by $ES_{m,t}(C)$, its marginal contribution of Firm i is called the Marginal Expected Shortfall:

$$MES_{it}\left(C\right) = \frac{\partial ES_{mt}\left(C\right)}{\partial w_{it}} = E_{t-1}(r_{it} \mid r_{mt} < C)$$

and measures the increase in a system's risk resulting from a marginal increase in weight w_{it}. The second measure is ΔCoVaR, which is based on the concept of Value-at-Risk (Adrian and Brunnermeier, 2011). Suppose $\mathbb{C}(r_{it})$ is some event for Asset i. Then, CoVaR at confidence level α corresponds to conditional VaR of the market return:

$$P\left(r_{mt} \leq \mathrm{CoVaR}_t^{m \mid \mathbb{C}(r_{it})} \mid \mathbb{C}\left(r_{it}\right)\right) = \alpha$$

The difference between the CoVaR at level alpha and CoVaR computed in the median state is denoted as ΔCoVaR (Benoit et al., 2013):

$$\Delta\text{CoVaR}_{it}\left(\alpha\right) = \text{CoVaR}_t^{m|r_{it}=VaR_{it}(\alpha)} - \text{CoVaR}_t^{m|r_{it}=Median(r_{it})}$$

MES and ΔCoVaR can be calculated with various approaches. In this paper, we consider the bivariate GARCH model of Brownless and Engle (2012):

$$r_t = H_t^{1/2}\epsilon_t \tag{1}$$

where $r_t = (r_{mt}, r_{it})'$ is the vector of demeaned returns and $\epsilon_{it} = (\varepsilon_{mt}, \xi_{it})'$ is the vector of *i.i.d.* shocks with zero means and an identity covariance matrix. The time varying covariance matrix is defined as:

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\sigma_{it}\rho_{it} \\ \sigma_{mt}\sigma_{it}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{2}$$

where σ_{mt} and σ_{it} are conditional standard deviations of the market and asset, whereas ρ_{it} is the conditional correlation between r_{it} and r_{mt}.

Following (1) and (2), we can formulate the following equations:

$$r_{mt} = \sigma_{mt}\varepsilon_{mt},$$

$$r_{it} = \sigma_{it}\rho_{it}\varepsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it} \tag{3}$$

$$\epsilon_{it} = (\varepsilon_{mt}, \xi_{it})' \sim F$$

It is worth mentioning that the asset return can be described as:

$$r_{it} = \beta_{it}r_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it}$$

where $\beta_{it} = \rho_{it}\dfrac{\sigma_{it}}{\sigma_{mt}}$. This is the formulation of one-factor CAMP with systematic risk measure β_{it}. From (3), we can express MES_{it} as:

$$MES_{it}\left(C\right) = E_{t-1}\left(r_{it}|r_{mt} < C\right) = \sigma_{it}E_{t-1}\left(\rho_{it}\varepsilon_{mt} + \sqrt{1-\rho_{it}^2}\xi_{it} \mid \varepsilon_{mt} < C\!\big/\!\sigma_{mt}\right) =$$

$$= \sigma_{it}\rho_{it}E_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < C\!\big/\!\sigma_{mt}\right) + \sigma_{it}\sqrt{1-\rho_{it}^2}E_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < C\!\big/\!\sigma_{mt}\right)$$

that is as a function weighted by the tail expectations of the standardized residuals of the market and asset, respectively. Similar to Benoit et al. (2013), we now set threshold C equal to the conditional Value-at-Risk of the market return (given information $\mathcal{F}_{t-1}$ available up to time $t-1$):

$$P\left(r_{mt} \left\langle \text{VaR}_{mt}\left(\alpha\right) \middle| \mathcal{F}_{t-1}\right.\right) = \alpha$$

In their paper, Benoit et al. (2013) showed that MES_{it} is proportional to the systemic risk measured by the time varying beta, where the proportionality coefficient is the expected shortfall of the market:

$$MES_{it}\left(\alpha\right) = \beta_{it} ES_{mt}\left(\alpha\right)$$

They showed that, given (3) and defining conditioning event $r_{it} = VaR_{it}(\alpha)$, ΔCoVaR can be expressed as follows:

$$\Delta\text{CoVaR}_{it}\left(\alpha\right) = \gamma_{it}\left[VaR_{it}\left(\alpha\right) - VaR_{it}\left(0.5\right)\right]$$

with $\gamma_{it} = \rho_{it}\sigma_{mt}/\sigma_{it}$.

