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How macroeconomic conditions affect systemic risk in the short and long-run?*

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Abstract

This study quantifies the effects of macroeconomic variables on various market-based systemic-risk measures in 24 European banks over the 2008-2019 period. In a first step, I measure daily systemic risk for banks based on ΔCoVaR, MES, and SRISK frameworks, and examine the contributions of individual banks to aggregate systemic risk during specific stress events. Systemic risk in European banks has risen in the wake of the global financial crisis and the Brexit referendum result. In a second step, I investigate how macroeconomic conditions affect systemic risk in the short and long-run. I find that three systemic risk measures have a long-run stable relationship with EU industrial production, EU inflation, Euribor, and US equity market volatility, but some variables have opposite effects in the short and long-run.

Keywords: *Systemic Risk, Value at Risk, Quantile Regression, DCC-GJRGARCH, ARDL, Banking Sector*

JEL classification: *C*22, *G*01, *G*18, *G*21, *G*32

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1 Introduction

After the 2007 global financial crisis, banks were extremely vulnerable to systemic risk, which became the most important concern for the European banking system. The importance of systemic risk in the banking sector and bank fragility is an important issue for policy makers and regulators.

From a bank's perspective, systemic risk adresses the possibility that a bank in financial distress will lead other banks into distress, potentially generating a crisis in the financial system. Systemic risk can occur instantly and suddenly, causing high uncertainty in the financial system and a significant negative impact on the real economy. Systemic risk can hurt the real economy because it leads to a contraction in bank credits and an unexpected decline in asset values.

The regulatory debate has focused on reforms that would provide financial stability, including through the use of macro-prudential policies to mitigate the systemic risk. Macro-prudential regulation tries to ensure the right balance between financial stability and economic growth. In this sense, understanding the systemic risk in the banking sector in terms of supervision, regulation, and market discipline, as well as for practitioners and academics, is essential.

The objective of this paper is to understand how macroeconomic conditions affect overall systemic risk. The first step is to apply a theoretical and empirical framework to the systemic risk. I employ a variety of market-based systemic-risk measures that are used by central banks for 24 European banks for the period between 2008 and 2019. I can therefore conclude which banks are more sensitive to a systemic event, or see which bank spreads distress to the overall financial system.

I compute three main measures of systemic risk. First, I calculate the conditional value at risk ($\Delta CoVaR$), which captures the risk-spillover effects from a particular bank that is under financial stress to the overall financial system, as suggested by Adrian and Brunnermeier (2016). Second, I adopt the marginal expected shortfall (MES) systemic-risk measure that was first advanced by Acharya et al. (2016) and was expanded to a conditional release by Brownlees and Engle (2016). MES represents the short-run expected equity loss invested in a particular bank conditional on the overall market if a future crisis happens. In other words, it measures the marginal contribution of an institution or a bank to systemic risk overall system. Lastly, following Acharya et al. (2012) and Brownlees and Engle (2016), I employ the systemic-risk measure ($SRISK$) that calculates how much capital is required if another crisis happens. My findings indicate various measures of systemic-risk can disagree substantially about the systemic risk importance of individual banks. For instance, $\Delta CoVaR$ move in tandem with MES, but $SRISK$ moves more independently and inconsistently. The results show each European bank's level of distress is affected by two important stress events: The global financial crisis in 2008 and the Brexit vote result in 2016. All three systemic-risk measures reacted to the Greece agreement to the first bailout package in May 2010, the Black Monday stock market crash on August 2011, the Chinese market crash in August 2015, and the Italian banking crisis in January 2016. The systemic-risk threat to European banks seems to have been more controlled during the sovereign-debt crisis (2010-2012).

In the second step, I examine the effects of macro-economic variables, such as European Union (EU) industrial production (as a proxy for economic growth), EU inflation, Euribor (as a proxy for monetary policy transmission in the euro-area), [1] and the Equity Market Volatility tracker (EMV) (as a proxy for monthly US stock market volatility that surges with the macroeconomic news outlook) on systemic risk in European banks.[2]

A panel autoregressive distributed lag (PARDL) model with three estimators: pooled mean group (PMG), mean group (MG) and dynamic fixed effects (DFE) are computed to distinguish the short and long-run effects between systemic risk and macroeconomic variables. This study aims to contibute to the literature by developing how macroeconomic conditions affect systemic risk in European banks in short- and long-run effects. The efficient results confirmed by the DFE estimator on a number of criteria demonstrate the error correction coefficient (EC) or the speed adjustment to the long run is very fast: 50% per period on average for MES and 48% per period on average for $\Delta CoVaR$, but slow 17% per period on average for $SRISK$. The results from the DFE estimator indicate macroeconomic variables have considerable significant effects on systemic risk in European banks in the short and long-run. For example, an increase in EU industrial production leads to a decrease in the systemic risk in European banks in the long-run. Nevertheless, systemic risk in European banks can be shaped by the European Central Bank's (ECB) monetary policy decisions via transmission of euribor. For instance, an increase in euribor triggers systemic risk

[1] ECB monthly bulletin October (2013) article notes Euribor plays a major role in the monetary policy transmission mechanism in the euro area.

[2] Baker et al. (2016) create a newspaper-based Equity Market Volatility (EMV) tracker that moves with the VIX and with the realized volatility of returns on the S&P 500. **?** obtains monthly counts of articles that contain at least one term in each of E (Equity), M (Market), and V (Volatility) for 11 major U.S. newspapers. Baker et al. (2019) shows that macroeconomic factors are the major driver of US stock market fluctuations. Nevertheless, EMV trackers perform much better than VIX in predicting volatilities of US stock markets at different time horizons (Zhu et al. (2019)).

more in European banks in the long-run while decreasing it in the short-run.

In summary, short- and long-run macroeconomic drivers have different effects on systemic risk. For instance, US equity volatility and Euribor have opposite effects in the short and long-run in European banks.

The remainder of the chapter is organized as follows. Section 2 presents the literature review. Section 3 provides the theoretical background about the various market-based systemic-risk measures and describes the data and methodology. Section 4 presents the systemic-risk indicators' results for individual banks by highlighting the financial market events. Section 5 contains the empirical evidence of the short- and long-run relationship between macroeconomic variables and systemic-risk measures by using PARDL for 24 European banks with three estimators: PMG, MG, and DFE. Finally, section 6 concludes.

2 Literature Review

This paper is related to three strands of the literature. The first strand tries to measure systemic risk. To measure it, I adopt methods that have been applied in a banking sector (e.g., Acharya et al. (2012), Acharya et al. (2016), Brownlees and Engle (2016), and Adrian and Brunnermeier (2016)). The first well-known method, $\Delta CoVaR$, has been used in several studies for the measurement of systemic risk. I follow Adrian and Brunnermeier (2016) who suggest $\Delta CoVaR$ as a measure of systemic risk, defined as the change in the value-at-risk of the financial system, contingent on a bank being under distress relative to its median state. Following Adrian and Brunnermeier (2016), $\Delta CoVaR$ is a directional measure and can measure the increase in systemic risk given that a bank is in financial distress. Borri et al. (2014) also consider $\Delta CoVaR$ a useful tool for regulators by enabling estimation of which factors are most relevant in terms of their contribution to systemic risk. The second measure of systemic risk, MES, measures a bank's contribution to systemic risk, as applied by Acharya et al. (2016). Banks with higher MES contribute the most to the market decline; hence, they are more likely to be systemically risky (Danielsson et al. (2016)). The last measure, $SRISK$, is proposed by Acharya et al. (2012) and Brownlees and Engle (2016) and measures the capital shortfall a firm or a bank would experience in the event of a crisis. They develop the model of MES considering both the liabilities and size of the bank. The effect of bank under-capitalization results in negative externalities to the entire economy and an experienced capital shortfall. In other words, $SRISK$ measures capital shortage that can be expected for a given bank in the event of another financial crisis. The model consists of a dynamic process for the volatility of each firm's or bank's return and its dynamic correlation with an overall equity index.

Some papers study systemic risk only in European banks (e.g, Acharya et al. (2012), and Borri et al. (2014)), Black et al. (2016), whereas others focus on systemic risk at the corporate level. (e.g, Adrian and Brunnermeier (2016), Acharya et al. (2016), Billio et al. (2012)). One related paper to mine is by Black et al. (2016), who measure systemic risk in European banks. They apply the distress insurance premium (DIP) methodology and find the systemic importance of Italian and Spanish banks increased during the European sovereign debt crisis. Although I use a different systemic-risk-measure methodology than them, one of my findings aligns with this result.
The literature usually includes the global financial crisis and the European sovereign debt crisis when analysing systemic risk. My sample covers not only these financial crises, but also other important stress events, such as the Brexit referendum.

The second strand of literature relevant to this paper is the relationship between the macroeconomy and systemic risk. A growing literature seeks to understand the relationship between systemic risk and the macroeconomy, e.g, Gang and Qian (2015), Giglio et al. (2016), Deev and Hodula (2016), Laséen et al. (2017), de Mendonça and Silva (2018), Faia and Karau (2019), and Kabundi and De Simone (2020). Some papers focus on how systemic risk affects the real economy, e.g, Giglio et al. (2016) and Kabundi and De Simone (2020)), whereas others consider how macroeconomy affects systemic risk. (e.g, de Mendonça and Silva (2018), Gang and Qian (2015), Deev and Hodula (2016), and Faia and Karau (2019)). My paper fits into the second strand, focusing on how the macroeconomy affects systemic risk in European banks in the short and long run. For this purpose, this study contributes to the literature by estimating the effects of macroeconomic conditions on systemic risk in the short and long run.

One closely related paper to mine is by de Mendonça and Silva (2018), who investigate the most relevant determinants of the systemic risk in the Brazilian banking sector based on the $\Delta CoVaR$ framework, by using panel data analysis between 2011 and 2015. They conclude systemic risk is mainly driven by bank liquidity, leverage, profitability, and interest rates. The most important finding of their analysis is that a strong coordination between regulation and monetary policy enables a reduction in systemic risk. This finding is in line with my paper is that an increase in the monetary policy interest rate can heighten systemic risk in the long run. The other closest paper to mine is by Deev and Hodula (2016), who examine the impact of the ECB's monetary policy decisions on systemic risk in the banking sector. They employ a time-varying parameter structural vector autoregressive model by using the market-based $SRISK$ indicator. Their results show the low-interest-rate environment causes banks to take more risks and increases systemic risk. This result is in line with my analysis of the short-run effects of macroeconomic variables on systemic risk. Furthermore, based on the risk-taking channel of monetary policy through systemic-bank-risk measures ($\Delta CoVaR$ and $LRMES$), Faia and Karau (2019) use Panel VARs for banks to examine the banks' risk-taking channel in judging monetary policy. They find that a decrease in short-term interest rates results in a high systemic risk due to the consequences of large banks' leverage ratios. Therefore, banks tend to take more risks in response to a short-term interest rate cut.

The third strand of literature seeks to explain the relationship between the macroeconomy and financial markets, by distinguishing between the short and long run. For this purpose, I follow Pesaran et al. (1999)'s methodology to analyze short and long-run relationship between the three market-based systemic-risk measures in European banks and some important macroeconomic variables in the euro area. Some papers in the literature look at the short- and long-run relationship by using the autoregressive distributed lag (ARDL) approach. (e.g., Bhattacharjee and Das (2021), Pokhrel and Khadka, Alam and Murad (2020), Asteriou et al. (2021), and Lee and Wang (2015))

3 Data, Model, and Methodology

I calculate systemic-risk measures between 2008 and 2019 for 24 European banks. I obtain the daily stock prices for each bank from Thomson Reuters and take the logs of all indexes to calculate the daily equity returns for each bank and the larger market index to which the banks belong, in this case, the STOXX Euro 600 Banks Index. Additionally, I collect the quarterly data on the book value of total liabilities and market capitalization for each bank from Bloomberg to construct the $SRISK$ indicator.[3]

3.1 Conditional Value at Risk ($CoVaR$)

I use $\Delta CoVaR$ as a methodology for measuring systemic risk introduced by Adrian and Brunnermeier (2016). They outline a method to construct a countercyclical, forward-looking systemic-risk

[3] Some systemic-risk-measures codes are used from: https://github.com/TommasoBelluzzo/SystemicRisk.

measure by predicting future systemic risk using current institutional characteristics such as size, leverage,and maturity mismatch. According to them, $\Delta CoVaR$ captures the marginal contribution of a particular institution (in a non-causal sense) to the overall systemic risk. Whereas $\Delta CoVaR$ focuses on the contribution of each institution to overall system risk, traditional risk measures focus on the risk of individual institutions.

I employ the $\Delta CoVaR$ to compute the transmission of contagion risk from the one bank to others. $VaR(\alpha)$ is the worst (maximum) loss in a given time horizon within the $\%\alpha$ confidence interval (see Wipplinger (2007)). Statistically, $VaR(\alpha)$ defines for a confidence level $1-\alpha$ corresponds to the quantile α of the projected distribution of gains and losses over a given time horizon:

$$Pr(r_i) \leq VaR_{\alpha}^{i} = \alpha \tag{1}$$

where r_i is the daily return of each bank i, and the probability of this return is less than or equal to the VaR of institution i equal to α.

