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International Trade, Foreign Direct Investment (FDI) and Economic Interdependence: Evidence from 22 OECD countries between 1989 and 2019

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Abstract

This paper investigates whether international trade volume and foreign direct investment (FDI) flows between two countries contribute to their economic interdependence. To achieve this, a quantitative measure of economic interdependence is derived from an adapted version of social interactions networks. The degree of influence within asymmetrical interdependence relationships are quantified as the strength of the network link directed from a country to another within a network of macroeconomic interactions. Later on, estimated network links are used to test the hypothesis that the degree of a country's influence over another correlates with their international trade and FDI levels. The results confirm the hypothesis and indicate that trade partnership and foreign investment lead to economic interdependence between countries.

Contents

1 Introduction

With increasing political integration experienced since the end of Second World War and recent advancements in information and communication technologies, the world economy has experienced a process of globalization of supply chains and finance unprecedented in history. As means of global and regional integration across economies, international trade and foreign investment stand out as substantial forces within the context of globalization. In fact, increased reliance on international trade and foreign investment establishes relationships between countries that are of macroeconomic and political significance. I anticipate that a large trade volume and sizable foreign direct investment (FDI) flows from one country to another establish potentially asymmetrical influence and have substantial structural consequences. Yet, while the economic impact of international trade and foreign investment has been studied extensively, research on the structural consequences of trade and investment between countries is not substantive. For this reason, this paper aims to present a comprehensive account of the consequences of international trade and foreign investment in terms of economic interdependence.

Today, the conditions that emerge due to the ongoing process of rapid globalization has a distinctive impact on policy discussion across the globe. It is clear to many scholars in economics, political science and international relations fields that national economies are not separable from the global developments and are increasingly influenced by global and regional forces. It is noted that the domestic economic conditions across countries are dependent on each other to a larger extent. This situation has been described as economic interdependence between nations. Given that the consequences of economic interdependence have important social and economic implications relevant for future policies, the subject attracted considerable attention in social, political and economic sciences and a vast literature on business cycle synchronisation and interaction across global and regions was produced in the past decades. (Cooper, 1985; Kose et al., 2008; Doyle and Faust, 2005; Miśkiewicz and Ausloos, 2010; Antonakakis, 2012; Antonakakis and Scharler, 2012; Gomez et al., 2013) Diverging from the established line of quantitative methods to assess economic interdependence, I adopt the linear social network approach advanced by Manski (1993) to formulate and estimate a measure of economic interdependence. Afterwards, I use the estimated interdependence links between countries to test the hypothesis that economic interdependence correlates with international trade and foreign investment volume. Results indicate that both factors strengthen the influence a country has over its trade and investment partner.

In the following section, I outline the theoretical framework underlying the research. In Section 2.1 and Section 2.2, I present an overview of the studies examining the relationship between trade, FDI and economic growth and outline the measure of economic interdependence devised considering the empirical evidence. Data and methods employed to estimate this measure of economic interdependence and to analyze its relationship to international trade and foreign investment are outlined in Section 3 and Section 4. Later on, I present and discuss the results of the analysis in Section 5. Finally, I give an account of the conclusions and limitations of the study and potential directions for future research in Section 6.

2 Theoretical Framework

2.1 Trade, Foreign Investment and Economic Growth

Within the endogenous growth framework, it is anticipated that international trade and foreign direct investment (FDI) stimulate economic growth by promoting innovation, technology diffusion, human capital accumulation and *know-how* transfer. Borensztein et al. (1998) indicate that FDI flows play an extensive role in technology transfer and, in case the level of human capital is sufficient, make lasting contributions by facilitating the absorption of the foreign technology. In fact, evidence from a number of studies suggest that the relationship between FDI flows and economic growth is large and significantly positive. Omri et al. (2014) and Bengoa and Sanchez-Robles (2003) found positive impact in both directions between innovation, economic growth and inward FDI flows. Tiwari and Mutascu (2011) and Nair-Reichert and Weinhold (2001), on the other hand, show that economic gains from inward FDI flows are heterogeneous across time and economy, yet still significantly positive.

