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## Connectedness between G10 currencies: Searching for the causal structure

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# Non-technical summary

## Research Question

Recently, some studies have looked into the connectedness between the rates of change of exchange rates. However, they were unable to establish any causal links between the exchange rates because of the methods chosen. This research paper aims to examine the link between key currency pairs for the period from 2010 to 2017 and to identify a causal structure. To do so, the currencies of the G10 currencies are analysed, with the pound sterling serving as the numéraire as it is a comparatively independent currency.

## Contribution

This paper uses methods taken from the literature on machine learning in seeking to empirically identify a causal structure between the rates of change of various exchange rates. The results help to divide the analysed currencies into clusters, whereby the currencies in a cluster are strongly linked with one another. The results are of particular relevance to risk management and foreign exchange policy.

## Results

The analysis indicates that over the period under observation the US dollar and Norwegian krone, in particular, are relatively independent currencies and have a comparatively strong influence on other currencies. By contrast, the Swiss franc and New Zealand dollar have a negligible impact on other currencies. Moreover, further analyses suggest that the currencies of the G10 currencies can be divided into three groups, which can be classified as commodity currencies (Australian dollar, Canadian dollar, New Zealand dollar), European currencies (euro, Norwegian krone, Swedish krona) and safe haven/carry trade financing currencies (Swiss franc, US dollar, yen).

# Nichttechnische Zusammenfassung

## Fragestellung

In der jüngsten Zeit haben verschiedene Studien die Zusammenhänge zwischen Änderungsraten von Wechselkursen untersucht. Dabei konnten sie jedoch aufgrund der gewählten Methoden keine Aussagen über die Kausalität zwischen den Wechselkursen treffen. Ziel dieses Forschungspapiers ist es, die Zusammenhänge zwischen wichtigen Währungspaaren für den Zeitraum 2010 bis 2017 zu untersuchen und dabei eine kausale Struktur zu identifizieren. Dazu werden die G10-Währungen betrachtet, wobei das Pfund Sterling als vergleichsweise unabhängige Währung als Numéraire dient.

## Beitrag

In diesem Papier werden Methoden aus der Literatur zum maschinellen Lernen verwendet, um erstmals empirisch nach einer kausalen Struktur zwischen den Veränderungsraten verschiedener Wechselkurse zu suchen. Die dabei gewonnenen Ergebnisse helfen, die betrachteten Währungen in Gruppen zu unterteilen, die in aller Regel besonders stark miteinander verbunden sind. Die Ergebnisse sind besonders für das Risikomanagement und die Währungspolitik von Bedeutung.

## Ergebnisse

Die Analyse legt nahe, dass während des Untersuchungszeitraums insbesondere der US-Dollar und die norwegische Krone relativ unabhängige Währungen waren und einen vergleichsweise starken Einfluss auf andere Währungen besaßen. Dagegen sind die Einflüsse des Schweizer Frankens und Neuseeland-Dollars auf andere Währungen zu vernachlässigen. Außerdem legen weitere Analysen nahe, dass sich die G10-Währungen in drei Gruppen unterteilen lassen: Rohstoffwährungen (australischer Dollar, kanadischer Dollar, Neuseeland-Dollar), europäische Währungen (Euro, norwegische Krone, schwedische Krone) und „Safe Haven“- oder „Carry Trade“-Finanzierungswährungen (Schweizer Franken, US-Dollar, Yen).

# Connectedness between G10 Currencies: Searching for the Causal Structure\*

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## Abstract

This paper presents a new approach for modelling the connectedness between asset returns. We adapt the measure of [Diebold and Yilmaz \(2014\)](#), which is based on the forecast error variance decomposition of a VAR model. However, their connectedness measure hinges on critical assumptions with regard to the variance-covariance matrix of the error terms. We propose to use a more agnostic empirical approach, based on a machine learning algorithm, to identify the contemporaneous structure. In a Monte Carlo study we compare the different connectedness measures and discuss their advantages and disadvantages. In an empirical application we analyse the connectedness between the G10 currencies. Our results suggest that the US dollar as well as the Norwegian krone are the most independent currencies in our sample. By contrast, the Swiss franc and New Zealand dollar have a negligible impact on other currencies. Moreover, a cluster analysis suggests that the currencies can be divided into three groups, which we classify as: commodity currencies, European currencies and safe haven/carry trade financing currencies.

**Keywords:** connectedness, networks, graph theory, vector autoregression, exchange rates

**JEL classification:** C32, C51, F31.

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# 1 Introduction

Triggered by the seminal work of [Diebold and Yilmaz \(2014\)](#), the measurement of spillover effects and connectedness between asset returns gained popularity in the economic literature. Their approach, which is based on the forecast error variance decomposition of a VAR model, hinges on critical assumptions with regard to a recursive ordering of the variables (e.g., Cholesky). In this paper we propose an alternative and more agnostic approach for modelling the connectedness between asset returns, which is based on a causal search algorithm that imposes no a priori recursive ordering. We compare its properties with those of other identification measures using a Monte Carlo experiment and apply it to the G10 currencies.<sup>1</sup>

Given the new procedure, our first goal is to estimate the network structure between nine currencies vis-à-vis an appropriate numéraire currency (i.e. pound sterling).<sup>2</sup> Such estimates provide important information for policy makers and practitioners. The network indicates to what extent a certain currency or group of currencies is affected by domestic and foreign shocks. In this sense, it helps to gain a better understanding of potential contagion. The second goal is to utilise spillover intensities in order to identify clusters which can be interpreted as currency blocs or groups of common influence factors such as target currencies for carry trades.

Research in this area has created several extensions to the original work by [Diebold and Yilmaz \(2009\)](#), who estimated the return and volatility spillovers with respect to global equity markets. [Diebold and Yilmaz \(2014\)](#) studied the connectedness of financial institutions during the financial crisis period. In [Diebold and Yilmaz \(2015\)](#), they also estimated the connectedness between returns of other asset classes such as bilateral exchange rates, for instance. The approach is based on the idea that the network – or the spillover effects – between asset returns can be estimated given a forecast error variance decomposition (FEVD) of a structural vector autoregressive (SVAR) model. [Diebold and Yilmaz \(2009\)](#) suggest orthogonalising the VAR model residuals with the help of a Cholesky decomposition, while pointing to the problem that the results of such a factorisation depend on the ordering of the variables, as zero restrictions are imposed on the upper triangular variance-covariance matrix without any theoretical or statistical motivation (i.e. preventing contemporaneous spillover effects between certain variables). Given the arbitrariness with respect to the ordering of the variables, the estimated model may not capture the spillover effects correctly. Instead of choosing one specific ordering, [Klößner and Wagner \(2014\)](#) propose considering all possible variable permutations. They replicate the paper by [Diebold and Yilmaz \(2009\)](#) and show that given different permutations, differences in spillover intensity can be large. Their approach, however, is not only computationally intensive, but also induces a high degree of model uncertainty. In other words, [Klößner and Wagner \(2014\)](#) average on many misspecified models and one correct model, which is unknown.

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<sup>1</sup>Note that the G10 currencies refer to the ten most heavily traded currencies and not to the Group of Ten countries.

<sup>2</sup>In order to measure spillover effects using variance decompositions, the numéraire currency should neither be an anchor currency nor be pegged to another currency. Returns of fixed exchange rates have no volatility, implying that variance decompositions would be meaningless. Moreover, we interpret an exchange rate as an asset price and focus in our empirical analysis on exchange rate changes. Within this strand of literature, exchange rate changes (log differences) are referred to as exchange rate returns.

Apart from Cholesky decompositions, the literature also employs generalized impulse response functions (see [Pesaran and Shin, 1998](#)) in order to obtain variance decompositions which are invariant to the ordering of the variables. [Greenwood-Nimmo, Nguyen, and Rafferty \(2016\)](#), for instance, use generalized variance decompositions to study exchange rate return and volatility connectedness. In a rolling-window approach, [Greenwood-Nimmo, Nguyen, and Shin \(2017\)](#) apply the generalized approach in order to analyse the change of European debt connectedness distributions over time. The disadvantage of this approach, however, is that the explained shares of forecast error variance do not sum to unity. In order to avoid re-scaling the shares, [Lanne and Nyberg \(2016\)](#) propose an alternative generalized forecast error variance decomposition which yields shares summing up to unity by construction. However, shocks are not orthogonalised. The weaknesses of generalized variance decompositions have been pointed out by [De Santis and Zimic \(2017\)](#), who instead propose absolute magnitude restrictions to identify the SVAR models. They show that generalized variance decompositions tend to overestimate connectedness.

An alternative and more agnostic approach is identification with the help of causal search algorithms from the machine learning literature. Such an approach for structural VAR models has been suggested by [Swanson and Granger \(1997\)](#). [Demiralp and Hoover \(2003\)](#) introduced the causal search methods for identification. These algorithms use information from the reduced VAR residuals in order to uncover the contemporaneous causal structure. Applications can be seen in [Heinlein and Krolzig \(2012\)](#) and [Demiralp, Hoover, and Perez \(2014\)](#). We follow this literature on empirical identification and systematically analyse in a Monte Carlo experiment as well as in an application on returns of G10 currencies how the identification strategy impacts on the measures of connectedness. To the best of our knowledge, the only paper using an empirical identification strategy in the connectedness literature is [Scida \(2016\)](#), but she does not systematically study the impact of this approach or compare the empirical identification with other identification methods. The machine learning approach is very appealing because it does not require any prior assumptions with regard to the contemporaneous causal structure between the variables. On the contrary, we derive with our data-driven approach a causal ordering, which can be evaluated and discussed.

Another important strand of literature in this context focuses on VAR model parameter reduction. With an increasing number of variables to be modelled, the number of coefficients to be estimated increases exponentially. This problem is often referred to as the *curse of dimensionality*. [Demirer, Diebold, Liu, and Yilmaz \(2018\)](#) use lasso-type dimension reduction methods combined with generalized variance decompositions in order to estimate the connectedness between 150 bank stocks. An even sparser approach is proposed by [Barigozzi and Brownlees \(2018\)](#), who use lasso-type reduction methods not only to shrink the VAR lag matrices but also to shrink the variance-covariance matrix. Our causal search algorithm delivers an over-identified model, reducing the number of coefficients to be estimated, and hence eases the issue of dimensionality.

This paper contributes in several ways to the existing literature. First, we propose an alternative identification strategy which detects causal linkages. As [Demiralp and Hoover \(2003\)](#) show, the empirical procedure is very effective in detecting the true causal connections among different variables. Second, we analyse the performance of our algorithm with respect to the [Diebold and Yilmaz \(2014\)](#) measure of connectedness and show in a

Monte Carlo experiment that our algorithm outperforms other approaches.<sup>3</sup> Third, we apply our algorithm to the G10 currencies and pay special attention to the choice of the numéraire currency. This choice is of particular importance because it can have strong effects on the estimates, as we will discuss later.

Our results suggest that the US dollar as well as the Norwegian krone are the most independent currencies in our sample. By contrast, the Swiss franc and New Zealand dollar have a negligible impact on other currencies. Moreover, a cluster analysis suggests that the currencies can be divided into three groups, which can be identified as: commodity currencies, European currencies and safe haven/carry trade financing currencies. We show that following the Brexit referendum, the within cluster dispersion is very low.