$CoVaR_{\alpha}^{m|i}$ is the VaR_{α}^{m} of the financial system m conditional on some event $C(r_i)$ of bank i. Event $C(r_i)$ materializes when the return of this institution r_i is equal to the VaR for the quantile α. $CoVaR_{\alpha}^{m|i}$ is defined by the quantile α of the conditional probability distribution of the returns of the market index or system, which is represented by r_{mt}:

$$Pr(r_m) \leq CoVaR_{\alpha}^{m|C(r_i)}|C(r_i) = \alpha \tag{2}$$

$\Delta CoVaR$ presents the marginal contribution of a financial institution (bank) to the risk of the entire financial system when this institution is in distress. Based on Adrian and Brunnermeier (2016), $\Delta CoVaR$ is the difference between the $CoVaR$ of the entire financial system m (m=system) when a bank i is in distress (e.g, 1 % of VaR) and the $CoVaR$ conditional on the median state of the entire financial system (when the institution is earning returns in its median state - 50 %): bank i's contribution to the entire system (m=system) can be presented by

$$\Delta CoVaR_{\alpha}^{m|i} = CoVaR_{\alpha}^{m|r_i=VaR_i(\alpha)} - CoVar_{\alpha}^{m|r_i=Median^i} \tag{3}$$

3.2 Time-Varying $\Delta CoVaR$

Following Bernal et al. (2013) and Adrian and Brunnermeier (2016), I estimate $CoVaR$ through quantile regressions (see Koenker (2005)). According to the methodology, the system comprises the whole economy and is represented by a broad index which represents the system, or the benchmark of the bank stock index. In my study, it is the STOXX Euro 600 Banks Index (r_{mt}), which measures average stock performance tracking changes in the prices of the 600 most actively traded and best representative stocks of the European banking sector, and the individual bank stock return is represented by a banking index.

$\Delta CoVaR$ identifies the tail dependence between the daily returns distributions of both indexes between April 2008 and June 2019. To estimate $CoVaR$ and $\Delta CoVaR$, the first step is to compute the demeaned[4] market index log returns (r_{mt}) with time t in the quantile α conditional on demeaned bank log returns (r_{it}) with time t and the variables representative of the state of the economy (M).

I estimate the $CoVaR$ with time variation. Thus, to capture time variation in the joint distribution of bank stock return r_{it} and aggregate bank stock return r_{mt}, I estimate the conditional distribution as a function of state variables. M_{t-1} is a a vector of lagged state variables, where the returns on each equity depend on the set of lagged variables and the system's equity return. Following Adrian and Brunnermeier (2016), state variables must catch the time variation in the conditional moments of stock returns and they must be liquid. These state variables are as follows: European banks CDS spreads, which are a good proxy for bank riskiness and default probability; VSTOXX, which is a benchmark for market volatility in European markets; the euro 5-year/5-year forward swap rate as a proxy for eurozone medium-term inflation expectations; the Volatility Index (VIX) as a proxy for market risk; bond yield spreads or credit spreads (the 10-year bond rate minus the 2-year bond rate) as a proxy for the risk premium; and the Libor-OIS spread as a proxy for market credit conditions.

I run two quantile regressions in the daily data for each bank i and for the aggregate system m:
For bank i,

$$r_{it} = \lambda^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{4}$$

[4] I calculate demeaned returns by subtracting the sample mean from each value of the daily returns.

For the aggregate system m,

$$r_{mt} = \lambda^{m|i} + \beta^{m|i} r_{it} + \gamma^{m|i} M_{t-1} + \varepsilon_t^{m|i} \tag{5}$$

After generating the coefficients from these quantile regressions, I can reach $CoVaR_t^i(\alpha)$, which is the value at risk, VaR, of the system conditional on the difficulties in banking sector.[5]

I use the predicted values from the regressions are used in order to compute time-varying VaR_t^i:

$$VaR_t^i(\alpha) = \hat{\lambda}_\alpha^i + \hat{\gamma}_\alpha^i M_{t-1} \tag{6}$$

Time varying $CoVaR_t^i$:

$$CoVaR_t^i(\alpha) = \hat{\lambda}^{m|i} + \hat{\beta}^{m|i} VaR_t^i(\alpha) + \hat{\gamma}^{m|i} M_{t-1} \tag{7}$$

$\Delta CoVaR$ is obtained by the difference between $CoVaR$ for the fifth quantile and the CoVaR for the 50th quantile (the relationship between the banking sector and the rest of the economy in a median state). Therefore,

$$\Delta CoVaR_t^i(\alpha) = CoVaR_t^i(\alpha) - CoVaR_t^i(50\%) \tag{8}$$

$$= \hat{\beta}^{m|i}(VaR_t^i(\alpha)) - VaR_t^i(50\%)) \tag{9}$$

In other words, $\Delta CoVaR$ is an estimation of how much the financial system adds to VaR of the benchmark of the bank stock index when the system moves from the median state to the 5% VaR level. $\Delta CoVaR$ usually assumes negative values, because it is a result of the difference between the $CoVaR$ of the system in distress (i.e., the distribution of the worst 5 % returns - 5^{th} quantile), and the $CoVaR$ of the system in the median state (i.e., the distribution of medium returns - 50^{th} quantile). In my study, I multiply the related systemic-risk measures $\Delta CoVaR$ and MES by -1 to get the absolute value, such that higher $\Delta CoVaR$ and MES values imply higher systemic-risk contributions.[6]

[5] In summary, $CoVaR(\alpha)$ represents the α percent value-at-risk of the aggregate bank stock return conditional on the stock return of an individual bank. $VaR(\alpha)$ represents the α percent value-at-risk of an individual bank stock return.

[6] $\Delta CoVaR$ and MES—but not $SRISK$– are multiplied by -1.

3.3 Marginal Expected Shortfall (MES)

MES is the short-run expected daily equity loss in euros conditional on the market taking a loss larger than a specified threshold (C) typical of market distress:

$MES_{i,t-1}(C) = E_{t-1}(r_{it}|r_{mt} < C)$

where r_{it} and r_{mt} are the demeaned log returns of the equity of each bank i and the market index at time t, respectively. I assume the systemic event or system crisis defined by C, which is set to the market non-parametric 5% VaR. The threshold C (distress event) implies the conditional VaR. ($C = VaR_{mt}(\alpha)$).

In the spirit of Shaw and Dunne (2017), I begin with the bivariate process of bank and market returns:

$$r_{mt} = \sigma_{mt}\epsilon_{mt} \tag{10}$$

$$r_{it} = \sigma_{it}\epsilon_{it} \tag{11}$$

$$r_{it} = \sigma_{it}\rho_{it}\epsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it} \tag{12}$$

$$(\epsilon_{mt}, \xi_{it}) \sim F \tag{13}$$

where σ_{it} and σ_{mt} are volatilities of the market and bank i at time t, and ρ_{it} represents the correlation at time t between r_{mt} and r_{it}. Eq. (2.13) shows each bank's equity returns, r_{it}, consist of both a function of the market shock ϵ_{mt} and the equity i's correlation with the market, ρ_{it}, and equity volatility, σ_{it}. Also, Eq (2.12) includes the idiosyncratic part; the equity-specific shock ξ_{it} and equity volatility σ_{it}. Following the assumption about the disturbances that they are ϵ_{mt} and ξ_{it} time independent and uncorrelated. They are jointly distributed as performed by the non-parametric distribution F, and they have tail dependence, which is represented by a conditional kernel measure. Let the expected value of the market return in the tail be $E_{t-1}(\epsilon_{mt}|\epsilon_{mt} < C/\sigma_{mt})$, and let the conditional expected equity return be obtained by $E_{t-1}(\xi_{it}|\epsilon_{mt} < C/\sigma_{mt})$. Then, MES can be rewritten:

$$MES_{it-1}(C) = E_{t-1}(r_{it}|r_{mt} < C) \tag{14}$$

$$MES_{it-1}(C) = \sigma_{it} E_{t-1}(\rho_{it}\epsilon_{mt} + \sqrt{1-\rho_{it}^2}\xi_{it}|\epsilon_{mt} < C/\sigma_{mt}) \quad (15)$$

$$MES_{it-1}(C) = \sigma_{it}\rho_{it} E_{t-1}(\epsilon_{mt}|\epsilon_{mt} < C/\sigma_{mt}) + \sigma_{it}\sqrt{1-\rho_{it}^2} E_{t-1}(\xi_{it}|\epsilon_{mt} < C/\sigma_{mt}) \quad (16)$$

Eq. (2.16) demonstrates that MES is a function of banks' equity-price volatility, with its correlation with the market return and tail expectations representing the standardized market and equity returns conditional on a market tail event. As in Scaillet (2004), I compute the conditional tail expectations:

$$\hat{E}_{t-1}(\epsilon_{mt}|\epsilon_{mt} < C/\sigma_{mt}) = \frac{\sum_{t=1}^{T} \epsilon_{mt}\Phi(\frac{c-\epsilon_{mt}}{h})}{\sum_{t=1}^{T} \Phi(\frac{c-\epsilon_{mt}}{h})} \quad (17)$$

$$\hat{E}_{t-1}(\xi_{it}|\epsilon_{mt} < C/\sigma_{mt}) = \frac{\sum_{t=1}^{T} \xi_{it}\Phi(\frac{c-\epsilon_{mt}}{h})}{\sum_{t=1}^{T} \Phi(\frac{c-\epsilon_{mt}}{h})} \quad (18)$$

where Φ represents the cumulative normal density. I employ Scott's rule of thumb (Scott (2010)) to determine a bandwidth h. The MES and dynamic $Beta$ time-varying volatility and correlation are modeled via asymmetric $GJR-GARCH$ and dynamic conditional correlation (DCC) models. (Engle (2002), Engle (2009), Engle (2001), and Engle and Sheppard (2001)).[7]

3.4 Systemic Risk ($SRISK$)

SRISK extends MES and includes the idiosyncratic bank characteristic and measures the expected capital shortage of one bank conditional on a systemic event or a market decline. According to Acharya et al. (2016), a firm is systemically risky if it faces a capital shortage, which could hurt the real economy and create financial instability.

$SRISK$ consists of market and balance-sheet data together:

$$SRISK_{it} = max[0; k[L_{it} + (1 - LRMES_{it})E_{it})] - (1 - LRMES_{it})E_{it} \quad (19)$$

$$SRISK_{it} = max[0; kL_{it} - (1-k)(1 - LRMES_{it})E_{it}] \quad (20)$$

$$SRISK(srisk < 0) = 0 \quad (21)$$

where k is the prudential capital ratio (equal to 8% according to the Basel-III rules), L_{it} is the book value of total liabilities, and E_{it} is the market value of equity or current market capitalization of the bank. The original methodology is mainly interested in estimating capital shortages that,

[7]See the appendix.

by definition, cannot take on negative values. If the capital shortage is negative, the bank has a capital surplus. Thus, I restrict $SRISK$ to O when capital surplus is available.

Long-run MES (LRMES) is based on the expectation of the cumulative 6-month bank return conditioned on the event that the market falls by more than 40% in six months. In other words, $LRMES$ is a bank equity loss if market returns decline by 40% in the next six months.

SRISK analysis can be calculated as follows:

$LRMES_t$=1-exp(log(1-d)*β),

where d is the six-month crisis threshold for the market index decline and its default value is 40%, and β is the bank's capital asset pricing modelling (CAPM) $Beta$ coefficient.[8]

The equity volatility and DCC with the market are used for the measurement of MES, $LRMES$, and $SRISK$.[9]

4 Systemic-Risk Indicators' Results for Individual European Banks

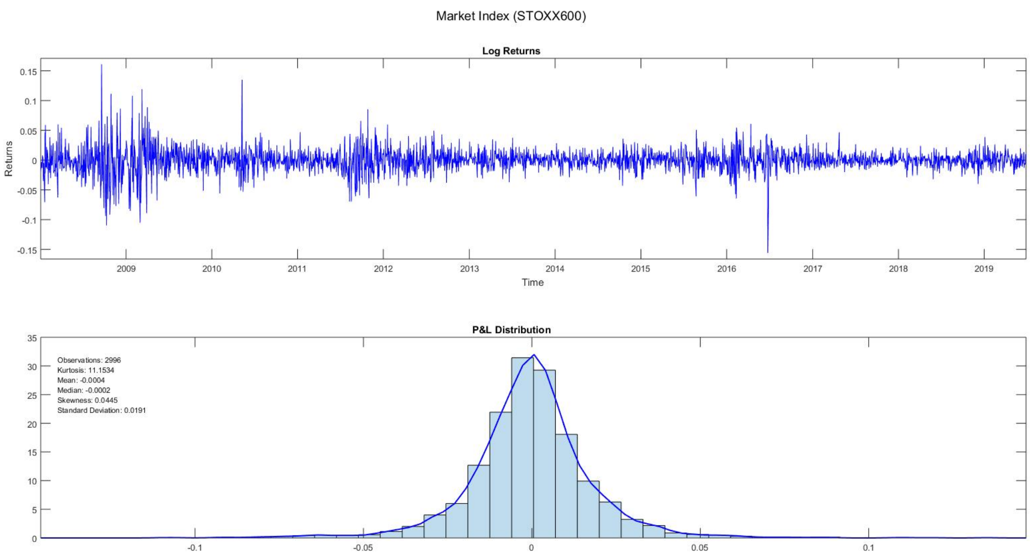
Figure 1 represents the benchmark index or the Stoxx 600 banks index, which declined sharply with the global financial crisis (2008-2009) and Brexit referendum in June 2016. The Stoxx 600 banks index had its biggest points drop during the Brexit referendum and the global financial crisis.

