Journal of
Risk and Financial Management

MDPI

Article

Are Banks Still a Risk Source for Stock Market? Some Empirical Evidences

Michele Anelli [1], Michele Patanè [1] and Stefano Zedda [2,*]

[1] Department of Business and Law, School of Economics and Management, University of Siena, 53100 Siena, Italy; anelli2@student.unisi.it (M.A.); michele.patane@unisi.it (M.P.)
[2] Department of Business and Economics, University of Cagliari, 09123 Cagliari, Italy
* Correspondence: szedda@unica.it

Abstract: The global financial crisis of 2008 proved that what initially appeared to be relatively small losses in the financial system can be magnified to systemic ones. The European Union debt crisis has thus revived interest in the interdependence across different markets, especially sovereign debt markets and the banking sector, and in the interlinkages among idiosyncratic and common shocks. This paper analyzes the evolution over time of the incidence of common shocks on the main Italian banking groups starting from the period of European Central Bank's Quantitative Easing program. Results show that the banking sector is no longer perceived by the markets as a common risk source, overcoming the negative picture coming from the financial crisis of 2008–2009. The analysis also suggests that the common risk is broadly affected by the ECB monetary policy, and the idiosyncratic risk is linked to the recapitalization processes.

Keywords: common shock; idiosyncratic shock; relative strength; VECM; rolling regression

JEL Classification: G01; G12; G14; G20

check for updates

Citation: Anelli, Michele, Michele Patanè, and Stefano Zedda. 2022. Are Banks Still a Risk Source for Stock Market? Some Empirical Evidences. *Journal of Risk and Financial Management* 15: 310. https://doi.org/10.3390/jrfm15070310

Academic Editor: Shigeyuki Hamori

Received: 19 June 2022
Accepted: 13 July 2022
Published: 15 July 2022

1. Introduction and Literature Review

The global financial crisis of 2008 proved that what initially appear to be relatively small losses in the financial system can be magnified to systemic ones. The EU debt crisis has thus revived interest in the interdependence across different markets, especially sovereign debt markets and the banking sector, and in the interlinkages among idiosyncratic and common shocks.

Financial contagion can be defined as a sudden shock in a crisis market that spreads to other markets, and whose transmission cannot be explained by a contemporaneous change in economic fundamentals (Pericoli and Sbracia 2003).

With reference to banking systems, the crisis spreading through direct linkages (interbank exposures) has been explored by means of simulation starting from Allen and Gale (2000). A comprehensive description of this approach is in Zedda (2017). The indirect linkages, passing through market's comovements, are instead based on the analysis of market data, as in the CoVar model developed in Adrian and Brunnermeier (2011).

The issue of spillover/contagion was traditionally studied for emerging countries and stock/foreign exchange markets (Kaminsky and Reinhart 2000; Bekaert et al. 2011), while the empirical literature aimed at the EU countries mainly looked at comovements and linkages between sovereign bond markets and the banking sector (Paltalidis et al. 2015; Blatt et al. 2015; Claeys and Vašíček 2014).

With reference to the methodologies, the empirical modeling of contagion was reviewed by Dungey et al. (2005) already in 2005, but more recent studies included the lessons coming from the global crisis, developing the procedures for endogenous break date determination, as in Candelon and Manner (2010) and Metiu (2012), or at the direction and strength of all bilateral linkages, as in Bekaert et al. (2011) and in Forbes (2012).

When trying to capture the feedback relationship among the correlation effect and contagion effect, the analysis unavoidably ends with an investigation into the shock's original cause. Moreover, financial markets offer the opportunity to observe the changing environment through history and assess the existence of dynamic equilibrium that can diverge in the short- and long-term (Güth and Ludwig 2000).

In empirical terms, many studies analyzed the comovements of the main financial markets. Eichengreen et al. (2012), by means of a dynamic factor model, assessed the impact of the 2008 crisis on the global banking system, finding that the heightened counterparty risks coupled with the deterioration of banks' loan portfolio heavily impacted the movement of banks' credit default swap spreads. Vo (2014) demonstrated the particular significance of market comovements in the case of extreme negative returns during the global financial crisis and the Eurozone crisis. Choudhry and Jayasekera (2015) showed that during the global financial crisis, betas increased for most firms. More recently, Alexandridis and Hasan (2020), using daily data of eight major European equity markets over the period of 2005–2018, analyzed the impact of the global financial crisis on systematic risk and market risk, showing that the size of CAPM betas and R^2s tend to increase during the crisis period compared with the precrisis period.

Due to the evidence that the global financial crisis shocks come from banks' distress, low scientific interest was devoted to assessing to what extent banks were perceived as a risk source by the market. Yet, to our knowledge, no studies analyzed the diffusion of shocks process by means of VECM models with reference to banks' market values and indexes.

In this paper, we analyzed the market continuously from January 2015 to December 2021, which includes the period after the main financial crisis of 2008 and its subsequent evolution on European sovereigns of 2012, in which banks played a central role as risk sources and channeled significant risks of feedback loops (Galliani and Zedda 2015). The considered time span, instead, includes the pandemic crisis, which hugely hit both the Italian stock market values, inducing a drop of the Italian FTSE MIB index from 25,223 of 16 February 2021, to 14,894 of March 12[1], and on the real economy, determining a drop in the Italian GDP of 9% in 2021[2]. During this crisis, banks played a central role in ensuring continuity to the payment system, and in helping the government to channel its financial sustain to the firms and sectors which mostly suffered the lockdown. Differently from the 2008 crisis, within and after the COVID-19 pandemic crisis, no signals of banks' financial instability were evident. In this framework, our analysis aims at testing whether the market dynamics reported the banks' role as risk sources, meaning they were involved in transmitting shocks to the market, or, instead, as risk absorbers, meaning they were involved in receiving shocks from the market. The results showed that this latter role was the one exhibited by the market dynamics, suggesting that the important banks' regulation reforms issued after the 2008–2011 crisis restored the banks soundness.

