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Spillovers between sovereign bonds and the banking sector: evidence from Italy

Gianluca Cafiso* Giulia Rivolta†

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Abstract

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

Keywords: sovereign spread, banks, volatility, connectedness measures, spillovers, time-varying parameters, VAR.

JEL Codes: G01, G21, E60, H12.

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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. 2011, 2012, 2014, Acharya & Steffen 2015) published a series of seminal papers about 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 destabilise banks in their jurisdiction, and across borders (Breckenfelder & Schwaab 2018, Capasso et al. 2023), at the same time large banks could destabilise their sovereign. These theoretical conclusions derive from what was 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 materialised neatly in Ireland and Spain. The bidirectional and mutually reinforcing nature of the sovereign-bank risk transmission is the cornerstone of this branch of literature. This paper contributes by quantifying, comparing and explaining both directions of transmission. We believe this is crucial for assessing the direction of contagion across sectors, and provides valuable insights for risk management at both the micro and macro levels. We apply state-of-the-art econometric techniques that allow us to examine how spillovers have evolved in Italy over the last 20 years and then to assess the role of certain bank-specific characteristics in explaining them.

In the first part, we compute the connectedness measures in Diebold & Yilmaz (2012) at monthly frequency, through the estimation of a VAR model with time-varying parameters and stochastic volatility à la Koop & Korobilis (2013). At this stage, we quantify the spillovers between the sovereign spread and banks, i.e. we infer the underlying network structure, regardless of their source. The investigation of the sources is in the second part of our paper and it is based on a regression analysis. In details, the connectedness measures quantify the spillovers from the sovereign spread 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 stock prices of the seven largest Italian banks; we use monthly realized volatility (based on daily data) 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 ingredients 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, Italian sovereign spreads have been highly sensitive to macroeconomic and financial developments since the Euro area debt crisis. Finally, Italy has a significant 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, the results of our analysis show that, for most of the time, the sovereign spread is a "net receiver" in the sense that the spillover from banks to the spread is usually higher than the spillover from the sovereign spread to banks. 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, i.e. after several interventions by the ECB to contain financial market tensions. The analysis of spillovers at the bank level allows to show for which banks the link with the spread is stronger and during which periods. Additionally, we conducted 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. Our findings provide a clear picture of the evolving link between sovereign and banking sector risks.

In the second part, we aim to explain the spillovers. To this end, we link the spillovers from the sovereign spread to banks, and vice versa, to banks' balance sheet data to examine whether banks' financial conditions drive their exposure to and the transmission of spillovers. This is achieved using a regression analysis with controls for factors that vary over time but are common to all banks, such as global and country-specific ones, and for factors that do not vary over time but are specific to each bank; their inclusion disentangles the different possible origins of the spillovers. Our results suggest that the capital adequacy ratio, in particular, acts as a brake on both the transmission and absorption of spillovers. Banks' portfolio structure also matters, as financial investments are associated with higher spillovers, while loans help to mitigate them. These results are novel in the literature and improve the understanding of the relationship between sovereign and banking sector volatility.

In short, we document the size and the direction of the spillovers between the banking sector and its sovereign, describe how their evolution responds to events and policy measures, and show that the strength of the spillovers is influenced by banks' idiosyncratic characteristics. This analysis offers crucial insights for risk measurement and management both at the bank and macroeconomic level.

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 explain the connectedness measures through banks' balance-sheet characteristics is in Section 5. Section 6 concludes.

2 Literature review

The theoretical literature suggests that connectedness between sovereign debt risk and the banking sector risk may depend on three main factors: global market trends or sentiment, country-specific conditions, or bank-specific characteristics. In this regard, we review some relevant theoretical contributions in what follows. Truly, our research draws on two different strands of literature. The first examines the link between sovereign risk and the financial sector of the economy, while the second is methodological and relates to the approach of Diebold & Yilmaz (2009).

The relationship between sovereign credit risk and the banking sector has been modelled since Acharya et al. (2012, 2014). This topic has been the focus of a growing literature, which has gradually expanded its scope to identify all transmission channels between sovereigns and banks, both in one direction and the other. 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 & Zuccardi Huertas (2019) confirm the relevance of this topic by showing that the sovereign-bank nexus is growing, as 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 paper, Acharya et al. (2014) assert that during periods of financial distress, bank bailouts to stabilise the economy require substantial public spending, which increases government debt and the perceived risk associated with government creditworthiness, as reflected in widening sovereign credit default swap (CDS) spreads.[1] This increase in sovereign credit risk has a negative impact on banks' balance sheets, as they often hold large amounts of government bonds. In addition, as sovereign creditworthiness deteriorates, the implicit guarantees provided to banks become less credible, further increasing banks' credit risk. Empirical evidence from the Euro area over the 2007-

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[1] A vast literature examines the interaction between sovereign risk and bank credit risk using CDS data. See Fratzscher & Rieth (2019) and the references therein.

2010 period supports these relationships.[2] Farhi & Tirole (2018) provide a theory for such a 'doom loop', formalising 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.

The central role of banks' balance sheets in transmitting sovereign distress to the economy has been recently documented by Cafiso et al. (2025). They find that a spread shock leads to losses in the value of government bonds held by banks, forcing them to reduce lending. The credit squeeze undermines economic growth and, as a consequence, public finances deteriorate, leading to a further increase in sovereign market stress.[3] Altavilla et al. (2017) analyse the determinants of sovereign exposure and show that public banks' purchases increased significantly, especially around the largest ECB liquidity injections. These provided banks with the means to satisfy the "moral suasion" of governments in favour of those purchases. Regarding the ECB's liquidity injections, Rivolta (2014) finds that they led to an increase in market spreads for lower-rated Euro area countries due to flight-to-safety behaviour, so that positive effects from the banking sector to sovereign debt only materialised for higher-rated countries. Böhm & Eichler (2020) introduce a novel instrumental variable approach to address reverse causality and omitted variable bias in estimating the transmission of bank distress to sovereigns within the Euro area. Their results show that the transmission is weaker than previously estimated, but bank distress still plays a crucial role in determining sovereign creditworthiness.

Several studies document that the transmission of risk between sovereign bonds and the banking sector can occur also across different countries. Breckenfelder & Schwaab (2018) focus on the cross-border spillovers from bank risk to sovereign risk during the ECB' Comprehensive Assessment in 2014. The authors analyze how the health of individual banks, as revealed through the assessment, impacted sovereign credit risk both domestically and across borders within the Euro area. Sovereign risk appears to be affected by credit risk in other countries and by global financial risk. Alter & Beyer (2014) examine the dynamics of financial contagion between sovereigns and banks in the Euro area by analyzing daily CDS spreads. They focus on the European sovereign debt crisis period and construct contagion indices

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[2] The study finds that announcements of financial sector bailouts are associated with an immediate widening of sovereign CDS spreads and a narrowing of bank CDS spreads. Over time, however, a significant co-movement between bank and sovereign CDS spreads emerges, highlighting the two-way feedback loop between the health of the financial sector and sovereign credit risk.