Figure 2 shows VaR which measures the bank's risk in isolation for each bank between 2008

[8]Source: https://vlab.stern.nyu.edu/docs/srisk/MES and see the appendix.

[9]See the appendix.

Figure 1: Market Index

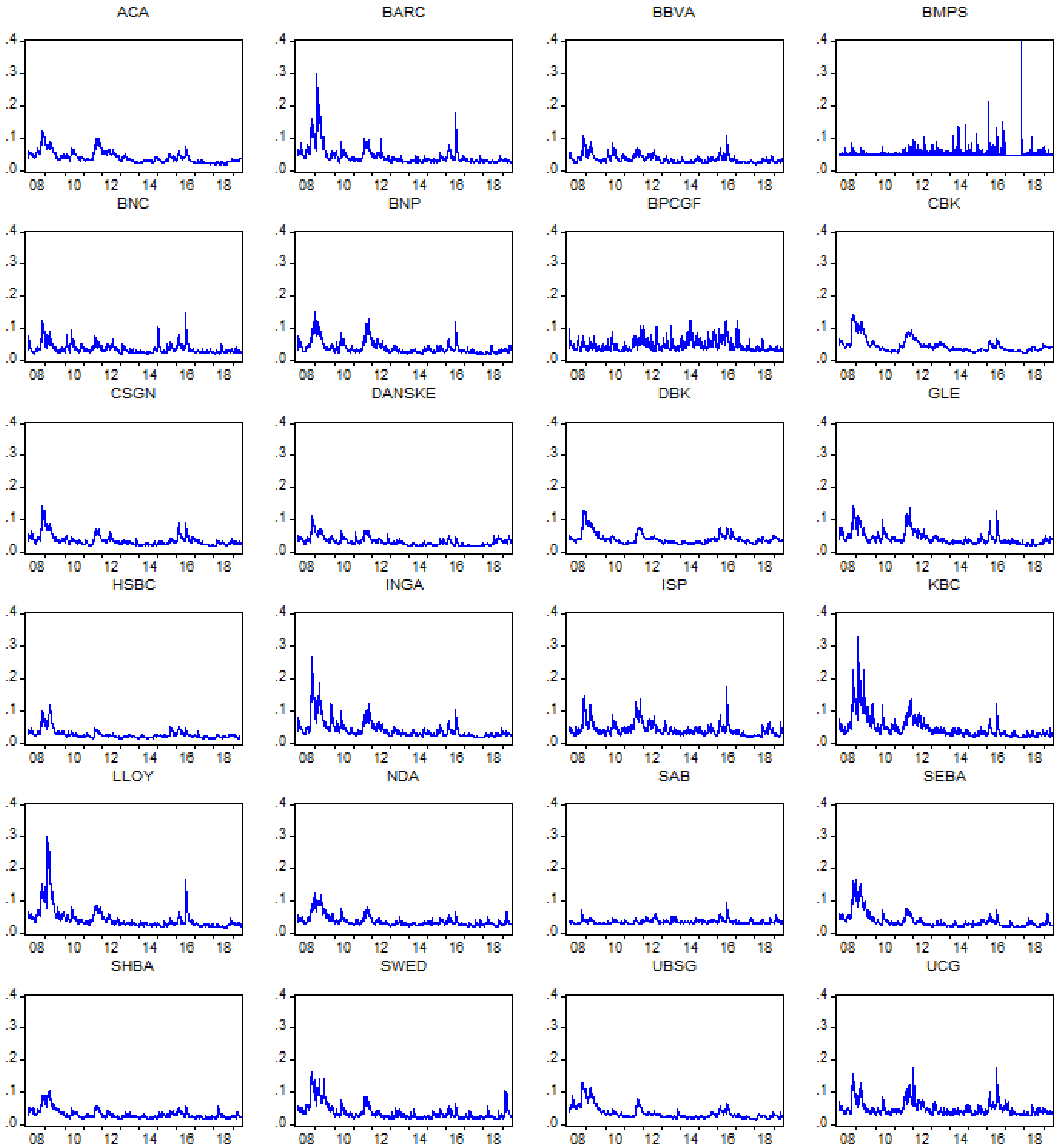


and 2019. In general, VaR values peaked for Barclays (BARC), LLyods (LLOY), and the KBC group during the global financial crisis (2008-2009) and for Barclays, Intesa SanPaolo (ISP), and Unicredit (UCG) following the Brexit referendum (2016). Banca monte dei paschi (BMPS), Italy's fourth-largest bank, which the Italian government bailed out in July 2017, has suffered from bad loans over the years. On October 25, 2017, it returned to the stock market after 10 month absence. Its VaR reached its highest (65%) on October 26, 2017. In other words, the level of financial risk within this bank was very high on this day.

Figure 3 plots the $\Delta CoVaR$ systemic-risk indicator and shows Banco Santander, Intesa Sanpaolo, and Barclays, were in financial distress, which led to increased systemic risk after the Brexit referendum in June 2016. During the global financial crisis, the ING Group's contribution to the systemic risk was the highest in 2008, and then Barclays and Llyods became the major contributors to systemic risk in 2009. These banks' distress spread quickly to the whole financial system. During the European sovereign debt crisis, Italian, Spanish, and French banks' contributions to the entire systemic risk were the highest. This result is in line with Black et al. (2016). These $\Delta CoVaR$ results are also consistent with MES, as seen in Figure 4. By contrast, Swedbank faced serious difficulties following the financial crisis in the Baltics. After the money laundering scandal, Swedbank's and Danske's financial distress escalated, leading an increase in their contributions to the entire systemic risk in the European banking sector in April 2019. The higher the bank MES, the higher the individual contribution of that bank to systemic risk. Barclays, Lloyds, and ING Group banks were the biggest contributors to the risk of the entire financial system during the global financial crisis, whereas Intesa San Paolo, Barclays, and Lloyds were the largest contributors during the Brexit referendum. In other words, these four different banks were systemically risky during these financial stress events. In Europe, at the peak of systemic risk post-Brexit (end of July 2016), banking institutions reported the highest MES values. Of the top two contributors, two were UK banks (Barclays and Llyods) and one was Spanish (Intesa San Paolo).

After the global recession in 2008, the share of non-performing loans or bad loans, increased significantly and Italy had the largest number of non-performing loans in the entire European banking sector. Non-performing loans can have negative effects on bank lending (Kang and Jassaud (2015) and Kang et al. (2015)). For example, Banca Monte dei Paschi has the highest ratio of non-performing loans in Italy. On January 21, 2016, this bank completed the securitization of a 1.6 bln

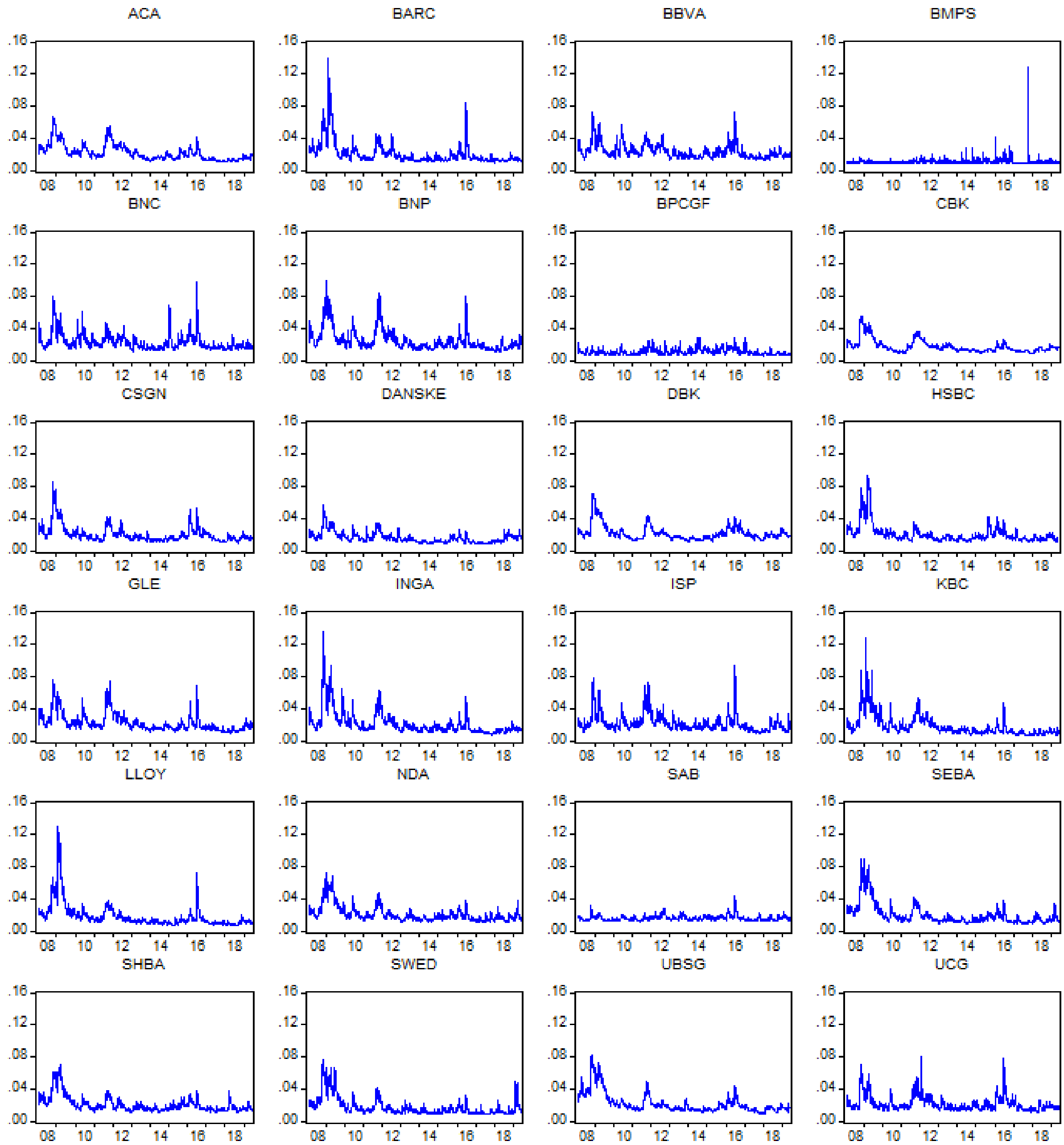
Figure 2: Value at Risk (VaR) for Each Bank



euro lease-receivables portfolio.[10] Then, on January 22, 2016, its MES reached the highest point, which means this bank's individual contribution to systemic risk increased most in February 2016, as shown in Figure 4. On 29 July 2016, the EU bank stress test was announced. As a result of this test, Banca Monte dei Paschi di Siena had the biggest failure in the Common Equity Tier 1 (CET1) ratio (in full Basel III basis) among the 51 banks. In December 2016, following the failure of Banca

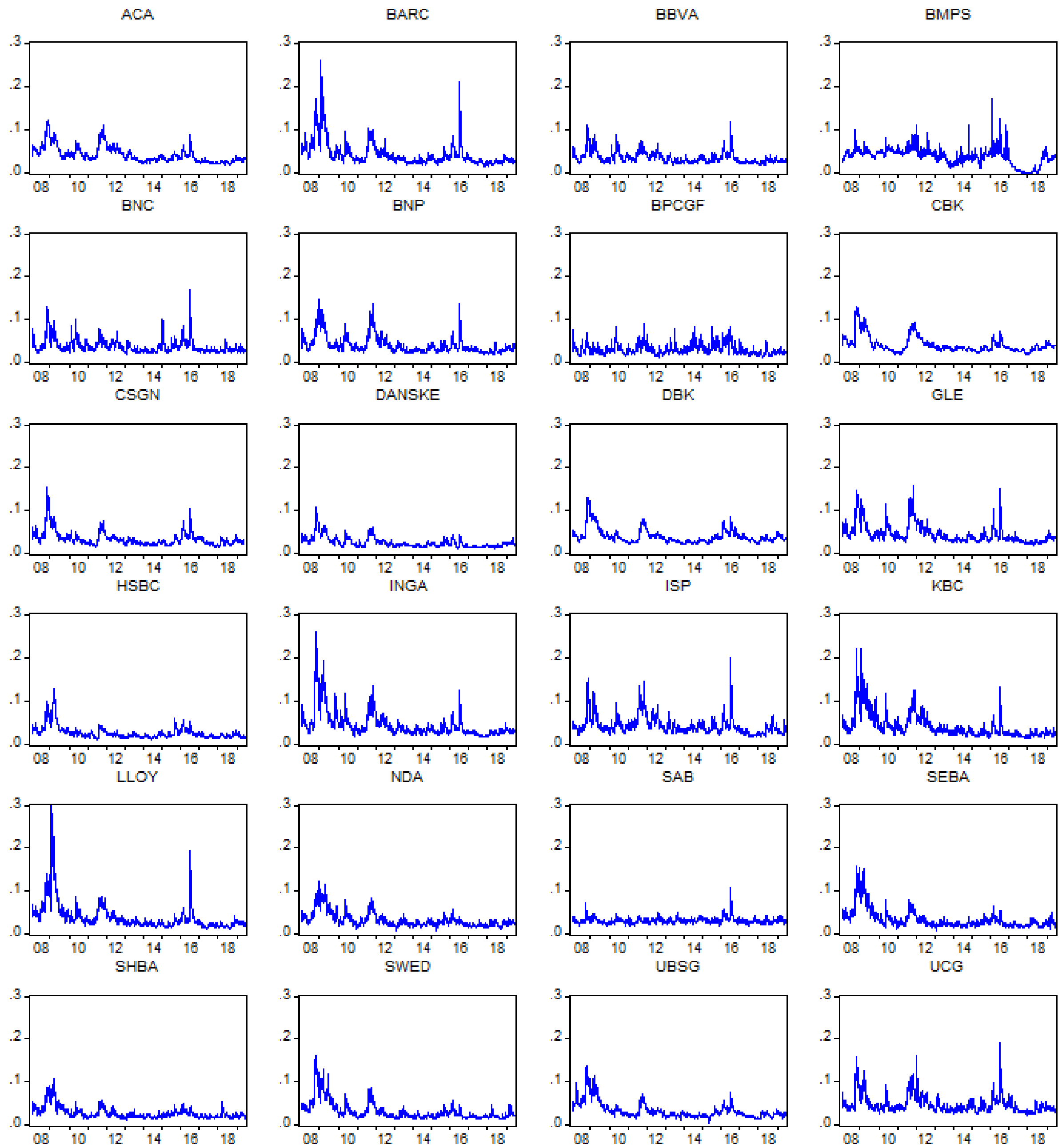
[10] https://en.wikipedia.org/wiki/Banca_Monte_dei_Paschi_di_Siena

