Internet Appendix

A. Technical proofs

***Proof of Proposition* 1**: See Pastor and Veronesi (2009).

***Proof of Lemma* 1**: Proof follows from the fact that $RootSqErr_{f,i,t} = \sqrt{\left(Error_{f,i,t}\right)^2} = |Error_{f,i,t}|$. Thus, we need to calculate the correlation between $|Error_{f,A,t}|$ and $|Error_{f,B,t}|$. Nabeya (1951) and Nabeya (1961) show that the correlation $Corr(|x|,|y|)$ has a closed-form expression in the case that $x \sim N(0,Var(x))$, $y \sim N(0,Var(y))$ and $Corr(|x|,|y|) = \rho_{x,y}$, where $Corr(|x|,|y|)$ is given by:

$$Corr(|x|,|y|) = \frac{\frac{2}{\pi}\left[\sqrt{1-\rho_{x,y}^2} + \rho_{x,y}\cdot arcsin(\rho_{x,y}) - 1\right]}{1-\frac{2}{\pi}}. \tag{23}$$

Given that both $Error_{A,i,t}$ and $Error_{B,i,t}$ are normally distributed with zero mean, we need to calculate $Corr(Error_{A,i,t}, Error_{f,B,t})$, which is:

$$Corr(Error_{A,i,t}, Error_{f,B,t}) = \frac{Var(Error_{g,t})}{Var(Error_{g,t}) + Var(Error_{v,t})}, \tag{24}$$

with

$$\mathrm{V}ar(Error_{g,t}) = \frac{\tau_{g,0} + \lambda^2\tau_{g,\varepsilon}}{(\tau_{g,0} + \lambda\tau_{g,\varepsilon})^2} \quad \text{and} \quad Var(Error_{v,t}) = \frac{1}{\left(\tau_{v,0} + \tau_{v,\varepsilon}\right)}.$$

In the numerator of equation (24), $Var(Error_{g,t})$ appears, reflecting that the overlapping component of the variance in $Error_{A,i,t}$ and $Error_{B,i,t}$ arises from the forecast error of the common factor (see equation (7)). Here, $Var(Error_{g,t})$ and $Var(Error_{v,t})$ are obtained using Proposition 1.

***Proof of Proposition* 2**: Proof follows from showing that $InfLink_{A,B}$ decreases as a function of λ when $0 \le \lambda < 1$ (i.e. $dInfLink_{A,B}/d < 0$), while $InfLink_{A,B}$ increases as a function of λ when $1 < \lambda$ (i.e. $dInfLink_{A,B}/d > 0$). In addition, we needs to show that $0 \le InfLink_{A,B}$ when $\lambda = 1$. Consequently, as a first step, we need to calculate $dInfLink_{A,B}/d\lambda$, which is given by:

$$\begin{aligned}
\frac{dInfLink_{A,B}}{d\lambda} &= \frac{dCorr(RootSqErr_{f,A,t}, RootSqErr_{f,B,t})}{d\lambda} \\
&= \frac{4\cdot arcsin\left(\rho\right)\tau_{g,\varepsilon}\tau_{g,0}(\lambda-1)}{\pi(1-\frac{2}{\pi})(\tau_{g,0}+\lambda\tau_{g,\varepsilon})^3(\tau_{v,0}+\tau_{v,\varepsilon})\left(\frac{\tau_{g,0}+\lambda^2\tau_{g,\varepsilon}}{(\tau_{g,0}+\lambda\tau_{g,\varepsilon})^2} + \frac{1}{\tau_{v,0}+\tau_{v,\varepsilon}}\right)^2}
\end{aligned} \tag{25}$$

where ρ is given by equation (12). Here, it is important to note that ρ is always positive, as the shared component of the variance in $Error_{A,i,t}$ and $Error_{B,i,t}$ is related to the forecast error of the common factor (see equation (7)), which makes the forecasting errors positively correlated. Then, $arcsin\left(\rho\right) > 0$. Therefore, $dInfLink_{A,B}/d\lambda < 0$ when $0 \leq \lambda < 1$, and $dInfLink_{A,B}/d\lambda > 0$ when $1 < \lambda$.

Moreover, $dInfLink_{A,B}/d\lambda = 0$ when $\lambda = 1$. Actually, we know that $InfLink_{A,B} = 0$ when $\lambda = 1$ since inside (13) both correlations are equal, and they cancel out, because there are no learning biases in the case that $\lambda = 1$.

***Proof of Lemma* 2**: We can write the correlation between the posterior beliefs $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ as:

$$Corr(\hat{f}_{A,t+1}, \hat{f}_{B,t+1}) = \frac{Var(\hat{g}_{t+1})}{Var(\hat{g}_{t+1}) + Var(\hat{v}_{t+1})}. \tag{26}$$

In equation (26), the numerator is $Var(\hat{g}_{t+1})$, because the overlapping component of the variance in $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ is associated with the common factor (see equation (7)). Moreover, $Var(\hat{g}_{t+1})$ and $Var(\hat{v}_{t+1})$ can be obtained using Proposition 1, and are given by:

$$Var(\hat{g}_{t+1}) = \frac{\lambda^2\left(\tau_{g,0} + \tau_{g,\varepsilon}\right)\tau_{g,\varepsilon}}{\left(\tau_{g,0} + \lambda\tau_{g,\varepsilon}\right)^2\tau_{g,0}} \text{ and } Var(\hat{v}_{t+1}) = \frac{\tau_{v,\varepsilon}}{\left(\tau_{v,0} + \tau_{v,\varepsilon}\right)\tau_{c,0}}. \tag{27}$$