## 2 Methodology

For  $\mathbf{y}_t$  being a  $K \times 1$  vector of endogenous variables, we consider a SVAR(1) as follows:

$$\mathbf{B}_0 \mathbf{y}_t = \mathbf{B} \mathbf{y}_{t-1} + \mathbf{w}_t, \quad (1)$$

where  $\mathbf{B}$  refers to the  $K \times K$  coefficient matrix of the lagged vector of endogenous variables.  $\mathbf{B}_0$  defines the  $K \times K$  contemporaneous coefficient matrix. Uncorrelated structural shocks are denoted by  $\mathbf{w}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_w)$ . Note that the off-diagonal entries of  $\boldsymbol{\Sigma}_w$  are 0. We follow the notation of [Kilian and Lütkepohl \(2017\)](#). For brevity, we work here with just one lag and no deterministic terms. For the estimation, however, a constant is included and the lag order is chosen according to the AIC.

The reduced form of this model can be written as follows:

$$\mathbf{y}_t = \mathbf{A} \mathbf{y}_{t-1} + \mathbf{u}_t, \quad (2)$$

with  $\mathbf{A} = \mathbf{B}_0^{-1} \mathbf{B}$  and  $\mathbf{u}_t = \mathbf{B}_0^{-1} \mathbf{w}_t$ .

Traditionally, the contemporaneous matrix  $\mathbf{B}_0$  is uncovered with the help of restrictions motivated by economic theory. For a VAR model of exchange rate returns, economic theory does not provide a unique causal structure that can be imposed on the contemporaneous matrix. However, we achieve (over-)identification using a graph theoretical causal search algorithm which finds contemporaneous causality in the reduced form residuals  $\mathbf{u}_t$ . The correct contemporaneous effects are an important factor in the computation of the forecast error variance decomposition and consequently in the connectedness measure of [Diebold and Yilmaz \(2014\)](#).

### 2.1 The PC causal search algorithm and its application to the identification of SVAR models

The PC algorithm belongs to the literature on graph-theoretic analysis of causal structures, see [Pearl \(2000\)](#) and [Spirtes, Glymour, and Scheines \(2001\)](#).<sup>4</sup> A causal structure is

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<sup>3</sup>Previous studies have focussed on the ability of the PC algorithm, a causal search algorithm which will be explained in the following sections, to detect the correct causal structure. We, however, focus on the ability of different approaches to detect the correct degree of network connectedness.

<sup>4</sup>PC stands for the initials of its inventors Peter Spirtes and Clark Glymour.



represented by a graph with arrows from causes to caused variables. The algorithm uses the residual variance-covariance matrix of the reduced form model as input to detect the causal structure of a system, a directed acyclical graph (DAG). The PC algorithm cannot necessarily determine the DAG uniquely, but only down to a Markov equivalence class of the DAG. All members of an equivalence class encode the same conditional independence information. By using the conditional independence information the algorithm can only determine the equivalence class, but not distinguish between members of a class. In this way the algorithm finds some undirected edges. We will determine these undirected edges with the help of a bootstrap procedure, which we will explain in the following.

To find the DAG, the algorithm performs an elimination and an orientation stage. The elimination stage starts with a graph where all variables are linked to each other with an undirected link. Then, links are removed based on unconditional and conditional correlation tests, whereby a tuning parameter  $\alpha$  for Fisher's Z-statistic is used as a significance level. First, connections are removed between two variables which are unconditionally uncorrelated. Then, connections are eliminated for variables which are uncorrelated conditional on other variables. Here, the correlation of a pair of variables is conditioned on every other variable individually, then on all possible pairs of variables, thereafter on all subsets of three variables and so on up to all possible subsets of conditioning. When there is no more link to be removed, the elimination stage is finished and the skeleton of the graph is identified.

In the orientation stage, triples of linked variables  $A - B - C$  are analysed. Unshielded colliders (v-structures)  $A \rightarrow B \leftarrow C$  can be determined when A and C are independent when conditioned on possible sets of variables, but dependent when conditioned also on B. The algorithm searches for unshielded colliders and directs the edges accordingly. Finally, some more links might be oriented on the basis of logic. Some directions of links would lead to new unshielded colliders or to cyclicity, hence need to be directed the other way around. Cyclicity, like  $A \rightarrow B \rightarrow C \rightarrow A$ , is not permitted, hence bi-directional links are likewise not possible. [Demiralp, Hoover, and Perez \(2008\)](#) show that a bootstrap procedure is successful in directing the undirected edges. The residuals of the reduced form VAR are drawn randomly with replacement and new data sets are generated, to which the PC algorithm is applied. The undirected edges are finally directed in the direction which is more often prominent in the bootstrap runs. Sampling errors or latent variables can lead to conflicting information about edge directions. In these cases the algorithm returns a bi-directed edge. We decide on the bi-directed edges via our bootstrap procedure. Thus, the bootstrap procedure decides on the undirected edges (Markov equivalence class) and on the edges with conflicting information.

If the final graph is a directed acyclical graph (DAG), then it can be mapped in the contemporaneous matrix  $B_0$ , and due to the acyclicity property of the DAG, the contemporaneous matrix can be written as an overidentified lower triangular matrix for some ordering of the variables. Hence the SVAR model is identified. If the final graph contains cyclicity, which might arise due to some conflicting information about certain v-structures, the order condition is fulfilled, but it will not be possible to write the SVAR model as an overidentified recursive form.<sup>5</sup>

It is not clear from the onset which alpha value should be chosen in the PC algorithm. With increasing alpha values the algorithm becomes more liberal and so chooses fewer

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<sup>5</sup>On these grounds, we estimate our SVAR models equation by equation using OLS.

zero restrictions. Following our Monte Carlo simulation and [Demiralp et al. \(2014\)](#), we choose an alpha value of 10% in our application.

## 2.2 A connectedness measure using forecast error variance decompositions

We use the connectedness measure of [Diebold and Yilmaz \(2014\)](#). The approach is based on the computation of forecast error variance decompositions (FEVD).<sup>6</sup>

The stationary SVAR model in equation (1) can be written in an MA representation as

$$\mathbf{y}_t = \sum_{i=1}^{\infty} \Phi_i \mathbf{u}_{t-i} = \sum_{i=1}^{\infty} \Theta_i \mathbf{w}_{t-i}, \quad (3)$$

where  $\Phi_i$  are reduced-form impulse responses and  $\Theta_i$  are the structural impulse responses with  $\Theta_i \equiv \Phi_i \mathbf{B}_0^{-1}$ . The matrixes  $\Phi_i$  can be retrieved recursively by computing  $\Phi_0 = \mathbf{I}_K$  and  $\Phi_i = (\mathbf{B}_0^{-1} \mathbf{B})^i$ .

We compute a forecast error variance decomposition

$$d_{jk}^h = 100 \sum_{i=0}^{h-1} (e_j' \Theta_i e_k)^2 / \sum_{i=0}^{h-1} \sum_{k=1}^K \theta_{jk,i}^2, \quad (4)$$

where  $\theta_{jk,i}$  are the  $jk^{th}$  element of  $\Theta_i$  and  $e_k$  is the  $k^{th}$  column of  $\mathbf{I}_K$ . The measure  $d_{jk}^h$  is the proportion of the  $h$ -step forecast error variance of variable  $j$ , accounted for by innovations from variable  $k$ . We multiply the fractions by 100 to obtain percentages. Following [Diebold and Yilmaz \(2014\)](#) the pairwise directional connectedness from  $k$  to  $j$  is defined as

$$C_{j \leftarrow k}^h = d_{jk}^h. \quad (5)$$

In general  $C_{j \leftarrow k}^h \neq C_{k \leftarrow j}^h$ , so there are  $K^2 - K$  separate pairwise directional connectedness measures.

The measure of total connectedness can be defined as

$$C^h = \frac{1}{K} \sum_{j,k=1, j \neq k}^K d_{jk}^h. \quad (6)$$

In the following sections, we will compare this measure with other measures of connectedness. One of these alternative measures is the generalized forecast error variance decomposition (GFEVD). For the computation of a GFEVD we follow [Lanne and Nyberg \(2016\)](#)<sup>7</sup>

$$d_{jk,g}^h = 100 \frac{\sum_{i=0}^{h-1} (e_j' \Phi_i \Sigma_{\mathbf{u}} e_k \sigma_{kk}^{-1/2})^2}{\sum_{i=0}^{h-1} \sum_{k=1}^K (e_j' \Phi_i \Sigma_{\mathbf{u}} e_k \sigma_{kk}^{-1/2})^2}, \quad (7)$$

where  $\sigma_{kk}$  are the diagonal entries of  $\Sigma_{\mathbf{u}}$ .

<sup>6</sup>For an introduction to FEVDs, see [Lütkepohl \(2005\)](#).

<sup>7</sup>[Chan-Lau \(2017\)](#) studies the advantages of the [Lanne and Nyberg \(2016\)](#) approach in a connectedness application.

## 2.3 The algorithm

We make use of the R software package "pcalg" by Kalisch, Mächler, Colombo, Maathuis, Bühlmann, et al. (2012).<sup>8</sup> Our proposed algorithm (see Algorithm 1) starts with the estimation of a reduced form VAR model where the lag order is determined by the Akaike Information Criterion (AIC). Then, we apply the PC algorithm (PC) to the reduced form residuals and test if the resulting graph is a directed acyclical graph (DAG). If this is the case, we can proceed and determine the contemporaneous matrix ( $\mathbf{B}_0$ ) in accordance with the obtained DAG. Otherwise, we bootstrap the reduced form VAR 10,000 times, apply the PC algorithm in each run, and collect the 10,000 suggested graphs. Note that it is important to draw vectors from the residuals in such a way that the correlation between the residuals is preserved. Afterwards, we modify the original graph in such a way that the undirected edges become directed according to the direction preferred by the bootstrap. Note that we consider the bootstrap only in order to decide on edges which were originally undirected or bi-directed. Having obtained a DAG, we may proceed with the specification of  $\mathbf{B}_0$  (line 10 of Algorithm 1). Finally, the connectedness measure – or spillover matrix – can be derived from the estimated structural VAR model where the shocks are orthogonalised by  $\mathbf{B}_0$ .

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### Algorithm 1

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```

1: procedure IDENTIFICATION
2:    $[\mathbf{u}_t, \mathbf{A}] \leftarrow \text{VAR}(\text{data}, p=\text{AIC})$ 
3:    $\text{graph} \leftarrow \text{PC-Algorithm}(\alpha, \mathbf{u}_t)$ 
4:   if  $\text{graph}$  is directed-acyclical-graph then
5:      $\text{DAG} \leftarrow \text{graph}$ 
6:   else
7:      $\text{DAG} \leftarrow \text{Bootstrap}(\mathbf{u}_t, \mathbf{A}, \alpha, \text{graph})$ 
8:   end if
9:    $\mathbf{B}_0 \leftarrow \text{DAG}$ 
10:   $\text{connectedness} \leftarrow \text{FEVD}[\text{SVAR}(\mathbf{B}_0, \mathbf{A})]$ 
11: end procedure

