WIFO WORKING PAPERS 718/2025

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WIFO Working Papers 718/2025
December 2025

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2025/1/W/0

Media owner (publisher), producer: Austrian Institute of Economic Research
1030 Vienna, Arsenal, Objekt 20 | Tel. (43 1) 798 26 01 0 | https://www.wifo.ac.at
Place of publishing and production: Vienna

THE VIENNA INITIATIVE AS A SIGNALING MECHANISM TO DISRUPT THE BANKING DOOM LOOP

Abstract. We investigate the emergence of the Vienna Initiative (VI) as a public-private partnership established in response to the global financial crisis, and assess its short-term impact on the risk metrics of Western European banks. Our findings suggest that negative herding behavior toward certain banks can be associated with their decision to participate in the initiative. Banks with weaker balance sheet fundamentals showed a higher likelihood of participation. The measures implemented through the VI proved effective in curbing risk transmission within the network of participating banks, underscoring a strong signaling effect on investor sentiment. Our findings underscore the value of coordinated information disclosure and conditional support in curbing short-run risk transmission.

JEL codes: D85; F34; F42; G01; G21; G28
Keywords: Banking; Financial crisis; Herding behavior; Vienna Initiative; Network analysis; Event study

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This version: December 2025

The authors would like to thank the editor in charge of this paper (Peter G. Szilagyi), two anonymous referees, Benjamin Klaus, Silvio Petriconi and Edgar Vogel for valuable comments and helpful discussions. Excellent research assistance by Ursula Glauninger, Nicole Schmidt-Padickakudy and Tim Slickers is gratefully acknowledged.

1. Introduction

The global financial crisis (GFC) exposed vulnerabilities in Europe's integrated yet still nationally regulated and supervised financial system, with particularly acute stress in Central, Eastern, and Southeastern Europe (CESEE) where foreign-owned bank subsidiaries relied on funding from their Western European parent banks. After the bankruptcy of Lehman Brothers, mutual distrust spread throughout financial markets, which became illiquid. Asymmetric information about the quality of a bank's assets made it difficult to roll over maturing debt. Banks exposed to CESEE faced additional challenges. The publication of the first stand-by agreements between the International Monetary Fund (IMF) and CESEE governments in October 2008, due to expected fiscal adjustment requirements, made their vulnerabilities particularly apparent, as did the deteriorating macroeconomic outlook in the region. As a consequence, these banks quickly found themselves exposed to a barrage of negative news and faced a collective action problem, as the withdrawal of funds by individual banks exacerbated pressures on those that remained active in CESEE. Consequently, investor sentiment toward these banks collapsed and bank equity prices tumbled.

Against this background, on November 27, 2008, six Western European parent banks (Raiffeisen, Erste, Société Générale, KBC, UniCredit, Intesa Sanpaolo) wrote to the European Commission and the G20 Chair highlighting the urgency of coordinated action. In February 2009, the Vienna Initiative (VI) was launched as a public-private coordination platform to solve collective action problems by offering liquidity support to banks with CESEE operations, strengthening the deposit insurance system, and implementing support measures for the real economy in conjunction with international financial institutions (IFIs), namely the European Bank for Reconstruction and Development (EBRD), the European Investment Bank (EIB), and the World Bank Group (Allen, 2019; Stepic, 2019). The VI brought together IFIs, EU institutions, home and host country governments, national supervisory authorities, and major banking groups. Both home and host country governments had strong incentives to participate in the initiative, seeking to prevent disorderly deleveraging by Western European banks in CESEE and to maintain stable credit flows in host markets.

Key to the functioning of the VI were the provision of liquidity support, continuous monitoring, information dissemination, and commitment letters. The International Monetary Fund (IMF) established a burden-sharing framework between home and host countries to ensure coordinated crisis management. In partnership with other IFIs, a joint IFI Action Plan was launched in 2009, committing EUR 24.5 billion to support Western European parent banks in maintaining their exposures to CESEE and recapitalizing subsidiaries through senior loans, capital instruments, trade finance, and credit lines for small businesses and syndicated loans. In 2013, a second joint IFI Action Plan provided another EUR 30 billion of support. Access to this funding, however, was conditional on signing commitment letters, accepting close monitoring, and implementing recapitalization measures. These commitment letters and public statements issued under the VI were closely followed by the media, serving as credible signals that helped restore market confidence (Berglöf et al., 2019). The VI monitored compliance of participating banks, reinforcing accountability and transparency. The combination of liquidity support, macroeconomic stabilization policies, and information dissemination across all investors by an independent body reduced information asymmetries among investors about counterparty risks of banks active in CESEE, limited the first-mover advantage of withdrawing funds from the region, and hence mitigated synchronized negative investor behavior.

The VI's emergence as a public-private partnership (PPP) is intriguing for a number of reasons. First, unlike most crisis management frameworks, the VI was initiated by private banks rather than by public authorities or IFIs, offering a unique setting to study the incentives for private-sector cooperation. Secondly, while previous studies (see below) have examined the VI using balance sheet outcomes or low-frequency cross-border credit data, our study takes a high-frequency approach. This allows us to identify short-term mechanisms resulting from a combination of asymmetric information and a collective action problem—investor herding and market segmentation—that underpinned subsequent credit developments. Third, the VI's cross-border design distinguishes it from national support programs, thereby sending stronger signals to market participants, hence influencing investor behavior across borders.

Regarding the first point, we examine the role of investor sentiment and herding behavior in shaping banks' decisions to join the VI. Among the many foreign banks active in CESEE (see Allen et al., 2017, for an overview), only 17 participated. While the VI was distinctive as it was initiated by private banks, participation implied a binding commitment to maintain credit exposures during a period of severe uncertainty. We conjecture that negative herding behavior toward Western European banks with significant CESEE exposure and weak balance sheets at the onset of the global financial crisis led to segmentation and increased their willingness to participate. Negative investor sentiment typically increases equity price return volatility and worsens refinancing conditions. This can be amplified by herding, particularly where risk concentration heightens investors' concerns, resulting in highly synchronized movements in equity price returns. This conjecture is motivated by recent studies demonstrating how herding can destabilize asset prices and amplify liquidity and solvency risks (Choi and Sias, 2009; Deng et al., 2018; Cai et al., 2019).

The second point concerns the perception of the VI in financial markets. In addition to stabilizing credit flows to CESEE, a key intention of the VI was to send a signal to financial market participants with the immediate aim of reducing the counterparty risk of individual parent banks with CESEE exposure and providing these banks with easy access to refinancing sources. To this end, we assess the VI's success in dissipating the negative herding behavior toward these banks and thus dissolving financial market segmentation.

We consider Western European banks and distinguish three groups of banks (see also Allen et al., 2017): (i) VI banks (Western European banks active in CESEE and part of the VI), (ii) non-VI banks (Western European banks active in CESEE and not part of the VI), and finally (iii) other Western European banks not active in CESEE (and hence not part of the VI). Given these groups, we then proceed in three steps. First, we assess whether excess volatility and market segmentation can be detected through a network analysis of individual banks' equity price returns. Using the banks' idiosyncratic equity price returns (i.e., accounting for global and domestic factors), we measure excessive volatility based on their time-varying stochastic volatility components and market segmentation based on the within- and across-block densities of their correlation network. We interpret within-block densification and across-block thinning as segmentation resulting from adverse herding. Second, we use bank balance sheet characteristics from 2008 to estimate the likelihood of VI participation, measured by whether a bank signed a commitment letter during 2009. Third, we use an event study design at a daily frequency to study the announcement effects of VI measures on the volatility of equity price returns of banks and network characteristics. This allows us to identify short-run signaling and coordination effects and hence to assess the success of the measures of the VI.

To preview some results, first, we find evidence of negative herding behavior toward VI-participating banks relative to non-VI-participating banks and banks not active in CESEE. Second, we find that weaker balance sheet fundamentals are significantly associated with a higher likelihood of VI participation, suggesting that financially more vulnerable banks had stronger incentives to join the initiative. Third, our results show that the VI measures were successful in mitigating negative herding behavior toward VI-participating banks, underscoring their strong signaling effect on investor sentiment.

Our study is related to two strands of the literature: one addressing the VI and the other examining national financial sector rescue programs. The first strand assesses the VI's effectiveness in stabilizing credit conditions in CESEE during the global financial crisis. Whereas Adams-Kane et al. (2015)

document that lending contracted despite the VI's support measures in CESEE, Cetorelli and Goldberg (2011) find that VI-targeted countries experienced comparatively milder credit declines. Similarly, De Haas et al. (2015) find that while domestic banks curtailed credit supply, foreign banks with VI commitments maintained lending, underscoring the stabilizing role of the initiative. Temesvary and Banai (2017) further highlight that stable credit provision was concentrated among subsidiaries participating in the VI, with outcomes shaped by both parent and subsidiary characteristics. A common feature of these contributions is their reliance on low-frequency data on cross-border credit flows or balance sheet data, thereby constraining the analysis to a medium-term horizon. By contrast, our study employs daily risk metrics, enabling a short-term assessment of the VI's effectiveness in taming herding behavior. The second strand addresses the broader role of financial sector rescue programs in mitigating market stress. For instance, Aït-Sahalia et al. (2012) find that policy measures, particularly recapitalization programs, were associated with a reduction in interbank risk premia, unlike bailouts, which had a less pronounced effect. Besides recapitalizations, Glocker and Url (2022) identify public guarantees as effective forms of government intervention. They also highlight that, while the announcement of public financial support for banks appears to have been successful in breaking negative network externalities, it increased credit risk associated with sovereign debt. The latter is corroborated by results in Kizys et al. (2016). Common to these studies is their focus on measures implemented nationally and their effects on domestic financial markets. In contrast, our study considers measures from the VI, which span national borders. This adds an international dimension to the studies on the effects of financial sector rescue programs.

The paper is structured as follows. Section 2.1 describes the economic environment in which the VI emerged and its historical affinities, and Section 2.2 provides a theoretical discussion. Section 3.1 measures excess volatility and adverse herding and inspects changes thereof by relying on tools of network analysis. Section 3.2 examines the probability of VI participation and Section

3.3 examines the effects of the VI measures on herding behavior of Western European banks. Section 3.4 provides a general discussion of the results and Section 4 concludes.

2. Institutional background and literature review

This section establishes the foundation for the subsequent analysis in two parts. First, it describes the institutional environment in which the VI emerged. Second, it discusses the theoretical concepts of herding behavior and signaling, which provide a lens for understanding the VI's purpose and the impact of its interventions.

2.1. **The economic environment surrounding the VI and historical affinities.** At the onset of the global financial crisis, decoupling theories suggested that emerging markets would be less affected because the turmoil originated in advanced economies (Kose et al., 2008). In CESEE, however, early currency appreciation was soon followed by rising CDS spreads, signaling deteriorating investor sentiment and the unwinding of accumulated imbalances (Heinz and Sun, 2014). Western European governments quickly recognized that recessions in CESEE posed not only local but also cross-border risks: large Western European banks had funded credit booms in CESEE by borrowing cheaply in European money markets and transferring funds to their subsidiaries. A disorderly deleveraging threatened financial intermediation in both the host and home countries, potentially creating sovereign risks through costly bailouts.

The situation was reminiscent of the Latin American debt crisis of the 1980s, when U.S. banks suddenly withdrew funding due to rising interest rates and deteriorating investor sentiment (Sachs, 1985; Berg and Sachs, 1988). The disorderly retreat of banks prolonged the crisis and left debtor countries with a lost decade (Hayes, 1988; Felix, 1990). The Brady Plan was designed in response to the debt crisis and combined debt relief with collateralization through U.S. Treasury securities, enhancing debt tradability (Sachs and Huizinga, 1987;

Sachs, 1988). While it too represented a PPP, it was initiated by a public entity. By contrast, the VI was distinctive in being launched by private banks themselves.

Another important distinction concerns the involvement of debtor countries. While the Brady Plan largely excluded Latin American governments from its design, the VI institutionalized burden-sharing among actors in the European financial system. For the first time, host (debtor) countries participated directly alongside home regulators and banks, establishing a forum for cross-border coordination beyond traditional lobbying channels. This framework encouraged home governments to assume fiscal responsibility for financial stability in CESEE markets where their banks operated, thereby extending governance beyond national borders (see Pistor, 2012).

Empirical evidence from the Brady Plan further illustrates how coordinated debt relief influenced financial markets. Unal et al. (1993) find that major U.S. multinational banks exhibited strong positive abnormal equity price returns—around 6.9 percent over two days—following President Bush and Chairman Greenspan's endorsement of the plan in March 1989, whereas non-multinational U.S. banks showed no response. Similarly, Arslanalp and Henry (2005) report that equity prices of the eleven largest U.S. commercial banks with substantial Latin American exposure rose by an average of 35 percent, indicating that creditors with international portfolios benefited significantly from the Brady Plan.

2.2. **Herding and VI participation: theoretical considerations.** The limited participation of Western European banks in the VI suggests segmentation in investor sentiment, consistent with adverse herding behavior (Mobarek et al., 2014). The central channel is informational: prior to and during the crisis, asymmetric information about Western European banks' actual exposures in CESEE elevated uncertainty at the group level and fostered adverse herding. Under such conditions, investors may rationally cluster banks with perceived shared exposures (risk concentration), amplifying idiosyncratic volatility and segmentation.

In theory, herding arises when agents with incomplete information imitate others: either because payoffs depend on collective actions (payoff externalities) or because observed actions dominate private signals (information externalities). The VI can be understood as a mechanism to mitigate both. The provision of liquidity support and policy guarantees reduced payoff externalities by strengthening banks' solvency and resilience (see Repullo and Suarez, 2004; Corsetti et al., 2006). At the same time, public commitments and information sharing served as signals to investors, alleviating information externalities that otherwise fuel cascades (Banerjee, 1992; Welch, 1992). Without coordination, investors expecting a liquidity crunch for banks active in CESEE in combination with excessive loan losses would rationally follow suit. Banks observing peers retreating would be incentivized to imitate, amplifying systemic stress through strategic complementarities (Goldstein et al., 2024).

In this environment, the VI thus acted as a coordination device: it reduced information asymmetries about exposures and portfolios, made banks' solvency more transparent, and signaled collective commitment to provide liquidity to CESEE banks. From a theoretical perspective, the VI thus acted as a monitoring and signaling device aimed at curbing payoff and informational externalities.

Our subsequent empirical analysis focuses on daily bank-level stock market data, for two reasons. First, high-frequency data allow timely identification of herding behavior in financial markets. Second, they enable the evaluation of the signaling effects of policy interventions such as the VI announcements. Although balance sheet data would provide additional insights, their low publication frequency precludes the study of short-term dynamics and behavioral responses related to herding.

3. Empirical methodology

In the following analysis, we first estimate volatilities and connectivities for a large set of European banks to identify elements of herding behavior. Given these results, we subsequently examine their role in shaping banks' decisions to join the VI. Finally, we assess the effectiveness of VI measures in taming adverse herding behavior, specifically their immediate effects on the volatilities and connectivities of the bank network.

3.1. **Foreign banks in CESEE and financial market stress.** We examine a sample of 55 Western European banks over the period January 2007 to December 2016, regardless of their activity in CESEE, and use equity price returns as the main indicator of excess volatility and herding behavior. We distinguish three groups of banks following Allen et al. (2017): (i) 15 VI banks[1] (Western European banks with CESEE exposure that participated in the VI), (ii) 15 non-VI banks (Western European banks with CESEE exposure but not participating), and (iii) 25 non-CESEE banks (Western European banks without exposure to CESEE). This classification enables us to assess whether adverse financial market dynamics motivated banks with CESEE exposure to coordinate via the VI.[2]

Excess volatility and herding are measured using a time-varying vector autoregressive model of equity price returns. Excess volatility is identified through the stochastic volatility component, while herding is proxied by the density of a dynamic correlation network of bank equity price returns[3] which is consistent with the approach in Gębka and Wohar (2013) and Klein (2013). In accordance with Section 2.2, the consequence of herding behavior, whether intentional or not, is strong co-movement among high-frequency financial indicators within the affected group of banks (compare Apostolakis and Papadopoulos, 2014; Song et al., 2021). Since co-movement may also result from common shocks, we focus on the idiosyncratic component of equity price returns, obtained after partialling out global and domestic factors from bank-specific equity price returns. This adjustment is critical for network correlation

[1]We only consider 15 of the 17 banks that joined the VI, due to a lack of equity price data for the remaining two.