2. Econometric Model

For verifying the role of banks in the market dynamics, we analyzed its continuity by means of econometrics. One of the main econometric tools to isolate the causing and effected variables is the Vector Error Correction Model (VECM) as defined by Engle and Granger (1987). The VECM model (Vector Error Correction Model) is a Vector AutoRegression (VAR) model which includes the Error Correction Mechanism (ECM) for evaluating the speed of adjustment after any deviation from the long-run equilibrium, making it particularly suited for testing the inter-relationship among different risk sources.

Our analysis is developed in two sequential steps. In the first step, we run a VECM Model using the methodology suggested by Gonzalo and Granger (1995) in order to isolate the cause–effect relationship among the variables. Then, in the second step, the leading variable is used as the regressor (*causing variable*) of the lagging variable (*affected variable*). This second part consists in performing a *rolling* (*moving window*[3]) *regression* in order to analyze the changing relationships among variables over time. We estimated the parameters using a fixed window of ninety days (i.e., the quarterly earnings disclosure timeframe), with one day rolling.

2.1. VECM Model

Firstly, we consider the *relative return* of each sector, meaning, the differential return that an asset achieves over a time interval compared to a benchmark.

Posing

${SRR^B}_t$ as the Sector Relative Return to Benchmark at time t,

And

${BRR^S}_{it}$ the i-th Bank Relative Return to Sector at time t,

We can define:

$$ {SRR^B}_t = \ln\left(\frac{SI_t}{BI_t}\right) \tag{1} $$

$$ {BRR^S}_{it} = \ln\left(\frac{BS_{it}}{SI_t}\right) \tag{2} $$

where:

- SI_t is the sector price index at time t;
- BI_t is the market benchmark price index at time t;
- BS_{it} is the i-th bank stock price at time t.

The advantage of the natural logarithmic transformation is not only the straightforward interpretation of the regression coefficients, but also the possibility to deal with nonstationary series. We can interpret the ${SRR^B}_t$ and the ${BRR^S}_{it}$ variables, respectively, as a proxy of the *common shock* and *idiosyncratic shock*[4].

For disentangling the cause–effect relationship among variables, we start form the following equations:

$$ \Delta {SRR^B}_t = \beta_{10} + \sum_{l=1}^{p} \beta_{1l} \Delta {SRR^B}_{t-l} + \sum_{l=1}^{p} \alpha_{1l} \Delta {BRR^S}_{i(t-l)} + \lambda_1 ECT_{t-1} + \varepsilon_{1t} \tag{3} $$

$$ \Delta {BRR^S}_{it} = \beta_{20} + \sum_{l=1}^{p} \beta_{2l} \Delta {SRR^B}_{t-l} + \sum_{l=1}^{p} \alpha_{2l} \Delta {BRR^S}_{i(t-l)} + \lambda_2 ECT_{t-1} + \varepsilon_{2t} \tag{4} $$

where:

- $\Delta {SRR^B}_t$ and $\Delta {BRR^S}_{it}$ are, respectively, the first differences for the *Sector Relative Return to Benchmark* and the i-th *Bank Relative Return to Sector* series;
- β_{10} and β_{20} are, respectively, the constant terms of the Equations (3) and (4);
- $\Delta {SRR^B}_{t-l}$ and $\Delta {BRR^S}_{i(t-l)}$ are, respectively, the delayed first differences for *Sector Relative Return to Benchmark* and for the i-th *Bank Relative Return to Sector* series;
- l is the number of lags;
- ECT_{t-1} is the Error Correction Term (ECT). It is defined as $ECT_{t-1} = {SRR^B}_{t-1} - \alpha - \gamma {BRR^S}_{i(t-1)}$, where γ is the cointegrating coefficient and α is the intercept of the cointegrating term. The ECT measures the deviations between the *Sector Relative Return to Benchmark* and the i-th *Bank Relative Return to Sector* at time $(t-1)$ with respect to the theoretical long-period equilibrium;
- λ_1 and λ_2 are the adjustment coefficients, which describe the adjustment speed to the long period equilibrium, meaning, the strength of correction from the series deviations back to the long-run relationship;
- ε_{1t} and ε_{2t} are, respectively, the error terms of the Equations (3) and (4).

In this model, the signs and significance of λ_1 and λ_2 (the adjustment coefficients) is the key point, as it allows one to determine which variable contributes to the adjustment process toward the long-period equilibrium, and which variable shows a faster move than the other one. The process can result in four possible cases[5]:

1. λ_1 is statistically significant and negative. This means that i-th *Bank Relative Return to Sector* series adjusts more rapidly than the *Sector Relative Return to Benchmark*. This means that the latter is trying to restore the long-run equilibrium;
2. λ_2 is statistically significant and positive. This means that the *Sector Relative Return to Benchmark* series adjusts more rapidly than the i-th *Bank Relative Return to Sector*. This means that the latter is trying to restore the long-run equilibrium;
3. λ_1 is statistically significant and negative and λ_2 is statistically significant and positive. In this case, both variables contribute to the adjustment process towards the long-run equilibrium. Following Gonzalo and Granger (1995), in order to evaluate the effective contribution of each variable in the adjustment process, in terms of the *Market Share* (*MS*)[6] concept, we can distinguish three subcases:
   - If $MS \approx 1$, then the *Sector Relative Return to Benchmark* variable is the leading (causing) variable and the i-th *Bank Relative Return to Sector* variable is the lagging (effected) variable;
   - If $MS \approx 0$, then the i-th *Bank Relative Return to Sector* variable is the leading (causing) variable and the *Sector Relative Return to Benchmark* variable is the lagging (affected) variable;
   - If $MS \approx 0.5$, then both variables contribute in the same way;
4. Only one of the adjustment coefficients is statistically significant and it presents the correct sign. Then, only the significant variable contributes to the adjustment process toward the equilibrium.

This concludes the first part. Allow us to introduce the second (and last) part of the whole analysis.