Figure 3: Conditional Value at Risk ($\Delta CoVaR$)



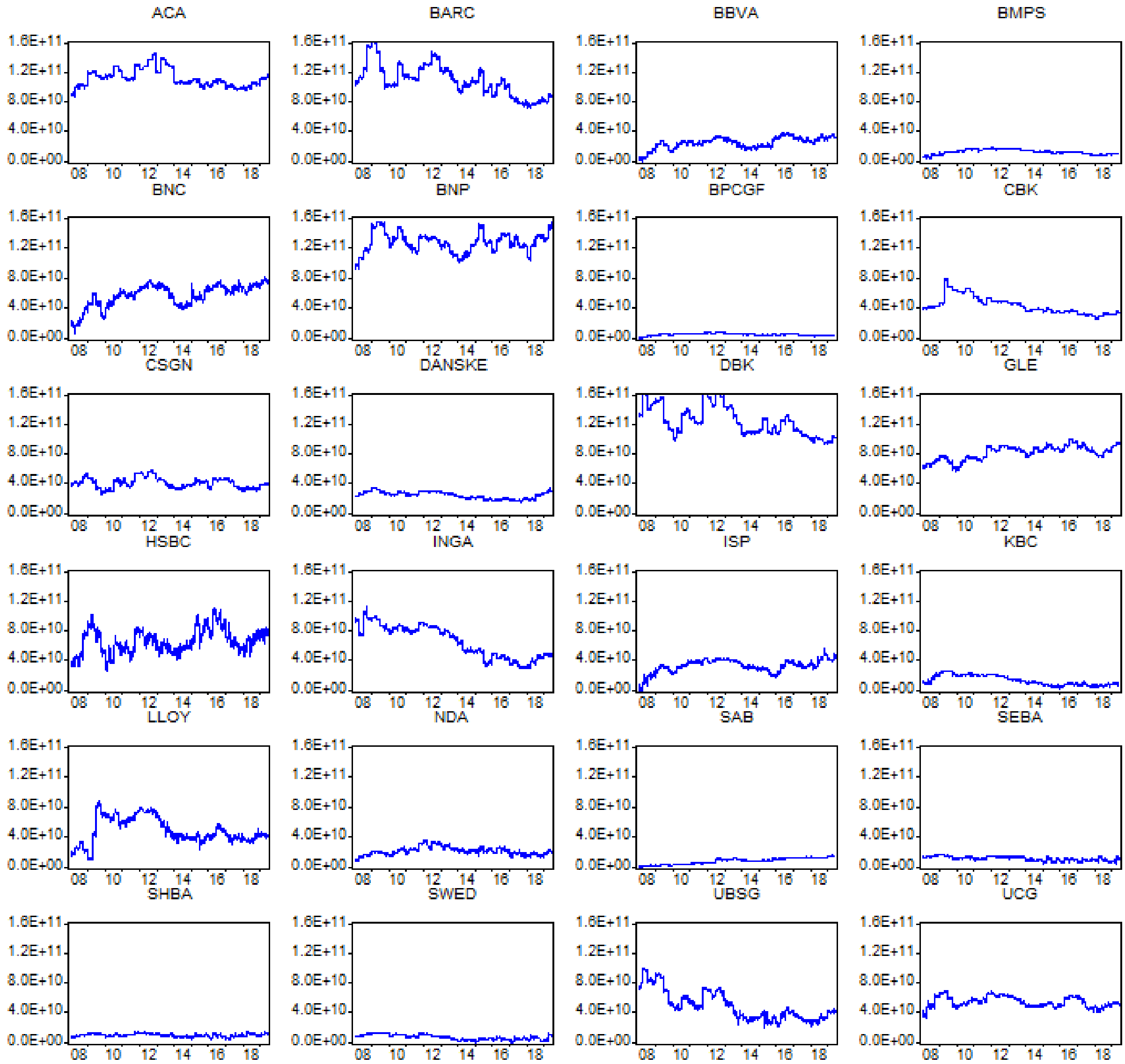
Monte Dei Paschi's attempts to boost private capital on the markets, the Italian authorities decided to apply for state aid in the form of a precautionary recapitalization. The European Commission and Italy agreed on a bailout for Banca Monte de Paschi di Siena on June 1, 2017. At the end of the 2016, Banca Monte Dei Paschi's contribution to overall systemic risk had declined remarkably after the agreement on its restructure, and plan. On December 23, 2016, it was suspended from trading. Figure 5 shows the $SRISK$ measure for each bank between 2008 and 2019. BNP Paribas,

Figure 4: Marginal Expected Shortfall (MES)



the top contributor, and Deutsche bank had the highest $SRISK$ values, which implies these banks faced a higher capital shortfall in the aftermath of the Brexit vote. This indicates the contribution to systemic risk coming from the French and German banks. Previously, BNP's contribution to the overall systemic risk had been high due to sanctions violations in May 2015. BNP Paribas (BNP) also has faced the highest capital shortfall in 2019. This higher capital shortfall creates negative externalities for the entire banking system and implies the need for banking-system reforms that

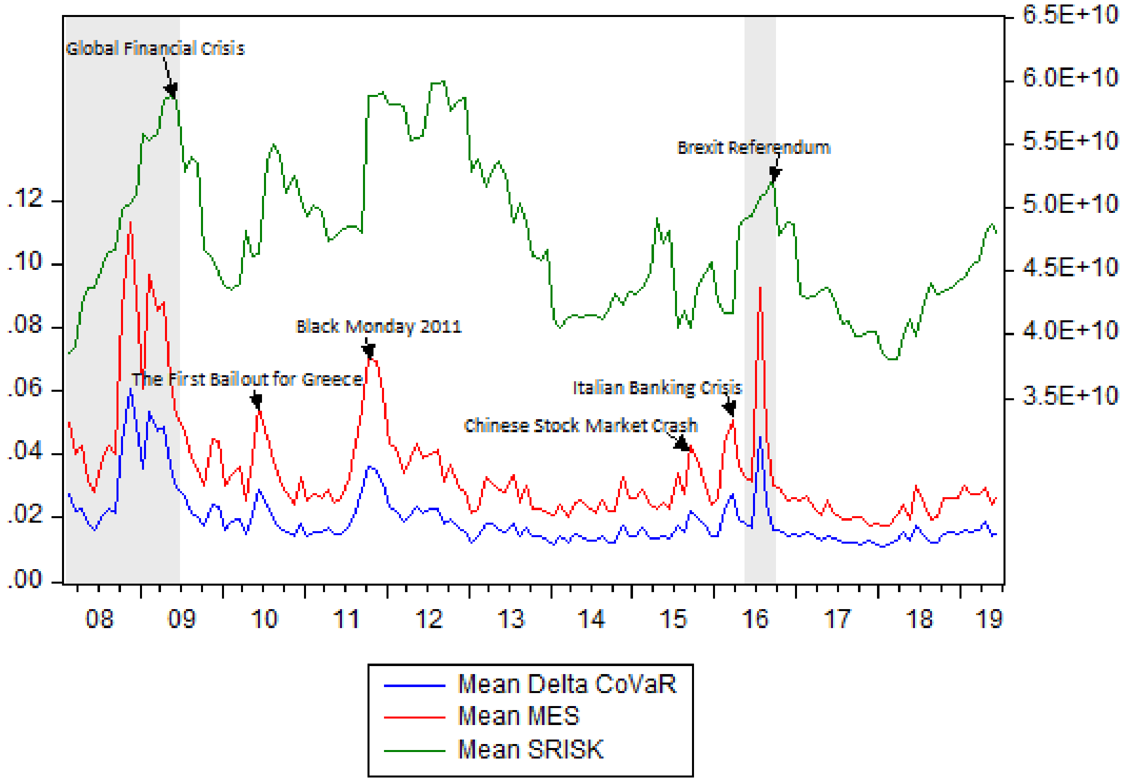
Figure 5: SRISK measure for each bank ($SRISK$)



would provide financial stability and use of macro-prudential policies. In summary, systemic risk increases temporarily in the wake of important stress events.

More importantly, these results shed light on the contributions of individual financial institutions to specific stress conditions. Various systemic-risk measures give different results about the systemic importance of individual banks. Drehmann and Tarashev (2013a) also find that other measures of systemic risk can disagree substantially about the systemic importance of individual banks. Figure 6 shows average systemic-risk measures for 24 banks. The graph depicts MES and $\Delta CoVaR$ moving in tandem over the whole period, and their time-series patterns are similar

Figure 6: Mean of $\Delta CoVaR$ - MES - $SRISK$



despite disagreements about the contribution of individual banks. These systemic-risk measures reached their peak with the bankruptcy of Lehman Brothers in September 2008 and the Brexit referendum in June 2016. All systemic-risk measures reacted to the Greece agreement of the first bailout package in May 2010, the Black Monday stock market crash in August 2011, the Chinese market crash in August 2015, and the Italian banking crisis in 2016. After a peak, $\Delta CoVaR$ and MES reduce their values in a shorter period than $SRISK$, which does not react immediately to a change in market conditions, because it must take into consideration balance-sheet variables. On average, this measure reacts the signs of the financial crisis or financial market events later than other measures. $SRISK$ reacted to the global financial crisis and the European sovereign debt crisis more than to the Brexit referendum. Table 1 shows the correlation relationships between monthly systemic-risk measures. Results indicate a strong and positive correlation between MES and $\Delta CoVaR$ and a weak relation between $SRISK$ and other two systemic-risk measures.

5 The Effect of Macroeconomic Variables on Systemic Risk in European Banks

5.1 Panel Auto-regressive Distributed Lag (PARDL) Methodology

To examine the relationships between the macroeconomic variables and systemic risk, I adopt the PARDL methodology, using a least-squares regressions that contain lags of both the dependent variable and independent variables as regressors (Greene (2003)). Hence, I can also examine the long-run and cointegrating relationships among variables (Pesaran and Smith (1998), Pesaran et al. (1999), Pesaran et al. (2001)). PARDL models are widely used to examine the relationship between economic variables and enables the analysis of both short-run dynamic and long-run relationship between systemic risk in European banks and macroeconomic variables. I convert the daily various systemic-risk-measures data for each bank to the monthly level and build a panel data set for 24 European banks from February 2008 to June 2019.

5.2 PMG, MG, and DFE estimators

I estimate the PARDL of 24 banks with three different estimators. The results of these estimators, namely, PMG, MG, and DFE are reported in Table 2. These three estimators are appropriate for large time and cross-section panels. The model in Eq. (2.22) has been treated as a heterogeneous panel, estimating an equation for each bank by ordinary least squares (OLS).[11]

In MG, which represents averages across banks, all coefficients are heterogenous. PMG has homogeneous long-run coeffiecients (θ_i=θ), and heterogeneous short-run coefficients. In other words, this estimator restricts the long-run coefficients to be same while allowing the short-run coefficients and variances (σ_i^2) to vary across banks in the long-term. In DFE, all slope coefficients are homogeneous (β_i=β, $\lambda_i = \lambda$, $\theta_i = \theta$), but α_i are not restricted. This implies the short- and long-run coefficients are identical for all cross sections, with only intercepts differing between banks (Pesaran

[11] Each bank's PARDL equation results are reported in the appendix; see Tables 2.6, 2.7, 2.8, 2.9, 2.10, and 2.11.

Table 1: Correlation between Systemic-Risk Measures

	$\Delta CoVaR$	MES	$SRISK$
$\Delta CoVaR$	1.00		
MES	0.90	1.00	
$SRISK$	0.26	0.23	1.00

et al. (1999)).