[3] Brunnermeier et al. (2011, 2016) name this dynamics “diabolic loop” to emphasize the self-reinforcing vicious cycle between turmoil in sovereign markets, worsening economic conditions and the public budget.

using generalized impulse-response functions. Their findings indicate that the connectedness between banks and sovereigns increased during the analysis period, and several policy interventions helped to mitigate spillover risk.[4] Capasso et al. (2023) examine how Italian sovereign risk affects other Euro area members, particularly through financial markets, economic linkages, and market sentiment. They find that the transmission is most pronounced during crises and disproportionately affects countries such as Spain, Portugal and Greece due to similar vulnerabilities. Claeys & Vašíček (2014) achieve similar conclusions.

Along the same line of research is the contribution of Fernández-Rodríguez et al. (2015). Their results suggest that slightly more than half of the total variance of forecast errors is explained by cross-country shocks rather than idiosyncratic shocks. Antonakakis & 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 & Yilmaz (2020) who estimate the global network structure of sovereign credit risk. The relationship between sovereign risk and global financial risk is also examined by Gilchrist et al. (2022), their results show that a significant part of the observed co-movement in sovereign spreads can be explained by fluctuations in global financial risk and is therefore not dependent on the financial health of national banks.[5]

Other studies look at the transmission of sovereign credit risk beyond the banking sector. Augustin et al. (2018) find that sovereign credit risk is transmitted to the corporate sector through government bond yields, which influence borrowing costs. Gross & Siklos (2020) use network analysis to examine how credit risk is transmitted from the financial sector to the non-financial sector in Europe. Their study identifies key nodes (e.g. large banks or firms) and pathways through which risk spreads, high-

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[4] Our work is closely related to this paper, as both studies analyze spillovers between banks and sovereign risk. However, we differ in several methodological and analytical aspects. First, we use a TVP model, with our spillover measures based on the FEVD, while they estimate a static model with a rolling window and use impulse-responses to compute the spillovers. Second, their analysis covers eleven Euro area countries over a three-year period, whereas we focus exclusively on Italy over a span of more than twenty years. Third, they incorporate some exogenous variables in their model to correct for common trends and focus on the idiosyncratic component in the data, while we rely on a purely autoregressive structure.

[5] Barbieri et al. (2024) investigate the synchronization of the Euro area's government bond yields at different maturities. They reveal that synchronization decreased significantly during the Great Recession and the Euro area debt crisis, to partially recover after 2015. They point to divergence trades as a source of the self-sustained yield asynchronous dynamics.

lighting the role of financial institutions in transmitting credit risk to the wider economy. Apostolakis & Papadopoulos (2015) study interdependence across the banking, securities and foreign exchange sectors for the major advanced economies, they find that securities markets are the major net transmitter of financial stress.

The methodology we employ was developed by Diebold & Yilmaz (2009). In the last decade, it has been applied with different variations (among the others, see Claeys & Vašíček 2014) to study contagion in different fields, including the link between sovereign risk and the credit sector. Apostolakis et al. (2022) is close to us in terms of methodology, as they use conditional correlation analysis and dynamic connected analysis as in Antonakakis et al. (2020). Their study examines the dynamics of spillovers across G7 countries and identifies which national banking industries act as primary transmitters or receivers of financial instability.[6] Another work applying Diebold & Yilmaz (2012)'s 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.

The key innovation in the Diebold & 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 & Yilmaz (2012) improve on Diebold & Yilmaz (2009) by making the output independent from the order of the variables through the generalized approach of Koop et al. (1996) and Pesaran & Shin (1998). Diebold & Yılmaz (2014) interpret the connectedness measures of Diebold & Yilmaz (2012) as representing a network structure. Along this line, 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 & Korobilis (2013). More recent methodological developments are represented by Baruník & Křehlík (2018), Chatziantoniou et al. (2022) and Chatziantoniou et al. (2023), who compute connectedness measures on the frequency domain, for different quantiles and with time-varying parameters. More details on these contributions are in the next section.

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[6] Their study shows a significant link between banking markets in EU countries, with the strongest correlations observed between France, Germany and Italy. Moreover, the interconnectedness of EMU markets intensified during the sovereign debt crisis. The results also show that internal shocks affected member countries differently, with France and Italy experiencing significant effects on their banking markets, while Germany was only marginally affected.

3 Methodology and data

The econometric model and the methodology used to quantify the spillovers between the sovereign spread and banks' stock price are described in this section. Spillovers are quantified using Diebold & Yilmaz (2012)'s 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 stress that the DY12 method is designed and applied solely to quantify connectedness, not to control for or explain its origin. Indeed, we address that task in a further section (5) of our work through regression analysis. In what follows, we first describe the estimation of the VAR and then briefly review the DY12 connectedness measures. As detailed in subsection 3.3, all variables enter the VAR in terms of volatility, i.e. we use their realized volatility, so we study volatility spillovers.

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 & 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.[7]

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.[8] We estimate it applying the methodology of

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[7] Alternative approaches for a sophisticated connectedness analysis are represented by the following papers. Baruník & 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. These last two approaches allow to extend the connectedness analysis over different dimensions but are limited to constant-parameter models. Chatziantoniou et al. (2023) perform time and frequency domain connectedness computing the measures developed by Baruník & Křehlík (2018) on the output of a time-varying parameter model.

[8] 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.

Koop & 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 & 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 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 & 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:

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

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 (EWMA) 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 & 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 $\lambda, \kappa \text{ and } \gamma$. Koop & 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 & 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 & Spencer (1996), and the parameter governing the prior shrinkage γ is set to 0.99 following Raftery et al. (2010).

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.

3.2 Diebold-Yilmaz connectedness analysis

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

Given a set of variables, the DY12 approach allows to evaluate how much a shock to one, 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 & 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 & Shin (1998). Indeed, they are derived from the historical correlations but the contemporaneous relationships are not explicitly modelled. 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 proportion of the forecast error variance of each variable that can be ascribed to shocks to the other variables. It is therefore useful for understanding the inter-dependencies between variables and provides insights into the sources of uncertainty in the future values of each variable over different time horizons.

The starting point of the analysis is the estimation of a covariance-stationary VAR model:

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

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. Diebold & Yilmaz (2012) propose to overcome the identification problem relying on the generalized VAR framework of Koop et al. (1996) and Pesaran & Shin (1998) in which the shocks only take into account historical correlations but the contemporaneous relationships are not explicitly modelled. 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 indices 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 summarised 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, respectively. 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:

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

In our analysis, we focus on the directional connectedness from the spread (s) to each bank (i), $C_{i \leftarrow s}^{H}$, and from each bank to the spread, $C_{s \leftarrow i}^{H}$. Having the spread as reference, we call them *spill-To* and *spill-Fm*, respectively. Spillover and connectedness are synonyms in this context.