2.2. Rolling Regression

Based on these results, we can define y_t as the lagging (effected) variable and x_t the leading (causing) variable at time t. The second part of the analysis is then devoted to an OLS rolling (moving) window regression, to be performed, for each entity in the selected sample (i.e., $i = 1, \ldots, N$), as specified in the following Equation (5):

$$y_t = c_t + \beta_t x_t + \varepsilon_t \tag{5}$$

where:

- c_t is the constant at time t;
- β_t is the beta coefficient of regression at time t;
- ε_t is the error term at time t.

The *log–log* econometric specification allows (as variables express elasticities, i.e., returns calculated as natural logarithm ratios) one to transform a nonlinear model into a linear one, and to interpret a coefficient as the estimated percent change of the dependent variable due to a percent change in the independent variable.

3. Data Description

3.1. Euro Area General Framework

The increased pace of the expansive ECB monetary policy starting from 2014 was related to the fear of deflation. In June 2014, the ECB announced the Targeted Long-Term Refinancing Operation (TLTRO), preferential lending to banks (with an expiry date of four years for banks that respect the ECB rules) to support the real economy. In September of the same year, the policy rate level went down at 0.05% (Anelli et al. 2021). In January 2015, the ECB launched the Quantitative Easing (QE) strategy, one of the most powerful unconventional monetary policy tools to reduce the high-risk premium. In January 2015, indeed, the ECB announced an expanded Asset Purchase Programme (APP), a program of public and private sector securities for a monthly average of 60bn euro purchases, aimed to provide additional stimulus in a framework in which further cuts in short-term rates were constrained. These interventions put further downward pressure on long-term interest rates and flattened the yield curve's slope. At the same time, it led to a big expansion of the central bank's balance sheet (Hartmann and Smets 2018).

Notwithstanding the economic strengthening of 2016, the underlying inflation remained subdued. Therefore, in March 2016, the ECB reduced the policy rate to 0.00% (zero-lower bound on interest rates) and in December 2016, it extended the net APP until the end of 2017.

During 2018, the European economic growth smoothened from 2.5% in 2017 to 1.8% in 2018, while the headline inflation increased, averaging 1.7% over 2018. This mostly reflected the rise of energy prices and the negative effects of world trade protectionism (i.e., the US–China trade war). As a result, the Governing Council (anticipated to June 2018) reduced the monthly pace of net purchases under the APP to EUR 15 billion from September and ended the net purchases in December. In December, the Governing Council reviewed the economic outlook and concluded that the June assessment remained broadly accurate (European Central Bank 2019). Therefore, the APP led to a further expansion of the Eurosystem's balance sheet in 2018, although at a lower rate than in previous years.

After peaking in mid-2018, the global economy slowed down considerably within 2019, and the resulting growth rate fell below its historical average, reaching its lowest level since the global financial crisis (European Central Bank 2019). Against the background of a weakening of the Euro area economy, the Governing Council provided several rounds of additional monetary accommodation within 2019 (Figure 1). Specifically, the Governing Council confirmed its intention to continue reinvesting (in full) the principal payments from maturing securities purchased under the APP, for an extended period of time past the date when it started raising the key ECB interest rates and a new series of quarterly targeted, longer-term refinancing operations (TLTRO III) was announced. These operations would start in September 2019 and end in March 2021, and each operation would have a maturity of two years (European Central Bank 2019). The expansionary monetary policy, easing the banks' liquidity and funding, contributed to a substantial reduction of the idiosyncratic risk.

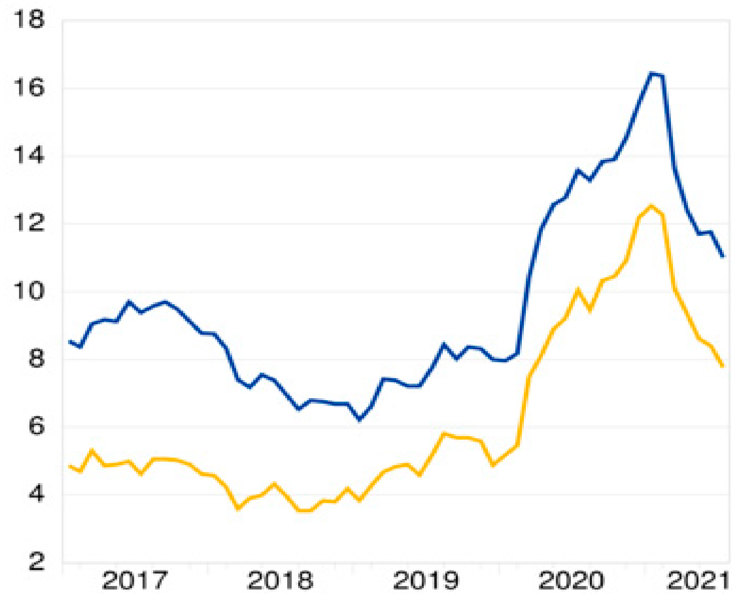

Figure 1. Euro monetary aggregates' M1 (blue) and M3 (yellow) annual growth rate. Source: ECB.

In the first half of 2020, the coronavirus pandemic shock (COVID-19) and the subsequent lockdowns struck the Euro area economy (European Central Bank 2020). Central bank liquidity in the banking system increased by EUR 2.2 trillion, introducing a temporary pandemic emergency purchase program (PEPP), relaxing eligibility and collateral criteria and offering new pandemic, longer-term refinancing operations (PELTROs). All this contributed to reducing risk premia and stabilizing the economy.

3.2. Data

To conduct the empirical investigation we use, for the common and the idiosyncratic component, the following dataset:

- $SI_t = EuroStoxx$ 50 $Banks\ Index$ at time t;
- $BS_{it} = Bank\ Stock\ Price$ for the i-th bank in the selected sample at time t;
- $BI_t = EuroStoxx$ 50 $Equal\ Weight\ Index$ at time t.