Both MES and ΔCoVaR require the estimation of the conditional standard deviations, conditional correlation, and tail expectations. For this purpose, Brownless and Engle (2012) use the TARCH and DCC models for modeling the standard deviations and correlation. Tail expectations $E_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt})$ and $E_{t-1}(\xi_{mt}|\varepsilon_{mt} < C/\sigma_{mt})$ are estimated with nonparametric estimators (Sciallet, 2005) with Gaussian kernel:

$$\hat{E}_{t-1}\left(\varepsilon_{mt} \mid \varepsilon_{mt} < c\right) = \frac{\sum_{t=1}^{T}\varepsilon_{mt}\Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}{\sum_{t=1}^{T}\Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}$$

$$\hat{E}_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < c\right) = \frac{\sum_{t=1}^{T}\xi_{it}\Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}{\sum_{t=1}^{T}\Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}$$

where $c = C/\sigma_{mt}$ and $h = T^{-1/5}$.

In order to model the standard deviations and correlations, Brownless and Engle (2012) use the TARCH and DCC models. In this paper, we use the GARCH-MIDAS and DCC-MIDAS models described in the next section.

GARCH-MIDAS and DCC-MIDAS models

Following Engle et al. (2013), we assume that univariate returns t_{jt} (on day j in period t) follows the GARCH-MIDAS process:

$$r_{j,t} = \mu + \sqrt{\tau_t g_{jt}}\, \varepsilon_{jt} \quad \forall i = 1,\ldots,N_t \tag{4}$$

where N_t is the number of days in period t and $\varepsilon_{jt}|\mathcal{F}_{i-1,t} \sim N(0, 1)$. Short-run volatility component g_{it} follows the mean-reverting GARCH(1,1) process:

$$g_{it} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{j-1,t} - \mu\right)^2}{\tau_t} + \beta g_{j-1,t} \tag{5}$$

whereas long-run volatility component τ_t is smoothed realized volatility:

$$\log\left(\tau_t\right) = m + \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) RV_{t-k} \tag{6}$$

where realized volatility:

$$RV_t = \sum_{i=1}^{N_t} r_{j,t}^2$$

does not change within a time span (period, month), and the weighting shame is based on beta polynomials with weights w_1, w_2, and parameter K:

$$\varphi_k\left(w_1, w_2\right) = \frac{\left(\dfrac{k}{K}\right)^{w_1 - 1}\left(1 - \dfrac{k}{K}\right)^{w_2 - 1}}{\sum_{j=1}^{K}\left(\dfrac{j}{K}\right)^{w_1 - 1}\left(1 - \dfrac{j}{K}\right)^{w_2 - 1}}$$

We adopt the restricted beta weighting scheme. The weights are computed as:

$$\varphi_k\left(w\right) = \frac{\left(1 - \dfrac{k}{K}\right)^{w - 1}}{\sum_{j=1}^{K}\left(1 - \dfrac{j}{K}\right)^{w - 1}}$$

For $w > 1$, this guarantees a decaying pattern (slow or rapid) depending on the values of w (small or large).

The GARCH-MIDAS model is used to model the conditional deviations of r_{mt} and each asset return r_{it}. Natural extension is the DCC-MIDAS model of Colacito et al. (2011) in which as the input standardized residuals from the GARCH-MIDAS models are taken. The (i, j) element of quasi-correlation matrix Q_t has GARCH(1,1)-like dynamics:

$$q_{ijt} = \left(1 - a - b\right)\overline{\rho}_{ijt} + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{ij,t-1}$$

where $a > 0$, $b \geq 0$ and $a + b < 1$.

In the equation above, $\overline{\rho}_{i,j,t}$ represents element (i, j) of long-run quasi-correlation matrix ρ_t:

$$\rho_t = \sum_{k=1}^{K_c}\varphi_k\left(w\right)c_{t-k}$$

that is the weighted sum of sample correlation matrices c_{t-k}.

