Macroeconomic Dynamics (2026), **30**, e51, pp. 1–31
doi:10.1017/S1365100526101229

CAMBRIDGE UNIVERSITY PRESS

ARTICLE

The connectedness between sovereign risk and the banking sector

Gianluca Cafiso[1] and Giulia Rivolta[2]

[1]Dipartimento di Economia e Impresa, Università di Catania, Catania, Italy
[2]Dipartimento di Scienze Umane e Sociali, Università eCampus, Novedrate, Italy
Corresponding author: Gianluca Cafiso; Email: gianluca.cafiso@unict.it

Abstract

This study examines the relationship between sovereign spreads and bank shares in terms of risk transmission, using a sample of the largest Italian banks over the period 2003–2023. Our objective is to quantify and compare volatility spillovers and to investigate whether bank-specific characteristics help to explain them. We perform a dynamic connectedness analysis based on the Bayesian estimation of a vector autoregression with time-varying parameters. Our results suggest that, with the exception of the period of the euro area debt crisis, banks tend to transmit more spillovers than they absorb. Moreover, these spillovers are related to factors such as capital adequacy and the composition of banks' portfolios.

Keywords: Sovereign spread; banks; volatility; connectedness measures; spillovers; time-varying parameters; VAR

JEL classifications: G01; G21; E60; H12

1. Introduction

In the aftermath of the global financial crisis and in the midst of the euro area debt crisis, Acharya and others (Acharya et al. 2012, 2014; Acharya and Steffen, 2015) published a series of seminal papers on the relationship between banks and their sovereign in terms of risk transmission. Periods of turmoil in sovereign bond markets were judged to have the potential to destabilize banks in their jurisdiction, and across borders (Breckenfelder and Schwaab, 2018; Capasso et al. 2023). At the same time, large banks could destabilize their own sovereign. The bidirectional and mutually reinforcing nature of the sovereign-bank risk transmission is the cornerstone of this branch of literature.[1] This paper contributes by quantifying, comparing and explaining both directions of transmission. We believe this is crucial to understand contagion across sectors and for risk management both at the micro and macro levels.

In the first part, we compute Diebold and Yilmaz's (2012) connectedness measures at monthly frequency, through the estimation of a VAR model with time-varying parameters and stochastic volatility à la Koop and Korobilis (2013). In details, we quantify the spillovers from the sovereign to the banking sector, as well as the reverse spillovers from the banking sector to its sovereign. Our dataset contains the 10-year sovereign bond yield spread and bank share prices of the seven largest Italian banks; we use monthly realized volatility as a measure of risk. We focus on Italy because it has a large public debt, which accounts for a large portion of banks' assets. These are the main elements of the "diabolic loop" described by Brunnermeier et al. (2011, 2016), Acharya et al. (2014) and, more recently for Italy, by Cafiso et al. (2025). Moreover, Italy has a significant

© The Author(s), 2026. Published by Cambridge University Press. This is an Open Access article, distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike licence (https://creativecommons.org/licenses/by-nc-sa/4.0), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the same Creative Commons licence is used to distribute the re-used or adapted article and the original article is properly cited. The written permission of Cambridge University Press or the rights holder(s) must be obtained prior to any commercial use.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

number of systemically important banks with sufficiently long historical data. This allows a more detailed analysis of the relationship between sovereign risk and the banking sector, as well as a better exploration of the role of individual bank characteristics.

Contrary to common perception, and some previous conclusions on this topic (Erce, 2020), our results show that the sovereign receives more spillover from banks than it transmits to them for most of the sample period. This means that sovereign risk is more often fed by volatility that originates in the banking sector rather than the other way around. The only exception is the period between mid-2011, which marks the beginning of the second phase of the euro area debt crisis, and the end of 2012, after several interventions by the ECB aimed at containing financial market tensions. Additionally, we conduct an event-study analysis that shows how spillovers change in response to key economic events and that policies designed to reduce them can be effective.

In the second part, we investigate some specific factors at the bank level that potentially can amplify or mitigate the observed spillovers. Building on the insight that banks' balance-sheet structure plays a key role, we relate spillovers from the sovereign to banks, and vice versa, to banks' balance-sheet data. Overall, our results indicate that capital adequacy acts as a key buffer, limiting both the propagation and the absorption of spillovers. Moreover, the composition of banks' assets matters: a higher weight of securities is associated with stronger spillovers, while more traditional lending mitigates them.

In short, the contribution of our research to the existing literature is to document both the size and the direction of spillovers between the banking sector and its sovereign by applying a methodology never used in this field with bank-level data. Furthermore, we show how these spillovers evolve in response to major events and we provide evidence that policy measures designed to reduce them can be effective. Most importantly, we demonstrate that the strength of the spillovers is shaped by banks' idiosyncratic characteristics. By focusing on spillover intensity rather than credit quantities, our findings complement existing evidence on the bank lending channel (e.g. Gennaioli et al. 2018; Bottero et al. 2020) and provide new insights into how banks' balance-sheet structure shapes the sovereign–bank nexus.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology and the data used. Section 4 shows the results of the dynamic connectedness analysis. The regression analysis to study how much the transmission of spillovers is related to bank-specific variables is in Section 5. Section 6 concludes.

2. Literature review

Our research draws on two different strands of literature. The first examines the relationship between sovereign risk and the financial sector of the economy, while the second is methodological and relates to the approach of Diebold and Yilmaz (2009). The so-called *sovereign-bank nexus* has been modeled since Acharya et al. (2012, 2014) and it is the object of a growing literature, which has gradually expanded to identify all transmission channels between sovereigns and banks in both directions. Using a bibliometric analysis, Bajaj et al. (2022) show that studies on sovereign credit risk started to pick up in 2005 and, not surprisingly, gained momentum from 2012 onwards. Feyen and Zuccardi Huertas (2019); Kund et al. (2025) confirm the relevance of this topic by showing that the sovereign-bank nexus is growing since, globally, banks have increased their exposure to sovereigns over the past decade.

The literature has provided several possible explanations for the link between the banking sector and sovereign risk. In their seminal contribution, Acharya et al. (2014) argue that during periods of financial distress, bank bailouts aimed at stabilizing the economy require substantial public spending, thereby increasing government debt and the perceived risk associated with government liabilities, which are largely held by banks.[2] Brunnermeier (2011; 2016) were among the first to emphasize the "diabolic loop" linking sovereign and bank solvency risks, which arises from balance-sheet effects driven by the substantial exposure of European banks to their own

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

government bonds. Farhi and Tirole (2018) provide a theory for such a "doom loop," formalizing how sovereign risk increases either because of the budgetary impact of lower growth or because of bailout expectations. Leonello (2018) builds a model to explore the role of government guarantees in triggering the feedback loop between banking and sovereign debt crises. ECB (2016) notes that rising sovereign credit risk can also affect banks through the funding channel. As a country's creditworthiness declines, funding conditions tighten and banks, especially those dependent on wholesale markets, face higher funding costs.[3]

The central role of banks' balance sheet in transmitting sovereign distress to the real economy has been documented empirically by Gennaioli et al. (2018). Using bank-level data for more than 20,000 banks across 191 countries and 20 sovereign default episodes, the authors show that banks with higher exposure to government bonds experience a significantly larger contraction in lending relative to less exposed banks during sovereign default episodes. Focusing on Italy, Bottero et al. (2020) exploit loan-level data around the 2010 Greek bailout and show that banks with higher pre-crisis exposure to sovereign debt reduced credit supply significantly more than less exposed banks. At the macroeconomic level, Palmen (2020) provides complementary evidence using a structural panel VAR for several euro area countries. The study shows that increases in sovereign default risk lead to persistent declines in bank lending and economic activity. More recently, Cafiso et al. (2025) focus on Italy and show that a spread shock generates valuation losses in banks' bond portfolios, forcing banks to deleverage and reduce lending. These findings support a credit supply channel that has contractionary effects on output and, in turn, deteriorates public finances, generating a self-reinforcing vicious cycle.

Several contributions provide explanations of why the sovereign-bank nexus has expanded. Altavilla et al. (2017) analyze the determinants of banks' sovereign exposures and document that public banks' purchases of government bonds increased significantly around major ECB liquidity injections, partly reflecting moral suasion by national governments. Related evidence is provided by Becker and Ivashina (2018), who show that during the European sovereign debt crisis governments increasingly relied on domestic banks to absorb public debt. This crowded out corporate lending, particularly in crisis countries, consistent with a form of financial repression and moral suasion. However, Rivolta (2014) showed heterogeneous consequences across countries, as she finds that ECB liquidity injections led to an increase in market spreads for lower-rated euro area countries due to flight-to-safety behavior, so that positive effects from the banking sector to sovereign debt only materialized for higher-rated countries.

Several studies document that the transmission of risk between sovereign bonds and the banking sector is also across countries (Popov and Van Horen, 2015; Breckenfelder and Schwaab, 2018; Capasso et al. 2023). More closely to our framework, Fernández-Rodríguez et al. (2015) suggest that slightly more than half of the total variance of forecast errors is explained by cross-country shocks rather than idiosyncratic shocks. Antonakakis and Vergos (2013) examine the evolution of bond yield spread spillovers in the euro area during the Great Financial Crisis and euro area debt crisis, distinguishing between core and peripheral countries. They show that spillovers within these two groups are larger than spillovers across groups, and that spillovers explain a relevant fraction of the forecast error variance. A wider international perspective is adopted by Bostanci and Yilmaz (2020) who estimate the global network structure of sovereign credit risk.[4]

The methodology we employ was developed by Diebold and Yilmaz (2009). In the last decade, it has been applied with different variations to study contagion in different fields, including the link between sovereign risk and the credit sector. The key innovation in the Diebold and Yilmaz (2009) approach consists in the design of a connectedness analysis based on the notion of forecast error variance decomposition obtained from a VAR model identified with the Cholesky decomposition. Diebold and Yilmaz (2012) improve on Diebold and Yilmaz (2009) by making the output independent from the order of the variables through the generalized approach of Koop et al. (1996) and Pesaran and Shin (1998). Diebold and Yılmaz (2014) interpret the connectedness measures of Diebold and Yilmaz (2012) as representing a network structure. Along this line,

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Le et al. (2022) have recently used connectedness measures to understanding the global financial network for sovereign debt. Antonakakis et al. (2020), like us, develop a dynamic connectedness analysis by means of a large time-varying parameters VAR estimated with the algorithm of Koop and Korobilis (2013).[5] Apostolakis et al. (2022) is close to us both in terms of methodology and objective, as they use conditional correlation analysis and dynamic connected analysis. Their study examines the dynamics of spillovers across G7 countries and identifies which national banking sectors act as primary transmitters and receivers of financial instability. Another work applying Diebold and Yilmaz's (2012) approach in a dynamic way, but to study how financial risk spreads across global stock markets is Yu et al. (2024). They investigate the channels of risk contagion combining multiple factors such as financial opening, international trade and cross-border capital flows.

3. Methodology and data

The methodology used to quantify the spillovers between the sovereign spread and banks' share price is described in this section. Spillovers are calculated using Diebold and Yilmaz's (2012) connectedness analysis (hereafter DY12), which is based on the estimation output of a Bayesian VAR with time-varying parameters and heteroskedasticity. The DY12 approach involves first estimating a VAR to obtain the forecast error variance decomposition (hereafter FEVD). This FEVD is then used to compute the connectedness measures. We underline that the DY12 method is designed and applied solely to quantify connectedness, not to control for or explain its origin. Indeed, we address such a task in a further section (5) of this work through regression analysis. In what follows, we first describe the estimation of the VAR and then briefly review the DY12 connectedness measures.

3.1. VAR estimation

The simplest approach to obtain time-varying connectedness measures is to estimate the VAR model over a rolling window (see Diebold and Yilmaz, 2012). Rather, we use a large time-varying parameters VAR model (hereafter TVP-VAR) estimated using Bayesian methods. Indeed, it is more robust as the results do not depend on the arbitrarily-chosen size of the rolling window and no observations are lost, the TVP-VAR technique is less sensitive to the presence of outliers than other methods, and Bayesian estimation makes it possible to avoid the curse of dimensionality present in VAR models with many variables.

Our model consists of eight monthly variables, it is estimated over the period 2003–2023, and six lags are included to capture the dynamics in the data.[6] We estimate it applying the methodology of Koop and Korobilis (2013), who use the Kalman filter with forgetting factors to substantially reduce the computational burden. This approach was first applied to a VAR model by Doan et al. (1984). More recently, Koop and Korobilis (2013) have developed an algorithm to estimate large TVP-VAR models and to perform model selection based on forecasting accuracy. More specifically, forgetting factors can be used to obtain analytical formulae for the posterior of the coefficients, so that no MCMC algorithm is needed. We refer to their paper and the papers cited therein for a detailed discussion of the methodology. In the following, we focus on the main features necessary to describe our setup.