12: function BOOTSTRAP( $\mathbf{u}_t, \mathbf{A}, \alpha, p, \text{graph}$ )
13:  for  $\text{runs} \in \{1, 2, \dots, 10,000\}$  do
14:     $\text{artificial data} \leftarrow \text{Create artificial data}(\mathbf{u}_t, \mathbf{A})$ 
15:     $[\mathbf{u}_t^{BS}] \leftarrow \text{VAR}(\text{artificial data}, p)$ 
16:     $\text{bootstrap-graph}(\text{runs}) \leftarrow \text{PC-algorithm}(\alpha, \mathbf{u}_t^{BS})$ 
17:  end for
18:   $\text{return} \leftarrow \text{direct undirected edges in } \text{graph} \text{ according to } \text{bootstrap-graph}$ 
19: end function

```

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<sup>8</sup>The chosen settings are: (conservative = TRUE, solve.confl = TRUE, u2pd = c("relaxed")). By choosing the conservative rule instead of the retry option, the algorithm produces a fully order-independent output; see Colombo and Maathuis (2014).

### 3 The effectiveness of the PC algorithm in the connectedness approach – A Monte Carlo study

In this section we evaluate the impact of different identification strategies on the measures of connectedness by performing a Monte Carlo experiment. We generate artificial data with the help of a known data generating process (DGP). Afterwards, we estimate the connectedness matrices for different identification strategies and benchmark them with the theoretical result of the known DGP. We compare the empirical identification with the generalized approach (see Lanne and Nyberg, 2016) and the average-of-all-Cholesky-orderings (see Klößner and Wagner, 2014) approach. The empirical identification is performed with two different algorithms, the PC algorithm and the greedy equivalence search (GES) algorithm of Chickering (2002).<sup>9</sup> Because the appropriate significance level alpha for the individual conditional independence tests of the PC algorithm is not clear, we use two conventional options: 5% and 10%.

The artificial data is generated recursively according to the SVAR(1):

$$\mathbf{y}_t = \mathbf{B}_0^{-1} \mathbf{B} \mathbf{y}_{t-1} + \mathbf{B}_0^{-1} \mathbf{w}_t, \quad (8)$$

with structural shocks  $\mathbf{w}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_w)$  and  $\mathbf{y}_0 = \mathbf{0}$ . To eliminate dependence on the initial condition we discard the first 80% of the generated data in all cases. The lag matrix,  $\mathbf{B}$ , is  $K \times K$  with random uniform coefficients between -0.05 and 0.05. The residuals,  $\mathbf{w}_t$ , are drawn randomly from independent normal distributions with mean 0 and variance 1. For the contemporaneous matrix,  $\mathbf{B}_0$ , we generate random directed acyclic graphs (DAGs) with a fixed expected number of neighbours. We use random Erdős-Rényi graphs for the DAGs, multiply the matrix entries by -1 and add an identity matrix. In this way we generate a sparse contemporaneous matrix with some negative off-diagonal entries between 0 and -1.<sup>10</sup> We perform this Monte Carlo study for N=100 data sets in each MC experiment. The categories are: two different system dimensions ( $K = 8/16$ ), three different levels of sparsity ( $d = 1/3/5$ ) and two different sample lengths ( $T = 250/2500$ ).<sup>11</sup>

The results are evaluated as follows. For each identification method we compute four measures in terms of recovering the true connectedness matrix. For all four measures we report the mean absolute error (MAE) of the estimated measure relative to measure for the true connectedness matrix. The first measure,  $\mathcal{C}$ , is the MAE of the off-diagonal elements of the connectedness matrix:

$$\mathcal{C} = \frac{1}{N} \sum_{i=1}^N \frac{1}{K^2 - K} \sum_{j,k=1, j \neq k}^K |C_{j \leftarrow k, i}^h - C_{j \leftarrow k, i}^{h*}|, \quad (9)$$

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<sup>9</sup>Note that the PC algorithm is a constraint-based approach, while the GES algorithm is a score-based method. Constraint-based approaches work with conditional independence tests. Score-based approaches assign scores to particular graph structures based on the data fit, for example using scoring metrics like the BIC score, which we use here.

<sup>10</sup>Given positive correlations between variables in applications to most markets, it is a reasonable assumption to focus on negative entries in the contemporaneous matrix.

<sup>11</sup>In contrast to our application, we perform 100 bootstrap runs in the Monte Carlo experiment.

whereby the variables with a star are the true connectedness values.  $\mathcal{C}$  is an important measure, as it puts a strong weight on the direction of the connectedness. The second measure,  $\mathcal{T}$ , is the MAE of the total connectedness:

$$\mathcal{T} = \frac{1}{N} \sum_{i=1}^N |C_i^h - C_i^{h*}|. \quad (10)$$

Here, not so much the direction of the links is evaluated, but rather whether the over-identifying zeros of the PC algorithm are appropriate. The third measure,  $\mathcal{S}$ , is the MAE of the skewness of the distribution of the off-diagonal entries of the connectedness matrix:

$$\mathcal{S} = \frac{1}{N} \sum_{i=1}^N |Skew\{C_{j \leftarrow k, i}^h\}_{j, k=1 \dots K, j \neq k} - Skew\{C_{j \leftarrow k, i}^{h*}\}_{j, k=1 \dots K, j \neq k}|. \quad (11)$$

While the fourth measure,  $\mathcal{K}$ , is the MAE of the kurtosis of the distribution of the off-diagonal entries of the connectedness matrix:

$$\mathcal{K} = \frac{1}{N} \sum_{i=1}^N |Kurt\{C_{j \leftarrow k, i}^h\}_{j, k=1 \dots K, j \neq k} - Kurt\{C_{j \leftarrow k, i}^{h*}\}_{j, k=1 \dots K, j \neq k}|. \quad (12)$$

These distributional measures aim to evaluate whether the extreme values in the connectedness matrices of the identification strategies are comparable to the theoretical connectedness. The results of the Monte Carlo experiments are displayed in Tables (1) and (2).

The PC algorithm performs, in general, better than the average-of-all-Cholesky-orderings approach and the generalized approach. While the other two identification strategies usually split the connectedness between  $j$  and  $k$  in such a way that  $C_{j \leftarrow k}^h \approx C_{k \leftarrow j}^h$ , the causal search algorithm manages to find the true causal connectedness. Even when the PC algorithm might find incorrect directions for some links, overall the true causal structure is uncovered to a much higher degree, which can be seen in the lower MAE values of our measure  $\mathcal{C}$ . The generalized approach overestimates the total connectedness in all cases, which can be seen in the high MAE in the measure  $\mathcal{T}$ . This result is in line with findings by [De Santis and Zimic \(2017\)](#). There is no clear favorite between a PC algorithm with 5% and 10% significance level. The GES algorithm performs equally well as the PC algorithm and is particularly strong for sparse contemporaneous matrices.

To reinforce the relevance of the Monte Carlo simulation to our empirical application, we perform a simulation experiment where we mimic the settings of the application, see Table (3). In the application we have a dimension of 9, a level of sparsity of  $d=3.8$  and 2,048 observations.<sup>12</sup> In the Monte Carlo experiment the causal search PC algorithm performs strongly, achieving low MAEs, especially in category  $\mathcal{C}$ , which measures the direction of connectedness.

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<sup>12</sup>We identified 17 links in our application. Hence, the sum of in- and out-degree is 34. 34 divided by 9 is 3.8.

Table 1: Monte Carlo simulation: comparing connectedness measures for different identification strategies relative to the correct connectedness measures using 100 random DAGs dimension 8.

d = 1	T=250				T=2500			
	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	1.849	3.648	1.798	14.836	1.487	0.558	1.576	13.606
GFEVD	2.823	12.233	1.523	11.965	2.233	7.126	1.260	10.400
PCalg 5%	1.644	2.594	0.455	4.245	1.031	0.534	0.228	2.166
PCalg 10%	1.664	2.824	0.452	4.334	1.045	0.548	0.245	2.300
GES	1.421	2.731	0.444	4.243	1.017	0.405	0.238	2.290
d = 3	T=250				T=2500			
	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	5.386	4.337	1.331	5.342	5.195	2.219	1.310	5.350
GFEVD	8.276	28.478	1.207	4.644	8.284	23.241	0.862	3.637
PCalg 5%	4.722	3.249	0.520	3.261	3.584	2.738	0.354	2.217
PCalg 10%	4.668	3.256	0.502	3.086	3.630	2.554	0.366	2.247
GES	5.221	3.983	0.411	2.449	4.143	1.811	0.363	2.208
d = 5	T=250				T=2500			
	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	9.695	6.007	1.559	3.596	9.643	5.091	1.564	3.586
GFEVD	11.552	30.634	1.113	3.098	13.508	28.869	0.858	2.642
PCalg 5%	9.592	8.656	0.754	3.730	9.157	6.858	0.576	2.561
PCalg 10%	9.728	7.621	0.671	3.217	9.227	6.807	0.579	2.634
GES	10.914	6.249	0.442	1.865	10.628	5.452	0.415	1.762

*Notes:* 100 random Erdős-Rényi graphs with 8 nodes. d (1, 3, 5) corresponds to the expected number of neighbours per node, more precisely the expected sum of the in- and out-degree. Sample size 250/2500 observations.  $\mathcal{C}$  is the MAE of the off-diagonal entries of the connectedness matrix.  $\mathcal{T}$  is the MAE of the total connectedness.  $\mathcal{S}$  and  $\mathcal{K}$  are the MAEs of the skewness and kurtosis of the distribution of the off-diagonal entries of the connectedness matrix.

Table 2: Monte Carlo simulation: comparing connectedness measures for different identification strategies relative to the correct connectedness measures using 100 random DAGs dimension 16.

d = 1	T=250				T=2500			
	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	1.291	8.006	2.603	33.602	0.864	0.997	2.219	30.262
GFEVD	2.066	20.489	2.572	30.278	1.334	8.775	1.763	22.862
PCalg 5%	1.020	5.867	0.613	10.554	0.581	0.680	0.322	5.870
PCalg 10%	1.023	6.179	0.586	9.586	0.586	0.670	0.321	5.810
GES	0.995	6.202	0.602	9.510	0.497	0.641	0.251	4.384
d = 3	T=250				T=2500			
	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	3.021	7.009	1.791	12.483	2.762	2.477	1.752	12.510
GFEVD	4.871	36.769	2.112	13.264	4.468	26.757	1.460	9.546
PCalg 5%	2.309	2.932	0.505	5.531	1.729	1.896	0.494	5.094
PCalg 10%	2.276	3.332	0.515	5.633	1.671	1.796	0.453	4.607
GES	2.455	5.582	0.430	4.572	1.881	1.850	0.417	4.272
d = 5	T=250				T=2500			
	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	5.018	8.309	2.163	10.084	4.900	5.410	2.140	10.111
GFEVD	6.420	37.451	1.720	9.183	6.684	33.617	1.593	8.289
PCalg 5%	4.662	4.533	0.772	6.909	3.952	4.408	0.640	5.155
PCalg 10%	4.606	4.381	0.822	7.276	4.000	4.532	0.685	5.542
GES	5.262	7.762	0.648	4.871	4.854	5.255	0.511	3.802

