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Article

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Measuring the Dynamics of Czech Republic Output Connectedness with the Global Economy

*Jonathan E. OGBUABOR**

Abstract

Czech Republic is a Central European market economy that emerged following the peaceful dissolution of the former Czechoslovakia. It is an economy driven mainly by manufacturing, services and innovation, with a dynamic external sector. Its dependence on exports makes output growth vulnerable to shocks or contractions in external demand, thereby necessitating this study, which examines the dynamics of its output connectedness with the global economy from 1990Q1 to 2016Q4 using the Diebold and Yilmaz (2009) network approach. The results indicate that Czech's output connectedness with the rest of the world is quite sizeable, with a total connectedness index of 82% over the above period. The results also show that EU member countries, especially Germany, exert the most dominant output influence on the Czech economy and therefore have the potential to spread output shocks to it, while Poland and Slovakia are most susceptible to output shocks emanating from the Czech economy. Furthermore, the role of the USA in the Czech economy increased remarkably after the 2012/2013 economic recession in the Czech Republic. These results suggest that the Czech economy is considerably open, deeply interconnected and sensitive to international output shocks such that policymakers in the Czech Republic must be constantly conscious of headwinds originating from the aforementioned sources.

Keywords: *connectedness, network approach, vector autoregressive (VAR) model, economic recession, Czech Republic*

JEL Classification: F43, C53, C32, E32, N14

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Introduction

Following the seminal work of Diebold and Yilmaz (2009), which advanced a simple but intuitive network approach for measuring and evaluating financial and macroeconomic connectedness of entities across the globe, a large literature has considered the complex issue of the connectedness structure of the global economy. While some studies focused on either output or financial connectedness, others considered both output and financial connectedness. In their paper, Diebold and Yilmaz (2009) analyzed the connectedness of 19 global equity markets over the period 1992M1 – 2007M11 and found significant evidence of divergent behavior in the dynamics of return spillovers and return volatility spillovers such that while return spillovers displayed a gently increasing trend but no bursts, return volatility spillovers displayed no trend but clear bursts. Other studies that have examined financial connectedness using this framework include: Diebold and Yilmaz (2016), which investigated the connectedness of 18 European and 17 U.S. financial institutions; Guimarães-Filho and Hong (2016), which examined the connectedness of Asian equity markets within the region and vis-à-vis other major global markets; Echevarria-Icaza and Rivero (2016), which investigated the connectedness of European Economic and Monetary Union (EMU) sovereign and bank Credit Default Swap (CDS); and Bostanci and Yılmaz (2015), which studied the network structure of global sovereign credit risk; Yilmaz (2014), which studied the connectedness of major bank stocks in the U.S. and the European Union (EU) member countries.[1]

In the case of output connectedness, Diebold and Yilmaz (2015) studied the business cycle connectedness of six advanced economies (i.e. G-7 less Canada) using industrial production data for 1958M1 – 2011M12 and found that business cycle connectedness fluctuates substantially over time such that the global output connectedness is not only sizable but also time-varying over the business cycle, and that the United States (U.S.) and Japan are the main net transmitters of output shocks to other countries, while Germany is the major net receiver of shocks. Furthermore, Ogbuabor et al. (2018) investigated the dynamics of output connectedness of Asian Pacific Economic Cooperation (APEC) economies using time-varying, region-specific, generalised connectedness measures constructed on the basis of the Diebold and Yilmaz (2009) network framework, and find that the connectedness of APEC economies with the rest of the world is also substantial,

[1] A review of the literature shows that the following studies also applied or extended the Diebold and Yilmaz (2009) framework in their study of financial connectedness and international transmission of financial contagion: Félix, Fernandez-Perez and Sosvilla-Rivero (2017); Demirer et al. (2017); Rodríguez and Sosvilla-Rivero (2016); Gätjen and Schienle (2015); Barunik and Krehlik (2016); Erkol (2015); Diebold and Yilmaz (2012); and the references therein.

with the USA, China, and Korea dominating APEC's real activities. However, studies that examined both real and financial connectedness include Ogbuabor et al. (2016); Greenwood-Nimmo, Nguyen and Shin (2015); and Park and Shin (2014). Ogbuabor et al. (2016) investigated the real and financial connectedness of selected African economies with the global economy and find that the U.S., EU and Canada dominate Africa's equity markets, while China, India and Japan dominate Africa's real activities, with the global financial crisis increasing the connectedness measures above their pre-crisis levels. Greenwood-Nimmo, Nguyen and Shin (2015) extended the Diebold and Yilmaz (2009) framework to more complex multi-country multivariate situations, thereby addressing the 'dual curse of dimensionality' problem and find that the U.S., the Eurozone and crude oil market exert dominant influence in the global economy, while China and Brazil also play non-negligible roles. Park and Shin (2014) evaluated the connectedness of the Korean economy with the global economy and find that the U.S., Europe, China, and the Association of Southeast Asian Nations (ASEAN) group (comprising Singapore, Thailand, Malaysia, Philippines and Indonesia) exert dominant influence on the Korean economy.

The foregoing paragraphs indicate that studies evaluating macroeconomic connectedness among entities in the global economy using the network approach of Diebold and Yilmaz (2009) have mainly focused on financial connectedness among the highly industrialized economies such as the U.S., Canada, EU, China, Japan, among others; while those that focused on output connectedness appear scanty. In fact, none of the existing studies has investigated either the output or financial connectedness of Czech Republic with the rest of the world. It is the goal of this paper to fill this gap in the literature.

Specifically, this paper: (i) estimates the size of output connectedness of Czech economy with the global economy and how it changed following the 2012/2013 recession episode; (ii) determines the economies that exert the most dominant output influence on the Czech economy and therefore have the potential to spread output shocks to it; (iii) determines the economies that are most vulnerable to output shocks emanating from the Czech economy; and (iv) determines if there has been a shift in terms of dominant output shock transmitters to the Czech economy and main output shock receivers from the Czech economy after the recession.

Czech Republic is a developed, high-income export-oriented Central European market economy that emerged following the peaceful dissolution of the former Czechoslovakia, with a 2018 population of 10.63 million residents (Worldometers, 2018; IMF, 2017). It is an economy driven mainly by manufacturing, services and innovation, with a dynamic external sector. With one of the highest gross domestic product (GDP) growth rates and lowest unemployment levels in the EU, its GDP grew from 192.9 billion U.S. dollars (USD) in 2016 to 209.65 billion USD in 2017 (Central Intelligence Agency, 2018; IMF, 2017; OECD, 2017a). Its exports mainly consist of automobiles, and industrial and electrical machineries, with other EU member countries accounting for over 84% of total exports. Also, its major import products are automobile and machinery components, chemicals, raw materials and fuels, with other EU member countries, China and South Korea being the key import sources. In fact, with a total trade amounting to 301.56 billion USD in 2016, it is easily seen that Czech Republic is an open and dynamic economy that is strongly integrated into global supply chains (World Integrated Trade Solutions, 2018; OECD, 2017b; UN Comtrade, 2016).