[2]Consider the Online Appendix for a detailed list of the banks in our sample.

[3]Dynamic networks have many applications in finance, including the study of contagion, risk sharing, and investor sentiment. See Hasse (2021); Kumar et al. (2022) among others.

analysis, as it prevents spurious linkages stemming from common dependencies (see Barigozzi et al., 2018; Rahman et al., 2023).

3.1.1. *Data and estimation of volatility and connectivity.* We construct a dynamic correlation network based on parametric estimates of the conditional correlation between banks' idiosyncratic equity price returns, obtained after controlling for global and domestic financial market-wide fluctuations. Our objective is to derive a promptly updating measure of conditional correlation; accordingly, parameters are allowed to vary over time so that synchronous changes in idiosyncratic equity price returns are reflected immediately in the correlation coefficients.

Starting from daily bank equity price returns: $r_{i,t} = \log(P_t^i) - \log(P_{t-1}^i)$, we follow common practice[4] and estimate bivariate time-varying vector autoregressive models with exogenous variables (TVP-VARX) for pairs of equity price returns $r_{\cdot,t}$ from banks i and j:

$$(1) \qquad \left(\boldsymbol{I} - \boldsymbol{B}_t^{i,j}(L)\right) \begin{bmatrix} r_{i,t} \\ r_{j,t} \end{bmatrix} = \boldsymbol{H}\boldsymbol{x}_t + \boldsymbol{\varepsilon}_t^{i,j}, \quad \boldsymbol{\varepsilon}_t^{i,j} \sim N(0, \boldsymbol{\Sigma}_t^{i,j}),$$

where $i, j = 1, \ldots, n$, $i \neq j$, n is the number of banks considered, $\boldsymbol{B}_t^{i,j}(L)$ is a time-varying lag-polynomial with two lags, and $\boldsymbol{\varepsilon}_t^{i,j}$ is a 2-dimensional vector of residuals (i.e., idiosyncratic equity price returns) with $\boldsymbol{\Sigma}_t^{i,j}$ its time-varying variance-covariance matrix. Restricting the number of lags to 2 ensures that synchronous changes in returns immediately alter stochastic volatility and the correlation coefficients. $\boldsymbol{x}_t$ denotes a 4×1 vector of exogenous controls and $\boldsymbol{H}$ is the associated coefficient matrix. Exogenous control variables include: (i) home country-specific factors of parent banks (domestic stock index returns and changes in the slope of the yield curve, measured as the 10Y–3M spread), and (ii) global factors (EURO STOXX 50 and S&P500 returns). This ensures that $\boldsymbol{\varepsilon}_t^{i,j}$ reflects bank-specific risks (e.g., CESEE exposures) rather than global or home country-specific shocks.

[4]See Antonakakis et al. (2020); Stenfors et al. (2022); Zhou and Liu (2023); Wang et al. (2024); Sila et al. (2024) among others, all of which take a similar approach.

We compute conditional correlations by extending the autocovariance generating function $\boldsymbol{\Gamma}_h^{i,j}(t)$ of the TVP-VARX to obtain the cross-correlation matrix (see Hamilton, 1994, Chapter 10):

$$\tilde{\boldsymbol{P}}_h^{i,j}(t) = \boldsymbol{D}^{i,j}(t)^{-1}\boldsymbol{\Gamma}_h^{i,j}(t)\boldsymbol{D}^{i,j}(t)^{-1}, \tag{2}$$

where $\boldsymbol{D}^{i,j}(t) = \mathrm{diag}(\sigma_{ii,t}, \sigma_{jj,t})$ denotes the 2×2 diagonal matrix of time-varying standard deviations extracted from $\boldsymbol{\Sigma}_t^{i,j}$ and h is the temporal distance. This approach combines the information from the lag polynomial and the variance-covariance matrix of the TVP-VARX model for the computation of conditional correlations. We use the standard deviations $\sigma_{ii,t}$ as measures of stochastic volatility and collect them into a 55×1 vector $[\boldsymbol{\sigma}_{1,t}, \boldsymbol{\sigma}_{2,t}, \boldsymbol{\sigma}_{3,t}]$, covering (1) VI banks, (2) non-VI banks, and (3) non-CESEE banks, respectively.

We estimate all $n(n-1)/2$ bivariate models sequentially, which is computationally more efficient than a high-dimensional TVP-VARX. We consider contemporaneous correlations only ($h = 0$) and the set of time-varying conditional correlations $\tilde{\varrho}_{ij,0}(t) \in \tilde{\boldsymbol{P}}_0^{i,j}(t)$ from the bivariate estimations is then assembled into the overall contemporaneous correlation matrix $\tilde{\boldsymbol{P}}_0(t) = [\tilde{\varrho}_{ij,0}(t)]_{i,j=1,\ldots,n}$.

We rely on the Bayesian estimation approach of Primiceri (2005) to estimate equation (1). The Kalman filter is initialized with OLS estimates from the first 365 daily observations. Posterior distributions are obtained from 500,000 MCMC draws, discarding the first 100,000, leaving $D = 400,000$ effective draws for inference. These distributions of $\tilde{\boldsymbol{P}}_0(t)$ and the vector of stochastic volatilities $[\boldsymbol{\sigma}_{1,t}, \boldsymbol{\sigma}_{2,t}, \boldsymbol{\sigma}_{3,t}]$ form the basis for our subsequent network and volatility analysis.

3.1.2. *Excess volatility: Measurement and results.* The first panel of Table 1 reports mean daily equity price returns $r_{i,t}$ by bank group across three subperiods. The *pre-GFC* period spans from January 2007 to September 2008, the *GFC & EDC* period covers October 2008 to December 2012, and the *post-EDC* period runs from January 2013 to December 2016. Before the crisis, VI banks exhibit the highest average returns, while non-VI banks occupy the lower end of the distribution. During the crisis, this pattern reverses: VI banks record

Table 1. Daily equity price returns, estimated stochastic volatilities and conditional correlations: Descriptive statistics by bank group and subperiod

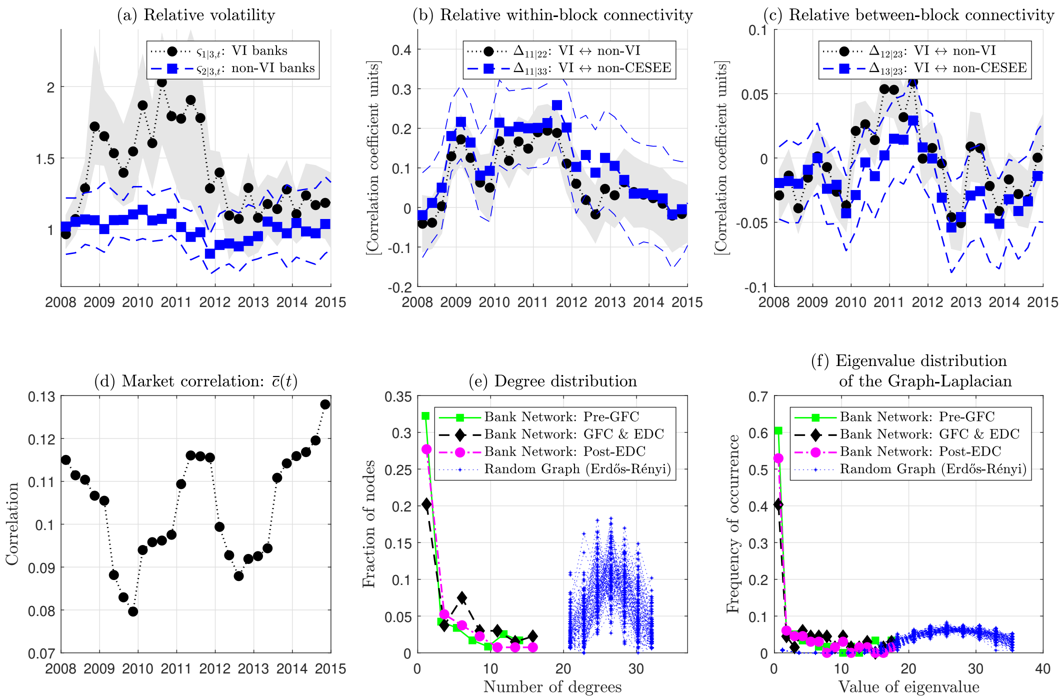
	Pre-GFC	GFC & EDC	Post-EDC
	Mean equity price returns ($r_{i,t}$)		
VI banks	0.012	-0.048	0.013
non-VI banks	0.008	-0.041	0.027
non-CESEE banks	0.010	-0.021	0.009
	Median (stochastic) volatilities ($\sigma_{ii,t}$)		
VI banks ($\boldsymbol{\sigma}_{1,t}$)	0.061	0.205	0.069
non-VI banks ($\boldsymbol{\sigma}_{2,t}$)	0.064	0.117	0.061
non-CESEE banks ($\boldsymbol{\sigma}_{3,t}$)	0.059	0.116	0.064
	Median conditional correlations ($\tilde{\varrho}_{ij,0,t}$)		
VI banks	0.104	0.261	0.106
non-VI banks	0.130	0.154	0.128
non-CESEE banks	0.113	0.097	0.117

The three subperiods are (i) the pre-crisis period (*Pre-GFC*, prior to Sep 2008), (ii) the global financial crisis and the European debt crisis (*GFC & EDC*, Oct 2008–Dec 2012), and (iii) the post-crisis recovery (*Post-EDC*, Jan 2013 and beyond). The table reports the mean of equity price returns for the banks in a group for each period (cleaned for extreme values). Stochastic volatilities are scaled up by a factor of ten to enable comparison between bank groups and episodes. The median value for the stochastic volatility and the conditional correlation corresponds to the median across banks in a group for each period over all draws from the posterior distribution.

higher average daily losses than those of non-CESEE banks, with non-VI banks falling between the two groups. In the post-EDC period, average returns turn positive again, though VI banks continue to underperform relative to non-VI banks, which is primarily due to the four Greek banks within the VI group.

The middle panel of Table 1 shows the median stochastic volatility separated by bank group and subperiod and multiplied by 10 to enable better comparison across groups and periods. Volatilities during the pre-GFC and post-EDC periods are similar across groups. The crisis period stands out owing to a striking pattern: while volatility doubles for non-VI and non-CESEE banks, it triples for VI banks during the stress episode. A similar pattern emerges for conditional correlations in the lower panel but here both VI and non-VI banks show higher correlations compared to non-CESEE banks, with synchronicity among VI banks more than doubling.

FIGURE 1. Bank network: volatility and connectivity



Note: Daily data are aggregated to quarterly frequency by taking the mean over the quarter. The median is taken across all banks in a group and draws from the posterior. The grey shaded area and the area between the blue dotted lines represent 68 percent credible intervals. Relative volatilities (panel a) are defined as the posterior equity price return volatilities of VI and non-VI banks, normalized by the median volatility of the non-CESEE group. Relative within-group connectivity (panel b) reports the posterior network density of each group relative to the median density of non-CESEE banks, while relative between-group connectivity (panel c) provides the corresponding cross-group measures. Panel d presents the average market correlation among non-CESEE banks, and panels e and f summarize key aspects of the network topology. The time dimension is divided into three subperiods: *Pre-GFC* (before the global financial crisis), *GFC & EDC* (global financial crisis and European debt crisis), and *Post-EDC* (after the European debt crisis).

The numbers in Table 1 already reveal time-varying and group-specific patterns. We now explore the evolution of stochastic volatilities $[\boldsymbol{\sigma}_{1,t}, \boldsymbol{\sigma}_{2,t}, \boldsymbol{\sigma}_{3,t}]$ over time in more detail. Panel a of Figure 1 shows the posterior distribution of stochastic volatilities for VI banks ($\boldsymbol{\sigma}_{1,t}$, black dotted) and non-VI banks ($\boldsymbol{\sigma}_{2,t}$, blue dashed) relative to the median volatility across non-CESEE banks ($\boldsymbol{\sigma}_{3,t}$): $\varsigma_{i|3,t} = \boldsymbol{\sigma}_{i,t}/\bar{\boldsymbol{\sigma}}_{3,t}$, $i = 1, 2$, where $\bar{\boldsymbol{\sigma}}_{3,t}$ denotes the median across non-CESEE banks. This normalization immediately unveils whether and when stochastic volatilities became elevated for banks active in CESEE. For clarity, daily volatilities are first aggregated to quarterly frequency by taking the mean over all trading days in a quarter, and we show the median over banks and draws from the posterior, together with the 68 percent credible intervals of relative volatilities. Due to the initialization of the Kalman filter we lose the observations of 2007.

The results reinforce the impression of segmentation among banks. While the stochastic volatility of non-VI banks remains close to that of non-CESEE banks, it markedly increases for VI banks starting in autumn 2008, at the onset of the global financial crisis. As shown by the non-overlapping credible intervals, the divergence is statistically significant in the fourth quarter of 2008. The divergence diminishes somewhat by late 2009, as VI banks' volatility declines and non-VI banks' volatility rises moderately. By mid-2010, the European debt crisis triggers a renewed increase in volatility among VI banks, largely driven by a sharp surge in the four Greek banks, which also produces a widening of the 68 percent credible interval. Volatility rises more modestly among the remaining VI banks.

Panel d of Figure 1 shows the evolution of the average conditional correlations ($\tilde{\varrho}_{ij,0}(t)$) among non-CESEE banks. Correlations are again aggregated to quarterly frequency by taking the mean over daily observations to enhance visibility. The average correlation among non-CESEE banks $\bar{c}(t)$ provides a dynamic benchmark for the extent of synchronized market movements for the other groups. Co-movement among non-CESEE banks was already elevated in 2008 and reached its minimum at the end of 2009. The onset of the European debt crisis triggered renewed market turbulence, with conditions stabilizing only in early 2012. From mid-2013 onward correlations increased steadily, peaking toward the end of the sample period.

3.1.3. *Herding behavior: Measurement and results .* We assess herding behavior by analyzing the degree of co-movement in banks' equity price returns through a dynamic network representation. The intuition is simple: if banks' equity price returns move more closely together than can be explained by common market factors, this reflects herding behavior among investors.

Formally, we construct a time-varying network $\mathcal{G}(t) = (\mathcal{N}, \mathcal{E}(t), \mathcal{W}(t))$, where the $n = 55$ nodes $\mathcal{N} = \{\nu_1, \ldots, \nu_n\}$ represent all banks in the sample, $\mathcal{E}(t)$

denotes connections (edges) between them, and $\mathcal{W}(t)$ captures the strength of these connections (edge weights). In this representation, banks whose idiosyncratic equity price returns move closely together are directly linked, with higher-valued edges indicating stronger co-movement. The network evolves over time t as market conditions change (see Holme and Saramäki, 2012).

The network $\mathcal{G}(t)$ is described by the $n \times n$ adjacency matrix $\boldsymbol{P}(t) = [\varrho_{ij}(t)]_{i,j=1,\ldots,n}$, which is a restricted version of the correlation matrix $\tilde{\boldsymbol{P}}_0(t)$. Each element $\varrho_{ij}(t)$ quantifies the correlation-based link between banks i and j but a link is included only if the conditional correlation $\tilde{\varrho}_{ij,0}(t)$ (see equation 2) from the TVP-VARX model (equation 1) is statistically meaningful and sufficiently strong:

$$\varrho_{ij}(t) = \begin{cases} \tilde{\varrho}_{ij,0}(t) & \text{if } \forall i \neq j : \Pr(\tilde{\varrho}_{ij,0}(t) \neq 0) \geq 1 - \bar{p} \ \wedge \ \tilde{\varrho}_{ij,0}(t) \geq \bar{c}(t) \\ 0 & \text{else} \end{cases}$$

This procedure transforms the correlation matrix $\tilde{\boldsymbol{P}}_0(t)$ into a sparse adjacency matrix $\boldsymbol{P}(t)$ that retains only statistically and economically meaningful connections $\varrho_{ij}(t)$ (see Glocker and Piribauer, 2025). Two thresholds govern this conversion. First, a statistical threshold ($\bar{p} = 0.05$) ensures links reflect correlations that are credibly different from zero. Second, the average market correlation among non-CESEE banks $\bar{c}(t)$, already introduced in Section 3.1.2, requires correlations to exceed the average market-wide co-movement. This means we focus only on stronger-than-market clustering, i.e., those cases where some banks move together much more closely than the broader market. This dynamic threshold adapts over time, reflecting the evolving intensity of market-wide correlations (see Figure 1, panel d).[5]

This step is important because even after controlling for global and domestic shocks, industry- or home-country-specific factors may still drive common patterns across banks. Given the heterogeneity of Western European banking systems and CESEE markets, correlations may arise from factors not captured

[5]This approach contrasts with studies imposing arbitrary, time-invariant thresholds (e.g., Isogai, 2016; Chen et al., 2022).