*Notes:* 100 random Erdős-Rényi graphs with 8 nodes. d (1, 3, 5) corresponds to the expected number of neighbours per node, more precisely the expected sum of the in- and out-degree. Sample size 250/2500 observations.  $\mathcal{C}$  is the MAE of the off-diagonal entries of the connectedness matrix.  $\mathcal{T}$  is the MAE of the total connectedness.  $\mathcal{S}$  and  $\mathcal{K}$  are the MAEs of the skewness and kurtosis of the distribution of the off-diagonal entries of the connectedness matrix.

Table 3: Monte Carlo simulation: comparing connectedness measures for different identification strategies relative to the correct connectedness measures using 100 random DAGs. Specification similar to the application: dimension=9, d=3.8, T=2048.

	$\mathcal{C}$	$\mathcal{T}$	$\mathcal{S}$	$\mathcal{K}$
avgChol	6.042	3.342	1.332	4.750
GFEVD	9.371	28.402	0.803	3.249
PCalg 5%	4.863	4.033	0.467	2.725
PCalg 10%	4.875	3.661	0.484	2.831
GES	5.410	2.939	0.463	2.645

*Notes:* 100 random Erdős-Rényi graphs with 9 nodes. d=3.8 corresponds to the expected number of neighbours per node, more precisely the expected sum of the in- and out-degree. Sample size 2048 observations.  $\mathcal{C}$  is the MAE of the off-diagonal entries of the connectedness matrix.  $\mathcal{T}$  is the MAE of the total connectedness.  $\mathcal{S}$  and  $\mathcal{K}$  are the MAEs of the skewness and kurtosis of the distribution of the off-diagonal entries of the connectedness matrix.

## 4 An application to exchange rate data

The bilateral exchange rate can be interpreted as the relative price between two currencies. Here, it is defined as the foreign currency price of buying one unit of home currency (quantity quotation). A positive shock to the bilateral exchange rate in quantity quotation can thus be interpreted as a positive shock to the demand of the home currency or a negative shock to the demand of the foreign currency. These shocks can trigger movements in other exchange rates as well. The reasons behind the international effects are manifold. One could think of currency (basket) pegs or international substitution effects, for instance.

The aim of this exercise is to uncover the network of spillover effects between exchange rate returns. We apply the proposed algorithm to the G10 bilateral euro exchange rates and cluster the exchange rates in order to unveil potential currency blocs afterwards. All bilateral exchange rates are downloaded in daily frequency from the ECB statistical data warehouse (SDW) and correspond to the ECB reference rates, representing the 14:15 CET fixing.<sup>13</sup> The sample covers the period between January 2010 and December 2017. We start in 2010 in order to exclude potential effects arising from the 2008 financial crisis. As ECB reference rates are expressed in quantity quotation and quoted against the euro, we transform the rates in such a way that the pound sterling becomes the numéraire. All transformed series enter our model in log differences. The reasoning behind changing the numéraire currency is discussed in the following section.

### 4.1 Choice of the numéraire currency

The bilateral (or multilateral) nature of exchange rates poses a problem for researchers and practitioners. When regressing exchange rates on exchange rates, the correct choice of the numéraire currency (or basket) is crucial, because the numéraire can have substantial effects on the estimates. This problem has been extensively discussed by [Frankel and Xie \(2010\)](#) in the context of estimations with regard to currency weights in baskets. Several studies such as [Frankel and Wei \(2008\)](#) and [Ohno \(1999\)](#) relied on the Swiss franc as numéraire currency. The Swiss franc seemed to be an appealing choice, because its trading volume is high and the currency was independent at that time. The Swiss franc lost this property when the Swiss National Bank introduced a minimum rate vis-à-vis the euro on 6 September 2011.<sup>14</sup> When the numéraire currency is pegged to another currency in the sample, the exchange rate has no variance, which can be explained by other currencies. Apart from the numerical problems that arise from this, the series would not have a variance and should thus not be employed within the [Diebold and Yilmaz \(2014\)](#) approach.<sup>15</sup>

The literature on basket weights proposes to use a basket of different currencies as numéraire. [Frankel and Xie \(2010\)](#) claim that monetary authorities are more likely to use a weighted average of currencies as reference for possible interventions when the exchange

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<sup>13</sup>Note that all exchange rates are fixed at the same time. Hence, trading times do not overlap.

<sup>14</sup>The minimum rate was abandoned on 13 January 2015, which caused the Swiss franc to appreciate strongly against several major currencies.

<sup>15</sup>Note that even if the numéraire is an independent currency, hard pegs among other currencies in the sample cause collinearity.



rate regime is a managed float or target zone and propose the IMF Special Drawing Right (SDR) basket as numéraire. On the other hand, [Aloosh and Bekaert \(2018\)](#) propose the use of unweighted baskets in a somewhat different setting. Nevertheless, a closed basket as numéraire cannot be employed in the [Diebold and Yilmaz \(2014\)](#) approach, because the first currency basket is nothing but a linear combination of the other  $N - 1$  currency baskets. A VAR model cannot be estimated for such a dataset. Hence, also when using baskets, one currency needs to be excluded. Therefore, we have to find a suitable numéraire currency which is freely floating, not an anchor currency and preferably not, or at least only to a small extent, part of currency baskets which central banks peg their currency to. A currency which sufficiently fulfills these criteria is the pound sterling (see [IMF, 2016](#)).<sup>16</sup>

## 4.2 Uncovering the causal structure

We follow the proposed algorithm and estimate the VAR model equation (2) for the rate of change in nine G10 exchange rates, taking the pound sterling as numéraire currency. The number of observations is 2,048 and the lag length of  $p = 1$  is chosen according to the Akaike Information Criterion (AIC). Before applying the PC algorithm, we investigate the correlation structure of the residuals  $\mathbf{u}_t$  (see Table (4)).

Table 4: Correlation between residuals ( $\mathbf{u}_t$ )

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY
AUD	1.00								
CAD	<b>0.66</b>	1.00							
CHF	0.31	0.33	1.00						
EUR	0.44	0.42	<b>0.61</b>	1.00					
NOK	<b>0.53</b>	<b>0.50</b>	0.40	<b>0.64</b>	1.00				
NZD	<b>0.76</b>	<b>0.57</b>	0.33	0.43	0.48	1.00			
SEK	<b>0.51</b>	0.45	0.44	<b>0.75</b>	<b>0.73</b>	0.46	1.00		
USD	0.34	<b>0.53</b>	0.39	0.43	0.24	0.31	0.30	1.00	
JPY	0.31	0.36	0.48	0.45	0.22	0.33	0.28	<b>0.64</b>	1.00

*Notes:* The table shows the cross-correlation between reduced form VAR residuals. Correlation coefficients  $> 0.5$  are marked in bold.

The table unveils relatively strong correlations between the residuals of commodity currencies such as the Australian dollar, Canadian dollar, New Zealand dollar and Norwegian krone. Particularly striking is the strong correlation between the Australian dollar and the New Zealand dollar ( $\rho_{AUD,NZD}^{ut} = 0.76$ ). The correlation between the Swedish krona and euro residuals ( $\rho_{SEK,EUR}^{ut} = 0.75$ ) is similarly strong. The Swedish krona residuals, however, are also correlated with the Norwegian krone residuals, thus linking the euro to the commodity currencies. The euro itself is also correlated with the Swiss franc. The correlation between the Japanese yen and the US dollar ( $\rho_{JPY,USD}^{ut} = 0.66$ ) is somewhat uncoupled. These correlations provide us with a first insight into international exchange

<sup>16</sup>The yen is also a very independent currency, but evidence suggests that there are ties between the yen and other Asian currencies. Therefore, we prefer to use the pound sterling as numéraire.

rate connectedness. They suggest the existence of a commodity currency bloc which is connected with the euro and a strong relationship between the Japanese yen and US dollar. These correlations, however, do not reflect any type of causality. We only learn that certain relationships may exist.

In order to estimate the causal structure we apply the PC algorithm with an  $\alpha$  size of 0.1 to the residuals. The algorithm yields the adjacency matrix

$$F = \begin{array}{cccccccccc} & \text{AUD} & \text{CAD} & \text{CHF} & \text{EUR} & \text{NOK} & \text{NZD} & \text{SEK} & \text{USD} & \text{JPY} \\ \left[ \begin{array}{cccccccccc} \mathbf{1} & \mathbf{1} & 0 & 0 & \mathbf{1} & 0 & \underline{\mathbf{1}} & 0 & 0 & 0 \\ 0 & \mathbf{1} & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} & 0 \\ 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & \underline{\mathbf{1}} & 0 & 0 & 0 & \mathbf{1} \\ 0 & 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & \mathbf{1} & \underline{\mathbf{1}} & \mathbf{1} & \mathbf{1} \\ 0 & 0 & 0 & 0 & \mathbf{1} & 0 & \underline{\mathbf{1}} & 0 & 0 & 0 \\ \mathbf{1} & \mathbf{1} & \underline{\mathbf{1}} & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} \\ \underline{\mathbf{1}} & 0 & 0 & 0 & \underline{\mathbf{1}} & 0 & 0 & \mathbf{1} & 0 & 0 \\ 0 & 0 & 0 & \underline{\mathbf{1}} & 0 & 0 & 0 & 0 & \mathbf{1} & \underline{\mathbf{1}} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \underline{\mathbf{1}} & \mathbf{1} \end{array} \right. & \begin{array}{l} \text{AUD} \\ \text{CAD} \\ \text{CHF} \\ \text{EUR} \\ \text{NOK} \\ \text{NZD} \\ \text{SEK} \\ \text{USD} \\ \text{JPY} \end{array} \end{array} ,$$

where 1 indicates that the currency of the related column is causing the currency of the corresponding row. By contrast, 0 indicates that the currency of the related column is not causing the currency of the corresponding row. Hence, if  $F[i, j] \neq F[j, i]$  (with  $i \neq j$ ) the algorithm was able to direct the link between the two currencies: if  $F[i, j] = F[j, i] = 0$ , then there is no contemporaneous relationship between the two currencies and an over-identification of the variance covariance matrix is possible. A problem occurs, however, if  $F[i, j] = F[j, i] = 1$  (see underlined numbers). In that particular case, the PC algorithm was unable to direct the link between the two currency pairs (Markov equivalence class). This is the case for the pairs  $AUD - SEK$ ,  $CHF - NZD$ ,  $EUR - USD$ ,  $NOK - SEK$  and  $USD - JPY$ . As explained earlier, we apply the bootstrap approach by Demiralp et al. (2008) in order to direct the undirected edges.<sup>17</sup>