A VAR model with time-varying parameters can be written in state-space form as follows:

$$\begin{aligned} y_t &= X_t \beta_t + \varepsilon_t, \\ \beta_t &= \beta_{t-1} + u_t, \end{aligned} \tag{1}$$

where y_t is a $(N \times 1)$ vector of endogenous variables, X_t is a $(N \times k)$ matrix containing a constant and the lags of the endogenous variables, β_t are the coefficients that evolve over time following

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

an AR(1) process, ε_t is i.i.d. $N(0, \Sigma_t)$ and u_t is i.i.d. $N(0, Q_t)$. The matrices Σ_t and Q_t are time-varying as well and determine, respectively, heteroskedasticity in the residuals of the VAR model and the degree of time variation in the coefficients.

Classical estimation methods are based on the Kalman filter and smoother, and Gibbs sampling to draw recursively from the conditional distributions of the model's parameters, as explained in Koop and Korobilis (2010). MCMC methods would be necessary as there is no analytical solution for the posterior distribution of the parameters. On the other hand, forgetting factors modify the Kalman filter equations replacing Σ_t and Q_t with estimates so that analytical formulae for the posterior of β_t exist. More in details, the Kalman filter allows to compute the filtering and the prediction densities of the parameters β, conditional on the observations through time t, y^t:

$$\beta_t | y^t \sim N\left(\beta_{t|t}, V_{t|t}\right),$$
$$\beta_{t+1} | y^t \sim N\left(\beta_{t+1|t}, V_{t+1|t}\right).$$

The standard formula for the variance-covariance matrix of the coefficients in the prediction step is: $V_{t+1|t} = V_{t|t} + Q_t$. This equation can be approximated including a forgetting factor λ $(0 < \lambda \leq 1)$ as follows:

$$V_{t+1|t} = \frac{1}{\lambda} V_{t|t}.$$

The parameter λ allows to avoid the estimation or simulation of Q_t and implies that the observation j periods in the past has weight λ^j in the filtered estimate of β_t. The model also considers heteroskedastic error terms by modeling volatility with an Exponentially-Weighted Moving Average as follows:

$$\hat{\Sigma}_t = \kappa \hat{\Sigma}_{t-1} + (1 - \kappa) \hat{\varepsilon}_t \hat{\varepsilon}_t'.$$

This equation stipulates that the covariance matrix of the measurement error is a weighted average of its lags and the residuals of the measurement equation.

In this setup, prior information is required only for the parameters β. As in Koop and Korobilis (2013), we use a Normal prior that is similar to a Minnesota prior, with mean zero and variance-covariance matrix that depends on only one shrinkage parameter γ. The hyperparameters of the prior are initialized using a pre-sample of three years of data, from January 2000 until December 2002.

Overall, the estimation requires the selection of the parameters λ, κ and γ . Koop and Korobilis (2013) select optimal values for these parameters and the VAR dimensionality, with a dynamic model selection algorithm that is based on forecasting accuracy. In our application, we do not need to perform model selection across variables and since the dynamic selection procedure increases the computational burden significantly, we rely on a simpler setting: we choose the remaining parameters as in Koop and Korobilis (2012). More specifically, the forgetting factor λ is set to 0.99, this value introduces a low degree of time-variation in the coefficients as it is close to the constant-coefficient case $\lambda = 1$. The decay factor for the volatility κ is set to 0.96 following Longerstaey and Spencer (1996), and the parameter governing the prior shrinkage γ is set to 0.99 following Raftery et al. (2010).[7]

3.2. Diebold-Yilmaz connectedness analysis

Diebold and Yilmaz (Diebold and Yilmaz, 2009, 2012; Diebold and Yılmaz, 2014) have proposed several connectedness measures to analyze interdependence across a set of variables. Their methodology has been widely adopted, with recent applications in the study of systemic risk and network analysis (Diebold and Yilmaz, 2023). We first provide a simple intuition of their technique, more details follow.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Given a set of variables, the DY12 approach allows to evaluate how much a shock to one variable, comparatively, impacts itself and the others, thus creating a hierarchy of effects between the variables considered. Those effects are called spillovers and are quantified with specific connectedness measures. Diebold and Yılmaz (2014) interpret the size of the spillovers between two variables as the strength of the connection between two nodes of a network. Importantly, the set of variables is not chosen with the intention of explaining one of the variables with the others and vice versa, but merely to examine their relationship in terms of spillovers. The shocks are not structural as they are identified using the generalized approach of Koop et al. (1996) and Pesaran and Shin (1998). They are derived from the historical correlations but the contemporaneous relationships are not explicitly modeled. Therefore, no causal interpretation can be ascribed to the spillovers and, as in the original version of DY12 approach, there is no room to disentangle across their possible sources.

The connectedness measures are based on the generalized FEVD obtained from the estimation of a VAR model. This technique quantifies the portion of the forecast error variance of each variable that can be ascribed to shocks to the other variables over different time horizons. The starting point of the analysis is the estimation of a covariance-stationary VAR model:

$$y_t = \alpha + \sum_{l=1}^{P} B_l y_{t-l} + \varepsilon_t \quad \varepsilon_t \sim N(0, \Sigma), \tag{2}$$

where y_t is a N-variable vector and α, B and ε_t are conformable vectors and matrices of coefficients, and i.i.d. shocks, respectively. This model can be inverted to obtain its moving-average representation: $y_t = \sum_{l=1}^{\infty} A_l \varepsilon_{t-l}$. Here, $A_l = \sum_{i=1}^{P} B_i A_{l-i}$ are the coefficients from which one can derive impulse-response functions, the FEVD and the historical decomposition. In principle, these coefficients can be obtained after identifying the shocks in the system. As above-mentioned, Diebold and Yilmaz (2012) propose to overcome the identification problem relying on the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998). In this framework, the H-step ahead generalized FEVD from variable j to variable i is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_j\right)}, \tag{3}$$

where σ_{jj} is the standard deviation of the error term for equation j and e_i is a selection vector with one as i th element. Since the variance shares do not sum to one, they are normalized as follows:

$$C_{i \leftarrow j}^{H} \equiv \widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{4}$$

The measures in eq. (4) can be interpreted as percentage shares: they quantify how much each shock contributes to the forecast error variance of all variables in the model, creating a hierarchy of effects. These measures can be summarized in a connectedness table, which shows pairwise connectedness to and from each variable in the model, and total connectedness to and from others, calculated as the sum of the rows and columns (see Table 2). More in details, total connectedness to others and from others are, respectively:

$$C_{\cdot \leftarrow j}^{H} = \sum_{i=1, i \neq j}^{N} C_{i \leftarrow j}^{H}, \quad C_{i \leftarrow \cdot}^{H} = \sum_{j=1, i \neq j}^{N} C_{i \leftarrow j}^{H}. \tag{5}$$

The index of total connectedness is the average of the off-diagonal elements of the connectedness table:

$$C^{H} = \frac{1}{N} \sum_{i,j=1, i \neq j}^{N} C_{i \leftarrow j}^{H}. \tag{6}$$

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

In our analysis, we focus on $C^H_{i\leftarrow j}$ and on $C^H_{j\leftarrow i}$, the connectedness from the sovereign spread to each bank's shares, and vice versa, to which we refer as *spillStB* and *spillBtS* respectively. We also use their directional aggregation, $C^H_{\cdot\leftarrow j}$ and $C^H_{i\leftarrow\cdot}$, to which we refer as *TspillStB* and *TspillBtS* respectively. Spillover and connectedness are synonyms in this context. Since all variables enter the VAR in terms of volatility, we study volatility spillovers.

3.3. Data

Our analysis is based on two sets of data. The first consists of daily series: i) the share price of the banks in our sample, ii) the yield to maturity of the 10-year benchmark bond of Italy and Germany. These data come from Datastream. Daily data are aggregated to obtain monthly variables, as explained below. These variables are used for the analysis in the first step, which consists in estimating the VAR model and calculating the DY12 connectedness measures.

The second is a quarterly dataset of balance-sheet variables for the Italian banks object of our investigation. It serves for our regression analysis in the second step, in which we aim to understand how much the spillovers from the sovereign spread to the banks (spillStB), and their opposite (spillBtS), are related to bank-specific characteristics; the source is Standard & Poor's Capital IQ.

In the following, we first motivate the sample of Italian banks used for the analysis, then describe the variables used to apply the DY12 methodology, and finally list the variables included in the regression analysis in the second step. The period under analysis is 2003–2023, for which we use data starting from 2000. The DY12 analysis in the first step is based on daily data and provides monthly measures of connectedness. These are later averaged quarterly to match the banks' balance sheet data and to run the regression analysis at a quarterly frequency in the second step.

Sample of banks

We started with the sample of Italian listed banks for which share price series were available since 2000. Among these, we restricted the focus to banks supervised by the ECB, i.e. systemically important institutions. This resulted in eight banks, but we had to exclude Monte dei Paschi di Siena due to serious inconsistencies in its share price series over the period considered.[8] Eventually, our sample includes: (1) Banca Popolare di Sondrio, (2) Banco BPM, (3) BPER Banca, (4) Credem, (5) Intesa Sanpaolo, (6) Mediobanca, (7) Unicredit. The list of these banks, together with summary statistics of the balance sheet variables taken into account, can be found in Table 1.

Variables for DY12 analysis

We derive the DY12 connectedness measures, i.e. the spillovers, using the realized volatility of returns. As regards shares, returns are computed directly as the logarithmic difference of daily prices P^s_t:

$$r^S_t = log\left(P^S_t/P^S_{t-1}\right). \tag{7}$$

As for government bonds, to ensure consistency across asset classes, we work also with returns computed on prices derived from bond yields. First, we calculate the sovereign spread between the Italian (Y^{IT}_t) and the German (Y^{DE}_t) 10-year government bond yields: $Y^B_t = Y^{IT}_t - Y^{DE}_t$. Second, we retrieve bond prices applying the well-known formula that links the price of a zero-coupon bond to its yield, using the spread as follows:

$$P^B_t = \frac{100}{\left(1 + Y^B_t\right)^n}, \tag{8}$$

where Y^B_t is in decimal units and $n = 10$ since we consider the 10-year benchmark bond. In this way, we obtain the price of a *synthetic* bond that represents the price of Italian sovereign risk. Then, we use it to compute its return $\left(r^B_t\right)$ with eq. (7), as done for share prices.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 1. Italian banks, summary statistics of balance-sheet ratios

BPER	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	10.823	0.465	1.657	12.868	1.833	8.615	76.026	2,582.130
median	9.797	0.360	1.589	12.199	1.916	9.409	76.868	2,379.790
stand.dev	3.025	0.603	0.621	6.926	0.247	4.825	6.589	814.636
min	6.710	−1.102	0.645	2.013	1.355	2.674	54.072	1,169.430
max	15.020	3.431	5.562	23.334	2.307	20.761	85.516	4,697.910
obs	80	82	84	64	84	84	84	84
BP Sondrio	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.206	0.485	1.556	9.500	1.454	5.180	75.142	1832.020
meadian	10.460	0.547	1.212	10.773	1.456	2.948	75.530	1682.600
stand.dev	2.798	0.377	1.286	5.213	0.076	5.199	4.943	649.320
min	7.590	−1.264	0.501	2.197	1.300	1.413	59.773	661.020
max	16.750	1.338	8.047	16.980	1.679	27.434	83.937	3,963.840
obs	83	78	82	42	84	84	84	84
Banco BPM	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.444	0.272	9.106	12.030	2.387	8.404	68.307	4,395.550
meadian	11.860	0.336	1.306	8.721	2.321	6.573	67.386	4,086.670
stand.dev	3.560	1.626	19.205	7.668	0.661	6.845	5.776	2,097.850
min	5.160	−5.959	0.569	1.802	1.392	1.232	52.157	1815.640
max	16.710	9.007	76.797	26.467	3.573	25.557	80.369	11,749
obs	73	82	84	78	84	84	84	84
Credem	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	10.689	0.551	12.268	3.532	2.017	17.045	62.662	1930.960
meadian	10.040	0.467	1.367	3.198	2.039	15.417	62.331	1858.770
stand.dev	2.834	0.332	36.474	1.938	0.303	9.748	5.219	548.110
min	6.600	−0.157	0.726	0.442	1.469	0.281	51.809	955.277
max	15.070	1.772	146.93	6.722	2.728	34.272	79.791	3,314.930
obs	83	84	84	81	84	84	83	84
Intesa SP	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.814	0.365	1.730	9.406	2.395	16.065	56.634	34,581.600
meadian	12.180	0.446	1.204	9.443	2.455	16.970	56.732	34,464.300
stand.dev	3.510	1.033	1.828	4.742	0.338	9.919	6.846	12,562.100
min	6.300	−6.169	0.294	2.087	1.668	0.990	45.953	12,315.700
max	16.900	3.259	10.956	17.937	3.231	31.430	73.446	69,043.000
obs	84	83	84	79	83	83	83	84
Mediobanca	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	13.396	1.009	2.444	3.172	5.210	11.956	54.557	7,764.840
meadian	13.125	0.978	1.141	3.083	4.320	11.436	53.914	7,468.930
stand.dev	2.182	0.870	3.494	1.679	3.069	4.755	5.323	2,616.580
min	10.180	−1.241	0.239	0.891	1.271	4.593	44.610	2,913.870
max	18.260	3.380	24.012	6.737	16.393	25.346	68.783	14,667.200
obs	80	80	84	71	84	84	84	84

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 1. Continued

Unicredit	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.508	0.229	1.795	8.098	1.744	10.453	63.456	32,777.000
meadian	11.120	0.380	1.368	6.730	1.689	9.277	63.322	27,854.500
stand.dev	3.970	1.311	1.557	4.010	0.311	5.302	5.323	14,864.900
min	5.740	−6.613	0.700	2.382	1.278	2.366	52.236	12,971.600
max	19.170	1.852	8.337	16.160	2.339	20.759	72.440	76,698.700
obs	83	84	84	84	84	84	84	84
Total	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.551	0.480	4.375	8.207	2.434	11.094	65.274	12,266.300
meadian	11.425	0.466	1.312	5.960	1.993	9.638	65.522	4,093.450
stand.dev	3.264	1.012	16.148	6.101	1.684	7.990	9.655	15,583.800
min	5.160	−6.613	0.239	0.442	1.271	0.281	44.610	661.020
max	19.170	9.007	146.93	26.467	16.393	34.272	85.516	76,698.700
obs	566	573	586	499	587	587	586	588

Notes: CAR is the capital-asset ratio, ROA is return on assets, OEI is operating expenses to non-interest income, NPL is the non-performing loans ratio, TAD is total assets to deposits, ISA is investments in securities to total assets, GLA is gross loans to total assets, MKV is market value.