TABLE 2. Bank network: summary statistics

	Pre-GFC	GFC & EDC	Post-EDC	Hypothesis Tests (6) Test 1	Test 2
(Dis-)Assortativity(1)	-0.31	-0.02	-0.14	H_1	H_0
Degree (Link) density(2)	0.07	0.12	0.08	H_1	H_0
Av. degree(3)	3.02	5.02	3.53	H_1	H_0
Av. number of connected nodes(4)	0.40	0.62	0.47	H_1	H_0
Transitivity(5)	0.53	0.51	0.66	H_0	H_1

(1) Assortativity measures whether highly connected banks tend to link with similarly connected peers (positive values) or with less connected ones (negative values).
(2) Degree (link) density is the fraction of possible connections that are actually present, indicating overall network connectedness.
(3) Average degree is the mean number of direct connections per bank.
(4) The average number of connected nodes captures the share of banks with at least one active link.
(5) Transitivity measures the extent to which connections close into clusters (triangles), capturing the tendency of banks to form tightly knit groups.
(6) Test 1 examines: H_0: $X_{\text{Pre-GFC}} = X_{\text{GFC \& EDC}}$ vs. H_1: $X_{\text{Pre-GFC}} \neq X_{\text{GFC \& EDC}}$, where X denotes a network topology measure. Test 2 examines: H_0: $X_{\text{Pre-GFC}} = X_{\text{Post-EDC}}$ vs. H_1: $X_{\text{Pre-GFC}} \neq X_{\text{Post-EDC}}$, where X denotes a network topology measure. The entry H_0 indicates the null hypothesis cannot be rejected and H_1 indicates rejection of the null hypothesis at the 10 percent significance level.

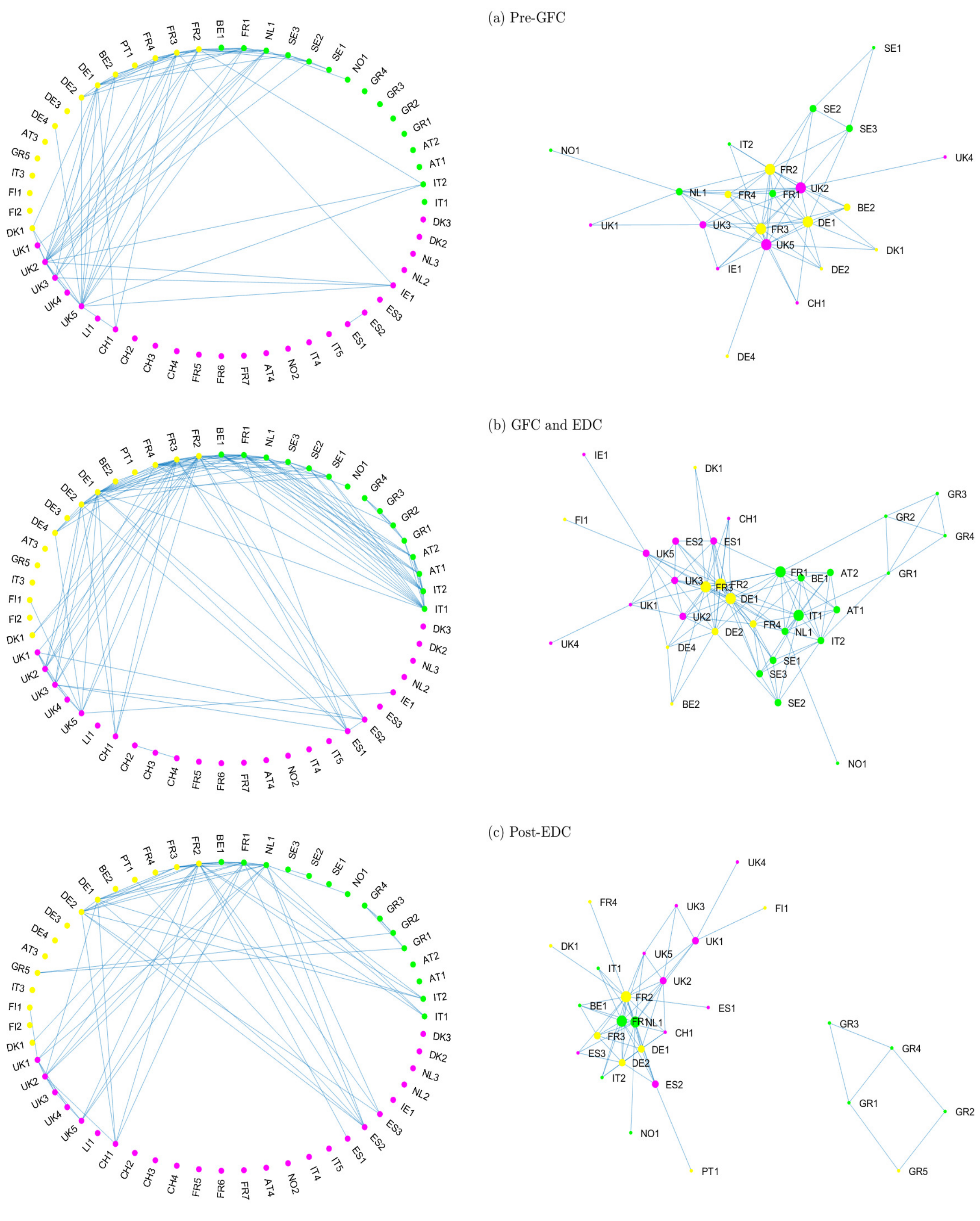
by the global controls. The thresholding therefore isolates excess co-movement that can be meaningfully interpreted as herding.

A potential problem is negative correlations, which complicate network interpretation. In practice, however, we find these correlations are small and eliminated by statistical thresholding. Hence, all retained links are nonnegative, and since $\varrho_{ij}(t) = \varrho_{ji}(t)$, the network is undirected. The resulting structure is therefore a weighted, undirected graph in which clusters represent groups of banks moving unusually closely together.

From an economic point of view, herding occurs when the network densifies–i.e., when more banks become connected to each other–indicating that investors treat a group of banks as if they carry highly similar risks. For example, if all VI banks cluster tightly while non-CESEE banks remain sparsely connected, this provides direct evidence of herding specific to VI banks.

Inspecting the network across distinct episodes. To study the evolution of herding behavior, we again focus on the three subperiods (*Pre-GFC*, *GFC & EDC* and *Post-EDC*). The network structure for each period is derived by averaging the adjacency matrix $\boldsymbol{P}(t)$ over daily estimates within each period.

FIGURE 2. Bank network: visualization



Note: Nodes in green refer to VI banks, nodes in yellow to non-VI banks and nodes in magenta to non-CESEE banks. The size of the nodes in the panels on the right-hand side is set by the node degree of each node. The names of the banks associated with the acronyms are provided in the Online Appendix. For better visualization, some connected nodes which are, however, disconnected from the giant component are not displayed (for instance, ES1 connected with ES2 in the pre-GFC period; CH2 connected with CH4 in the GFC and EDC period; SE2 connected with SE3 in the post-EDC period).

Panels e and f in Figure 1, together with Table 2, summarize key network properties (see Newman, 2010). Both panels in Figure 1 are based on the posterior median for all banks. Sparse connectivity characterizes the banking network in all periods, reflected by a spike of the degree distribution at one in panel e, indicating that around 20% to 30% of the banks have just one link to another bank. The share of banks having more than one connection becomes small very quickly as the number of connections rises. There is no bank in the sample with more than 16 connections. The sparsity of the bank network is significant when compared to (a series of realizations of) an Erdős-Rényi random graph (blue dotted lines in panel e of Figure 1). In random adjacency matrices, the share of elements with less than 20 connections is zero. Similarly, the eigenvalues of the graph Laplacian in panel f are mostly zero, a few do have small values and eigenvalues above 20 do not occur. This suggests disconnected elements in the network and it is in sharp contrast to the structure of eigenvalues resulting from an Erdős-Rényi random graph: zero eigenvalues are non-existent while eigenvalues above 25 occur most frequently. The visualizations in Figure 2 reinforce these statistics. Across all episodes, the network reveals a core–periphery structure that is typical in financial systems (Zhang et al., 2023).

However, during the GFC & EDC, the degree distribution flattens and the number of connections rises sharply (Figure 1, panel e). This reflects intensified co-movement across idiosyncratic equity returns of banks, consistent with stronger herding. Figure 2 highlights that this arises specifically from a clustering among VI banks (green nodes) during the GFC & EDC: they are densely connected both with one another and with non-VI banks (yellow), reflecting heightened investor focus on their shared CESEE exposures. Economically, this implies that only subsets of banks—rather than the entire system—were subject to herding.

By contrast, before and after the crisis period these group-specific herding patterns are far less pronounced. The Pre-GFC and Post-EDC periods show sparser structures that resemble one another, but with some important differences. Post-EDC transitivity is highest, reflecting increased clustering, particularly driven by the co-movement among Greek banks, which form a distinct community separated from the rest of the network, cf. panel c in Figure 2. The clustering of VI and non-VI banks disappears but the core is now dominated by French and German banks, while U.K. banks tend toward the periphery.

Table 2 presents the average of several network characteristics for each period. The increase in average degree, density, and share of connected nodes corroborates the densification of the network during the GFC & EDC episode, while the drop in disassortativity indicates that even highly connected banks were now linked with one another rather than only to peripheral institutions. The heterogeneity of the banking network across the three episodes is supported by the hypothesis tests reported in the final two columns of Table 2. Using draws from the posterior distribution of the adjacency matrix $\boldsymbol{P}(t)$, Test 1 evaluates H_0: $X_{\text{Pre-GFC}} = X_{\text{GFC \& EDC}}$ versus H_1: $X_{\text{Pre-GFC}} \neq X_{\text{GFC \& EDC}}$, and Test 2 examines H_0: $X_{\text{Pre-GFC}} = X_{\text{Post-EDC}}$ versus H_1: $X_{\text{Pre-GFC}} \neq X_{\text{Post-EDC}}$, where X denotes a network topology measure. Both tests use a 10 percent significance level. While the test results highlight a genuine similarity in network structure between the Pre-GFC and Post-EDC episodes across various network topology measures, a significant discrepancy arises between the Pre-GFC and GFC & EDC periods.

In sum, the crisis episode was marked by denser and more interconnected networks—evidence that banks' equity price returns co-moved more closely and consistent with adverse herding behavior (compare Balcilar et al., 2023; Mobarek et al., 2014). The next section analyzes the extent to which herding concentrates within VI banks relative to other groups.

Stochastic block model analysis with predefined groups. To understand how herding behavior differs across groups of banks, we apply a *stochastic block model* (SBM) (Holland et al., 1983; Snijders and Nowicki, 1997; Karrer and Newman, 2011). In network theory, an SBM is a random graph model where nodes are divided into predefined groups (blocks), and connection probabilities differ within and between these groups. Economically, this approach allows us to investigate whether banks with similar exposures (e.g., VI banks) are more strongly interconnected—an indicator of stronger herding—than those without.

Formally, we partition the symmetric adjacency matrix $\boldsymbol{P}(t)$ into three blocks reflecting the three bank groups: VI, non-VI, and non-CESEE. The block structure is given by

$$\boldsymbol{P}(t) = \begin{bmatrix} \boldsymbol{P}_{11}(t) & \boldsymbol{P}_{12}(t) & \boldsymbol{P}_{13}(t) \\ & \boldsymbol{P}_{22}(t) & \boldsymbol{P}_{23}(t) \\ & & \boldsymbol{P}_{33}(t) \end{bmatrix}, \tag{3}$$

where the diagonal blocks $(\boldsymbol{P}_{11}(t), \boldsymbol{P}_{22}(t), \boldsymbol{P}_{33}(t))$ represent within-group correlations, and the off-diagonal blocks capture between-group linkages (e.g., $\boldsymbol{P}_{12}(t)$ for VI$\leftrightarrow$non-VI spillovers).

As our key network topology measure, we compute the (network) *density* of each block in $\boldsymbol{P}(t)$. The network density is defined as the average weight of connections (see also Horvath, 2011):

$$\delta(\boldsymbol{P}_{..}(t)) = \frac{\sum_{i=1}^{N} \sum_{j>i}^{N} \varrho_{ij}(t)}{N(N-1)/2}, \tag{4}$$

A density close to one means the nodes (banks) within that block are tightly connected, while a density close to zero implies little co-movement. In financial terms, higher density indicates that banks' equity price returns move more closely together, signaling stronger herding within or across groups. A change in density may arise either from more connections (more banks moving together) or from stronger correlations among existing links (amplified co-movement).

Panel b of Figure 1 presents relative within-group densities by comparing VI banks to non-VI and non-CESEE banks: $\Delta_{11|22} = \delta(\boldsymbol{P}_{11}(t)) - \delta(\boldsymbol{P}_{22}(t))$ and $\Delta_{11|33} = \delta(\boldsymbol{P}_{11}(t)) - \delta(\boldsymbol{P}_{33}(t))$. The results show that during the global financial crisis, connectivity among non-VI banks was not different from non-CESEE banks. By contrast, VI banks exhibited significantly higher within-group connectivity, suggesting that investors grouped them together more tightly—a hallmark of adverse herding that coincides with their excess volatility.

Panel c of Figure 1 shows between-group linkages. We track $\Delta_{12|23} = \delta(\boldsymbol{P}_{12}(t)) - \delta(\boldsymbol{P}_{23}(t))$ (VI$\leftrightarrow$non-VI connectivity relative to non-VI$\leftrightarrow$non-CESEE) and $\Delta_{13|23} = \delta(\boldsymbol{P}_{13}(t)) - \delta(\boldsymbol{P}_{23}(t))$ (VI$\leftrightarrow$non-CESEE relative to non-VI$\leftrightarrow$non-CESEE). These measures reveal a marked fall in VI banks' connectivity with the other groups at the onset of the GFC, followed by a prolonged period of segmentation. The return to pre-crisis patterns occurred only around 2012–2013. Economically, this segmentation indicates that VI banks became increasingly differentiated—and potentially stigmatized—by investors, consistent with negative herding toward them.

In summary, the SBM analysis confirms that both within-group clustering and reduced between-group connectedness were concentrated among VI banks during the crisis period. This provides evidence of adverse herding, helping explain their elevated volatility. Additional evidence supporting these conclusions in the form of posterior edge probabilities is reported in the Online Appendix which corroborates the presence of the VI-specific block structure in the network.

Stochastic block model analysis with non-predefined groups. The preceding analysis employed a stochastic block model based on an a priori classification of banks into three groups (VI banks, non-VI banks, and non-CESEE banks). While this classification arises naturally from banks' participation in the VI and their exposure to the CESEE region, an important question is whether statistical clustering methods would yield a similar partition—specifically, whether the network exhibits a latent community structure. To address this, we adopt a more agnostic approach and apply clustering techniques to endogenously determine bank clusters. In particular, we employ *spectral clustering*. This method requires pre-specifying the number of clusters, which we set to three, corresponding to the three groups investigated previously. Detailed technical explanations of the spectral clustering method and results are provided in the Online Appendix. Here, we summarize the main findings.

For the pre-GFC period, the banks located in the upper part of the network (panel a of Figure 2) form cluster A, while those in the lower part constitute cluster B. The remaining banks, including all zero-degree nodes, belong to cluster C. Each cluster exhibits substantial country-level heterogeneity.