Paralleling the findings of Borensztein et al. (1998), Schneider (2005) found the impact of inward FDI flows to be significantly positive only for developed countries which have large stocks of human capital. In addition, Bengoa and Sanchez-Robles (2003) and Alfaro et al. (2004) suggest that other domestic factors such as economic openness and financial development are also influential in translating inward FDI flows into economic growth. A number of studies point out a multilayered relationship between international trade, foreign investment and economic performance. Bhagwati (1973) hypothesizes that foreign investment stimulates economic growth in countries with export promoting trade regimes as well as being pulled towards such economies. Balasubramanyam et al. (1996) found evidence in support of Bhagwati's hypothesis that export promotion contributes to efficiency effect of FDI flows.

With regards to international trade, theoretical studies offer contrasting views over the impact of trade on economic growth. Classical theories of international trade imply gains for both participants from openness to trade, regardless of their absolute or comparative advantage. However, more recent literature acknowledges that a variety of effects emerge due to intra-industry trade and play a role in determining the overall effect of international trade for different parties. Helpman and Krugman (1985) show that classical theory fails to explain the dynamics of trade under market imperfections and suggest a revised model with imperfect competition and increasing returns to scale. On the other hand, Bernard et al. (2003) and Melitz (2003) show that firm-level heterogeneity induce disproportionate effects on the parties involved. Baldwin and Robert-Nicoud (2008) explore the implications of firm-level heterogeneity and hypothesize that greater openness to international trade results both in anti- and pro-growth effects. They indicate that the overall effect of international trade on economic growth is ambiguous and dependent on the exact balance between the forces hindering or promoting innovation.

However, empirical evidence largely suggests that trade contributes to economic growth both in developed and developing economies. Schneider (2005) indicate that the impact of high-technology imports on domestic innovation and economic growth is significantly positive both in developed and developing countries. Michaely (1977), Feder (1983) and Kormendi and Meguire (1985), on the other hand, found a significantly positive relationship between the proportion of the export sector and economic growth. Frankel and Romer (1999) point out that trade share may be endogenous and estimate the impact by instrumenting trade share with bilateral gravity.

Their findings confirm that the positive effect of trade on income is robust and significant.

2.2 Economic Interdependence

Overall, empirical findings support the idea that international trade and inward FDI flows contribute to economic growth through stimulating productivity gains, innovation, technology diffusion and human capital accumulation. This implies that, for any given bilateral trade or FDI relationship, both parties are exposed to the events impacting the other's economic performance. For instance, an aggregate positive (or negative) demand shock in a country is likely to yield a positive (or negative) effect on the economic growth of its largest trade partners due to increased (or decreased) demand for their exports. Another example is the adoption of technological innovations originating in an investing country by its FDI partners. Given that inward FDI flows have a direct positive impact on domestic innovation in the recipient economy[1], productivity gains (and consequently economic growth) from innovation in an investing country are likely to indirectly stimulate economic growth also in the recipient country. Thus, in the light of these insights, I hypothesise that economic interdependence between two countries correlates positively with both international trade and foreign investment.

There are two obstacles to testing the hypothesis put forward. Firstly, a quantitative measure of interdependence has to be defined. In general, economic interdependence is formulated as business cycle synchronisation in earlier studies.(Cooper, 1985; Kose et al., 2008; Doyle and Faust, 2005;Miśkiewicz and Ausloos, 2010; Antonakakis, 2012; Antonakakis and Scharler, 2012) However, this approach does not allow for studying the asymmetrical formations of interdependence. In the context of this study, interdependence can be interpreted as to broadly describe a bilateral relationship which involves the influence of the economic conditions or output in at least one of the countries over the output of the other. To illustrate this, consider a pair of countries i, j and let $w_{i,j}$ denote the degree of influence j has over i. The set $\{w_{i,j}, w_{j,i}\}$ describes the structure of interdependence between the countries. Given that a relationship of interdependence may or may not be asymmetrical, the degree of this influence may be heterogeneous across peers. This implies that $w_{j,i}$ is not necessarily equal to $w_{i,j}$. Based on the definition above, a reasonable measure of economic influence $w_{i,j}$ can be formulated as the degree to which exogenous conditions and shocks in country j impact the output in country i. In specific terms, this implies that, if the hypothesis holds, the impact of a foreign economic shock correlates with (i) the (average) volume of goods and services traded with the origin of the shock (ii) the (average) size of the inward FDI flows from the origin of the shock.