However, its dependence on exports makes output growth vulnerable to shocks or contractions in external demand, thereby necessitating this study, which evaluates the output connectedness of Czech Republic with the global economy. For instance, after gradually recovering from a steep recession in 2009 resulting from the 2007 – 2008 Global Financial Crisis (GFC), the Czech economy again fell into recession in 2012 and 2013 due mainly to fall in demand within the EU and the government's austerity measures following the GFC. This 18-month recession that ended in 2013Q2 is particularly of interest in this study because it is the longest economic recession in the history of the Czech Republic (Central Intelligence Agency, 2018; Indexmundi, 2018). In the rest of this paper and except otherwise stated, the term recession is used to refer to this particular economic recession.

The remainder of this paper proceeds thus: Section 1 presents the data and methodology; Section 2 presents the empirical results; while Section 3 concludes and discusses policy implications.

1. Data and Methodology

The full sample data for this study consists of the log of real GDP for the period 1990Q1 – 2016Q4, while the reference (or sub) sample covers the period 1990Q1 – 2011Q4. For the full sample, the choice of period is based on data availability; but for the reference sample, the choice of period is based on the need to capture pre-recession results. Apart from the Czech economy, other economies included in this study are Austria, China, France, Germany, Italy, Japan, Korea, Poland, Slovakia, United Kingdom (UK) and United States of America (USA). These economies account for the larger chunk of Czech Republic's bilateral trade. The entire data were taken from the World Development Indicators' (WDI) GDP at constant

2010 U.S. dollars (Indicator Code = NY.GDP.MKTP.KD).[2] To ensure that there are enough observations, the data were converted from annual to quarterly using Eview's quadratic match average option. Also, to reduce noise and ensure uniform scaling, the entire data were converted into indices (2010Y = 100) and logged prior to estimation. The time series plots of the data are presented in Appendix 1 based on the log transformation of the data3. The graphs show close co-movement, signifying that the series track themselves closely. Most of the series witnessed slight downward movement around 2009Q1, corresponding with the impact of the GFC. The timing of this downward movement suggests that the propagation of the crisis through the real economy was gradual rather than rapid and forceful.

1.1. The Choice of Diebold and Yilmaz (2009) Framework

A number of methodologies have been employed in the study of macroeconomic linkages among entities in the global economy. For instance, cross-country correlations-based measures have been used to characterize macroeconomic connectedness (Kehoe, Backus and Kydland, 1995; Kose, Prasad and Terrones, 2003; Bollerslev, 1990; Engle, Ito and Lin, 1990; Mantegna, 1999; Tumminello et al., 2005; Taylor, 2007; Gray and Malone, 2008; Engle, 2009; Engle and Kelly, 2012). The pitfalls of this approach are twofold, namely: correlation is simply a pairwise measure of association and it is non-directional. This means that correlation-based approach cannot handle such questions as "how connected is Czech Republic to all other economies across the globe?" Unlike the correlation-based measures of connectedness, the connectedness measures of Diebold and Yilmaz (2009) are non-pairwise, yet directional. Granger Causality measures have also been used characterize networks so that the macroeconomic connectedness among entities in the global economy can be described and understood (Caraiani, 2013; Hiemstra and Jones, 1994; Dahlhans and Eichler, 2003; Shojaie and Michailidis, 2010; Billio et al., 2012). The main weakness of the Granger Causality approach is that it captures only pairwise relations and may not be useful in answering important questions like "What is the size of the output connectedness of Czech Republic with the global economy?"[4]

[2] The methodology used by the World Bank in compiling the data indicates that dollar figures for GDP were converted from domestic currencies using 2010 official exchange rates. However, for a few countries where the official exchange rate did not reflect the rate effectively applied to actual foreign exchange transactions, an alternative conversion factor was used.

[3] Non-stationarity of the output data is dealt with in Section 2.

[4] Other techniques have also been used in the literature for the study of macroeconomic connectedness. Ogbuabor et al. (2018) provides an overview of such alternative methodologies such as the dynamic latent factor models of Kose, Otrok and Whiteman (2008) and Canova, Ciccarelli and Ortega (2007), the CoVaR approach of Adrian and Brunnermeier (2011), and the marginal expected shortfall (MES) approach of Acharya et al. (2017) and Brownlees and Engle (2012).

Furthermore, as noted by Diebold and Yilmaz (2016), these alternative methodologies generally dwell exclusively on testing rather than measurement and estimation of macroeconomic connectedness, which are the key issues in this paper. This study therefore follows the network approach of Diebold and Yilmaz (2009) based on its ability to transparently use the size and direction of shocks to build both directional and non-directional connectedness measures over a given forecast horizon.

As shown in the introductory Section above, several studies have applied this approach with great success. According to Ogbuabor et al. (2016), such studies have four common features, namely: (i) they are generally based on connectedness measures distilled from forecast error variance decompositions (FEVDs) of an approximating vector autoregressive (VAR) model; (ii) they measure the direction and strength of linkages among entities in the system; (iii) they can identify systemically important entities in the system; and (iv) they can study the dynamic nature of shock propagation among entities in the system. In what follows, the underlying VAR model for this study and the construction of the generalized connectedness measures (GCMs) are presented to guide the ensuing analysis.

1.2. Model Specification: The Vector Autoregression (VAR) Model

The goal of this study is to evaluate the output connectedness of Czech Republic with the global economy. Let $\boldsymbol{Z}_{t}$ be the log of real GDP for all the countries selected for this study so that $\boldsymbol{Z}_{jt}$ stands for the logged real GDP of the $\boldsymbol{j}$-th country in the system, with $\boldsymbol{j} = \mathbf{1},\ \mathbf{2},\ \ldots, \boldsymbol{N}$ and $\boldsymbol{N}$ is the number of countries selected for the study. Following Diebold and Yilmaz (2009), the connectedness measures for this study are based on the normalized generalized forecast error variance decompositions (NGFEVDs) of an underlying $\boldsymbol{p}$-th order VAR model for the $\boldsymbol{N}\ \boldsymbol{x}\mathbf{1}$ vector of endogenous variables $\boldsymbol{Z}_{t}$. The VAR($\boldsymbol{p}$) model is specified as follows:

$$\boldsymbol{Z}_{t} = \alpha_z + \sum_{j=1}^{p} \Phi_j \boldsymbol{Z}_{t-j} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{\alpha}$ is $\boldsymbol{N}\ \boldsymbol{x}\ \mathbf{1}$ vector of intercepts; Φ_j is $\boldsymbol{N} \times \boldsymbol{N}$ coefficient matrix; $\boldsymbol{p}$ is the lag order; and the residuals $\boldsymbol{\varepsilon}_{it} \sim \boldsymbol{iid}\left(\mathbf{0}, \Sigma_{\varepsilon,ii}\right)$ so that $\boldsymbol{\varepsilon}_t \sim \left(\mathbf{0}, \Sigma_{\varepsilon}\right)$, where Σ_{ε} is positive definite covariance matrix. The optimal VAR lag order selected by Schwarz Information Criterion (SIC) for this study is one. Using the Wold's Representation Theorem, the model in equation (1) is expressed as an infinite order vector moving average representation given by:

$$\boldsymbol{Z}_{\boldsymbol{t}} = \varepsilon_t + \boldsymbol{\Theta}_1\varepsilon_{t-1} + \boldsymbol{\Theta}_2\varepsilon_{t-2} + \ldots = \sum_{j=0}^{\infty} \boldsymbol{\Theta}_j \boldsymbol{\varepsilon}_{t-j} \tag{2}$$

where $\boldsymbol{\Theta_0} = \boldsymbol{I}_N$, $\boldsymbol{\Theta}_j = \Phi^j$, $j = 1, 2, \ldots$, and $\boldsymbol{I}_N$ stands for an $\boldsymbol{N} \times \boldsymbol{N}$ identity matrix in which all the principal diagonal elements are ones and all other elements are zeros.