During the GFC and EDC period, spectral clustering classifies the banks positioned on the far right of the network (panel b of Figure 2) into a distinct cluster A, composed predominantly of VI banks, though not all VI banks are included. Cluster B comprises the remaining VI banks (with the exception of the Norwegian bank NO1, part of the VI) and also includes one non-VI French bank (FR4). The remaining banks fall under cluster C. Overall, the spectral clustering method largely isolates VI banks but divides them into two distinct clusters: cluster A, consisting of Italian, Greek, and Austrian banks, and cluster B, containing Dutch, Belgian, French, and Swedish banks. The distinction between non-VI and non-CESEE banks remains weak.

In the post-EDC period, the spectral clustering analysis identifies the banks located on the left side of the network (panel c of Figure 2) as forming cluster A, composed exclusively of Italian and Belgian banks. Several core banks in the network, primarily French, German, and Dutch institutions—all of which are high-degree nodes—form cluster B. The remaining banks belong to cluster C, which again shows no distinct country pattern.

Taken together, the spectral clustering results broadly confirm the presence of a structural segmentation of VI banks from the rest of the network.

3.2. **Excess volatility and participation in the VI.** We now examine whether higher idiosyncratic equity price return volatility can be associated with a higher likelihood of a bank joining the VI. Table 3 presents results from a linear probability model estimated using an instrumental variable (IV) approach. The binary dependent variable, VI_i, equals one if bank i joined the initiative in 2009. The first commitment letters were signed on March 26, 2009

TABLE 3. Volatility and VI participation in the year 2009: IV regression results from a linear probability model

	1^{st} stage	2^{nd} stage
Response variable ($\rightarrow$):	$\log(\mathrm{Vol}_i)$	$\Pr(\mathrm{VI}_i = 1)$
Explanatory variables ($\downarrow$):		
Equity to assets$^{(1)}$	-0.13 (-5.29)	—
NPL$^{(2)}$	-0.009 (-1.05)	—
RoA$^{(3)}$	-0.35 (-4.25)	—
Assets to liabilities$^{(4)}$	-0.003 (-3.65)	—
Loan to deposits$^{(5)}$	0.002 (0.95)	—
$\log(\widehat{\mathrm{Vol}}_i)$	—	0.008 (2.41)
Constant term	3.95 (8.19)	-0.37 (-2.08)
No. of Observ.	55	55

Notes: Values in parentheses are t-values. $\log(\widehat{\mathrm{Vol}}_i)$ are the fitted values from the first-stage regression, used in the second-stage regression. The number of observations is made up of 55 banks (i) in 2009. Instruments are taken from balance sheets of the year 2008.
$^{(1)}$ Equity to assets is the ratio of equity to total assets.
$^{(2)}$ NPL is the ratio of non-performing loans to total loans.
$^{(3)}$ RoA is the return on (average) assets.
$^{(4)}$ Assets to liabilities refers to liquid assets to short-term liabilities.
$^{(5)}$ Loan to deposits is the loan-to-deposit ratio.

and all VI banks signed a commitment letter during the course of 2009 for one of the participating CESEE countries.

A direct regression of VI-participation of a bank on volatility would be prone to endogeneity: once a bank joins the VI, its equity price return volatility may simultaneously decline. To address this problem, we employ five bank-specific balance sheet indicators from the year 2008, i.e., the year before the VI was initiated, as instruments: (i) the ratio of equity-to-assets (loss absorption capacity), (ii) the non-performing loan (NPL) ratio (asset quality), (iii) the return on assets (profitability), (iv) the loan-to-deposit ratio (funding structure), and (v) liquid assets to short-term liabilities (funding stability). To make daily volatility data compatible with annual balance sheet information we compute the mean over the year 2009. The time lag between the balance sheet's reference period and the decision to participate in the VI helps to ensure the instruments' exogeneity. At the same time, weak balance sheet indicators are a strong signal for possible funding problems. In the first stage, the balance sheet indicators explain variation in log volatility; in the second stage, predicted volatility is used to estimate the probability of VI participation:

$$\begin{aligned} \log(\mathrm{Vol}_i) &= \boldsymbol{z}_i'\boldsymbol{\zeta} + u_i, \\ Pr(\mathrm{VI}_i = 1|\boldsymbol{z}_i) &= \beta_0 + \beta_1 \log(\widehat{\mathrm{Vol}}_i) + e_i, \end{aligned}$$

where $\boldsymbol{z}_i$ contains the five instruments, a constant, and a dummy for CESEE activity (compare Allen et al., 2017).

3.2.1. *Results of the IV estimation.* The results in Table 3 show that balance sheet fundamentals significantly predict bank-specific volatility in the first stage. The first-stage coefficients generally have the expected signs (e.g., stronger capitalization and profitability are associated with lower volatility), though not all are individually statistically significant. In the second stage, we estimate $\hat{\beta}_1 = 0.008$ (t-value 2.41), providing support that higher idiosyncratic volatility can be associated with a higher probability of VI participation. Economically, a 1 percent increase in volatility implies a rise in the probability of participation by 0.008 percentage points. Given that volatility increased tenfold (and more) for some banks in the sample, the implied increase in participation probability is economically relevant. The finding that relative volatility increased across the entire group of VI banks, rather than being confined to individual outliers, is consistent with the presence of adverse herding toward this group.

3.3. **The effects of the VI measures.** This section evaluates the short-term effectiveness of Vienna Initiative measures in normalizing market conditions through event study analysis. We examine the impact of VI announcements on two key dimensions: excess volatility and herding behavior among Western European banks over the period 2009–2016.

3.3.1. *VI measures and event database construction.* The VI introduced comprehensive policy measures to restore confidence and normalize financial conditions during the crisis. Importantly, the VI functioned as a coordination, monitoring, and communication platform for home and host countries, the European Commission, IFIs, and participating banks rather than a direct policy-implementing body. Consequently, our analysis focuses on the announcement effects of VI policies rather than the effects of their implementation, consistent with the signaling hypothesis as put forth in Section 2.2.

We consolidate diverse policy interventions into a unified category, allowing aggregation across various measure types and repeated actions. The database encompasses crisis-response measures under the VI from 2009 to 2016, including both direct financial interventions (subsidies, liquidity provisions) and indirect measures aimed at reducing information asymmetries among financial intermediaries and investors. The latter category serves a critical signaling function within the VI framework.

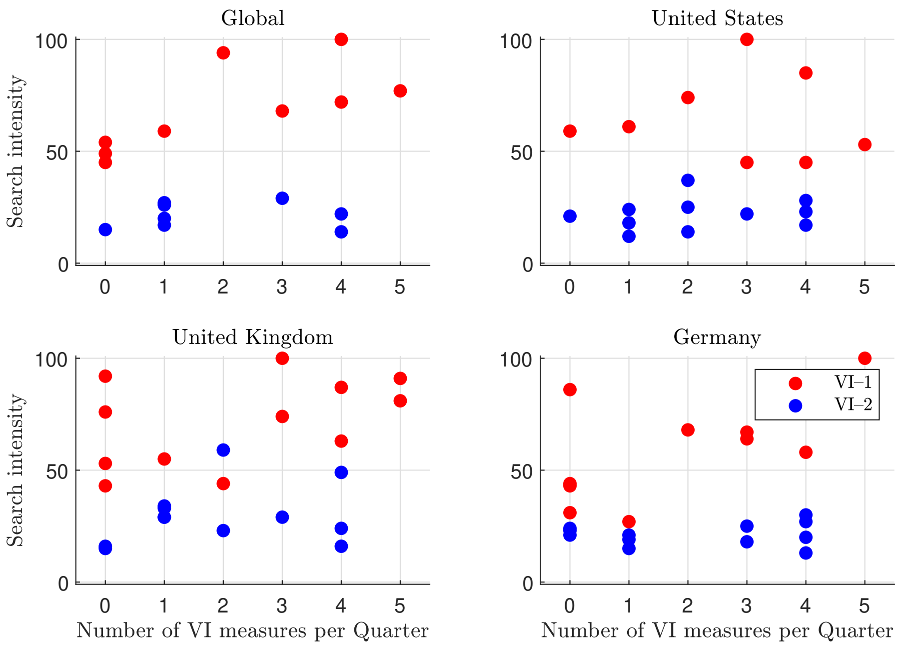
Following VI procedural guidelines, parent banks signed commitment letters at each meeting, with announcements subsequently publicized (Allen, 2019). To capture immediate market reactions, our event study dataset records announcement dates from official press releases, major newspapers, and news search engines, prioritizing measures with significant media coverage. Supplementary information was obtained from official sources including the EBRD, EIB, ECB, IMF, World Bank, and relevant national authorities. All measures were selected based on their potential to mitigate financial market stress. The database comprises over 80 measures, detailed in the Online Appendix.

The VI policy dummy variable ξ_t is defined as:

$$\xi_t = \begin{cases} 1, & \text{if a VI policy measure is announced at day } t \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Since multiple VI measures were announced at different dates, the dummy variable contains several unit entries, each corresponding to the announcement date of a specific measure.

Figure 3. Public interest in the announcement activity of the VI



Note: The figure shows the number of VI measures per quarter relative to the search intensity from Google Trends for a search query on "Vienna Initiative" for Germany, the United Kingdom, the United States and globally. As regards the scaling of the search intensity: a value of 100 indicates the period with the largest search volume. Every other number is measured relative to the time period with the highest number of searches. The absolute value of the (maximal) searches is not reported by Google Trends. We display only those quarters (dots in the sub-panels) for each country/region in which a search activity occurred. VI 1.0 refers to the early phase of the Vienna Initiative (Jan. 2009 — Jan. 2012) and VI 2.0 to the period after Jan. 2012.

An initial indication of public interest in VI announcements can be obtained from a Google Trends search. Figure 3 plots the quarterly number of VI measures announced against Google Trends search intensity for "Vienna Initiative" across selected countries/regions, distinguishing the VI 1.0 period (Jan. 2009–Jan. 2012; orange) from VI 2.0 (post Jan. 2012; blue). Only quarters with nonzero search activity are displayed. The value 100 at the global level indicates the overall peak of search activity within a region; all other dots present the search intensity relative to the peak. Interestingly, even during quarters without any announcements, the VI attracted international interest, though interest was highest during quarters with 3 to 5 announcements. While the average number of VI-measures published is similar across VI 1.0 and VI 2.0, search intensity is markedly higher during VI 1.0 across all reported geographies (Germany, U.K., U.S.) and especially at the global level, consistent with stronger contemporaneous salience and market attention in the earlier phase.

3.3.2. *Event study methodology.* A more formal analysis about the relation between excess volatility and herding toward VI and non-VI banks can be derived from statistical tests. The econometric framework closely follows Glocker and Url (2022). Let $\boldsymbol{y}_t$ denote a vector of n_y daily financial variables (detailed in Section 3.3.3), and let ξ_t be the intervention indicator capturing announcement surprises of VI measures at day t. The baseline specification is a vector-autoregressive (VAR) model with ξ_t as policy variable, $\boldsymbol{y}_t$ as the vector of endogenous variables, $\boldsymbol{v}_t$ as a vector of control variables, and the restriction that ξ_t is not driven by past values of ξ_t, $\boldsymbol{v}_t$, or $\boldsymbol{y}_t$:

$$\begin{bmatrix} \boldsymbol{H}(L) & \mathbf{0} \\ \boldsymbol{\Psi}(L) & \boldsymbol{\Theta}(L) \end{bmatrix} \begin{bmatrix} \boldsymbol{v}_t \\ \boldsymbol{y}_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\zeta} \\ \boldsymbol{\beta} \end{bmatrix} \xi_t + \begin{bmatrix} \boldsymbol{Z} \\ \boldsymbol{B} \end{bmatrix} \boldsymbol{\eta}_t + \begin{bmatrix} \boldsymbol{e}_t^v \\ \boldsymbol{e}_t^y \end{bmatrix}, \tag{6}$$

where the error vector $[(\boldsymbol{e}_t^v)', (\boldsymbol{e}_t^y)']'$ has a block-diagonal variance-covariance matrix (Hamilton, 1994, p. 311), and $\boldsymbol{H}(L) = \boldsymbol{H}_0 - \sum_{k=1}^{K} \boldsymbol{H}_k L^k$, $\boldsymbol{\Psi}(L) = \boldsymbol{\Psi}_0 - \sum_{k=1}^{K} \boldsymbol{\Psi}_k L^k$, and $\boldsymbol{\Theta}(L) = \boldsymbol{\Theta}_0 - \sum_{k=1}^{K} \boldsymbol{\Theta}_k L^k$ are lag polynomials of order K. The scalar ξ_t captures VI policy announcements, while $\boldsymbol{\eta}_t$ includes strictly exogenous variables (described below). The zero block enforces block exogeneity: global financial conditions $\boldsymbol{v}_t$ can affect $\boldsymbol{y}_t$ contemporaneously, but not vice versa. This implies that $\boldsymbol{v}_t$ is neither contemporaneously related to nor Granger-caused by $\boldsymbol{y}_t$. Model selection tests (Schwarz information criterion) support this block exogeneity restriction.

Under this setup, international financial turmoil is explicitly controlled for via $\boldsymbol{v}_t$, while ξ_t isolates announcement effects attributable to VI measures.

On the exogeneity assumption of the policy instruments. The baseline specification is a VAR focusing on ξ_t and $\boldsymbol{y}_t$, with inference based on impulse response functions (IRFs). We adopt equation (6) because it allows a transparent identification of announcement effects: the innovation to the system is the VI announcement indicator ξ_t, treated as an exogenous input. A unit innovation to ξ_t then traces the dynamic adjustment of $\boldsymbol{y}_t$ via IRFs.

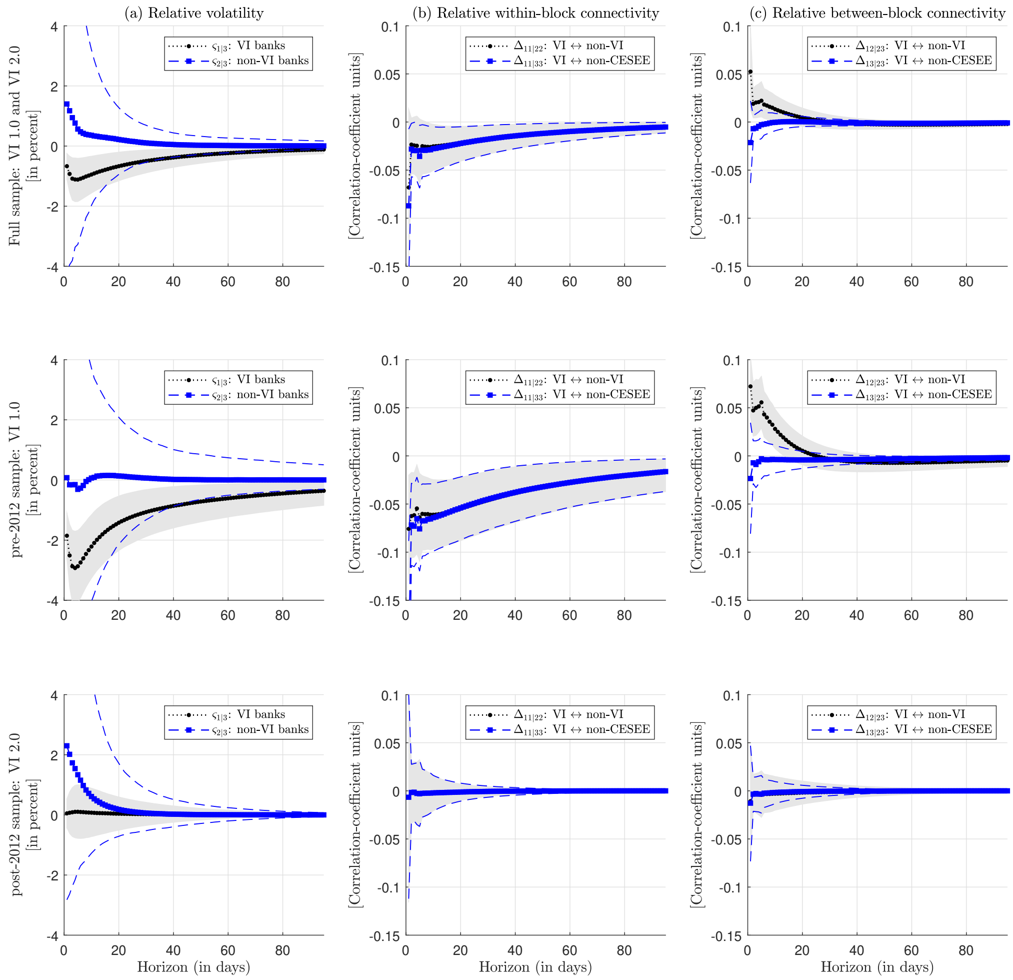
A potential concern is endogeneity arising from anticipatory behavior: if markets systematically predict the exact announcement day, ξ_t would be correlated with contemporaneous shocks. We assess this by testing whether elements of $\boldsymbol{y}_t$ have predictive power for ξ_t in logistic regressions. Joint tests of the coefficients on $\boldsymbol{y}_t$ fail to reject the null of no predictability across all specifications examined (see Online Appendix for model details and results). Hence, while market participants may perceive the likelihood of policy action in general terms, the precise day-to-day timing of announcements is not anticipated in a statistically detectable manner, supporting the exogeneity of ξ_t at the daily frequency.