The PARDL (1,1) model can be considered an error correction model (ECM) :

$$\Delta y_{it} = \alpha_i + \boldsymbol{\beta}_i' \Delta x_{it} + \lambda_i(\theta' x_{it-1} - y_{it-1}) + \epsilon_{it}, \epsilon_{it} \sim iidN(0, \sigma_i^2) \tag{22}$$

where $x_{it} = (lnIP_t, lnHICP_t, EURIBOR_t, lnEMV_t)$, y_{it}=$(MES_{it}, \Delta CoVaR_{it}, SRISK_{it})$

where x_{it} consists of $lnIP_t$, log of European industrial production (proxy for economic growth), $lnHICP_t$, log of European Harmonized Index of Consumer Prices (proxy for EU inflation), $EURIBOR_t$, the Euro Interbank Offered Rate (proxy for monetary policy transmission in the euro area), $lnEMV_t$, US Equity Market Volatility tracker based on macroeconomic outlook news (proxy for monthly US stock market volatility that surges with macroeconomic news outlook).[12] In Eq. (2.22), y_{it}, which represents the MES or $\Delta CoVaR$ or $SRISK$ is the each bank's systemic risk. $\boldsymbol{\beta}_i$ are the short-run effects, θ_i are the long-run effects, λ_i are the adjustment coefficients $0 \leq \lambda_i' \leq 1$ and $i = (1, 2, 3, ...24)$, and i represents 24 European banks. This method assumes error terms are not serially correlated and independent variables follow independently identically distributed. The optimal lag length is chosen based on Schwartz criteria. The optimal lag length of this study is 1 for all the variables.

In summary, the MG estimator is the least restrictive model, all coefficients are heterogeneous, the PMG restricts the long-run slope coefficients to be homogenous but allows short-run coefficients to be heterogeneous, and the DFE is the most restrictive, with all slope coefficients are homogeneous and only intercepts are heterogeneous. Asymptotically, the DFE estimator should be the most efficient. Pesaran et al. (1999) suggest using a Hausman test to compare the estimators. The results of Hausman tests preferred the DFE, and the differences of variances between PMG and MG were not significant, and also variance-covariance matrix was not positive definite between PMG and MG, which can happen with the Hausman test.[13] Hence, DFE is the most efficient estimator among three estimators. The analysis of this study centers on its result.

[12] Macroeconomic variables' data sources are provided by Eurostat, https://www.euribor-rates.eu/en/ and http://www.policyuncertainty.com/EMV_monthly.html

[13] See the appendix.

5.3 Measuring the Effects of Macrovariables on Systemic Risk

Table 2 shows error correction (EC) coefficients, which measure the speed of adjustment, are significantly negative, representing the long-run relationship between systemic-risk measures and macroeconomic variables in PMG, MG, and DFE estimators. For instance, the DFE-estimator results indicate that the adjustment to the long run is fast approximately 50% per period, on average, for MES and 48% per period, on average, for $\Delta CoVaR$, but slow 17% per period, on average, for $SRISK$. All results in Table 2 confirm the long-run relationship between the variables as established earlier for MES and $\Delta CoVaR$ relative to $SRISK$. Specifically, PMG estimation leads to a much smaller speed of adjustment, relative to MG and DFE.

The results using the DFE estimator suggest all three systemic-risk measures have a negative significant relationship with EU industrial production (the proxy for economic growth) in the long-run. Thus, an increase in EU industrial production leads to a decrease in systemic risk in European banks in the long run. When the economy is growing, the leverage and risk exposure for banks can decrease. For example, the long-run finding in DFE estimation suggests a 1% increase in EU industrial production leads to a 3.55% decrease in $\Delta CoVaR$, an 8.26% decrease in MES, and a 1.63% decrease in $SRISK$.

Meanwhile, EU industrial production is insignificant on these indicators, MES and $\Delta CoVaR$ in the short run. An increase in EU industrial production leads to an increase of $SRISK$ in DFE short-run results. Unlike the other two systemic-risk measures, $SRISK$ considers the combined effect of the sensitivity of the bank returns to aggregate shocks, leverage and market capitalization of the bank, and the weakness of the entire financial system. Although EU industrial production grows, some banks' negative idiosyncratic characteristics (e.g., high leverage, low capital ratio, or bad management) might encourage the spread of systemic risk within network (Kabundi and De Simone (2020)).

All three systemic-risk measures have a positive significant relationship with Euribor in the long-run. Euribor rates represent the unsecured rate at which a large panel of European banks borrow funds from one another if liquidity demand is low. Nonetheless, the effects of Euribor are different in the short and long-run. An increase in Euribor might be a worrying sign in the long run; an increase in interest rates causes asset prices to fall, because investors can receive a higher return on a risk-free investment, which could trigger systemic risk more in the long-run. This result

Table 2: Results for Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed-Effects Estimators (DFE)

	Short-run coefficients (SR)					Long-run coefficients (LR)			
Pooled Mean Group	EC	$\Delta lnIP$	$\Delta lnHICP$	$\Delta EURIBOR$	$\Delta lnEMV$	$lnIP$	$lnHICP$	$EURIBOR$	$lnEMV$
$\Delta CoVaR$	-0.48***	-1.08	10.82***	-1.02***	-0.75***	-3.34***	1.98*	0.12**	1.96***
	(0.03)	(0.95)	(2.15)	(0.18)	(0.06)	(0.79)	(1.11)	(0.03)	(0.09)
MES	-0.51***	-2.09	13.56***	-1.66***	-1.44***	-6.72***	4.79**	0.27***	3.60***
	(0.02)	(2.16)	(3.87)	(0.36)	(0.10)	(1.42)	(2.01)	(0.07)	(0.16)
$SRISK$	-0.14***	0.96**	3.71**	-0.05**	-0.01**	-1.36**	2.03**	0.12***	0.07
	(0.01)	(0.31)	(1.48)	(0.02)	(0.00)	(0.48)	(0.67)	(0.02)	(0.05)
Mean Group									
$\Delta CoVaR$	-0.59***	-1.35**	11.28***	-1.06***	-0.77***	-3.26***	1.17	0.10**	1.79***
	(0.02)	(0.63)	(2.05)	(0.16)	(0.06)	(0.57)	(0.96)	(0.03)	(0.15)
MES	-0.57***	-1.74	14.59***	-1.64***	-1.55***	-7.63***	3.32*	0.24***	3.63***
	(0.02)	(1.30)	(3.86)	(0.30)	(0.12)	(1.20)	(1.85)	(0.06)	(0.26)
$SRISK$	-0.20***	1.09**	3.52**	-0.04*	-0.01*	-1.65***	1.46**	0.08**	0.07**
	(0.02)	(0.38)	(1.37)	(0.02)	(0.00)	(0.42)	(0.64)	(0.02)	(0.03)
Dynamic Fixed Effect									
$\Delta CoVaR$	-0.48***	-1.04	10.16***	-0.83***	-0.73***	-3.55***	2.08	0.12**	1.94***
	(0.01)	(1.58)	(2.84)	(0.10)	(0.04)	(0.92)	(1.29)	(0.04)	(0.10)
MES	-0.50***	-1.16	13.23**	-1.26***	-1.48***	-8.26 ***	4.78**	0.27**	3.86***
	(0.01)	(3.16)	(5.68)	(0.19)	(0.08)	(1.78)	(2.50)	(0.08)	(0.20)
$SRISK$	-0.17***	1.22**	3.75***	-0.04*	-0.01	-1.63**	1.56	0.10**	0.05
	(0.00)	(0.44)	(0.80)	(0.02)	(0.01)	(0.73)	(1.00)	(0.03)	(0.07)

Note: The terms in parentheses are the standard errors, and *** indicate significance level at the 1%, ** at the 5%, and * at the 10%. Δ is the first-difference operator. Because $\Delta CoVaR$ and MES coefficients are in natural logarithm variables, their results are multiplied by 100 to be converted to percentages. The estimations and Hausman test were conducted using the (xtpmg) routine in Stata. The first panel (SR) shows the short-run effects, whereas the second panel reports the long-run effects (LR) and the speed of adjustment or error correction (EC).

is in line with Deev and Hodula (2016), who find an interest rate increase causes an increase in the amount of capital financial firm needs in the event of a crisis. Euribor plays an important role in the transmission of the ECB's monetary policy. It is closely linked to the interest rates that affect many businesses and households in the euro area. An increase in inflation and ensuing rate hikes will cause problems for many assets, thus creating financial instability in the long-run. This result suggests ECB's monetary policy decisions react to financial instability concerns. ECB reduces the interest rates at which financial institutions borrow from them, expand their balance sheets by broadening the type of collateral that banks can use, increase the maturity of their loans to the banks to alleviate the liquidity crunch and the overall financial turmoil. (Giannone et al. (2012)).

DFE short-run results show Euribor have a significantly negative relationship with all three systemic-risk measures. In other words, a decrease in the Euribor leads to an increase systemic risk in European banks in the short run for all three measures. This finding implies the low-interest-rate environment might encourage bank risk-taking and financial-stability concerns in the short run. This result is in line with Deev and Hodula (2016), who find the lowering of interest rates increased the systemic risk measured by $SRISK$ with a lag of up to three months.

US EMV plays a major role in systemic risk in European banks. This variable has a positive significant effect on MES and $\Delta CoVaR$ in the DFE estimator's long-run results. This finding implies that when uncertainty or bad news about the near-term macroeconomic outlook in the US economy is unusually high, systemic risk increases in European banks in the long run. Meanwhile, US EMV is insignificant on $SRISK$ in the long and short run. On the other hand, US EMV, which is driven by macroeconomic outlook news, doesn't affect the idiosyncratic bank characteristic and the expected capital shortage for European banks in the long-run. US EMV has a significantly negative effect on MES and $\Delta CoVaR$ in the short-run. Macroeconomic news, developments, concerns, and anticipation drive this volatility. Therefore, some developments in macroeconomic news or little uncertainty about the macro outlook in the US economy can lead to a decrease in systemic risk in European banks through regime changes in the short-run. For instance, the steadiness of the ECB's monetary policy can decrease uncertainty about the near-term macroeconomic outlook. Another reason may exist for a decrease in systemic risk in the short run. When US EMV is high, in most cases, capital flows will decrease in the US (Passari and Rey (2015)) and these flows might transfer to the European banks, so systemic risk might decrease in European banks.

EU inflation has a positive significant impact on MES in the long-run. For example, the DFE estimator reveals that a 1% increase in EU inflation causes a 4.78% increase in MES in European banks. This result suggests ECB's inflation target is important to reduce the systemic risk in European banks, and the systemic-risk indicators are affected by EU inflation changes in the long term. An increase in EU inflation tends to increase the rate of loans, so the cost of funds for banks increases, which can then increase systemic risk in European banks. By contrast, EU inflation is insignificant on $\Delta CoVaR$ and $SRISK$ in DFE long-run results. In the short run, EU inflation has a positively significant relationship with all systemic-risk measures in DFE results. For instance, DFE short-run results in Table 2 indicate a 1% increase in EU inflation leads to a 10.16% increase in $\Delta CoVaR$, 13.23% increase in MES and 3.75% increase in $SRISK$.

6 Conclusion

In this paper, I quantify how macroeconomic conditions affect systemic risk in the European banking sector. Using three market-based systemic-risk measures for 24 European banks with the

2008-2019 sample, I find which banks are more sensitive to a systemic event, and which banks spread systemic banking distress to the overall system. The results indicate systemic risk had the highest increase temporarily in the wake of the global financial crisis and Brexit referendum. Each bank's contribution to the aggregate system varies with these important distress events. Three systemic-risk measures also demonstrate different results on the importance of individual banks. Specifically, MES and $\Delta CoVaR$ move in tandem, whereas $SRISK$ moves more independently and inconsistently.

In the second part, I use PARDL model is performed by applying the mean group, pooled mean group, and dynamic-fixed effects estimators to examine the short-run and long-run relations between systemic risk in European banks and macroeconomic variables.

The empirical evidence shows a long-run stable relationship between macroeconomic variables and systemic risk in European banks. Most importantly, policymakers monitoring systemic risk in the European banking system should distinguish between short- and long-run macroeconomic drivers. For instance, US equity market volatility and Euribor have opposite effects in the short and long run. Euribor has a positive significant effect on all three systemic risk indicators in the long run. After an increase in euribor, capital requirements for a bank might increase in the event of a crisi, leading to an increase in the systemic risk in the long run. On the other hand, a decline in Euribor leads to an increase in systemic risk in the short run. A possible reason is that bank risk-taking could be increased in the low-interest-rate environment in the euro area after a decrease in Euribor (Deev and Hodula (2016)). ECB's monetary policy decisions via transmission of Euribor affects the spread of systemic risk in European banks significantly. The risks of high EU inflation results in higher systemic risk in European banks in the short-run. This result suggests high EU inflation could have a more serious impact on systemic risk on European banks in the short run. Finally, high US equity market volatility that creates uncertainty and a slowdown in EU industrial production trigger systemic risk more in European banks in the long run.

7 Appendix

7.1 Additional Results

Common Framework

This appendix explains how to calculate: $LRMES$, MES and $SRISK$ and provides essential results for this study.

This equation H_t below shows the variance-covariance matrix of returns of bank and market which consists of stochastic volatilities and time varying conditional correlations (Engle (2001),Engle and Sheppard (2001)).

$$H_t = \begin{bmatrix} \sigma_{i,t}^2 & \rho_{i,t}\sigma_{i,t}\sigma_{m,t} \\ \rho_{i,t}\sigma_{i,t}\sigma_{m,t} & \sigma_{m,t}^2 \end{bmatrix}$$

H_t is the variance covariance matrix of $r_t = (r_{it}, r_{mt})'$

Following the model used in Brownlees and Engle (2016):

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

where $\epsilon_t = \epsilon_{mt}, \epsilon_{it}$ determines a vector of zero mean innovations

Time varying conditional correlation and volatility are used for estimating MES. Furthermore, in order to compute $SRISK$, it requires to calculate $LRMES$. I calculate time varying bank Capital Asset Pricing Model (CAPM) $Beta$'s using formula below to determine $LRMES$:

$\hat{\beta}_{it} = cov(r_{it}, r_{mt})/var(r_{mt}) = \hat{\sigma}_{it}\hat{\rho}_{it}/\hat{\sigma}_{mt}$ that represents time varying bank CAPM $Beta$'s and measures the covariance of a stock's return with the market return, divided by the variance of the market return.