For both asset classes, realized volatility at monthly frequency is computed as the arithmetic average of squared returns:

$$RV_m = \frac{1}{D_m} \sum_{t=1}^{D_m} \left(r_t^i\right)^2, \tag{9}$$

where r_t^i is the return of shares or bonds ($i = S, B$) and D_m is the number of days t in month m. In contrast to daily prices, daily returns provide dynamic information related to price changes over one day. Realized volatility (RV) is a popular statistical measure used in finance to quantify the variability of asset returns over a specific period, based on actual observed data.[9] Since VAR models are based on normality assumptions, we take the log of realized volatility to normalize its distribution.[10]

The realized volatility of bank and sovereign returns is included as a dependent variable in the VAR model described in the previous subsection.

Bank's balance-sheet variables for the regression analysis

Our regression analysis in the second part is intended to help to explain the spillover from the sovereign spread to banks, and vice versa. We use balance-sheet variables for the seven banks under investigation and, as mentioned above, the source of data is S&P Capital IQ.[11] To avoid data inconsistencies related to banks' mergers and acquisitions, we consider only variables in terms of ratios, plus each bank's market capitalization.

Our primary focus is on the capital-asset ratio as it is a measure of bank's resilience to adverse shocks. Overall we use the following variables at a quarterly frequency: (1) the capital-asset ratio, CAR, in which the numerator is Tier 1 capital, as an indicator of capital adequacy; (2) return on assets, ROA, as an indicator of income performance; (3) operating expenses over non-interest income, OEI, to account for operational efficiency; (4) non-performing loans over total loans, NPL, as an indicator of asset quality; (5) total assets over deposits, TAD, as an indicator of the source of financing; (6) investments in securities over total assets, ISA, and (7) gross loans over total assets, GLA, both to account for the portfolio composition; (8) the market value, MKV, as an indicator of size and each bank's relevance. Table 1 reports summary statistics of these variables for each bank in our sample, a more detailed discussion of their use in the context of our regression analysis is in Section 5.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 2. Dynamic DY12 output

	Spread IT	Intesa SP	Unicredit	BPER	Banco BPM	BP Sondrio	Credem	Mediobanca	FROM OTH.S
Spread IT	51.679	9.138	7.285	5.246	6.643	5.927	5.485	8.599	48.321
Intesa SP	6.635	35.583	15.061	7.263	10.431	5.917	9.633	9.477	64.417
Unicredit	5.482	14.202	31.399	7.512	13.414	6.345	10.889	10.757	68.601
BPER	4.616	8.478	9.180	42.801	11.228	8.445	6.588	8.664	57.199
Banco BPM	5.154	10.410	14.317	9.759	33.483	6.463	10.487	9.926	66.517
BP Sondrio	5.902	7.635	8.997	9.375	8.429	45.795	5.900	7.968	54.205
Credem	4.845	10.891	12.997	6.653	11.727	5.102	37.752	10.034	62.248
Mediobanca	7.016	9.889	12.099	7.839	10.199	6.364	9.416	37.179	62.821
TO OTHERS	39.650	70.642	79.936	53.647	72.071	44.563	58.399	65.423	60.541
NET	−8.671	6.225	11.335	−3.552	5.553	−9.642	−3.850	2.602	
Background estimation: Time-varying parameters VAR. 1-month FEVD used for calculations.									

4. Connectedness analysis: Spillovers between the sovereign and banks

This section presents the results of DY12 connectedness analysis. We focus on measures of connectedness, i.e. *volatility spillovers*, computed at the 1-month horizon. Although no relevant difference emerges with respect to the 3-month horizon, we believe that spillovers in high-frequency financial markets are particularly relevant in the short run, as their longer-term effects may blend with other events or fade away. To better understand the evolution of the spillovers, and to relate them to key economic events, we examine them also in an event study based on univariate autoregressive models.

4.1. Dynamic connectedness

We start with an overview of the connectedness measures derived from the estimation of the TVP-VAR described in Section 3.1. The TVP-VAR yields connectedness measures at each point in time, we summarize them in Table 2 through their arithmetic average as in Antonakakis et al. (2020); values are for the 1-month horizon of the FEVD. Table 2 is organized in the usual DY12 way: it contains both directional spillover (from i to j) as well as total-to (from i to $\sum j$) and total-from (from $\sum j$ to i) by rows and columns. Values in the table are to be read as the percentage of the forecast error variance of variable i explained by shocks to variable j.

The first important result from the table is that the sovereign spread is a net receiver; meaning that the contagion from banks to the spread (48.32) is on average higher than from the spread to banks (39.65) and the difference is statistically significant.[12] The largest contributors are major banks, e.g. Intesa Sanpaolo and Unicredit. In general, average connectedness across entities is quite low while self-spillovers are more relevant. These results can be compared for robustness with those from the static connectedness analysis based on the same VAR, but estimated with ordinary least squares; those are in Table A1 in the appendix. The comparison confirms the main findings, i.e. the sovereign spread is a net receiver and the largest banks generate a larger spillover.

The whole point of using a TVP-VAR model for the DY12 connectedness analysis is to have a time series of the connectedness measures and therefore to explore the spillover evolution. Then, we plot the time values of the sum of the spillovers from the spread to each bank (TspillStB), and from each bank to the spread (TspillBtS), as well as their difference, in Figure 1; while the Total Spillover Index is in Figure A1 in the appendix. The Figure shows that the link between the spread and the banking sector volatility was weak until the onset of the global financial crisis. From then on, the size of the spillovers increased up to eight times, reaching values between 70 and 80 during the Euro area debt crisis. Thereafter, the measures of connectedness declined and

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

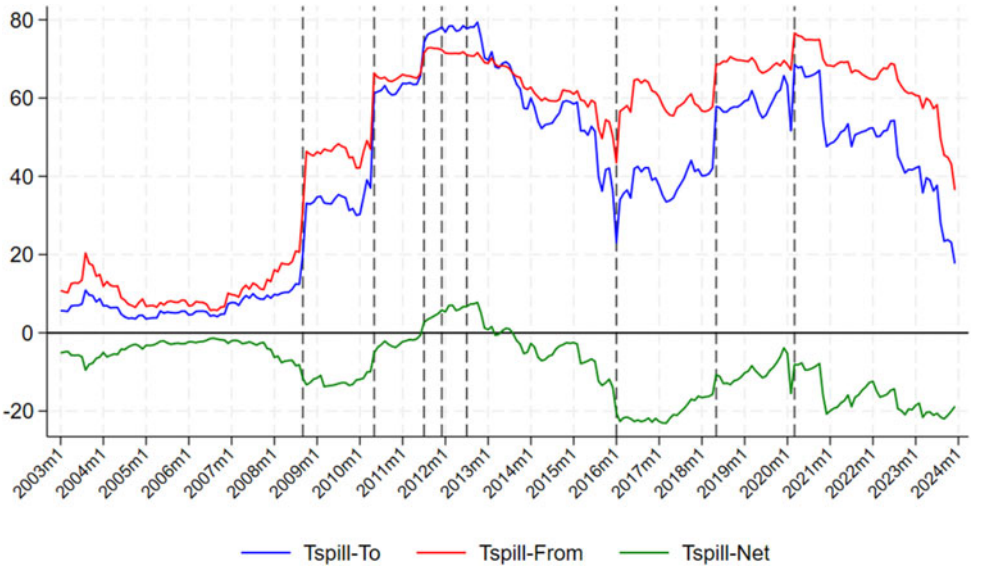


Figure 1. Total directional spillovers.
Notes: Tspill-To stands for TspillStB, Tspill-From is for TspillBtS, Tspill-Net is their difference. Vertical dashed lines, from left to right: Lehman Brothers' bankruptcy (Sept 2008), first Greek bailout (May 2010), Italian sovereign stress episode (July 2011), first ECB's LTRO (December 2011), "whatever it takes" statement and announcement of the OMT programme (July 2012), introduction of new bail-in regulation and NPL turmoil (January 2016), Italian general election without a clear majority (May 2018), start of lockdown for COVID-19 pandemic (March 2020). 1-month FEVD used for calculations.

fluctuated, alternating between decreasing and increasing trends. The last relevant increase in the measures of connectedness can be attributed to the Covid-19 pandemic. Both measures decline significantly in the last part of the sample, signaling a loosening of the link between the banking sector and the sovereign spread.

The plot shows that the sovereign spread is generally a net receiver, as for most of the period TspillBtS exceeds TspillStB. The only exception is the period between mid-2011, i.e. the beginning of the second phase of the euro area debt crisis, and the end of 2012, after several ECB interventions aimed to containing financial market tensions. Overall, this evidence is consistent with the narrative of events and with the findings of Acharya et al. (2014) and Cafiso et al. (2025), which show that sovereign credit risk and the banking sector were closely linked and that the feedback loop between the two became large in the second half of 2008.

The connectedness measures peak on certain dates. To interpret their variation, we have included lines for major economic and policy events that are widely regarded as turning points, and are therefore particularly relevant for the transmission of spillovers in Italy.[13] We detect eight major events, which will serve for the event study in Subsection 4.3: the collapse of Lehman Brothers that represents the start of the Global Financial Crisis (September 2008); the emergence of the euro area sovereign debt crisis with the first Greek bailout and the implementation of the Securities Market Programme by the ECB (May 2010); the escalation of the crisis to core euro area countries during the Italian sovereign stress episode (July 2011); the first LTRO of the ECB (December 2011); the announcement of ECB President Mario Draghi's "whatever it takes" commitment and of the OMT program (July 2012); the introduction of the bail-in regime amid heightened banking-sector stress in Italy (January 2016); the Italian general election resulting in political uncertainty and renewed sovereign stress (May 2018); and the onset of the Covid-19 pandemic and associated lock-down measures (March 2020).

