Cross Country Shock Transmission in European Banking Sector: Network Approach

Vít Illichmann

1 Introduction

In the globalised financial economy value of assets on a bank's balance sheet is often closely tied to decisions made by other financial institutions. Even though banks try to divert risks through portfolio diversification and the use of hedging instruments, interdependencies cannot be fully avoided due to the tight connection of modern European economies facilitated mainly by international trade but also political co-dependencies, migration of workforce and flows investment capital. The topology of network connections between individual financial institutions is increasingly of interest to regulators on national and international level. Dense and no-regular network connections increase systemic risk and lead to highly nonlinear behaviour, especially during major economic downturns.

Recent developments in econometrics allow us to identify the underlying network structures of complex systems based on the observed panel data (Souza, Rasul, de Paula, 2019). In this paper, I attempt to identify the network between the banking systems of European countries. My aim is to identify to what degree idiosyncratic shocks in individual countries transmit across borders through the financial links between their banking institutions. I add to the existing literature on systemic risk in European banking by using a novel technique developed by (Souza, Rasul, de Paula, 2019) which to my best knowledge has been yet adopted in this context.

A similar paper by (Torri, Giacometti, & Tichý, 2021) attempts to map a network of risk transmission among a set of systemically important European banks by estimating co-dependence between quantiles of selected indicators used as proxies for measuring risk. Klinger and Teply (2017) use a network agent-based model to assess systemic risk in European banking, however, the authors exploit a dataset with already identified institutional connections.

2 Data

To estimate my model I use panel data containing aggregate values of banking assets structured by individual countries. The dataset has a monthly frequency and is publicly available from the ECB database. Due to the time span of available data, several countries have been excluded leaving a total of 18 observational units. The data span from the start of the year 2004 to the end of 2021. In the visualisations and tables, each country is referred to by its respective EU code. I use aggregate assets for initial identification of the model, however, for future applications more detailed data would be advisable.

3 Model

Let $E = (C, R, \Omega)$ be an oriented graph with a set of nodes C representing individual countries, set of edges R where each $r_{ij} \in R$ establishes existence (nonexistence) of a transmission channel between i and j and finally set of weights Ω regulating the intensity of the transmission channel. Shock to the banking system in period t and country i, $\varepsilon_{i|t}$ can then be expressed as:

$$\varepsilon_{i|t} = \sum_{j \in C \setminus i} r_{ij} \omega_{ij} \varepsilon_{j|t} + \phi_{i|t} \tag{1}$$

Where ϕ_i is the true idiosyncratic iid component of the total shock $\varepsilon_{i|t}$, with $\mathbb{E}[\phi_{i|t}] = 0$. And weight parameter ω_{ij} is an element of Ω. Elements of R are equal either to 1 (transmission channel exists) or to 0 (no transmission occurs). Weights $\omega_{ij} \in \Omega$ are assumed to be strictly positive. The set of edges can be also represented by a symmetric adjacency matrix M with unit entry for each existing transmission channel and zero entry otherwise. The orientation of edges is facilitated by the weights, which are not necessarily symmetric, i.e. the intensity of transmission may vary depending on the country of origin.

4 Estimation Strategy

Naturally, monthly data are subject to seasonal fluctuations as well as long-term trends in the financial economy which rules out direct estimation. To isolate shocks from the raw data I use the following 3-step scheme.

1. Remove long-term trend and seasonal component from the monthly data.
2. Remove inter-temporal dependence using an autoregressive model.
3. Use residuals from the previous steps to estimate network links based on their cross-sectional covariance structure using penalised LASSO estimation.

A detailed description of each step follows.

4.1 Seasonal-Trend Decomposition

Let $a_{i|t}$ be the value of total assets in the banking sector of the country i at time t. Then $a_{i|t}$ can be decomposed as:

$$a_{i|t} = \rho_{i|t} + \tau_{i|t} + \eta_{i|t} \tag{2}$$

To estimate the decomposition I use the STL procedure by (Cleveland et al., 1990) which is implemented as a part of the Statsmodels Python library. The implementation allows for robust and non-robust configurations of the method. An advantage of the robust method is that it treats major shocks to the observed system (e.g. financial crises) as exogenous events instead of treating them as fluctuations in overall trade. A demonstration of the results is shown in Figure 1.

