Network Analysis of Economic and Financial Uncertainties in Advanced Economies: Evidence from Graph-Theory*

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Abstract

The paper investigates the nonlinear dependencies and interconnectedness of macroeconomic and financial uncertainties in 11 developed countries. The study applies structure learning with weakly additive noise model using Directed Acyclic Graphs (DAGs) to data covering 1997:01 to 2017:09. The results indicate the existence of nonlinear dependencies of macroeconomic and financial uncertainties among the 11 advanced economies considered. That an increased macroeconomic and financial uncertainty in a particular economy affects other economies. Overall, Spain happens to be a major receiver of macroeconomic and financial uncertainties from the other developed economies. The findings call for macroprudential policies to ensure stability in these economies.

Keywords: Connectedness; Economic and Financial Uncertainties; Advanced Economies; Directed Acyclic Graphs.

JEL: B26; C32; C58.

1. Introduction

Uncertainty is one of the important factors affecting economic and political activities. Many economies perform poorly because of uncertainty since it affects investment, employment and economic policy decisions which consequently distresses the overall growth of the economy (Bernanke, 1983; Bloom, 2009; Lensink et al., 1999; Pindyck, 1991). Indeed, empirical studies have shown that uncertainty (macroeconomic and financial) can have dire consequences on bond and stock markets (Antonakakis et al., 2013; Gao et al., 2019; Li et al., 2015), and GDP and inflation (Jones & Olson, 2013) as well as exchange rates (Kido, 2016). As a result, policymakers have become more concerned about the uncertainties. The reason being that macroeconomic and financial uncertainties have high potential to generate sharp recessions and recoveries, or even delay recoveries in times of recession (Ajmi et al., 2014; Bloom, 2009).

One general characteristic of uncertainties is their dependencies and spillover effect. In a globalised and interdependent world, uncertainty in one economy can spillover to other economies with its associated consequences (Christou et al., 2019; Diebold & Yilmaz, 2012). The consequences of economic events like the global financial crisis in 2007-09, 2010–12 European debt crisis and 2013 taper tantrum have spread globally (Kang & Yoon, 2019). Thus, with no change in domestic uncertainties, a particular economy may end up witnessing the negative impact of uncertainties due to globalisation, or even has its level of uncertainty changed due to variations in uncertainties in external markets (Antonakakis et al., 2018; Christou et al., 2019).

Further, international uncertainty feedbacks are likely to prolong the adverse effects on the domestic economy when domestic uncertainty rises, and such negative effects are usually stronger during the economic slowdown (Antonakakis et al., 2018; Gupta et al., 2019). For these reasons, investigating spillover of uncertainties are important for policy. In fact, the [negative] effects of uncertainties have led to several studies analysing causes, consequences or spillovers of uncertainty (see for instance Ajmi et al., 2014; Antonakakis et al., 2018; Baker et al., 2016; Bloom, 2009; Gupta et al., 2019; Kang & Yoon, 2019; Klößner & Sekkel, 2014; Luk et al., 2018).

While many studies have analysed uncertainty spillovers, many of these have focused on macroeconomic uncertainty (Antonakakis et al., 2018; Kang & Yoon, 2019; Klößner & Sekkel, 2014; Luk et al., 2018), based on Baker et al. (2016) and Scotti (2016) indices, thus ignoring

financial uncertainties spillover. Financial uncertainties can have a devastating impact on economic performance. According to Cesa-Bianchi et al. (2019), the negative effect of financial uncertainties shocks may be large and persistent, and such uncertainties or their consequences may transmit to other economies.

Given that macroeconomic and financial uncertainties do affect economic performance, it is significant to study how both macroeconomic and financial uncertainties in one economy may spillover to other economies to inform policy. Therefore, using graph-theory, we study nonlinear dependencies of uncertainty or how macroeconomic and financial uncertainties in domestic economies affect external ones. The analysis is done in a panel of 11 developed economies using data for the period 1997:01 to 2017:09. To our knowledge, this is the first attempt to study spillover of both macroeconomic and financial uncertainties in advanced economies using graph-theory based on directed acyclic graphs (DAGs).

Following this introduction, the remainder of the paper proceeds as follows: Section 2 presents details on the data and methodology; Section 3 presents and discusses the empirical results, while Section 4 concludes.

2. Materials and Methods

2.1. Data and Uncertainty Measures

Given that uncertainty is a latent variable, one requires ways to measure it. Gupta et al. (2018) summarises three broad approaches usually used to quantify uncertainty in the literature. These measures are namely (1) A news-based approach where one performs searches of major newspapers for terms related to economic and policy uncertainty and use the results to construct indices of uncertainty (e.g., Baker et al., 2016); (2) Deriving uncertainty from stochastic-volatility estimates of various types of small and large-scale structural models related to macroeconomics and finance (e.g., Carriero et al., 2018); and (3) Uncertainty obtained from the dispersion of professional forecaster disagreements (e.g., Scotti, 2016).

Other approaches to quantify uncertainty are associated with financial markets and measures such as the implied-volatility indices (popularly called the VIX), realized volatility, and idiosyncratic volatility of equity returns (e.g., Caldara et al., 2016).

We use uncertainty measure based on the second approach. Here, the uncertainty is derived from stochastic-volatility estimates of various types of small and large-scale structural models relating to macroeconomics and finance. These measures of uncertainty have been

constructed by Redl (2018) for 11 advanced economies (i.e., Canada, France, Germany, Italy, Japan, Netherlands, UK, USA, Spain, Sweden, and Switzerland) and the dataset is publicly available. The data used cover the period 1997:01 to 2017:09.

2.2. Model

In order to study nonlinear dependencies and interconnectedness of economic and financial uncertainty in 11 developed countries, we employ the nonlinear directed acyclic structure learning with weakly additive noise model. Traditionally, constraint-based and score-based algorithms for learning directed graphical models from continuous data assumed linear relationships with Gaussian noise between variables concerned. There are cases where variables may have nonlinear dependencies and/or data do not tend towards Gaussianity and are unable to identify a unique structure (Gretton et al., 2009). In this regard, Hoyer et al. (2009) propose the additive noise model to address these shortfalls of the algorithms for structure learning. Due to its ability to cater for nonlinearity and non-Gaussianity of the data, it allows a unique directed acyclic structure to be identified in many contexts.

The limitations of the additive noise model are that it may be invertible in certain distributions and therefore not useful for structure learning aside the fact that it was originally proposed for two variables with a multivariate extension that requires enumerating all possible Directed Acyclic Graphs (DAGs) (Gretton et al., 2009). The weakly additive noise model by Gretton et al. (2009) permits to express greater uncertainty about the data generating mechanism, but can still identify a unique structure or a smaller equivalence class in most cases. Thus, the weakly additive noise model is able to identify a unique DAG when the assumptions of the additive noise model hold and when some additive noise model assumptions fail. The model, as defined by Gretton et al. (2009), is outlined as follows:

$$\psi = \left\langle V_i, Pa_G{}^{V_i} \right\rangle \ldots 1$$

Equation (1) is a local additive noise model for distribution P over V, that is Markov:

$$\text{DAG } G = \left\langle v, \varepsilon \right\rangle \ldots \quad (2)$$

when $V_i = f(Pa_G^{V_i}) + \in$ is an additive noise model. A weakly additive noise model is defined as:

$M = \langle G, \Psi \rangle$ for distribution P over V is a DAG $G = \langle v, \varepsilon \rangle$ and a set of local additive noise models Ψ such that P is Markov to G, $\psi \in \Psi$ if and only if ψ is a local additive noise for P; $\forall \langle V_i, Pa_G^{V_i} \rangle \in \Psi$,

The additive noise representation for data generating process (DGP) implies that there are no cases where $X \rightarrow Y$ can be written in the form $X = f(Y) + \in_X$, but not $Y = f(X) + \in_Y$ for $X \leftarrow Y$ That is, the data cannot appear as though it admits an additive noise model representation, but only in the incorrect direction. This representation is still appropriate when additive noise models are invertible, and when additive noise is not present (Gretton et al., 2009).