The Diebold and Yilmaz (2009) approach requires that after estimating the underlying VAR model, the forecast error variance decompositions (FEVDs) are then generated and used to build connectedness measures. In this study, the interest is in the shocks to the disturbances, $\boldsymbol{\varepsilon_{jt}}$ in the country-specific equations. Hence, following Pesaran and Shin (1998), Diebold and Yilmaz (2016) and Greenwood-Nimmo, Nguyen and Shin (2015), this study adopts the order-invariant generalized forecast error variance decompositions (GFEVDs) defined as:

$$\boldsymbol{GFEVD}\left(\boldsymbol{Z}_{it};\ \varepsilon_{jt},\ \boldsymbol{H}\right) = \boldsymbol{d}_{ij}^{gH} = \frac{\boldsymbol{\sigma}_{\varepsilon,jj}^{-1} \sum_{h=0}^{H-1} \left(\boldsymbol{e}_i' \boldsymbol{\Theta}_h \boldsymbol{\Sigma}_\varepsilon \boldsymbol{e}_j\right)^2}{\sum_{h=0}^{H-1} \left(\boldsymbol{e}_i' \boldsymbol{\Theta}_h \boldsymbol{\Sigma}_\varepsilon \boldsymbol{\Theta}_h' \boldsymbol{e}_i\right)} \tag{3}$$

where $i, j = 1, \ldots, N$; $H = 1, 2, \ldots$ is the forecast horizon; $e_i\left(e_j\right)$ is $N\,x\,1$ selection vector whose *i*-th element (*j*-th element) is unity with zeros elsewhere; Θ_h is the coefficient matrix multiplying the *h*-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR; $\sum_{\boldsymbol{\varepsilon}}$ is the covariance matrix of the shock vector in the non-orthogonalized VAR; and $\boldsymbol{\sigma_{\varepsilon,jj}}$ is the *j*-th diagonal element of $\sum_{\boldsymbol{\varepsilon}}$ (i.e. the standard deviation of ε_j). It must be stressed that the choice of GFEVDs for this study rather than the orthogonalized forecast error variance decompositions (OFEVDs) of Diebold and Yilmaz (2009) is particularly based on the fact that the OFEVDs depend on the reordering of the variables in the system such that once the order of variables in the VAR is reshuffled, a different outcome results. This choice is consistent with Greenwood-Nimmo, Nguyen and Shin (2015) and Diebold and Yilmaz (2016).

Diebold and Yilmaz (2014; 2015; 2016) explain that shocks are rarely orthogonal in the GFEVD environment so that sums of forecast error variance contributions are not necessarily unity, that is, row sums of the generalized variance decomposition matrix, D^{gH} are not necessarily unity. This renders the interpretation of the GFEVDs complicated. Thus, to restore a percentage interpretation of the GFEVDs, this study follows Diebold and Yilmaz (2014) to define the normalized GFEVDs (NGFEVDs) given by:[5]

[5] In what follows and without loss of generality, the superscript *H* is dropped whenever it is not needed for clarity so that D^{gH} and d_{ij}^{gH} are simply written as D^g and d_{ij}^g respectively.

$$D^g = \left[d_{ij}^g \right], \text{ where } d_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^{N} d_{ij}^g}, \; d_{ij}^g = \boldsymbol{GFEVD}\left(\boldsymbol{Z}_{\boldsymbol{it}};\ \boldsymbol{\varepsilon}_{\boldsymbol{jt}},\ \boldsymbol{H} \right) \quad (4)$$

By construction, $\sum_{j=1}^{N} d_{ij}^g = \mathbf{1}$ and $\sum_{i,j=1}^{N} d_{ij}^g = N$, so that the total sum of the generalized forecast error variance share of each variable is normalized to 100%.

1.3. The Generalized Connectedness Measures (GCMS)

This sub-section defines the various connectedness measures that are relevant for the ensuing analysis. The intuition behind this framework is fairly simple. Variance decomposition permits the splitting of the forecast error variances of each variable in the VAR system into parts attributable to the various system shocks. By so doing, it becomes easy to answer the question: What fraction of the h-step-ahead error variance in forecasting $\boldsymbol{Z}_{\mathbf{1}\boldsymbol{t}}$ is due to shocks to $\boldsymbol{Z}_{\mathbf{1}\boldsymbol{t}}$? Shocks to $\boldsymbol{Z}_{\mathbf{2}\boldsymbol{t}}$? Similarly, what fraction of the h-step-ahead error variance in forecasting $\boldsymbol{Z}_{\mathbf{2}\boldsymbol{t}}$ is due to shocks to $\boldsymbol{Z}_{\mathbf{1}\boldsymbol{t}}$? Shocks to $\boldsymbol{Z}_{\mathbf{2}\boldsymbol{t}}$? And in general, what fraction of the h-step-ahead error variance in forecasting $\boldsymbol{Z}_{\boldsymbol{jt}}$ is due to shocks to $\boldsymbol{Z}_{\boldsymbol{it}}$, $\boldsymbol{i} = \mathbf{1},\ \mathbf{2},\ \ldots,\ \boldsymbol{N}$. Thus, the approach marries VAR variance decomposition theory and network topology theory by recognizing that variance decompositions of VARs form networks and also characterizing connectedness in those variance decomposition networks. This in turn characterizes connectedness of the variables in the VAR system. This is the intuition behind this framework, which is fully exploited in this study. Diebold and Yilmaz (2015) authoritatively documents this framework and its relation to network theory.

Table 1

Connectedness Table Schematic

Variables	$\boldsymbol{Z}_{\mathbf{1}}$	$\boldsymbol{Z}_{\mathbf{2}}$	$\cdots$	$\boldsymbol{Z}_{\boldsymbol{N}}$	**From Others (** $\boldsymbol{F}_{\boldsymbol{j}}$ **)**
$\boldsymbol{Z}_{\mathbf{1}}$	$d_{\mathbf{11}}$	$d_{\mathbf{12}}$	$\cdots$	d_{1N}	$\sum_{j=1}^{N} d_{1j},\ j \neq 1$
$\boldsymbol{Z}_{\mathbf{2}}$	$d_{\mathbf{21}}$	$d_{\mathbf{22}}$	$\cdots$	d_{2N}	$\sum_{j=1}^{N} d_{2j},\ j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
$\boldsymbol{Z}_{\boldsymbol{N}}$	$d_{N\mathbf{1}}$	d_{N2}	$\cdots$	d_{NN}	$\sum_{j=1}^{N} d_{Nj},\ j \neq N$
To Others ($\boldsymbol{T}_{\boldsymbol{j}}$ **)**	$\sum_{i=1}^{N} d_{i1}$ $i \neq 1$	$\sum_{i=1}^{N} d_{i2}$ $i \neq 2$	$\cdots$	$\sum_{i=1}^{N} d_{iN}$ $i \neq N$	$\frac{1}{N} \sum_{i,j=1}^{N} d_{ij},\ i \neq j$

Note: For simplicity, each time series variable in this table $\boldsymbol{Z}_{\boldsymbol{jt}}$ is written as $\boldsymbol{Z}_{\boldsymbol{j}}$, $\boldsymbol{j} = \mathbf{1},\ \mathbf{2},\ \ldots,\ \boldsymbol{N}$.