3.3 Data

Our analysis is based on two sets of data. The first consists of daily series: i) the stock 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 of 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 explain the spillover from the sovereign spread to the banks (spill-To), and its opposite (spill-Fm); the source of this second dataset 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 stock 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 stock price series over the period considered. Finally, 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.

To check whether our results are robust when we increase the sample size, we add four Spanish banks to our sample in a separate exercise. These are selected using the same criteria as for the Italian banks. The Spanish banks considered are Banco Bilbao Vizcaya Argentaria (BBVA), Banco Sabadel, Banco Santander, Bankinter. Table 9 in the appendix reports summary statistics for the balance sheet variables of these Spanish banks.

Variables for DY12 analysis

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

$$r_t^S = log\left(P_t^S / P_{t-1}^S\right). \tag{7}$$

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_t^{IT}) and the German (Y_t^{DE}) 10-year government bond yields: $Y_t^B = Y_t^{IT} - Y_t^{DE}$. 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:

$$P_t^B = \frac{100}{(1 + Y_t^B)^n}, \tag{8}$$

where Y_t^B 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 $\left(r_t^B\right)$ with eq. 7, as done for stock prices.

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 stocks 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. Realized

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[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.

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).

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 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.[10] 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 management efficiency; 4) non-performing loans relative 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.

3.4 Robustness checks

The two main analyses in this paper have undergone a series of robustness checks to confirm the validity of our conclusions.

As for the connectedness analysis discussed in section 4, we have estimated the underlying VAR

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[10] 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.

Table 1: Italy's banks, summary statistics of balance-sheet ratios

BPER	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	10.8239	0.46581	1.3521	12.8684	1.8339	8.61589	76.0263	2582.13
meadian	9.7975	0.3608	1.57484	12.1998	1.91617	9.40912	76.8688	2379.79
stand.dev	3.0259	0.60392	2.21102	6.92667	0.24796	4.82507	6.58995	814.636
min	6.71	-1.102	-18.129	2.0134	1.35548	2.67464	54.0721	1169.43
max	15.02	3.4316	3.0897	23.3345	2.30789	20.761	85.5169	4697.91
obs	80	82	84	64	84	84	84	84
BP Sondrio	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.2067	0.48551	1.27098	9.50015	1.45439	5.1808	75.1427	1832.02
meadian	10.46	0.5472	1.20241	10.7738	1.4567	2.94848	75.5307	1682.6
stand.dev	2.79884	0.377	1.52281	5.2135	0.07697	5.19957	4.94317	649.32
min	7.59	-1.2644	-6.6369	2.1977	1.30049	1.41376	59.7733	661.02
max	16.75	1.338	8.04787	16.9807	1.67901	27.4342	83.9371	3963.84
obs	83	78	82	42	84	84	84	84
Banco BPM	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.4449	0.27266	0.75074	12.0304	2.38743	8.40446	68.3076	4395.55
meadian	11.86	0.336	1.19209	8.72113	2.32155	6.57317	67.3866	4086.67
stand.dev	3.56007	1.62614	10.9155	7.66824	0.66139	6.84533	5.77658	2097.85
min	5.16	-5.9596	-40.87	1.8021	1.39208	1.2324	52.1574	1815.64
max	16.71	9.0072	76.7973	26.4673	3.57308	25.5573	80.3694	11749
obs	73	82	84	78	84	84	84	84
Credem	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	10.6897	0.55189	2.7932	3.53287	2.01751	17.0459	62.6622	1930.96
meadian	10.04	0.4672	1.26913	3.1984	2.03991	15.4179	62.3311	1858.77
stand.dev	2.83455	0.33245	15.4705	1.93871	0.30366	9.74855	5.2192	548.11
min	6.6	-0.1576	-6.1891	0.4428	1.46924	0.28185	51.8094	955.277
max	15.07	1.772	142.36	6.7226	2.72825	34.272	79.7917	3314.93
obs	83	84	84	81	84	84	83	84
Intesa SP	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.8142	0.36504	1.06124	9.40623	2.39528	16.0655	56.634	34581.6
meadian	12.18	0.446	1.10984	9.4435	2.45566	16.9703	56.7329	34464.3
stand.dev	3.51017	1.03337	1.10357	4.74221	0.33885	9.91936	6.84639	12562.1
min	6.3	-6.1692	-3.2873	2.087	1.66841	0.99004	45.9535	12315.7
max	16.9	3.2596	5.11359	17.9376	3.23112	31.4309	73.4467	69043
obs	84	83	84	79	83	83	83	84
Mediobanca	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	13.3963	1.00955	0.84842	3.17236	5.21001	11.9568	54.5577	7764.84
meadian	13.125	0.978	1.00233	3.0836	4.32069	11.4361	53.914	7468.93
stand.dev	2.18202	0.87071	3.91324	1.67919	3.06958	4.75578	5.32303	2616.58
min	10.18	-1.2416	-26.431	0.891	1.27149	4.59341	44.6104	2913.87
max	18.26	3.38	14.5663	6.737	16.3938	25.3463	68.7832	14667.2
obs	80	80	84	71	84	84	84	84
Unicredit	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.5083	0.22909	1.06333	8.09836	1.74432	10.4539	63.4569	32777
meadian	11.12	0.3804	1.35172	6.7303	1.68986	9.27743	63.3227	27854.5
stand.dev	3.97044	1.31158	3.91101	4.01012	0.31192	5.30231	5.32367	14864.9
min	5.74	-6.6136	-25.468	2.3826	1.27853	2.36638	52.2368	12971.6
max	19.17	1.8524	8.08904	16.1606	2.33973	20.759	72.4406	76698.7
obs	83	84	84	84	84	84	84	84
Total	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.5514	0.48009	1.30584	8.20783	2.43476	11.0949	65.2745	12266.3
meadian	11.425	0.4662	1.23095	5.9603	1.99347	9.63856	65.5228	4093.45
stand.dev	3.26457	1.01293	7.53668	6.10101	1.68415	7.99072	9.65515	15583.8
min	5.16	-6.6136	-40.87	0.4428	1.27149	0.28185	44.6104	661.02
max	19.17	9.0072	142.36	26.4673	16.3938	34.272	85.5169	76698.7
obs	566	573	586	499	587	587	586	588

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.

with both 6 and 12 lags and found no relevant difference. The coefficients from the dynamic analysis (averaged over the whole period) are also compared with those from a static connectedness analysis based on the same VAR estimated using ordinary least squares. Overall, the size of the effects is comparable. In addition, the size of the spillovers was compared alternatively 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 in the next section, the conclusions remain the same in both cases.