Estimation details. The VAR is estimated on daily data from early 2008 through end-2016. The control vector $\boldsymbol{v}_t$ includes $\log(\text{VSTOXX}_t)$ and $\log(\text{VIX}_t)$ to capture U.S./global and European financial stress. The vector of strictly exogenous variables $\boldsymbol{\eta}_t$ contains a constant and additional event controls at the CESEE country level: (i) dummies for announcements of (non-) standard monetary policy decisions by local authorities; (ii) dummies for announcements related to IMF and European Commission financial assistance programs (Hungary, Poland, Romania); and (iii) dummies constructed from the announcements of rating agencies (coded +1 for upgrades, -1 for downgrades, 0 otherwise; see Online Appendix and Glocker and Url (2022)).

We estimate equation (6) using Bayesian methods under a flat prior and sample 1,000 draws of the posterior distribution. Further details on the estimation of the Bayesian VAR (BVAR) model can be found in the Online Appendix.

3.3.3. *Results of the event study methodology.* We evaluate the announcement effects of VI measures on Western European banks using the indicators in Figure 1, panels a–c: (i) excess volatility of VI and non-VI banks, $\varsigma_{1,t}$ and $\varsigma_{2,t}$ (each normalized by non-CESEE banks), (ii) relative within-group connectivity, $\Delta_{11|22,t}$ and $\Delta_{11|33,t}$, and (iii) relative between-group connectivity, $\Delta_{12|23,t}$

FIGURE 4. The effects of the VI on banks



Note: The sub-panels report the median and the 68 percent credible interval of the posterior distribution of the impulse response functions to an announcement of a VI policy measure. The sub-panels in the first row show the results based on the full sample (VI 1.0 and VI 2.0), those in the second row for the pre-2012 period (VI 1.0) and those in the third row for the post-2012 period (VI 2.0).

and $\Delta_{13|23,t}$. These six series are stacked in $\boldsymbol{y}_t \in \mathbb{R}^6$, and the BVAR in equation (6) is estimated with three lags ($K = 3$), as suggested by the Schwarz information criterion.

The BVAR uses inputs that are themselves estimated: excess volatility and relative connectivity measures are obtained from the TVP-VARX (equation (1)). Both are obtained as posterior draws from their respective models. To propagate this estimation uncertainty, we feed each draw of the posterior distribution, $\hat{\boldsymbol{y}}_{t,d}$, into the BVAR of equation (6) and re-estimate the BVAR for every draw $d = 1, \ldots, D$. This integrates uncertainty from constructing the volatility and network measures with uncertainty from the BVAR of equation (6), such that the resulting impulse responses reflect all layers of estimation uncertainty.[6] Figure 4 reports the posterior median impulse responses (IRFs) with 68 percent credible intervals for horizons up to 90 trading days. Three results stand out.

- *Excess volatility.* VI announcements reduce the excess volatility of VI banks (relative to non-CESEE banks) by about one percentage point on impact, with a hump-shaped and persistent profile (first row, column a, black line). The corresponding response for non-VI banks is not statistically different from zero (first row, column a, blue line). This pattern is consistent with a credible signal that selectively reassesses the risk of banks directly associated with VI commitments.
- *Within-group connectivity.* Relative within-group connectivity declines after VI announcements: both $\Delta_{11|22}$ and $\Delta_{11|33}$ decrease by roughly 0.08 (in correlation units) on impact (first row, column b, black line). This indicates that the unusually strong co-movement within the VI group—an indicator of adverse herding—is mitigated following policy announcements, reducing excess clustering within that group.
- *Between-group connectivity.* VI announcements increase the relative connectivity between VI and non-VI banks compared with non-VI and non-CESEE banks (first row, column c, black line). Since $\Delta_{12|23}$ turned negative after the GFC—signaling segmentation between VI and non-VI banks—the positive response suggests that announcements helped arrest further separation, consistent with partial reintegration of VI banks into broader Western European return dynamics.

In sum, the IRFs indicate that VI announcements (i) dampened excess volatility where exposures were most salient (VI banks), (ii) reduced abnormal within-group co-movement characteristic of adverse herding, and (iii) curbed the post-crisis segmentation between VI and other Western European banks.

[6]The VAR is re-estimated for each of the $D = 400,000$ draws, retaining a large number of posterior samples per replication to characterize the full distribution of impulse responses.

The effects on banks: variation over time. The second and third rows of Figure 4 indicate substantial heterogeneity across subsamples. Effects are most pronounced during the pre-2012 interval (Jan. 2008–Jan. 2012), corresponding to the initial phase of the initiative (VI 1.0). By contrast, in the post-2012 period (VI 2.0), announcement effects are not statistically different from zero. This pattern is consistent with two, non-mutually exclusive explanations. First, the bulk and salience of measures occurred during the initial phase, when market stress and information frictions were most acute. Second, announcement effects may have been stronger under heightened uncertainty, when credible coordination signals exert greater influence on risk assessments and co-movement.

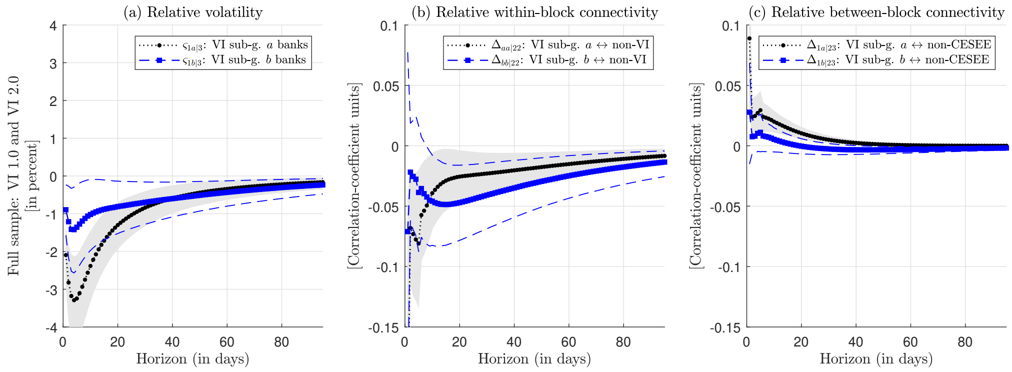
The effects on banks: cross-sectional variation. Complementary evidence from a stochastic block model with data-driven groups (reported in Section 3.1.3) points to segmentation among VI banks, especially during the GFC and EDC. To examine this structure within the predefined VI block, the within-VI adjacency matrix $\boldsymbol{P}_{11}(t) \in \mathbb{R}^{15\times15}$ is decomposed into sub-blocks that correspond to two dominant VI subgroups identified by spectral clustering in Section 3.1.3. The explicit decomposition is:

$$\boldsymbol{P}_{11}(t) = \begin{bmatrix} \boldsymbol{P}^{\mathrm{VI}}_{aa}(t) & \boldsymbol{P}^{\mathrm{VI}}_{ab}(t) & \cdots \\ \boldsymbol{P}^{\mathrm{VI}}_{ba}(t) & \boldsymbol{P}^{\mathrm{VI}}_{bb}(t) & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}, \tag{7}$$

where $\boldsymbol{P}^{\mathrm{VI}}_{aa}(t) \in \mathbb{R}^{5\times5}$ collects links among subgroup a (Austrian, Italian, Greek banks), $\boldsymbol{P}^{\mathrm{VI}}_{bb}(t) \in \mathbb{R}^{6\times6}$ among subgroup b (Belgian, French, Dutch, Swedish banks), and $\boldsymbol{P}^{\mathrm{VI}}_{ab}(t) = \boldsymbol{P}^{\mathrm{VI}}_{ba}(t)'$ captures cross-links between them. Four additional VI banks, all of which are Greek banks (subgroup c), are excluded from this decomposition to preserve sub-block comparability.

To align volatility and connectivity, relative volatilities are constructed for each subgroup by normalizing by the non-CESEE benchmark: $\varsigma_{1a|3,t} = \boldsymbol{\sigma}_{1a,t}/\bar{\boldsymbol{\sigma}}_{3,t}$ and $\varsigma_{1b|3,t} = \boldsymbol{\sigma}_{1b,t}/\bar{\boldsymbol{\sigma}}_{3,t}$, where $\boldsymbol{\sigma}_{1a,t}$ and $\boldsymbol{\sigma}_{1b,t}$ collect subgroup-specific volatilities and $\bar{\boldsymbol{\sigma}}_{3,t}$ is the median volatility of non-CESEE banks. Relative within-group

FIGURE 5. The effects of the VI on sub-groups of VI banks



Note: The sub-panels report the median and the 68 percent credible interval of the posterior distribution of the impulse response functions to an announcement of a VI policy measure.

connectivity is measured as

$$\Delta_{aa|22}(t) = \delta(\boldsymbol{P}_{aa}^{\mathrm{VI}}(t)) - \delta(\boldsymbol{P}_{22}(t)), \qquad \Delta_{bb|22}(t) = \delta(\boldsymbol{P}_{bb}^{\mathrm{VI}}(t)) - \delta(\boldsymbol{P}_{22}(t)),$$

while between-group connectivity is summarized by

$$\Delta_{a2|23}(t) = \delta(\boldsymbol{P}_{a2}^{\mathrm{VI}}(t)) - \delta(\boldsymbol{P}_{23}(t)), \qquad \Delta_{b2|23}(t) = \delta(\boldsymbol{P}_{b2}^{\mathrm{VI}}(t)) - \delta(\boldsymbol{P}_{23}(t)),$$

with $\boldsymbol{P}_{a2}^{\mathrm{VI}}(t), \boldsymbol{P}_{b2}^{\mathrm{VI}}(t) \in \boldsymbol{P}_{12}(t)$. Economically, the within-group densities capture the intensity of co-movement inside each subgroup relative to non-VI banks, while the between-group densities gauge integration or segmentation with non-VI and non-CESEE banks.

Figure 5 reports impulse responses for the full sample. VI announcements attenuate relative volatility in both VI subgroups, with a somewhat larger impact for subgroup a. The difference is only marginally statistically significant but is consistent with greater sensitivity of banks with larger CESEE exposures. Within-group connectivity declines for both subgroups on impact, with subgroup a exhibiting a slightly stronger immediate reduction before converging to a similar adjustment path as subgroup b. This indicates a mitigation of abnormal within-group co-movement consistent with a reduction in adverse herding pressures.

Between-group results reveal a pronounced increase in connectivity for subgroup a relative to the benchmark between non-VI and non-CESEE banks, characterized by a strong impact response and slow normalization. No statistically significant effect is detected for subgroup b. The combined evidence suggests that banks in subgroup a were more affected on average, consistent with their higher total CESEE exposures documented in Glocker and Url (2022), among others. From an economic standpoint, the stronger responses for subgroup a align with the interpretation that announcement effects are amplified when common exposures are more salient and when baseline co-movement is elevated by concentrated regional risk.

3.4. **Discussion.** This section distills the mechanisms uncovered by our high-frequency evidence and clarifies how they complement prior balance sheet and nationally framed rescue-program studies. First, we document immediate signaling effects of VI measures: excess volatility of VI banks declines; abnormal within-group connectivity among VI banks recedes; and between-group segmentation vis-à-vis non-VI banks partially reverses. According to our results, these dynamics unfold on a daily basis, which is a level of granularity that cannot be measured using annual balance sheet data (De Haas et al., 2015; Temesvary and Banai, 2017) or medium-run lending outcomes (Cetorelli and Goldberg, 2011; Adams-Kane et al., 2015).

Second, the results are not directly inferable from existing studies on national financial sector rescue programs. The structure of the VI implies that its measures are cross-border by design. The documented desegmentation in return network effects hinges on this transnational design and on the public commitments communicated at specific dates—features that cannot be extrapolated from domestic (compare Aït-Sahalia et al., 2012), or medium-run policy evaluations (compare Temesvary and Banai, 2017) alone.

Third, our results highlight heterogeneity in the effects of VI measures, consistent with CESEE-specific frictions as highlighted in Jakubík and Reininger (2013) which involve, among others, host-country regulatory constraints (Glocker, 2021), relationship capital of subsidiaries, and heterogeneous risk management technologies. These frictions raise the value of credible "stay" signals as they arose from VI participation and VI measures, helping to explain stronger responses during the VI's early phase (VI 1.0) and among banks with higher CESEE exposure (e.g., the Austrian–Italian–Greek cluster) (Hameter et al., 2012; Lahnsteiner, 2020).

Finally, some limitations merit emphasis and our results must be interpreted with caution: they primarily capture immediate market reactions, which may not necessarily reflect medium- or long-term implications. Nevertheless, they highlight the capacity of the VI to disrupt negative informational cascades and provide a stabilizing signal in a highly fragile, transnational environment. Perhaps most interestingly, all of this corroborates the findings in Unal et al. (1993); Arslanalp and Henry (2005) who examined the Brady Plan to resolve the Latin American debt crisis.

4. Conclusion

This paper assessed the effectiveness of the Vienna Initiative (VI) as a public-private partnership (PPP) and signaling mechanism in mitigating financial market stress. The analysis focused on the VI's influence on investor sentiment, herding behavior, and country risk during the global financial crisis—a period that exposed the fragility of the European financial system and underscored the need for coordinated transnational responses. The VI marked a novel form of cross-border crisis management: initiated by private banks, coordinated with international institutions, and inclusive of both home and host countries in a joint effort to stabilize an integrated European financial system.

With regard to the three guiding questions, our findings may be summarized as follows:

- We provide evidence of adverse herding toward VI banks, helping to explain why these institutions clustered together in the form of a PPP that provided conditional public support and coordinated action among stakeholders.

- VI measures effectively broke informational cascades, reduced excess equity price return volatility, and sent a credible signal to restore investor confidence, particularly in the home markets of participating banks.

The success of the VI can be attributed to its reliance on credible monitoring and signaling that countered informational externalities. Crucially, the timely launch of the initiative heightened its effectiveness during the most acute phase of the crisis.

Policy implications. The VI demonstrates that credible PPPs can act as powerful coordination devices during systemic crises. By combining resources and expertise from both the private and public sectors, such initiatives can mitigate funding pressures and counter adverse herding dynamics. The VI thus offers important lessons for future cross-border crisis management: well-structured PPPs can break destabilizing feedback loops and meaningfully reduce financial market stress. Their effectiveness, however, depends on transparent communication, monitoring, and credible conditionality. While short-run stabilization is of immediate importance, policymakers must remain mindful that longer-run effects may diverge from contemporaneous market responses.