7.2 Volatilities

Following Glosten et al. (1993a), I use an asymmetric $GJR-GARCH$ (1,1) model for the demeaned returns to calculate the conditional volatilities of the equity returns.

The volatility of a bank i and the system m are :

$\sigma_{it}^2 = \omega_i + \alpha_i r_{it-1}^2 + \gamma_i r_{it-1}^2 I_{it-1} + \beta_i \sigma_{it-1}^2$

$\sigma_{mt}^2 = \omega_m + \alpha_m r_{mt-1}^2 + \gamma_m r_{mt-1}^2 I_{mt-1} + \beta_m \sigma_{mt-1}^2$

where σ_{it}^2 and σ_{mt}^2 are the conditional volatilities of the bank and the market. The indicator variables if $r_{t-1} \geq 0 \rightarrow I_{t-1} = 0$ and if $r_{t-1} < 0 \rightarrow I_{t-1} = 1$

These equations can capture a leptokurtic distribution in returns and the asymmetric effects of leverage on volatility as Alexander (2008) and Alexander and Lazar (2009) show that negative returns have a greater volatility effect than positive returns. The persistance of conditional volatility is measured by β_m and β_i. Lastly, γ represent the leverage effect.

7.3 Correlation

By knowing the volatility adjusted returns $\epsilon_{mt} = r_{mt}/\sigma_{mt}$ and $\epsilon_{it} = r_{it}/\sigma_{it}$, I model the Dynamic Conditional Correlation (DCC) approach that is the time-varying conditional correlation between the bank and the market (or system). I use the Quasi Maximum Likelihood (QML) method to estimate parameters; α_{ci}, and β_{ci} in DCC model (Engle (2002), Engle (2009))

Corr $\begin{bmatrix} \epsilon_{it} \\ \epsilon_{mt} \end{bmatrix}$ $=R_t = \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix}$$=diag(\mathbb{Q}_{it})^{-1/2}\mathbb{Q}_{it}diag((\mathbb{Q}_{it})^{-1/2}$

$\mathbb{Q}_{it} = (1 - \alpha_{ci} - \beta_{ci})S_i + \alpha_{ci} \begin{bmatrix} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{bmatrix} \begin{bmatrix} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{bmatrix}' + \beta_{ci}\mathbb{Q}_{it-1}$, where $\mathbb{Q}_{i,t}$ is a pseudo correlation matrix and S is the unconditional correlation matrix of the bank and market (or system) adjusted returns.(Engle (2009))

7.4 Auto Regressive Distributed Lag (ARDL) Methodology

ARDL(1,1) model can be considered :

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \mu_t \tag{23}$$

It is stable if -1 $< \alpha_1 < 1$, and then has a long run solution:

$$y_t^* = \frac{\alpha_0}{1 - \alpha_1} + \frac{\beta_0 + \beta_1}{1 - \alpha_1} x_t = \theta_0 + \theta_x x_t \tag{24}$$

where y_t^* is the target or long run equilibrium value for y_t to which it would tend in the absence of further shocks to x_t and u_t. It can be estimated the long run effect of x_t on y_t^* from the OLS estimates of Eq. (2.23):

$$\hat{\theta_x} = \frac{\hat{\beta}_0 + \hat{\beta}_1}{1 - \hat{\alpha}_1} \tag{25}$$

Writing Eq. (2.23) as:

$$y_t - y_{t-1} = \alpha_0 + (\alpha_1 - 1)y_{t-1} + \beta_0(x_t - x_{t-1)} + (\beta_0 + \beta_1)x_{t-1} + \mu_t \tag{26}$$

where $\alpha_0 = \alpha_0$, $b_0 = \beta_0$; $\alpha_1 = (\alpha_1 - 1)$; $b_1 = \beta_0 + \beta_1$; or as regards adjustment to a long-run target;

$$\Delta y_t = \lambda_1 \Delta y_t^* + \lambda_2 (y_t^* - y_{t-1}) + \mu_t \tag{27}$$

where the λ_1 and λ_2 are the adjustment coefficients which quatify how y adapts to changes in the target and deviations from the target. Notice: from Eq. (2.25); $\alpha_0 = \lambda_2\theta_0$; $\alpha_1 = -\lambda_2$; $b_0 = \lambda_1\theta_x$; $b_1 = \lambda_2\theta_x$

In ARDL or Error Correction Model (ECM) form is robust to whether the variables are I(0) or I(1) and whether or not they are cointegrated. If they are I(1) and not cointegrated $\lambda_2 = 0$ giving a first difference model. The ARDL (1,1) model can be rewritten in Eq. (2.27) (that is reparameterized) as in ECM form by substituting y^* using Eq. (2.24):

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + b_0 \Delta x_t + b_1 x_{t-1} + \mu_t \tag{28}$$

where y_t is the single endogeneous variable, x_t is a vector of exogenous variables, μ_t is the white noise, optimal lag lenght can be chosen by Schwarz criterion. This form (Eq. (2.28)) is usually known as Error Correction Model (ECM). The dependent variable differs in response to changes in the target and to the error, the deviation of the actual from the equilibrium in the previous period: $(y_t^* - y_{t-1})$

7.5 ARDL Short and Long Run Results between Macroeconomic Variables and Three Systemic-Risk Measures for Individual Banks

Dynamic Fixed effect (DFE) estimator is more efficient and has smaller standard errors so it has more significant coefficients whereas the individual banks' coefficients are quite noisy, so standard errors are larger. The PARDL results for individual banks follow almost the same dynamics impact of macroeconomic variables on MES and $\Delta CoVaR$ in the short-run and long-run, but differ from $SRISK$. PARDL results for all individual banks (24) show EU industrial production is insignificant on three systemic risk indicators in the short-run.[14] Some of the panel ARDL results for individual banks and panel DFE estimator results are same. For example, in the short-run,

[14] See the appendix - that reports the PARDL short and long-run results between macroeconomic variables and three systemic-risk measures for individual banks in Tables 2.6, 2.7, 2.8, 2.9, 2.10, and 2.11.

euribor is significantly negative for 16 banks of the 24 on $\Delta CoVaR$ and for 15 banks of the 24 on MES, whereas EU inflation is positively significant for eight banks of the 24 on $SRISK$. US equity market volatility is insignificant for all banks on $SRISK$ in the long-run. Different from the DFE estimator short-run results, EU inflation is insignificant for all 24 banks on MES and for all banks on $\Delta CoVaR$, except CBK bank. Specifically, EU inflation is positively significant on $\Delta CoVaR$ only for CBK bank. PARDL short-run results demonstrates that US equity market volatility is positively significant for three banks (CBK, $LLOYD$, $SWED$)[15] on MES and for four banks (CBK, $LLOYD$, $SWED$ and $INGA$) on $\Delta CoVaR$. When there is unusual high uncertainty or bad news about the near-term macroeconomic outlook in US equity market, these three banks' systemic risk increases in the short-run and are sensitive to changes in the US equity market volatility. In other words, these banks have largest exposure to US equity market volatility which is driven by macroeconomic news outlook news relatively.

Specifically, Euribor is negatively significant for one bank (SAB) on $SRISK$ in the long-run. Spanish bank (SAB) has the most pressure on low interest rates. In the long-run, an increase in euribor decreases $SRISK$ in SAB bank.

7.6 Hausman Test

In the Hausman test is $\tilde{\beta}$ is significanlty different from $\hat{\beta}$. Test Statistics:

$$(\tilde{\beta} - \hat{\beta})'[V(\hat{\beta}) - V(\tilde{\beta})]^{-1}[\tilde{\beta} - \hat{\beta}] \sim X^2(k) \tag{29}$$

where test statistic represents the chi-squared distribution $X^2(k)$ with k degrees of freedom, V represents the variance. Under null and alternative hypothesis, $\tilde{\beta}$ is consistent. $\hat{\beta}$ is inconsistent under alternative hypothesis, but efficient under null. V($\hat{\beta}$) should be bigger than V($\tilde{\beta}$), but sometimes the difference of covariance matrices ($[V(\hat{\beta}) - V(\tilde{\beta})]$) may not be positive definite in small samples. This implies that V($\tilde{\beta}$) is more efficient because it has smaller varience in small samples.

[15]Banks' abbreviations can be found in the appendix.

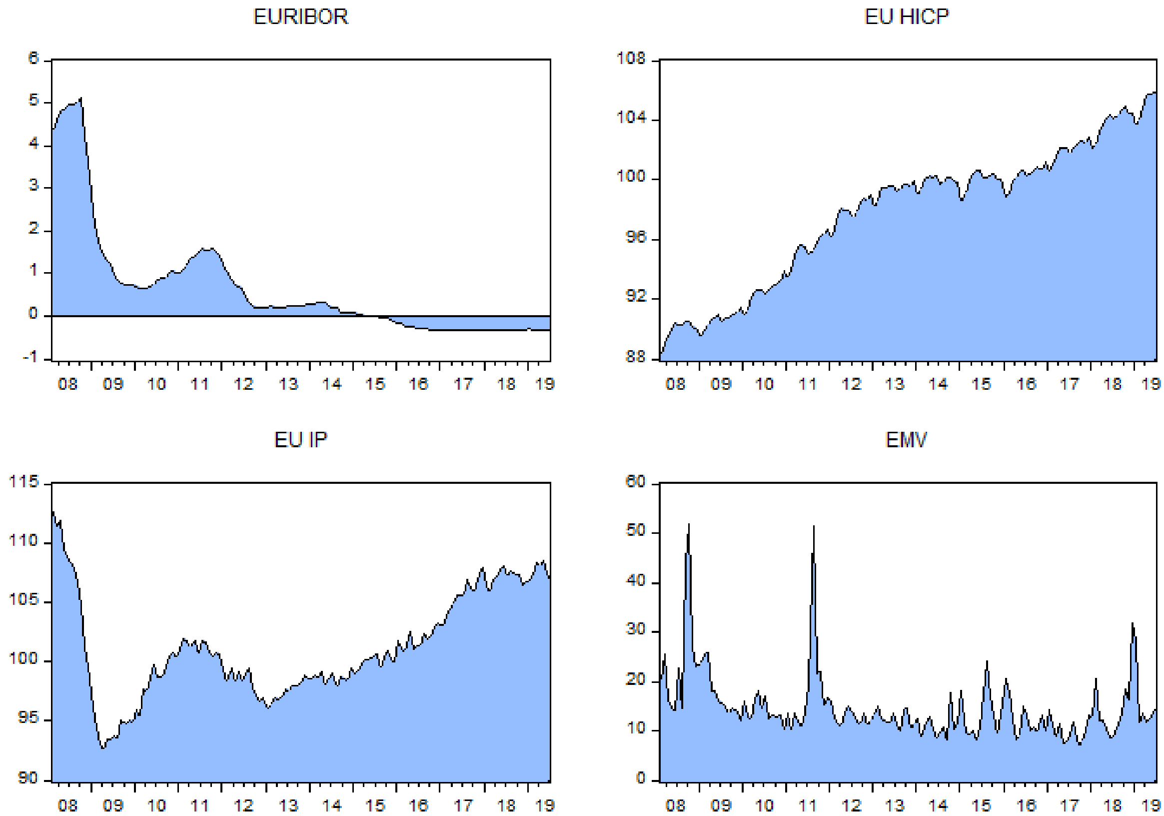
Table 3: Abbreviation of Banks

Country	BANK	Abbreviation
BELGIUM	KBC GROEP	KBC
DENMARK	DANSKE	DANSKE
FRANCE	BNP PARIBAS	BNP
FRANCE	CREDIT AGRICOLE	ACA
FRANCE	SOCIETE GENERALE	GLE
GERMANY	COMMERZBANK	CBK
GERMANY	DEUTSCHE	DBK
ITALY	BANCA MONTE DEI PASCHI DI SIENA	BMPS
ITALY	INTESA SANPAOLO	ISP
ITALY	UNICREDIT	UCG
NETHERLANDS	ING GROUP	INGA
PORTUGAL	BANCO COMERCIAL PORTUGUESE	BPCGF
SPAIN	BANCO SABADELL	SAB
SPAIN	BANCO SANTANDER	BNC
SPAIN	BBV ARGENTARIA	BBVA
SWEDEN	NORDEA BANK	NDA
SWEDEN	SKANDINAVISKA ENSKILDA BANKEN	SEBA
SWEDEN	SVENSKA HANDELSBANKEN	SHBA
SWEDEN	SWED	SWED
SWITZERLAND	UBS GROUP	UBSG
SWITZERLAND	CREDIT SUISSE	CSGN
UNITED KINGDOM	BARCLAYS	BARC
UNITED KINGDOM	HSBC	HSBC
UNITED KINGDOM	LLOYDS	LLOY

Table 5: Descriptive Statistics for Systemic-Risk Measures in Monthly Panel Data

	$\Delta CoVaR$	MES	$SRISK$	$EUIP$	$EUHICP$	EMV	$EURIBOR$
Mean	0.01	0.03	$4.76E+10$	101.18	97.79	14.60	0.66
Median	0.01	0.02	$3.60E+10$	100.40	99.36	13.13	0.22
Maximum	0.12	0.29	$1.68E+11$	112.60	105.90	51.64	5.11
Minimum	0.00	-0.00	0.00	92.60	88.29	6.98	-0.33
Std. Dev.	0.01	0.02	$3.98E+10$	4.41	4.64	6.90	1.33
Skewness	2.84	3.08	0.89	0.41	-0.41	3.053	2.14
Kurtosis	15.72	19.76	2.79	2.46	2.04	15.16	7.06
Observations	3288	3288	3288	3288	3288	3288	3288

Figure 7: Descriptive Statistics of Monthly Macroeconomic Variables



7.7 Results for The Impact of Macroeconomic Variables on Systemic-Risk Indicators in the Short- and Long-Run by Using ARDL for Individual Banks

This section shows results for the impact of macroeconomic variables on systemic-risk measures for individual banks in the short- and long run. I use methdology of ARDL for individual banks.