We perform the regression analysis in section 5 using the spillovers based on both the 1-month and the 3-month FEVD. Overall, the estimated coefficients are comparable between the two and lead to the same conclusions. We also extend our regression analysis to four additional Spanish banks and the results for Italy are also robust to this extended sample.

4 Spillovers between the sovereign and banks

This section presents the results of DY12 connectedness analysis based on time-varying parameter estimates. We focus on measures of connectedness, *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.

As explained in the previous section, the spillovers are derived from a reduced-form VAR model with no structural identification and capture total connectedness, without distinguishing its different sources. The spillovers are used to examine the relationship between government bond volatility and banking sector volatility by decomposing total connectedness into spillovers from sovereign to banks and from banks to sovereign. Furthermore, to better understand the evolution of the spillovers and to relate them to key economic events, we examine them in an event study based on univariate autoregressive models. Overall, our measures of volatility connectedness appear to be consistent with the narrative of major economic events and to capture the links between the sovereign and the banking sector in a meaningful way.[11]

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[11] Our results for the Euro area debt crisis period are consistent with Alter & Beyer (2014) who document that, in several European countries, spillovers between banks and sovereigns increased during the crisis.

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). 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 8 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.

Table 2: Dynamic DY12 output

Row	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.

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 total spillover-to (Tspill-To) and spillover-from (Tspill-Fm), and their difference (Tspill-Net) for the sovereign-spread in Figure 1; the Total Spillover Index is in Figure 3 in the appendix.

The graph 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 fluctuated, alternating between decreasing and increasing trends. The last relevant increase in the measures of connectedness can be attributed to the Covid pandemic. Both measures decline significantly in the last part of the sample, signalling a loosening of the link between the banking sector and the sovereign spread. The plot shows that the spread is generally a net receiver, as for most of the period the total spillover from Italian banks to the sovereign spread (Tspill-Fm) exceeds that from the spread (Tspill-To). 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 try to interpret their variation, we have included lines for major economic and policy events that are known to have driven Italy's sovereign-spread.[12] We mark nine events: the bankruptcy of Lehman Brothers (September 2008), the beginning of the first phase of the Euro-area debt crisis (March 2010), the beginning of the second phase of the Euro area debt crisis (July 2011), ECB President Mario Draghi's "whatever it takes" statement (July 2012), the establishment of the ECB's Outright Monetary Transaction programme (September 2012), the introduction of the new bail-in regulation and the non-performing loan turmoil in Italy (January 2016), the establishment of the ESM (June 2016), general election in Italy without a clear majority (May 2018), and the beginning of the lock-down for the Covid pandemic (March 2020). In line with the narrative, we observe significant variation in the spillovers around such events. This issue will be further explored in the event-study analysis in the next section.

Directional spillovers from the sovereign spread to each bank, and from each bank to the spread, at the 1-month horizon are plotted in Figure 2; the charts include the same lines for the nine events mentioned above. Overall, relevant variations in the measures of connectedness are found also at the

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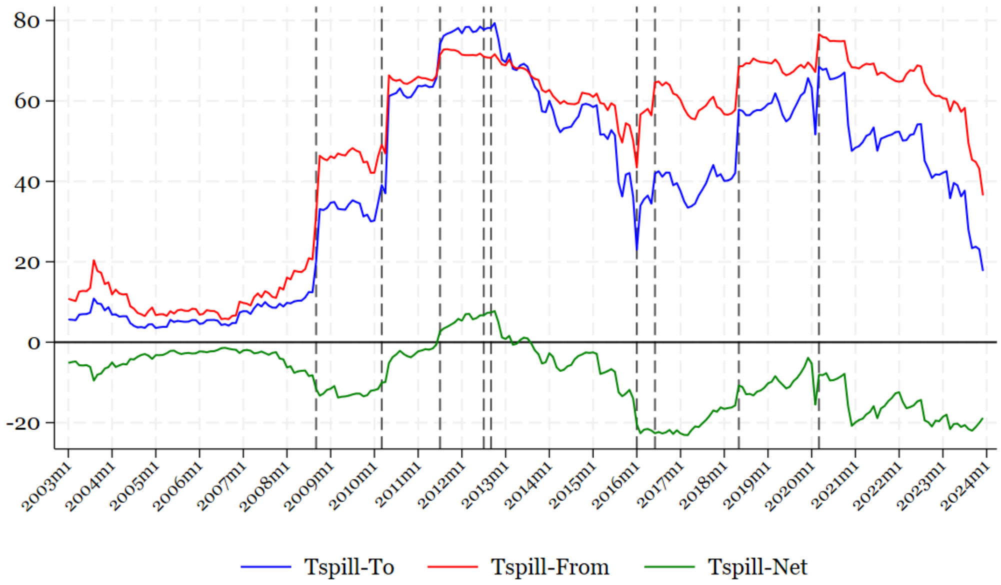
[12] The same type of analysis is performed by Baruník & Křehlík (2018) to study the evolution of their connectedness measures during the great financial crisis and the Euro-area debt crisis.