Since the degree of interdependence between countries is not observed, the second challenge is to estimate the real-life levels of $w_{i,j}$. The common approach in literature is to consider the co-movement of economic growth over a time window as indicative of interdependence and examine the correlation between time-series of economic growth.(Cooper, 1985; Kose et al., 2008; Doyle and Faust, 2005; Antonakakis, 2012; Antonakakis and Scharler, 2012) A more accurate measure of economic interdependence between two countries can be formulated by considering their position within a larger network of relationships. For instance, consider three countries i, j and k with $w_{i,j} = w_{j,i} = 0$. While this indicates that i and j do not interact with each other, their economic growth may be correlated if in fact they both have a relationship to k, e.g. $w_{i,k} > 0$ and $w_{k,j} > 0$. Thus, incorporating the larger network, through which the pairwise

[1] See Omri et al., 2014.

interactions take effect, provides a better framework to investigate the interdependence between pairs. Miśkiewicz and Ausloos (2010) and Gomez et al. (2013) construct such a network using a measure of statistical distance between two time-series and examine the clustering patterns across the network. However, this approach does not incorporate asymmetrical formations across the network. Given that the definition I proposed above allows for asymmetry, it is required to estimate a weighted and directed network, in which the edge from node j to node i represents the degree of influence $w_{i,j}$, to describe the structure of pairwise interdependence across a set of countries.

In this paper, I employ the linear social interactions model proposed by Manski (1993) to estimate a network representation of economic interdependence across countries. The social interactions model incorporates network ties between actors as structural parameters in a system of equations. A simple social interactions model can be formulated as follows:

$$y_t = \rho_0 W_0 y_t + \beta_0 x_t + \gamma_0 W_0 x_t + \epsilon_t \tag{1}$$

where $y_t = (y_{1t}, ..., y_{Nt})'$ is a $N \times 1$ is a vector of outcomes, $x_t = (x_{1t}, ..., x_{Nt})'$ is a $N \times 1$ vector of individual characteristics, $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})'$ is the $N \times 1$ vector of error terms, W_0 is the $N \times N$ adjacency matrix and, β_0, ρ_0 and γ_0 are scalars. ρ_0 and γ_0 capture the endogenous and exogenous social effects respectively. In most applications of the model, adjacency matrix W_0 is considered to be known and partially known. Yet, De Paula et al. (2019) demonstrate that the parameters are is globally identified under certain conditions even if W_0 is unknown. They outline the following assumptions regarding the parameters:

(A1) $(W_0)_{ii} = 0$, $i = 1, ..., N$.

(A2) $\sum_{j=1}^{N} |\rho_0 (W_0)_{ij}| = 0$ for every $i = 1, ..., N$, $||W_0|| < C$ for some positive $C \in \mathbb{R}$ and $|\rho_0| < 1$.

(A3) $\beta_0 \rho_0 + \gamma_0 \neq 0$.

(A4) There is an i such that $\sum_{j=1}^{N} (W_0)_{ij} = 1$.

(A5) There exists l, k such that $(W_0^2)_{ll} \neq (W_0^2)_{kk}$.

In the case that y_{it} and x_{it} denote economic growth and exogenous characteristics of country i at time t respectively, W_0 can be interpreted as the adjacency matrix of a macroeconomic interactions network. Then, $(W_0)_{ij}$ represents the degree of influence $(w_{i,j})$ country j has over country i. To illustrate this, consider the reduced form equation from which the parameters can be identified:

$$y_t = \Pi_0 x_t + \nu_t \tag{2}$$

where $\Pi_0 = (I - \rho_0 W_0)^{-1} (\beta_0 I + \gamma_0 W_0)$ and $\nu_t = (I - \rho_0 W_0)^{-1} \epsilon_t$. The reduced form coefficient matrix and error term shows that individual and social exogenous effects and exogenous shocks are intensified by propagating through the network if endogenous social effects are present. However, exogenous variable $x_j t$ and exogenous shock $\epsilon_j t$ have a direct impact on y_i that is proportional to $(W_0)_{ij}$. This can be illustrated by rewriting the error term ν_t using the Neumann expansion $(I - \rho_0 W_0)^{-1} = \sum_{j=0}^{N} (\rho_0 W_0)^j$:

$$\nu_t = \sum_{j=0}^{N} (\rho_0 W_0)^k \epsilon_t \tag{3}$$

It can be seen that, since exogenous shocks propagate through the network and possibly have an impact through a path other than the immediate edge directed from j to i, the total impact of an exogenous shock $\epsilon_j t$ on y_i is possibly larger than its immediate impact. However, the immediate impact of an exogenous shock $\epsilon_j t$ on y_i, which is limited to the effect realised through the edge directed from j to i, is proportional to $\rho_0 (W_0)_{ij}$. Similarly, the immediate impact of exogenous variable $x_j t$ on y_i is proportional to $\gamma_0 (W_0)_{ij}$. Thus, assuming that the economic conditions and exogenous shocks in country j have a correlated impact on country i, $(W_0)_{ij}$ captures the isolated effect of country j over country i. For this reason, $(W_0)_{ij}$ is an accurate measure of the degree of influence country j has over country i through their bilateral relationship. Considering the hypothesis that economic interdependence correlates with trade and FDI flows, I anticipate that the average volume of trade between i to j and FDI flows from j to i are significantly correlated with estimates of $(W_0)_{ij}$.

3 Data

The Organisation for Economic Co-operation and Development (OECD) publishes monthly, quarterly and annual economic indicators gathered from 37 member countries. Percentage change in the quarterly GDP of 22 countries[2] is retrieved from OECD's public database. (OECD, 2020) These countries are selected based on data availability over the full publication period between 1960 and 2020. Given that Germany is an OECD member included in the selection of countries, it is reasonable to consider unification of East and West Germany in 1989 as an influential event regarding the data set as well as a turning point in the political landscape. (Sinn and Dornbusch, 1992) For this reason, the data set is divided into two periods (before and after 1989) with relatively homogeneous political conditions across the included countries. In addition, data points from 1989 are excluded to remove the impact of the unification event. Foreign Direct Investment (FDI) levels between partner countries are also retrieved from the OECD database. The data set includes FDI flows, income payments and stocks in both directions (inward and outward) for the included subset of countries from 2005 and 2020. Given no data on FDI is available before 2005 for the set of countries, it is assumed that the available data reflects the variation of FDI levels across countries as well. However, this undermines the accuracy of the findings. For this reason, the analysis of the relationship between economic interdependence and trade is limited to the period after 1989. On the other hand, international trade volume by partner country for each in the selected set of countries is retrieved from the World Bank's World Integrated Trade Solution (WITS) database and is available for the complete period after 1989. All trade and FDI indicators are proportioned to the GDP of the receiving country and input as fractions.

While the focus of this study is the recent period during which globalization phenomenon plays a strong role, the change in the strength of network ties over time provides insights into

[2] Selected member countries are Australia (AUS), Austria (AUT), Belgium (BEL), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Ireland (IRL), Iceland (ISL), Italy (ITA), Japan (JPN), South Korea (KOR), Mexico (MEX), Netherlands (NLD), Norway (NOR), Portugal (PRT), Sweden (SWE) and the United States (USA).

Table 1: Descriptive statistics per country

	1960Q2-1988Q4			**1990Q1-2019Q4**		
Country	Mean[1]	Std.Dev.[2]	Kurtosis	Mean	Std.Dev.	Kurtosis
AUS	0.956	1.344	-0.26	0.741	0.585	2.25
AUT	0.888	1.203	2.58	0.481	0.568	2.72
BEL	0.859	0.761	1.73	0.453	0.578	3.68
CHE	0.699	1.326	1.89	0.400	0.589	2.52
DEU	0.804	1.250	1.36	0.395	0.869	9.23
DNK	0.758	1.085	0.58	0.438	0.948	0.83
ESP	1.153	1.189	2.02	0.521	0.763	4.98
FIN	0.984	1.606	2.11	0.408	1.280	7.39
FRA	0.943	1.493	29.37	0.388	0.452	4.25
GBR	0.694	1.203	2.32	0.488	0.571	5.48
GRC	1.157	2.965	0.43	0.218	1.838	8.92
IRL	0.987	0.669	-0.13	1.387	2.900	27.43
ISL	1.157	1.331	1.66	0.769	2.694	1.52
ITA	1.004	1.135	2.89	0.174	0.671	4.37
JPN	1.581	1.231	2.25	0.252	0.968	6.09
KOR	2.358	2.396	-0.21	1.237	1.280	13.39
MEX	1.223	1.111	1.52	0.622	1.258	10.62
NLD	0.841	1.871	4.33	0.524	0.657	11.89
NOR	0.981	1.009	2.33	0.575	1.205	0.20
PRT	1.167	1.279	0.71	0.385	0.859	1.28
SWE	0.768	1.538	1.49	0.517	0.883	4.84
USA	0.889	0.995	0.53	0.612	0.582	4.20
Average	1.039	1.363	2.80	0.545	1.045	6.28
Number of obs.		T = 115			T = 120	

[1] Average quarterly GDP growth rate over the given period in percentage points
[2] Standard deviation of quarterly GDP growth rate over the given period

the impact of political and economic globalization. Table 1 presents descriptive statistics for both samples. Period between 1990Q1 and 2019Q4 is marked by lower average growth rates and standard deviations. Another feature of this period is the considerably higher kurtosis values for most countries, mostly due to two major financial crises (bursting of Dot-Com Bubble and 2008 Financial Crisis).