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Appendix A. Stochastic block model: Edge probabilities

A key element of the stochastic block model (SBM) is the symmetric $r \times r$ matrix $\mathbf{\Pi}$ of edge probabilities which partitions the set of nodes $\{1, ..., n\}$ into disjoint subsets $C_1, ..., C_r$ which are called *communities*. In our case, $r = 3$ and the matrix of edge probabilities is

$$\mathbf{\Pi} = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ & \pi_{22} & \pi_{23} \\ & & \pi_{33} \end{bmatrix} \tag{8}$$

where in contrast to a Markov transition matrix, the column-sum ($\varsigma_j = \sum_i \pi_{ji}$ where $\varsigma_j \neq 1 \; \forall \; j$) does not necessarily add up to unity; this arises when nodes of a particular block are neither linked to other nodes of the same block nor to nodes of other blocks. The matrix $\mathbf{\Pi}$ identifies the link probabilities of the nodes to (i) other nodes of the same community, and (ii) to nodes of another community. Referring to the three groups as VI banks, non-VI banks, and non-CESEE banks, then, for instance, π_{11} captures the probability that a VI bank is connected with another VI bank; and π_{12} is the probability that a VI bank is connected with a non-VI bank. The matrix $\mathbf{\Pi}$ is hence directly associated with the matrix $\boldsymbol{P}(t)$ and its submatrices as defined in the main part of the paper.

We estimate the edge probabilities by computing the link densities across the submatrices of the network captured by the adjacency matrix $\boldsymbol{P}(t)$. We do so for the three periods (pre-GFC, GFC & EDC, post-EDC). The results are provided in Table 4 and illustrate that, first of all, the network is characterized by a weakly assortative SBM since across the three periods $\pi_{ij} \leq \pi_{ii} \; \forall \; i, j = 1, \ldots, 3$ in most of the cases. Secondly, however, the size of the edge probabilities changes noticeably over the three periods. Considering the pre-GFC period first, it can be seen that the probability of a VI bank linking with another VI bank is the same as that of linking with a non-VI or non-CESEE bank. Non-VI banks, on the other hand, tend to link primarily with other non-VI banks and to a slightly lesser extent with non-CESEE banks. Non-CESEE banks are more likely to link with non-VI banks rather than with other non-CESEE banks. Within the GFC & EDC period, the pattern among non-VI and non-CESEE banks remains the same despite a slight increase in the size of the probabilities; the pattern changes considerably for the VI banks. Most striking is the remarkable increase in π_{11}, which indicates a sharp rise in the probability that a VI bank is connected to another VI bank. The probability of connecting with a non-CESEE bank actually drops to zero, while the connection intensity with non-VI banks increases marginally. The high degree of linkages among the VI banks is resolved in the post-EDC period. The linkage probability of 0.11 is, however, still higher than in the pre-GFC period; this is primarily due to the still-high linkage within the Greek banks. Apart from that, the size of the edge probabilities is largely the same as in the pre-GFC period; this also applies to the non-VI and non-CESEE banks.

Table 4. Edge probabilities ($\mathbf{\Pi}$)

Pre-GFC	GFC & EDC	Post-EDC
$\begin{bmatrix} 0.04 & 0.04 & 0.03 \\ & 0.10 & 0.05 \\ & & 0.03 \end{bmatrix}$	$\begin{bmatrix} 0.31 & 0.07 & 0.00 \\ & 0.16 & 0.08 \\ & & 0.05 \end{bmatrix}$	$\begin{bmatrix} 0.11 & 0.06 & 0.03 \\ & 0.08 & 0.04 \\ & & 0.02 \end{bmatrix}$

These results confirm those put forth in the main part of the paper. One possible extension worth considering is to analyze the change in network centrality over the three periods for the three groups of banks. While this is an interesting area of study, it is beyond the scope of the present analysis, so we do not pursue it further here.

Appendix B. VI participation and bank equity price return volatility: Model, identification, and inference

This section provides a technical account of the empirical strategy used to assess whether higher idiosyncratic equity return volatility is associated with an increased likelihood that a bank participates in the Vienna Initiative (VI). The key econometric challenge is endogeneity: while high volatility may incentivize participation, the act of participating (once announced) may contemporaneously dampen volatility, generating a two-way interaction. To address this, we estimate a two-stage linear probability model (LPM) with instrumental variables (IV), in which the endogenous regressor is the (annual) log idiosyncratic volatility. The analysis is conducted in a cross section dimension i using the sample of Western European banks listed in Table 10. Daily idiosyncratic equity return volatilities are aggregated to the annual level for the year 2009 by taking the mean to align with the frequency of the balance sheet information. We source balance-sheet information for 2008 from the *Bankscope* database[7]. This staggers the timing between the reference year of the balance sheet and the subsequent decision to participate in the VI. The first commitment letters were signed on March 26, 2009 and all VI banks signed a commitment letter during the course of 2009 for one of the participating CESEE countries.

Let $\mathrm{VI}_i \in \{0,1\}$ indicate whether bank i participates in 2009, and let $\log(\mathrm{Vol}_i)$ denote the (annual) log of idiosyncratic equity return volatility constructed from daily data and aggregated for 2009. The first-stage regression projects volatility on a vector of bank fundamentals and controls from the previous year,

$$\log(\mathrm{Vol}_i) \;=\; \mathbf{z}_i'\boldsymbol{\zeta} \;+\; u_i,$$

where $\mathbf{z}_i$ includes equity-to-assets (loss absorption capacity), the non-performing loan (NPL) ratio (asset quality), return on assets (profitability), the loan-to-deposit ratio (funding structure), and liquid assets to short-term liabilities (funding stability), as well as a constant and an indicator for CESEE activity. The fitted values $\log(\widehat{\mathrm{Vol}}_i)$ serve as the instrumented regressor in the second stage. The LPM for the annual participation probability is specified as

$$\Pr(\mathrm{VI}_i = 1 \mid \mathbf{z}_i) \;=\; \beta_0 \;+\; \beta_1 \log(\widehat{\mathrm{Vol}}_i) \;+\; e_i,$$

so that β_1 captures the semi-elastic effect of (instrumented) volatility on the probability of VI participation (in percentage-point units). The LPM is employed for its transparency in IV contexts and the direct interpretability of β_1, with inference based on robust standard errors. While the LPM can yield predicted probabilities outside $[0,1]$, the consistency of the IV estimator for

[7] The *Bankscope* database contains a range of information, including balance sheets, revenues, company shareholders, and branches.

β_1 under standard conditions and the clarity of interpretation recommend this specification for our purpose.

Identification hinges on two requirements. First, *instrument relevance*: the bank fundamentals in $\mathbf{z}_i$ must strongly predict $\log(\mathrm{Vol}_i)$. Empirically, the first-stage F-statistic on the excluded instruments exceeds conventional thresholds (e.g., 10), indicating that weak-instrument concerns are limited. Second, *exclusion*: conditional on controls (including the CESEE indicator), the instruments should affect the VI participation decision only through their effect on idiosyncratic volatility. We assess this with overidentification tests (Hansen's J-test). In the baseline specification, the p-value of the J-test exceeds conventional significance levels, so the null of instrument validity is not rejected. In addition, the IV estimates are contrasted with single-stage (OLS) LPM results to illustrate the consequences of endogeneity: the coefficient on volatility in the OLS specification is smaller in magnitude and statistically weaker than its IV counterpart, consistent with attenuation bias when volatility is treated as exogenous.

For completeness, we report the canonical two-stage setup used in the main text and appendix tables. The first-stage regression is

$$\begin{aligned}\log(\mathrm{Vol}_i) &= \zeta_0 \;+\; \zeta_1\,\mathrm{Equity/Assets}_i \;+\; \zeta_2\,\mathrm{NPL}_i \;+\; \zeta_3\,\mathrm{RoA}_i \\ &\quad+\; \zeta_4\,\mathrm{Loans/Deposits}_i \;+\; \zeta_5\,\mathrm{Liquid/ShortLiab}_i \\ &\quad+\; \zeta_6\,\mathbf{1}\{\mathrm{CESEE}_i = 1\} \;+\; u_i\,.\end{aligned}$$

and the second-stage LPM is

$$\mathrm{VI}_i \;=\; \beta_0 \;+\; \beta_1\,\log(\widehat{\mathrm{Vol}}_i) \;+\; e_i,$$

estimated with heteroskedasticity-robust standard errors. In the reported results, the first-stage coefficients generally have the expected signs (e.g., stronger capitalization and profitability associate with lower volatility), though not all are individually statistically significant; relevance is established by the joint F-test on the excluded instruments. In the second stage, the estimated slope $\widehat{\beta}_1 \approx 0.008$ (t-statistic ≈ 2.4) indicates that a 1% increase in idiosyncratic volatility is associated with an increase in the annual participation probability of approximately 0.8 percentage points. Given that volatility nearly doubled for some banks, the implied change in participation probability is economically meaningful.

One caveat is important for interpretation. The LPM is a linear approximation to a latent-index participation model; while the coefficient interpretation is straightforward, predicted probabilities outside the unit interval may occur. These limitations notwithstanding, the IV-LPM provides a transparent and statistically supported framework in which exogenous variation in bank fundamentals shifts idiosyncratic volatility, facilitating consistent estimation of the semi-elastic effect β_1 under standard IV assumptions.

For reference, Table 5 reports the first- and second-stage estimates (these are replications of the results of Table 1 of the main part, put here for convenience) alongside a single-stage OLS LPM. The single-stage results display weaker statistical significance for the volatility coefficient (p-value ≈ 0.11) relative to the IV estimate (p-value ≈ 0.017), highlighting the role of endogeneity. The accompanying diagnostics document instrument strength (first-stage $F \approx 21.7$) and overidentification (Hansen's J p-value ≈ 0.31), supporting the identification strategy. Overall, the evidence indicates that higher annual idiosyncratic equity return volatility is associated with a higher probability of VI participation, after instrumenting volatility with bank fundamentals and conditioning on CESEE activity.

Appendix C. Stochastic block analysis using spectral clustering

The analysis in Section 4 of the main part of the paper was based on a stochastic block model analysis using predetermined groups of banks (VI banks, non-VI banks and non-CESEE banks). In a more agnostic approach, we apply clustering techniques to endogenously determine the bank clusters. In what follows, we discuss the technique in detail.

Table 5. Volatility and VI participation: Regression results from the linear probability model

	Instrumental variable (IV)		OLS
	1^{st} stage	2^{nd} stage	Single stage
Response variable($\rightarrow$):	$\log(\text{Vol}_i)$	$\Pr(\text{VI}_i = 1)$	$\Pr(\text{VI}_i = 1)$
Explanatory variables($\downarrow$):			
Equity to assets[(1)]	-0.13 (-5.29)	—	-0.02 (-1.96)
NPL[(2)]	-0.009 (-1.05)	—	0.004 (-1.17)
RoA[(3)]	-0.35 (-4.25)	—	-0.03 (-1.30)
Assets to liabilities[(4)]	-0.003 (-3.65)	—	-0.000 (-0.05)
Loan to deposits[(5)]	0.002 (0.95)	—	0.009 (0.91)
$\log(\widehat{\text{Vol}}_i)$	—	0.008 (2.41)	—
$\log(\text{Vol}_i)$	—	—	0.007 (1.28)
Constant term	3.95 (8.19)	-0.37 (-2.08)	0.11 (1.27)
No. of Observ.	55	55	55

[(1)] Equity to assets refers to the ratio of equity capital to total assets.
[(2)] NPL refers to the ratio of non-performing loans relative to total loans.
[(3)] RoA refers to the return on (average) assets.
[(4)] Assets to liabilities refers to liquid assets relative to short-term liabilities.
[(5)] Loan to deposits refers to the loan to deposit ratio.
Further remarks: The values in parentheses are t-statistics. $\log(\widehat{\text{Vol}}_i)$ are the predicted values from the first stage regression which are then used in the second stage regression.

Spectral clustering is a method of cluster analysis. The objects to be clustered are considered as nodes of a graph (network). The distances or dissimilarities between the nodes are represented by the weighted edges between the nodes of the graph. Graph theoretic results on Laplace matrices of graphs with k connected components are the basis of spectral clustering. The eigenvalues of a matrix are also called a spectrum, hence the name of the method (see Fiedler, 1973; Donath and Hoffman, 1973, for further details). Spectral clustering hence allows for a quantitative assessment of the relative similarity of each pair of nodes in the graph. Compared to the "traditional" algorithms such as k-means or single linkage, spectral clustering generally performs better, it is simple to implement and can be solved efficiently by standard linear algebra methods (von Luxburg, 2007; Fortunato, 2010).

Spectral clustering is a graph-based algorithm for partitioning data points, or observations, into k blocks (clusters). The data points are considered as nodes

Table 6. Banking network: Spectral clustering

Group		ID	Pre-GFC	GFC & EDC	Post-EDC
VI banks	1	IT1	c	a	a
	2	IT2	a	a	a
	3	AT1	c	a	c
	4	AT2	c	a	c
	5	GR1	c	a	c
	6	GR2	c	c	c
	7	GR3	c	c	c
	8	GR4	c	c	c
	9	NO1	c	c	c
	10	SE1	c	b	c
	11	SE2	a	b	c
	12	SE3	a	b	c
	13	NL1	c	b	b
	14	FR1	a	b	b
	15	BE1	c	b	a
non-VI banks	1	FR2	c	c	b
	2	FR3	c	c	b
	3	FR4	a	b	c
	4	PT1	c	c	b
	5	BE2	a	c	c
	6	DE1	c	c	b
	7	DE2	b	c	c
	8	DE3	c	c	c
	9	DE4	b	c	c
	10	AT3	c	c	c
	11	GR5	c	c	c
	12	IT3	c	c	c
	13	FI1	c	c	c
	14	FI2	c	c	c
	15	DK1	b	c	c
non-CESEE banks	1	UK1	c	c	c
	2	UK2	c	c	c
	3	UK3	b	c	c
	4	UK4	c	c	c
	5	UK5	c	c	c
	6	LI1	c	c	c
	7	CH1	c	c	c
	8	CH2	c	c	c
	9	CH3	c	c	c
	10	CH4	c	c	c
	11	FR5	c	c	c
	12	FR6	c	c	c
	13	FR7	c	c	c
	14	AT4	c	c	c
	15	NO2	c	c	c
	16	IT4	c	c	c
	17	IT5	c	c	c
	18	ES1	c	c	c
	19	ES2	c	c	c
	20	ES3	c	c	c
	21	IE1	c	c	c
	22	NL2	c	c	c
	23	NL3	c	c	c
	24	DK2	c	c	c
	25	DK3	c	c	c

of the connected graph and they are grouped (clustered) by partitioning the graph (Ng et al., 2001; Fortunato, 2010; Clauset et al., 2004). The technique hence involves representing the data in a low dimension for which a distance measure is needed. We utilize the Jaccard distance, which measures the dissimilarity between sample sets (Fender et al., 2017). The Jaccard distance is complementary to the Jaccard coefficient and is obtained by subtracting the Jaccard coefficient from 1, or, equivalently, by dividing the difference of the sizes of the union and the intersection of two sets by the size of the union.

Spectral clustering requires pre-specifying the number of clusters k. We assume the presence of $k = 3$ clusters corresponding to the three blocks analyzed in the previous section. The results are provided in Table 6 for the three periods (pre-GFC period, GFC and EDC period and post-EDC period), with a discussion of the results provided in the main part.