Proof of the Empirical Implication: Proof follows from showing that $AbnInterd_{A,B}$ is increasing in relation to λ (i.e. $dAbnInterd_{A,B}/d\lambda$ >0) when $0 \leq \lambda$. In addition, we need to show that $AbnInterd_{A,B} = 0$ when $\lambda = 1$. Thus, first, we know from equation (13) that:

$$\begin{aligned}\frac{dAbnInterd_{A,B}}{d\lambda} &= \frac{dCorr(\hat{f}_{A,t+1}, \hat{f}_{B,t+1})}{d\lambda} \\ &= \frac{\frac{2\lambda(\tau_{g,0}+\tau_{g,\varepsilon})\tau_{g,\varepsilon}}{(\tau_{g,0}+\lambda\tau_{g,\varepsilon})^3} \cdot \frac{\tau_{v,\varepsilon}}{(\tau_{v,0}+\tau_{v,\varepsilon})\tau_{c,0}}}{\left(\frac{\lambda^2(\tau_{g,0}+\tau_{g,\varepsilon})\tau_{g,\varepsilon}}{(\tau_{g,0}+\lambda\tau_{g,\varepsilon})^2\tau_{g,0}} + \frac{\tau_{v,\varepsilon}}{(\tau_{v,0}+\tau_{v,\varepsilon})\tau_{c,0}}\right)^2}\end{aligned} \tag{28}$$

Therefore, $dAbnInterd_{A,B}/d\lambda$ >0 when $0 \leq \lambda$. After that, we need to show that $AbnInterd_{A,B} = 0$ when $\lambda = 1$, which is straightforward because inside equation (15) both correlations are equal (and thus they cancel out in equation (15)), given that there are no learning biases when $\lambda = 1$.

B. The spatial two-stage least squares procedure we implement

We adapt Kelejian and Prucha (1998)'s spatial two-stage least squares procedure, or S2SLS, for the case of multiple spatial weight matrices. We consider the following instruments:

$$\mathbf{H_n} = \left\{(\mathbf{W}_p^q \otimes \mathbf{I_T})\mathbf{X}_{i,t-1}\right\}_{p\in\mathscr{P}, q\in\{0,1,2\}} \tag{29}$$

which allows the estimation of parameters

$$\widehat{\theta} = \begin{bmatrix}\widehat{\rho}\\ \widehat{\beta}\end{bmatrix} = \left[\mathbf{Z}'\mathbf{QH_n}(\mathbf{H_n'QH_n})^{-1}\mathbf{H_n'QZ}\right]^{-1}\mathbf{Z}'\mathbf{QH_n}(\mathbf{H_n'QH_n})^{-1}\mathbf{H_n'Qy}, \tag{30}$$

where $\mathbf{Z}$ denotes the matrix of all LHS variables (including the spatial lags of the dependent variables) and $\mathbf{Q}$ is a matrix that sweeps all fixed effects, that is,

$$\mathbf{Q} = \left(\mathbf{I_N} - \mathbf{N^{-1}J_N}\right)\otimes\left(\mathbf{I_T} - \mathbf{T^{-1}J_T}\right),$$

with $\mathbf{J}$ a square matrix of ones. The standard errors can be obtained as

$$\operatorname{se}\left(\widehat{\theta}\right) = \widehat{\sigma}^2\left[\mathbf{Z}'\mathbf{QH_n}(\mathbf{H_n'QH_n})^{-1}\mathbf{H_n'QZ}\right]^{-1} \tag{31}$$

with

$$\widehat{\sigma}^2 = \frac{\widehat{\mathbf{v}}'\mathbf{Q}\widehat{\mathbf{v}}}{(N-1)(T-1)-(k+p)}. \tag{32}$$

C. Summary statistics of analysts' forecasts and an explanation of how real and informational linkages are estimated

C.1 Summary statistics of analysts' forecasts

[Insert Table C1 here]

C.2 Real linkages

Regarding the matrix that describes the real channel of interdependence, the procedure for consistently estimating the non-zero elements of $\mathbf{W}_R$ is based on five steps. First, relying on annual bilateral export and import data (source: Direction of Trade Statistics, DOTS), we compute the trade intensity measure $z_{ij,t}$ as

$$z_{ij,t} = \frac{EX_{ij,t} + IM_{ij,t}}{GDP_{i,t} + GDP_{j,t}} \tag{33}$$

where $EX_{ij,t}$ ($IM_{ij,t}$) refers to the exports (imports) going from country i to country j in year t, and $GDP_{i,t}$ stands for the gross domestic product of country i in year t.