Empirical results from Székely et al. (2007) suggest that the Distance Covariance (dCov) test may be more powerful than the parametric Likelihood Ratio Test (LRT) when the dependence structure is nonlinear, while the dCov test may be quite close in power to the LRT for a multivariate normal case. For this reason, all estimations were done using the gaussian independence method, distance covariance permutation independence tests, Hilber Schmidt Independence Criterion (HSIC) permutation independence tests, and the HSIC cluster independence tests. The results are presented in graphs.

2.3. Interpretation of the Graphical Models

The use of graphical models in analysing dependencies, network and drawing causal inferences have been applied in fields such as economics (Kang & Yoon, 2019) and medicine (Kalisch et al., 2010) as well as energy market analyses (Xia et al., 2020). Following Pearl (2000), Kalisch et al. (2010), Kalisch et al. (2012) and other literature on graphical models, we briefly describe graphical models and the possible interpretations used in this study.

Graphical models are considered as maps of dependence structures of a given probability distribution or a sample (Kalisch et al., 2010). These models act like a map, consisting of a graph with dots or lines and potentially arrowheads, and always comes with a rule for interpretation. The nodes or vertices in the graph represent variables which may be random in nature. In our case, the node is macroeconomic or financial uncertainty in a certain

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country at a particular time. The graph also has edges representing some kind of dependence and may also be used as an alternative to counterfactuals to represent causal relationships (Kalisch et al., 2010; Wasserman, 2004).

An example of a graphical model is the DAG model. This graph usually consists of nodes and arrows (only one arrowhead per line) connecting the nodes. As a further restriction, the arrows must be directed in a way, so that it is not possible to trace a circle when following the arrowheads (Kalisch et al., 2010). The interpretation rule is the d-separation, which is closely related to conditional independence.

The d-separation rule is a criterion for deciding, from a given a causal DAG, whether a set X of variables is independent of another set Y, given a third set Z (Pearl, 2000). The idea is to show that there exists a connection path, associating *dependence* with *connectedness,* or the absence of a connection path, i.e., to associate *independence* with *un-connectedness*. To account for the orientations of the arrows the terms d-separated and d-connected are used. The sets of nodes or vertices that are not d-separated are considered d-connected (Pearl, 2000; Wasserman, 2004).

The "skeleton" of a DAG model is another example of a graphical model used to analyse data. The map in this model is a graph consisting of dots and lines (without arrowheads). The "skeleton" of DAGs has the following rules for interpretation: Two nodes are connected by an edge, if and only if the corresponding random variables are dependent if conditioning on any subset of the remaining random variables. Thus, an edge indicates a strong kind of dependence; this is useful for estimating the bounds on causal effects or intervention effects (Kalisch et al., 2010). Further details on DAGs and their interpretations are provided in the literature (Kalisch et al., 2010; Kalisch et al., 2012; Pearl, 2000; Wasserman, 2004).

This paper uses the DAGs with nodes and arrowheads per line; therefore, we interpret the graphs using the d-separation rules and based on the extant literature. No edge implies (conditional) independence between the two variables, for instance uncertainty in Germany and uncertainty in Italy are independent. An edge with arrowhead (e.g., Germany $\rightarrow$ Italy) implies that changes in uncertainty in Germany causes variations in the uncertainty in Italy; furthermore, the directed edge would also imply that uncertainty in Germany and that of Italy are interconnected. Table 1 (see appendix) provides a description of the nodes in the DAGs.

3. Results and Discussion

Our empirical results are presented in graphical form, i.e., DAGs. There are two figures or graphs for macroeconomic uncertainty for each sample considered: full sample (1997 – 2017), pre-crisis period (1997 – 2007) and the post-crisis period (2008 – 2017). The same analysis is repeated using financial uncertainty index; this gives twelve DAGs in total for analyses. Although different methods were used for estimation, we analyse results based on the kpc for reasons mentioned earlier.

3.1. Macroeconomic Uncertainty Index

Figures 1A and 1B depicts the interconnectedness of macroeconomic uncertainty among the countries in the study for the full sample (1997 – 2017). As discussed earlier the DAG is also used for causality analysis.

[Figure 1A here]

In the kpc-resid-gamma algorithm (Figure 1A), variations in macroeconomic uncertainties in Canada causes variations in Netherland's macroeconomic uncertainty. This suggests that Canada is a net transmitter of macroeconomic uncertainty to the Netherlands. Also, changes in economic uncertainty in Sweden caused variations uncertainties in the UK, Spain and Switzerland to change. This also suggests the interconnectedness of economic and financial uncertainties in these countries. Similarly, Japan's uncertainty is transmitted to Switzerland via France and Spain.

While there is a high interconnectedness between USA and Italy, uncertainties from the Italy and US spills over to Spain through the UK. Using the kpc-resid-perm algorithm (Figure 1B), macroeconomic uncertainties in Japan causes variation in economic uncertainties in France and onward transmission to the US through the UK and Sweden. There is an interconnectedness of uncertainty between US and UK. Figure 2A also shows that uncertainties in Italy spillover directly to the US economy.

[Figure 1B here]

Prior to the financial crisis, the kpc-resid-gamma algorithm show that macroeconomic uncertainties in Canada, Italy, and Sweden were transmitted to Switzerland through Germany while Switzerland also received uncertainty shocks directly from the Netherlands. Again,

uncertainties from the Netherlands were transmitted to Spain via UK and the US aside receiving shocks from Japan and France.

[Figure 2A here]

In the kpc-resid-perm algorithm (Figure 2B), Spain was a recipient of economic and financial uncertainty from Canada and Sweden through Germany, Italy and the US. Uncertainties were also transmitted from the Netherlands and Japan to Spain through the UK and US aside direct transmission from France. Thus, the DAG suggests that variations in Spain's economic uncertainty prior to the financial crisis were caused by changes in uncertainties in other markets.

[Figure 2B here]

During the post-crisis period, there was an interconnectedness of macroeconomic uncertainties among the 11 developed countries. For instance, there was an interconnectedness of uncertainties between Germany and the US. Germany's uncertainty was transmitted to France through Canada, the Netherlands and Spain with some spillover to Sweden. At the same time, uncertainties in Switzerland and Japan spilled over to France, Spain and Italy. These results are based on the kpc-resid-gamma algorithm (Figure 3A).

[Figure 3A here]

The kpc-resid-perm algorithm (Figure 3B) suggests that macroeconomic uncertainties in Japan were transmitted to Canada through Italy, US, and Germany as well as the France and the UK. Canada then transmits its uncertainties to Italy through the Netherlands, Spain, France and the UK. This clearly shows that uncertainties in one economy actually spills over to other economies.

[Figure 3B here]

3.2. Financial Uncertainty Index

The DAGs from the kpc-resid-gamma and kpc-resid-perm algorithms show that financial uncertainties spillover to Switzerland from the other countries for the period 1997-2017. For instance, in the kpc-resid-gamma, financial uncertainties from the UK were transmitted to Switzerland through Sweden, while the Netherlands was a receiver of uncertainties from Spain, Japan, US and Italy through Canada, Germany and France (Figure 4A).

[Figures 4A and 4B here]

In the pre-crisis period, there was interconnection between financial uncertainties in Germany and the Netherlands. Spain and Sweden were the recipients of financial uncertainties from other countries. The kpc-resid-perm algorithm also show that Sweden is a receiver of uncertainties.