Source: Adapted from Diebold and Yilmaz (2014).

To construct the GCMs for this study, let us denote the H-step ahead NGFEVDs for the $N\ x\ 1$ vector of endogenous variables Z_t obtained from equation (4) by d_{ij}. By cross-tabulating d_{ij}, the connectedness table shown in Table 1 is formed, which is analogous to the connectedness matrix in Greenwood-Nimmo, Nguyen and Shin (2015). The sum of each row in Table 1 is normalized to 100% in line with equation (4). This table is now used to define the various GCMs and their relationships. The diagonal entries in Table 1 measure own variance shares (or *own-effect*), while the off-diagonal entries measure variance shares arising from shocks to other variables in the system and are therefore referred to as pairwise directional connectedness. Accordingly, the *own-effect* (H_j), also known as the heatwave, is defined as:

$$H_j = d_{ij} \tag{5}$$

The use of the term "heatwave" follows the nomenclature in Diebold and Yilmaz (2009), which defined a spillover index that measures the relative importance of spillovers between variables in the system as a percentage of the systemwide forecast error variance at a given horizon. Thus, heatwave here measures the own variance share, that is, the contribution of the shock to the i-th variable by the variable itself.

The total cross-variable variance share (F_j) captures the spillovers from all other variables to Z_{jt} as fractions of the H-step-ahead error variance in the forecasts of Z_{jt} resulting from Z_{it}, where $i = 1,\ 2,\ \ldots,\ N$ and $i \neq j$. This measures the total directional connectedness from other variables (countries) in the system (i.e. the *from-effect*) to Z_{jt}. This means that the *from-effect* can be used to capture the role each individual economy in the system plays in the Czech economy, and it is computed in this study by aggregating the spillovers from a given economy in the system to Czech economy across all horizons. Hence, the economy contributing the highest of such aggregate spillover is deemed to play a dominant role in the Czech economy. This study therefore defines F_j as:

$$F_j = \sum_{i=1, i \neq j}^{N} d_{ij} \tag{6}$$

By construction, $H_j + F_j = 1 \quad \forall j$. An important innovation in this study is the construction of *own-EU-ROW effect*, which is used to assess how sensitive Czech economy is to domestic conditions and to conditions in other EU member economies within the VAR system as well as conditions in the rest of the world.

The rest of the world (ROW) includes all non-EU member economies, namely: China, Japan, Korea and USA. Let the Czech economy be the j^{th} economy in the system and let Q_j^{own}, Q_j^{EU} and Q_j^{ROW} denote the *own-effect*, *EU-effect* and *ROW-effect* respectively, then:

$$Q_j^{own} = \frac{F_j^{own}}{F_j^{own} + F_j^{EU} + F_j^{ROW}}; \; Q_j^{EU} = \frac{F_j^{EU}}{F_j^{own} + F_j^{EU} + F_j^{ROW}} \quad \text{and}$$

$$Q_j^{ROW} = \frac{F_j^{ROW}}{F_j^{own} + F_j^{EU} + F_j^{ROW}} \tag{7}$$

This study defines the total spillover or total contributions of Z_{jt} to all other variables (denoted by T_j) as:

$$T_j = \sum_{i=1, i \neq j}^{N} d_{ij} \tag{8}$$

By construction, T_j measures the total directional connectedness from Z_{jt} to other variables in the system (i.e. the *to-effect*). In other words, the *to-effect* measures the directional connectedness from a given economy (for instance, the Czech economy) to other economies in the system, thereby showing the impact or influence of that particular economy on other economies in the VAR system. The most aggregative (non-directional) connectedness measure in this study is known as the *total connectedness index* (***C***) or *total-effects*, and it is defined as:

$$C = \frac{1}{N} \sum_{j=1}^{N} F_j = \frac{1}{N} \sum_{j=1}^{N} T_j \tag{9}$$

This measure captures the grand total of the off-diagonal elements in Table 1, that is, the sum of the “From Others” column or “To Others” row. There is only one total connectedness measure analogous to total global imports or total global exports, since the two are identical.

2. Findings and Discussions

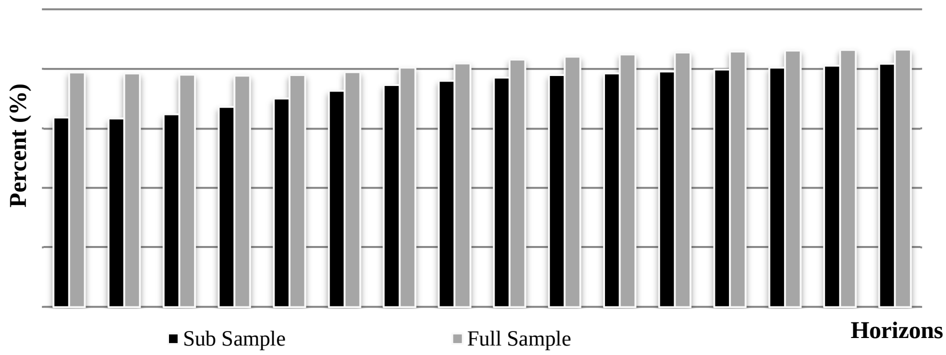
This empirical analysis began by examining the time series properties of the data. Both the Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests showed that the series are overwhelming I(1) for majority of the countries. However, the test for long-run or equilibrium relationship using the Johansen System Cointegration test showed that both the Trace and Maximum Eigenvalue statistics returned full rank, indicating that the data are not cointegrated. Therefore, a VAR in first differences was estimated rather than a vector error correction model (VECM). The underlying model in equation (1) was estimated separately using the reference sample and the full sample in order to obtain the results before and after the recession. Thereafter, the GCMs were computed for all forecasting horizons, $H = 1, 2, \ldots, 16$, while the average values of the GCMs over all the horizons are reported, since Diebold and Yilmaz (2016) had shown that the GCMs follow similar patterns regardless of the choice of window lengths and forecast horizons. Here, the maximum forecast horizon is set at 16 in order to capture the long-run results better.

2.1. The Total Connectedness Index

The plots of the total connectedness index across all horizons for both the sub sample (i.e. before the 2012/2013 recession episode) and the full sample (i.e. after the recession) are shown in Figure 1.

Figure 1

Total Connectedness Index



Notes: The *Total Connectedness Index* reported here is the most aggregated non-directional connectedness index computed as average for all horizons following equation (9). The full sample indices (i.e. post-recession) are generally higher than those of the sub sample (i.e. pre-recession), suggesting that the connectedness of Czech economy increased after the crisis. Overall, the index shows that Czech economy is more connected in the long-run (i.e. towards horizon 16) than in the short-run (i.e. around Horizon 1).