Second, we instrument the trade intensity measure, relying on standard variables used in the trade literature (Frankel and Romer, 1999; Frankel and Rose, 2002; Cavallo and Frankel, 2008). We instrument bilateral trade to account for the possibility of trade being endogenous.[25] Specifically, we consider the log of the product of the land areas, the log-distance, and indicator variables for whether the two countries in a pair have a common language, common borders, preferential trade agreements, regional trade agreements, are landlocked and are part of a currency union, respectively. Thus, we estimate the following gravity equation:

$$z_{ij,t} = \alpha + \mathbf{H}_{ij}\boldsymbol{\phi} + \delta_{i,t} + \delta_{j,t} + \varepsilon_{i,t}, \tag{34}$$

where $\delta_{i,t}$ and $\delta_{j,t}$ are country-year fixed effects, $\mathbf{H}_{ij}$ denotes the vector of the previously listed variables used to instrument the trade intensity measure, corresponding to the country pair i,j, $\boldsymbol{\phi}$ is a vector of parameters and $\varepsilon_{i,t}$ are the residuals. We then predict trade intensity based on equation (34), that is, $\widehat{z}_{ij,t} = \mathbf{H}_{ij}\widehat{\boldsymbol{\phi}} + \hat{\delta}_{i,t} + \hat{\delta}_{j,t}$. Gravity estimates should provide good instrumental variables because they are based on geographical factors, which are plausibly exogenous and yet, when aggregated across all bilateral trading partners, are highly correlated with a country's overall trade (Cavallo and Frankel, 2008).

Third, we average across periods:

$$\bar{\widehat{z}}_{ij} = \frac{1}{T}\sum_{t=1}^{T} \widehat{z}_{ij,t}, \tag{35}$$

25. One reason why trade could be endogenous is because of income; that is, richer countries might tend to reduce their trade barriers and, hence, trade more. Another possibility is that it is endogenous due to the simultaneous feedback between trade openness and financial interdependence, with the two possibly being jointly determined. Alternatively, reverse causality may be an issue, whereby, for example, greater financial interdependence may reduce the cost of trade credit and encourage foreign direct investment, with both adjustments facilitating more commercial trade between countries (Cavallo and Frankel, 2008).

and compute the standard deviation,

$$\sigma_z = \sqrt{n_{ij}^{-1} \sum_{ij=1}^{n_{ij}} \left(\bar{\hat{z}}_{ij} - \bar{\bar{\hat{z}}} \right)}, \tag{36}$$

where $\bar{\bar{\hat{z}}}$ is the average of $\bar{\hat{z}}_{ij}$ across country pairs.

Fourth, we standardize the instrumented trade intensity measure using

$$\widehat{\epsilon}_{R,ij} = \frac{\bar{\hat{z}}_{ij} - \bar{\bar{\hat{z}}}}{\sigma_z}. \tag{37}$$

Fifth, as with the informational linkages in Section 3.1, we use an equivalent version of equation (19) to consistently estimate the non-zero elements of $\mathbf{W}_R$, by following Bailey, Holly, and Pesaran (2016b)'s methodology. After that, we multiply each element of $\mathbf{W}_R$, $w_{R,ij}$, by its corresponding $\widehat{\epsilon}_{R,ij}$ and row-normalize.

C.3 Financial linkages

We construct the financial interdependence matrix $\mathbf{W}_F$ based on whether a country relies on investment funds that are overexposed to other countries (Broner, Gelos, and Reinhart, 2006). Data on institutional investors and mutual funds come from EPFR (https://epfr.com/); specifically, we rely on the monthly assets under management of bond and equity investment funds, from EPFR, in each country.

We denote by $re_{i,k,t}$ country i's reliance on a fund k, which we define as

$$re_{i,k,t} = \frac{a_{k,i,t}}{\sum_{k'} a_{k',i,t}}, \tag{38}$$

where $a_{k,i,t}$ are the assets under management of fund k on securities issued in country i in month t. Let $s_{k,t} = \sum_j a_{k,j,t}$ be the size of fund k and $b_{k,j,t}$ its country weight; that is, $b_{k,j,t} = a_{k,j,t}/s_{k,t}$. Also, let $\bar{b}_{j,t}$ be the average country-j weight across funds. The overexposure of fund k to country j in period t, $oe_{k,j,t}$, becomes

$$oe_{k,j,t} = b_{k,j,t} - \bar{b}_{j,t}. \tag{39}$$

We then define the financial interdependence index $d_{ij,t}$ as country i's reliance on funds from investors overexposed to country j, that is,

$$d_{ij,t} = \sum_k re_{i,k,t} \cdot oe_{k,j,t}. \tag{40}$$

To clean out the country-time-specific factors and keep only the country-pair-specific part, we estimate

$$d_{ij,t} = \alpha + \delta_{i,t} + \delta_{j,t} + \varepsilon_{ij,t} \tag{41}$$

and keep the residuals from equation (41), which we denote by $\widehat{\varepsilon}_{ij,t}$. Next, we average the $\widehat{\varepsilon}_{ij,t}$ across periods:

$$\bar{\widehat{\varepsilon}}_{ij} = \frac{1}{T}\sum_{t=1}^{T} \widehat{\varepsilon}_{ij,t}, \tag{42}$$

and compute the standard deviation:

$$\sigma_{\varepsilon} = \sqrt{n_{ij}^{-1} \sum_{ij=1}^{n_{ij}} \left(\bar{\widehat{\varepsilon}}_{ij} - \bar{\bar{\widehat{\varepsilon}}}\right)}. \tag{43}$$

Finally, we construct $\widehat{\epsilon}_{F,ij}$ as

$$\widehat{\epsilon}_{F,ij} = \frac{\widehat{\varepsilon}_{ij} - \bar{\bar{\widehat{\varepsilon}}}_{ij}}{\sigma_{\varepsilon}} \tag{44}$$

and, following Bailey, Holly, and Pesaran (2016b) to consistently estimate the non-zero elements of $\mathbf{W}_F$, we use equation (19), but this time we replace the sub-index I with F. As before, to allow for varying degrees of intensity of the significant financial connections, we multiply each element of $\mathbf{W}_F$, $w_{F,ij}$, by its corresponding $\widehat{\epsilon}_{F,ij}$ and row-normalize.