[Figures 5A and 5B here]

This implies that during the pre-crisis period there were nonlinear dependencies among financial uncertainties in these economies.

The post-crisis period saw uncertainties spilling over from the UK to Sweden and Switzerland through France, Italy, Netherlands, USA and Canada based on the kpc-resid-gamma algorithm. Uncertainties in Japan also spilled over to Sweden and Switzerland through Canada and USA. The results from the kpc-resid-perm algorithm provide a slightly different route where uncertainties spillover from the UK to Switzerland through France, Italy, and Spain.

[Figures 6A and 6B here]

The DAG from the kpc-resid-perm (Figure 6B) shows that financial uncertainties in Germany, Sweden and Japan were independent of the uncertainties in the other jurisdictions.

4. Conclusion

This paper analysed the nonlinear dependencies and interconnectedness of macroeconomic and financial uncertainties of 11 developed countries for the period 1997:01 to 2017:09. We

applied the structure learning with weakly additive noise model. We found nonlinear dependencies among uncertainties across economies considered, such that uncertainties actually spillover. That is, an increased macroeconomic and financial uncertainty in a particular economy is likely to affect the level of uncertainties in other economies. This will consequently affect other economic outcomes. Overall, the DAGs suggests that Spain and Switzerland appear to be the receivers of macroeconomic and financial uncertainties spillovers from other developed economies.

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Appendix

Table 1

Descriptions of the nodes/vertices used

Nodes/Vertices of the DAGs	Descriptions
Canada	Macroeconomic/financial uncertainty in Canada
Germany	Macroeconomic/financial uncertainty in Germany
USA	Macroeconomic/financial uncertainty in USA
Italy	Macroeconomic/financial uncertainty in Italy
UK	Macroeconomic/financial uncertainty in the UK
Sweden	Macroeconomic/financial uncertainty in Sweden
Japan	Macroeconomic/financial uncertainty in Japan
France	Macroeconomic/financial uncertainty in France
Spain	Macroeconomic/financial uncertainty in Spain
Netherlands	Macroeconomic/financial uncertainty in the Netherlands
Switzerland	Macroeconomic/financial uncertainty in Switzerland

Figure 1A

Connectedness of Macroeconomic Uncertainty using kpc-resid-gamma: Full-Sample
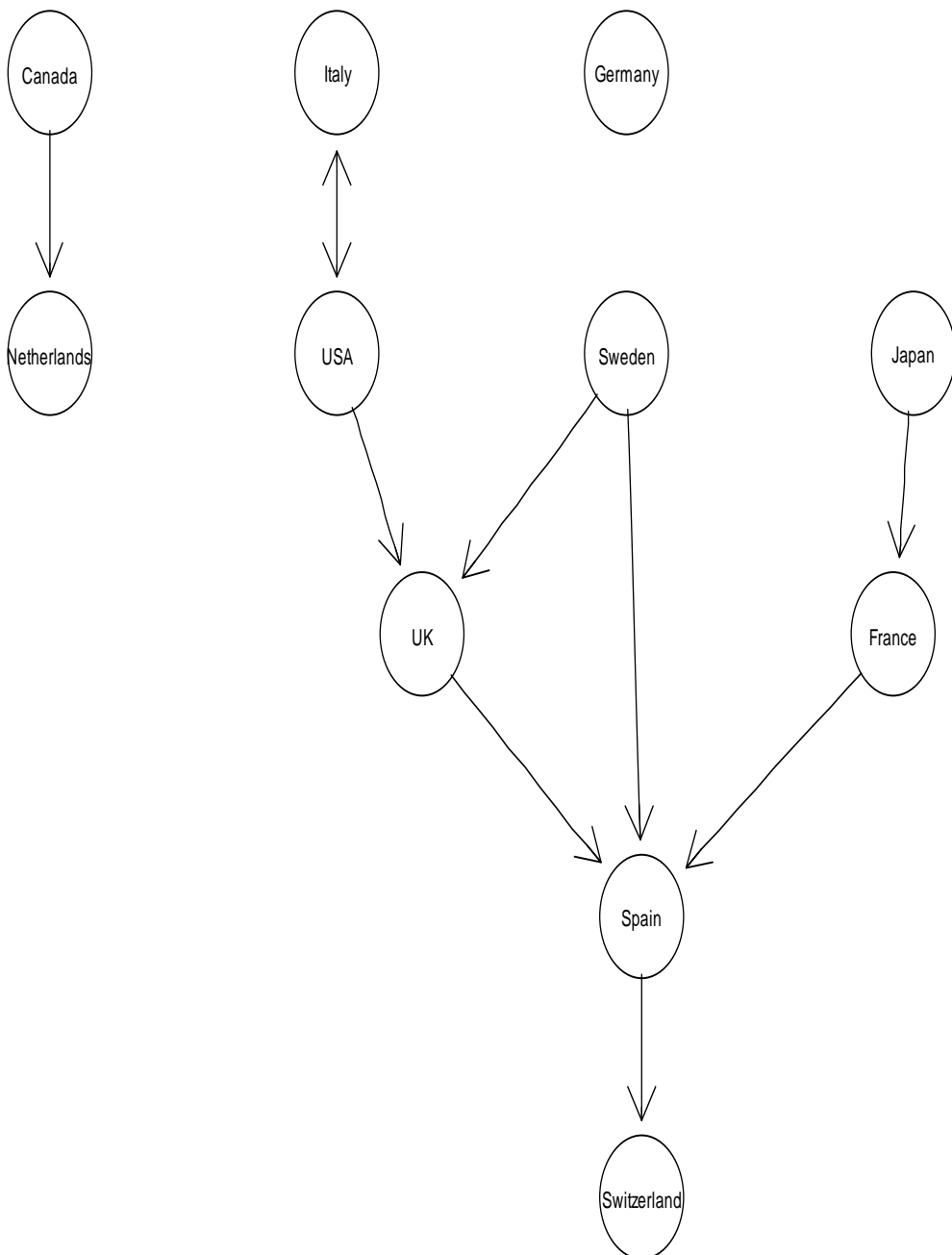
kpc-resid-gamma