Directional spillovers from the sovereign spread to each bank's shares, and from each bank to the spread, at the 1-month horizon are plotted in Figure 2; the charts include the lines for

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

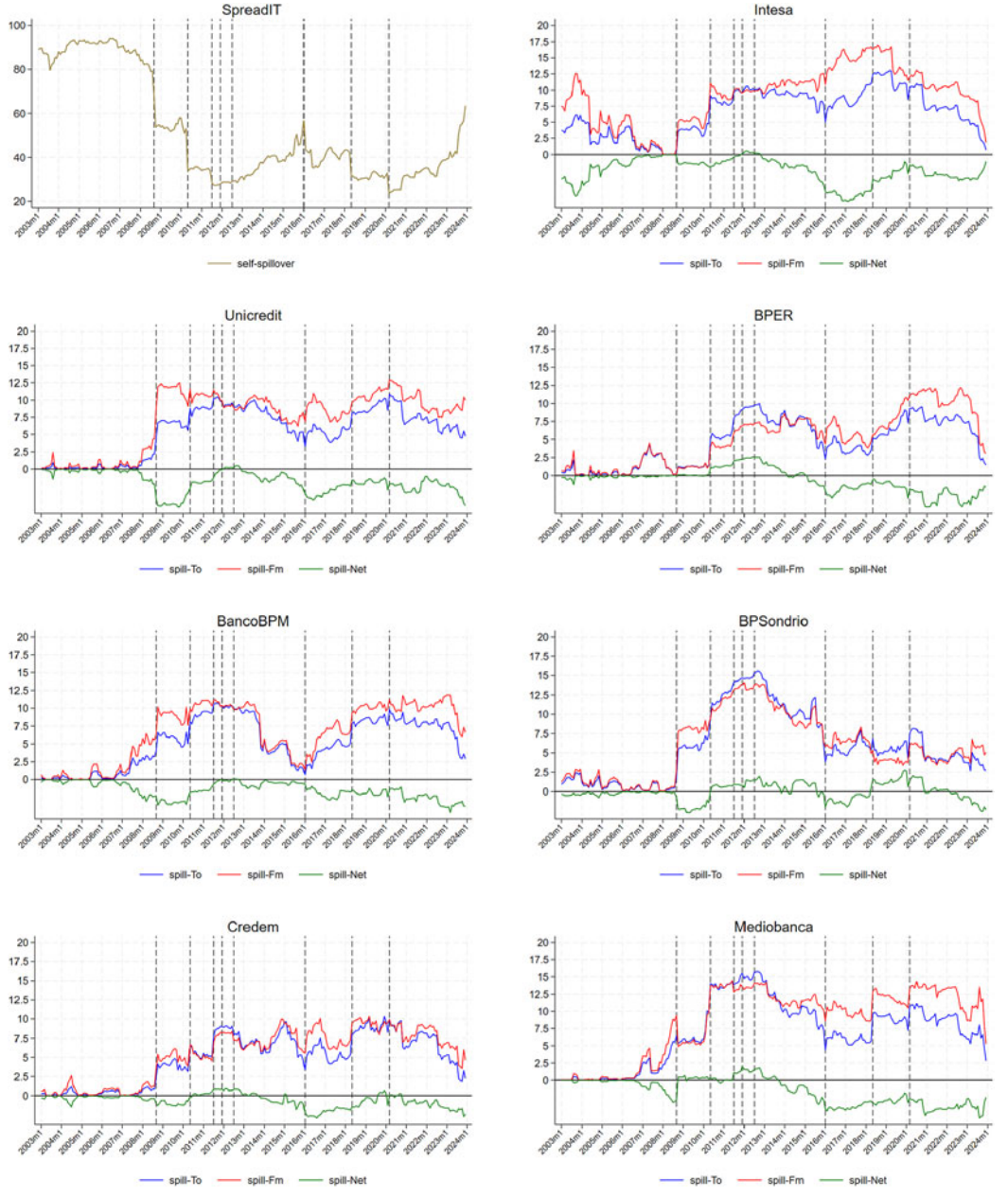


Figure 2. Directional spillovers.
Notes: Tspill-To stands for TspillStB, Tspill-From is for TspillBtS, Tspill-Net is their difference. Vertical dashed lines, from left to right: Lehman Brothers' bankruptcy (Sept 2008), first Greek bailout (May 2010), Italian sovereign stress episode (July 2011), first ECB's LTRO (December 2011), "whatever it takes" statement and announcement of the OMT programme (July 2012), introduction of new bail-in regulation and NPL turmoil (January 2016), Italian general election without a clear majority (May 2018), start of lockdown for COVID-19 pandemic (March 2020). 1-month FEVD used for calculations.

the eight events mentioned above. Overall, relevant variations in the measures of connectedness are found also at the bank level around those dates. The first chart shows the self-spillover index of the Italian spread, i.e. how much of the spread's error variance is due to its own shocks. This chart should be read in conjunction with Figure 1. It is interesting to note that this index

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 3. Correlations across spillStB and spillBtS

spillStB	Spread IT	Intesa SP	Unicredit	BPER	Banco BPM	BP Sondrio	Credem	Mediobanca
Spread IT	1.000							
Intesa SP	−0.715	1.000						
Unicredit	−0.911	0.788	1.000					
BPER	−0.789	0.729	0.846	1.000				
Banco BPM	−0.874	0.641	0.911	0.823	1.000			
BP Sondrio	−0.712	0.709	0.816	0.775	0.745	1.000		
Credem	−0.899	0.831	0.939	0.866	0.853	0.725	1.000	
Mediobanca	−0.862	0.743	0.930	0.866	0.883	0.911	0.875	1.000
spillBtS	Spread IT	Intesa SP	Unicredit	BPER	Banco BPM	BP Sondrio	Credem	Mediobanca
Spread IT	1.000							
Intesa SP	−0.609	1.000						
Unicredit	−0.853	0.267	1.000					
BPER	−0.726	0.427	0.517	1.000				
Banco BPM	−0.677	0.029	0.779	0.390	1.000			
BP Sondrio	−0.708	0.283	0.647	0.267	0.454	1.000		
Credem	−0.899	0.728	0.687	0.726	0.416	0.491	1.000	
Mediobanca	−0.897	0.507	0.685	0.699	0.571	0.544	0.821	1.000

was very high until September 2008, indicating that the contribution of the banking sector to spread volatility was negligible, and then it declined abruptly as spillovers from banks increased due to the financial and sovereign debt crises. With the easing of the sovereign debt crisis and the improvement in general economic conditions, the link to the banking sector decreased and self-connectedness increased again in 2015–2016. This link became stronger again during the Covid-19 pandemic, as self-connectedness declined. However, the subsequent recovery led to an increase in self-connectedness again. Overall, it seems clear that crisis periods are characterized by a stronger link between volatilities.[14]

The results show some heterogeneity in the dynamics of the connectedness measures across banks. In general, the spillover from each bank to the spread is stronger than the opposite. This relationship is reversed for most banks during the sovereign debt crisis, however, spillStB is only slightly higher than spillBtS for Intesa Sanpaolo, Unicredit and Banco BPM also during the crisis. These are the largest Italian banks, so it is reasonable to interpret this finding as evidence of their systemic importance: their feedback on the spread is strong even in a situation of financial market turmoil. The observed heterogeneity could depend also on bank-specific characteristics and we explore this issue in Section 5.

Table 3 shows the correlation between the different directional spillovers at the bank level plotted in Figure 2. Consistent with Figure 2, the spread self-spillover is strongly and negatively correlated with spillovers from the spread to banks (spillStB), and from banks to the spread (spillBtS). On the other hand, the directional spillovers across banks (to and from) are positively correlated with each other, with coefficients indicating a high degree of co-movement. Likely, the factors discussed in Section 2 determine the strong inverse relationship between banks and the sovereign spread, some others the strong positive relationship across-banks.

4.2. Robustness checks of the connectedness analysis

The connectedness analysis discussed in this section has undergone a series of robustness checks to confirm the reliability of our conclusions. First, we have estimated the underlying VAR with

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 4. Event windows

CLUSTER	DATE	EVENT
Great financial crisis	**2008–09**	Lehman-Brothers collapse
	2008–10	Post-Lehman panic & coordinated bailouts
Greek crisis	**2009–10**	Greek deficit revelation
	2009–12	Fitch downgrade of Greek debt
Early EA debt crisis	2010–02	Spread tensions
	2010–04	S&P downgrade of Greek debt
	2010–05	First Greek bailout & ECB SMP
Second phase of EA debt crisis	**2011–07**	Italian sovereign debt crisis
ECB LTROs	**2011–12**	LTRO I
	2012–02	LTRO II
"Whatever it takes" and OMT	**2012–07**	Whatever it takes & OMT announcement
	2012–09	OMT technical details release
	2012–10	Operational start of the ESM
Bail-in and banking stress	2015–10	ECB QE expectations & Italian banking stress
	2015–12	Pre-bail-in repricing
	2016–01	Bail-in enters into force and NPL turmoil
	2016–02	European banking crisis
Italy political crisis	**2018–05**	Italian political turmoil (Italexit fears)
Covid	**2020–03**	Global Covid crash & PEPP

both 6 and 12 lags and found no relevant difference. Second, the coefficients from the dynamic analysis, averaged over the entire period (Table 2), have been compared with those from a static analysis based on the same VAR estimated using ordinary least squares; see Table A1 in the appendix. Overall, the magnitude of the effects is similar. Third, we have calculated the spillovers using the 1-month and 3-month horizons as basis for the FEVD. While our benchmark for the analysis is the 1-month horizon for the reasons explained, the conclusions remain the same in both cases.

4.3. Event-study analysis

Figures 1, 2 and A1 suggest that historical events may drive the evolution of the spillovers. Accordingly, to characterize the evolution of spillovers around major episodes of financial stress and policy intervention, we conduct an event-study analysis based on the *total directional* connectedness measures: TspillStB and TspillBtS as defined in eq. (5). A separate event-study regression is estimated for each event. For an event occurring at time T, we define a symmetric event window spanning seven months, from three months before to three months after the event. Then, we include seven dummy variables in each regression.

Table 4 reports nine major event windows that we consider for the event study.[15] The central event month is highlighted in bold. While the central event represents the main shock of interest, the neighboring months capture closely related market, policy, or institutional developments, which we take into account in the interpretation of the results. This structure allows the event-study framework to capture both anticipation effects and short-run post-event dynamics, and accounting for the presence of other shocks occurring within the same window.

For each event, we estimate the following univariate regression model:

$$\Delta z_t = \alpha + \sum_{l=1}^{P} \phi_l \Delta z_{t-l} + \sum_{w=-3}^{3} \gamma_w D_t^{(w)} + \nu_t, \tag{10}$$

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

where z_t denotes the spillover measure under consideration. The spillover measures enter the regressions in first differences, to correct their non-stationary behavior in levels. The coefficients ϕ_l capture the autoregressive dynamics of the series, while γ_w measures deviations from the normal evolution of spillovers at different points in the event window. We include twelve lags of the dependent variable in each specification to account for serial correlation. Inference is based on a variance–covariance matrix that is robust to both heteroskedasticity and autocorrelation (Newey and West, 1987). The event-time dummy variables $D_t^{(w)}$ are defined as:

$$D_t^{(w)} = \begin{cases} 1 & \text{if } t = T + w \\ 0 & \text{otherwise} \end{cases}$$

where T denotes the month in which the main event occurs.

For brevity, we discuss only the results based on the 1-month horizon. The estimates for the 3-month horizon are reported in Table A2 in the Appendix and confirm the robustness of our findings to the choice of forecasting horizon.

Overall, the output reveals clear and economically meaningful patterns across the main episodes of financial stress and policy intervention (Table 5). Crisis events are generally associated with sharp increases in spillovers, while policy interventions are associated to a dampening in the volatility transmission across markets. To assess whether the response to an event differs significantly across spillover directions, Table A3 in the appendix complements the analysis with Wald tests of equality between the central-month coefficients estimated for the sovereign-to-bank and bank-to-sovereign spillover measures. A statistically-different effect emerges most of the times.[16]

The collapse of Lehman Brothers in September 2008 marks a dramatic increase in the spillover measures. The strongest response is in spillovers from banks to the sovereign, consistent with the origin of the crisis in the banking sector and its rapid propagation to the sovereigns; this is confirmed also by the Wald test.

The revelation of the Greek fiscal deficit in October 2009 is associated with a decrease in both directional spillover measures. This pattern may reflect the fact that, at that stage, financial markets still perceived Greece's fiscal difficulties as largely country-specific rather than as a source of broader systemic risk. However, since our analysis focuses exclusively on Italy, these results should be interpreted with caution. This also applies to the downgrade of Greek debt in December 2009, which is associated to a decline in the spillover measures too.

The early phase of the euro area debt crisis generated a significant increase in the spillovers already in February 2010, but particularly in May 2010 when the Greek bailout occurred and the ECB implemented the Securities Market Programme. The increase in spillovers appears quantitatively larger along the sovereign-to-banks direction (the Wald test confirms) consistently with the nature of the crisis characterized by sovereign debt sustainability concerns.

The July 2011 event represents a turning point in the crisis, as sovereign stress spreads to Italy and other core euro area countries. Spillovers increase sharply across both directions, with particularly strong effects from the sovereign to the banking sector. This reflects the central role of sovereign risk in driving financial instability during this phase. Spillovers from banks to the sovereign rise too, pointing to the emergence of a negative feedback loop. Anticipation effects emerge for this event.