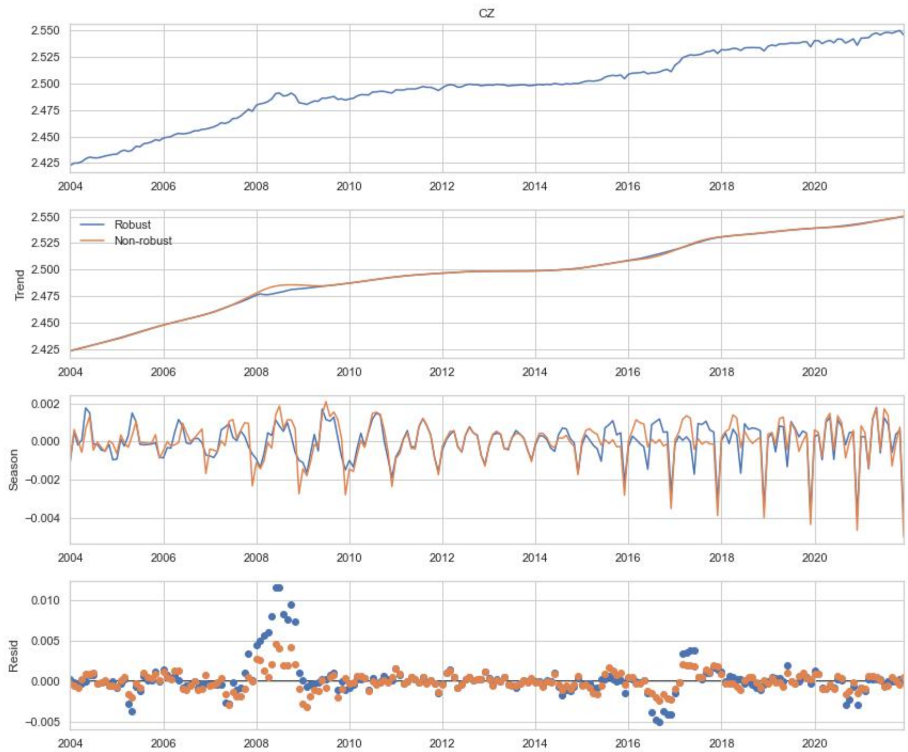

Figure 1: Decomposed time series of the total banking assets for the Czech Republic. Comparison of robust and non-robust methods.

Based purely on visual inspections of the residuals $\hat{\eta}_{i|t}$ the robust version of the STL procedure creates a comparatively smoother long-term trend and treats abrupt changes as external shocks rather than as fluctuations in the trend itself. Further, the flexible localised regression algorithm used to estimate the seasonal component allows us to account for changes in the seasonal pattern over time.

4.2 Removal of Inter-Temporal Dependencies

Effects of shocks tend to propagate over time in the financial system, leading to autocorrelation in the $\{\eta_{i|t}\}$ process.

$$\eta_{i|t} = \alpha_1 \eta_{i|t-1} + ... + \alpha_k \eta_{i|t-k} + \varepsilon_{i|t} \tag{3}$$

This can be seen from the autocorrelation plot of the estimates $\{\hat{\eta}_{i|t}\}_{i \in C,\ t \in \{0,...,T\}}$.

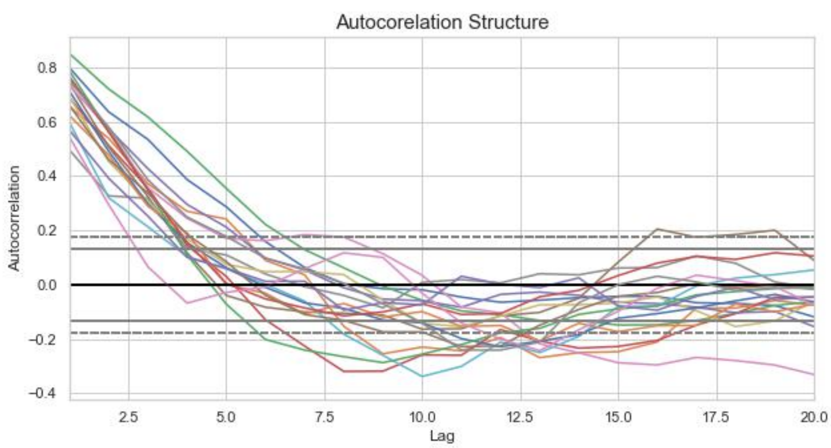

Figure 2: Autocorrelation structure of estimated $\hat{\eta}_{i|t}$ component, individual countries are not distinguished. Full and dashed lines correspond to the 95% and 99% confidence bands respectively.