More specifically, we bootstrap the VAR, let the PC algorithm determine the causal structure between the residuals, and save the output of the algorithm for each of the 10,000 runs. The results are reported in Table (5). Of particular interest are the entries  $F[7, 1]$  ( $AUD - SEK$ ),  $F[6, 3]$  ( $CHF - NZD$ ),  $F[8, 4]$  ( $EUR - USD$ ),  $F[7, 5]$  ( $NOK - SEK$ ), and  $F[9, 8]$  ( $JPY - USD$ ).

The table shows for currency pair  $AUD - SEK$  that  $AUD \rightarrow SEK$  is preferred over  $AUD \leftarrow SEK$  by 35.68% vs. 1.17% of the draws. The results are slightly less clear for  $CHF - NZD$ , as only 9.23% of the draws prefer  $CHF \rightarrow NZD$ . According to the bootstrap, the edge  $EUR - USD$  should be directed such that  $EUR \leftarrow USD$ . Lastly, we direct the edges  $NOK - SEK$  and  $JPY - USD$  such that  $NOK \rightarrow SEK$  and  $JPY \leftarrow USD$ .

Given the bootstrap information, the matrix  $F$  can now be updated and written as

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<sup>17</sup>Bi-directed edges have not been found in our application. Where a bi-directed edge is detected in the bootstrap of the application, these edges are displayed under “bi-directed” in Table (5). Overall, bi-directed edges are not prominent in our application, no bi-directed edge has been found on the original data, and only one edge showed a relevant occurrence of bi-directed outcomes in the bootstrap. The absence of bi-directed edges indicates that the system of exchange rates is contemporaneously self-contained. Latent variables, which might affect several exchange rates, seem to enter only with a lag.

Table 5: PC algorithm results in percent (bootstrap with 10,000 draws)

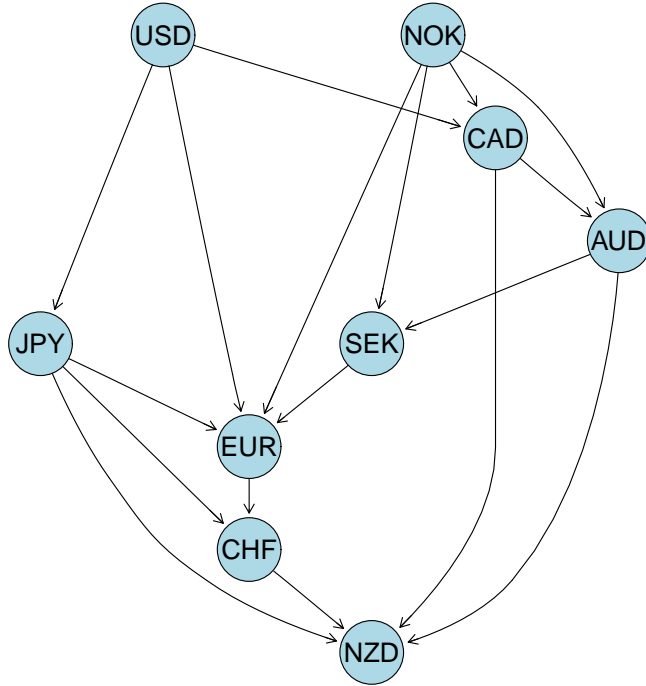
$F[i, j]$		PC	# of undirected	# of left	# of no edge	# of right	# of bi-directed
$i$	$j$						
2	1	-1	38.41	0.60	0.00	60.98	0.01
3	1	0	0.00	0.01	99.99	0.00	0.00
4	1	0	0.00	0.00	100.00	0.00	0.00
5	1	-1	43.65	12.72	2.28	41.28	0.07
6	1	1	46.13	22.10	0.00	31.59	0.18
7	1	2	62.26	35.68	0.84	1.17	0.05
8	1	0	11.00	0.07	87.40	1.53	0.00
9	1	0	0.00	0.00	99.95	0.00	0.05
3	2	0	0.00	0.00	100.00	0.00	0.00
4	2	0	0.00	0.00	100.00	0.00	0.00
5	2	-1	39.84	11.43	0.00	48.60	0.13
6	2	1	12.79	77.39	8.15	0.66	1.01
7	2	0	0.19	0.05	99.71	0.05	0.00
8	2	-1	46.67	1.15	0.00	51.29	0.89
9	2	0	2.15	0.22	97.28	0.35	0.00
4	3	-1	31.55	5.88	0.00	62.56	0.01
5	3	0	0.81	1.45	97.59	0.15	0.00
6	3	2	31.41	9.23	54.85	4.46	0.05
7	3	0	11.48	1.49	85.70	1.33	0.00
8	3	0	16.96	2.04	79.69	1.31	0.00
9	3	-1	32.84	4.85	0.00	62.31	0.00
5	4	-1	33.40	4.74	0.00	61.78	0.08
6	4	0	9.68	4.57	83.26	2.33	0.16
7	4	-1	55.26	10.49	0.00	34.24	0.01
8	4	2	57.21	8.06	18.79	15.81	0.13
9	4	-1	1.90	0.03	37.10	60.97	0.00
6	5	0	18.55	12.59	68.59	0.27	0.00
7	5	2	67.08	29.71	0.00	3.19	0.02
8	5	0	0.01	0.00	99.99	0.00	0.00
9	5	0	0.00	0.00	100.00	0.00	0.00
7	6	0	0.68	0.17	98.79	0.36	0.00
8	6	0	0.00	0.00	100.00	0.00	0.00
9	6	-1	6.54	4.32	15.80	60.98	12.36
8	7	0	0.03	0.01	99.95	0.01	0.00
9	7	0	0.89	0.03	98.77	0.31	0.00
9	8	2	75.20	17.25	0.00	7.55	0.00

*Notes:* The table shows the decisions of the PC algorithm for each entry in the adjacency matrix  $F[i, j]$ . The PC column refers to the PC algorithm decision with respect to the VAR point estimate residuals. Here, “0” denotes “no edge”, “1” stands for “right”, “-1” for “left” and “2” for an “undirected” linkage. The columns for the percentages (abbreviated as #) of the decisions “undirected”, “left”, “no edge”, “right” and “bi-directed” refer to the bootstrap. Whenever the algorithm finds no direction using the point estimate residuals (i.e. where the PC column has the entry 2), the edge is directed according to the (maximum) percentage in the “left” and “right” columns.

$$F_{BS} = \begin{array}{cccccccccc} & \text{AUD} & \text{CAD} & \text{CHF} & \text{EUR} & \text{NOK} & \text{NZD} & \text{SEK} & \text{USD} & \text{JPY} \\ \left[ \begin{array}{cccccccccc} \mathbf{1} & \mathbf{1} & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \mathbf{1} & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} & 0 \\ 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & 0 & 0 & 0 & 0 & \mathbf{1} \\ 0 & 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & \mathbf{1} & \mathbf{1} & \mathbf{1} & 0 \\ 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \\ \mathbf{1} & \mathbf{1} & \mathbf{1} & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} \\ 1 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & \mathbf{1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & \mathbf{1} \end{array} \right] & \begin{array}{l} \text{AUD} \\ \text{CAD} \\ \text{CHF} \\ \text{EUR} \\ \text{NOK} \\ \text{NZD} \\ \text{SEK} \\ \text{USD} \\ \text{JPY} \end{array} \end{array} .$$

This matrix no longer exhibits any cycles or undirected edges and can now be used to (over-)identify the variance-covariance matrix of the VAR model. Each 1-entry represents a coefficient which has to be estimated. Figure (1) presents the adjacency matrix  $F_{BS}$  as a graph.

Figure 1: Visualisation of the adjacency matrix  $F_{BS}$



*Notes:* This figure shows the contemporaneous causality structure which is used to orthogonalise the SVAR residuals (see matrix  $\mathbf{B}_0$ ). Note that this graph does not represent the connectedness matrix, which will be estimated in section (4.3).

For a better understanding of the dynamics, we re-order the adjacency matrix into the over-identified matrix  $\mathbf{B}_0$  in such a way that we recover its recursive form.<sup>18</sup>

<sup>18</sup>Note that due to the over-identifying restrictions, this ordering is not unique. For example, the Japanese yen could also be ordered behind the Norwegian krone and the following other currencies, but it needs to be before the euro. Hence, some other orderings would also be consistent with the output

$$\mathbf{B}_0 = \begin{array}{cccccccccc}
& \text{USD} & \text{JPY} & \text{NOK} & \text{CAD} & \text{AUD} & \text{SEK} & \text{EUR} & \text{CHF} & \text{NZD} \\
\left[ \begin{array}{cccccccccc}
1 & & & & & & & & & \\
b_{21} & 1 & & & & & & & & \\
0 & 0 & 1 & & & & & & & \\
b_{41} & 0 & b_{43} & 1 & & & & & & \\
0 & 0 & b_{53} & b_{54} & 1 & & & & & \\
0 & 0 & b_{63} & 0 & b_{65} & 1 & & & & \\
b_{71} & b_{72} & b_{73} & 0 & 0 & b_{76} & 1 & & & \\
0 & b_{82} & 0 & 0 & 0 & 0 & b_{87} & 1 & & \\
0 & b_{92} & 0 & b_{94} & b_{95} & 0 & 0 & b_{98} & 1 & 
\end{array} \right] \begin{array}{l}
\text{USD} \\
\text{JPY} \\
\text{NOK} \\
\text{CAD} \\
\text{AUD} \\
\text{SEK} \\
\text{EUR} \\
\text{CHF} \\
\text{NZD}
\end{array}
\end{array}$$

This enables us to unveil and interpret the causal structure between the structural shocks. Note here that the ordering is entirely determined by the data-driven causal-search algorithm (PC). We observe that the USD is ordered first, suggesting that it is the most independent currency in the sample. Shocks to the US dollar affect the Japanese yen, the Canadian dollar and the euro contemporaneously, while no foreign shock has contemporaneous effects on the US dollar. The New Zealand dollar is ordered last. Thus, shocks to this currency have no contemporaneous effects on any other currency in the sample. However, it is affected by shocks to the Japanese yen, the Canadian dollar, the Australian dollar and the Swiss franc. Interestingly, these are all currencies which are related to carry trades. The commodity currencies (AUD, CAD) are often referred to as carry trade target currencies, while the other two (CHF, JPY) are used by market participants for carry trade funding (see [Hossfeld and MacDonald, 2015](#); [Ferreira Filipe and Suominen, 2013](#)). The Norwegian krone appears to be another important currency. It is ordered third, but the PC algorithm suggests that shocks to the US dollar and the Japanese yen, which is ordered second, have no contemporaneous effects on the krone. However, shocks to the krone affect other commodity currencies (CAD, AUD) and geographic neighbours (EUR, SEK) contemporaneously. Overall, we observe a causal structure which is not only closely related to the correlation of reduced form residuals (Table 4), but also economically plausible.

The coefficients in the contemporaneous matrix ( $\mathbf{B}_0$ ) can be obtained by re-estimating the (structural) VAR equation by equation, whereby the contemporaneous effects (according to  $\mathbf{B}_0$ ) are included in each equation. The estimates are presented in Appendix (A).

The matrix  $\mathbf{B}_0$  is overidentified with 19 zero restrictions. When testing the 19 restrictions with a likelihood ratio test, the null hypothesis that all these 19 coefficients can be restricted to zero needs to be rejected with a test statistic of 268.66 and a p value of 0.000. When we return more coefficients to the contemporaneous matrix, beginning with the highest entries in the variance covariance matrix of the SVAR model, we find that already with 7 overidentifying restrictions the null needs to be rejected with a test statistic of 16.17 and a p value of 0.024. We attribute this finding to the fact that we are working with bilateral exchange rates. The contemporaneous correlations of the currency pairs are high in all cases, see Table (4), which might be due to a UK effect in all exchange rates. To further scrutinise this point we perform a robustness check at the end of section (4.3), where we compare the connectedness matrix for the PC algorithm approach with the connectedness matrix of a version of the SVAR model without overidentifying

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of the causal search algorithm. However, the computed connectedness measures in the following are not influenced by our choice of a recursive ordering.

restrictions on the contemporaneous matrix.

### 4.3 Connectedness

This section shows the connectedness between exchange rates for different identification methods. First, we use a simple Cholesky decomposition as in the seminal paper by Diebold and Yilmaz (2009). As we are completely agnostic with regard to causality, the ordering of the variables is random. Table (6) presents the forecast error variance decomposition (i.e. the connectedness). The entries represent the shares of forecast error variance (in percent) of the variables in rows, which are explained by shocks to the variables in columns. Hence, rows sum up to 100. For instance, the estimates suggest that 16.8% of US dollar forecast error variance is explained by shocks to the Canadian dollar, while only 0.3% of Canadian dollar forecast error variance is explained by shocks to the US dollar. This result is surprising, because the United States is usually considered as a large and less dependent economy. Accordingly, one would expect causality to point from USD to CAD rather than the other way round. Later, we will see that a different causal ordering yields completely different results from those obtained by the PC algorithm. But also the measures of total connectedness show a surprising picture. The row “IN” represents the contribution of international shocks to the forecast error variance of the variables in rows (i.e. the row sum minus the idiosyncratic contribution). This measure is referred to as in-connectedness. Particularly the Australian dollar, which is ordered first, is almost entirely driven by its own shocks. Then again, the out-connectedness of the Australian dollar (OUT; i.e. the column sum of contributions subtracted by the idiosyncratic component) is extraordinarily high compared with other currencies. Overall, we observe that the shares on the lower diagonal are substantially higher than those on the upper diagonal, reflecting the lower diagonal structure of the Cholesky factorisation which has been applied. Hence, a Cholesky decomposition has to be applied with caution.