Figure 1: Total spillover to, from and net



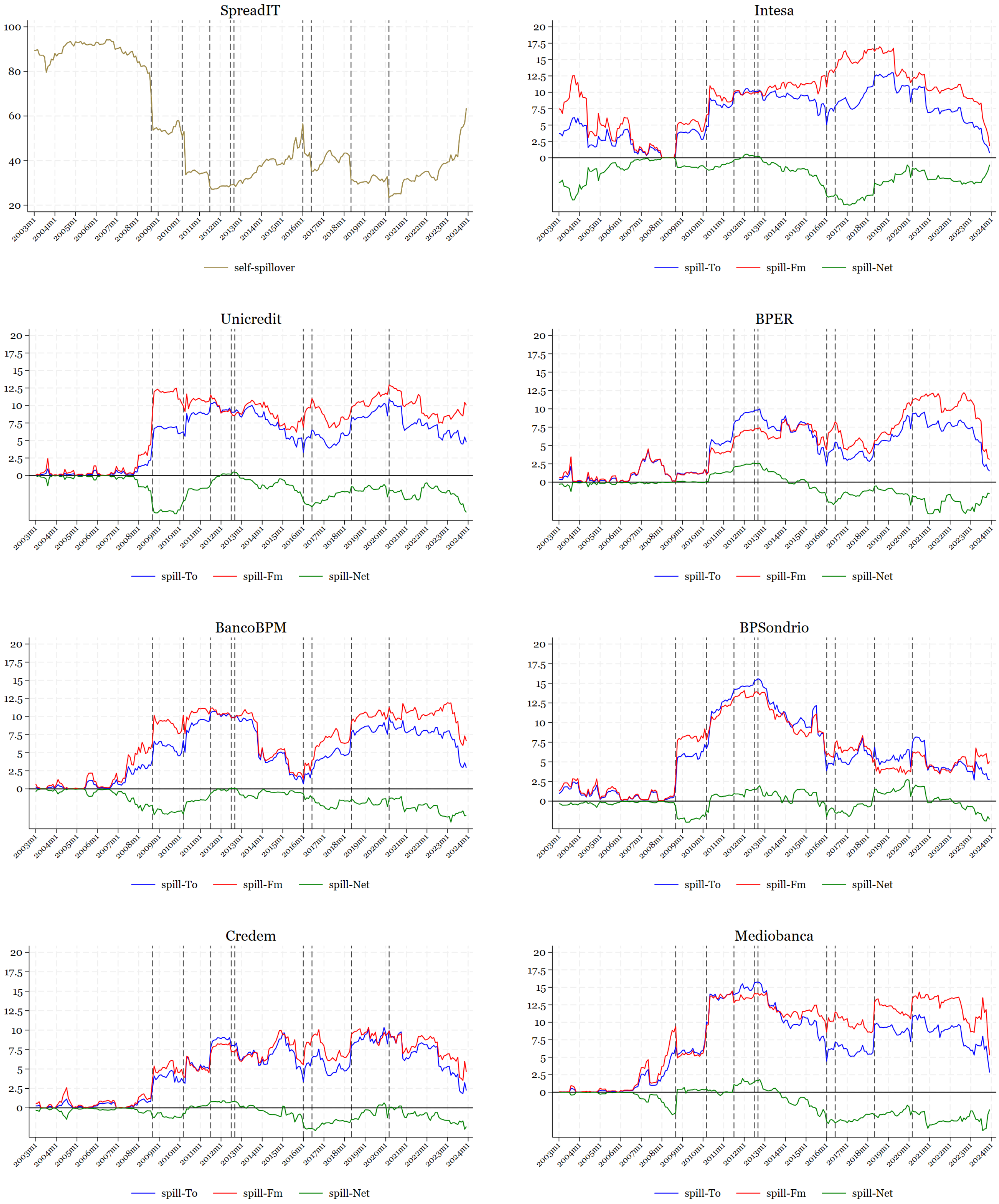
Vertical dashed lines, from left to right: Lehman Brothers' bankruptcy (Sept 2008), first phase of the EA debt crisis (March 2010), second phase of EA debt crisis (July 2011), "whatever it takes" statement (July 2012), ECB's OMT programme (Sept 2012), New bail-in regulation and NPL turmoil (Jan 2016), establishment of the ESM (June 2016), General election without a clear majority (May 2018), Lockdown for COVID-19 pandemic (March 2020). 1-month FEVD used for calculations.

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 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 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 characterised by a stronger link between volatilities.

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, spill-To is only slightly higher than spill-Fm 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.

Figure 2: Directional spillovers



Vertical dashed lines, from left to right: Lehman Brothers' bankruptcy (Sept 2008), first phase of the EA debt crisis (March 2010), second phase of EA debt crisis (July 2011), "whatever it takes" statement (July 2012), ECB's OMT programme (Sept 2012), New bail-in regulation and NPL turmoil (Jan 2016), establishment of the ESM (June 2016), General election without a clear majority (May 2018), Lockdown for COVID-19 pandemic (March 2020). 1-month FEVD used for calculations.

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 (spill-To), and from banks to the spread (spill-Fm). 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 explained in section 2 determine the strong inverse relationship between banks and the sovereign spread, some others the strong positive relationship across-banks.

Table 3: Correlations across spill-To and spill-Fm

spill-To	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
spill-Fm	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

4.2 Event-study regressions

Figure 1, 2, and 3 suggest that specific historical events may drive the evolution of the spillovers. To better understand the significance of those events, we have conducted an event-study analysis based on the *total* connectedness measures. The total spillover index (Tspill-I) is the average of the spillovers across the variables in the system excluding self-connectedness (eq. 6), the total spillover-to (Tspill-To) quantifies connectedness from the sovereign spread to the banking sector, the total spillover-from (Tspill-Fm) quantifies spillovers from the banking sector to the spread, as defined in eq. 5. Both 1-month and 3-month horizon-based spillover indices are used to ensure the robustness of the results.

We evaluate the short-term effect of the nine selected events by means of univariate autoregressive models in which we include nine dummies, one for each event.[13] Twelve lags of the dependent variable

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[13] The Lehman Brothers' bankruptcy (September 2008), the beginning of the first phase of the Euro-area debt crisis (March 2010), the beginning of the second phase of the Euro area debt crisis (July 2011), the "whatever it takes"

are included in each regression to capture autocorrelation, so we estimate an AR(12) model for each of the three total spillover indices, both at 1-month and 3-month horizons. Given the non-stationarity of the spillover indices, they enter the regressions in first differences. The computed variance-covariance matrix is robust to heteroskedasticity and autocorrelation. Table 4 shows the estimation output.

The onset of the global financial crisis in September 2008 (d_sep08) marks a significant increase in all volatility spillover indices, with the largest in the spillover from banks to the sovereign spread (Tspill-Fm). As the crisis originated in the banking sector and then affected the entire economy, this is a reasonable result. The onset of the first phase of the Euro area debt crisis in March 2010 (d_mar10) only led to a significant increase in the spread-from-banks spillover (Tspill-Fm), probably because Italy was only marginally affected by the turmoil at that time. In contrast, the second phase of the Euro area debt crisis in July 2011 (d_jul11) is characterized by a large increase in all indices, but higher in those capturing spillovers from the sovereign spread to the banking sector (Tspill-To). This is consistent with the nature of the turmoil, which was mainly driven by financial market tensions due to fears of sovereign debt defaults. However, the spillover from banks to the spread is also positive and significant (Tspill-Fm), suggesting a negative feedback loop. In July 2012 (d_jul12) almost all indices fell significantly. This was due to ECB President Mario Draghi's famous "whatever it takes" statement, which conveyed full support for the Euro and consequently reduced financial market volatility. In contrast, the announcement of the ECB's Outright Monetary Transaction programme in September 2012 (d_sep12) did not lead to significant changes in the connectedness measures. We include two dummies in 2016, one in January (d_jan16) meant to capture the introduction of the new bail-in regulation and the non-performing loan turmoil in Italy, and one in June (d_jun16) for the establishment of the European Stability Mechanism. The January 2016 dummy is negatively signed and significant for both spread-to-banks and spread-from-banks spillovers. The reduction they reflect can be explained by the stabilising effect of the new bail-in regulation. At the same time, however, the decrease in spread-from is smaller, most likely due to the non-performing loan turmoil, which manifested some of its effects by increasing the volatility of banks' stock returns. As for the establishment of the ESM (d_jun16), it is marked by a generalized increase in all spillover indices. The last two events, the Italian general election without a clear majority in May

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statement by ECB President Mario Draghi (July 2012), the establishment of ECB's Outright Monetary Transaction programme (September 2012), the introduction of the new bail-in regulation and the non-performing loan turmoil in Italy (January 2016), the establishment of the ESM (June 2016), general election in Italy without a clear majority (May 2018), and the beginning of the lock-down for the COVID-19 pandemic (March 2020)

2018 (d_may08) and the start of the lockdown for the Covid pandemic in March 2020 (d_mar20), led to significant increases in all spillover indices, but more in those from the sovereign spread to the banking sector. This is reasonable, as these events are not specific to the banking sector, but to the economy as a whole.