To estimate the autoregressive model given by equation 3, I use the AR model implemented as part of the statsmodels library, estimation method is conditional maximum likelihood. The choice of the autoregressive order $k = 4$ is based on the estimated autocorrelation function shown in Figure 4 as well as on the tail stability of resulting residuals. Although the estimated ACF seems to dictate a slightly higher order, this is most likely due to the qualitative differences in the propagation of outlier shocks. This could be resolved by a non-parametric specification of mean dependence in the model, however, due to the relatively small number of observations per each country in the panel the uncertainty concerning the validity of the non-parametric estimate would be unacceptably high. Figure 3 shows an example q-q plot of $\hat{\varepsilon}_{i|t}$ residuals estimated for Czech data. Theoretical quantiles on the x-axis are derived from the student's t distribution fitted by maximum likelihood. The plot shows reasonable correspondence with quantiles of the model t distribution, however, there are significant fluctuations in tail observations.

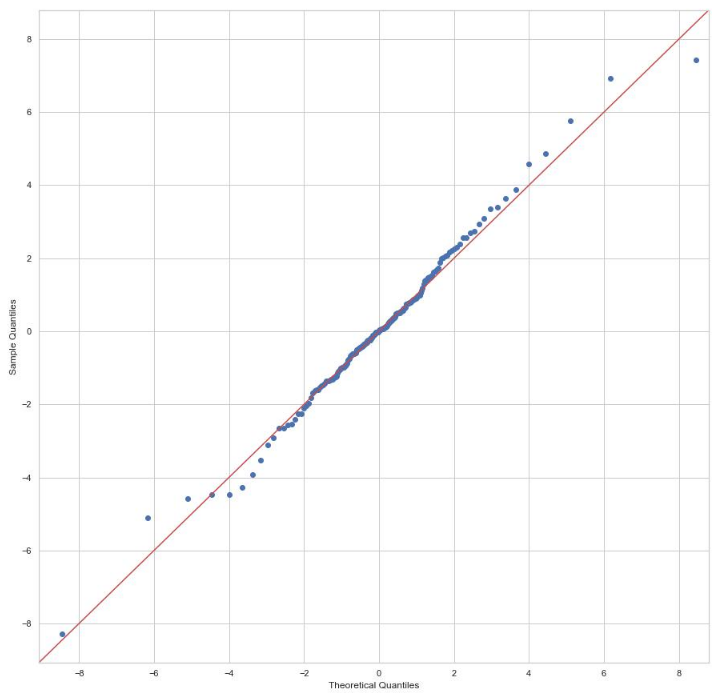

Figure 3: q-q plot of residuals $\hat{\varepsilon}_{i|t}$ estimated on Czech data. Theoretical quantiles (x-axis) are derived from a fitted student t distribution.

We can further explore distributional properties of $\hat{\varepsilon}_{i|t}$ estimates by fitting their empirical distribution with a smooth kernel density estimate. Results are plotted in Figure 4 below. For the purpose of comparison, the residuals of each country were scaled by their respective standard deviation. We can observe fluctuations mostly in the right tail suggesting that during financial crises or similar high-magnitude shocks, the financial systems have a qualitatively different behaviour. Because the removal of outliers would lead to, the loss of a significant share of the observations I choose to keep them in the dataset. Furthermore, the bootstrap experiment with the estimated network links shows that coefficients identified as non-zero by the LASSO algorithm are with a high probability non-zero regardless of the choice of sample.