Source: Author's computations.

This figure shows how the most aggregated generalized connectedness measure based on equation (9) evolved from the short-run (i.e. from horizon 1) through the long-run (i.e. until horizon 16). We find that the index witnessed an upward movement after the recession, such that the reported values are higher at each horizon for the full sample than the sub sample. In other words, the output connectedness of Czech economy with the global economy increased after the

2012/2013 recession episode. This finding is consistent with Diebold and Yilmaz (2016), which showed that after all U.S. recessions, the connectedness index recorded significant upward movements. It is also consistent with Ogbuabor et al. (2016), which found that the GFC increased the connectedness measures above their pre-crisis levels. We also find that the total connectedness index is higher in the long-run (with the highest values of 82% and 87% at horizon 16 for the sub sample and the full sample, respectively) than in the short-run (with the overall lowest value of 64% occurring in the sub sample at horizons 1 and 2). This shows that in the long-run, Czech economy becomes more interconnected with the global economy as the business cycles become more synchronized. This finding is particularly consistent with the trend of global connectedness reported by Greenwood--Nimmo, Nguyen and Shin (2015), Diebold and Yilmaz (2016) and Ogbuabor et al. (2018) that the ongoing globalization process is engendering more significant comovement in industrial production fluctuations. In sum, we find that the total connectedness index recorded average values of 74% and 82% across all horizons in the pre-recession and post-recession periods, respectively. This shows that the connectedness of Czech economy with the global economy is quite substantial.

2.2. *From-effect* and *Own-EU-ROW Effect* Connectedness of Czech Economy

In Table 2, we report the total directional connectedness from all the economies in the system to the Czech economy following equation (6). This is to enable us determine the economies that exert the most dominant output influence on the Czech economy and therefore have the potential to spread output shocks to it. We include the heatwave (or *own-effect*) of equation (5) in Table 2 so that it sums up to 100%.

Table 2

The *From-effect* Connectedness of Czech Economy (%)

Country	**Sub Sample (1990Q1 – 2011Q4)**	**Full Sample (1990Q1 – 2016Q4)**
USA	3.7303	9.4866
Austria	6.5768	9.7559
China	1.5339	0.9124
Czech	37.7215	15.9711
France	7.4801	9.4526
Germany	11.0105	11.1278
Italy	7.0914	11.2216
Japan	6.3882	9.8248
Korea	8.2850	1.9094
Poland	3.5306	4.0052
Slovakia	3.0842	8.8665
UK	3.5675	7.4661
Total	**100**	**100**

Notes: This table captures the total directional connectedness from other economies in the system to the Czech economy following equation (6). Notice that the total directional connectedness from Czech economy to itself is the *own-effect* or heatwave following equation (5).

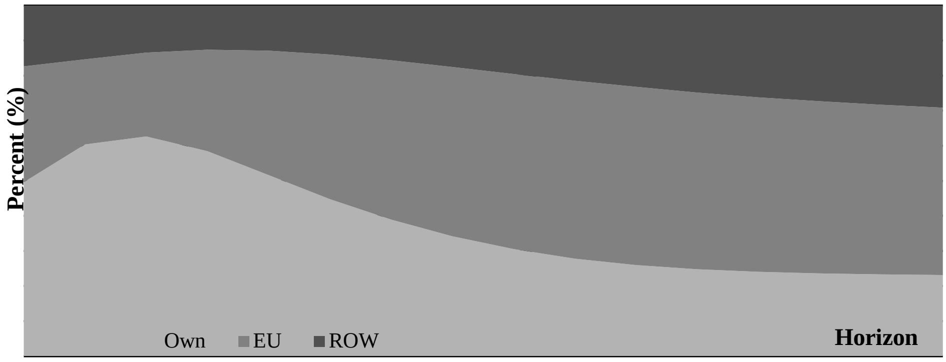
Source: Author's computations.

The results in Table 2 indicate that Germany is the highest contributor to Czech economy's GFEVD, especially before the recession. Its contribution of 11% in the pre-recession and post-recession periods indicates that it is exerting dominant influence on Czech economy's real activities and hence has the greatest potential to spread output shocks to it. We find that in the post-recession period, Italy (11%), Austria (10%), Japan (10%), USA (9%), France (9%), Slovakia (9%) and UK (7%) also play important roles in Czech economy's real activities. Furthermore, apart from Germany, other economies that dominated Czech's real activities in the pre-recession period include Korea (8%), France (7%), Italy (7%), Austria (7%) and Japan (6%). These findings are consistent with the bilateral trade structure of the Czech economy, which shows that Germany is Czech's topmost trade partner and that Czech's bilateral trade is dominated by other EU member countries, especially those that share borders with it, including Germany, Slovakia, Austria and Poland. Indeed, we find that the role of Poland cannot be called negligible as it makes a contribution of 4% in both the pre- and post--recession periods. We find that the role of the USA increased from 4% pre--recession to 9% post-recession, thereby reflecting its dominant status in global economic activities. This is consistent with the bulk of the established literature, such as Greenwood-Nimmo, Nguyen and Shin (2015), Diebold and Yilmaz (2016) and Ogbuabor et al. (2018), which also found that USA is an important transmitter of output shocks in the global economy.

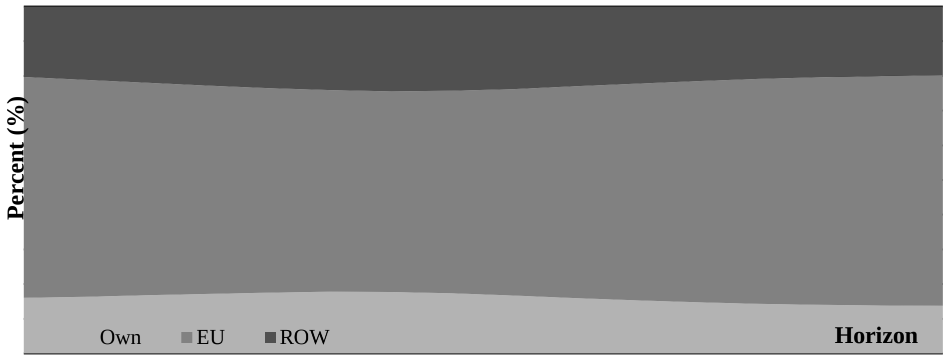
Figure 2 reports the output connectedness of Czech economy with the other economies in the system for both the sub sample and the full sample by decomposing the GFEVDs of Czech economy into three parts, namely *own*, *EU* and *ROW* as defined in the *own-EU-ROW effect* of equation (7). The overall patterns in Figure 2 indicate that: *EU-effect* generally dominates Czech real activities; *own-effect* is more pronounced during the pre-recession period; while the *ROW--effect* cannot be called negligible. The patterns are consistent with our earlier finding that the EU dominates Czech's real activities. The results show that while the *own-effect* declined after the recession, the *EU-effect* increased remarkably. This is consistent with the dynamics of the Czech economy, which has become closely integrated with the EU especially in the aftermath of its 2012/2013 recession episode. It is also consistent with the fact that the growth of the Czech economy is strongly influenced in recent years by export demand and flow of investments from other EU economies, particularly Germany. The non-negligible *ROW-effect* indicate that the Czech economy remains considerably open to international trade, particularly with the USA. In fact, the combined roles of the EU and the rest of the world suggests that the Czech economy presently remains considerably open and sensitive to international output shocks, especially those emanating from other EU economies and the USA.