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.

Table 4: Event study regressions

main	Tspill-I:h1	Tspill-I:h3	Tspill-To:h1	Tspill-To:h3	Tspill-Fm:h1	Tspill-Fm:h3
d_sep08	7.155**	7.252**	5.696*	7.584**	11.583**	10.498**
d_mar10	0.413	-0.513	7'481	6'964	2.955**	-0.767
d_jul11	4.744**	4.617**	8.599**	10.160**	5.467**	4.688**
d_jul12	-0.914**	-0.899**	-0.561	-0.869**	-0.787**	-0.752**
d_sep12	0.23	0.078	-0.511	-0.828	0.216	0.129
d_jan16	5.084**	3.735**	-13.343**	-19.895**	-7.029**	-7.268**
d_jun16	4.255**	3.491**	8.049**	4.570**	5.935**	4.937**
d_may18	5.103**	4.239**	14.907**	12.677**	10.452**	10.423**
d_mar20	6.087**	5.716**	19.668**	16.759**	10.019**	11.645**
constant	-0.068	-0.051	-0.159	-0.126	-0.053	-0.049
ARMA						
L.ar	-0.059	-0.136*	0.111	0.019	-0.035	-0.058
L2.ar	-0.021	-0.017	-0.138	-0.139	-0.019	-0.013
L3.ar	0.045	0.026	0.116	0.045	0.155*	0.062
L4.ar	0.069	0.079	-0.007	-0.003	0.131	0.209**
L5.ar	-0.013	-0.008	0.013	0.015	-0.074	-0.135
L6.ar	0.002	-0.016	-0.058	-0.028	-0.077	-0.136
L7.ar	0.061	0.057	-0.013	-0.016	-0.043	-0.021
L8.ar	0.067	0.06	0.071	0.075	0.059	0.034
L9.ar	-0.041	-0.066	0.062	0.093	0.072	0.094
L10.ar	0.009	-0.006	0.078	0.094*	-0.003	0.000
L11.ar	0.125	0.138	-0.065	-0.036	0.004	0.027
L12.ar	0.033	0.08	0.01	0.04	-0.024	-0.002
constant	1.403**	1.228**	2.933**	3.004**	2.290**	2.257**
obs.	251	251	251	251	251	251
bic.	1'009'756	942'744	1'379'725	1'391'764	1'255'688	1'248'617

Dependent variables: Tspill-I stands for the total spillover index, Tspill-To stands for the total spillover from the sovereign spread TO banks, Tspill-Fm stands for the total spillover FROM banks to the sovereign spread, 1h/3h are for the 1-month and 3-month horizons of the FEVD. Explicatives: d-monthYEAR are for the event dummies. Significance levels * are based on robust standard errors; * $p<0.1$, ** $p<0.05$.

5 Regression analysis of the spillovers

In this section we report on the regression analysis aimed to explain the directional spillovers from the sovereign spread to each bank (spill-To), and vice versa (spill-Fm), through some relevant banks' features. While controlling for external time varying and internal time invariant determinants, we estimate the importance of those features using the balance-sheet variables listed in section 3.3, we provide here the rationale for their inclusion in the analysis.

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:* return on assets (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 stocks of more profitable banks could be more volatile, so we have no clear expectation regarding the sign of its effect. *Management Efficiency:* we construct the total-operating expenses to non-interest income ratio (OEI) as an indicator of management efficiency.[14] The rationale is that higher costs relative to revenues reflect lower managerial efficiency, so we might expect higher spillovers. The underlying link would be between management efficiency, the volatility of stock returns and the response to shocks. *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:* 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 structure:* investments in securities relative to total assets (ISA) is included to reflect the investment profile of banks; a comparatively higher amount of securities would reflect a riskier profile and, consequently, be associated with a higher spillover. Gross loans relative to total assets (GLA) is also included to account for the investment profile of banks and it is to compare with ISA. In contrast to ISA, a higher GLA value would signal a lower risk profile and could therefore be associated with a lower spillover. *Size:* we include market capitalization (MKV) to account for the dimension of each bank. Larger banks could be more systemic and therefore associated with larger spillovers, or instead be more financially stable and associated with less spillover. We only include the first lag of this variable in all regressions to avoid potential simultaneity with the dependent variable. Summary statistics of these variables for our sample of seven Italian banks are in Table 1.[15]

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[14] This is the best proxy we manged to build for the more common cost-to-income ratio, which is full of missing values in our sample of banks.

[15] We would have liked to include an indicator of the risk perceived by market participants for each bank, such as the spread of credit default swaps along the lines of Acharya et al. (2014). However, as in Acharya et al. (2014), publicly

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

$$y_{b,t} = \alpha + \lambda_b + \gamma_t + \boldsymbol{\beta} \boldsymbol{x}_{b,t} + \varepsilon_{b,t}, \tag{10}$$

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, $\boldsymbol{x}_{b,t}$ and $\boldsymbol{\beta}$ are, respectively, the vector of explicatives and the related vector of coeficients to be estimated; t is for the quarterly dimension of the dataset. The time and individual fixed-effects allow to control for, respectively, factors that vary over time but are common across banks (like global and country determinants that shape the macroeconomic environment) and for unobserved banks' characteristics that do not change over time.

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 (spill-To:1h, spill-Fm:1h), which is our benchmark, and 3 months (spill-To:3h, spill-Fm:3h). Although we believe that 1-month horizon is sufficient to capture transmission in financial markets, we cannot rule out the possibility that spillovers extend beyond the first month.

Bivariate regressions

Table 5 reports the output of the panel estimations where we insert the regressors one by one ($\boldsymbol{x}_{b,t} = x_{b,t}$). These estimations are useful to gain a first insight into the relationship between the dependent variable and the explicatives, particularly for those variables that we will not include in the multivariate regressions due to their missing values. Detailed comments on the effect of each variable are for the output of the multivariate regressions in the next subsection, 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. In contrast, all the other variables, with the exception of investment in securities relative to total assets (ISA) at the 1-month horizon, do not seem to have any significant effect. Already in this preliminary exercise, it is apparent that a higher CAR is associated with less spillover as expected. Truly, the bulk of the variables considered seems to signal a

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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 dropped this variable from the analysis.

limited role of balance-sheet characteristics. The R^2 $within$ is high in all the estimations, this suggests that much of the spillover variability is captured by bank (time invariant) and time (bank invariant) -specific effects.