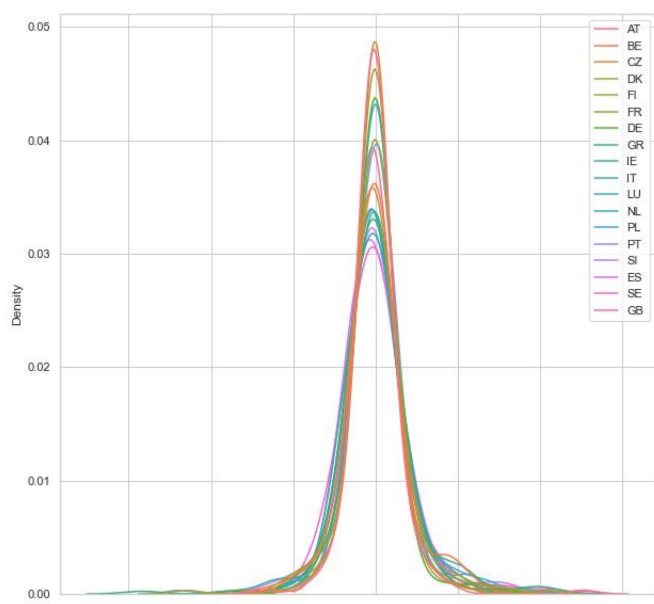

Figure 4: Plot of kernel density estimates of distributions of residuals $\hat{\varepsilon}_{i|t}$ for each country in the dataset.

4.3 Network Estimation by LASSO and Identification

Using estimated residuals $\hat{\varepsilon}_{i|t}$ from the previous stage I estimate the model specified in the section 3 as:

$$\hat{\varepsilon}_{i|t} = \sum_{j \in C \setminus i} b_{ij} \hat{\varepsilon}_{j|t} + f_{i|t} \tag{4}$$

$$b_{ij} = \hat{r}_{ij} \hat{\omega}_{ij} \tag{5}$$

The coefficient b_{ij} is the actual product of the estimation process. To identify the estimated adjacency matrix $\hat{M}$, I assume that its element $\hat{r}_{ij}$ is equal to 1 if either b_{ij} or b_{ji} are different from zero. Finally, the identification for arbitrary estimated weight $\hat{\omega}_{ij}$ is $b_{ij} = \hat{\omega}_{ij}$ if $b_{ij} > 0$. If either b_{ij} or b_{ji} are estimated as negative then we have to compute the net transmission effect of i on j by adding the absolute value of the negative parameter to its positive counterpart. The last term $f_{i|t}$ is mean zero iid estimation error, for any t and pair of countries $i \neq j$ it should further hold that $Cov(f_{i|t}, f_{j|t})$.

To estimate the coefficients $\{b_{ij}\}_{i,j \in C}$ I use the procedure designed Souza, Rasul & de Paula (2019). The estimation algorithm uses LASSO regression to eliminate irrelevant links between different elements of the observed panel. For some observed data $\{(y, x_t)\}_{t=0}^{T}$ the LASSO regression searches for the parameter vector $\hat{\theta}$ such that:

$$\hat{\theta} = \arg\min_{q \in \Theta} \{ \frac{1}{T} \sum_{t=0}^{T} (y_t - q' x_t)^2 + \alpha ||q||_1 \} \tag{6}$$

Where Θ is the space of admissible parameters and α is the hyperparameter which regulates the intensity of the penalisation term. Because the results of LASSO estimation depend on the relative scale of the explanatory variables I work with data scaled by their sample standard deviations. The choice of the hyperparameter α was based on the stability of the estimated coefficients, the α was set to $\exp(-2.5)$. Figure 5 how the estimated values change depending on α in the case of the Czech Republic.