Table 6: Connectedness: Cholesky (random ordering)

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY	IN
AUD	99.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2
CAD	43.8	55.5	0.0	0.0	0.1	0.1	0.0	0.3	0.1	44.5
CHF	9.9	2.7	86.9	0.0	0.1	0.0	0.3	0.0	0.0	13.1
EUR	18.8	3.2	22.0	55.4	0.0	0.0	0.1	0.2	0.3	44.6
NOK	28.5	3.6	4.5	13.3	49.5	0.0	0.2	0.0	0.4	50.5
NZD	58.1	0.6	0.8	0.4	0.0	39.9	0.0	0.0	0.2	60.1
SEK	25.9	2.3	7.2	24.9	7.0	0.0	32.2	0.1	0.4	67.8
USD	12.0	16.8	5.4	1.7	3.2	0.0	0.1	60.9	0.0	39.1
JPY	9.4	4.1	14.0	1.8	2.9	0.4	0.2	16.9	50.3	49.7
OUT	206.5	33.4	53.8	42.2	13.4	0.5	0.9	17.4	1.5	$C^{10}=41.1$

*Notes:* The table shows the (10 periods ahead) forecast error variance decomposition of the SVAR model which is identified by a Cholesky decomposition with random ordering. The column “IN” corresponds to the row sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by (international) shocks). The column “OUT” corresponds to the column sum of the non-diagonal variance shares (i.e. the total share of variance, which is explained by the corresponding column variable).  $C^{10}$  refers to the measure of total connectedness (see section 2.2).

A way to circumvent this problem is to apply a generalized forecast error variance decomposition. This decomposition is derived from generalized impulse response functions which were originally proposed by [Pesaran and Shin \(1998\)](#). The intuition behind this approach is that every variable is treated as it would be ordered first in a Cholesky decomposition. Hence, any variable can have contemporaneous effects on any variable in the system. The problem, however, is that this approach does not orthogonalise the shocks, implying that forecast error variance shares do not sum to unity for any given variable.<sup>19</sup> Instead of normalising the variance shares in such a way that they sum to unity (see [Greenwood-Nimmo et al., 2016](#), for instance), we proceed as outlined in section (2.2) and apply an alternative form of the generalized forecast error variance decomposition where variance shares sum to unity by construction (see [Lanne and Nyberg, 2016](#)). This decision is based on the results of [Chan-Lau \(2017\)](#), who finds that the generalized variance decomposition by [Lanne and Nyberg \(2016\)](#) performs better than the one by [Pesaran and Shin \(1998\)](#).

Table 7: Connectedness: GFEVD ([Lanne and Nyberg, 2016](#))

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY	IN
AUD	33.7	11.4	3.8	3.9	9.3	21.6	8.0	2.8	5.5	66.3
CAD	17.2	28.9	4.7	4.1	9.6	13.3	7.1	7.5	7.7	71.1
CHF	4.6	3.8	44.1	8.9	7.6	5.0	8.1	4.3	13.5	55.9
EUR	7.4	5.2	13.8	20.6	13.6	7.1	17.4	4.3	10.6	79.4
NOK	11.7	7.3	6.5	9.2	32.9	9.3	17.8	1.5	3.9	67.1
NZD	20.8	8.7	4.4	4.0	7.9	38.7	6.8	2.3	6.3	61.3
SEK	10.3	6.0	7.4	12.1	17.4	8.2	30.9	2.2	5.4	69.1
USD	6.0	10.4	7.7	5.2	4.4	4.7	4.0	31.3	26.2	68.7
JPY	4.1	4.1	9.8	4.8	3.9	4.5	3.4	11.2	54.0	46.0
OUT	82.2	56.9	58.0	52.2	73.7	73.7	72.6	36.2	79.3	$C^{10}=65.0$

*Notes:* The table shows the (10 periods ahead) forecast error variance decomposition of the SVAR model which is identified by using generalized impulse responses. The column “IN” corresponds to the row sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by (international) shocks). The column “OUT” corresponds to the column sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by the corresponding column variable).  $C^{10}$  refers to the measure of total connectedness (see section 2.2).

The results of the GFEVD measure are presented in Table (7). Now, we observe that the differences between in- and out-connectedness have decreased for all currency pairs. For many pairs, the degrees have even become roughly equivalent: 3.9% of the Japanese yen’s forecast error variance is explained by the Norwegian krone *and vice versa*. Overall, the linkages are qualitatively similar to those obtained from the Cholesky decomposition with the difference that the information with regard to the direction of causality has been lost.

The same applies to the results based on the fastSOM algorithm by [Klößner and Wagner \(2014\)](#), which represent the average variance shares over all possible Cholesky permutations (Table 8). Here, the differences between in- and out-connectedness are even smaller than in the previous case. We learn, for instance, that the Australian dollar and

<sup>19</sup>We observe that the sum of variance shares is close to unity, but not exactly unity.



Table 8: Connectedness: fastSOM

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY	IN
AUD	53.5	11.2	1.3	2.8	5.5	17.6	4.7	1.9	1.5	46.5
CAD	11.4	59.3	1.6	2.5	5.0	6.9	3.2	7.8	2.3	40.7
CHF	1.3	1.5	69.7	10.1	3.1	1.7	3.7	3.0	5.9	30.3
EUR	2.8	2.6	8.7	51.0	9.3	2.8	15.3	3.3	4.1	49.0
NOK	5.8	4.8	2.8	9.7	56.3	4.0	14.6	0.9	1.1	43.7
NZD	18.6	7.1	1.7	2.9	4.1	58.9	3.4	1.4	1.9	41.1
SEK	4.8	3.3	3.4	15.7	14.1	3.4	52.4	1.3	1.6	47.6
USD	2.1	8.4	3.0	3.8	1.0	1.5	1.3	65.1	13.8	34.9
JPY	1.4	2.3	5.8	4.5	1.0	1.8	1.2	14.2	67.8	32.2
OUT	48.2	41.3	28.4	52.0	43.0	39.7	47.6	33.7	32.1	$C^{10}=40.7$

*Notes:* The table shows the (10 periods ahead) forecast error variance decomposition of the SVAR model as an average of all possible Cholesky orderings. The column “IN” corresponds to the row sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by (international) shocks). The column “OUT” corresponds to the column sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by the corresponding column variable).  $C^{10}$  refers to the measure of total connectedness (see section 2.2).

the New Zealand dollar are connected, but the differences between the variance shares ( $AUD \rightarrow NZD$  [18.6%] and  $AUD \leftarrow NZD$  [17.6%]) are not strong enough to make a statement about the direction. Additionally, when studying all possible permutations of orderings, the maximum and minimum levels of connectedness per country pair can be computed, see Appendix (B). It is obvious that the connectedness between currency pairs depends crucially on an arbitrary ordering of the variables in the model.

The ambiguity diminishes drastically when our proposed algorithm is applied (Table 9). Clear causal patterns appear which help in understanding the network topology of G10 exchange rates and the direction of edges, in particular. The estimates suggest that the US dollar and the Norwegian krone are both important drivers of international exchange rate fluctuations. Their in-connectedness is very low (0.7 and 1.4, respectively), suggesting that they are barely affected by shocks to foreign currencies. However, their out-connectedness is relatively high (91.1 and 152.4, respectively). Shocks to the US dollar explain 21.2% of Canadian dollar and 41.2% of Japanese yen forecast error variance. Note that these are clearly not bi-directed linkages. Our estimates suggest that the causality is directed from the US dollar to both currencies. The Norwegian krone appears to explain high shares of the Australian dollar, Canadian dollar, Swiss franc, euro, New Zealand dollar and Swedish krona forecast error variance. Hence, there seem to be strong ties between commodity currencies and European currencies. The strong effects of the Norwegian krone are somewhat surprising. It is possible that the Norwegian krone also reflects influences of other currencies of oil exporting countries.

We also find evidence suggesting that the Australian dollar causes the New Zealand dollar, which was not obvious when other measures of connectedness were applied. The same accounts for the  $USD \rightarrow JPY$  relationship. Another interesting edge is the  $EUR \rightarrow CHF$  link, which reflects the minimum exchange rate of CHF 1.20 per EUR.<sup>20</sup>

<sup>20</sup>The minimum exchange rate was introduced by the Swiss National Bank on 6 September 2011 and



Table 9: Connectedness: PC algorithm ( $\alpha = 0.1$ )

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY	IN
AUD	53.0	16.8	0.1	0.0	24.1	0.0	0.0	5.9	0.1	47.0
CAD	0.1	61.6	0.1	0.1	16.8	0.0	0.0	21.2	0.1	38.4
CHF	0.1	0.0	61.9	9.1	8.4	0.0	3.5	8.9	8.0	38.1
EUR	0.5	0.3	0.1	39.6	36.1	0.0	13.8	6.9	2.7	60.4
NOK	0.4	0.1	0.0	0.0	98.6	0.0	0.2	0.2	0.5	1.4
NZD	24.3	11.2	0.4	0.0	14.5	42.3	0.0	6.6	0.6	57.7
SEK	1.6	0.6	0.0	0.0	52.0	0.0	45.1	0.3	0.5	54.9
USD	0.2	0.1	0.0	0.1	0.2	0.0	0.0	99.3	0.0	0.7
JPY	0.0	0.0	0.0	0.0	0.3	0.0	0.1	41.2	58.4	41.6
OUT	27.1	29.2	0.7	9.4	152.4	0.1	17.6	91.1	12.5	$C^{10}=37.8$

*Notes:* The table shows the (10 periods ahead) forecast error variance decomposition of the SVAR model which is identified by the PC algorithm. The column “IN” corresponds to the row sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by (international) shocks). The column “OUT” corresponds to the column sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by the corresponding column variable).  $C^{10}$  refers to the measure of total connectedness (see section 2.2).

As a robustness analysis, we estimate the spillover matrix of Table 9 without over-identifying restrictions on the contemporaneous matrix. More specifically, we use one of the possible causal orderings which is consistent with the findings of the PC algorithm and estimate the structural VAR using a Cholesky decomposition. The obtained spillover matrix (see Table 12 in Appendix C) shows a very similar pattern when compared to Table 9.<sup>21</sup> The total connectedness increases slightly because of missing over-identifying restrictions.<sup>22</sup> However, the relative importance of the shocks remains the same, therefore the results are qualitatively similar. For instance, shocks to the euro explain 8.1% (9.1% with over-identifying restrictions) of Swiss franc forecast error variance and only 0.3% (0.0% with over-identifying restrictions) of New Zealand forecast error variance, although the coefficient  $b_{97}$  is now unrestricted. It is also surprising to see that the measure of total connectedness,  $C^{10} = 41.0$  is very similar to the Cholesky application with random ordering (here,  $C^{10} = 41.1$ ). This finding is in favour of Diebold and Yilmaz (2014), who argue that the system-wide summary measure ( $C^h$ ) is often robust to the Cholesky ordering. However, this does not change the fact that the result is due to a random ordering and thus (potentially) a result of misspecification.