D. Robustness checks

[Insert Table D1 here]

[Insert Table D2 here]

[Insert Table D3 here]

[Insert Table D4 here]

[Insert Table D5 here]

[Insert Table D6 here]

[Insert Table D7 here]

[Insert Table D8 here]

E. Economic significance

In this appendix, we explain how to calculate the economic significance of informational interdependence. Specifically, we include the economic significance of the estimates related to the information channel in Tables 2 and 3. We do so by measuring how shocks transmitted through informational connections affect sovereign CDS spreads, net of the effects arising from the fundamental real and financial channels.

To accomplish this, we apply a one-standard-deviation shock to a given country i and estimate the average percentage change in the CDS spreads of other countries $j \neq i$. Because the baseline spatial econometric model in equation (20) inherently captures higher-order spillovers across all three channels, isolating the economic effect of the informational channel alone is not straightforward. Instead, we calculate the total effect of shocks propagated through the baseline model (which includes the informational, real and financial linkages) and then subtract the effect derived from a restricted model (which includes only the real and financial linkages). The difference between the baseline and restricted models provides a clean measure of the economic significance attributable to informational interdependence, which we then normalize using the mean value of the CDS spreads.

Based on the spatial econometric model presented in equation (20), and following LeSage and Pace (2009), we can express the marginal effects of a simultaneous CDS shock in all countries, $\Delta \mathbf{v}$, on $\Delta \mathbf{y}_{\mathbf{I},\mathbf{R},\mathbf{F}}$, which includes the three channels of interdependence, as follows:

$$\frac{\Delta \mathbf{y}_{\mathbf{I},\mathbf{R},\mathbf{F}}}{\Delta \mathbf{v}} = \mathbf{Q}_{\mathbf{I},\mathbf{R},\mathbf{F}} \quad with \quad \mathbf{Q}_{\mathbf{I},\mathbf{R},\mathbf{F}} = \left(\mathbf{I_N} - \left(\rho_I \mathbf{W}_I + \rho_R \mathbf{W}_R + \rho_F \mathbf{W}_F\right)\right)^{-1}. \tag{45}$$

Here, $\mathbf{Q}_{\mathbf{I},\mathbf{R},\mathbf{F}}$ is an $N \times N$ matrix containing the marginal effects of the shock $\Delta \mathbf{v}$, and $\mathbf{I_N}$ is an $N \times N$ identity matrix.[26] Consequently, the changes following a one-standard-deviation CDS shock in all other countries connected to country i, simultaneously considering informational, real and financial linkages, are given by:

26. Equation (45) is derived because our specification in equation (20) can be written as $\mathbf{y}t = \left(\mathbf{I_N} - \sum p \in \mathscr{P} \rho_p \mathbf{W}p\right)^{-1} (\mathbf{X}t - 1\beta + \gamma g_{t-1} + \mu + \delta_t + \mathbf{v}_t)$.

$$\Delta \mathbf{y_{I,R,F}} = \mathbf{Q_{I,R,F}} \Delta \mathbf{v} \tag{46}$$

However, we want to calculate the economic significance of informational interdependence without considering the fundamental real and financial channels. Thus, we need to subtract from equation (46) the changes induced by shocks transmitted solely through fundamental real and financial linkages. These changes can be obtained by calculating:

$$\Delta \mathbf{y_{R,F}} = \mathbf{Q_{R,F}} \Delta \mathbf{v} \quad with \quad \mathbf{Q_{R,F}} = \left(\mathbf{I_N} - \left(\rho_R \mathbf{W}_R + \rho_F \mathbf{W}_F\right)\right)^{-1}. \tag{47}$$

Here, equation (47) reflects the potential changes induced by shocks in a restricted spatial model that includes the real and financial links but excludes the informational links (i.e. the baseline spatial model in equation (20), but without the informational links, meaning $\mathbf{W}_I$ is eliminated from the spatial specification).

Consequently, the vector capturing the economic significance of informational interdependence in each country i, denoted as $\mathbf{E_I}$, can be obtained as follows:

$$\begin{aligned} \mathbf{E_I} &= \Delta \mathbf{y_{I,R,F}} - \Delta \mathbf{y_{R,F}} \\ &= \left(\mathbf{Q_{I,R,F}} - \mathbf{Q_{R,F}}\right) \Delta \mathbf{v}. \end{aligned} \tag{48}$$

We then calculate the average economic significance of informational interdependence across countries, $Average(\mathbf{E_I})$, which is normalized by dividing by the mean value of the CDS spreads, $C\bar{D}S$:

$$EconSign_I = \frac{Average(\mathbf{E_I})}{C\bar{D}S} \tag{49}$$

Here, $EconSign_I$ represents the economic significance of informational interdependence reported in our study. A similar approach can be applied to calculate the economic significance for other parameters in spatial econometric models.

F. Direct and indirect effects of transmission due to domestic economic shocks

In this appendix, we explain how to calculate the direct and indirect effects of shocks in domestic economic variables, relying on our empirical model. In equation (20), a direct effect corresponds to the impact of a change in country i in one domestic variable (i.e., one of the country-specific economic variables in the matrix $\mathbf{X}_{t-1}$) on the CDS spread of the same country i. In contrast, an indirect (or spillover) effect comprises the impact of a change in one domestic variable of country i on the CDS spreads of other countries.