Appendix D. Bayesian estimation and prior densities

Our benchmark BVAR model can be re-arranged to the following expression

$$Y_t = \tilde{Z} H_t + \sum_{k=1}^{K} \left(\tilde{A}_k Y_{t-k} + \left[\tilde{B}_k Y_{t-k} + \tilde{C}_k \right] \xi_{t-k} \right) + U_t, \tag{9}$$

where $H_t = \left[\begin{array}{cc} (\eta_t)' & (\xi_t)' \end{array} \right]'$ and the matrices $\tilde{Z}$, $\tilde{A}$'s, $\tilde{B}$'s and $\tilde{C}$'s involve the coefficient matrices of equations (4) and (5). We use an uninformative version of the natural conjugate prior densities. Rewriting equation (9) as $Y = Xb + \epsilon$, where X now includes all regressors in equation (9) (that is, lagged endogenous, exogenous and interacted variables), and ϵ has a variance-covariance matrix Σ, we utilize the Normal-Wishart prior density for b and Σ^{-1}: $p(b, \Sigma^{-1}) = p(b)p(\Sigma^{-1})$, where $b|\Sigma \sim N(\underline{b}, \underline{V})$ and $\Sigma^{-1} \sim W(\underline{H}, \underline{v})$. The non-informativeness of the prior densities is then obtained by using $\underline{v} = 0$ and $\underline{H}^{-1} = I$, where I is the identity matrix of conformable size. Given this particular specification for the prior densities, we obtain the following conditional posterior densities for $p(b|Y, \Sigma^{-1})$ and $p(\Sigma^{-1}|Y, b)$

$$b|Y, \Sigma^{-1} \sim N\left(\bar{b}, \bar{V}\right) \qquad \Sigma^{-1}|Y, b \sim W\left(\bar{H}, \bar{v}\right), \tag{10}$$

Table 7. Testing for possible endogeneity of policy measures and bank volatility/connectivity measures

Variable	p-value
Relative volatility	
$\varsigma_{1\vert 3}$: VI banks	0.589
$\varsigma_{2\vert 3}$: non-VI banks	0.082
Relative within block connectivity	
$\Delta_{11\vert 22}$: VI $\leftrightarrow$ non-VI	0.636
$\Delta_{11\vert 33}$: VI $\leftrightarrow$ non-CESEE	0.733
Relative between block connectivity	
$\Delta_{12\vert 23}$: VI $\leftrightarrow$ non-VI	0.065
$\Delta_{13\vert 23}$: VI $\leftrightarrow$ non-CESEE	0.328

Notes: Numbers in columns are p-values from a joint significance test for all coefficients of a country to be zero based on logistic regressions with the VI (event)dummy variable (ξ_t) as dependent variable (see equation (11)).

with $\bar{V} = \left(\underline{V}^{-1} + \sum_{t=1}^{T} X'\Sigma^{-1}X\right)^{-1}$, $\bar{b} = \bar{V}\left(\underline{V}^{-1} + \sum_{t=1}^{T} X'\Sigma^{-1}Y\right)$, $\bar{v} = T - \underline{v}$ and $\bar{H} = \left(\underline{H}^{-1} + \sum_{t=1}^{T} X'\Sigma^{-1}(Y - Xb)(Y - Xb)'\right)^{-1}$.

We employ a Gibbs sampler to draw from the multivariate Normal $p(b|Y, \Sigma^{-1})$ and the Wishart $p(\Sigma^{-1}|Y, b)$ distribution.

We sample 6,000 draws from the posterior distribution. After discarding the first 5,000, we are left with 1,000 draws for each parameter. As is common in the literature for Bayesian estimation of VARs and SVARs, we use rejection sampling to impose stability on the BVAR coefficients and only keep stable draws. Our results are qualitatively not affected by this choice of the sampling.

Appendix E. On the exogeneity assumption of the VI measures

Our baseline model is a VAR with a focus on ξ_t and $\tilde{\boldsymbol{y}}_t \equiv [(\boldsymbol{x}_t)', (\boldsymbol{y}_t)]'$ and a restriction that ξ_t does not depend on the lags of either ξ_t or $\tilde{\boldsymbol{y}}_t$. When analyzing the success of policy measures at mitigating financial market stress, we rely on the concept of impulse response functions. We choose the VAR in equation (8) for this purpose because the inference is particularly simple in this case (Jarociński and Karadi, 2020). In our case the shock to the dynamic system emerges from the vector ξ_t of policy measures. This vector enters our model as an exogenous variable. Hence, we can simply induce a unit shock in ξ_t and examine the corresponding dynamic adjustment of $\boldsymbol{y}_t$ by means of the

TABLE 8. Testing for possible endogeneity of policy measures and country-risk measures

	Country	p-value Stock Market Volatility	 Term-structure
VI-CESEE countries			
1	BH	0.56	0.88
2	HU	0.13	0.05
3	LV	0.45	0.18
4	RO	0.32	0.61
5	RS	0.18	0.24
non-VI-CESEE countries			
1	BG	0.21	0.16
2	CZ	0.83	0.36
3	EE	0.19	0.15
4	HR	0.22	0.07
5	LT	0.78	0.05
6	PL	0.08	0.32
7	SK	0.08	0.66
8	SL	0.85	0.08
Lending VI countries			
1	AT	0.10	0.43
2	BE	0.34	0.08
3	EL	0.19	0.37
4	FR	0.75	0.05
5	IT	0.06	0.36
6	NL	0.12	0.47
7	NO	0.07	0.30
8	SE	0.13	0.05

Notes: Numbers in columns are p-values from a joint significance test for all coefficients of a country to be zero based on logistic regressions with the VI (event-) dummy variable (ξ_t) as dependent variable (see equation (11)).

impulse response functions of the BVAR model (see Jarociński and Karadi, 2020, for further details). However, since the intervention dummy variable ξ_t enters the BVAR model contemporaneously, an endogeneity problem could be present. This would arise if financial markets could correctly anticipate the particular day of an announcement (or implementation) of a specific policy measure as part of the VI.

We examine the exogeneity assumption by evaluating the predictive content of the (i) volatility, (ii) connectivity, and (iii) country-risk measures on the policy variable ξ_t. We do so by means of the following logistic regression:

$$P(\xi_t = 1) = \frac{1}{1+e^{-x_t}} \quad \text{with} \quad x_t \equiv \boldsymbol{\alpha}'\boldsymbol{\eta}_t + \sum_{\nu\in\mathcal{V}}\sum_{h=0}^{\bar{h}_\nu} \beta_{h,\nu}\mu^{\nu}_{t-h} + \epsilon_t \tag{11}$$

where μ^{ν}_{t-h} represents (i) the relative volatility and (ii) relative connectivity measures as depicted in Figure 1 (main part of the paper) and (iii) the country-risk measures involving the stock market volatility and the term structure. We use all of these variables (two volatility measures, four connectivity measures (within block and between block), and the two risk measures for the 21 countries) simultaneously in the logit regression. The variables enter the model contemporaneously jointly with $\bar{h}_\nu = 4$ lags as suggested by the Schwarz criterion. Moreover, we use the median of the posterior distribution in each case of the six banking specific variables – the two volatility measures and the four connectivity measures. The vector $\boldsymbol{\eta}_t$ is the same as in the BVAR model.

The values provided in Tables 7 and 8 refer to p-values of the following Null-hypothesis $H_0 : \beta_{0,\nu} = \ldots = \beta_{\bar{h}_\nu,\nu} = 0$, that is, all coefficients of the three bank group's risk metrics (excess volatility and excess connectivity) and so too the risk metrics at the country level (c) are jointly equal to zero. With respect to Tables 7 and 8, the null hypothesis is not rejected in any of the cases examined.[8] Thus, none of the stress metrics - both for banks and for individual countries - has any predictive content for VI policy actions. We conclude that while market participants may ultimately be correct in their perception of an impending policy action, they are not able to get the timing right on a day-to-day basis.

Appendix F. An alternative approach for network construction

In this section we implement an additional robustness exercise that reconstructs the bank network using an alternative methodology based on forecast error variance decompositions, following Diebold and Yılmaz (2014). This alternative approach yields a weighted directed network, in contrast to the

[8]Using each draw d of the posterior distribution of $\{\hat{\mu}^{c}_{t,d}\}_{d=1}^{D}$ rather than the median thereof yields even larger p-values.

TABLE 9. Bank network: summary statistics

	Pre-GFC	GFC & EDC	Post-EDC
(Dis-)Assortativity (directed, degree–degree)[(1)]	-0.28	-0.05	-0.15
Arc density (directed)[(2)]	0.10	0.15	0.12
Avg. out-degree[(3)]	3.80	5.70	4.60
Share with out-degree > 0[(4)]	0.78	0.92	0.85
Transitivity (directed, weighted)[(5)]	0.47	0.45	0.58

[(1)] Directed assortativity uses Pearson correlation of source and target degrees on arcs; values reflect disassortative mixing (negative) with four-way variants (in–in, in–out, out–in, out–out) collapsing to a single scalar for summary reporting.
[(2)] Directed density $= m/[n(n-1)]$; reported as the fraction of realized arcs, aligning with increased connectivity during stress.
[(3)] Average out-degree equals m/n; for a given n, this co-moves with density via $d = \bar{k}/(n-1)$, explaining the pattern across periods.
[(4)] Share of banks with at least one outgoing link captures activation breadth in FEVD spillovers; higher in crisis, then partially normalizes.
[(5)] Transitivity is the directed/weighted global clustering coefficient (Barrat-type generalization), showing tighter triadic closure post-EDC as structures consolidate.

weighted *undirected* correlation network used in our main analysis. For comparability, the same sample, frequency, and subperiods are retained, and network topology statistics are adapted to the directed setting. The resulting table and an interpretation parallel to Section 3.4.1 (of the manuscript) are provided below.

We again construct adjacency matrices, though now from variance-share spillovers inferred from a standard connectedness framework in the sense of Diebold and Yılmaz (2014), applied to idiosyncratic equity return innovations after filtering out global and domestic factors exactly as in the main specification. For each day t, the FEVD-based spillover matrix contains elements interpreted as weights $w_{ij}(t) \in [0,1]$ $\forall$ t that shape the strength of connection between node i and j, and interpreted as a time-varying weighted adjacency for a directed graph (we refer the reader to Diebold and Yılmaz (2014) for technical details). Analogous to Section 3.4.1, we time-average the daily adjacency matrices within each of the three subperiods: (i) Pre-GFC (Jan 2007–Sep 2008), (ii) GFC & EDC (Oct 2008–Dec 2012), and (iii) Post-EDC (Jan 2013–Dec 2016). We then compute directed-network counterparts of the summary measures used in the manuscript: directed assortativity (degree–degree), arc density, average out-degree, the share of nodes with strictly positive out-degree, and directed/weighted transitivity. The measures are selected to remain as close as possible to those in the main text in order to preserve interpretability and facilitate direct comparison, though they need to be adjusted to take into account that the graph is now a *directed* graph (consider Newman, 2010; Fortunato, 2010; Horvath, 2011; Karrer and Newman, 2011, among others).

The results are provided in Table 9. The FEVD-based connectedness network remains sparse in all subperiods, but it densifies markedly during the GFC & EDC period and partially normalizes afterward, mirroring the undirected results. Arc density and average out-degree rise from Pre-GFC to GFC & EDC and then decline but remain above pre-crisis levels, indicating broader and stronger spillover sending during stress, with a persistent though attenuated footprint in the recovery. Directed assortativity is negative throughout, weakest in magnitude during the crisis, and more negative again post-crisis, consistent with a temporary flattening of the hierarchy when stress binds tightly connected senders together, followed by a re-emergence of hub–periphery structure. The share of active senders increases sharply in the crisis and recedes later, indicating that more banks contribute non-trivially to outward variance spillovers when systemic uncertainty peaks. Directed/weighted transitivity dips slightly during the crisis and rises to its highest level in the recovery, consistent with post-crisis consolidation of tightly knit, direction-respecting influence circuits rather than broad, diffuse spillovers.

In economic terms, the FEVD-based directed network tracks who transmits risk to whom. During the GFC & EDC period, more banks become active transmitters and send stronger spillovers, which aligns with investors' tendency to co-move evaluations across institutions that share salient exposures—an expression of adverse herding. The modest weakening of disassortativity during the crisis indicates that stress compresses the hierarchy, bringing large transmitters into tighter mutual interaction, while the post-crisis rebound of dis-assortativity and the increase in directed clustering suggest that market perceptions re-segment into a core–periphery with more cohesive core triads. Within the context of the VI, this pattern is consistent with the notion that coordinated commitments helped arrest broad-based, undirected comovement and re-anchor perceptions of specific risk channels, so that post-crisis spillovers are less diffuse but more confined within cohesive influence groups. Put differently, when herding recedes, the system evolves from "panic" comovement toward more structured, directional influence consistent with better information and coordination.

In summary, the directed, FEVD-based construction offers an alternative network—one that encodes directional spillovers rather than symmetric comovement—yet it delivers qualitatively the same conclusions: crisis periods are characterized by higher connectedness and broader participation in transmission, a temporary compression of network hierarchy, and subsequently a re-emergence of structured clustering and core–periphery features. This convergence across undirected and directed representations strengthens the evidence that the manuscript's main findings on herding dynamics and the role of the VI are robust to the network construction and to the choice of topology measures.

Appendix G. Data description

This section documents the data underlying the empirical analysis, including variable definitions, sources, transformations, frequency, and sample coverage. Unless explicitly stated otherwise below, the source for series is Macrobond.

Bank-level equity data are obtained at the daily frequency for a cross-section of 55 Western European banks over the period January 2007 to December 2016. Daily closing prices (adjusted for corporate actions where available) are transformed into log returns, which serve as inputs to the high-frequency models. To isolate bank-specific risk, raw returns are orthogonalized with respect to a set of global and domestic factors, producing idiosyncratic returns used in the time-varying parameter VAR (TVP–VARX) and network construction. The orthogonalization regressors comprise Eurostoxx 50 and S&P 500 log returns (global equity conditions), as well as domestic stock index returns and the change in the slope of the local yield curve measured by the 10-year minus 3-month spread (domestic conditions); all are sourced from Macrobond. For the instrumental-variables (IV) analysis, daily idiosyncratic volatilities are averaged to the annual frequency by calendar year and transformed by the natural logarithm.

Bank balance-sheet instruments used in the IV first stage are annual series drawn from Bankscope for 2007–2012: equity-to-assets (loss-absorption capacity), non-performing loans to total loans (asset quality), return on assets (profitability), loan-to-deposit ratio (funding structure), and liquid assets to short-term liabilities (funding stability). These enter levels at the annual frequency. All balance-sheet ratios are explicitly constructed from their underlying accounting components. A bank-level CESEE activity dummy is coded from institutional and academic references where available; when not explicitly documented, the default source is Macrobond.

Country-level financial indicators are compiled at the daily frequency for three country groups spanning early 2008 to end-2016: borrowing VI–CESEE countries (Bosnia and Herzegovina, Hungary, Latvia, Romania, Serbia), borrowing non-VI–CESEE countries (Bulgaria, Czech Republic, Estonia, Croatia, Lithuania, Poland, Slovakia, Slovenia), and lending VI countries (Austria, Belgium, Greece, France, Italy, Netherlands, Norway, Sweden). Two variables are used for each country: First, stock market volatility is included in logarithms; where a country-specific daily volatility index is unavailable, a realized-volatility proxy is constructed from daily equity index returns using standard rolling-window estimators at the daily sampling frequency. Second, the term-structure slope is computed as the daily difference between 10-year and 1-year government benchmark yields; where 1-year yields are unavailable, the 3-month money-market tenor is used as the short end. Both the stock index levels and government yield benchmarks are sourced from Macrobond, and the slope is a transformation thereof.

The (log of the) VSTOXX (Euro area implied equity volatility) and the log of the VIX (US implied equity volatility), both sourced from Macrobond.

Event data are encoded as daily dummies and detailed in Table 11.

All daily series are aligned to trading calendars without interpolation; missing observations arising from local holidays are left as gaps, and bivariate TVP systems are estimated only when overlapping data are available.