Finally, the correlation matrix (rescaled quasi-correlation matrix to obtain unity on the diagonal) is defined as follows:

$$R_t = diag\left\{Q_t\right\}^{-1/2} Q_t diag\left\{Q_t\right\}^{-1/2}$$

4. Empirical results

We consider the prices (in euros) of the EURO STOXX BANKS index with 18 components of this index. Although the index contains 25 components, we excluded some of them (a list of the banks used in this paper is given in the appendix). First, we excluded the series due to the sample size. The second reason was the large number of zero returns (more than 10%). The dataset covers the period of January 2002 through June 2017. As usual, we computed the logarithmic return percentage as $r_t = 100 \cdot (\ln P_t - \ln P_{t-1})$ and descriptive statistics of returns. The mean of the return index is equal to -0.018 with a standard deviation of 2.000. The skewness equals to –0.032, and the kurtosis is 10.567. The high value of the kurtosis results in the non-normality formally confirmed with the Jarque-Bera test. As expected, we observed significant autocorrelation (from the Ljung-Box test with 15 lags). In Table 1, we present the statistics of all banks under study.

Table 1

Descriptive statistics

Statistics	Mean	Std	Skewness	Kurtosis	pLB	pJB
min	−0.08	1.83	−1.26	6.63	0.00	0.00
q1	−0.03	2.27	−0.19	10.33	0.00	0.00
med	−0.01	2.64	−0.07	10.67	0.00	0.00
q2	0.00	2.84	0.17	13.12	0.00	0.00
max	0.02	4.34	0.55	44.34	0.10	0.00

Source: own elaboration

The statistics are similar to those of the returns index. We observed a departure from normality for all banks and insignificant autocorrelation in only two cases.

Using the methodology presented in the previous sections, we estimated the models that were used to calculate the risk represented by MES and ΔCoVaR (during this estimation, we use the Midas Matlab Toolbox by Hang Qian). We used periods of 22 days to compute the monthly realized volatility and 36 lags in Equation (3). The conditional Value-at-Risk of the market return (threshold or conditioning event) is computed with a 95% confidence level. In Figure 1, we present VaR for the bank BAMI (top) and index (bottom) along with the returns.
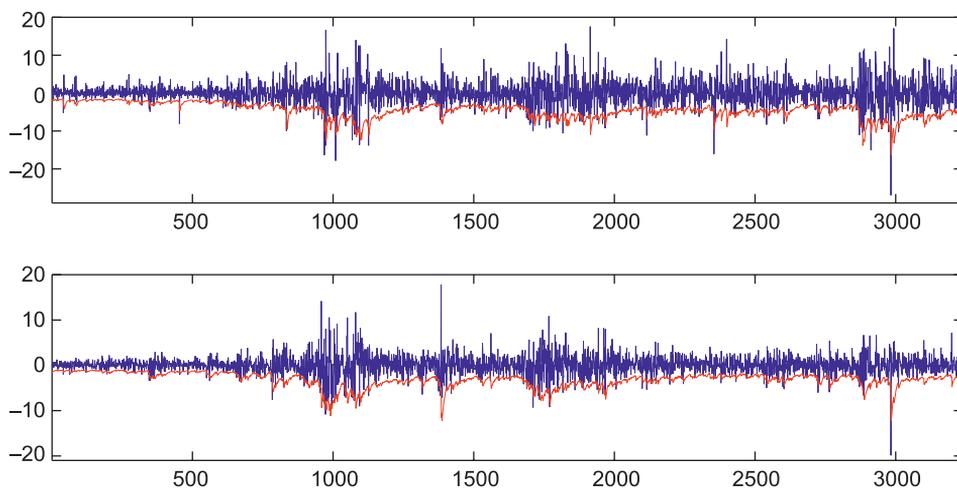

Figure 1. Value at Risk for BAMI and index

Source: own elaboration

In the Table 2, we present a ranking of banks according to the systemic risk measures from the Midas-type models (to save space, we omitted the tables with parameter estimates; details are available from the authors upon request).