ECB liquidity provision through the LTROs in late 2011 and early 2012 is associated with a non-significant change in directional spillovers. Total spillover from the spread to bank shares has a contrasting evolution in the following months. A generalized decline in spillovers followed the "whatever it takes" commitment in July 2012. This result is consistent with the interpretation of the announcement as a regime-changing intervention that restored confidence and reduced systemic risk transmission.[17]

The January 2016 episode displays a particularly rich dynamic pattern, reflecting the coexistence of anticipation effects and contrasting dynamics. In the months preceding the event,

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 5. Event study regressions

Event	Date	TspillStB:h1	TspillBtS:h1
Lehman-Brothers collapse	2008–06	0.919***	0.905***
	2008–07	1.385***	2.579***
	2008–08	0.002	0.076
	2008–09	7.685***	11.018***
	2008–10	13.263***	15.249***
	2008–11	0.238	−0.129
	2008–12	1.214	−0.808
Greek deficit revelation	2009–07	0.461	0.156
	2009–08	−1.096	−0.497
	2009–09	−0.164	−0.735
	2009–10	−4.124***	−3.176***
	2009–11	0.261	0.156
	2009–12	−1.829***	−2.736***
	2010–01	0.463	0.244
First Greek bailout & ECB SMP	2010–02	4.315***	4.167***
	2010–03	4.584***	2.364***
	2010–04	−1.879***	−2.200***
	2010–05	25.124***	19.527***
	2010–06	−0.901	−3.663*
	2010–07	2.411**	0.216
	2010–08	2.037	0.265
Italian sovereign debt crisis	2011–04	0.978	−0.458
	2011–05	−0.906	−0.073
	2011–06	2.052***	1.240***
	2011–07	8.824***	5.200***
	2011–08	1.988***	1.026*
	2011–09	0.904	−0.255
	2011–10	−0.135	−0.918**
LTRO I	2011–09	0.822	−0.294
	2011–10	−0.179	−0.936**
	2011–11	−0.298	−0.750
	2011–12	0.321	−0.092
	2012–01	−1.049**	−0.479
	2012–02	1.560***	−0.030
	2012–03	−0.147	−0.424
Whatever it takes & OMT announcement	2012–04	−1.446***	−0.184
	2012–05	−0.338	−0.147
	2012–06	1.279***	0.360
	2012–07	−1.113**	−0.932***
	2012–08	0.562	−0.278
	2012–09	−0.171	−0.172
	2012–10	1.024***	0.779***

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 5. Continued

Event	Date	TspillStB:h1	TspillBtS:h1
Bail-in in force & NPL turmoil	2015–10	6.029***	5.157***
	2015–11	1.017	0.083
	2015–12	−5.585***	−3.466***
	2016–01	−13.310***	−7.493***
	2016–02	10.834***	13.473***
	2016–03	2.457*	0.663
	2016–04	1.882	1.143*
Italian political turmoil	2018–02	0.069	−0.027
	2018–03	0.712*	0.639
	2018–04	1.538***	0.825***
	2018–05	15.848***	10.734***
	2018–06	−0.360	−0.634
	2018–07	−0.605	0.664
	2018–08	−0.834	−1.190*
Global Covid crash & PEPP	2019–12	3.273***	1.083***
	2020–01	−3.164***	−1.129***
	2020–02	−11.116***	−1.233***
	2020–03	17.777***	9.548***
	2020–04	−2.806	−1.415
	2020–05	1.525	−0.124
	2020–06	−2.477	−1.650*

Notes: TspillStB is total spillover from the sovereign to banks, TspillBtS is total spillover from banks to the sovereign, h1 is for the 1-month horizon at the basis of the FEVD.

spillovers increase significantly, likely because of the rise of tensions on Italian banks. This is followed by a decoupling in December 2015, which strengthens in January 2016 with the introduction of the bail-in framework.[18] The following month is associated, again, with an opposite evolution. A tentative interpretation is that spillovers rebounded in February 2016 because, despite the gradual decline in aggregate NPL ratios, market participants remained concerned about the large stock of legacy non-performing loans on banks' balance sheets and the uncertainty surrounding their resolution.

The Italian political crisis in May 2018 is associated with a renewed increase in spillovers, particularly from sovereign spreads to the banking sector, reflecting heightened political uncertainty, concerns about fiscal sustainability, and fears related to a potential departure from the Euro area. These are partially anticipated in April 2018, when difficulties in forming a stable parliamentary majority had already become apparent, and gradually receded in the subsequent months as political uncertainty eased. The larger response of the sovereign-to-bank channel is statistically significant according to the Wald tests.

Finally, the onset of the Covid-19 pandemic in March 2020 generates a large and highly significant increase in spillovers across both measures. The largest estimated effect is for the sovereign-to-bank direction, consistent with the economy-wide nature of the shock and its direct implications for public finances and financial stability.[19]

Overall, the measures of connectedness appear to evolve in line with the narrative of the major economic events in our sample. This event study highlights the importance of a dynamic perspective when studying spillovers. In the following, we relate their evolution to some bank-specific characteristics.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

5. Regression analysis of the spillovers

In this section, we present the regression analysis aimed to study the spillovers from the sovereign spread to each bank (spillStB), and vice versa (spillBtS), as a function of a set of relevant bank-specific characteristics. Overall, the estimated coefficients are interpreted primarily in terms of association rather than causality; some robustness checks about this issue are discussed in Section 5.3.

In the case of spillStB, the coefficients capture the extent to which a given bank characteristic is associated with a greater capacity to shield the bank from incoming spillovers (negative coefficients) or, conversely, with a higher exposure to such spillovers (positive coefficients). By contrast, for spillBtS, the coefficients can be interpreted as measuring the extent to which a specific bank feature is associated with the bank's soundness, and thus with a lower propensity to transmit shocks to the sovereign.

5.1. Design of the regression analysis

We estimate the importance of some banks' features using the balance-sheet variables listed in Section 3.3, we provide the rationale for their inclusion in the analysis in what follows.

Capital-adequacy: the Tier 1 capital ratio (CAR), which is the ratio of Tier 1 capital over risk-weighted asset, is our main focus. We expect that banks with higher CARs, being more resilient to shocks, should be less sensitive to market turmoil. For the same reason, the spillovers from these banks could be weaker as they are less risky. *Profitability:* ROA, it is an indicator of performance, a better performance could be associated with fewer spillovers, as the bank is in a sounder earnings position. However, the shares of more profitable banks could be more volatile, so we have no clear expectation regarding the sign of its effect. *Operational Efficiency:* we construct the total-operating expenses to non-interest income ratio (OEI) as an indicator of efficiency.[20] The rationale is that higher costs relative to revenues reflect lower operational efficiency, i.e. less performing banks, so we might expect higher spillovers. *Asset quality:* to capture asset quality and balance sheet soundness, we use non-performing loans over total loans (NPL), a higher ratio could imply a higher spillover since a bank is less financially sound and weaker in terms of asset quality. If so, it could be more sensitive to spread shocks and, at the same time, could also transmit more risk to the economy. *Funding structure:* we include total assets over deposits (TAD) because a higher value would suggest that banks finance more their activities with resources other than deposits, to wit, debt. As deposits are the cheapest and safest source of funding, a higher value could signal a riskier balance sheet position and thus be associated with more spillovers to and from the economy. *Portfolio composition:* we include investments in securities relative to total assets (ISA) and gross loans relative to total assets (GLA).[21] We consider a portfolio skewed towards securities, compared to loans, more prone to risk transmission because securities are generally more liquid and, except for the share of government bonds, potentially more risky. We therefore view such a portfolio as a stronger vehicle through which spillovers can be transmitted or absorbed. In contrast, a higher GLA value typically signals a lower risk profile and could consequently be associated with a lower spillover. *Size:* we include market capitalization (MKV) to account for the dimension of each bank. Summary statistics of these variables for our sample of seven Italian banks are in Table 1, we report also their correlation matrix in Table A4 in the appendix to provide a first overview of their relationship.[22]

With the exception of market value, which is included at its first lag, all the above-mentioned regressors are included at their contemporaneous value. Indeed, the first lag is used to avoid potential simultaneity with the dependent variable since market value is a market-based variable that can react almost instantaneously to changes in sovereign risk perceptions and bank stress. In contrast, the other explanatory variables are accounting-based indicators that primarily capture structural balance-sheet characteristics and business model features. Those variables evolve relatively slowly over time and are largely shaped by medium-term managerial decisions, regulatory

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

constraints, and accounting outcomes. Given their persistence and quarterly frequency, they are unlikely to respond contemporaneously to short-term fluctuations in spillovers within the same quarter, making them plausibly exogenous in our specification.[23]

We estimate a panel static regression, the estimator is OLS with two-way fixed-effects and standard errors are robust and clustered by bank. The regression equation is:

$$y_{b,t} = \alpha + \lambda_b + \gamma_t + \boldsymbol{\beta} x_{b,t} + \varepsilon_{b,t}, \tag{11}$$

where $y_{b,t}$ is the spillover from the sovereign spread to bank b, or vice versa, α is the constant term, λ_b are the bank fixed-effects, γ_t are the time fixed-effects, $x_{b,t}$ and $\boldsymbol{\beta}$ are, respectively, the vector of explicatives and the related vector of coefficients to be estimated; t stands for the quarterly dimension of the dataset.

The time and bank fixed-effects allow us to control for factors that vary over time but are common across banks (such as global and country-specific determinants that shape the macroeconomic environment), and for unobserved bank characteristics that remain constant over time. In particular, the time fixed-effects are intended to capture major events that have been shown to affect the evolution of spillovers, as from the event study in Section 4.3.

As for the $y_{b,t}$ dependent variable, to check the robustness of our results, we include both the directional spillover when the horizon of the FEVD at the basis of the connectedness measures is 1 month (spillStB:1h, spillBtS:1h), which is our benchmark, and 3 months (spillStB:3h, spillBtS:3h). Although we believe that the 1-month horizon is sufficient to capture transmission in financial markets, we cannot rule out the possibility that spillovers extend beyond the first month.

5.2. Regression outputs

Table 6 reports the output of preliminary panel estimations where we insert the regressors one by one $\left(x_{b,t} = x_{b,t}\right)$. These are useful to gain a first insight into the relationship between the dependent variable and the explicatives, particularly for the NPL ratio, which will not be included in the multivariate regressions due to its missing values. Detailed comments on the effect of each variable are for the output of the multivariate regressions in Table 7, here we simply note that only the capital-asset ratio is significant for the spread-to-banks spillover, both at the 1-month and 3-month horizons, and for the spread-from-banks spillover at the 1-month horizon. Then, already in this preliminary exercise, it is apparent that a higher CAR is associated with less spillover as expected. Truly, each variable taken one-by-one suggests a limited role of the balance-sheet characteristics but, since the R^2 *within* is high in all the estimations, we can deduce that much of the spillover variability is captured by bank (time invariant) and time (bank invariant)-specific effects.

Table 7 reports the output of the panel estimations in which we include all the previous regressors at the same time $\left(x_{b,t} = x1_{b,t} + x2_{b,t} + \ldots\right)$. We have excluded the NPL ratio because it has several missing values and, combined with the few of the others, would reduce the estimation sample excessively. All in all, we observe robust results for most of the variables over the two horizons, as they retain the same sign. Again, significance is strong for the capital-assets ratio, but we also find significance for investment in securities relative to total assets, GLA and market value.

Capital-adequacy therefore confirms itself as crucial for banks' soundness, not just in terms of shock absorption, but also for reduced shock transmission. A portfolio skewed towards comparatively less liquid, and potentially safer assets (lower investments in securities, higher loans) is associated with lower spillovers too, this is in line with our expectations. Moreover, although the magnitude of the effect is small, larger banks are significantly associated with weaker spillovers. A plausible explanation is that their shares could be less volatile. Return on assets, operational efficiency and the funding structure are confirmed as being nonsignificant.[24]

In conclusion, we report the estimates of the time fixed-effects in Figure 3. Unsurprisingly, those turn out significant starting from 2008q4 onwards, and pick in 2011q4 (the period of the

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 6. Bivariate panel regressions

Directional spillovers from the sovereign-spread to banks								
ITA	**spillStB:1h**	**spillStB:1h**	**spillStB:1h**	**spillStB:1h**	**spillStB:1h**	**spillStB:1h**	**spillStB:1h**	**spillStB:1h**
CAR	−0.235*							
ROA		0.064						
OEI			−0.005					
NPL				−0.146				
TAD					−0.098			
ISA						0.032*		
GLA							−0.046	
L.MKV								0.000
const.	4.154**	0.755	0.801	1.788**	0.959	0.474	3.969**	1.082
obs.	*566*	*573*	*586*	*499*	*587*	*587*	*586*	*581*
R^2 *within*	*0.819*	*0.817*	*0.819*	*0.84*	*0.821*	*0.822*	*0.824*	*0.817*
	spillStB:3h	**spillStB:3h**	**spillStB:3h**	**spillStB:3h**	**spillStB:3h**	**spillStB:3h**	**spillStB:3h**	**spillStB:3h**
CAR	−0.209*							
ROA		0.044						
OEI			−0.002					
NPL				−0.133				
TAD					−0.051			
ISA						0.023		
GLA							−0.027	
L.MKV								0.000
const.	5.477**	1.606**	1.636**	2.366**	1.717**	1.399	3.530*	2.062**
obs.	*566*	*573*	*586*	*499*	*587*	*587*	*586*	*581*
R^2 *within*	*0.841*	*0.84*	*0.842*	*0.854*	*0.843*	*0.844*	*0.844*	*0.842*
Directional spillovers from banks to the sovereign-spread								
ITA	**spillBtS:1h**	**spillBtS:1h**	**spillBtS:1h**	**spillBtS:1h**	**spillBtS:1h**	**spillBtS:1h**	**spillBtS:1h**	**spillBtS:1h**
CAR	−0.289*							
ROA		0.119						
OEI			−0.009					
NPL				−0.187				
TAD					−0.177			
ISA						0.028		
GLA							−0.043	
L.MKV								0.000
cons.	6.901**	1.443	1.516	2.730**	1.797	1.219	4.499	1.976
obs.	*566*	*573*	*586*	*499*	*587*	*587*	*586*	*581*
R^2 *within*	*0.693*	*0.701*	*0.702*	*0.727*	*0.707*	*0.706*	*0.708*	*0.7*
	spillBtS:3h	**spillBtS:3h**	**spillBtS:3h**	**spillBtS:3h**	**spillBtS:3h**	**spillBtS:3h**	**spillBtS:3h**	**spillBtS:3h**
CAR	−0.327							
ROA		0.218						
OEI			−0.016					
NPL				−0.22				
TAD					−0.236			

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table 6. Continued

Directional spillovers from the sovereign-spread to banks								
ISA						0.045		
GLA							−0.035	
L.MKV								0.000
const.	11.467**	2.647*	2.778*	4.689*	3.152**	2.306	5.217	2.772
obs.	*566*	*573*	*586*	*499*	*587*	*587*	*586*	*581*
R^2 *within*	*0.549*	*0.544*	*0.539*	*0.555*	*0.546*	*0.546*	*0.544*	*0.535*

Notes: Panel FE estimations, bank and quarter dummies included. Dependent variables: spillStB stands for the spillover from the sovereign spread to banks, spillBtS stands for the spillover from banks to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD. Explicatives: CAR is the capital-asset ratio, ROA is return on assets, OEI is total operating expenses to non-interest income, TAD is total assets to deposits, ISA is investments in securities to total assets, GLA is gross loans to total assets, L.MKV is the first lag of market value. Significance levels * are based on robust (id-clustered) standard errors; $^{*}p < 0.1$, $^{**}p < 0.05$.