Table 6: Short Run Results

Banks	C	$lnIP$	$lnHICP$	$EURIBOR$	$lnEMV$	SE of regression	R^2
	Variables for systemic risk indicator (MES) in the short-run						
ACA	0.06 (0.53)	-0.002 (-0.02)	0.16 (0.94)	-0.00 (-0.06)	0.00 (1.54)	0.00	0.40
BARC	0.39 (1.27)	-0.04 (-0.19)	0.15 (0.32)	-0.03** (-2.16)	0.00 (1.08)	0.02	0.44
BBVA	0.14 (0.96)	-0.04 (-0.39)	0.01 (0.05)	-0.01* (-1.76)	0.00 (0.28)	0.01	0.39
BMPS	0.12 (1.13)	-0.05 (-0.68)	0.11 (0.70)	-0.01* (1.67)	0.00 (1.57)	0.00	0.16
BNC	0.16 (0.91)	-0.03 (-0.24)	-0.00 (-0.01)	-0.02** (-2.40)	0.00 (0.48)	0.01	0.43
BNP	0.11 (0.62)	-0.07 (-0.54)	0.06 (0.24)	-0.02** (-2.61)	0.00 (1.14)	0.01	0.38
BPCGF	0.01 (0.09)	0.02 (0.23)	-0.25 (-1.15)	0.00 (1.13)	0.00 (0.20)	0.01	0.38
CBK	-0.22* (-1.89)	-0.12 (-1.27)	0.25 (1.37)	0.00 (0.21)	0.00** (2.01)	0.00	0.43
CSGN	-0.09 (-0.81)	-0.05 (-0.51)	0.00 (0.02)	-0.02** (-2.86)	0.00 (0.35)	0.00	0.47
DANSKE	-0.00 (-0.00)	-0.02 (-0.30)	-0.05 (-0.35)	-0.01** (-2.28)	-2.41 (-0.01)	0.00	0.51
DBK	-0.12 (-1.09)	-0.06 (-0.66)	0.07 (0.44)	-0.02** (-3.18)	0.00 (0.83)	0.00	0.44
GLE	0.00 (0.00)	-0.01 (-0.10)	0.31 (0.99)	-0.01 (-1.45)	0.00 (0.16)	0.01	0.44
HSBC	0.10 (0.89)	-0.06 (-0.71)	0.20 (1.16)	-0.01** (-2.39)	0.00 (1.10)	0.00	0.44
INGA	0.37 (1.41)	-0.17 (-0.87)	0.41 (1.09)	-0.03** (-2.26)	0.01** (2.04)	0.01	0.45
ISP	0.02 (0.11)	-0.20 (-1.03)	0.21 (0.57)	-0.01 (-1.37)	0.00 (1.17)	0.01	0.42
KBC	0.68** (2.46)	-0.01 (-0.06)	0.46 (1.23)	-0.04** (-3.27)	0.00 (1.33)	0.01	0.44
LLOYD	0.54 (1.55)	-0.16 (-0.59)	0.54 (1.05)	-0.04** (-2.43)	0.01** (2.17)	0.02	0.34
NDA	-0.12 (-1.09)	-0.06 (-0.66)	0.07 (0.44)	-0.02** (-3.18)	0.00 (0.83)	0.00	0.44
SAB	-0.09 (-0.91)	-0.03 (-0.47)	0.09 (0.58)	0.00 (0.65)	0.00 (0.76)	0.00	0.38
SEBA	0.01 (0.08)	0.02 (0.18)	0.16 (0.80)	-0.02** (-2.71)	0.00 (1.33)	0.00	0.40
SHBA	0.04 (0.46)	-0.05 (-0.67)	0.14 (0.95)	-0.01** (-2.86)	0.00 (0.60)	0.00	0.41
SWED	-0.02 (-0.15)	-0.06 (-0.49)	0.26 (1.10)	0.00 (0.22)	0.00** (2.37)	0.01	0.39
UBSG	-0.05 (-0.39)	-0.02 (-0.21)	0.16 (0.84)	0.00 (0.69)	0.00* (1.74)	0.00	0.41
UCG	-0.05 (-0.22)	-0.14 (-0.74)	0.09 (0.26)	-0.00 (-0.70)	0.00 (0.87)	0.01	0.41

Note: The terms in the parentheses are the t-statistics and *** indicates a significance level of 1%, ** of 5%, and * of 10%. I take the logarithms for EU industrial production (IP), EU inflation (HICP), and US EMV tracker for macroeconomic news (EMV).

Table 7: Long Run Results

Banks	Variables for systemic risk indicator (MES) in the long-run				
	$MES(-1)$	$lnIP(-1)$	$lnHICP(-1)$	$EURIBOR(-1)$	$lnEMV(-1)$
ACA	-0.36***	-0.05**	0.04	0.00*	0.00***
	(-6.14)	(-2.05)	(1.13)	(1.79)	(6.35)
BARC	-0.76***	-0.03	-0.06	0.00	0.03***
	(-9.44)	(-0.52)	(-0.59)	(0.32)	(4.42)
BBVA	-0.65***	-0.01	-0.01	-0.00	0.01**
	(-8.45)	(-0.55)	(-0.30)	(-0.13)	(3.78)
BMPS	-0.21***	-0.03	0.00	0.00	0.00**
	(-4.13)	(-1.20)	(0.00)	(0.41)	(2.96)
BNC	-0.73***	-0.00	-0.04	-0.00	0.01***
	(-9.16	(-0.01)	(-0.66)	(-0.84)	(3.97)
BNP	-0.53***	-0.02	-0.00	-0.00	0.02***
	(-7.98)	(-0.66)	(-0.06)	(-0.05)	(4.64)
BPCGF	-0.68***	-0.05*	0.05	0.00	0.00**
	(-8.45)	(-1.72)	(1.19)	(0.84)	(2.16)
CBK	-0.36***	-0.06**	0.10**	0.00**	0.02***
	(-5.87)	(-2.35)	(2.72)	(2.37)	(7.03)
CSGN	-0.54***	0.00	0.00	0.00	0.01**
	(-8.16)	(0.16)	(0.23)	(0.56)	(6.23)
DANSKE	-0.63***	-0.01	0.01	0.00	0.01***
	(-9.23)	(-0.83)	(0.40)	(1.49)	(6.69)
DBK	-0.44***	0.00	0.01	-0.00	0.01***
	(-7.50)	(0.12)	(0.44)	(-0.11)	(6.37)
GLE	-0.58***	-0.06	0.05	0.00	0.02***
	(-8.35)	(-1.27)	(0.77)	(1.02)	(5.33)
HSBC	-0.57***	-0.01	-0.01	-0.00	0.01***
	(-8.37)	(-0.39)	(-0.48)	(-0.10)	(5.87)
INGA	-0.69***	-0.11*	0.01	0.00	0.03***
	(-8.31)	(-1.95)	(0.19)	(0.93)	(6.42)
ISP	-0.70***	-0.08	0.07	0.00	0.02***
	(-9.01)	(-1.49)	(0.91)	(0.35)	(4.27)
KBC	-0.76***	-0.13**	-0.02	0.00	0.02***
	(-9.13)	(-2.31)	(-0.26)	(0.91)	(4.77)
LLOYD	-0.58***	-0.02	-0.10	-0.00	0.03***
	(-7.80)	(-0.31)	(-0.95)	(-0.47)	(3.75)
NDA	-0.50***	-0.03	-0.00	0.00	0.01***
	(-7.20)	(-1.26)	(-0.05)	(0.70)	(4.87)
SAB	-0.70***	-0.02	0.04	0.00	0.00**
	(-8.37)	(-1.18)	(1.46)	(0.42)	(2.77)
SEBA	-0.49***	-0.02	0.01	0.00	0.01***
	(-7.21)	(-0.78)	(0.31)	(1.41)	(5.83)
SHBA	-0.55***	-0.01	-0.00	0.00	0.01***
	(-8.04)	(-0.55)	(-0.03)	(0.68)	(4.84)
SWED	-0.48***	-0.05	0.05	0.00**	0.02***
	(-5.71)	(-1.55)	(1.00)	(1.98)	(5.83)
UBSG	-0.42***	-0.03	0.03	0.00**	0.02***
	(-5.82)	(-1.02)	(0.78)	(1.92)	(6.33)
UCG	-0.67***	-0.07	0.07	0.00	0.02***
	(-8.22)	(-1.32)	(0.99)	(0.50)	(4.70)

Note: The terms in the parentheses are the t-statistics and *** indicates a significance level of 1%, ** of 5%, and * of 10%. I take the logarithms for EU industrial production (IP), EU inflation (HICP), and US EMV tracker for macroeconomic news (EMV).

Table 8: Short Run Results

Banks	Variables for systemic risk indicator ($\Delta CoVaR$) in the short-run						
	C	$lnIP$	$lnHICP$	$EURIBOR$	$lnEMV$	SE of regression	R^2
ACA	0.02 (0.49)	0.00 (0.02)	0.09 (1.12)	-0.00 (-0.32)	0.00 (1.35)	0.00	0.43
BARC	0.20 (1.36)	0.00 (0.00)	0.16 (0.69)	-0.02** (-2.92)	0.00 (1.07)	0.01	0.43
BBVA	0.10 (1.13)	-0.04 (-0.54)	0.03 (0.24)	-0.01** (-2.10)	0.00 (0.21)	0.00	0.40
BMPS	-0.01 (-0.84)	-0.00 (-0.19)	0.02 (1.24)	-0.0 (-0.92)	-0.00 (-0.63)	0.00	0.49
BNC	0.10 (0.92)	-0.01 (-0.22)	0.00 (0.03)	-0.01** (-2.44)	0.00 (0.38)	0.00	0.43
BNP	0.06 (0.58)	-0.06 (-0.67)	0.04 (0.25)	-0.01** (-2.94)	0.00 (1.10)	0.00	0.39
BPCGF	-0.01 (-0.23)	0.00 (0.13)	-0.05 (-0.76)	0.00 (0.69)	-0.00 (-0.48)	0.00	0.37
CBK	-0.06 (-1.37)	-0.06 (-1.64)	0.13* (1.85)	0.00 (0.27)	0.00** (2.02)	0.00	0.42
CSGN	-0.02 (-0.44)	-0.02 (-0.48)	0.05 (0.54)	-0.01** (-3.62)	0.00 (0.32)	0.00	0.49
DANSKE	0.00 (0.04)	-0.03 (-0.76)	0.05 (0.60)	-0.00** (-2.29)	0.00 (0.56)	0.00	0.46
DBK	-0.06 (-1.11)	-0.02 (-0.55)	0.05 (0.56)	-0.01** (-3.43)	0.00 (0.79)	0.00	0.45
GLE	0.00 (0.03)	-0.01 (-0.21)	0.18 (1.28)	-0.01** (-1.99)	0.00 (0.05)	0.00	0.45
HSBC	0.07 (0.82)	-0.03 (-0.46)	0.18 (1.41)	-0.01** (-2.90)	0.00 (0.86)	0.00	0.44
INGA	0.24* (1.84)	-0.10 (-1.06)	0.23 (1.27)	-0.02** (-2.91)	0.00** (2.00)	0.00	0.46
ISP	0.00 (0.04)	-0.10 (-1.13)	0.13 (0.74)	-0.01* (-1.68)	0.00 (1.08)	0.00	0.42
KBC	0.38** (2.93)	-0.02 (-0.28)	0.29 (1.61)	-0.02** (-4.05)	0.00 (1.49)	0.00	0.45
LLOYD	0.23 (1.66)	-0.07 (-0.66)	0.27 (1.31)	-0.01** (-2.39)	0.00** (2.28)	0.00	0.32
NDA	0.10 (1.22)	0.01 (0.29)	0.15 (1.29)	-0.01** (-3.31)	0.00* (1.82)	0.00	0.36
SAB	-0.04 (-1.00)	-0.03 (-1.05)	0.06 (1.02)	0.00 (0.73)	0.00 (0.48)	0.00	0.34
SEBA	0.00 (0.06)	0.02 (0.37)	0.13 (1.10)	-0.01** (-3.11)	0.00 (1.44)	0.00	0.41
SHBA	0.03 (0.52)	-0.02 (-0.51)	0.17 (1.70)	-0.01** (-2.97)	0.00 (0.99)	0.00	0.40
SWED	-0.03 (-0.38)	-0.01 (-0.23)	0.24 (1.79)	-0.00 (-0.29)	0.00** (2.17)	0.00	0.34
UBSG	-0.04 (-0.62)	-0.00 (-0.12)	0.06 (0.56)	0.00 (0.99)	0.00 (1.42)	0.00	0.42
UCG	-0.02 (-0.26)	-0.07 (-0.96)	0.04 (0.32)	-0.00 (-0.75)	0.00 (0.82)	0.00	0.41

Note: The terms in the parentheses are the t-statistics and *** indicates a significance level of 1%, ** of 5%, and * of 10%. I take the logarithms for EU industrial production (IP), EU inflation (HICP), and US EMV tracker for macroeconomic news (EMV).