4 Methodology

In this section, the macroeconomic interaction model and the estimation procedure are presented, respectively in subsections 4.1 and 4.2. Empirical specifications for the analysis of the relationship between existence/strength of network ties and FDI/trade relationships is presented in subsection 4.3.

4.1 Macroeconomic Interactions Network

Consider panel data of N countries $i = 1, ..., N$ with growth rates $g_{t,i}$ over $t = 1, ..., T$. Let $g_t = (g_{t,1}, ..., g_{t,N})'$ the $N \times 1$ vector of growth rates at time = t. A network model of economic interdependence can be formulated as follows:

$$g_t = \rho_0 W_0 g_t + \beta_0 g_{t-1} + \gamma_0 W_0 g_{t-1} + \alpha^* + \varepsilon_t \tag{4}$$

where ε_t is the $N \times 1$ vector of error terms $\varepsilon_t = (\varepsilon_{t,1}, ..., \varepsilon_{t,N})'$, α^* is the $N \times 1$ vector of individual fixed effects and W_0 is the $N \times N$ economic interactions matrix. Time-constant fixed effects are not included in order to allow for varying row sums in the W_0 and based on the assumption that common shocks are negligible and already originating from the included national economies. Scalars ρ_0 and γ_0 represent the scale of contemporaneous and leading (or respectively endogenous and exogenous) network effects and, assuming that autocorrelation is homogeneous across countries, β_0 captures the autocorrelation in economic performance.

The macroeconomic interaction model in Equation 4 is equivalent to the social interactions model in Equation 1 with individual fixed effects and the lagged values of the outcome variables as covariates. Each element $W_{0,ij}$ of the interactions matrix determines the degree to which the economic performance of country i is dependent on performance of country j in the current and previous period. A strong network tie $W_{0,ij}$ implies that the level of economic activity in country i is highly dependent on country j. On the other hand, a large difference in the strength of network ties $W_{0,ij}$ and $W_{0,ji}$ between a pair of countries i, j indicates an asymmetric influence of one country over another.

4.2 Estimation

The parameter vector $\theta = (\rho, \beta, \gamma, W)$ can be estimated from the following reduced form regression:

$$g_t^* = \Pi g_{t-1}^* + \nu_t \tag{5}$$

where $\Pi = (I - \rho W)^{-1}(\beta I + \gamma W)$ and $\nu_t = (I - \rho W)^{-1}\varepsilon_t$ and $g_t^* = g_t - \overline{g}$ with $\overline{g} = \frac{1}{N}\sum_{t=1}^{T} g_t$. Time averages of the outcome variable and lagged values are subtracted to account for individual fixed effects.

Since the number of parameters in θ is considerably large relative to the number of observations, effective number of parameters has to be significantly reduced in the estimation procedure to prevent over-fitting. Tibshirani, Taylor, et al., 2012) Within the context of this study, interaction matrix W_0 is required to be sufficiently sparse to attain accurate results. For estimating the network structure underlying the interactions between 22 countries over a period of 30 years (120 quarters), approximately 25 percent of the potential network ties are tenable.

Introducing a trade-off between explanatory power and coefficient magnitude, high dimensional estimation techniques allow for controlling the sparsity of the parameter vector θ. Caner and Zhang (2014) suggest an adaptive estimation procedure, namely Adaptive Elastic Net GMM, for utilizing generalized method of moments (GMM) with an Elastic Net penalty (both L1 and L2 norm) imposed over the high dimensional parameter vector. This study employs the following Adaptive Elastic Net GMM objective function as outlined by De Paula et al. (2019) for estimating their social interactions model:

$$G_{NT}(\theta, p) = g_{NT}(\theta)' M_T g_{NT}(\theta) + p_1 \sum_{i \neq j} |W_{i,j}| + p_2 \sum_{i \neq j} |W_{i,j}|^2 \tag{6}$$