Table 7. Multivariate panel regressions

ITA	spillStB:1h	spillStB:3h	spillBtS:1h	spillBtS:3h
CAR	−0.384**	−0.342**	−0.454**	−0.513**
ROA	0.113	0.086	0.187	0.228
OEI	−0.002	0.000	−0.006	−0.015
TAD	−0.050	−0.016	−0.120	−0.139
ISA	0.064**	0.056*	0.071*	0.093**
GLA	−0.057**	−0.037*	−0.058*	−0.050
L.MKV	−0.000**	−0.000**	−0.000**	0.000
const.	7.716**	6.993**	9.361**	9.822**
obs.	549	549	549	549
R^2within	0.835	0.851	0.710	0.582

Notes: Panel FE estimations, bank and quarter dummies included. Dependent variables: spillStB stands for the spillover from the sovereign spread to banks, spillBtS stands for the spillover from banks to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD. Explicatives: CAR is the capital-asset ratio, ROA is return on assets, OEI is total operating expenses to non-interest income, TAD is total assets to deposits, ISA is investments in securities to total assets, GLA is gross loans to total assets, L.MKV is the first lag of market value. Significance levels * are based on robust (id-clustered) standard errors; $^{*}p < 0.1$, $^{**}p < 0.05$.

EA debt crisis) and in 2020q2 (the period of the Covid-19 pandemic). Such evolution is consistent with the one of the TspillStB and TspillBtS in Figure 1 that we have discussed to be shaped by the events.

5.3. Robustness checks of the regression analysis

The regression analysis in this section has undergone several robustness checks. With respect to the horizon at the basis of the FEVD set to compute the spillovers, we have used both the 1-month and 3-month horizons. The estimation output shows that the conclusions remain similar regardless of the horizon.

Although we do not interpret the regression results in causal terms, concerns about simultaneity and reverse causality may arise. Cafiso et al. (2025) argue that a sovereign shock leads banks to reduce their lending to the economy, thus postulating a specific causal mechanism running from spread shocks to loans. Their analysis, however, differs markedly from ours in both nature and scope since they identify a structural shock to the BTP-Bund spread and observe the dynamic responses of the variables. By contrast, a standard regression framework implicitly assumes a direction of influence from the regressors to the dependent variable. Accordingly, in our setting

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

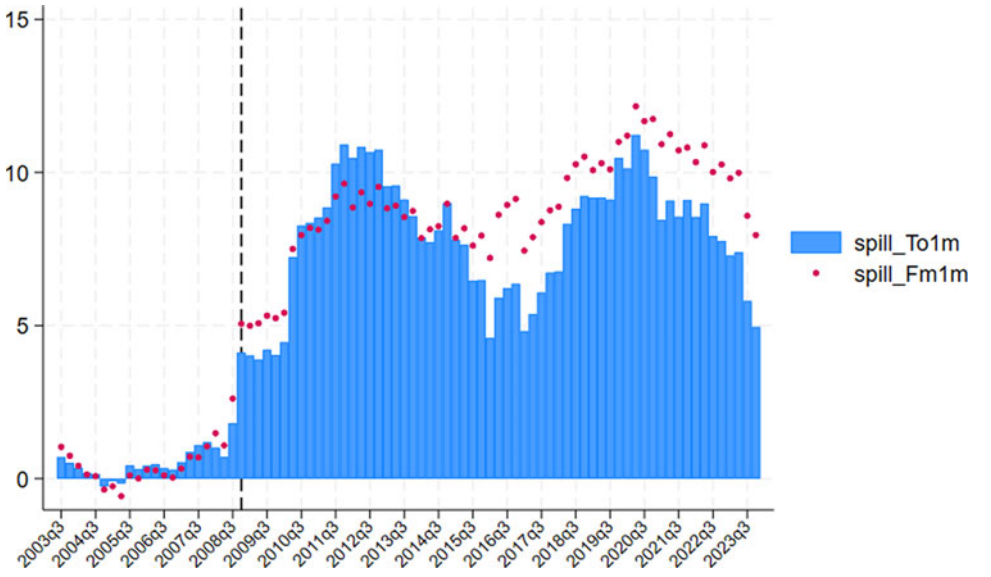


Figure 3. Time fixed-effects.
Notes: The blue bars are for the time fixed-effects related to the regression for spillStB, the red dots are for the time fixed-effects related to the regression for spillBtS; both refer to the 1-month horizon estimation. The dashed-vertical line is for 2008q4, the quarter from when the fixed-effects become significant in all the estimations.

we posit a relationship running from loans to spillovers (both spillStB and spillBtS) which is the opposite of the direction emphasized in Cafiso et al. (2025).[25]

To assess the plausibility of this assumption, we adopt two complementary approaches. First, to address simultaneity, we have re-estimated the regressions in Table 7 by replacing each variable with its first lag; only the market value entered the regressions with its first lag. The estimation output is in Table A5 in the appendix. It shows that, aside some loss of significance for gross-loans in some cases, our findings remain valid even when the variables are all predetermined, thereby mitigating concerns about simultaneity. Second, we perform Granger-causality tests to assess whether past values of loans contain predictive information for the spillovers beyond that embedded in their own past dynamics. Evidence of this kind would imply that loans Granger-cause spillovers. We also examine the reverse direction, namely whether the spillovers Granger-cause loans. Specifically, we perform the Dumitrescu and Hurlin's (2012) Granger-causality test for panel data.[26] The test results are reported in Table A6 in the appendix. In all cases we reject the null hypothesis that loans do not Granger-cause the spillovers, while we never reject the hypothesis that the spillovers do not Granger-cause the loans. Overall, these findings support the direction of dependence assumed in our regression framework.[27]

6. Conclusions

In this work, we have examined the volatility spillovers between the sovereign spread and the return of bank shares for a sample of Italian banks, with the aim of quantifying the risk transmission between the sovereign and the banking sector. Understanding the intensity and direction of this transmission is crucial for assessing systemic risk and its management at both the bank and macroeconomic levels. The interaction between sovereign risk and banks has long been at the center of the theoretical and empirical literature, which has identified several transmission channels linking public finance and financial stability (Acharya et al. 2014; Gennaioli et al. 2014; Brunnermeier et al. 2016; Cafiso et al. 2025).

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

We implement the connectedness framework of Diebold and Yilmaz (2012) in a dynamic setting based on a time-varying parameter vector autoregression. Our results show that, in general, the sovereign receives more spillovers from the banking sector than it transmits to banks, with this pattern reversing only during the euro area sovereign debt crisis. The evolution of the spillovers is largely driven by events, some of which are policy actions that turn out to be effective in reducing spillovers and therefore containing risk transmission.

In the second part, we studied whether bank-specific characteristics help to explain the spillovers by using key balance-sheet indicators. Among those, the capital-asset ratio stands out as a key factor in reducing spillovers, both from the sovereign spread to banks and vice versa. This result reinforces the role of bank capitalization as a stabilizing force, not only in absorbing shocks but also in limiting their propagation across sectors. In addition, the composition of banks' asset portfolio appears to play a significant role: a less liquid, and potentially less risky portfolio, characterized by a higher share of loans relative to securities, tends to be associated with smaller spillovers.

Overall, our findings provide new evidence on the mechanisms linking sovereign and banking sector risks, complementing existing structural analyses by focusing on the dynamic transmission of volatility. From a policy perspective, our results suggest that macroprudential frameworks aimed at strengthening bank capital buffers, and at discouraging excessive reliance on marketable securities, may contribute not only to individual bank resilience, but also to reducing the intensity of risk spillovers between the sovereign and the financial sector.

Acknowledgements. We thank Andrea Bastianin and the participants to the Macro Lunch Seminars at the Università Cattolica del Sacro Cuore (Milan) for their helpful comments and suggestions. We also acknowledge the useful comments received at the 66th annual conference of the Italian Economic Association.

Notes

1 These theoretical insights were inspired by the events observed during the sovereign debt crisis in 2010–2012. Risk transmission from sovereigns to banks was predominantly observed in Greece, Italy and Portugal, while transmission from banks to their sovereign materialized in Cyprus, Ireland and Spain.

2 This results in widening sovereign credit default swap (CDS) spreads. A vast literature examines the interaction between sovereign risk and bank credit risk using CDS data; see Fratzscher and Rieth (2019), Erce (2020) and the references therein.

3 A complementary theoretical perspective is proposed by Gennaioli et al. (2014), who develop a model in which sovereign defaults are costly primarily because they impair the balance sheets of domestic banks holding government bonds leading to contractions in credit supply.

4 The relationship between sovereign risk and global financial risk is also examined by Gilchrist et al. (2022), they show that a significant part of the observed co-movement in sovereign spreads can be explained by fluctuations in global financial risk rather than the financial health of national banks. Barbieri et al. (2024) reveal that the synchronization of the euro area's government bonds decreased significantly during the Great Recession and the euro area debt crisis, to partially recover after 2015.

5 Alternative approaches for a sophisticated connectedness analysis are represented by the following papers. Baruník and Křehlík (2018) compute connectedness measures in the frequency domain using the spectral representation of variance decomposition. Chatziantoniou et al. (2022) develop a quantile frequency connectedness approach that also considers the frequency domain. Chatziantoniou et al. (2023) perform time and frequency domain connectedness computing the measures developed by Baruník and Křehlík (2018) on the output of a time-varying parameter model.

6 As mentioned, the VAR is purely to derive measures of connectedness between the variables in the system, without distinguishing across its sources, which may include global market trends, country-specific factors or bank-specific characteristics. Also for this reason, the VAR model does not include exogenous variables. However, the lags of the dependent variables used as regressors contain information about contemporaneous economic developments.

7 A similar setup is applied by Antonakakis et al. (2020), they also estimate a time-varying parameter VAR model but use a Normal-Wishart prior as in Primiceri (2005), and they set the hyperparameters using an internal training sample. On the contrary, our prior is based on a pre-sample so that our posteriors are not influenced by information internal to the sample and are more robust from a Bayesian point of view.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