Figure 1B

Connectedness of Macroeconomic Uncertainty using kpc-resid-perm: Full-Sample
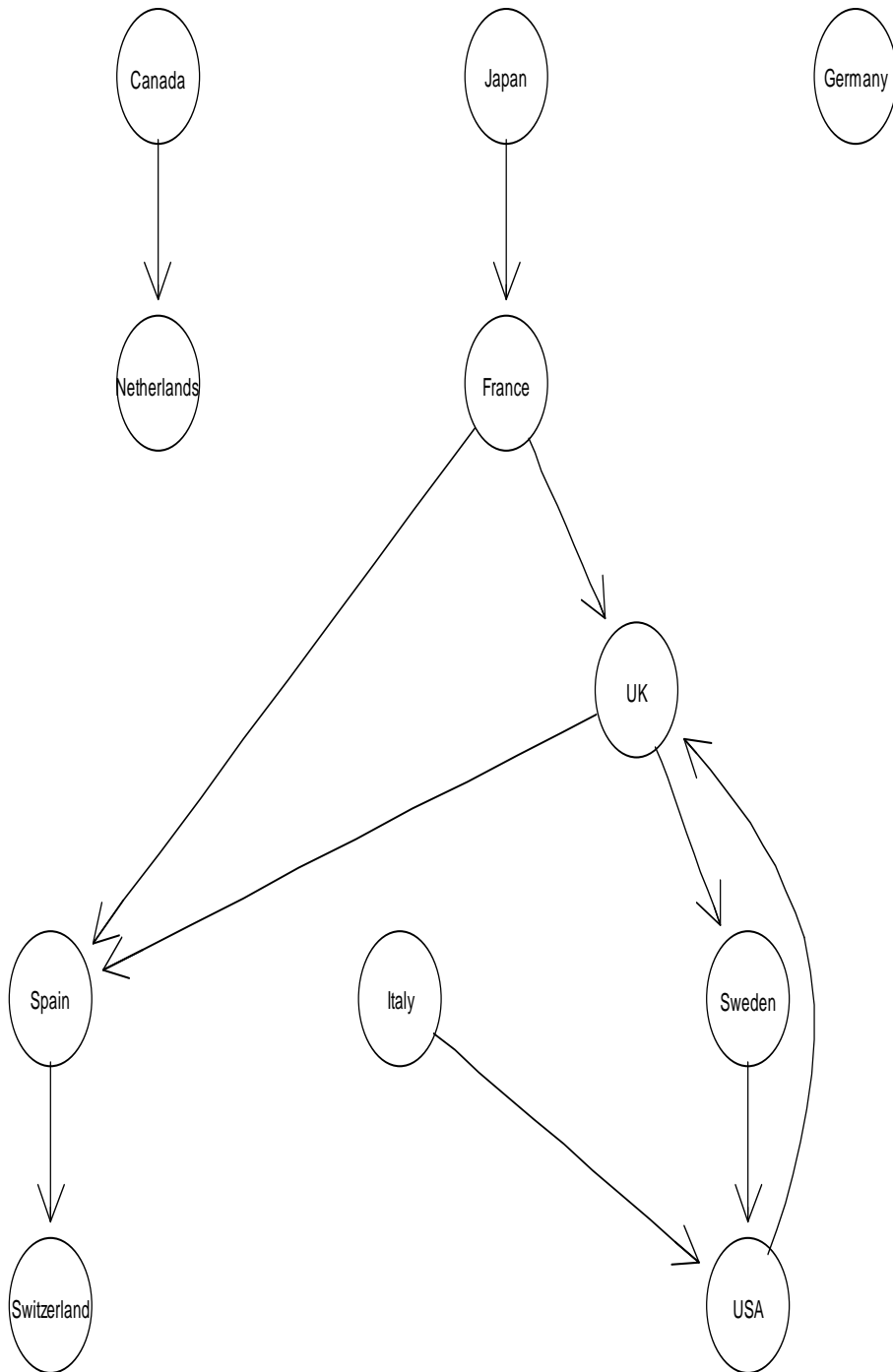
kpc-resid-perm

Figure 2A

Connectedness of Macroeconomic Uncertainty using kpc-resid-gamma: Pre-Crisis
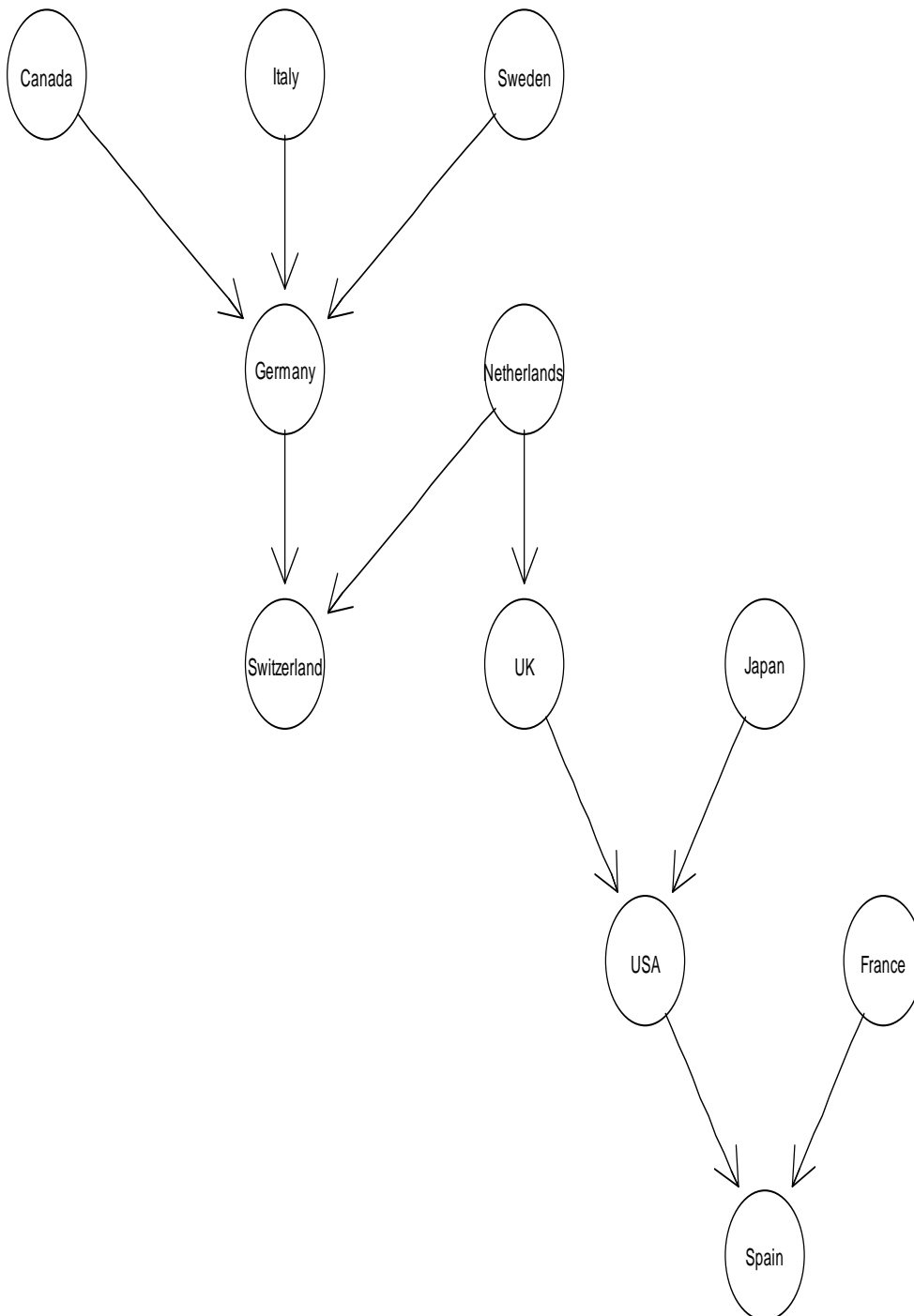
kpc-resid-gamma