The ranks (in descending order) refer to the last values of these measures in our sample (columns on the left) and mean values for year 2017 (two columns on the right). We consider the absolute values of MES and ΔCoVaR (these measures are typically negative). The higher values of these measures, the higher the individual contribution of the bank to the risk of the financial system.

Table 2

Ranking of banks according to systemic risk measures from Midas-type models

Rank	MES	ΔCoVaR	MES	ΔCoVaR
1	BAMI	ING	BAMI	SAN
2	UCG	BNP	UCG	BNP
3	KN	DBK	DBK	ING
4	SAN	BBVA	GLE	GLE
5	DBK	GLE	CBK	BBVA
6	GLE	SAN	BIRG	DBK
7	ACA	ACA	MB	ISP
8	CBK	UCG	ISP	CBK
9	BNP	MB	ACA	MB
10	MB	BKT	BNP	ACA
11	BBVA	CBK	SAN	UCG
12	EBS	ISP	KN	BKT
13	SAB	KN	SAB	KBC
14	ING	KBC	BBVA	SAB
15	ISP	BAMI	ING	KN
16	BIRG	SAB	EBS	BAMI
17	KBC	EBS	KBC	EBS
18	BKT	BIRG	BKT	BIRG

Source: own elaboration

The rankings resulting from both measures are different. In the top-five-riskiest banks, we can find only Deutsche Bank in both cases. BAMI is at the top of the table according to MES and is in 15th place in the ΔCoVaR ranking. A similar conclusion can be made for ING. Regarding first five places, only DBK can be found in both

columns. In the case of banks from the bottom of Table 2, we observe that BIRG and KBC are together in the last five places. When regarding the mean values, we observe some degree of similarity especially for the bank from the bottom of the table and from the top for the MES column. In Figures 2 and 3, we present the computed values of both measures for bank BAMI.
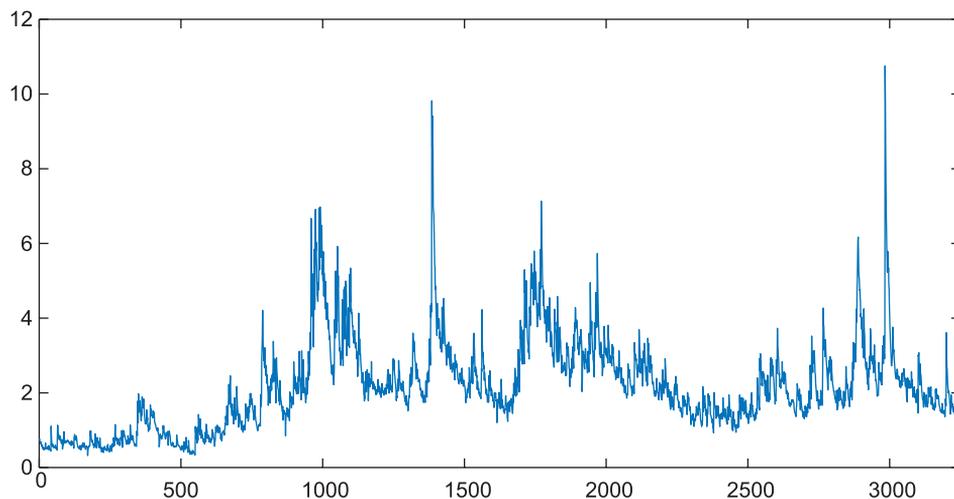

Figure 2. ΔCoVaR for BAMI from Midas-type models
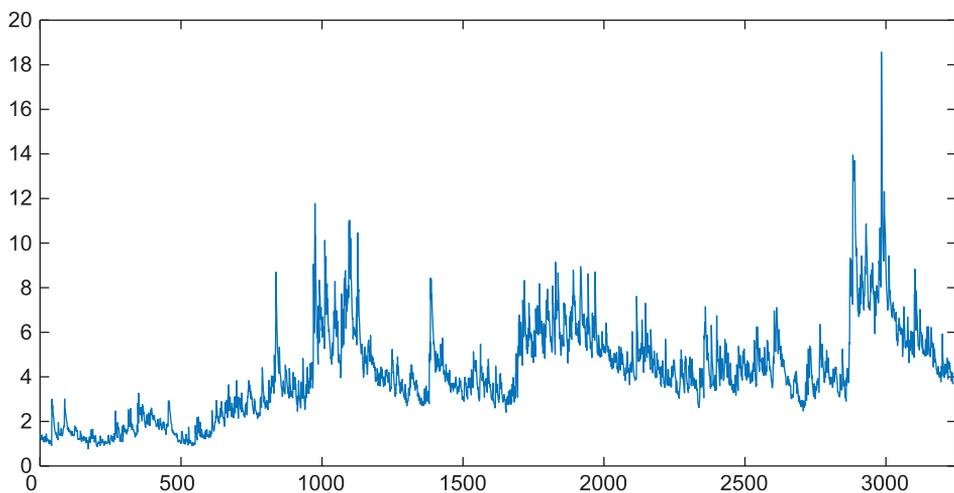
Source: own elaboration