In summary, the PC algorithm provides us with well defined directed edges, which enable us to unveil a directed network of exchange rates. This gives the PC algorithm a clear advantage over the other presented methods. However, the PC algorithm is computationally also the most intense procedure, particularly because of the time-consuming bootstrap.<sup>23</sup>

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abandoned on 15 January 2015. It served as a key monetary policy instrument.

<sup>21</sup>Note that in Table 12 in the appendix the currencies follow the recursive ordering.

<sup>22</sup>Given the Cholesky decomposition, we no longer have exact zero entries in the lower diagonal of the contemporaneous matrix. The non-zero coefficients translate into minor changes in the variance shares.

<sup>23</sup>However, we found that working with a small number of bootstrap runs usually leads to the same result as with a large number of runs. For example, for our application we made 100 experiments with

## 4.4 Cluster analysis

In this section we exploit the connectedness between exchange rates (displayed in Table 9) in order to divide the network into clusters (also known as communities or modules). A cluster is characterised by a high number of edges between nodes within the cluster, relative to the number of edges to nodes outside the cluster. In this sense, we visualise the previously estimated connectedness and identify groups of exchange rates with a relatively high intra-group connectedness. These groups can be interpreted as currency blocs. The currencies of a bloc are likely to move in tandem, which is important information for policy makers and the management of currency risk. Note that our definition of a currency bloc is more general than the definition by Fischer (2016), for instance.

The quality of the partitioning of a whole network, which can consist of as many clusters as nodes, is thus often expressed by a measure, depending on the differences between the numbers of edges within clusters and the numbers of edges that would exist if it were a random network model. Hence, positive values indicate the existence of clusters. This measure is referred to as *modularity*. For a detailed explanation, we refer the reader to Blondel, Guillaume, Lambiotte, and Lefebvre (2008), who propose a popular algorithm (hereafter: Louvain algorithm) which detects the *best* clustering by maximising modularity. Initially, the algorithm assigns each node to a single cluster. In a second step, the algorithm moves nodes to new clusters if gains in modularity can be achieved until no additional gain can be achieved (see Blondel et al., 2008). One drawback of the Louvain algorithm is that it is designed for undirected networks. Consequently, it is not feasible given the causal structure of our network. Dugué and Perez (2015) provide a solution to this common problem. They modify the Louvain algorithm in such a way that it accommodates for *directed modularity* as defined by Leicht and Newman (2008).

Using the Directed Louvain algorithm by Dugué and Perez (2015), we aim to partition the network in Table (9). We observe in Figure (2) that the algorithm classifies the G10 currencies into three different clusters. The first cluster contains the AUD, CAD and NZD, which are often referred to as commodity currencies. Another common property is that investments in these countries provide the investor with a relatively high yield. The NOK is often also referred to as a commodity currency, but it is part of the second cluster. In addition to the NOK, this cluster also contains the EUR as well as the SEK and thus European currencies only. The third cluster contains the CHF, USD and JPY. These currencies are often referred to as safe haven and/or carry funding currencies (see Hossfeld and MacDonald, 2015; Ferreira Filipe and Suominen, 2013). Thus, the latter group has the tendency to appreciate in times of financial stress, either because investors are seeking a safe haven for their investments or due to the unwinding of carry trades.

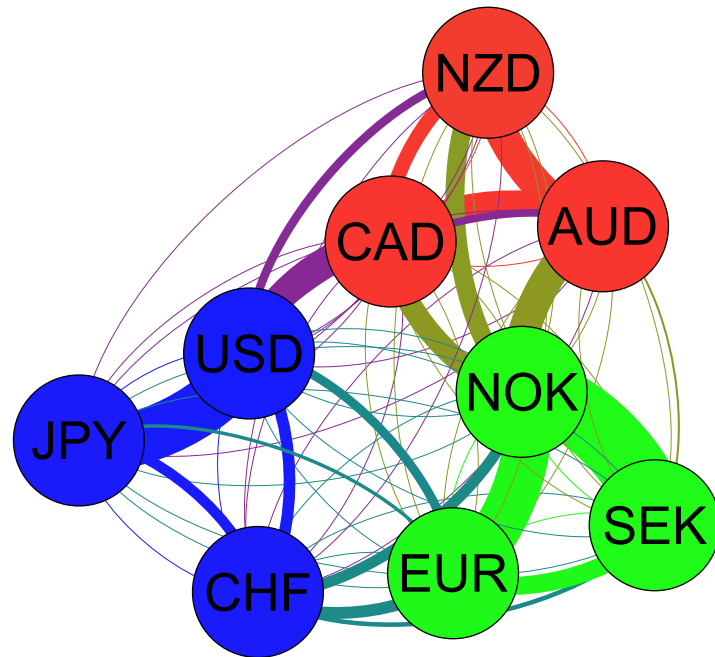
## 4.5 Empirical assessment of the clustering: Brexit referendum

In this section we assess the quality of the partition suggested by the Directed Louvain algorithm. To this end we normalise all exchange rates before the referendum on UK's membership of the EU, the result of which surprised many market participants, and discuss their movements during the trading days following the referendum (see Figure (3)).

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bootstraps with 100 runs each and found that 86 experiments lead to the same contemporaneous matrix as a bootstrap with 10,000 runs, while in 14 experiments one of the edges is found to be directed differently.

Figure 2: Partition according to the Directed Louvain algorithm

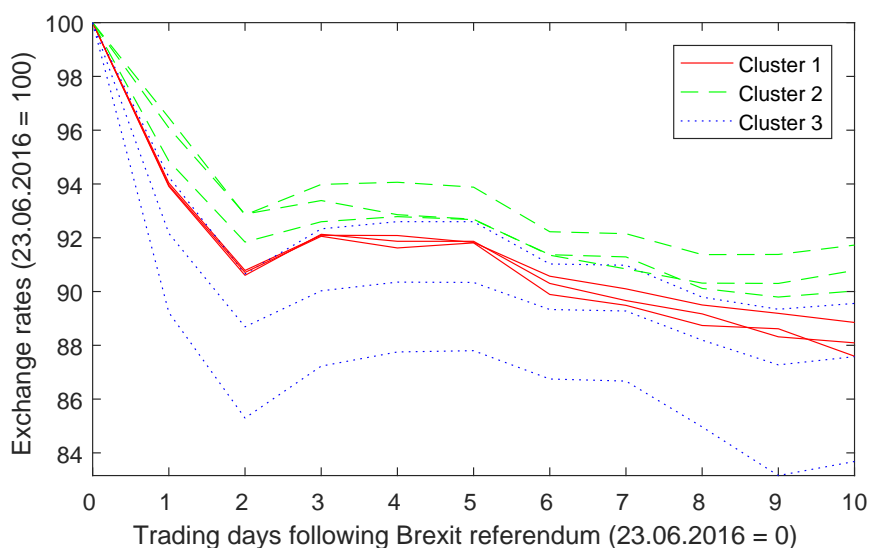


*Notes:* This figure shows the exchange rates clustered according to the spillover matrix of the PC algorithm (Table (9)). Cluster 1 (red): AUD, CAD, NZD; Cluster 2 (green): EUR, NOK, SEK; Cluster 3 (blue): CHF, USD, JPY. Causation propagates clockwise.

The Brexit referendum is an appealing example, as it is a shock to the numéraire which affects all other currencies. Following the referendum, the pound sterling depreciated against all currencies in our sample. Figure (3) shows the movements of the pound sterling exchange rates against all currencies in quantity quotation (cross rates of ECB reference rates). In order to simplify the interpretation, exchange rates have been normalised to 100 on the day of the referendum (23 June 2016 is day 0).<sup>24</sup> The similarity of movements within clusters is striking. Currencies within the first (red and solid lines) and second (green and dashed lines) cluster, in particular, move closely in tandem. Only currencies in the third cluster (blue and dotted lines) display a slightly larger dispersion. Nor is it surprising that the pound sterling depreciates strongly against the third cluster, which reflects safe haven and carry funding currencies. These are supposed to appreciate in times of financial stress. Additionally, it is expected that the European currencies appreciate the least of the three clusters, because the uncertainty surrounding Brexit means uncertainty for the European Monetary Union. The Swiss franc, which has been found by our procedure to belong to the cluster of safe havens, moves in the case of the Brexit experiment more closely in line with European currencies.

Overall, we observe that exchange rate movements follow a very similar pattern, but we also see that the dispersion within clusters is strikingly low.

Figure 3: Exchange rate movements following the Brexit referendum



*Notes:* This figure shows pound sterling exchange rate movements following the Brexit referendum (pound sterling in quantity quotation). Exchange rates are coloured according to their corresponding cluster. Cluster 1 (red, solid): AUD, CAD, NZD; Cluster 2 (green, dashed): EUR, NOK, SEK; Cluster 3 (blue, dotted): CHF, USD, JPY. Source: ECB.

<sup>24</sup>Note that the fixing of ECB reference rates takes place at 14:15 UTC – before the results of the referendum were published.

## 5 Conclusions

The literature on connectedness between exchange rates has so far ignored a potential causal structure. Research along the lines of [Diebold and Yilmaz \(2014\)](#) is based on a forecast error variance decomposition in a VAR framework. The difficulty in this context is the identification of the variance-covariance matrix in order to orthogonalise the shocks. We show that a Cholesky decomposition, which is frequently used, can lead to arbitrary results, as the outcome depends heavily on the ordering of the variables. A generalized FEVD is independent of the ordering of the variables, but it is unable to detect causality between the shocks. The same applies when all possible orderings of variables are considered (see [Klößner and Wagner, 2014](#)).

We address this problem by employing a causal search algorithm from the machine learning literature, which is able to find causality in contemporaneous data. This approach is then applied to the G10 currencies, whereby nine currencies are modelled vis-à-vis the pound sterling as numéraire currency. Our results suggest that the US dollar and the Norwegian krone are the most independent currencies in our sample. Shocks to these currencies affect a large set of other currencies. We also observe that connectedness between commodity currencies and those that are often referred to as safe haven and/or carry funding currencies is particularly high.

Using a clustering algorithm we identify three currency clusters which confirm the previous findings. The first cluster contains commodity currencies such as the AUD, CAD and NZD. The second cluster comprises the European currencies EUR, NOK and SEK. Finally, the third cluster contains the CHF, USD and JPY – currencies which are often referred to as safe haven or carry funding currencies. They have the tendency to appreciate in times of financial stress.

In an additional exercise we evaluate the movements of currencies with respect to their clusters following the Brexit referendum. We observe that the dispersion of exchange rate movements within clusters is indeed relatively low, particularly for the first and second clusters. The third cluster shows the strongest appreciation against the pound sterling following the referendum. The Swiss franc, however, appears to move more closely in line with other European currencies (second cluster).

Overall, these estimates provide important information for policy makers and practitioners, as they shed light on potential co-movements between certain exchange rates.

## References

- Aloosh, A. and G. Bekaert (2018). Currency factors. Technical Report 17–88, Columbia Business School Research Paper.
- Barigozzi, M. and C. T. Brownlees (2018). Nets: Network estimation for time series. *Unpublished Manuscript*.
- Blondel, V., J.-L. Guillaume, R. Lambiotte, and E. Lefebvre (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* (P10008).