Table 9: Long Run Results

Banks	$\Delta CoVaR(-1)$	$lnIP(-1)$	$lnHICP(-1)$	$EURIBOR(-1)$	$lnEMV(-1)$
	Variables for systemic risk indicator ($\Delta CoVaR$) in the long-run				
ACA	-0.36*** (-6.29)	-0.02** (-2.06)	0.02 (1.16)	0.00* (1.91)	0.00*** (6.67)
BARC	-0.75*** (-9.46)	-0.01 (-0.45)	-0.03 (-0.68)	0.00 (0.19)	0.01** (3.85)
BBVA	-0.66*** (-8.56)	-0.00 (-0.41)	-0.01 (-0.50)	-0.00 (-0.37)	0.00** (3.74)
BMPS	-0.95*** (-10.76)	-0.00* (-1.70)	0.00** (2.24)	0.00* (1.66)	0.00** (0.15)
BNC	-0.72*** (-9.10)	-0.00 (-0.06)	-0.02 (-0.63)	-0.00 (-0.82)	0.01** (4.09)
BNP	-0.53*** (-8.00)	-0.01 (-0.59)	-0.00 (-0.08)	-0.00 (-0.01)	0.01*** (4.63)
BPCGF	-0.71*** (-8.47)	-0.02** (-2.15)	0.02 (1.79)	0.00 (1.36)	0.00 (0.87)
CBK	-0.36*** (-5.63)	-0.03** (-3.00)	0.04** (2.93)	0.00** (2.76)	0.00*** (6.64)
CSGN	-0.55*** (-8.69)	0.00 (0.13)	0.00 (0.03)	0.00 (0.49)	0.01*** (6.38)
DANSKE	-0.63*** (-8.95)	-0.00 (-0.26)	0.00 (0.00)	0.00 (0.47)	0.00*** (5.98)
DBK	-0.44*** (-7.56)	0.00 (0.22)	0.01 (0.39)	-0.00 (-0.12)	0.00*** (6.30)
GLE	-0.59*** (-8.64)	-0.02 (-1.17)	0.02 (0.68)	0.00 (1.03)	0.01*** (5.44)
HSBC	-0.58*** (-8.43)	-0.00 (-0.38)	-0.01 (-0.42)	0.00 (0.05)	0.01*** (5.52)
INGA	-0.72*** (-8.62)	-0.05* (-1.87)	-0.00 (-0.16)	0.00 (0.76)	0.01*** (6.17)
ISP	-0.69*** (-9.02)	-0.03 (-1.40)	0.03 (0.90)	0.00 (0.36)	0.01*** (4.29)
KBC	-0.78*** (-9.50)	-0.05** (-2.13)	-0.02 (-0.72)	0.00 (0.46)	0.01** (4.17)
LLOYD	-0.51*** (-7.26)	-0.01 (-0.37)	-0.04 (-1.0)	-0.00 (-0.46)	0.01** (3.79)
NDA	-0.52*** (-7.68)	-0.00 (-0.52)	-0.01 (-0.58)	-0.00 (-0.03)	0.00*** (4.65)
SAB	-0.61*** (-7.57)	-0.01 (-1.62)	0.02 (1.85)	0.00 (0.51)	0.00** (2.76)
SEBA	-0.47*** (-7.44)	-0.00 (-0.47)	0.00 (0.10)	0.00 (1.17)	0.01*** (5.82)
SHBA	-0.48*** (-7.74)	-0.00 (-0.36)	-0.00 (-0.22)	0.00 (0.37)	0.00*** (5.10)
SWED	-0.46*** (-5.96)	-0.02 (-1.08)	0.02 (0.87)	0.00 (1.50)	0.01*** (4.92)
UBSG	-0.35*** (-5.43)	-0.01 (-1.15)	0.02 (1.01)	0.00** (2.16)	0.01*** (6.64)
UCG	-0.64*** (-7.98)	-0.03 (-1.30)	0.03 (1.00)	0.00 (0.48)	0.01*** (4.79)

Note: The terms in the parentheses are the t-statistics and *** indicates a significance level of 1%, ** of 5%, and * of 10%. I take the logarithms for EU industrial production (IP), EU inflation (HICP), and US EMV tracker for macroeconomic news (EMV).

Table 10: Short Run Results

	Variables for systemic risk indicator ($SRISK$) in the short-run						
Banks	C	$lnIP$	$lnHICP$	$EURIBOR$	$lnEMV$	SE of regression	R^2
ACA	3.27** (2.18)	0.08 (0.16)	1.97** (2.22)	-0.03 (-1.16)	-0.00 (-0.01)	0.04	0.12
BARC	5.52** (2.44)	-0.67 (-0.92)	2.83** (2.12)	0.02 (0.69)	0.00 (0.26)	0.06	0.17
BBVA	1.35 (0.57)	0.80 (0.44)	-0.95 (-0.28)	-0.22** (-2.02)	-0.03 (-0.70)	0.15	0.19
BMPS	6.70** (3.33)	-0.45 (-0.43)	0.56 (0.29)	0.02 (0.33)	0.02 (0.96)	0.08	0.15
BNC	1.19 (0.67)	-0.26 (-0.19)	0.87 (0.34)	-0.10 (-1.24)	0.02 (0.58)	0.11	0.09
BNP	3.45** (1.99)	0.12 (0.20)	2.49** (2.23)	-0.10** (-2.84)	-0.00 (-0.04)	0.05	0.16
BPCGF	8.67** (3.24)	2.56 (1.59)	-2.81 (-0.94)	0.06 (0.63)	-0.04 (-1.04)	0.13	0.32
CBK	8.95** (3.50)	-0.48 (-0.69)	4.23** (3.25)	0.01 (0.38)	-0.00 (-0.15)	0.05	0.22
CSGN	1.79 (1.17)	-0.05 (-0.05)	1.18 (0.65)	0.03 (0.54)	0.00 (0.13)	0.08	0.10
DANSKE	0.93 (0.59)	-0.56 (-0.69)	1.33 (0.87)	-0.01 (-0.28)	-0.01 (-0.68)	0.06	0.09
DBK	3.12** (1.98)	-0.22 (-0.33)	3.35** (2.72)	0.03 (0.84)	-0.01 (-0.77)	0.05	0.15
GLE	1.32 (1.44)	0.40 (0.91)	0.78 (0.95)	-0.00 (-0.12)	-0.01 (-0.84)	0.03	0.13
HSBC	2.31 (0.97)	-0.92 (-0.53)	6.73** (2.09)	-0.09 (-0.88)	0.07 (1.44)	0.14	0.19
INGA	3.34 (1.53)	0.50 (0.55)	2.46 (1.43)	-0.02 (-0.36)	0.05** (2.25)	0.07	0.08
ISP	4.07** (2.06)	0.60 (0.40)	2.55 (0.92)	-0.12 (-1.44)	-0.02 (-0.51)	0.12	0.37
KBC	2.63 (0.83)	2.61 (1.59)	4.73 (1.56)	-0.07 (-0.78)	-0.02 (-0.52)	0.13	0.12
LLOYD	12.66** (3.93)	1.18 (0.57)	2.98 (0.76)	0.25* (1.94)	0.01 (0.31)	0.17	0.18
NDA	4.96** (2.05)	0.76 (0.51)	5.61** (2.06)	-0.00 (-0.01)	0.00 (0.12)	0.12	0.16
SAB	-9.67** (-3.99)	0.84 (0.49)	0.52 (0.16)	0.12 (1.19)	0.04 (0.81)	0.14	0.41
SEBA	9.79** (3.01)	2.11 (1.11)	10.81** (3.10)	-0.11 (-1.00)	-0.03 (-0.61)	0.15	0.28
SHBA	6.64** (2.13)	0.73 (0.33)	6.50 (1.59)	-0.09 (-0.71)	-0.05 (-0.81)	0.18	0.22
SWED	23.96** (2.28)	7.62 (0.98)	29.32** (2.04)	-0.33 (-0.73)	-0.05 (-0.26)	0.64	0.28
UBSG	5.55** (1.98)	0.41 (0.27)	4.88* (1.72)	-0.02 (-0.23)	-0.01 (-0.33)	0.12	0.13
UCG	3.49** (2.04)	0.56 (0.79)	-0.04 (-0.03)	0.01 (0.31)	-0.01 (-0.53)	0.05	0.17

Note: The terms in the parentheses are the t-statistics and *** indicates a significance level of 1%, ** of 5%, and * of 10%. I take the logarithms for EU industrial production (IP), EU inflation (HICP), US EMV tracker for macroeconomic news (EMV), and systemic-risk measure of SRISK.

Table 11: Long Run Results

Banks	Variables for systemic risk indicator ($SRISK$) in the long-run				
	$lnSRISK(-1)$	$lnIP(-1)$	$lnHICP(-1)$	$EURIBOR(-1)$	$lnEMV(-1)$
ACA	-0.12**	-0.13	0.09	0.00	-0.00
	(-2.68)	(-0.82)	(0.48)	(0.82)	(-0.19)
BARC	-0.19**	-0.72**	0.57*	0.03**	0.01
	(-3.45)	(-2.50)	(1.97)	(3.10)	(0.77)
BBVA	-0.16**	0.31	0.27	-0.00	-0.03
	(-3.47)	(0.60)	(0.38)	(-0.15)	(-0.63)
BMPS	-0.14**	-0.67*	-0.03	0.01	-0.03
	(-3.56)	(-1.72)	(-0.08)	(0.69)	(-1.13)
BNC	-0.14**	-0.10	0.60	-0.00	0.02
	(-2.87)	(-0.28)	(1.12)	(-0.23)	(0.62)
BNP	-0.14**	0.11	-0.04	-0.00	-0.00
	(-2.96)	(0.69)	(-0.19)	(-0.19)	(-0.44)
BPCGF	-0.23***	-0.88	0.13	0.02	0.00
	(-5.44)	(-1.61)	(0.21)	(1.11)	(0.18)
CBK	-0.16**	-0.55**	-0.51	-0.00	0.01
	(-3.81)	(-2.54)	(-1.51)	(-0.09)	(0.87)
CSGN	-0.14 **	-0.18	0.51	0.01	0.03
	(-2.99)	(-0.62)	(1.28)	(1.28)	(1.38)
DANSKE	-0.07	0.14	0.03	0.00	0.01
	(-1.87)	(0.56)	(0.09)	(0.51)	(0.42)
DBK	-0.12**	-0.22	0.22	0.01	0.01
	(-2.78)	(-1.06)	(0.84)	(1.49)	(0.81)
GLE	-0.13**	-0.11	0.53**	0.00	0.01
	(-2.89)	(-0.86)	(2.45)	(1.54)	(1.35)
HSBC	-0.26***	-0.20	1.05	0.00	0.10
	(-4.36)	(-0.40)	(1.52)	(0.30)	(2.05)
INGA	-0.08**	-0.31	0.03	0.01	0.03
	(-2.28)	(-0.93)	(0.09)	(1.00)	(1.16)
ISP	-0.25***	0.51	-0.03	-0.00	-0.03
	(-6.12)	(1.14)	(-0.06)	(-0.28)	(-0.86)
KBC	-0.08**	-0.33	0.15	0.03	0.03
	(-2.37)	(-0.66)	(0.23)	(1.56)	(0.66)
LLOYD	-0.21***	-0.82	-0.76	-0.02	0.03
	(-4.84)	(-1.35)	(-0.92)	(-0.95)	(0.61)
NDA	-0.23**	-1.24**	1.37**	0.04**	-0.00
	(-3.93)	(-2.27)	(2.12)	(2.04)	(-0.09)
SAB	-0.48***	-0.38	4.91***	-0.06**	-0.02
	(-8.09)	(-0.74)	(4.91)	(-2.46)	(-0.50)
SEBA	-0.37***	-1.06*	0.86	0.08**	-0.05
	(-5.44)	(-1.90)	(1.16)	(2.86)	(-1.04)
SHBA	-0.35***	-0.30	0.65	0.03	-0.01
	(-5.14)	(-0.48)	(0.75)	(1.06)	(-0.19)
SWED	-0.48***	-0.47	-2.41	0.06	0.01
	(-6.27)	(-0.21)	(-0.76)	(0.59)	(0.08)
UBSG	-0.17**	-0.07	-0.22	0.02	0.02
	(-3.58)	(-0.16)	(-0.36)	(1.28)	(0.63)
UCG	-0.16**	-0.22	0.33	0.01*	0.02
	(-3.23)	(-1.01)	(1.17)	(1.89)	(1.12)

Note: The terms in the parentheses are the t-statistics and *** indicates a significance level of 1%, ** of 5%, and * of 10%. I take the logarithms for EU industrial production (IP), EU inflation (HICP), US EMV tracker for macroeconomic news (EMV), and systemic-risk measure of SRISK.

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