Figure 3. MES for BAMI from Midas-type models

Source: own elaboration

Additionally, we estimated the models used in Benoit et al. (2013), which are the GJR(1,1) models for conditional volatilities and standard DCC(1,1) with the bivariate normal distribution model for conditional correlation. In the Table 3, we present the rankings from these models (according to last values in the time series of systemic risk).

Table 3

Ranking of banks according to systemic risk measures from GJR-DCC models

Rank	MES	ΔCoVaR	MES	ΔCoVaR
1	BAMI	BBVA	BAMI	SAN
2	KN	BNP	UCG	BNP
3	DBK	DBK	DBK	GLE
4	UCG	SAN	GLE	BBVA
5	GLE	UCG	BIRG	ING
6	BNP	GLE	CBK	UCG
7	ACA	ING	BNP	DBK
8	SAN	CBK	ACA	ISP
9	CBK	ISP	KN	CBK
10	BBVA	BKT	ISP	ACA
11	ISP	ACA	MB	MB
12	ING	MB	SAN	KBC
13	EBS	KN	ING	SAB
14	BIRG	BAMI	BBVA	BKT
15	KBC	KBC	SAB	KN
16	MB	SAB	KBC	BAMI
17	BKT	EBS	EBS	EBS
18	SAB	BIRG	BKT	BIRG

Source: own elaboration

The conclusions about the congruence of ranks is similar when standard models are applied. The bank from the top according to ΔCoVaR (BBVA) is tenth according to MES, but DBK and KBC take the same places in both columns (regarding the values from the end of the sample). For the mean values of measures, we can identify a coincidence of ranks (BAMI and DBK for MES and BNP for ΔCoVaR) and banks (KN) that are placed in different rows.

From Tables 2 and 3, we can identify the most- and least-systemically-important banks. These banks can be found in the first few and last few rows of both tables, respectively. Banks BAMI, SAN, UCG, and BNP are simultaneously at the top of the table, and BKT, BIRG, and EBS are at the bottom. The results from both models are the same if we consider the highest values of the measures. In Tables 4 and 5, we present the highest and lowest mean values (respectively) of the systemic risk measures for the last ten years.

Table 4

Banks with highest mean values of MES and ΔCoVaR during years of 2007–2017

Model	MIDAS		GJR-DCC	
year	MES	ΔCoVaR	MES	ΔCoVaR
2007	BNP	DBK	KN	BNP
2008	ING	DBK	ING	SAN
2009	BIRG	SAN	BIRG	SAN
2010	BIRG	SAN	BIRG	SAN
2011	ISP	BBVA	ISP	SAN
2012	UCG	BBVA	UCG	SAN
2013	BAMI	BBVA	BAMI	SAN
2014	BAMI	BBVA	BAMI	SAN
2015	BAMI	BBVA	UCG	BBVA
2016	BAMI	BNP	BAMI	SAN
2017	BAMI	SAN	BAMI	SAN

Source: own elaboration

Table 5

Banks with lowest mean values of MES and ΔCoVaR during years of 2007–2017

Model	MIDAS		GJR-DCC	
year	MES	ΔCoVaR	MES	ΔCoVaR
2007	SAB	KN	SAB	BIRG
2008	MB	BIRG	MB	BIRG
2009	SAB	BIRG	SAB	BIRG
2010	SAB	BIRG	SAB	BIRG
2011	SAB	BIRG	SAB	BIRG

Table 5 cont.