Multivariate regressions

Table 6 reports the output of the panel estimations in which we include all the previous regressors at the same time ($\boldsymbol{x}_{b,t} = x1_{b,t} + x2_{b,t} + ...$). 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 in contrast to the bivariate estimations, we also find significance for investment in securities relative to total assets, gross loans relative to total assets and market value. In terms of the sign of the effects, it is confirmed that the capital-assets ratio limits volatility spillovers. Furthermore, more investment in securities is associated with higher spillovers, while more loans over total assets is associated with lower spillovers. Then, a portfolio skewed towards comparatively safer assets is associated with lower spillovers, which is an important confirmation. Moreover, although the magnitude of the effect is small, larger banks are unexpectedly significantly associated with weaker spillovers. A plausible explanation is that their stocks are less volatile. Return on assets, management efficiency and funding sources are confirmed as being non significant.

Multivariate regressions with interactions for Italy and Spain

In order to gain information on whether our results persist when we vary the sample, we extend our regression analysis using a sample including four additional Spanish banks. In detail, we first calculate the DY12 dynamic connectedness measures for a dataset consisting of Spain's sovereign spread and the realized volatility of the stock returns of those four large Spanish banks; see the paragraph "sample of banks" in subsection 3.3.[16] The procedure is similar to that used for the Italian sample. Once we have the spillover indices for each of these banks, we append the Italian dataset by adding the spillover

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[16] The Spanish banks are: Banco Bilbao Vizcaya Argentaria (BBVA), Banco Sabadel, Banco Santander, Bankinter.

Table 5: Bivariate Panel Regressions, Italy

Directional spillovers from the sovereign-spread to banks								
ITA	**spill-To:1h**	**spill-To:1h**	**spill-To:1h**	**spill-To:1h**	**spill-To:1h**	**spill-To:1h**	**spill-To:1h**	**spill-To: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
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*
	spill-To:3h	**spill-To:3h**	**spill-To:3h**	**spill-To:3h**	**spill-To:3h**	**spill-To:3h**	**spill-To:3h**	**spill-To: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
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	**spill-Fm:1h**	**spill-Fm:1h**	**spill-Fm:1h**	**spill-Fm:1h**	**spill-Fm:1h**	**spill-Fm:1h**	**spill-Fm:1h**	**spill-Fm: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
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*
	spill-Fm:3h	**spill-Fm:3h**	**spill-Fm:3h**	**spill-Fm:3h**	**spill-Fm:3h**	**spill-Fm:3h**	**spill-Fm:3h**	**spill-Fm:3h**
CAR	-0.327							
ROA		0.218						
OEI			-0.016					
NPL				-0.22				
TAD					-0.236			
ISA						0.045		
GLA							-0.035	
L.MKV								0.000
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*
Panel FE estimations, bank and quarter dummies included.								

Dependent variables: spill-To stands for the spillover from the sovereign spread TO banks, spill-Fm 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.MVL is the first lag of market value. Significance levels * are based on robust (id-clustered) standard errors; * p<0.1, ** p<0.05.

Table 6: Multivariate Panel Regressions, Italy

ITA	spill-To:1h	spill-To:3h	spill-From:1h	spill-From: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.MVL	-0.000**	-0.000**	-0.000**	0.000
obs.	549	549	549	549
R^2within	0.835	0.851	0.710	0.582
Panel FE estimations, bank and quarter dummies included.				

Dependent variables: spill-To stands for the spillover from the sovereign spread TO banks, spill-Fm 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.MVL is the first lag of market value. Significance levels * are based on robust (id-clustered) standard errors; * p<0.1, ** p<0.05.

of each Spanish bank and its balance sheet variables.[17] The extended dataset therefore includes seven Italian banks plus four Spanish banks. We then run a regression similar to Eq. 10, but in which we interact each variable with country dummies. This allows us to estimate the effect specific to each of the two countries considered, Italy and Spain. Table 7 shows the output of this panel estimation.

The estimation suggests that the results are country-specific, even with respect to the capital asset ratio, which we thought would act as a universal brake against spillover absorption and transmission. In fact, the results change both in sign and significance between the two countries. Nonetheless, and most importantly, with respect to what we obtain in the Italy-only estimation (Table 6), with the exception of investment in securities as a percentage of total assets, this estimation largely confirms the direction and the significance of the effects for Italy even when using this enlarged sample. This is a relevant information in favor of the robustness of our conclusions for Italy.[18]

6 Conclusions

In this work, we have examined the volatility spillovers between the sovereign spread and bank stock returns for a sample of Italian banks with the aim of quantifying the risk transmission between the

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[17] Importantly, the DY12 analysis is kept separated for the Italian and Spanish banks. Then, the calculation does not include spillovers from the Italian sovereign spread to Spanish banks, or from the Spanish sovereign spread to Italian banks, or between Italian and Spanish banks.

[18] We underline that the inclusion of only 4 foreign banks is too little to draw conclusions on the relationships we study for other countries, such as Spain. We consider this exercise more for the robustness of our conclusion for Italy.

Table 7: Multivariate Panel Regressions, Italy and Spain with interactions

ITA+ESP		**spill-To:1h**	**spill-To:3h**	**spill-Fm:1h**	**spill-Fm:3h**
CAR	*ES*	-0.286*	-0.330	-0.242	-0.482*
CAR	*IT*	-0.353**	-0.304**	-0.336*	-0.344*
ROA	*ES*	1.176	0.784	0.618	0.469
ROA	*IT*	0.015	0.004	0.149	0.192
OEI	*ES*	0.019*	0.039**	0.028	0.030
OEI	*IT*	-0.001	0.000	-0.005	-0.012
TAD	*ES*	0.089	-0.146	-0.320	0.403
TAD	*IT*	0.073	0.096	-0.039	-0.097
ISA	*ES*	-0.142	-0.076	-0.233	-0.170
ISA	*IT*	0.035	0.029	0.032	0.050
GLA	*ES*	0.124*	0.083	0.165*	0.099
GLA	*IT*	-0.062**	-0.041*	-0.072*	-0.064
L1.MVL	*ES*	0.000	0.000	0.000	0.000
L1.MVL	*IT*	0.000	0.000	0.000	0.000
obs.		848	848	848	848
R^2 within		0.764	0.798	0.661	0.533
Panel FE estimations, bank and year FE included.					