The sample of the selected Italian banks ($N = 5$) are the following:

- Intesa San Paolo;
- Unicredit;
- Banca Monte dei Paschi di Siena;
- Banco BPM;
- BPER Banca.

The considered banks represent more than 80% of the Ftse Italia All-Share Banks Index market capitalization. The *EuroStoxx 50 Equal Weight Index* represents our market benchmark because it gives equivalent Blue-chip representation of super sector leaders in the Eurozone, limiting the potential dependence on overweighted members. For all variables, we use daily closing prices (provided by Bloomberg) for the period of 2015–2021 (1827 observations) transformed in log returns. Table 1 reports the descriptive statistics of the variables.

Table 1. Descriptive statistics of SRR^B and BRR^S data: January 2015 to December 2021 (1827 observations).

Statistics	SRR^B	$BRR^S{}_{Intesa}$	$BRR^S{}_{Unicredit}$	$BRR^S{}_{Monte\ dei\ Paschi}$	$BRR^S{}_{Banco\ Popolare}$	$BRR^S{}_{BPER}$
Mean	−0.000427	0.000125	−0.000212	−0.002778	−0.000409	−0.000227
Median	−0.000802	0.000000	−0.000085	−0.001970	0.000000	−0.000341
Maximum	0.064980	0.068622	0.133033	0.331159	0.117850	0.169466
Minimum	−0.102873	−0.069129	−0.109237	−1.194854	−0.135432	−0.106444
Std. Dev.	0.010887	0.010526	0.014883	0.042432	0.021224	0.020546

Source: authors' calculations in Eviews on Bloomberg data.

Figure 2 shows the relative strengths, namely, the price performance of each bank stock compared with the sector index and the sector price performance compared with the market benchmark.

The concept of relative strength is very well-known and adopted operatively by many trading strategies such as *momentum investing* (Fernando 2022) in order to capture the alpha component of an investment. Figure 1, indeed, allows us to observe intuitively the different performance of each bank relative to the sector over time, simultaneously keeping in mind the outperformance/underperformance of the sector relative to the market benchmark. It is noteworthy that, since the beginning of Quantitative Easing (QE) by the European Central Bank (ECB) to the end of 2021, the European banking sector underperformed (negative trend) the market benchmark index, showing ongoing significant differences among the considered banks. (Only Intesa San Paolo shows a positive trend for the time span).

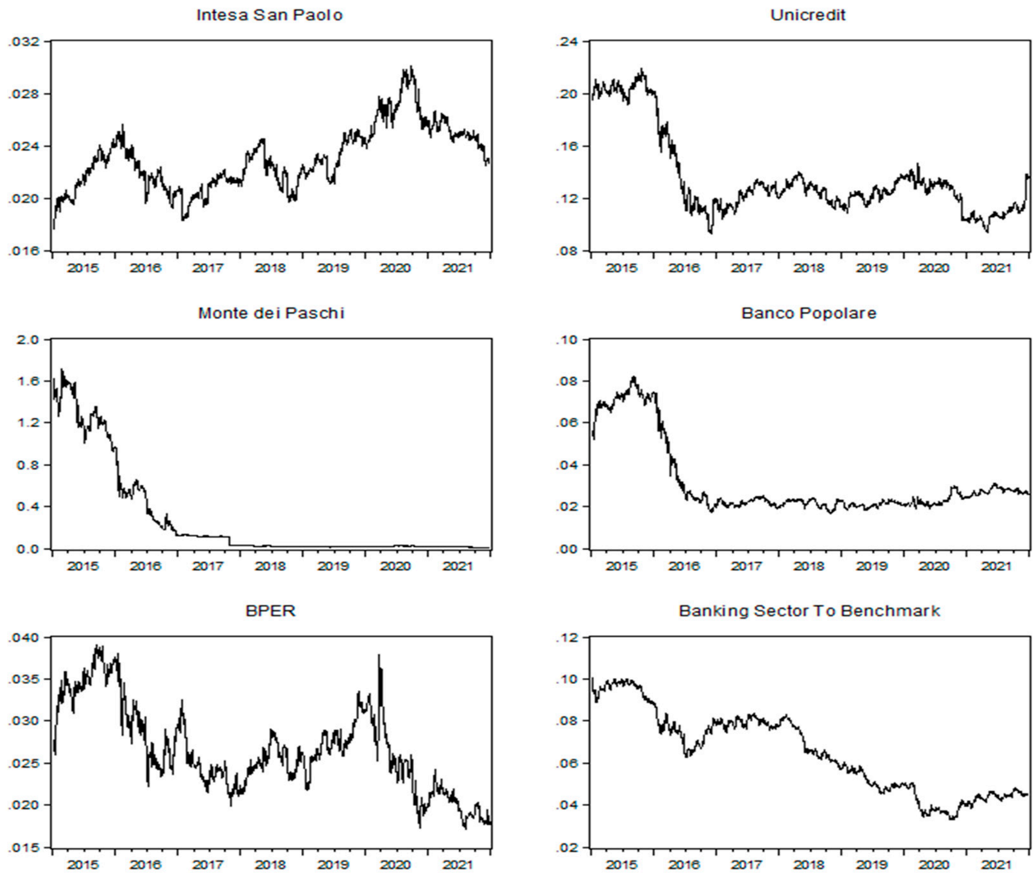

Figure 2. Relative strengths: January 2015 to December 2021. Source: authors'calculation in Eviews on Bloomberg data.

4. Empirical Findings

According to the first stage of the analysis, we evaluated the existence of cointegration between the two series through the Augmented Dickey–Fuller Test reported in Table 2.

Table 2. Augmented Dickey–Fuller Test: period of January 2015–December 2021.

Residuals	Intesa	Unicredit	Monte Dei Paschi	Banco BPM	BPER
t-Statistic	−41.71288	−41.50171	−41.44799	−41.06881	−41.46563
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

Source: authors' calculations in Eviews on Bloomberg data.