Suppose that the domestic variable k changes marginally in all countries. The vector of the changes in this domestic variable is denoted by $\Delta\mathbf{X}_k$. In the context of our econometric model given in equation (20), suppose that $\Delta\mathbf{X}_k$ induces changes in the CDS spreads of countries, which are reflected in the vector $\Delta\mathbf{y}$. Then, following LeSage and Pace (2009), the marginal effects of $\Delta\mathbf{X}_k$ on $\Delta\mathbf{y}$ are given by:

$$\frac{\Delta\mathbf{y}}{\Delta\mathbf{X}_k} = \mathbf{S}_k \quad with \quad \mathbf{S}_k = \left(\mathbf{I_N} - \sum_{p\in\mathscr{P}} \rho_p \mathbf{W}_p\right)^{-1} \beta_k \tag{50}$$

where $\mathbf{S}_k$ is an $N \times N$ matrix containing those marginal effects of changes in the variable k. Here, $\mathbf{I_N}$ is an $N \times N$ identity matrix, ρ_p and $\mathbf{W}_p$ were defined for equation (20) and β_k corresponds to the estimated coefficient for the domestic variable k. The diagonal elements of $\mathbf{S}_k$ (i.e., when $i = j$) correspond to the direct marginal effects; the off-diagonal elements (i.e., when $i \neq j$) are the indirect marginal effects. The sum of the direct and indirect marginal effects equals the total marginal effect.

Thus, thanks to equation (50), we can compute the marginal direct and indirect effects of changes in each of the domestic variables used in our econometric model.

G. Potential amplification effects of a CDS spread shock to Ukraine

In this appendix, we apply our model to analyze the economic interdependence between an idiosyncratic, exogenous shock to the CDS spreads in one country and the rest of the world's economy. Specifically, we examine the total direct and indirect effects of a CDS spread shock to Ukraine on the world economy.

In February 2022, Russia invaded Ukraine. This unexpected war has generated a massive economic shock, not only to Ukraine but also to the world's economy. Given that the total economic impact of the Ukrainian war on the world's economy is still to be seen, it is appealing to analyze how another relatively recent economic shock to the Ukrainian economy was propagated (and amplified) through Ukraine's economic interdependence with other countries. Specifically, we consider, in this application, the Ukrainian Revolution of Dignity that took place in February 2014. By doing this, we can shed some light on the likely international transmission of the large economic shock generated by the Ukrainian war.

In terms of the Ukrainian revolution of 2014, after political turmoil started in November 2013, protests led to the ousting of President Yanukovych in February 2014. Figure F1 depicts the six-month rolling window of CDS spread correlations between Ukraine and other countries (classified by region).

Figure F1 shows that, at the start of the crisis, particularly at the beginning of 2014, the reactions in the correlations between sovereign-debt markets reflected a moderate co-movement. There was then a hike in the correlations, after the announcement in January 2015 of a preemptive debt exchange operation, which was finally launched in September 2015 when private creditors agreed to a restructuring (for details, see Ams, Baqir, Gelpern, and Trebesch, 2019). Also note that the spike in the CDS spread correlations in January 2015 is comparable to the CDS increases observed following changes in common factors, such as with the *taper tantrum* of May 2013, when Ben Bernanke announced in a congressional speech the future tapering of quantitative easing.

Figure F1 also shows that, around the time of the Ukrainian debt-exchange program announcement, the CDS spread correlations between Ukraine and other economies increased greatly. In fact, according to our interdependence matrices, Ukraine has informational linkages with emerging countries (Brazil, Chile, China, Malaysia, Peru, Poland and Russia) and with advanced economies (Italy and Slovakia). In terms of the real and financial interdependence channels, Ukraine has real linkages with Hungary, Romania and Poland, and financial linkages with Russia (all of which are emerging economies, as is Ukraine).

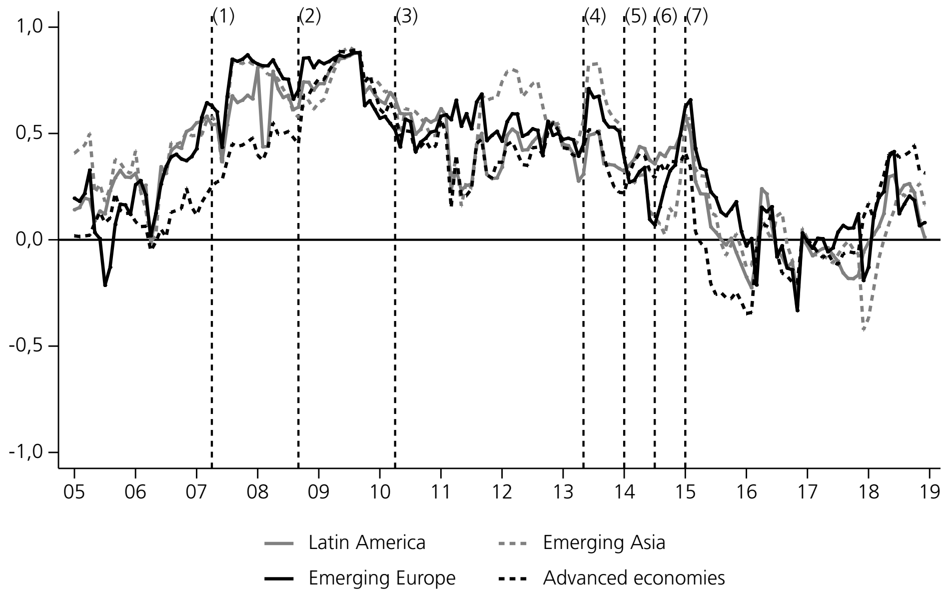

Figure F1: Six-month correlations of five-year CDS spreads with those of Ukraine (%)