Figure 2
Own-EU-ROW Effect Connectedness of Czech Economy

Sub Sample



Full Sample



Notes: This figure reports the output connectedness of Czech economy across all horizons for both the reference sample and the full sample. *Own* means proportion of the Czech's GFEV explained by the country itself; *EU* means proportion explained by other EU member economies within the system; while *ROW* means proportion explained by the rest of the world. These GCMs were computed following the *own-EU-ROW effect* in equation (7). The dominance of the *EU effect* is observed in both samples.

Source: Author's computations.

2.3. The *To-effect* Connectedness of Czech Economy

To determine the economies that are most vulnerable to output shocks emanating from the Czech economy, we computed the total directional connectedness from the Czech economy (i.e. the *to-effect*) to all other economies in the system following equation (8). Recall that the *to-effect* measures the directional connectedness from a given economy in the system to other economies, thereby showing the impact or influence of that particular economy on other economies in the VAR system. The results of our computations are shown in Table 3, which also includes the heatwave (or *own-effect*) from equation (5) and normalized to 100%. We find that the heatwave reduced by half from 30% in the pre-recession period to 15% post-recession. This shows that the Czech economy became more open and sensitive to external conditions following the recession. This is consistent with our earlier findings.

Before the recession, we find that Poland (14%) and Slovakia (12%) are most susceptible to output shocks emanating from the Czech economy. This finding is consistent with the structure of Czech's bilateral trade with both countries. For instance, in 2016, Czech's exports to Slovakia and Poland were 13.6 and 9.2 billion USD, while its imports from them were 9.2 and 12.7 billion USD, respectively (Simoes, 2018). Besides, both countries share common borders with Czech Republic. Our results further indicate that the role of Czech Republic in the real activities of the following economies is non-negligible: Japan (11%), Italy (10%), Germany (8%), and Austria (4.5%). Overall, we find that Czech's contribution to other EU member countries (53%) is far greater than its contribution to the rest of the world (16%), which supports our initial finding that the EU dominates Czech's real activities relative to other parts of the global economy. After the recession, we find that the Czech economy became relatively more open while its influence in the real economic activities of all the economies in the system became non-negligible. Again, we find that Czechs contributions to other EU member economies (59%) are still dominant relative to its contributions to the rest of the world (27%). In sum, the results show that Czech economy is considerably open and deeply interconnected, which is consistent with its position as the 22nd largest export economy in the world as of 2016 (Simoes, 2018).

Table 3

The *To-effect* Connectedness of Czech Economy (%)

Country	Sub Sample	Full Sample
USA	2.2940	8.8907
Austria	4.4976	8.8527
China	2.1330	5.7525
Czech	30.2885	14.5985
France	1.5125	8.5426
Germany	7.7174	8.8161
Italy	9.7319	8.9346
Japan	10.9444	8.3235
Korea	0.9149	3.8795
Poland	14.1939	7.0159
Slovakia	12.2806	8.6007
UK	3.4914	7.7926
Total	**100**	**100**

Notes: This table captures the total directional connectedness from the Czech economy to other economies in the system following equation (8). Notice that the total directional connectedness from Czech economy to itself is the *own-effect* or heatwave following equation (5).

Source: Author's computations.

On the whole, the above paragraphs indicate that if the roles of EU member economies and the rest of the world in the Czech economy are considered, then there has not been any shift in terms of dominant output shock transmitters to the Czech economy and main output shock receivers from the Czech economy before and after the recession since the EU member economies continuously dominated Czech's real activities. However, at country level, we find that Germany and Italy are the main output shock transmitters to Czech economy after the recession, while the roles of Austria, France, Japan, Poland, Slovakia, UK and USA are also non-negligible. The USA changed from a marginal output shock transmitter to the Czech economy before the recession to a more influential shock transmitter, thereby reflecting its dominant role in global economic activities. In the case of output shock receivers from the Czech economy, China, France, Korea, UK and USA were minor output shock receivers before the recession. However, after the recession, all the economies in the system became significant output shock receivers from the Czech economy. These results indicate that the Czech economy became more interconnected with the global economy after the crisis, which is consistent with the bulk of the literature that have shown that in general, economic crises increase the connectedness of economies as business cycles become more synchronized (Greenwood-Nimmo, Nguyen and Shin, 2015; Ogbuabor et al., 2016; Diebold and Yilmaz, 2016).

3. Conclusion and Policy Implications

This paper examined the dynamics of Czech Republic's output connectedness with the global economy using the connectedness approach of Diebold and Yilmaz (2009). The paper extended the empirical method by constructing a country--specific generalized connectedness measure, the *own-EU-ROW effect* connectedness. The main findings are summarized as follows. First, we find that the output connectedness of the Czech economy with the global economy is quite substantial, with the *total connectedness index* having average values of 74% and 82% before and after the recession. Second, we find that the EU member economies, especially Germany, exert the most dominant output influence on the Czech economy and therefore have the potential to spread output shocks to it. We also find that the role of the USA in Czech Republic's real economic activities increased considerably after the recession. Third, we find that Poland and Slovakia are the main output shock receivers from the Czech economy; and that after the recession, Czech economy became relatively more interconnected with the global economy while its influence in the real activities of all the economies in the system became non-negligible. Lastly, we find that if the roles of EU member economies and the rest of the world in the Czech economy are considered, then there has not been any remarkable shift in terms of main output shock transmitters to the Czech economy and key output shock receivers from the Czech economy before and after the recession since the EU member economies have continued to dominate Czech economy's real activities. These findings are consistent with Czech Republic's trade structure with the global economy.

The findings above have several policy implications. First, they provide evidence to assist policymakers in Czech Republic and the rest of the global economy in identifying the likely sources of future output shocks so that appropriate policy responses to such shocks can be designed.

Second, they provide evidence that can assist EU leaders and policymakers in designing policies for achieving the common goals of shared prosperity and enhanced living standards for all citizens of the region.

Third, the findings will assist policymakers in Czech Republic in understanding the dynamics of its output connectedness before and after the recession so that a more comprehensive understanding of how the crisis propagated through the economy may be learned. This will aid future responses to similar crises. Lastly, the findings provide evidence that can assist policymakers across the globe in understanding how connectedness measurement can be used to improve risk measurement and management, public policy, regulatory oversight and overall economic integration.

References

ACHARYA, V. V. – PEDERSEN, L. H. – PHILIPPON, T. – RICHARDSON, M. (2017): Measuring Systemic Risk. The Review of Financial Studies, *30*, No. 1, pp. 2 – 47. Available at: <https://doi.org/10.1093/rfs/hhw088>.

ADRIAN, T. – BRUNNERMEIER, M. K. (2011): CoVaR. [The National Bureau of Economic Research Working Paper, No. 17454.] Cambridge, MA: The National Bureau of Economic Research. Available at: <http://www.nber.org/papers/w17454.pdf>.