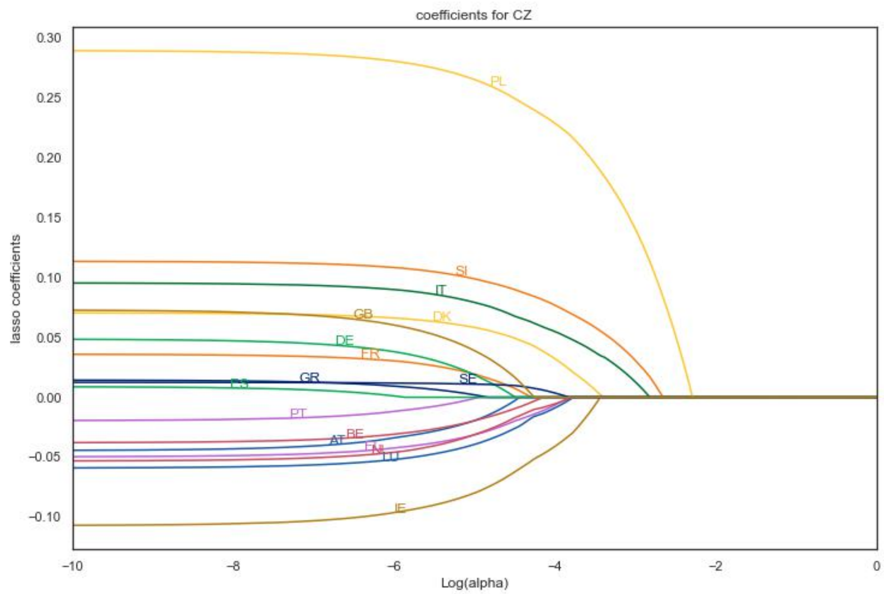

Figure 5: Stability of the estimates for Czechia as a function of the hyper-parameter α.

We can observe that the cross-sectional dependence between Czechia and Poland is a major determining factor regardless of the value of α used for estimation. A similar pattern seems to on average hold for other European countries, they all show a dense pattern of interconnections for very low α which is close to OLS regression, but most coefficients are close to 0 and tend to fully disappear around α close to $\exp(-2.5)$.

5 Results

The estimated weight matrix $\hat{\Omega}$ is shown in Table 5. Generally, coefficients are low, note however that we worked with natural logarithms of the original data. More suggestive than the magnitude of estimated weights on network nodes is the adjacency matrix itself, visualised in figure 6.