The test proves that the series are cointegrated. We can run the VECM to evaluate the leading–lagging variables and isolate the cause–effect relationship among them. As suggested by Liew (2004), we use Akaike's information criterion (AIC) as lag-length selection criteria in determining the autoregressive lag length. Table 3 reports the optimal lag length suggested by Akaike's information criterion for each series.

Table 3. AIC optimal lag length.

Lag Length	Intesa	Unicredit	Monte Dei Paschi	Banco BPM	BPER
Number	3	2	0	1	8

Source: authors' calculations in Eviews on Bloomberg data.

Since our aim is to isolate the cause–effect relationship, we only report the adjustment coefficients (λ_1 and λ_2) of the VECM estimation outputs in Table 4.

Table 4. VECM adjustment coefficients: period of January 2015–December 2021.

Adj. Coeff.	Intesa	Unicredit	Monte Dei Paschi	Banco BPM	BPER
λ_1	−0.005812 ***	−0.142740 ***	−0.090395 ***	−0.617247 ***	−0.035613
λ_2	0.031111 ***	0.674151 ***	1.070247 ***	0.873400 ***	0.653098 ***

Note: *** signals parameter significance at 1%. Source: authors' calculations in Eviews on Bloomberg data.

Table 4 shows that only λ_2 is statistically significant and positive while λ_1 is negative but not statistically significant for BPER. This means that the common shock (*Sector Relative Return to Benchmark*) is the causing variable because it adjusts more rapidly than the idiosyncratic shock (*Bank Relative Return to Sector*) in the specific case of BPER. Therefore, the latter (affected variable) moves in the direction of restoring the long-run equilibrium relationship. For all the other Italian banks, the reference variable becomes the *Market Share* (MS). Table 5 reports its estimation results.

Table 5. Market Share: period of January 2015–December 2021.

Market Share	Intesa	Unicredit	Monte Dei Paschi	Banco BPM
MS	0.84	0.83	0.92	0.59

Source: authors' calculations in Eviews on Bloomberg data.

Since $MS > 0.5$ for the whole sample, then, as the case of BPER, we can state that the common shock (*Sector Relative Return to Benchmark*) variable is the leading (causing) variable and the idiosyncratic shock (*Bank Relative Return to Sector*) variable is the lagging (effected) variable.

In order to add more color on the reading of the results, it could be useful to analyze the lead–lag relationship between the banking sector index and the relative stock market benchmark index. The idea is to test whether the banking sector induces market shocks or not, so as to assess if the phase of systemic risk coming from the banking sector is over. It can be obtained by performing a similar analysis as previously conducted (see Equations (3) and (4)), but considering the first differences for the *Banking Sector Return* and the *Stock Market Benchmark Return* series as main variables. In this way, it is possible to test the cause–effect relationship between the banking sector and the stock market benchmark index. Table 6 reports the estimations' results.

Table 6. VECM[7] adjustment coefficients: period of January 2015–December 2021.

Adj. Coeff.	Coefficient	Std. Error	t-Statistic	Prob.
λ_1	−0.437013 ***	0.084429	−5.176129	0.0000
λ_2	0.341257 ***	0.053634	6.362684	0.0000

Note: *** signals parameter significance at 1%. Source: authors' calculations in Eviews on Bloomberg data.

Once again, we have to calculate the *Market Share* (MS). Table 7 reports this information.

Table 7. Market Share: period of January 2015–December 2021.

Market Share	Value
MS	0.44

Source: authors' calculations in Eviews on Bloomberg data.

Since $MS < 0.5$, the results suggest that the market benchmark performance (*Stock Market Benchmark Return*) variable is the leading (causing) variable and the banking sector performance (*Banking Sector Return*) variable is the lagging (effected) variable. Therefore, during this period, the banking sector mostly suffers the global backdrop rather than producing market shocks. This also suggests that the phase of systemic risk coming from the banking sector is over (market beta[8] drives the banking sector performance), confirming the results found at the micro (idiosyncratic) level.

The previous results discussion needs a double-layer analysis, the first referring to the Euro area general framework, the second related to each considered bank-specific evolution.

Regarding the first layer, the first stage results highlight the common shock role as the causing variable of the banks' market performances, starting from the period of ECB's QE program. This empirical evidence is not surprising, as the high level of liquidity injected into the financial system induces a lower systemic sensitivity to contagion. The high level of bank reserves (fueled by the Central Bank monetary programs) and the parallel recapitalization process allows for the absorbing of potential contagion effects, which helps to minimize feedback loop risks (Zedda and Cannas 2020).

In fact, the market values of bank shares are affected by many other variables and effects, as it happens for all market values, but the capitalization level is of particular significance for the banking sector and is worth consideration in this study, while other variables are bank-specific, so would not be considered in the subsequent analysis.

The capital constraint is likely to have its most significant effect on bank lending and be particularly important for the lending channel of monetary policy (Peek and Rosengren 1995). Regarding capitalization, all the banks report a substantial growth in their TIER1 rate, which means a higher loss-absorbing capacity and thus a lower expected default probability. Thus, the previous analysis will be complemented by the analysis of each bank's main evolution, which included recapitalization programs and other specific events.

Since the economic environment tends to change considerably, it may not be reasonable to assume that a model's parameters are constant. Therefore, a rolling analysis of a time series model can be used to assess the model's stability over time (Zivot and Wang 2006). Figures 3–7 report the rolling beta coefficient[9], respectively, for Intesa, Unicredit, Monte dei Paschi, Banco BPM and BPER for the period of 2015–2021.