BARUNIK, J. – KREHLIK, T. (2016): Measuring the Frequency Dynamics of Financial and Macroeconomic Connectedness. [FinMaP-Working Paper, No. 54.] Helsinki: FinMaP. Available at: <http://hdl.handle.net/10419/125824>.

BILLIO, M. – GETMANSKY, M. – LO, A. W. – PELIZZON, L. (2012): Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors. Journal of Financial Economics, *104*, No. 3, pp. 535 – 559. Available at: <https://doi.org/10.1016/j.jfineco.2011.12.010>.

BOLLERSLEV, T. (1990): Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. The Review of Economics and Statistics, *72*, No. 3, pp. 498 – 505. DOI: 10.2307/2109358.

BOSTANCI, G. – YILMAZ, K. (2015): How Connected is the Global Sovereign Credit Risk Network? [Koç University-TUSIAD Economic Research Forum Working Papers, No. 1515.] Turkey: Koç University-TUSIAD. Available at: <http://dx.doi.org/10.2139/ssrn.2647251>.

BROWNLEES, C. T. – ENGLE, R. (2012): Volatility, Correlation and Tails for Systemic Risk Measurement. Available at: <https://bfi.uchicago.edu/sites/default/files/research/SSRN-id1611229.pdf>. [Accessed 21.03.2018.]

CANOVA, F. – CICCARELLI, M. – ORTEGA, E. (2007): Similarities and Convergence in G-7 Cycles. Journal of Monetary Economics, *54*, No. 3, pp. 850 – 878.

CARAIANI, P. (2013): Using Complex Networks to Characterize International Business Cycles. PLoS ONE, *8*, No. 3, e58109. DOI: 10.1371/journal.pone.0058109.

CENTRAL INTELLIGENCE AGENCY (2018): The World Factbook. Available at: <https://www.cia.gov/library/publications/the-world-factbook/fields/2116.html>. [Accessed 21.03.2018.]

DAHLHANS, R. – EICHLER, M. (2003): Causality and Graphical Models in Time Series Analysis. In: GREEN, P. J., HJORT, N. L. and RICHARDSON, S. (eds): Highly Structured Stochastic Systems. Oxford Statistical Science Series, *27*, pp. 115 – 137.

DEMIRER, M. – DIEBOLD, F. X. – LIU, L. – YILMAZ, K. (2017): Estimating Global Bank Network Connectedness. [NBER Working Paper, No. 23140.] Cambridge, MA: NBER. DOI: 10.3386/w23140.

DIEBOLD, F. X. – YILMAZ, K. (2009): Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. The Economic Journal, *119*, No. 534, pp. 158 – 171. Available at: <https://doi.org/10.1111/j.1468-0297.2008.02208.x>.

DIEBOLD, F. X. – YILMAZ, K. (2012): Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. International Journal of Forecasting, *28*, No. 1, pp. 57 – 66. Available at: <https://doi.org/10.1016/j.ijforecast.2011.02.006>.

DIEBOLD, F. X. – YILMAZ, K. (2014): On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms. Journal of Econometrics, *182*, No. 1, pp. 119 – 134. Available at: <https://doi.org/10.1016/j.jeconom.2014.04.012>.

DIEBOLD, F. X. – YILMAZ, K. (2015): Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring. New York: Oxford University Press. ISBN 978-0199338306.

DIEBOLD, F. X. – YILMAZ, K. (2016): Measuring the Dynamics of Global Business Cycle Connectedness. In: KOOPMAN, S.-J. and SHEPHARD, N. (eds): Unobserved Components and Time Series Econometrics: Essays in Honor of Andrew C. Harvey. Oxford: Oxford University Press, pp. 45 – 70. ISBN 13: 978-0199683666. DOI: 10.1093/acprof:oso/9780199683666.001.0001.

ECHEVARRIA-ICAZA, V. – RIVERO, S. S. (2016): Connectedness of Stress in EMU Bank and Sovereign CDS: The Role of Policy Measures 2008 – 2014. [Documentos de Economíay Finanzas Internacionales, DEFI Working Papers on International Economics and Finance, No. DEFI 16-01.] Spain: DEFI. Available at: <http://dx.doi.org/10.2139/ssrn.2726494>.

ENGLE, R. F. (2009): Anticipating Correlations: A New Paradigm for Risk Management. Princeton, NJ: Princeton University Press. ISBN 978-0691116419.

ENGLE, R. F. – ITO, T. – LIN, W. (1990): Meteor Showers or Heat Waves? Heteroskedastic Intra-daily Volatility in the Foreign Exchange Market. Econometrica, *58*, No. 3, pp. 525 – 542. DOI: 10.2307/2938189.

ENGLE, R. F. – KELLY, B. (2012): Dynamic Equicorrelation. Journal of Business and Economic Statistics, *30*, No. 2, pp. 212 – 228. Available at: <https://doi.org/10.1080/07350015.2011.652048>.

ERKOL, N. (2015): Market Connectedness: Return vs. Volatility Spillovers. Available at: <http://pagines.uab.cat/appliedeconomics/sites/pagines.uab.cat.appliedeconomics/files/Erkol,%20Narod_paper.pdf>. [Accessed 21.03.2018.]

FÉLIX, J. A. – FERNANDEZ-PEREZ, A. – SOSVILLA-RIVERO, S. (2017): Fear Connectedness among Asset Classes. [Research Institute of Applied Economics Working Paper, No. 2017/03.] Universitat de Barcelona: Research Institute of Applied Economics. Available at: <http://dx.doi.org/10.2139/ssrn.2910851>.

GÄTJEN, R. – SCHIENLE, M. (2015): Measuring Connectedness of Euro Area Sovereign Risk. [SFB 649 Discussion Papers, No. 2015-019.] Berlin: Humboldt University, Collaborative Research Center 649. ISSN 1860-5664. DOI: 10.18452/4576.

GRAY, D. F. – MALONE, S. W. (2008): Macrofinancial Risk Analysis. West Sussex, England: John Wiley & Sons. ISBN 978-0470058312. DOI: 10.1002/9781118467428.

GREENWOOD-NIMMO, M. – NGUYEN, V. H. – SHIN, Y. (2015): Measuring the Connectedness of the Global Economy. [Melbourne Institute Working Paper, No. 7/15.] Melbourne: The University of Melbourne, Melbourne Institute of Applied Economic and Social Research. Available at: <http://dx.doi.org/10.2139/ssrn.2586861>.

GUIMARÃES-FILHO, R. – HONG, G. H. (2016): Dynamic Connectedness of Asian Equity Markets. [IMF Working Paper, No. 16/57.] Washington, DC: International Monetary Fund. ISBN 978-1513572451. ISSN 1018-5941.

HIEMSTRA, C. – JONES, J. D. (1994): Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. The Journal of Finance, *49*, No. 5, pp. 1639 – 1664. Available at: <https://doi.org/10.1111/j.1540-6261.1994.tb04776.x>.

IMF (2017): IMF Country Report, No. 17/168 (CZECH REPUBLIC), June, 2017. Available at: <http://www.imf.org/en/Publications/CR/Issues/2017/06/26/Czech-Republic-2017-Article-IV-Consultation-Press-Release-Staff-Report-and-Statement-by-the-45003>. [Accessed 21.03.2018.]