Appendix H. Additional tables

Table 10. The sample of banks

	ID	Bank name	Country	Group
1	IT1	Intesa Sanpaolo	Italy	VI
2	IT2	UniCredit	Italy	VI
3	AT1	Raiffeisen Bank International	Austria	VI
4	AT2	Erste Group Bank	Austria	VI
5	GR1	Eurobank Holdings	Greece	VI
6	GR2	National Bank of Greece	Greece	VI
7	GR3	Alpha Services & Holdings	Greece	VI
8	GR4	Piraeus Financial Holdings	Greece	VI
9	NO1	DNB Bank	Norway	VI
10	SE1	Nordea Bank	Sweden	VI
11	SE2	Swedbank	Sweden	VI
12	SE3	Skandinaviska Enskilda Banken	Sweden	VI
13	NL1	ING Groep	Netherlands	VI
14	FR1	Société Générale	France	VI
15	BE1	KBC Groep	Belgium	VI
1	FR2	BNP Paribas	France	non-VI
2	FR3	Crédit Agricole	France	non-VI
3	FR4	AXA	France	non-VI
4	PT1	Banco Comercial Português	Portugal	non-VI
5	BE2	Dexia	Belgium	non-VI
6	DE1	Deutsche Bank	Germany	non-VI
7	DE2	Commerzbank	Germany	non-VI
8	DE3	Wüstenrot & Württembergische	Germany	non-VI
9	DE4	Aareal Bank	Germany	non-VI
10	AT3	BKS Bank	Austria	non-VI
11	GR5	Marfin Investment Group Holdings	Greece	non-VI
12	IT3	Banca Popolare di Sondrio	Italy	non-VI
13	FI1	Sampo	Finland	non-VI
14	FI2	Ålandsbanken	Finland	non-VI
15	DK1	Danske Bank	Denmark	non-VI
1	UK1	HSBC Holdings	United Kingdom	non-CESEE
2	UK2	Barclays	United Kingdom	non-CESEE
3	UK3	Lloyds Banking Group	United Kingdom	non-CESEE
4	UK4	Standard Chartered Plc	United Kingdom	non-CESEE
5	UK5	NatWest Group	United Kingdom	non-CESEE
6	LI1	Liechtensteinische Landesbank	Liechtenstein	non-CESEE
7	CH1	Crédit Suisse Group	Switzerland	non-CESEE
8	CH2	Basler Kantonalbank	Switzerland	non-CESEE
9	CH3	Vontobel Holding	Switzerland	non-CESEE
10	CH4	Zuger Kantonalbank	Switzerland	non-CESEE
11	FR5	Caisse Régionale de Crédit Agricole Mutuel de Paris et d'Île-de-France	France	non-CESEE
12	FR6	Union Financière de France Banque	France	non-CESEE
13	FR7	Caisse Régionale de Crédit Agricole Mutuel d'Ille-et-Vilaine	France	non-CESEE
14	AT4	Oberbank	Austria	non-CESEE
15	NO2	SpareBank 1 Nord-Norge	Norway	non-CESEE
16	IT4	Mediobanca Banca di Credito Finanziario	Italy	non-CESEE
17	IT5	Banca Mediolanum	Italy	non-CESEE
18	ES1	Banco Bilbao Vizcaya Argentaria	Spain	non-CESEE

Table 10. The sample of banks

	ID	Bank name	Country	Group
19	ES2	Banco Santander	Spain	non-CESEE
20	ES3	Banco de Sabadell	Spain	non-CESEE
21	IE1	Bank of Ireland Group	Ireland	non-CESEE
22	NL2	KAS Bank	Netherlands	non-CESEE
23	NL3	Van Lanschot Kempen	Netherlands	non-CESEE
24	DK2	Kreditbanken	Denmark	non-CESEE
25	DK3	Spar Nord Bank	Denmark	non-CESEE

Notes: The table reports the list of financial institutions included in the sample with their country of origin and abbreviation.

TABLE 11. Vienna Initiative: Events

	Subject	Place of Meeting	Date	Format
1	Vienna Initiative informal seminar; "Vienna club" to be established	Vienna	January 23, 2009	VI 1.0
2	Launch of Joint IFI Action Plan; Financial assistance to strengthen banks and support lending to the real economy (EUR 33 billions); IFI Initiative EBRD, EIB, and World Bank Group join forces to Support Central and Eastern Europe; Press Release https://vienna-initiative.com	-	February 27, 2009	VI 1.0
3	Meeting on improving coordination; Coordination of Exposure, maintenance and capitalization of subsidiaries for financial stability	-	March 1, 2009	VI 1.0
4	Meeting of official sector participants; Broad home-host burden-sharing rules agreed	Vienna	March 17, 2009	VI 1.0
5	Meeting on Romania; Agreement to support subsidiaries	Vienna	March 26, 2009	VI 1.0
6	Meeting on Serbia; Agreement to work towards supporting subsidiaries	Vienna	March 27, 2009	VI 1.0
7	Meeting of official sector participants; Stock-taking	Washington	April 25, 2009	VI 1.0
8	Meeting on Hungary; Joint IFI initiative: Private Sector Involvement; Coordination of exposure, maintenance and capitalization of subsidiaries for financial stability	-	May 1, 2009	VI 1.0
9	Joint International Financial Institutions Action Plan (JIFIAP) meeting; Stock-taking	London	May 15, 2009	VI 1.0
10	Coordination meeting on Hungary; Commitments to support subsidiaries	Brussels	May 19, 2009	VI 1.0
11	Coordination meeting on Romania; Commitments to support subsidiaries	Brussels	May 20, 2009	VI 1.0
12	Meeting on Bosnia-Herzegovina; Agreement to support subsidiaries	Vienna	June 22, 2009	VI 1.0
13	Meeting on Romania; Reaffirmation of support	-	July 22, 2009	VI 1.0
14	Meeting and Press Release on general issues; Policy discussion on regional issues and medium-term challenges	-	September 1, 2009	VI 1.0
15	Meeting on Latvia; Commitment letter signed	Stockholm	September 11, 2009	VI 1.0
16	First Full Forum; Stock-taking. Possible relaxation on deleveraging; European Bank Coordination Meeting: international coordination helped avert a systemic bank crisis in Central and Eastern Europe; Press Release https://vienna-initiative.com	Brussels	September 24, 2009	VI 1.0
17	IFI cooperation; IFIs Pledge Continued Drive to Support Central and Eastern Europe Through Recovery; Press Release https://vienna-initiative.com	Istanbul	October 5, 2009	VI 1.0
18	Meeting on Romania; Parent Banks Reafirm Commitment to Romania	Brussels	November 19, 2009	VI 1.0
19	Meeting on Hungary;	Brussels	November 20, 2009	VI 1.0
20	Official sector meeting;	Vienna	January 18, 2010	VI 1.0

TABLE 11. Vienna Initiative: Events

	Subject	Place of Meeting	Date	Format
21	Meetings on Serbia and Bosnia-Herzegovina; Relaxation of exposure commitments for Serbia; Vienna Initiative Largest Foreign Banks in Serbia Reaffirmed Commitments; Press Release https://vienna-initiative.com	Vienna	February 26, 2010	VI 1.0
22	Meeting on regional issues; Policy discussion on regional issues and medium-term challenges; Joint IFI Action Plan, Joint IFI Action Plan-One Year On; Press Release https://vienna-initiative.com	-	March 1, 2010	VI 1.0
23	Second Full Forum meeting; Discussion of use of VI framework beyond crisis management. Working Groups on local currency market and EU fund absorption set up.	Athens	March 17, 2010	VI 1.0
24	Meeting on Romania;	Bucharest	July 22, 2010	VI 1.0
25	Meeting on Hungary;	Budapest	July 23, 2010	VI 1.0
26	IFI cooperation; IFIs Exceed Targets in Support for Central and Eastern Europe During Crisis: The resources that have been made available as of end-August 2010 – EUR 27 billion - exceed the commitment of up to EUR 24.5 billion for 2009-2010.; Press Release https://vienna-initiative.com	-	October 6, 2010	VI 1.0
27	IFI cooperation; At EUR 33 billion, EBRD, EIB Group, World Bank Group Crisis Response for Banks Tops Target; Press Release https://vienna-initiative.com	-	March 11, 2011	VI 1.0
28	Meeting on Romania; Stock-taking	Brussels	March 16, 2011	VI 1.0
29	Third Full Forum; Vienna Initiative to shift focus to crisis prevention. Reports on local currency market and EU fund absorption adopted. Working Groups on Basel III and non-performing assets set up. European Bank Coordination "Vienna Initiative" Moves to Meet New Challenges; Press Release https://vienna-initiative.com	Brussels	March 18, 2011	VI 1.0
30	Special Official side meeting; Relaunch of Vienna Initiative 2.0	Vienna	January 16, 2012	VI 2.0
31	Debriefing for banks; Special Meeting of the European Bank Coordination "Vienna" Initiative"; Press Release https://vienna-initiative.com	Vienna	January 17, 2012	VI 2.0
32	Official Side Meeting; Understanding the new coordination framework (EC, EBA, ESRB, FSB); Principles and Responsibilities	Brussels	March 12, 2012	VI 2.0
33	Fourth Full Forum; Reports of Working Groups on Basel III and NPLs; Monitoring of economic situation; Coordination principles for Vienna 2.0	Brussels	March 13, 2012	VI 2.0
34	Steering Committee; Monitoring, Governance structure; Recommendations for implementing Vienna 2.0 principles	Washington	April 20, 2012	VI 2.0
35	Informal meeting with banks; Report on activities post-March	London	May 18, 2012	VI 2.0

Table 11. Vienna Initiative: Events

	Subject	Place of Meeting	Date	Format
36	Informal Steering Committee; Mission statement, Workstreams on supervisory colleges and resolution framework, Selection of Chairman, Ukraine	London	June 13, 2012	VI 2.0
37	Informal Steering Committee; Mission statement, Workstreams, HCCBF, Deleveraging report	Prague	June 26, 2012	VI 2.0
38	Steering Committee; Adoption of Vienna Initiative 2.0 mission statement. Discussion of deleveraging, supervisory colleges, resolution, HCCBFs, SEE/Greek banks	Warsaw	July 18, 2012	VI 2.0
39	Workshop on Bank Supervision and Resolution; Vienna 2.0 Initiative Holds Workshop on Cross-Border Bank Supervision and Resolution in Emerging Europe	London	September 12, 2012	VI 2.0
40	Steering Committee; Vienna 2 proposes enhancements in cross-border supervision to European authorities; Press Release https://vienna-initiative.com	-	October 26, 2012	VI 2.0
41	Steering Committee; Next steps: enhancing bank participation	Brussels	November 8, 2012	VI 2.0
42	Fifth Full Forum; Monitoring; EU Regulations; IFI lending; Progress under VI; Resolution and Banking Union	Brussels	November 9, 2012	VI 2.0
43	Steering Committee with Banks; DCM; BLS; NPL Working Group on BU; LCM dev; Addition of non-EU country to Steering Committee; Vienna 2 Initiative Steering Committee Discusses Deleveraging, Asset Quality and Implications of Banking Union Plans and delivers observations on cross-border bank resolution to European authorities; Press Release https://vienna-initiative.com	Vienna	January 14, 2013	VI 2.0
44	Steering Committee; Note from Working Group on BU and EE	Washington	April 19, 2013	VI 2.0
45	Steering Committee; Deleveraging abating in emerging Europe amid regulatory and structural shifts; Press Release https://vienna-initiative.com	-	May 2, 2013	VI 2.0
46	Steering Committee; SRM including SEE; NPLs and credit guarantees to help SMEs	Luxembourg	July 17, 2013	VI 2.0
47	Steering Committee; Focus on reviving credit growth as external funding withdrawal in emerging Europe picks up; Press Release https://vienna-initiative.com	-	July 30, 2013	VI 2.0
48	Technical Meeting for Regional Cooperation; Impact of Banking Union on SEE	Tirana	October 3, 2013	VI 2.0
49	Steering Committee; Funding WE banks; Report on SEE issues; note on success indicators	Washington	October 11, 2013	VI 2.0
50	Sixth Full Forum; Monitoring deleveraging and credit growth; NPLs; SRM; call for special SRM and EBA arrangements; Vienna 2 Initiative draws attention to weak credit growth and special challenges for South Eastern Europe; Press Release https://vienna-initiative.com	Brussels	October 21, 2013	VI 2.0
51	Steering Committee; Five Priorities established for 2014; Progress reports	Vienna	January 13, 2014	VI 2.0

Table 11. Vienna Initiative: Events

	Subject	Place of Meeting	Date	Format
52	Steering Committee; Update on Working Groups	Washington	April 11, 2014	VI 2.0
53	Steering Committee; Banking Union, NPLs	Warsaw	May 15, 2014	VI 2.0
54	First Ukraine Financial Forum;	Kiev	June 5, 2014	VI 2.0
55	Debt Restructuring and NPL Resolution; NPL Initiative Regional Conference; Vienna Initiative pushes for action plan to deal with NPLs in central and south-eastern Europe; Press Release https://vienna-initiative.com	Vienna	September 23, 2014	VI 2.0
56	Steering Committee; Monitoring; AQR and ECB measures on parent banks; Working Groups on Credit Enhancements, NPLs, BU, Ukraine and Bulgaria, Strategic Directions	Washington	October 10, 2014	VI 2.0
57	Steering Committee; Bank Deleveraging in Eastern Europe Slows Slightly in Second Quarter of 2014; Press Release https://vienna-initiative.com	-	November 4, 2014	VI 2.0
58	Seventh Full Forum; Monitoring, Banking Union, Working Group on Credit Enhancement, NPLs; Credit Recovery and Banking Union in focus at Vienna Initiative 2 Full Forum; Press Release https://vienna-initiative.com	Brussels	November 13, 2014	VI 2.0
59	Second Ukraine Financial Forum; Banks firmly behind Ukraine financial sector reform program at Vienna Initiative forum; Press Release https://vienna-initiative.com	Brussels	November 14, 2014	VI 2.0
60	Steering Committee; Banks Deleveraging in Emerging Europe Slightly Faster in the Third Quarter of 2014; Press Release https://vienna-initiative.com	Vienna	January 19, 2015	VI 2.0
61	Steering Committee; Monitoring, Progress report on NPL work, Banking Union Working Group, Work Programme	Washington	April 17, 2015	VI 2.0
62	Meeting with banks;	Tbilisi	May 14, 2015	VI 2.0
63	NPL Resolution in Emerging Europe; NPL Initiative Regional Conference; Vienna Initiative pushes for action plan to deal with NPLs in central and south-eastern Europe; Press Release https://vienna-initiative.com	Vienna	June 26, 2015	VI 2.0
64	Steering Committee; Monitoring, Impact of QE on region, NPL Workshop, Update on Working Groups on BU and Credit enhancements; Foreign banks' funding to emerging Europe continued to decline in late 2014, but trend may be reversing, new report shows; Press Release https://vienna-initiative.com	Vienna	June 30, 2015	VI 2.0
65	Memorandum of Cooperation Signing; EBA and Vienna Initiative; EBA signs memorandum of cooperation with South Eastern European supervisors; Press Release https://vienna-initiative.com	London	October 23, 2015	VI 2.0
66	Macroprudential Workshop; OeNB and NBP	Vienna	October 27, 2015	VI 2.0
67	Workshop on Bank Ownership Changes;	Warsaw	November 17, 2015	VI 2.0
68	Eighth Full Forum;	Warsaw	November 18, 2015	VI 2.0
69	Steering Committee; Greek banks, Work program implementation	Vienna	January 20, 2016	VI 2.0
70	Third Ukraine Financial Forum;	Kiev	March 15, 2016	VI 2.0

TABLE 11. Vienna Initiative: Events

	Subject	Place of Meeting	Date	Format
71	Steering Committee; Monitoring, NPL work, Working Groups on Banking Union and Guarantees, Organizational matters	Washington	April 15, 2016	VI 2.0
72	Ninth Full Forum; Monitoring, Bank regulation, Investment in CESEE, CMU, Ukraine	Luxembourg	March 6, 2017	VI 2.0
73	Steering Committee; Monitoring; West Balkans, Working Group IFI Instruments, CRD IV	Washington	April 27, 2017	VI 2.0
74	Steering Committee; Monitoring, West Balkan Banking systems, Working Group on IFI instruments, CRD Art.114	Washington	October 14, 2017	VI 2.0
75	Steering Committee; EBA signs memorandum of cooperation with South Eastern European supervisors; Press Release https://vienna-initiative.com	-	October 23, 2015	VI 2.0
76	Workshop on CRD114 impact on non-EU WB;	London	December 11, 2017	VI 2.0
77	Tenth Full Forum ; Monitoring, Working Groups on CMU and IFI instruments, NPL Initiative, Financing Innovation, MREL and Regulatory Issues; Vienna 2 Full Forum convenes in London seeking new growth model to drive forward innovation in emerging Europe; Press Release https://vienna-initiative.com	London	March 12, 2018	VI 2.0
78	Steering Committee; Monitoring, Working Groups on IFI Instruments, Innovation, CMU	Washington	April 21, 2018	VI 2.0
79	Workshop on Financial Restructuring and NPLs; NPL Initiative Regional Conference	Kiev	April 26, 2018	VI 2.0
80	Workshop on MREL;	Vienna	October 8, 2018	VI 2.0
81	Steering Committee; Monitoring, Working Groups on IFI Instruments, and Innovation, MREL	Bali	October 13, 2018	VI 2.0

Notes: The events comprise the key policy measures/interventions considered.