where $\theta = (\rho, \beta, \gamma, W_{1,2}, ..., W_{N,N-1})$ is the $N(N-1)+3 \times 1$ vector of parameters, $p = (p_1, p_2)$ is the vector of penalization terms and $g_{NT}(\theta)' M_T g_{NT}(\theta)$ is the unpenalized GMM objective function with the $N^2 \times 1$ vector of moment conditions $g_{NT}(\theta) = \sum_{t=1}^{T}[x_{1t}e_t(\theta)' ... x_{Nt}e_t(\theta)']'$ and the $N^2 \times N^2$ GMM weight matrix M_T. The term $e_t(\theta)$ indicates the $N \times 1$ vector of structural disturbance terms calculated as $e_t(\theta) = y_t - (I - \rho W)^{-1}(\beta I + \gamma W)x_t$. Given that the parameters belong to the identified set, De Paula et al. (2019) indicate that the objective function is uniquely minimized at the true parameter vector θ_0.

While M_t is set to be equal to $I_{N^2 \times N^2}$ for simplicity, growth rates of each country are standardized by dividing each observation by the standard deviation of the growth rates of the country. By this way, the moment conditions involving the covariates with large intervals are not represented disproportionately in the objective function. However,a minor modification in the reduced form coefficient matrix is required for identification after under transformation. Let $S = diag(\frac{1}{\sigma_1}, \frac{1}{\sigma_2}, ..., \frac{1}{\sigma_N})'$ denote an $N \times N$ diagonal matrix with the inverse of the standard deviation σ_i for country $i = 1, 2, ..., N$ along its main diagonal. After the transformation above, the reduced form regression can be re-written as follows:

$$S g_t^* = \Pi_S S g_{t-1}^* + \nu_t \tag{7}$$

where $\Pi_S = S \Pi S^{-1} = S(I - \rho W)^{-1}(\beta I + \gamma W)S^{-1}$. Since Π_S is a trivial transformation of the original reduced form coefficient matrix Π, identification results outlined by De Paula et al. (2019) apply for Π_S as well. In fact, the interactions matrix W_0 can be identified by estimating Equation 6 in the latter reduced form, implying that the structural disturbance terms are formulated as $e_t(\theta) = Sg_t^* - S(I-\rho W)^{-1}(\beta I + \gamma W)S^{-1}g_{t-1}^*$.

Due to the penalty terms in Equation 6, estimates of network ties $W_{i,j}$ shrink towards zero with respect to their explanatory power, resulting in a sparse but biased parameter vector. Caner and Zhang (2014) suggest a two step procedure to correct this bias by re-weighting the estimates. In the context of the network model, initial estimates are corrected for bias as follows:

$$\tilde{\theta} = (1 + p_2/T) \cdot \underset{\theta \in \mathbb{R}^p}{\operatorname{argmin}}\, G_{NT}(\theta, p) \tag{8}$$

In the second stage, first penalization term is re-weighted by the inverse the first-step estimates of network ties $\tilde{W}_{i,j}$ to improve the non-zero estimates:

$$\hat{\theta} = (1 + p_2/T) \cdot \underset{\theta \in \mathbb{R}^p}{\operatorname{argmin}} \left\{ g_{NT}(\theta)' M_T g_{NT}(\theta) + p_3 \sum_{i \neq j} \frac{|W_{i,j}|}{|\tilde{W}_{i,j}|^{\gamma}} + p_2 \sum_{i \neq j} |W_{i,j}|^2 \right\} \tag{9}$$

where p_3 is the second stage penalization term and inverse scaling term $\gamma = 2.5$, following De Paula et al. (2019) and Caner and Zhang (2014). Since penalization is infinite if $\tilde{W}_{i,j} = 0$, network ties with zero are kept the same and only the network ties with non-zero first step estimates are penalized in the second stage.