INDEXMUNDI (2018): Czech Republic Economy Profile 2018. Available at: <https://www.indexmundi.com/czech_republic/economy_profile.html>. [Accessed 21.03.2018.]

KEHOE, P. J. – BACKUS, D. K. – KYDLAND, F. E. (1995): International Business Cycles: Theory vs. Evidence. In: COOLEY, T. F. (ed.): Frontiers of Business Cycle Research. Princeton, NJ: Princeton University Press. ISBN 978-0691043234.

KOSE, M. A. – PRASAD, E. S. – TERRONES, M. E. (2003): How Does Globalization Affect the Synchronization of Business Cycles? American Economic Review, *93*, No. 2, pp. 57 – 62. DOI: 10.1257/000282803321946804.

KOSE, M.A. – OTROK, C. – WHITEMAN, C. H. (2008): Understanding the Evolution of World Business Cycles. Journal of International Economics, *75*, No. 1, pp. 110 – 130. Available at: <https://doi.org/10.1016/j.jinteco.2007.10.002>.

MANTEGNA, R. N. (1999): Hierarchical Structure in Financial Markets. The European Physical Journal B, *11*, No. 1, pp. 193 – 197. Available at: <https://doi.org/10.1007/s100510050929>.

OECD (2017a): Developments in Individual OECD and Selected Non-member Economies (Czech Republic). Paris: OECD. Available at: <http://www.oecd.org/eco/outlook/czech-republic-economic-forecast-summary.htm>. [Accessed 21.03.2018.]

OECD (2017b): International Trade, Foreign Direct Investment and Global Value Chains. Paris: OECD. Available at: <http://www.oecd.org/investment/Czech-Republic-trade-investment-statistical-country-note.pdf>. [Accessed 21.03.2018.]

OGBUABOR, J. E. – EIGBIREMOLEN, G. O. – ANEKE, G. C. – MANASSEH, C. O. (2018): Measuring the Dynamics of APEC Output Connectedness. Asian-Pacific Economic Literature, *32*, No. 1, pp. 29 – 43. DOI: 10.1111/apel.12218.

OGBUABOR, J. E. – ORJI, A. – ANEKE, G. C. – ERDENE-URNUKH, O. (2016): Measuring the Real and Financial Connectedness of Selected African Economies with the Global Economy. South African Journal of Economics, *84*, No. 3, pp. 364 – 399. DOI: 10.1111/saje.12135.

PARK, H. – SHIN, Y. (2014): Mapping Korea's International Linkages using Generalised Connectedness Measures. [Bank of Korea Working Paper, No. 2014-16.] Seoul: Bank of Korea. Available at: <http://dx.doi.org/10.2139/ssrn.2580633>.

PESARAN, M. H. – SHIN, Y. (1998): Generalized Impulse Response Analysis in Linear Multivariate Models. Economics Letters, *58*, No. 1, pp. 17 – 29. Available at: <https://doi.org/10.1016/S0165-1765(97)00214-0>.

RODRÍGUEZ, F. F. – SOSVILLA-RIVERO, S. (2016): Volatility Transmission between Stock and Exchange Rate Markets: A connectedness Analysis. [Bath Economics Research Papers, No. 54/16.] University of Bath: Department of Economics. Available at: <http://dx.doi.org/10.2139/ssrn.2851386>.

SHOJAIE, A. – MICHAILIDIS, G. (2010): Discovering Graphical Granger Causality Using the Truncating Lasso Penalty. Bioinformatics, *26*, No. 18, pp. i517 – i523. DOI: 10.1093/bioinformatics/btq377.

SIMOES, A. (2018): The Observatory of Economic Complexity: Czech Republic. Available at: <https://atlas.media.mit.edu/en/profile/country/cze/>. [Accessed 21.03.2018.]

TAYLOR, S. J. (2007): Asset Price Dynamics, Volatility, and Prediction. Princeton, NJ: Princeton University Press. ISBN 978-0691134796.

TUMMINELLO, M. – ASTE, T. – DI MATTEO, T. – MANTEGNA, R. N. (2005): A Tool for Filtering Information in Complex Systems. Proceedings of the National Academy of Sciences, *102*, No. 30, pp. 10421 – 10426. DOI: 10.1073/pnas.0500298102.

UN COMTRADE (2016): Czech Republic Trade Statistics. Available at: <https://comtrade.un.org/>. [Accessed 21.03.2018.]

WORLD INTEGRATED TRADE SOLUTIONS (2018): Czech Republic Trade at a Glance. Available at: <https://wits.worldbank.org/CountrySnapshot/en/CZE>. [Accessed 21.03.2018.]

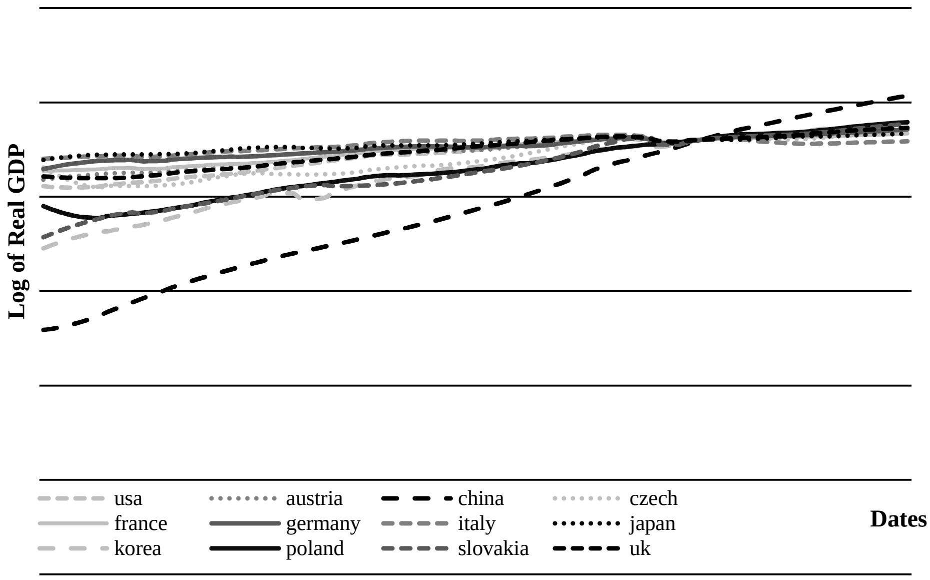
WORLDOMETER (2018): Population of Czech Republic: 2018 and Historical. Available at: <http://www.worldometers.info/world-population/czech-republic-population/>. [Accessed 21.03.2018.]

YILMAZ, K. (2014): Volatility Connectedness of Bank Stocks across the Atlantic. [Koç University-TÜSİAD Economic Research Forum Working Papers, No. 1402.] Turkey: Koç University-TUSIAD. Available at: <http://hdl.handle.net/10419/108641>.

Appendix 1

Figure 3

Time Series Plot of the Data over the Full Sample



Notes: This Figure plots the data series in order to highlight the fact that the data for the various countries generally track themselves very closely. Notice the slight downward movement around 2009Q1, corresponding with the period of the GFC.

Source: World Development Indicators and author’s computations.