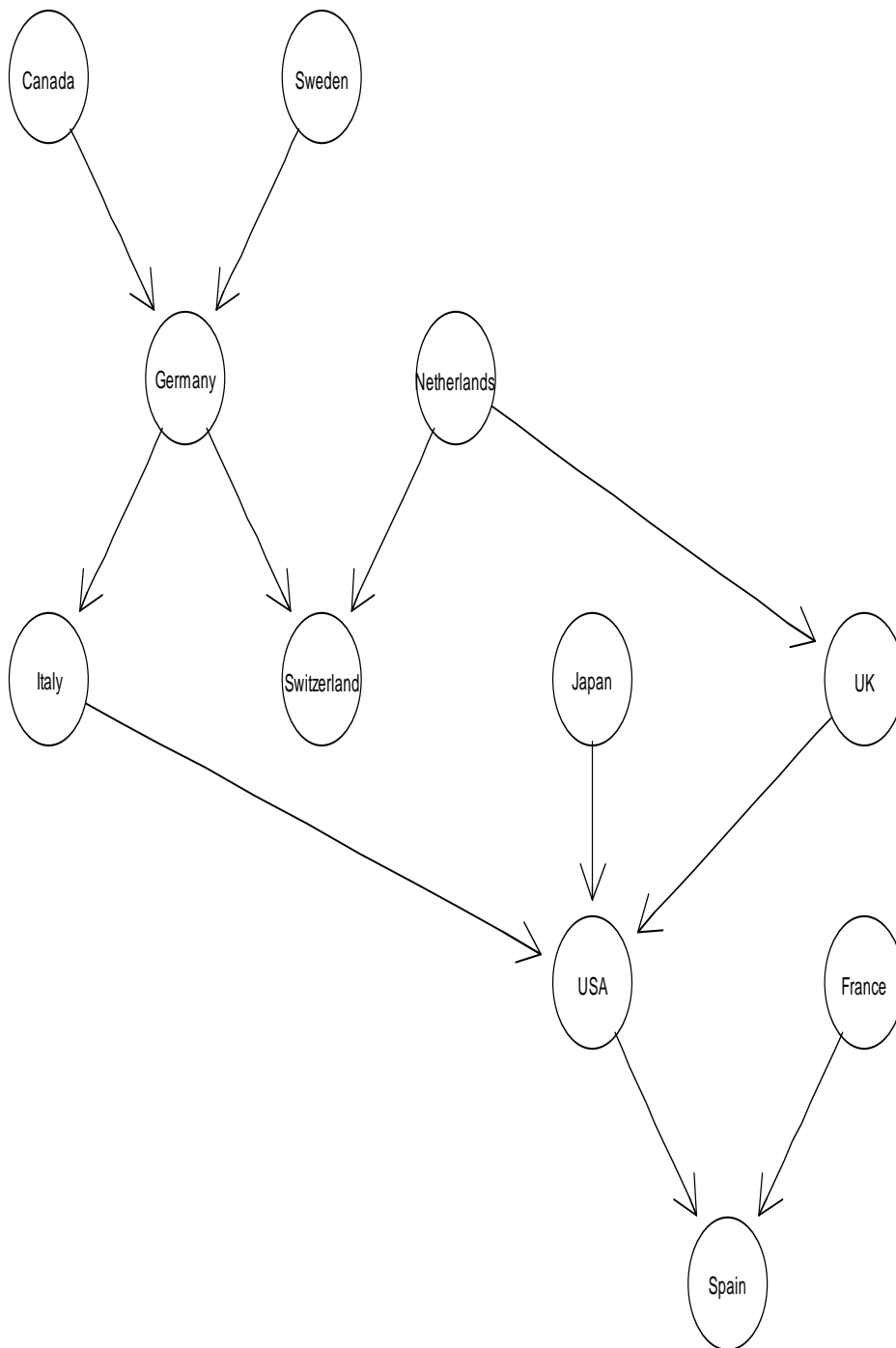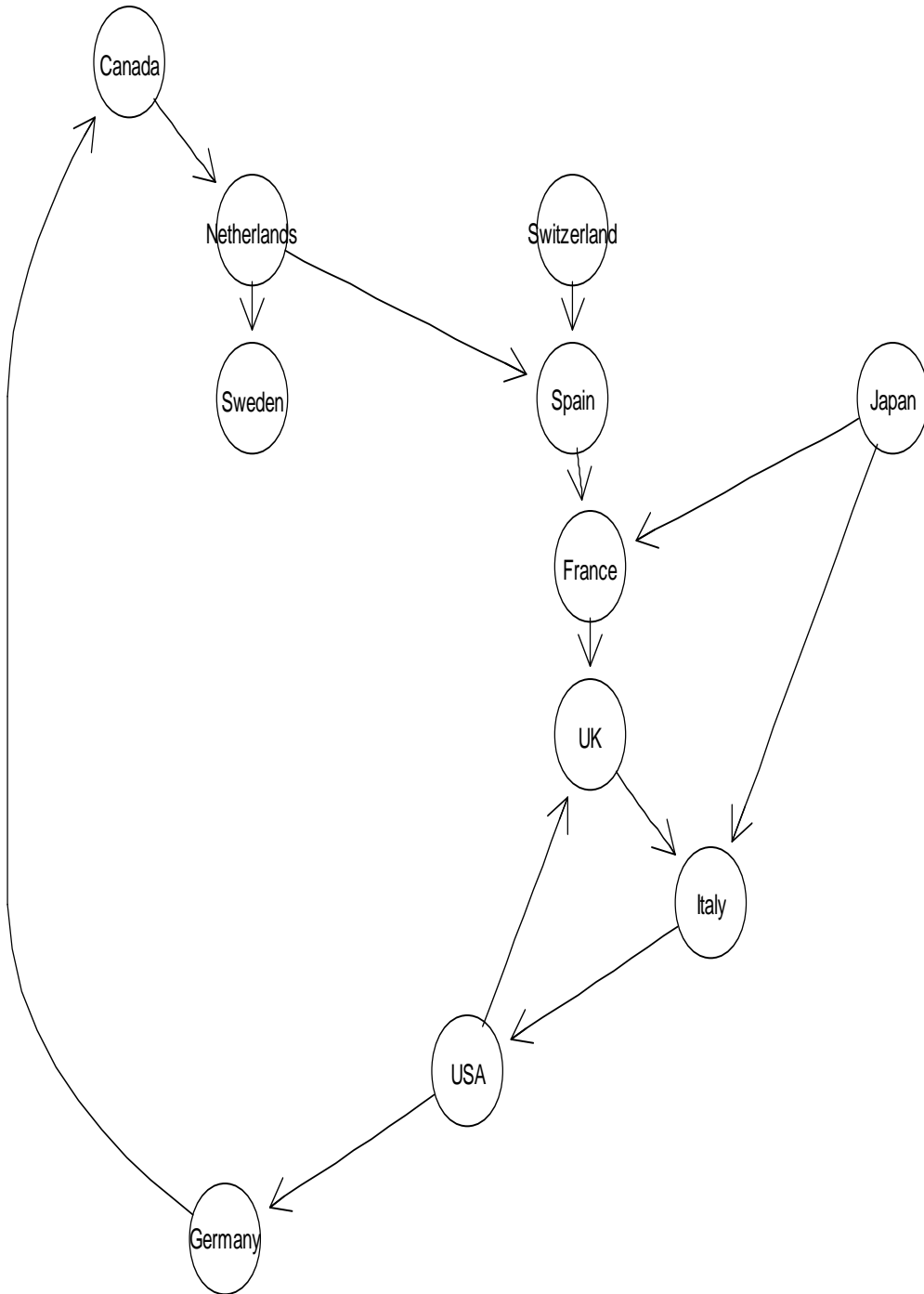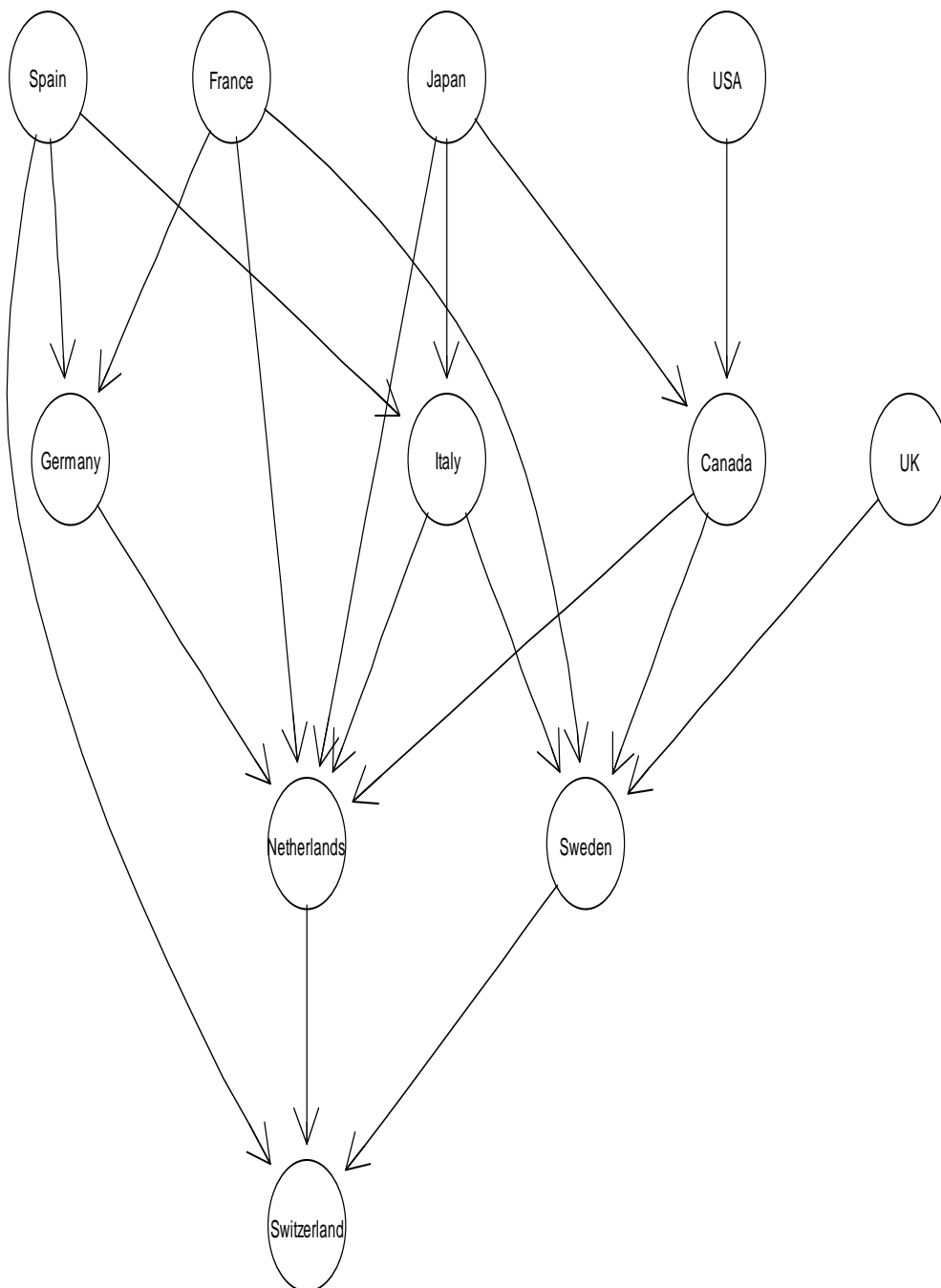**Connectedness of Macroeconomic Uncertainty using kpc-resid-perm: Pre-Crisis**