Notes: The country groups are as follows: Advanced economies (Australia, the Czech Republic, Germany, Spain, France, Great Britain, Italy, Japan, Korea, the Netherlands, Norway, Slovakia, Sweden and the USA); Latin America (Brazil, Chile, Colombia, Mexico and Peru); Emerging Asia (China, Hong Kong, Indonesia, Malaysia and Thailand); and Emerging Europe (Hungary, Poland, Romania, Russia and Turkey). Dates: (1) subprime crisis; (2) Lehman Bros. fall; (3) European sovereign-debt crisis; (4) taper tantrum; (5) Ukraine crisis; (6) Argentinian default; (7) Ukrainian debt-exchange program announcement. Source: Datastream.

In this context, we use our econometric model to analyze the idiosyncratic exogenous shock to the CDS spreads that was observed during the Ukrainian revolution of 2014. Table F1 exhibits the results. Specifically, in Table F1, we consider a one-standard-deviation shock to the Ukrainian CDS sovereign spread. This table presents the indirect impact of the CDS spread shock, distinguishing between countries that are linked to Ukraine (in informational, real and/or financial terms) and the remaining countries, which we classify by region and economic development. Table F1 shows that spillovers (generated by the CDS spread shock to Ukraine) are observed in countries connected in informational, real and financial terms with this country.

[Insert Table F1 here]

Most importantly, Table F1 also shows that countries without informational, real and financial linkages with Ukraine are affected by the CDS spread shock to this economy. This is because those disconnected (from Ukraine) countries are linked with economies that are connected with Ukraine;

hence, there are second- and higher-order effects of the economic transmission of the Ukrainian shock.

Table C1: Summary statistics of the analyst forecasts

	Mean	St.Dev.	p25	p50	p75	Obs.
Number of analysts per country-month	16.4	5.2	12.0	16.0	19.0	1815
Dispersion of the number of analysts per country	0.1	0.0	0.1	0.1	0.2	30
Frequency (in months) of analysts' revisions per country	1.5	0.5	1.1	1.3	2.0	30

Notes: This table reports summary statistics of the GDP one-year-ahead forecasts in relation to the the number of analysts per country-month, the dispersion of the number of analysts per country, and the frequency of analysts' revisions per country.

Table D1: Robustness check in terms of an alternative orthogonalization

Variable	Restricted model	$T-$stat.	Restricted model	$T-$stat.	Restricted model	$T-$stat.	Baseline model	$T-$stat.
W_I	0.27	6.10					0.26	7.06
W_R			0.19	5.70			0.27	9.99
W_F					0.55	24.79	0.49	20.90
Reserves/GDP	−0.31	−2.50	−0.35	−3.03	−0.07	−0.62	−0.08	−0.69
Ext. Debt/GDP	0.27	6.16	0.39	9.70	0.25	6.59	0.24	5.98
Δ GDP	−4.74	−17.38	−4.15	−15.66	−4.51	−18.20	−4.17	−16.86
Δ CPI	6.71	12.22	7.11	13.71	6.21	12.37	6.21	12.70
FDI/GDP	−0.13	−0.59	−0.35	−1.70	−0.39	−1.98	−0.26	−1.36
FB/GDP	−5.36	−15.88	−5.09	−15.49	−4.26	−13.70	−3.51	−11.41
Observations	4640		4350		4350		4350	
Log-likelihood	124.58		381.25		506.06		569.64	
Akaike crit.	170.84		−342.49		−592.13		−715.28	

Notes: This table is similar to Table 2, but here we use an alternative sequential order in the Gram-Schmidt orthogonalization procedure. Regarding the ordering of regressions in this successive orthogonalization procedure, we first run a regression with real links as the dependent variable and financial links as the explanatory variable. Next, we run a regression with informational links as the dependent variable, using two explanatory variables: financial links and the residuals obtained from the previous regression (representing real links orthogonal to the financial links). The residuals from this second regression provide the measure of informational links between countries used in this table, orthogonalized (cleaned) with respect to the fundamental real and financial connections.

Table D2: Robustness check in terms of placebo test

Variable	Restricted model	$T-$stat.	Restricted model	$T-$stat.	Restricted model	$T-$stat.	Baseline model	$T-$stat.
W_I	0.00	−0.09					0.01	0.47
W_R			0.27	8.68			0.29	11.13
W_F					0.53	23.65	0.43	18.90
Reserves/GDP	−0.34	−2.84	−0.39	−3.40	−0.43	−3.85	−0.47	−4.30
Ext. Debt/GDP	0.35	8.41	0.41	10.30	0.26	6.63	0.33	8.57
Δ GDP	−4.54	−16.96	−3.96	−15.04	−4.35	−17.49	−3.77	−15.29
Δ CPI	6.99	12.92	7.14	13.87	6.01	11.93	6.35	12.99
FDI/GDP	−0.31	−1.46	−0.40	−1.98	−0.45	−2.24	−0.52	−2.68
FB/GDP	−5.58	−16.85	−4.90	−15.10	−4.16	−13.27	−3.70	−12.12
Observations	4640		4350		4350		4350	
Log-likelihood	221.12		390.73		494.54		581.87	
Akaike crit.	−22.24		−361.46		−569.08		−739.74	

Notes: This table is similar to Table 2, but here we perform a placebo test by assigning random values to the informational links within the interdependence matrix, while keeping the real and financial matrices intact.