- Chan-Lau, M. J. A. (2017). Variance decomposition networks: Potential pitfalls and a simple solution. Working Paper 17/107, International Monetary Fund, Washington, D.C.
- Chickering, D. M. (2002). Optimal structure identification with greedy search. *Journal of machine learning research* 3(Nov), 507–554.
- Colombo, D. and M. H. Maathuis (2014). Order-independent constraint-based causal structure learning. *The Journal of Machine Learning Research* 15(1), 3741–3782.
- De Santis, R. A. and S. Zimic (2017). Spillovers among sovereign debt markets: identification by absolute magnitude restrictions. Working Paper 2055, ECB, Frankfurt.
- Demiralp, S. and K. D. Hoover (2003). Searching for the causal structure of a Vector Autoregression. *Oxford Bulletin of Economics and Statistics* 65, 745–767.
- Demiralp, S., K. D. Hoover, and S. J. Perez (2008). A bootstrap method for identifying and evaluating a structural vector autoregression. *Oxford Bulletin of Economics and Statistics* 70(4), 509–533.
- Demiralp, S., K. D. Hoover, and S. J. Perez (2014). Still puzzling: evaluating the price puzzle in an empirically identified structural vector autoregression. *Empirical Economics* 46(2), 701–731.
- Demirer, M., F. X. Diebold, L. Liu, and K. Yilmaz (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics* 33(1), 1–15.
- Diebold, F. X. and K. Yilmaz (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119(534), 158–171.
- Diebold, F. X. and K. Yilmaz (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182(1), 119–134.
- Diebold, F. X. and K. Yilmaz (2015). Financial and macroeconomic connectedness: A network approach to measurement and monitoring. *Oxford University Press, New York*.

- Dugué, N. and A. Perez (2015). Directed louvain: maximizing modularity in directed networks. *PhD thesis. Université d'Orléans.*
- Ferreira Filipe, S. and M. Suominen (2013). Currency carry trades and funding risk. *AFA 2014 Philadelphia Meetings Paper.*
- Fischer, C. (2016). Determining global currency bloc equilibria: An empirical strategy based on estimates of anchor currency choice. *Journal of International Money and Finance* 64, 214–238.
- Frankel, F. and S.-J. Wei (2008). Estimation of de facto exchange rate regimes: Synthesis of the techniques for inferring flexibility and basket weights. *IMF Staff Papers* 55(3), 384–416.
- Frankel, J. and D. Xie (2010). Estimation of de facto flexibility parameter and basket weights in evolving exchange rate regimes. *American Economic Review* 100, 568–572.
- Greenwood-Nimmo, M., V. H. Nguyen, and B. Rafferty (2016). Risk and return spillovers among the G10 currencies. *Journal of Financial Markets* 31, 43–62.
- Greenwood-Nimmo, M., V. H. Nguyen, and Y. Shin (2017). What's Mine Is Yours: Sovereign Risk Transmission during the European Debt Crisis. Working Paper 17/17, Melbourne Institute, Victoria, Australia.
- Heinlein, R. and H.-M. Krolzig (2012). Effects of monetary policy on the US Dollar/UK Pound exchange rate. Is there a 'delayed overshooting puzzle'? *Review of International Economics* 20, 443–467.
- Hossfeld, O. and R. MacDonald (2015). Carry funding and safe haven currencies: A threshold regression approach. *Journal of International Money and Finance* 59, 185–202.
- IMF (2016). Annual report on exchange arrangements and exchange restrictions 2016. Technical report, International Monetary Fund.
- Kalisch, M., M. Mächler, D. Colombo, M. H. Maathuis, P. Bühlmann, et al. (2012). Causal inference using graphical models with the R package pcalg. *Journal of Statistical Software* 47(11), 1–26.
- Kilian, L. and H. Lütkepohl (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.
- Klößner, S. and S. Wagner (2014). Exploring all VAR orderings for calculating spillovers? Yes, we can! - A note on Diebold and Yilmaz (2009). *Journal of Applied Econometrics* 29(1), 172–179.
- Lanne, M. and H. Nyberg (2016). Generalized forecast error variance decomposition for linear and nonlinear multivariate models. *Oxford Bulletin of Economics and Statistics* 78(4), 595–603.

- Leicht, E. A. and M. E. Newman (2008). Community structure in directed networks. *Physical Review Letters* 100(11), 118703.
- Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Berlin: Springer.
- Ohno, K. (1999). Exchange rate management in developing asia. Working Paper 1, Asian Development Bank Institute.
- Pearl, J. (2000). *Causality: Models, Reasoning, and Inference*. Cambridge: Cambridge University Press.
- Pesaran, H. M. and Y. Shin (1998). Generalized Impulse Response Analysis in Linear Multivariate Models. *Economics Letters* 58(1), 17–29.
- Scida, D. (2016). Structural VAR and financial networks: A minimum distance approach to spatial modeling. *Unpublished Manuscript*.
- Spirtes, P., C. Glymour, and R. Scheines (2001). *Causation, Prediction, and Search* (2nd ed.). Cambridge, MA: MIT Press.
- Swanson, N. R. and C. W. Granger (1997). Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions. *Journal of the American Statistical Association* 92(437), 357–367.



## A Estimated matrices

$$B_0 = \begin{bmatrix} \text{AUD} & \text{CAD} & \text{CHF} & \text{EUR} & \text{NOK} & \text{NZD} & \text{SEK} & \text{USD} & \text{JPY} \\ \mathbf{1.0000} & \mathbf{-0.6059} & 0.0000 & 0.0000 & \mathbf{-0.2865} & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & \mathbf{1.0000} & 0.0000 & 0.0000 & \mathbf{-0.3645} & 0.0000 & 0.0000 & \mathbf{-0.4582} & 0.0000 \\ 0.0000 & 0.0000 & \mathbf{1.0000} & \mathbf{-0.6591} & 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{-0.2328} \\ 0.0000 & 0.0000 & 0.0000 & \mathbf{1.0000} & \mathbf{-0.1597} & 0.0000 & \mathbf{-0.4512} & \mathbf{-0.0956} & \mathbf{-0.1258} \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{1.0000} & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ \mathbf{-0.7157} & \mathbf{-0.0903} & \mathbf{-0.0692} & 0.0000 & 0.0000 & \mathbf{1.0000} & 0.0000 & 0.0000 & \mathbf{-0.0542} \\ \mathbf{-0.1559} & 0.0000 & 0.0000 & 0.0000 & \mathbf{-0.6207} & 0.0000 & \mathbf{1.0000} & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{1.0000} & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{-0.9102} & \mathbf{1.0000} \end{bmatrix} \begin{matrix} \text{AUD} \\ \text{CAD} \\ \text{CHF} \\ \text{EUR} \\ \text{NOK} \\ \text{NZD} \\ \text{SEK} \\ \text{USD} \\ \text{JPY} \end{matrix},$$

which can be inverted and scaled by the standard deviations of the residuals to

$$\begin{bmatrix} \text{AUD} & \text{CAD} & \text{CHF} & \text{EUR} & \text{NOK} & \text{NZD} & \text{SEK} & \text{USD} & \text{JPY} \\ \mathbf{0.0047} & \mathbf{0.0026} & 0.0000 & 0.0000 & \mathbf{0.0032} & 0.0000 & 0.0000 & \mathbf{0.0015} & 0.0000 \\ 0.0000 & \mathbf{0.0044} & 0.0000 & 0.0000 & \mathbf{0.0023} & 0.0000 & 0.0000 & \mathbf{0.0026} & 0.0000 \\ \mathbf{0.0002} & \mathbf{0.0001} & \mathbf{0.0053} & \mathbf{0.0020} & \mathbf{0.0020} & 0.0000 & \mathbf{0.0012} & \mathbf{0.0020} & \mathbf{0.0019} \\ \mathbf{0.0003} & \mathbf{0.0002} & 0.0000 & \mathbf{0.0031} & \mathbf{0.0030} & 0.0000 & \mathbf{0.0018} & \mathbf{0.0013} & \mathbf{0.0008} \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{0.0062} & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ \mathbf{0.0034} & \mathbf{0.0023} & \mathbf{0.0004} & \mathbf{0.0001} & \mathbf{0.0026} & \mathbf{0.0045} & \mathbf{0.0001} & \mathbf{0.0018} & \mathbf{0.0005} \\ \mathbf{0.0007} & \mathbf{0.0004} & 0.0000 & 0.0000 & \mathbf{0.0044} & 0.0000 & \mathbf{0.0041} & \mathbf{0.0002} & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{0.0056} & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & \mathbf{0.0051} & \mathbf{0.0060} \end{bmatrix} \begin{matrix} \text{AUD} \\ \text{CAD} \\ \text{CHF} \\ \text{EUR} \\ \text{NOK} \\ \text{NZD} \\ \text{SEK} \\ \text{USD} \\ \text{JPY} \end{matrix}$$

## B Maximum and minimum connectedness

Table 10: Maximum connectedness considering all permutations of recursive orderings

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY
AUD	99.8	44.0	9.9	18.9	28.4	58.1	26.0	11.8	9.5
CAD	43.8	99.1	11.0	17.7	24.7	31.9	20.2	28.4	12.7
CHF	9.9	11.0	99.5	36.5	15.9	11.2	18.8	15.4	23.0
EUR	18.8	17.7	36.5	99.3	40.6	18.7	55.7	18.3	20.2
NOK	28.5	24.5	15.8	40.3	98.6	22.6	52.5	5.6	5.2
NZD	58.1	32.0	11.2	18.8	22.6	99.7	20.7	9.5	10.8
SEK	25.9	20.1	18.9	55.6	52.7	20.6	99.0	9.0	8.5
USD	12.0	28.4	15.4	18.2	5.7	9.6	9.1	99.4	41.1
JPY	9.4	12.7	23.0	19.9	4.9	10.7	8.1	41.2	99.6

*Notes:* The table shows (10 periods ahead) forecast error variance decomposition values of SVAR models which are identified by a Cholesky decomposition. The entries of the matrix show the maximum entries which can be achieved with a Cholesky decomposition approach considering all possible orderings.

Table 11: Minimum connectedness considering all permutations of recursive orderings

	AUD	CAD	CHF	EUR	NOK	NZD	SEK	USD	JPY
AUD	32.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
CAD	0.0	42.3	0.0	0.0	0.1	0.0	0.0	0.0	0.1
CHF	0.0	0.0	57.1	0.0	0.0	0.0	0.1	0.0	0.0
EUR	0.0	0.0	0.0	30.7	0.0	0.0	0.0	0.0	0.2
NOK	0.3	0.0	0.0	0.0	38.9	0.0	0.0	0.0	0.2
NZD	0.0	0.0	0.0	0.0	0.0	39.4	0.0	0.0	0.1
SEK	0.0	0.0	0.0	0.0	0.0	0.0	32.1	0.0	0.3
USD	0.0	0.0	0.0	0.0	0.1	0.0	0.0	45.6	0.0
JPY	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	50.3

*Notes:* The table shows (10 periods ahead) forecast error variance decomposition values of SVAR models which are identified by a Cholesky decomposition. The entries of the matrix show the minimum entries which can be achieved with a Cholesky decomposition approach considering all possible orderings.

## C Robustness analysis

Table 12: Connectedness: Cholesky (ordering according to PC algorithm)

	USD	JPY	NOK	CAD	AUD	SEK	EUR	CHF	NZD	IN
USD	99.4	0.0	0.2	0.1	0.2	0.0	0.1	0.0	0.0	0.6
JPY	41.2	58.4	0.3	0.0	0.0	0.1	0.0	0.0	0.0	41.6
NOK	5.6	1.2	92.5	0.1	0.4	0.2	0.0	0.0	0.0	7.5
CAD	28.4	0.1	14.6	56.5	0.1	0.0	0.1	0.1	0.0	43.5
AUD	11.8	1.3	20.9	16.2	49.6	0.0	0.0	0.1	0.0	50.4
SEK	9.0	1.9	44.4	0.3	1.1	43.2	0.0	0.0	0.0	56.8
EUR	18.3	5.2	28.6	0.2	0.1	12.3	35.1	0.1	0.0	64.9
CHF	15.4	8.9	8.5	0.0	0.0	2.0	8.1	57.2	0.0	42.8
NZD	9.5	3.0	16.1	10.6	21.0	0.0	0.3	0.1	39.4	60.6
OUT	139.2	21.6	133.6	27.5	22.9	14.7	8.6	0.4	0.1	$C^{10}=41.0$

*Notes:* The table shows the (10 periods ahead) forecast error variance decomposition of the SVAR model which is identified by a Cholesky decomposition determined by the PC algorithm. The column “IN” corresponds to the row sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by (international) shocks). The column “OUT” corresponds to the column sum of the non-diagonal variance shares (i.e. the total share of variance which is explained by the corresponding column variable).  $C^{10}$  refers to the measure of total connectedness (see section 2.2).