8 Monte dei Paschi di Siena underwent severe financial distress, which led to a full suspension of trading beginning in December 2016, as ordered by Consob, and lasting for about ten months. Trading resumed only on 25 October 2017, following the bank's recapitalization and re-listing approval. In addition, the bank carried out several extraordinary corporate finance operations affecting the structure and nominal value of its shares, including large capital increases and reverse stock splits. These discontinuities, driven by the bank's rescue process, state intervention, and the resulting distortions in its equity valuation, make the time series of its share price non-comparable with those of other listed banks.
9 Realized volatility differs from implied volatility, as the latter is derived from derivative prices and therefore it is a forward-looking measure of variability. A simpler alternative would be the standard deviation of prices. We opted for realized volatility because it is based on returns and informs about changes in asset values, so providing a clearer picture of market activity. Indeed, we calculated both measures of volatility and their correlation is positive but quite low since they reflect different dynamics.
10 Realized volatility is extremely skewed while its logarithm is approximately Gaussian (see Andersen et al. 2001). For this reason, the log of realized volatility is widely used in empirical studies; for example, see Bastianin et al. (2023).
11 We report that we lost access to this database in February 2024. Our ability to perform the regression analysis discussed in Section 5 is therefore crucially limited to what we extracted up to that point in time.
12 To assess whether spillovers from banks to the sovereign are, on average, larger than spillovers from the sovereign to banks, we compute the monthly difference between the two time-varying spillover series ($dt_t = TspillBtS_t - TspillStB_t$; see eq. (5) and test whether its mean is statistically different from zero by regressing dt_t on a constant term. Inference is based on Newey–West standard errors to account for heteroskedasticity and serial correlation in the spillover series. The results indicate that the average difference is highly statistically significant ($p - value < 0.001$), implying that spillovers from banks to the sovereign are, on average, significantly larger than spillovers from the sovereign to banks.
13 The same type of analysis is performed by Baruník and Křehlík (2018) to study the evolution of their connectedness measures during the great financial crisis and the Euro area debt crisis.
14 Our results for the euro area debt crisis period are consistent with Alter and Beyer (2014) who document that, in several European countries, spillovers between banks and sovereigns increased during the crisis.
15 These nine events correspond to the eight events mentioned in Section 4.1, plus the revelation of the Greek deficit in October 2009, which is not directly related to Italy but may be of interest for this econometric analysis.
16 The event-study regressions in Table 5 are estimated using Newey-West standard errors. However, the Wald tests require the estimation of the covariance between coefficients belonging to different equations. Since this covariance is not available from separate Newey-West regressions, the tests are implemented using a joint estimation framework based on seemingly unrelated estimation.
17 By contrast, the announcement of the OMT details in September 2012 did not generate additional significant changes in spillovers, suggesting that most of the stabilizing effect had already been priced following the announcement. The increase in spillovers observed around the operational start of the ESM possibly reflects enhanced financial integration and coordinated risk pricing and heightened uncertainty regarding potential program requests by Spain.
18 The bail-in framework was formally introduced by the Bank Recovery and Resolution Directive (BRRD), adopted in 2014, while the bail-in provisions entered into force in January 2016. Therefore, the January 2016 date should not be interpreted as the first moment at which markets became aware of the new resolution regime. To some extent, the effects of the reform may have already been incorporated into market expectations following the approval of the BRRD. Nevertheless, the entry into force of the bail-in provisions represented an important institutional milestone and coincided with a period of heightened stress in the Italian banking sector.
19 Three months before the event, spillovers increase across all channels, reflecting early global uncertainty related to the outbreak in China and initial disruptions to global supply chains. This is followed by a brief deceleration in January 2020, when markets probably and temporarily reassessed the likelihood of a fully systemic shock. Only in March 2020 spillovers increase strongly across all channels, signaling the transition to a fully systemic crisis and the activation of the sovereign–bank feedback mechanism.
20 This is the best proxy we managed to build for the more common cost-to-income ratio, which is full of missing values in our sample of banks.
21 Investment in securities includes both government and non-government bonds, with the former representing only a minority share of total securities given the size of the banks considered.
22 We would have liked to include an indicator of the risk perceived by market participants for each bank, such as the spread of CDSs along the lines of Acharya et al. (2014). However, as in Acharya et al. (2014), publicly traded CDS are only available for very few banks. We were only able to find them for Intesa Sanpaolo, Unicredit and Mediobanca from 2008 onwards. This reduced our sample to too few observations, so we did not include this variable in the analysis.
23 In any case, the conclusions based on this modeling choice are proved to be robust also when all regressors are lagged as described in Section 5.3
24 Overall, our results on banks' balance-sheet characteristics are consistent with the evidence in Bottero et al. (2020). Although the object of their analysis is different, as they focus on the transmission of a sovereign spread shock, they also

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

document that banks' capitalization and asset composition are key factors shaping the transmission of sovereign risk. In particular, portfolios more heavily tilted toward securities amplify risk transmission, while loan-based portfolios and stronger capital positions act as stabilizing forces.

25 Focusing on the GLA variable, which captures the share of loans over total assets, it is worth noting that this ratio reflects medium-term portfolio allocation and business-model decisions, and is therefore unlikely to adjust contemporaneously in response to short-run fluctuations in spillovers. Moreover, our results show that the estimated relationship points in the same direction for both spillStB and spillBtS. Taken together, these considerations suggest that, in our empirical setting, the direction running from GLA to spillovers is economically more plausible than the reverse.

26 Since the test critically depends on the lag order, we allow the lag length to be automatically selected based on the minimization of the Bayesian information criterion.

27 As a further, additional check about the robustness of our estimations, we extended our regression analysis by including four additional Spanish banks in the sample. The objective was to assess whether our results remain robust to changes in the sample composition. We included Spanish banks because these were the only additional data available before we lost access to the database. The extended dataset therefore comprises seven Italian banks and four Spanish banks, increasing the number of observations from 549 to 848. We then estimate a regression similar to eq. (11), but interact each variable with country dummies. Such a specification allows us to estimate country-specific effects for Italy and Spain within the same regression framework. We do not regard the estimates for Spain as informative per se, given both the limited number of Spanish banks in the sample and the fact that Spanish banks were affected by the assistance program implemented during the sovereign debt crisis, which makes direct comparisons with Italian banks problematic. Rather, the inclusion of Spanish banks is intended solely to enlarge the sample. Relative to the Italy-only estimation (Table 7), the results for Italy are largely confirmed, both in terms of sign and statistical significance, when using the enlarged sample. The results are not reported because of limited comparability and use, but they are available upon request.

References

Acharya, V., I. Drechsler and P. Schnabl. (2012). A tale of two overhangs: The nexus of financial sector and sovereign credit risks. In *Financial Stability Review*, Vol. 16. Banque de France.

Acharya, V., I. Drechsler and P. Schnabl. (2014). A pyrrhic victory? Bank bailouts and sovereign credit risk. *The Journal of Finance* 69(6), 2689–2739.

Acharya, V.V. and S. Steffen. (2015). The greatest carry trade ever? Understanding Eurozone bank risks. *Journal of Financial Economics* 115(2), 215–236.

Altavilla, C., M. Pagano and S. Simonelli. (2017). Bank exposures and sovereign stress transmission. *Review of Finance* 21(6), 2103–2139.

Alter, A. and A. Beyer. (2014). The dynamics of spillover effects during the European sovereign debt turmoil. *Journal of Banking & Finance* 42, 134–153.

Andersen, T.G., T. Bollerslev, F.X. Diebold and H. Ebens. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics* 61(1), 43–76.

Antonakakis, N., I. Chatziantoniou and D. Gabauer. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management* 13(4), 84.

Antonakakis, N. and K. Vergos. (2013). Sovereign bond yield spillovers in the Euro zone during the financial and debt crisis. *Journal of International Financial Markets, Institutions and Money* 26, 258–272.

Apostolakis, G.N., C. Floros and N. Giannellis. (2022). On bank return and volatility spillovers: Identifying transmitters and receivers during crisis periods. *International Review of Economics & Finance* 82, 156–176.

Bajaj, V., P. Kumar and V.K. Singh. (2022). Linkage dynamics of sovereign credit risk and financial markets: A bibliometric analysis. *Research in International Business and Finance* 59, 101566.

Barbieri, C., M. Guerini and M. Napoletano. (2024). The anatomy of government bond yields synchronization in the Eurozone. *Macroeconomic Dynamics* 28(8), 1635–1672.

Baruník, J. and T. Křehlík. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics* 16(2), 271–296.

Bastianin, A., C. Casoli and M. Galeotti. (2023). The connectedness of energy transition metals. *Energy Economics* 128, 107183.

Becker, B. and V. Ivashina. (2018). Financial repression in the European sovereign debt crisis. *Review of Finance* 22(1), 83–115.

Bostanci, G. and K. Yilmaz. (2020). How connected is the global sovereign credit risk network? *Journal of Banking & Finance* 113, 105761.

Bottero, M., S. Lenzu and F. Mezzanotti. (2020). Sovereign debt exposure and the bank lending channel: Impact on credit supply and the real economy. *Journal of International Economics* 126, 103328.

Breckenfelder, J. and B. Schwaab. (2018). Bank to sovereign risk spillovers across borders: Evidence from the ECB's comprehensive assessment. *Journal of Empirical Finance* 49, 247–262.

Brunnermeier, M., L. Garicano, P.R. Lane, M. Pagano, R. Reis, T. Santos, D. Thesmar, S. van Nieuwerburgh and D. Vayanos. (2011). European safe bonds (esbies). Executive summary.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Brunnermeier, M.K., L. Garicano, P.R. Lane, M. Pagano, R. Reis, T. Santos, D. Thesmar, S. Van Nieuwerburgh and D. Vayanos. (2016). The sovereign-bank diabolic loop and ESBies. *American Economic Review* 106(5), 508–512.
Cafiso, G., A. Missale and G. Rivolta. (2025). The credit channel of the sovereign spread: A Bayesian SVAR analysis. *Economic Modelling* 144, 106984.
Capasso, S., M. D'Uva, C. Fiorelli and O. Napolitano. (2023). Cross-border Italian sovereign risk transmission in EMU countries. *Economic Modelling* 126, 106424.
Chatziantoniou, I., E.J.A. Abakah, D. Gabauer and A.K. Tiwari. (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production* 361, 132088.
Chatziantoniou, I., D. Gabauer and R. Gupta. (2023). Integration and risk transmission in the market for crude oil: New evidence from a time-varying parameter frequency connectedness approach. *Resources Policy* 84, 103729.
Diebold, F.X. and K. Yilmaz. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal* 119(534), 158–171.
Diebold, F.X. and K. Yilmaz. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1), 57–66.
Diebold, F.X. and K. Yılmaz. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182(1), 119–134.
Diebold, F.X. and K. Yilmaz. (2023). On the past, present, and future of the Diebold–Yilmaz approach to dynamic network connectedness. *Journal of Econometrics* 234, 115–120.
Doan, T., R. Litterman and C. Sims. (1984). Forecasting and conditional projection using realistic prior distribution. *Econometric Review* 3, 1–100.
Dumitrescu, E.-I. and C. Hurlin. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling* 29(4), 1450–1460.
ECB. (2016). Recent developments in the composition and cost of bank funding in the Euro area. *Economic Bulletin* 1, European Central Bank. Issue 1/2016.
Erce, A. (2020). Bank and sovereign risk pass-through: Evidence from the Euro area. *International Finance* 23(1), 64–84.
Farhi, E. and J. Tirole. (2018). Deadly embrace: Sovereign and financial balance sheets doom loops. *The Review of Economic Studies* 85(3), 1781–1823.
Fernández-Rodríguez, F., M. Gómez-Puig and S. Sosvilla-Rivero. (2015). Volatility spillovers in EMU sovereign bond markets. *International Review of Economics & Finance* 39, 337–352.
Feyen, E. and I.E. Zuccardi Huertas. (2019). The sovereign-bank nexus in emdes: What is it, is it rising, and what are the policy implications? Technical Report 8950.
Fratzscher, M. and M. Rieth. (2019). Monetary policy, bank bailouts and the sovereign-bank risk nexus in the Euro area. *Review of Finance* 23(4), 745–775.
Gennaioli, N., A. Martin and S. Rossi. (2014). Sovereign default, domestic banks, and financial institutions. *Journal of Finance* 68(2), 819–866.
Gennaioli, N., A. Martin and S. Rossi. (2018). Banks, government Bonds, and default: What do the data say? *Journal of Monetary Economics* 98, 98–113.
Gilchrist, S., B. Wei, V.Z. Yue and E. Zakrajšek. (2022). Sovereign risk and financial risk. *Journal of International Economics* 136, 103603.
Koop, G. and D. Korobilis. (2010). Bayesian multivariate time series methods for empirical macroeconomics. In *Foundations and Trends in Econometrics*. Now Publishers.
Koop, G. and D. Korobilis. (2012). Large time-varying parameter vars. Working paper 11, Rimini Centre for Economic Analysis.
Koop, G. and D. Korobilis. (2013). Large time-varying parameter VARs. *Journal of Econometrics* 177(2), 185–198.
Koop, G., M.H. Pesaran and S.M. Potter. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74(1), 119–147.
Kund, A., M. Picarelli and J. Solé. (2025). Follow the yield: Unravelling the sovereign-bank nexus. *Finance Research Letters* 80, 107380.
Le, C., D. Dickinson and A. Le. (2022). Sovereign risk spillovers: A network approach. *Journal of Financial Stability* 60, 101006.
Leonello, A. (2018). Government guarantees and the two-way feedback between banking and sovereign debt crises. *Journal of Financial Economics* 130(3), 592–619.
Longerstaey, J. and M. Spencer. (1996). Riskmetrics. Technical report, J.P. Morgan and Reuters.
Newey, W.K. and K.D. West. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica: Journal of the Econometric Society* 55(3), 703–708.
Palmen, O. (2020). Sovereign default risk and credit supply: Evidence from the Euro area. *Journal of International Money and Finance* 109, 102257.
Pesaran, M.H. and Y. Shin. (1998). Generalized impulse response analysis in linear multivariate models. *Economics* 58, 17–29.
Popov, A. and N. Van Horen. (2015). Exporting sovereign stress: Evidence from syndicated bank lending during the Euro area sovereign debt crisis. *Review of Finance* 19(5), 1825–1866.
Primiceri, G. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies* 72(3), 821–852.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Raftery, A., M. Karny and P. Ettler. (2010). Online prediction under model uncertainty via dynamic model averaging: Application to a cold rolling mill. *Technometrics* 52, 52–66.
Rivolta, G. (2014). An event-study analysis of ECB unconventional monetary policy measures. Technical Report 02-2014, Università degli Studi di Milano (Dipartimento di Economia, Management e Metodi Quantitativi).
Yu, B., H. Ouyang, C. Guan and B. Lin. (2024). Network measurement and influence mechanism of dynamic risk contagion among global stock markets: Based on time-varying spillover index and complex network method. *The North American Journal of Economics and Finance* 74, 102258.