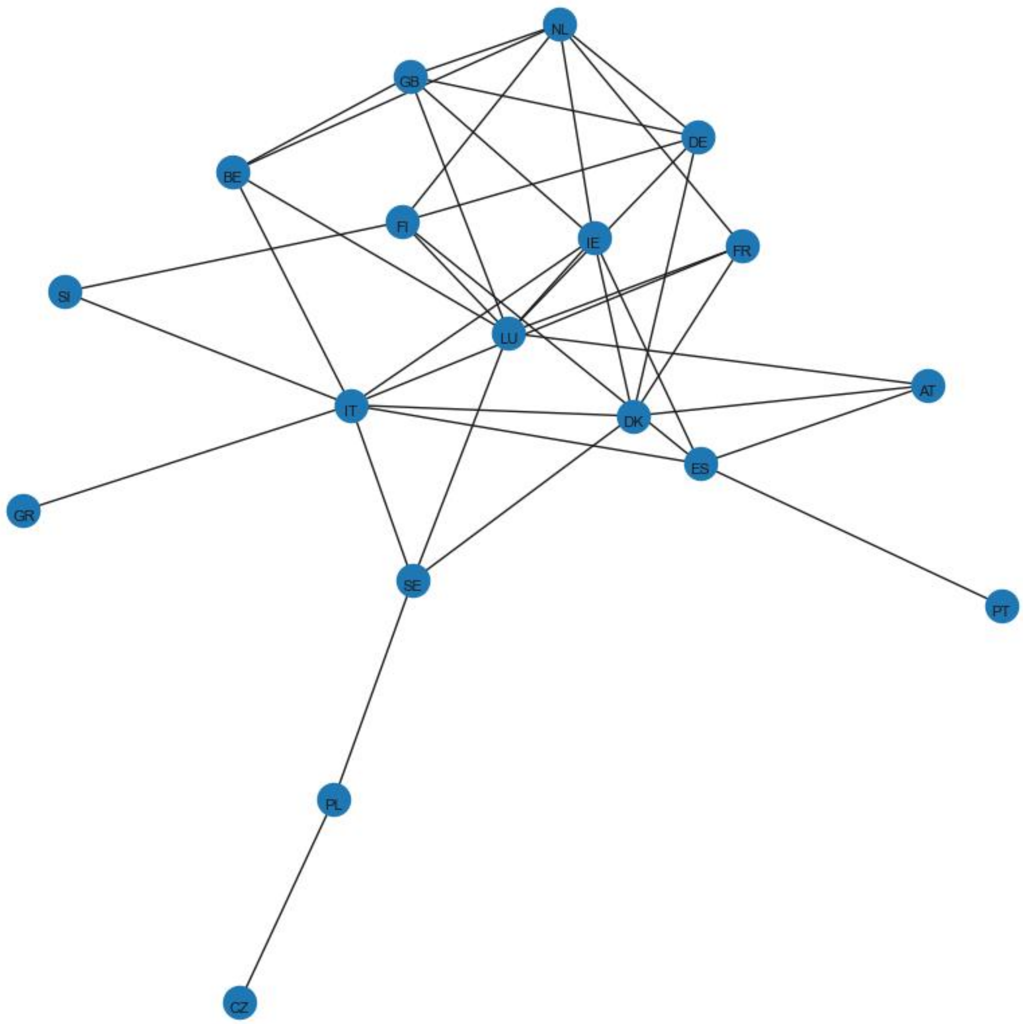

Figure 6: Estimated network of shock transmission between banking sectors of individual countries.

We can see that CEE countries together with the comparatively less advanced economies of Greece and Portugal lay on the "outskirts" of the network and are only sparsely connected to their Western peers. In contrast, advanced countries of Western Europe and Scandinavia are densely interconnected with several notable hubs. This suggests banking systems of the central nodes are more sensitive to the abrupt changes in adjacent economies and consequently more vulnerable. On the other hand, the high level of interconnection could imply a higher likelihood of international aid in case of collapse driven the internal factors, as the adjacent countries would like to avoid the spread of the financial contagion into their respective banking systems. The relative isolation of Greece could be a reason behind the lack of foreign financial aid during the debt crisis. The relationship between the network topology of the within-country banking systems and incentives for peer-to-peer bailouts is discussed in detail by Bernard, Capponi & Stiglitz, J. E. (2022), who prove that sparsely connected networks encourage regulators to deny financial aid to failing banks. The international environment is however vastly different from the within-country setup.

Finally, an example bootstrap distribution of coefficients estimated for the Czech Republic is shown in Figure 7. The bootstrap estimates show that regardless of the choice of sample the influence of Poland is dominant and with a high probability of non-zero. Several other adjacent countries (e.g. Slovakia) also have a non-negligible impact, however, most coefficients driven to zero by the penalty term remain close to zero across the majority of the simulated draws.

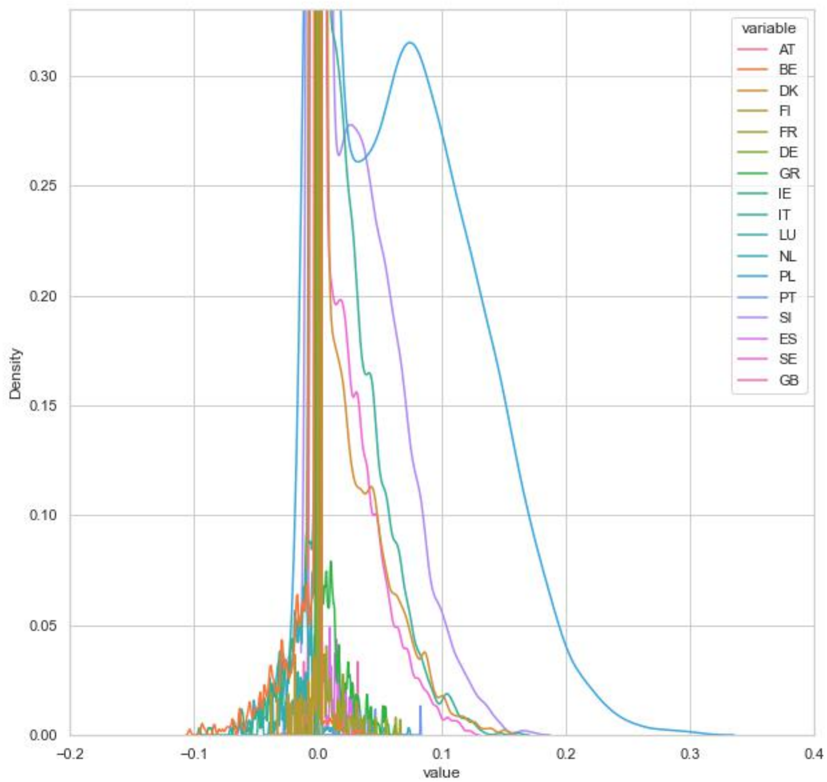

Figure 7: Bootstrap distributions of LASSO coefficients measuring the impact of peer countries on Czechia. The empirical distribution of estimates form 10000 drawn sub-samples is fitted by a pdf estimated by the kernel density estimation