kpc-resid-perm

Figure 3A

Connectedness of Macroeconomic Uncertainty using kpc-resid-gamma: Post-Crisis
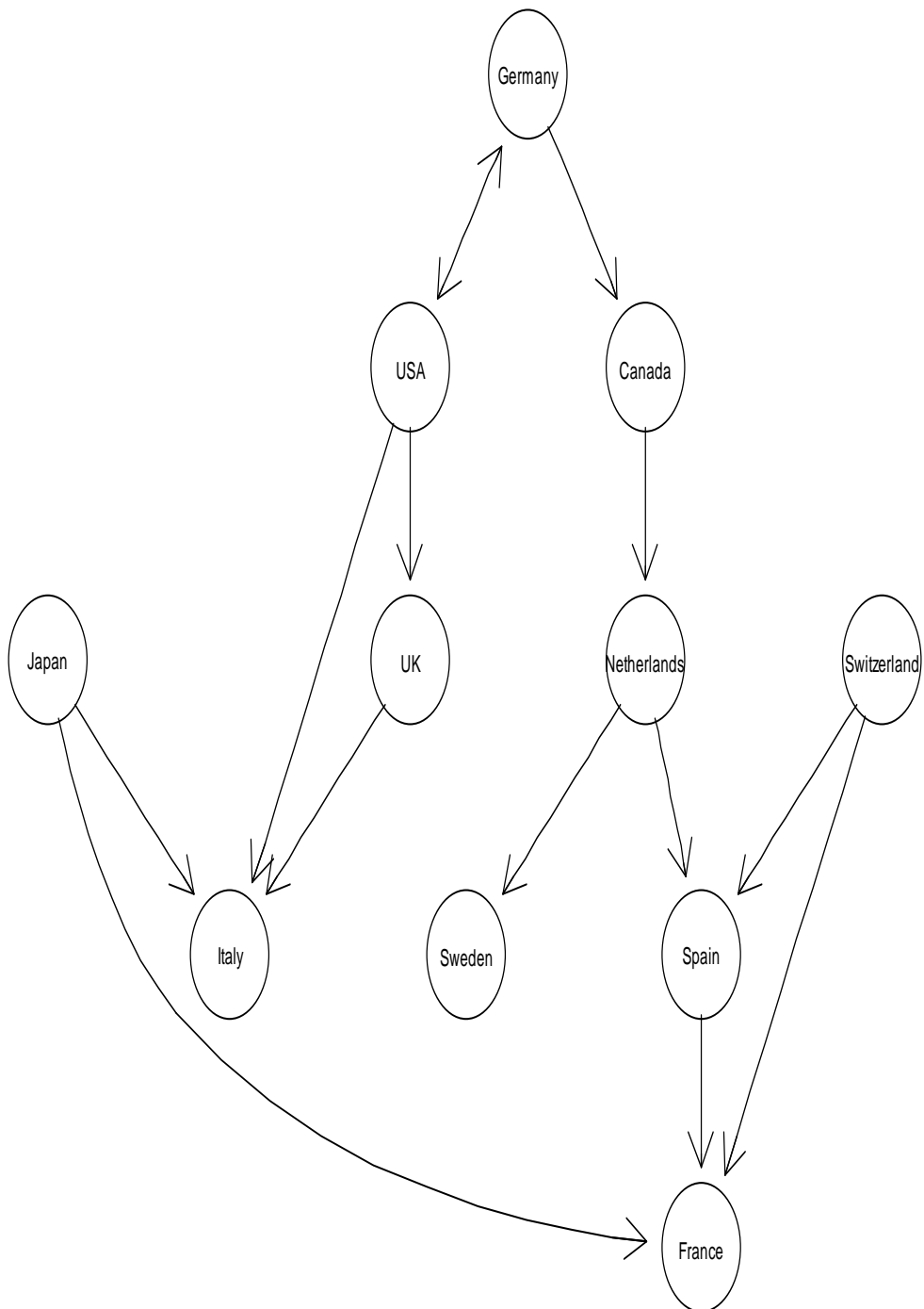
kpc-resid-gamma