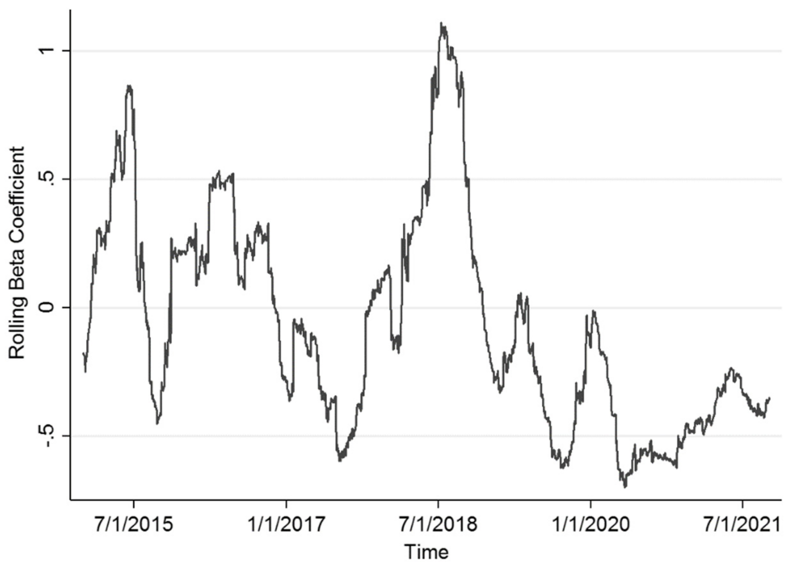

Figure 3. Common shock (rolling) impact on the *Intesa San Paolo* performance: period January 2015–December 2021. Source: authors' calculation in Stata on Bloomberg data.

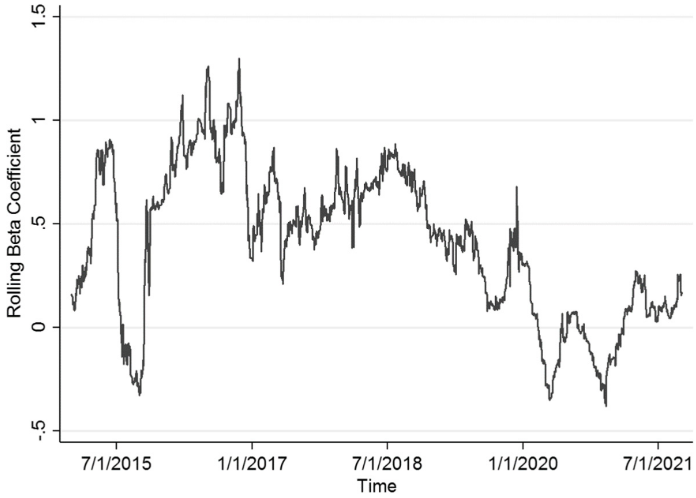

Figure 4. Common shock (rolling) impact on the *Unicredit* performance: period January 2015–December 2021. Source: authors calculations in Stata on Bloomberg data.

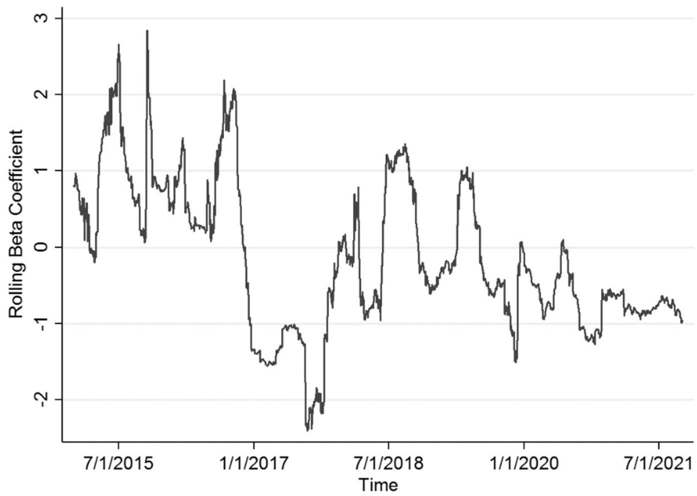

Figure 5. Common shock (rolling) impact on the *Monte dei Paschi* performance: period January 2015–December 2021. Source: authors calculations in Stata on Bloomberg data.

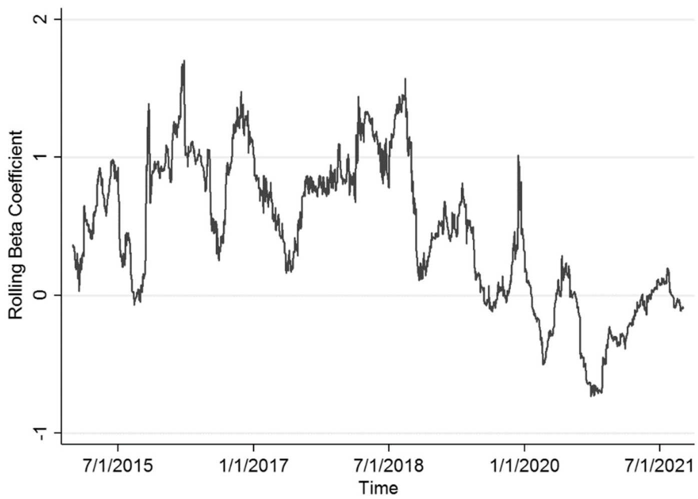

Figure 6. Common shock (rolling) impact on the *Banco BPM* performance: period January 2015–December 2021. Source: authors calculations in Stata on Bloomberg data.

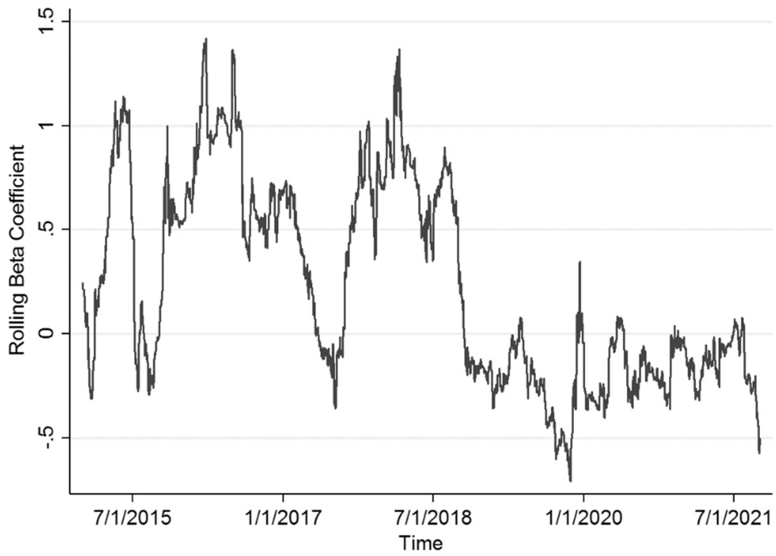

Figure 7. Common shock (rolling) impact on the *BPER* performance: period January 2015–December 2021. Source: authors calculations in Stata on Bloomberg data.