Model	MIDAS		GJR-DCC	
year	MES	ΔCoVaR	MES	ΔCoVaR
2012	SAB	BIRG	SAB	BIRG
2013	BIRG	BIRG	KN	BIRG
2014	DBK	BIRG	DBK	BIRG
2015	KBC	BIRG	KBC	BIRG
2016	BKT	BIRG	BKT	BIRG
2017	BKT	BIRG	BKT	BIRG

Source: own elaboration

We observe that, according to MES (with one exception – year 2015), BAMI refers to the highest values over the last five years. The information from ΔCoVaR is not as clear. Actually, two banks represent the highest values; those are BBVA and SAN from 2009 (with one exception). Regarding the lowest values of risk measures, we observe a coincidence of bank rankings between two models over the last ten years (with only two exceptions). For the last two years, BKT and BIRG are simultaneously at the bottom of the table. From Proposition 1 in Benoit et. Al (2013), we know that identifying SIFIs using MES is equivalent to comparing the betas of banks. In Figure 4, we present the estimated values of the betas for banks BKT and BAMI.
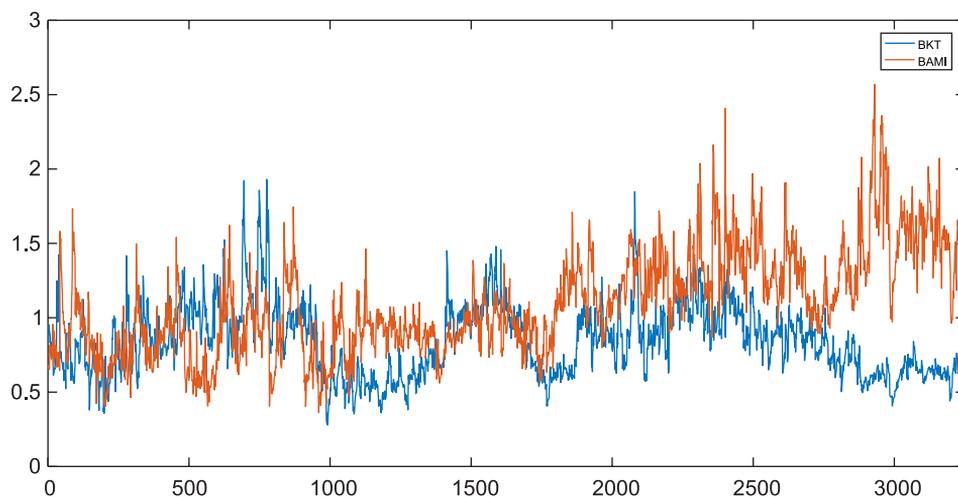

Figure 4. Betas for banks BKT and BAMI from Midas-type models

Source: own elaboration

5. Conclusions

The aim of this contribution is to apply MIDAS models in the assessment of risk measures in the banking sector. The modeling of systemic risk is an important issue in the financial literature. The successful use of MIDAS models in risk determination is value added of this contribution. The authors modeled the secular component by using monthly realized volatility calculated as a sum of squares of the daily returns. The promising option in modeling the long-run component of the risk and correlation is the application of macro-finance factors. Unfortunately, the necessary macroeconomic data with respect to volatility and correlation modeling was not available to the authors. Further research should be directed at finding the most-appropriate macro-finance factors with respect to volatility and correlation modeling that can influence systemic risk assessment.

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Appendix

Bank	Symbol
BANCO SANTANDER	SAN
BNP PARIBAS	BNP
ING GROEP	ING
BBV.ARGENTARIA	BBVA
INTESA SANPAOLO	ISP
CREDIT AGRICOLE	ACA
SOCIETE GENERALE	GLE
UNICREDIT	UCG
DEUTSCHE BANK (XET)	DBK
KBC GROUP	KBC
NATIXIS	KN
ERSTE GROUP BANK	EBS
BANCO DE SABADELL	SAB
COMMERZBANK (XET)	CBK
BANK OF IRELAND	BIRG
BANKINTER ,'R''	BKT
MEDIOBANCA BC.FIN	MB
BANCO BPM	BAMI