Figure 3B

Connectedness of Macroeconomic Uncertainty using kpc-resid-gamma: Post-Crisis

kpc-resid-perm

Figure 4A

Connectedness of Financial Uncertainty using kpc-resid-gamma: Full-Sample
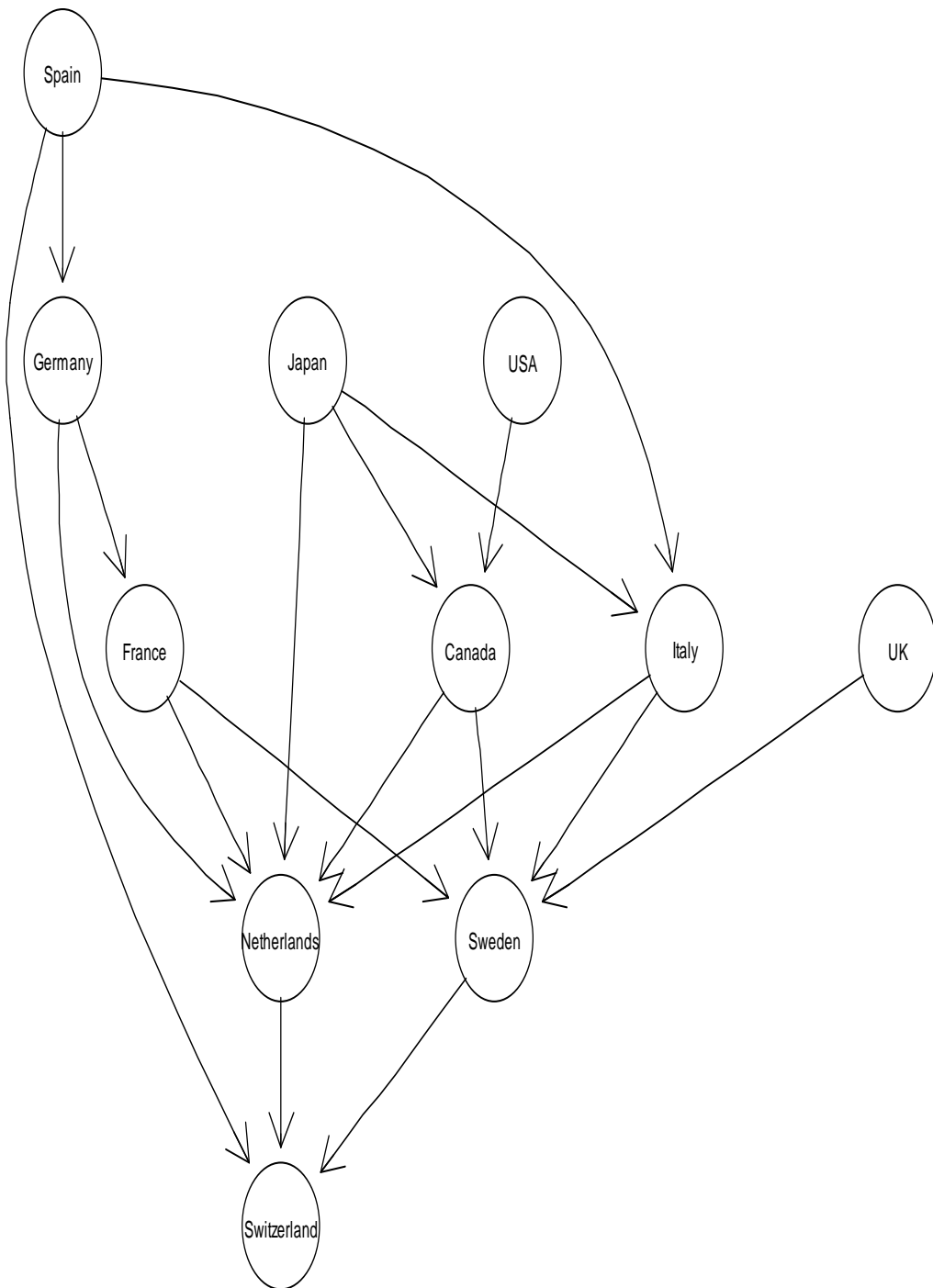
kpc-resid-gamma

Figure 4B

Connectedness of Financial Uncertainty using kpc-resid-perm: Full-Sample

kpc-resid-perm

Figure 5A

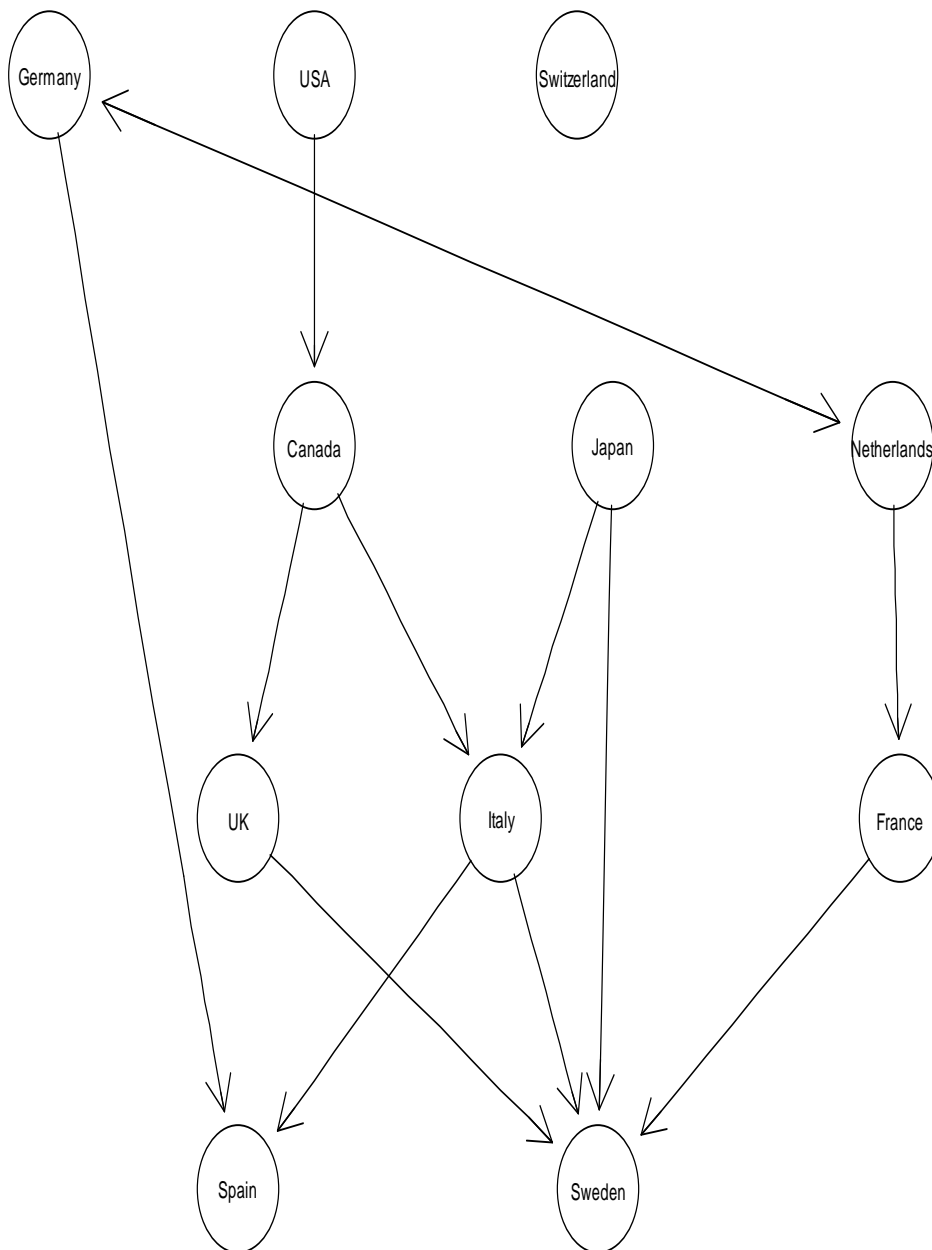## Connectedness of Financial Uncertainty using kpc-resid-gamma: Pre-crisis