Rolling regression results suggest that, for the examined sample, the common shock impact tends to vary over time but follows a bearish main (long-term) trend. Moreover, there are phases in which it tends to go down in a meaningful way, such as during the second part of 2015, the first half of 2017, 2019 and in the second half of 2020, in which the Central Bank responded to financial markets turmoil by fueling it with further stimulant liquidity injections in order to reduce volatility. Data show its ability to reach this target by the dominant effect produced at the macrolevel by monetary policies in reducing and isolating local shock and its spread at a global level.

With reference to single banks' specific evolutions, in early 2017, Unicredit proceeded with a capital increase of EUR 13 billion (the fourth capital increase after the GFC[10]). Figure 4 shows the Unicredit shares' underperformance (perceived idiosyncratic risk) relative to the banking sector performance (perceived common risk) during this period. Just after the capital increase process, the Unicredit shares started to overperform the sector benchmark because of waning idiosyncratic risk. Similar evidence can be observed on Monte dei Paschi and BPER (neither Intesa San Paolo nor Banco BPM realized capital increases during the analyzed period).

During the first half of 2015, Monte dei Paschi realized a capital increase of EUR 3 billion, with the participation of the Italian government through a capital share equal to 4%. In the summer of 2016, Monte dei Paschi proposed another capital increase of EUR 5 billion unsuccessfully. At the end of 2016, the Italian government proceeded with a precautionary recapitalization of EUR 5.4 billion (plus EUR 2.7 billion of subordinated bonds converted into bank shares), allowing it to reach a capital share of 68%. Figure 5 shows the Monte dei Paschi shares' underperformance during these periods, followed by a relative overperformance in the periods immediately following the capital increases.

With reference to BPER, the bank approved a capital increase of EUR 0.802 billion in the last part of the year 2020, in order to acquire around 532 Intesa San Paolo branches. Figure 7 shows the described trend for BPER.

In more general terms, the higher capitalization affects both the idiosyncratic and the contagion risk component, and its effect is substantially higher for the contagion risk component, as demonstrated by Zedda and Cannas (2020). This means that, in the present analysis, each capitalization episode is expected to result in a lower incidence of the idiosyncratic component.

In the case of Intesa San Paolo and Banco BPM, no cases of capital increase occurred during the examined period. As for the previous banks' cases, other variables should be exploited for a better understanding of the whole ongoing process of the cause–effect relationship, but as these variables are mainly bank-specific, its analysis goes beyond the scope of this study.

5. Conclusions and Discussion

This paper analyzed the evolution over time of the incidence of common shocks on the main Italian banking groups. The analysis developed by means of a VECM model shows that the banking sector is no more perceived by the markets as a common risk source in overcoming the negative picture coming from the financial crisis of 2008–2009.

This is clearly in line with other studies based on capitalization and banks' assets riskiness, which documented the important effects of the new banking regulation issued after the GFC (Benczur et al. 2017).

In fact, the double layer is one which, on the one side, the introduction of a huge program such as QE tends to continuously dominate the market, thus reducing the relative importance of idiosyncratic effects; on the other side, the recapitalization process highly reduced the idiosyncratic and contagion risk coming from banks, thus contributing to the same reduction of its relative role.

Finally, our results show that the main banks' common risk is broadly affected by the ECB monetary policy, while the idiosyncratic risk is mainly driven by the recapitalization processes, which, each one from its own side, highly contributed to keeping the European banking and financial system sound and safe, and allowed it to face, with no hesitation, the COVID-19 crisis.

Author Contributions: Conceptualization, methodology, formal analysis, and writing: M.A., M.P., and S.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

1 Source: Borsa Italiana, www.borsaitaliana.it (accessed on 19 March 2022).

2 Source: World Bank, https://data.worldbank.org (accessed on 19 March 2022).

3 A moving window regression is performed considering a fixed-length subset (window) of a time series, and by shifting the window's starting point of a specified value each time.

4 "Shock" is an unexpected changing event that can have positive or negative effects on one or more correlated variables.

5 Theoretically, we can not exclude that λ_1 results in a positive value, and that λ_2 can have a negative value, but in these cases the process would result in the shock amplification, instead of the adjustment toward the long-run equilibrium.

6 The formula suggested by Gonzalo and Granger (1995) is the following: $MS = \frac{\lambda_2}{\lambda_2 - \lambda_1}$.

7 ADF test proves that the series are cointegrated. The AIC criterion suggests that the optimal lag length is 2.

8 When Equation (5) is applied to single shares as a function of the market index, it corresponds to the Capital Asset Pricing Model (Sharpe 1964). Similarly, the ongoing banking sector as a function of the market index can be interpreted as the banking sector beta.

9 They are statistically significant at the 0.05 level (there is less than a 5% probability that the null is correct).

10 Great Financial Crisis (GFC).

References

Adrian, Tobias, and Markus K. Brunnermeier. 2011. CoVaR, Federal Reserve Bank of New York Staff Reports No 348. Available online: https://www.newyorkfed.org/research/staff_reports/sr348.html (accessed on 19 March 2022).

Alexandridis, Antonios K., and Mohammad S. Hasan. 2020. Global financial crisis and multiscale systematic risk: Evidence from selected European stock markets. *International Journal of Finance & Economics* 25: 518–46.