	AT	BE	CZ	DK	FI	FR	DE	GR	IE	IT	LU	NL	PL	PT	SI	ES	SE	GB
AT*	-	-	-	0.02	-	-	-	-	-	-	0.073	-	-	-	-	0.082	-	-
BE*	-	-	-	-	-	-	-	-	-	0.13	0.106	0.072	-	-	-	-	-	0.021
CZ*	-	-	-	-	-	-	-	-	-	-	-	-	0.052	-	-	-	-	-
DK*	0.0	-	-	-	-	0.162	0.03	-	0.036	0.159	-	0.006	-	-	-	-	-	-
FI*	-	-	-	-	-	-	0.129	-	-	-	0.012	0.03	-	-	-	0.009	-	-
FR*	-	-	-	0.125	-	-	-	-	-	0.065	0.183	0.058	-	-	-	-	-	-
DE*	-	-	-	0.002	0.086	-	-	-	-	-	0.022	0.186	-	-	-	-	-	0.046
GR*	-	0.003	-	-	-	-	-	-	-	0.091	-	-	-	-	0.0	-	0.003	-
IE*	-	-	-	0.041	-	-	-	-	-	0.091	0.0	0.049	-	-	-	0.024	-	0.152
IT*	-	0.114	-	0.173	-	0.098	-	0.039	0.059	-	-	-	-	-	0.009	0.018	0.007	-
LU*	0.037	0.077	-	-	-	0.202	0.01	-	0.007	-	-	-	-	-	-	-	0.003	0.131
NL*	-	0.049	-	-	-	0.091	0.227	-	0.045	-	-	-	-	-	-	-	-	0.084
PL*	-	-	0.07	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
PT*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.041	-	-
SI*	-	-	-	-	0.008	-	-	0.01	-	0.026	-	-	-	-	-	0.02	-	-
ES*	0.135	-	-	-	0.006	-	-	-	0.054	0.058	-	-	-	0.027	-	-	-	-
SE*	-	-	-	0.04	-	-	-	0.003	-	0.05	0.042	-	-	-	-	-	-	-
GB*	-	-	-	-	-	-	0.038	-	0.091	-	0.137	0.086	-	-	-	-	-	-

Table 1: A table of the estimated weights $\hat{w}_{ij}$ for each pair of countries. The country in the row designated by the (*) symbol represents a dependent variable in the model, and the country in the column represents the source of the shock.

References

1. Bernard, B., Capponi, A., & Stiglitz, J. E. (2022). Bail-Ins and Bailouts: Incentives, Connectivity, and Systemic Stability. Journal of Political Economy, 130(7), 1805–1859. https://doi.org/10.1086/719758

2. Klinger, T., & Teply, P. (2017). Agent-Based Risk Assessment Model of the European Banking Network. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3014576

3. R. B. Cleveland, W. S. Cleveland, J.E. McRae, and I. Terpenning (1990) STL: A Seasonal-Trend Decomposition Procedure Based on LOESS. Journal of Official Statistics, 6, 3-73.

4. Souza, P. C., Rasul, I., & de Paula, Á. (2019). Identifying network ties from panel data: theory and an application to tax competition. https://doi.org/10.1920/wp.cem.2019.5519

5. Torri, G., Giacometti, R., & Tichý, T. (2021). Network tail risk estimation in the European banking system. Journal of Economic Dynamics and Control, 127, 104125. https://doi.org/10.1016/j.jedc.2021.104125

Additional Resources

In addition, I used QuantEcon lectures as a reference for coding and data manipulation. And documentation to the Statsmodels Python library as a source of prebuild methods for quantitative analysis.