kpc-resid-gamma

Figure 5B

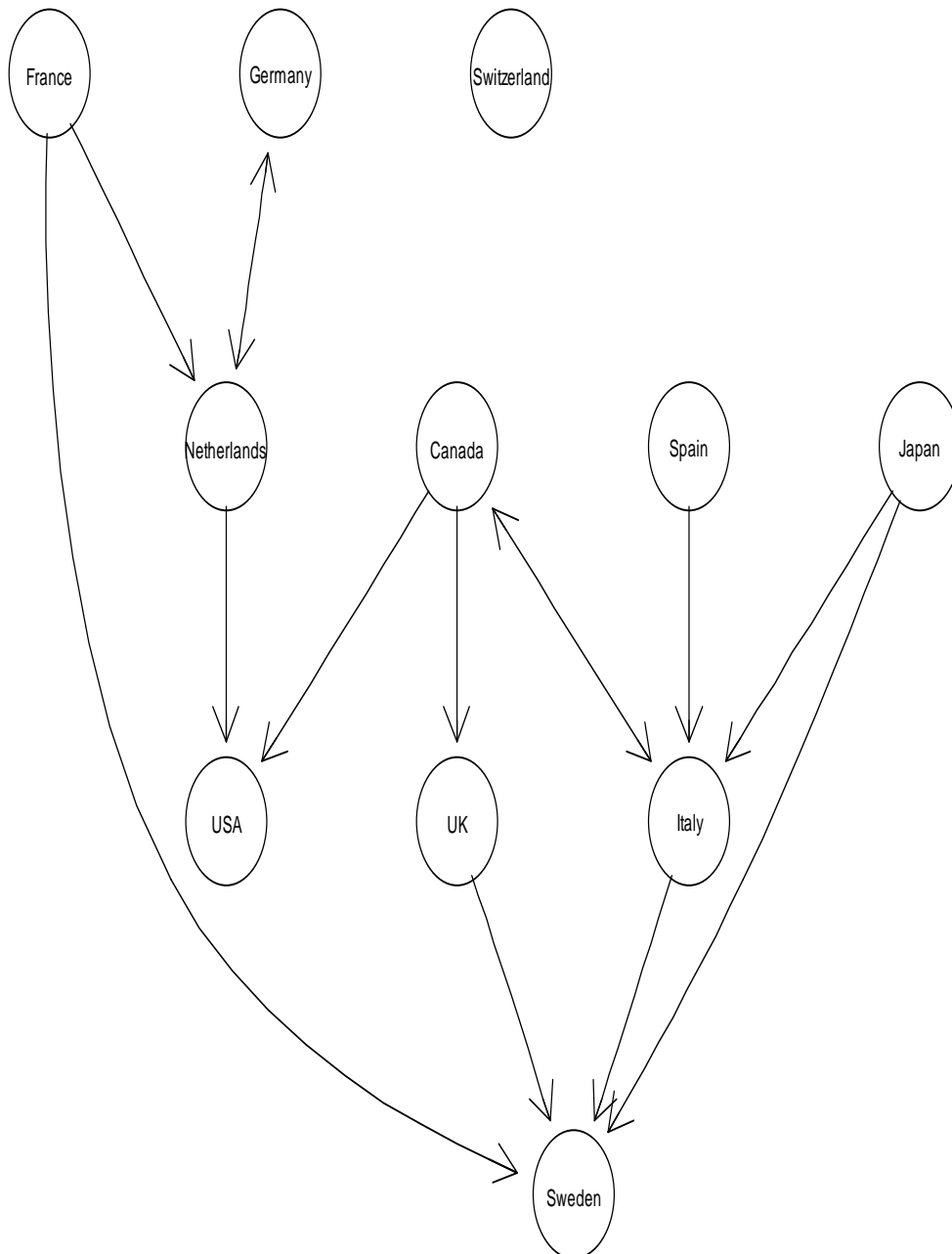## Connectedness of Financial Uncertainty using kpc-resid-perm: Pre-Crisis

kpc-resid-perm

Figure 6A

Connectedness of Financial Uncertainty using kpc-resid-gamma: Post-Crisis
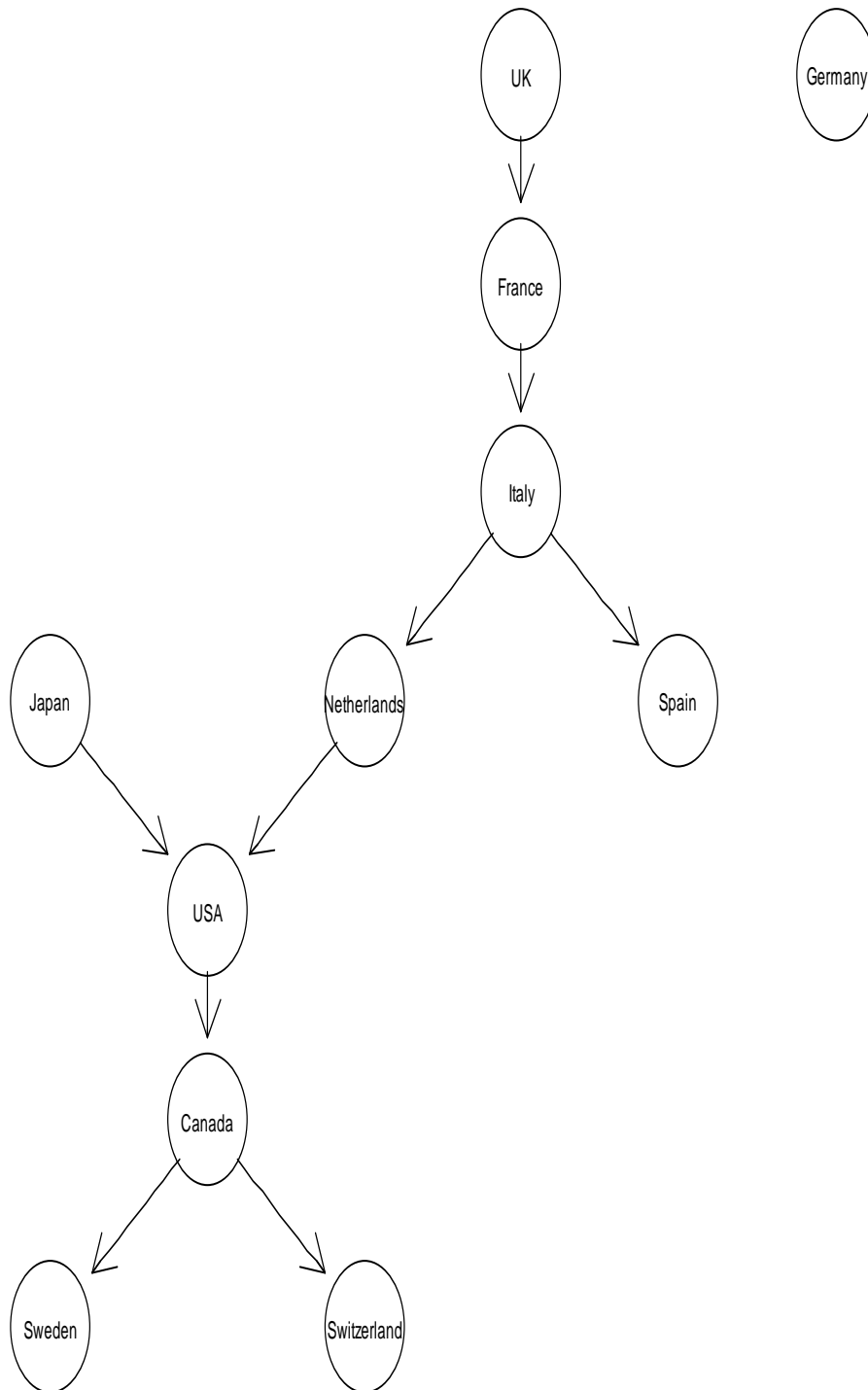
kpc-resid-gamma

Figure 6B

Connectedness of Financial Uncertainty using kpc-resid-perm: Post-Crisis

kpc-resid-perm