Appendix

Table A1. DY output, static (OLS-VAR), horizon 1

	Spread IT	Intesa SP	Unicredit	BPER	Banco BPM	BP Sondrio	Credem	Mediobanca	FROM OTH.S
Spread IT	45.080	8.336	9.482	4.045	8.015	6.709	6.414	11.919	54.920
Intesa SP	5.349	28.930	15.318	6.101	12.796	7.846	11.133	12.527	71.070
Unicredit	6.272	15.788	29.817	5.324	13.166	7.138	11.575	10.919	70.183
BPER	4.270	10.035	8.497	47.585	9.486	6.970	5.461	7.697	52.415
Banco BPM	5.613	13.962	13.939	6.293	31.567	6.380	10.348	11.899	68.433
BP Sondrio	6.279	11.443	10.101	6.180	8.527	42.193	6.911	8.367	57.807
Credem	5.030	13.604	13.724	4.057	11.589	5.790	35.353	10.853	64.647
Mediobanca	8.508	13.933	11.784	5.205	12.130	6.381	9.879	32.179	67.821
TO OTHERS	41.321	87.101	82.845	37.205	75.709	47.213	61.720	74.181	63.412
NET	−13.599	16.032	12.662	−15.210	7.276	−10.594	−2.928	6.360	
Background estimation: OLS VAR									

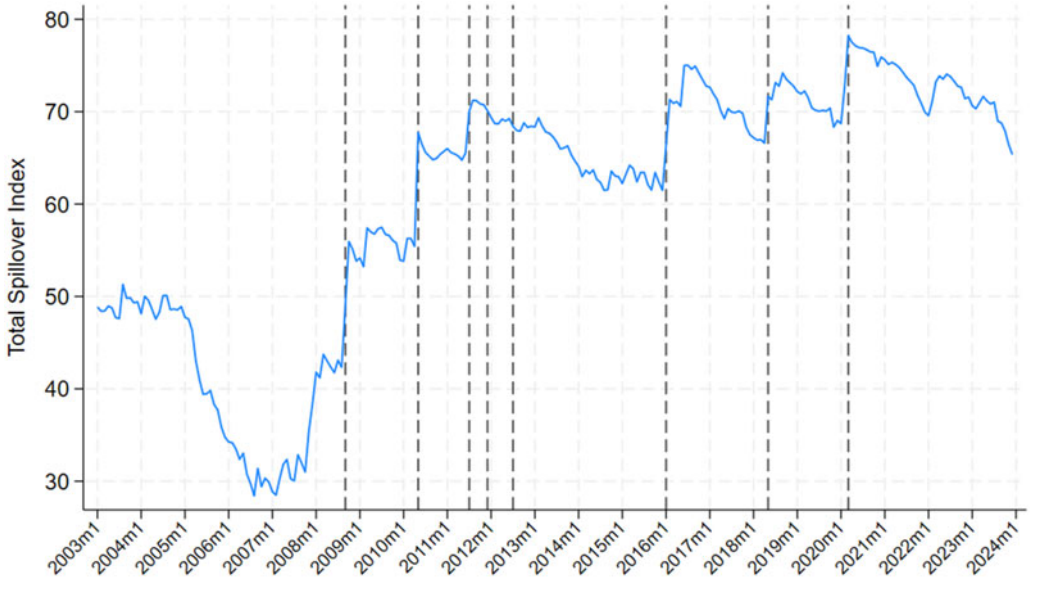


Figure A1. Total spillover index.
Notes: Vertical dashed lines, from left to right: Lehman Brothers' bankruptcy (Sept 2008), first Greek bailout (May 2010), Italian sovereign stress episode (July 2011), first ECB's LTRO (December 2011), "whatever it takes" statement and announcement of the OMT programme (July 2012), introduction of new bail-in regulation and NPL turmoil (January 2016), Italian general election without a clear majority (May 2018), start of lockdown for COVID-19 pandemic (March 2020). 1-month FEVD used for calculations.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table A2. Event study regressions, 3-month horizon based

Event	Date	TspillStB:h3	TspillBtS:h3
Lehman-Brothers collapse	2008–06	1.387***	0.337
	2008–07	1.321***	0.864
	2008–08	0.449	−0.267
	2008–09	8.222***	9.766***
	2008–10	14.822***	13.525***
	2008–11	0.861	1.490
	2008–12	2.018	−0.186
Greek deficit revelation	2009–07	−0.768	−1.100
	2009–08	−1.360*	−0.739
	2009–09	−0.718	−0.876
	2009–10	−4.768***	−1.973**
	2009–11	0.372	0.189
	2009–12	−2.868***	−0.966***
	2010–01	0.346	−0.115
First Greek bailout & ECB SMP	2010–02	4.218***	1.619***
	2010–03	4.069***	−0.722***
	2010–04	−1.275*	−1.064***
	2010–05	25.239***	11.013***
	2010–06	−0.894	−1.139
	2010–07	3.581***	−0.533
	2010–08	3.639	0.698
Italian sovereign debt crisis	2011–04	0.603	−0.685
	2011–05	−2.386	−0.450
	2011–06	2.618***	1.052***
	2011–07	10.073***	4.530***
	2011–08	3.054***	1.319***
	2011–09	2.057*	0.259
	2011–10	0.699	−0.393
LTRO I	2011–09	1.915*	0.212
	2011–10	0.615	−0.425
	2011–11	−0.019	−0.766
	2011–12	−0.132	0.020
	2012–01	−0.410	−0.239
	2012–02	1.592***	−0.133
	2012–03	−0.132	−0.194
Whatever it takes & OMT announcement	2012–04	−1.634***	−0.335
	2012–05	−0.676	−0.112
	2012–06	0.768	0.173
	2012–07	−2.007***	−0.925***
	2012–08	0.397	−0.202
	2012–09	−0.554**	−0.199
	2012–10	0.459	0.749***
Bail-in in force & NPL turmoil	2015–10	10.418***	4.271***
	2015–11	−0.437	−0.139

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table A2. Continued

Event	Date	TspillStB:h3	TspillBtS:h3
	2015–12	−4.023***	−2.858***
	2016–01	−20.921***	−8.546***
	2016–02	6.118***	15.549***
	2016–03	2.025	−0.018
	2016–04	1.240	1.749
Italian political turmoil	2018–02	−0.360	−0.076
	2018–03	0.230	1.211**
	2018–04	1.249***	0.814**
	2018–05	13.997***	10.989***
	2018–06	−0.317	0.183
	2018–07	−4.629***	1.095*
	2018–08	0.255	−0.506
Global Covid crash & PEPP	2019–12	4.022***	1.390***
	2020–01	−2.941***	−1.106***
	2020–02	−12.920***	−1.502***
	2020–03	16.094***	11.379***
	2020–04	−2.700	−0.983
	2020–05	0.806	0.271
	2020–06	−1.450	−0.551

Notes: TspillStB is total spillover from the sovereign spread to bank shares, TspillBtS is total spillover from bank shares to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD.

Table A3. Equality tests between spillStB and spillBtS at central event-months

Event	Horizon	Coeff. TspillStB	Coeff. TspillBtS	Difference	chi2	*p*-value
2008m9	h1	7, 68	11, 02	−3, 33	208, 32	0,000
	h3	8, 22	9, 77	−1, 54	8, 46	0,004
2009m10	h1	−4, 12	−3, 18	−0, 95	2, 92	0,087
	h3	−4, 77	−1, 97	−2, 80	10, 10	0,001
2010m5	h1	25, 12	19, 53	5, 60	181, 39	0,000
	h3	25, 24	11, 01	14, 23	654, 64	0,000
2011m7	h1	8, 82	5, 20	3, 62	315, 77	0,000
	h3	10, 07	4, 53	5, 54	363, 67	0,000
2011m12	h1	0, 32	−0, 09	0, 41	0, 47	0,493
	h3	−0, 13	0, 02	−0, 15	0, 04	0,842
2012m7	h1	−1, 11	−0, 93	−0, 18	0, 26	0,609
	h3	−2, 01	−0, 92	−1, 08	3, 14	0,076
2016m1	h1	−13, 31	−7, 49	−5, 82	38, 17	0,000
	h3	−20, 92	−8, 55	−12, 38	134, 43	0,000
2018m5	h1	15, 85	10, 73	5, 11	367, 20	0,000
	h3	14, 00	10, 99	3, 01	69, 17	0,000
2020m3	h1	17, 78	9, 55	8, 23	89, 18	0,000
	h3	16, 09	11, 38	4, 71	22, 85	0,000

Notes: TspillStB is total spillover from the sovereign spread to bank shares, TspillBtS is total spillover from bank shares to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table A4. Correlation matrix

	spillStB:1h	spillStB:3h	spillBtS:1h	spillBtS:3h	CAR	ROA	OEI	NPL	TAD	ISA	GLÃ	MKV
spillStB:1h	1.000											
spillStB:3h	0.981	1.000										
spillBtS:1h	0.909	0.889	1.000									
spillBtS:3h	0.830	0.799	0.939	1.000								
CAR	0.352	0.319	0.438	0.299	1.000							
ROA	−0.247	−0.270	−0.183	−0.189	0.060	1.000						
OEI	−0.104	−0.114	−0.095	−0.111	−0.145	−0.110	1.000					
NPL	0.182	0.265	0.138	0.136	−0.068	−0.291	−0.073	1.000				
TAD	0.011	−0.001	−0.006	−0.029	−0.019	0.168	−0.016	−0.187	1.000			
ISA	0.243	0.238	0.309	0.231	0.412	0.132	−0.118	−0.126	0.010	1.000		
GLA	−0.121	−0.095	−0.240	−0.187	−0.220	−0.082	−0.045	0.394	−0.372	−0.407	1	
MKV	−0.076	−0.054	0.063	0.149	−0.041	0.016	−0.117	−0.020	−0.048	0.123	−0.379	1

Notes: spillStB stands for the spillover from the sovereign spread to banks, spillBtS stands for the spillover from banks to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD. CAR is the capital-asset ratio, ROA is return on assets, OEI is operating expenses to non-interest income, NPL is the non-performing loans ratio, TAD is total assets to deposits, ISA is investments in securities to total assets, GLA is gross loans to total assets, MKV is market value.

Table A5. Multivariate panel regressions, all lagged regressors

ITA	spillStB:1h	spillStB:3h	spillBtS:1h	spillBtS:3h
L.CAR	−0.339**	−0.308**	−0.393**	−0.449**
L.ROA	0.107	0.075	0.194*	0.231
L.OEI	−0.001	0.001	−0.005	−0.014
L.TAD	−0.039	−0.029	−0.141	−0.148
L.ISA	0.065**	0.057*	0.076*	0.097**
L.GLA	−0.048**	−0.030	−0.048	−0.044
L.MKV	−0.000**	−0.000**	−0.000**	0.000
const.	8.926**	8.882**	12.495**	16.153**
obs.	545	545	545	545
R^2 within	0.829	0.849	0.705	0.583

Notes: Panel FE estimations, bank and quarter dummies included. Dependent variables: spillStB stands for the spillover from the sovereign spread to banks, spillBtS stands for the spillover from banks to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD. Explicatives: CAR is the capital-asset ratio, ROA is return on assets, OEI is total operating expenses to non-interest income, TAD is total assets to deposits, ISA is investments in securities to total assets, GLA is gross loans to total assets, MKV is the market value. All the explicatives are included with their first lag "L.". Significance levels * are based on robust (id-clustered) standard errors; *$p < 0.1$, **$p < 0.05$.

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press

Table A6. Dumitrescu & Hurlin (2012) Granger non-causality tests

causality from loans to the spillovers		
Test A1	(1-month horizon)	*p*-value (*Z*- bar tilde)
	H0 "GLA does not Granger-cause spillStB:1m"	0.030
	H1 "GLA does Granger-cause spillStB:1m"	
Test A2	(3-month horizon)	*p*-value (*Z*- bar tilde)
	H0 "GLA does not Granger-cause spillStB:3m"	0.002
	H1 "GLA does Granger-cause spillStB:3m"	
causality from the spillovers to loans		
Test B1	(1-month horizon)	*p*-value (*Z*- bar tilde)
	H0 "spillStB:1m does not Granger-cause GLA"	0.654
	H1 "spillStB:1m does Granger-cause GLA"	
Test B2	(3-month horizon)	*p*-value (*Z*- bar tilde)
	H0 "spillStB:3m does not Granger-cause GLA"	0.768
	H1 "spillStB:3m does Granger-cause GLA"	

Notes: GLA is gross loans to total assets, spillStB is the spillover from the spread to banks.

Cite this article: Cafiso G and Rivolta G (2026). "The connectedness between sovereign risk and the banking sector." *Macroeconomic Dynamics* **30**(e51), 1–31. https://doi.org/10.1017/S1365100526101229

https://doi.org/10.1017/S1365100526101229 Published online by Cambridge University Press