Table D3: Robustness checks in terms of dynamic interdependence matrices and considering an alternative threshold for the weights in the interdependence matrices

Variable	Dynamic interdependence matrices	$T-$stat.	Higher thresholds for weights in interd. matrices	$T-$stat.
W_I	0.13	8.82	0.10	2.96
W_R	0.21	8.55	0.27	10.21
W_F	0.45	21.63	0.41	18.29
Reserves/GDP	−0.47	−4.33	−0.32	−2.66
Ext. Debt/GDP	0.33	8.89	0.31	7.89
Δ GDP	−3.61	−14.70	−3.89	−15.84
Δ CPI	6.07	12.45	6.46	13.22
FDI/GDP	−0.59	−3.03	−0.47	−2.42
FB/GDP	−3.34	−10.90	−3.76	−12.19
Observations	4350.00		4350.00	
Log-likelihood	619.26		586.31	
Akaike Crit.	−814.52		−748.61	

Notes: This table presents two robustness checks. First, we re-estimate the same baseline model specification as in the last two columns of Table 2, but this time we allow the informational interdependence matrix to change over time. Second, we modify the levels of sparseness of the interdependence matrices by considering an alternative threshold, above which a linkage between a pair of countries for a given source of interdependence is said to be significant.

Table D4: Robustness checks in terms of using CPI forecasts and calculating informational links by using the correlation of the quartile-based dispersion of forecast errors

Variable	Using inflation (CPI) forecast errors for inf. links	$T-$stat.	Corr. of alternative error measure ($QUANT$) for inf. links	$T-$stat.
W_I	0.25	7.71	0.26	8.15
W_R	0.19	6.65	0.32	12.11
W_F	0.42	18.11	0.46	19.43
Reserves/GDP	−0.39	−3.61	−0.42	−3.79
Ext. Debt/GDP	0.34	9.17	0.35	9.11
Δ GDP	−3.99	−16.31	−3.67	−14.55
Δ	6.14	12.71	6.22	12.45
FDI/GDP	−0.43	−2.26	−0.90	−4.42
FB/GDP	−3.62	−12.00	−3.39	−10.77
Observations	4350.00		4350.00	
log-Likelihood	634.24		452.04	
Akaike Crit.	−844.49		−480.07	

Notes: This table presents two robustness checks. The first two columns report an empirical exercise in which we use analysts' inflation (CPI) forecast errors in equation (16), rather than analysts' GDP forecast errors, to measure informational links. In the last two columns, we calculate the matrix for the informational channels using correlations of alternative error measures. Specifically, in this second robustness check, instead of calculating the correlation between countries based on the root mean squared errors of the one-year-ahead GDP forecast (as in equation (16)), we calculate the correlation (between countries) of the quantile-based (QUANT) dispersion of the one-year-ahead GDP forecast.

Table D5: Robustness checks with informational links based on correlation of both root winsorized mean squared error ($RootSqErr_{Win}$) and root median squared error ($RootSqErr_{Med}$)

Variable	Corr. of altern. error measure ($RootSqErr_{Win}$) for inf. links	$T-$stat.	Corr. of altern. error measure ($RootSqErr_{Med}$) for inf. links	$T-$stat.
W_I	0.29	7.09	0.09	2.23
W_R	0.28	10.58	0.27	9.57
W_F	0.45	19.35	0.43	18.30
Reserves/GDP	−0.48	−4.36	−0.47	−4.33
Ext. Debt/GDP	0.24	5.89	0.31	8.14
Δ GDP	−4.03	−16.23	−3.95	−15.89
Δ CPI	6.03	12.23	6.27	12.85
FDI/GDP	−0.39	−1.99	−0.48	−2.50
FB/GDP	−3.15	−9.81	−3.55	−10.85
Observations	4350.00		4350.00	
log-Likelihood	531.16		595.22	
Akaike Crit.	−638.32		−766.44	

Notes: This table presents two additional robustness checks, where we calculate the matrix for the informational channels using the correlation of alternative error measures. In particular, instead of calculating the correlation between countries of the root mean squared errors of the one-year-ahead GDP forecast (as in equation (16), we calculate the correlation (between countries) of: (i) the root winsorized mean squared error ($RootSqErr_{Win}$) of the one-year-ahead GDP forecast, which is less sensitive to extreme values (see columns 1–2); (ii) the root median squared error ($RootSqErr_{Med}$) of the one-year-ahead GDP forecast, also less sensitive to extreme values (see columns 3–4).