Dependent variables: spill-To stands for the spillover from the sovereign spread TO banks, spill-Fm 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.MVL is the first lag of market value. Significance levels * are based on robust (id-clustered) standard errors; * $p<0.1$, ** $p<0.05$.

sovereign and the banking sectors. This serves to inform on the amount of risk and its management both at the bank and macroeconomic levels. The relationship between sovereign risk and banks has long been studied in the theoretical and applied literature, which has identified and documented several channels of transmission (Acharya et al. 2012, 2014, Acharya & Steffen 2015).

We have conducted the connectedness analysis of Diebold & Yilmaz (2012) in a dynamic version based on the estimation of a time-varying parameter vector autoregression. Our results suggest that, in general, the sovereign spread receives more spillovers from banks than what it transmits to banks, this revers only during the Euro area debt crisis. The evolution of the spillovers is driven by events, some of which are policy actions that turn out to be effective in reducing spillovers as intended.

In the second part, we studied whether bank-specific characteristics help to explain the spillovers by using key balance sheet ratios. Among the variables used, the capital-adequacy ratio stands out as a key factor in reducing spillovers, both from the sovereign spread to banks and vice versa. This is an important confirmation that further underlines the importance of capital adequacy. Moreover, the structure of banks' asset portfolio appears to play a significant role. In particular, a less risky portfolio, characterized by a higher share of loans relative to securities, tends to be associated with smaller spillovers. Limited evidence suggests that these findings on the effect of balance sheet variables might vary across countries, but we leave this point to future research.

Overall, our analysis provides deeper insights into the relationship between sovereign risk and banking sector risk, thus complementing the structural analyses in this branch of literature.

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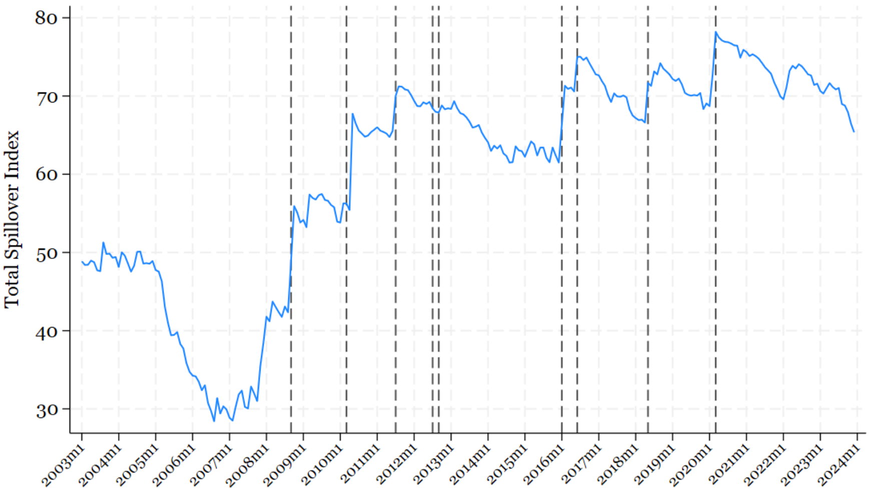
Appendix

Table 8: DY output, static (OLS-VAR), horizon 1

Row	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 3: Total Spillover Index



Vertical dashed lines, from left to right: Lehman Brothers' bankruptcy (Sept 2008), first phase of the EA debt crisis (March 2010), second phase of EA debt crisis (July 2011), "whatever it takes" statement (July 2012), ECB's OMT programme (Sept 2012), New bail-in regulation and NPL turmoil (Jan 2016), establishment of the ESM (June 2016), General election without a clear majority (May 2018), Lockdown for COVID-19 pandemic (March 2020). 1-month FEVD used for computation.

Table 9: ESP banks, summary statistics of balance-sheet ratios

BBVA	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.0308	0.83345	1.96206	3.788	1.70911	11.9717	59.6999	40868.7
meadian	11.4	0.8748	1.49193	4.1101	1.65107	13.14	59.8502	38815.3
stand.dev	2.6307	0.39928	2.85529	1.76655	0.14448	4.68041	5.20753	10866.2
min	6.8	-0.4772	0.62173	0.8158	1.31855	3.72664	46.715	17916
max	16.61	2.2968	25.829	7.6462	2.25159	21.7861	71.5872	66894.3
obs	84	80	84	81	81	81	84	84
Bankinter	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.0077	0.53005	1.40554	2.92328	1.70122	10.3485	73.6224	4270.66
meadian	11.98	0.5424	1.25719	2.9594	1.51974	10.632	74.0241	4175.6
stand.dev	2.16986	0.23488	1.07858	1.57661	0.53232	3.13739	5.3165	1650.17
min	6.32	-0.2396	-4.8606	0.2291	1.19835	0.83862	61.2777	1571.58
max	14.22	1.4228	6.25546	5.3831	3.43537	18.7381	86.3991	7827.69
obs	63	82	84	65	84	84	84	84
Sabadell	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.1587	0.43222	1.23315	5.25594	1.56366	10.7961	74.8851	6190.84
meadian	11.43	0.3814	1.43011	3.8499	1.43154	11.4421	73.9665	5716.13
stand.dev	2.70721	0.37685	5.97362	5.23481	0.32695	3.33856	6.58374	2422.66
min	6.55	-0.4404	-34.39	0.4035	1.20895	2.95692	63.8227	1866.09
max	15.47	1.1484	26.4421	21.6353	2.67286	17.6244	89.5131	11920
obs	78	84	84	81	84	84	84	84
Santander	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	10.9499	0.62646	1.58889	3.27158	1.8844	9.13825	60.5911	64518.9
meadian	11.37	0.649	1.6228	3.4228	1.63442	8.88697	61.2264	62201
stand.dev	2.29548	0.46715	0.47205	1.41006	0.46307	3.53855	3.78076	17053.5
min	7.16	-2.8224	0.40684	0.8559	1.43648	3.42755	50.4409	28814.6
max	14.24	1.282	2.82022	5.969	3.1584	18.0868	67.9841	95403.7
obs	83	82	84	83	83	83	83	84
Total	CAR	ROA	OEI	NPL	TAD	ISA	GLA	MKV
mean	11.0366	0.6031	1.54741	3.85198	1.71414	10.5552	67.2194	28962.3
meadian	11.6	0.6058	1.44332	3.63645	1.61452	10.7048	65.7711	14918
stand.dev	2.46445	0.40527	3.35825	3.12006	0.41121	3.83141	8.84711	27182.6
min	6.32	-2.8224	-34.39	0.2291	1.19835	0.83862	46.715	1571.58
max	16.61	2.2968	26.4421	21.6353	3.43537	21.7861	89.5131	95403.7
obs	308	328	336	310	332	332	335	336

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.