Allen, Franklin, and Douglas Gale. 2000. Financial contagion. *Journal of Political Economy* 108: 1–33. [CrossRef]

Anelli, Michele, Michele Patanè, Mario Toscano, and Alessio Gioia. 2021. The Evolution of the Lead-lag Markets in the Price Discovery Process of the Sovereign Credit Risk: The Case of Italy. *Journal of Applied Finance & Banking* 11: 151–75.

Bekaert, Geert, Michael Ehrmann, Marcel Fratzscher, and Arnaud Mehl. 2011. *Global Crises and Equity Market Contagion*. NBER Working Papers 17121. Cambridge, MA: National Bureau of Economic Research, Inc. Available online: https://www.nber.org/papers/w17121 (accessed on 19 March 2022).

Benczur, Peter, Giuseppina Cannas, Jessica Cariboni, Francesca Di Girolamo, Sara Maccaferri, and Marco Petracco Giudici. 2017. Evaluating the effectiveness of the new EU bank regulatory framework: A farewell to bail-out. *Journal of Financial Stability* 33: 207–23. [CrossRef]

Blatt, Dominik, Bertrand Candelon, and Hans Manner. 2015. Detecting contagion in a multivariate time series system: An application to sovereign bond markets in Europe. *Journal of Banking & Finance* 59: 1–13.

Candelon, Bertrand, and Hans Manner. 2010. Testing for asset market linkages: A new approach based on time-varying copulas. *Pacific Economic Review* 15: 364–84. [CrossRef]

Choudhry, Taufiq, and Ranadeva Jayasekera. 2015. Level of efficiency in the UK equity market: Empirical study of the effects of the global financial crisis. *Review of Quantitative Finance and Accounting* 44: 213–42. [CrossRef]

Claeys, Peter, and Bořek Vašíček. 2014. Measuring bilateral spillover and testing contagion onsovereign bond markets in Europe. *Journal of Banking & Finance* 46: 151–65.

Dungey, Mardi, Renée Fry, Brenda González-Hermosillo, and Vance L. Martin. 2005. Empirical modelling of contagion: A review of methodologies. *Quantitative Finance* 5: 9–24. [CrossRef]

European Central Bank. 2019. Annual Report 2018. Available online: https://www.ecb.europa.eu/pub/annual/html/ar2018~{}d08cb4c623.en.html (accessed on 19 March 2022).

European Central Bank. 2020. Annual Report 2019. Available online: https://www.ecb.europa.eu/pub/annual/html/ar2019~{}c199d3633e.en.html (accessed on 19 March 2022).

Eichengreen, Barry, Ashoka Mody, Milan Nedeljkovic, and Lucio Sarno. 2012. How the subprime crisis went global: Evidence from bank credit default swap spreads. *Journal of International Money and Finance* 31: 1299–318. [CrossRef]

Engle, Robert F., and Clive W. J. Granger. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55: 251. [CrossRef]

Fernando, Fernando. 2022. Relative Strength. Investopedia. Available online: https://www.investopedia.com/terms/r/relativestrength.asp (accessed on 19 March 2022).

Forbes, Kristin J. 2012. *The "Big C": Identifying and Mitigating Contagion*. Working Paper. MIT Sloan Research Paper No. 4970-12. Available online: https://ssrn.com/abstract=2149908 (accessed on 19 March 2022).

Galliani, Clara, and Stefano Zedda. 2015. Will the bail-in break the vicious circle between banks and their sovereign? *Computational Economics* 45: 597–614. [CrossRef]

Gonzalo, Jesus, and Clive Granger. 1995. Estimation of Common Long-Memory Components in Cointegrated Systems. *Journal of Business & Economic Statistics* 13: 27–35.

Güth, Sandra, and Sven Ludwig. 2000. How helpful is a long memory on financial markets? *Economic Theory* 16: 107–34. [CrossRef]

Hartmann, Philipp, and Frank Smets. 2018. The First Twenty Years of the European Central Bank: Monetary Policy. ECB Working Paper No. 2219. Available online: https://ssrn.com/abstract=3309645 (accessed on 19 March 2022). [CrossRef]

Kaminsky, Graciela L., and Carmen M. Reinhart. 2000. On crises, contagion and confusion. *Journal of International Economics* 51: 145–68. [CrossRef]

Liew, Venus Khim-Sen. 2004. What lag selection criteria should we employ? *Economics Bulletin* 33: 1–9.

Metiu, Norbert. 2012. Sovereign contagion risk in the eurozone. *Economics Letters* 117: 35–38. [CrossRef]

Paltalidis, Nikos, Dimitrios Gounopoulos, Renatas Kizys, and Yiannis Koutelidakis. 2015. Transmission channels of systemic risk and contagion in the European financial network. *Journal of Banking & Finance* 61: 36–52.

Peek, Joe, and Eric S. Rosengren. 1995. Bank lending and the transmission of monetary policy. In *Conference Series*. Boston: Federal Reserve Bank of Boston, vol. 39, pp. 47–79.

Pericoli, Marcello, and Massimo Sbracia. 2003. A primer on financial contagion. *Journal of Economic Surveys* 17: 571–608. [CrossRef]

Sharpe, William F. 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance* 19: 425.

Vo, Dinh-Vinh. 2014. A coexceedance approach on financial contagion. Paper Presented at 21st Multinational Finance Society Conference, Prague, Czech Republic, June 28–July 2.

Zedda, Stefano. 2017. *Banking Systems Simulation: Theory, Practice, and Application of Modeling Shocks, Losses, and Contagion*. Hoboken: Wiley.

Zedda, Stefano, and Giuseppina Cannas. 2020. Analysis of banks' systemic risk contribution and contagion determinants through the leave-one-out approach. *Journal of Banking and Finance* 112: 105–60. [CrossRef]

Zivot, Eric, and Jiahui Wang. 2006. *Modeling Financial Time Series with S-PLUS*. New York: Springer.