Table D6: Robustness checks in terms of calculating informational links using correlation of both mean absolute error (MAE) and dispersion (DISP) of forecast errors

Variable	Corr. of altern. error measure (MAE) for inf. links	$T-$stat.	Corr. of altern. error measure ($DISP$) for inf. links	$T-$stat.
W_I	0.30	7.36	0.17	5.47
W_R	0.28	10.58	0.34	11.65
W_F	0.45	19.33	0.42	18.08
Reserves/GDP	−0.48	−4.36	−0.54	−4.90
Ext. Debt/GDP	0.23	5.79	0.36	9.25
Δ GDP	−4.04	−16.23	−3.66	−14.73
Δ CPI	6.03	12.22	6.27	12.79
FDI/GDP	−0.38	−1.97	−0.47	−2.43
FB/GDP	−3.12	−9.70	−3.73	−12.18
Observations	4350.00		4350.00	
log-Likelihood	526.24		545.74	
Akaike Crit.	−628.47		−667.48	

Notes: This table presents two additional robustness checks, where we calculate the matrix for the informational channels using the correlation of alternative error measures. In particular, instead of calculating the correlation between countries of the root mean squared errors of the one-year-ahead GDP forecast (as in equation (16), we calculate the correlation (between countries) of the mean absolute error (MAE) and the dispersion ($DISP$) of the one-year-ahead GDP forecast.

Table D7: Robustness checks in terms of using quarterly data and an alternative lag structure to measure informational links

Variable	Using quarterly data (instead of monthly data)	$T-$stat.	Potential delayed effects on informational links	$T-$stat.
W_I	0.15	2.72	0.13	3.92
W_R	0.26	5.75	0.26	9.76
W_F	0.44	11.13	0.42	18.06
Reserves/GDP	−0.20	−0.98	−0.47	−4.37
Ext. Debt/GDP	0.30	4.42	0.31	8.13
Δ GDP	−4.01	−9.34	−3.94	−15.98
Δ CPI	5.85	6.90	6.23	12.73
FDI/GDP	−0.31	−0.91	−0.46	−2.37
FB/GDP	−3.41	−6.41	−3.70	−12.10
Observations	1470.00		4350.00	
log-Likelihood	212.46		588.74	
Akaike Crit.	−192.93		−753.48	

Notes: This table presents two robustness checks. The first two columns use quarterly data instead of monthly data, while the last two columns use a one-month-lagged structure to capture potential delayed effects on the measure of informational links.

Table D8: Robustness checks for analyses of influence of both crisis periods and common analysts

Variable	Altern. dummy var. *Crisis*	$T-$stat.	Altern. model extension with dummy var. *Crisis*	$T-$stat.	Altern. metric for links due to common analysts	$T-$stat.
W_I	0.20	5.46	0.24	6.43	0.19	4.93
W_R	0.26	9.82	0.25	9.19	0.30	10.73
W_F	0.43	18.69	0.44	18.58	0.39	16.16
$W_I * Crisis$	−0.02	−2.53	−0.04	−4.05		
$W_R * Crisis$			0.03	2.27		
$W_F * Crisis$			−0.01	−1.71		
W_A					0.12	2.82
Reserves/GDP	−0.43	−3.91	−0.37	−3.33	−0.44	−4.07
Ext. Debt/GDP	0.26	6.71	0.27	6.78	0.27	6.90
Δ GDP	0.26	6.71	0.27	6.78	0.27	6.90
Δ CPI	6.16	12.59	6.07	12.35	6.19	12.81
FDI/GDP	−0.38	−1.94	−0.35	−1.77	−0.21	−1.11
FB/GDP	−3.64	−11.86	−3.66	−11.82	−3.08	−10.01
Observations	4350.00		4350.00		4350.00	
log-Likelihood	545.90		541.05		628.76	
Akaike Crit.	−663.80		−650.10		−831.52	

Notes: This table presents robustness checks for the analyses regarding the influence of crisis periods and common analysts. Columns 1–4 relate to hypothesis 1, in which we examine whether the strength of informational links decreases during periods of stress, similarly to the first two columns of Table 3. In columns 1–2, unlike in Table 3, the dummy variable *Crisis* equals one if the monthly average of the Market Volatility Index (VIX) lies in the upper quartile of the sample values. In columns 3–4, we estimate an alternative extension of the baseline specification (see equation (20)). In this alternative extension, we interact the three interdependence matrices (reflecting informational, real and financial links) with the dummy variable *Crisis*, as defined in Table 3. Columns 5–6 extend the baseline specification in equation (20) by incorporating the influence of common analysts providing GDP forecasts for countries, similarly to the last two columns of Table 3. However, unlike in Table 3, we construct $\mathbf{W_A}$ by calculating, for each month and country pair (i, j), the ratio $q^*(i, j)$ as follows: the number of analysts common to both countries (i, j) divided by the geometric mean of the total number of analysts covering country i and the total number covering country j. We then set $w_{A,i:j} = 1$ if the monthly average of $q^*(i, j)$, denoted by $\bar{q}^*(i, j)$, is in the upper quartile; otherwise, $w_{A,i:j} = 0$.

Table F1: Average indirect effects of shock to Ukrainian 5-year CDS sovereign spread

	Value	Std. Err.
On countries linked to Ukraine (by type of linkage):		
Informational	0.067	(0.004)
Real	0.168	(0.004)
Financial	0.161	(0.003)
On other economies (by region):		
Emerging Europe	0.153	(0.003)
Non-European emerging markets	0.125	(0.002)
Advanced economies	0.030	(0.002)

Notes: Estimates correspond to the average indirect effects of a standard-deviation exogenous shock $\sigma_{v,i}$ to Ukraine's sovereign spread on the spreads of other countries $j \neq i$. Standard errors are in parentheses; they are obtained from 1000 simulated coefficients drawn from the multivariate normal distribution implied by the estimated variance-covariance matrix obtained from the estimates in the last two columns of Table 2.