I use the built-in Particle Swarm Optimization (PSO) algorithm from the MATLAB's *Global Optimization Toolbox*[3] to find the parameter vector θ minimizing of the objective function at both stages. Developed by Kennedy and Eberhart (1995), PSO is a reliable and effective algorithm for finding the global optimum of complicated objective functions. The algorithm starts by initializing a number of particles (points) distributed across the parameter space with varying velocities and updates the position and velocity of each particle based on its current velocity, its distance from the best point the particle itself has landed on and its distance from the best particle in a randomly selected neighbourhood. Kennedy and Eberhart (1995) illustrate that (at least) a sub-group of initial particles converge towards the global optimization after a large number of iteration. Given that the algorithm is initialized with a sufficient number of particles spread over the parameter space, it is highly unlikely that the algorithm will stop at local minima due to the selection of initial particles. The *particleswarm* function in MATLAB's *Global Optimization Toolbox* automatically initializes an array of particles uniformly distributed over the specified parameter space. I use the built-in initialization method with the initial span between -1 and 1 for each parameter in θ. As the parameters may fall over the boundaries of a constrained parameter space and get stuck at local solutions, instead of imposing a lower bound on $W_{i,j}$, the objective function is minimized with regards to $w_{i,j}$ such that $w_{i,j}w_{i,j} = W_{i,j}$ in order to avoid the pitfalls of the constrained optimisation.

Following Caner and Zhang (2014), I select the model with the lowest BIC criterion after repeating the procedure for a set of penalization terms $p = (p_1, p_2, p_3)$.[4] Finally, I re-estimate the

[3]The specific *Global Optimization Toolbox* version used in this study is part of the R2020a release of MATLAB. (See MathWorks, 2020) The code used for solving the Adaptive Elastic Net GMM problem can be found in ??.

[4]BIC criterion is calculated as follows:

$$\text{BIC}(p) = log\big[g_{NT}(\hat{\theta}(p))' M_T g_{NT}(\hat{\theta}(p))\big] + A(\hat{\theta}(p)) \cdot \frac{logT}{T}$$

where A(.) returns the number of non-zero parameters.

structural parameters ρ, β and γ from the model in Equation 4 with the estimated interactions matrix $\hat{W}$. Given that the neighbourhood structure is identified from 9, structural parameters can be estimated with two-stage least squares (2SLS).[5] Following De Paula et al. (2019), I use the covariates of the peers-of-peers as the instrumental variables.

4.3 Dyadic Regression

The identified network ties indicate macroeconomic interactions between selected countries with varying strengths. It is possible to exploit this variation to study the nature and formation of these interactions. De Paula et al. (2019) employ the following dyadic regression setup to investigate the factors driving network ties in a given estimate of the interactions matrix $\hat{W}$:

$$\hat{W}_{i,j} = \lambda_0 + \lambda_1 X_{i,j} + \lambda_2 X_i + \lambda_3 X_j + u_{i,j} \tag{10}$$

where $\hat{W}_{i,j}$ is the estimated network tie directed from country j to country i, $X_{i,j}$, X_i and X_j are respectively the characteristics of the pair of countries (i, j), country i and country j time-averaged over the estimation period. I employ the setup in Equation 10 in this study to investigate the correlation between economic interdependence and FDI and trade volume between countries. Covariates $X_{i,j}$, X_i and X_j refer to a subset of the time-averages of FDI and international trade indicators and control variables such as distance, income, output and economic similarities for countries i and j, which may be substantial determinants of economic interdependence. Thus, λ_1, λ_2 and λ_3 indicate to what extent the specified subset of factors correlate with the strength of network ties between countries i and j. With $N(N-1) = 22 \times 21 = 484$ possible ties in the interaction matrix, there is a sufficiently large number of observations. Given that the network ties are bounded such that $\hat{W}_{i,j} \in [0, 1]$, parameters λ_0, λ_1, λ_2 and λ_3 are estimated using the Tobit model. (Tobin, 1958)

5 Results

5.1 Identified Network Ties

Table 2 shows the summary statistics of the networks recovered from data published during the period from 1960Q2 to 1988Q4 and the period from 1990Q1 to 2019Q4.[6] The estimated network has a greater number of strong edges (17 compared to 3) in the period of 1990Q1-2019Q4, as well as more edges overall (116 compared to 90). Also, average weighted in/out-degree for this period is greater than those of 1960Q2-1988Q4 period (.553 compared to .408). These results indicate that the density of the macroeconomic interactions network has increased over time. In addition, clustering coefficient of the 1990Q1-2019Q4 period implies that network nodes exhibit a stronger tendency to cluster together and from stronger transitive paths. This indicates that there is a stronger degree of indirect influence between two countries on average.

[5] Bramoullé et al. (2009) establishes that the structural parameters in the linear social interaction model are identified if the adjacency matrix is known.

[6] Visualizations of the networks can be found in Appendix A.

Table 2: Summary statistics of the recovered network per estimation period

	1960Q2-1988Q4	**1990Q1-2019Q4**
Network-wide Statistics		
Number of edges	90	116
Number of strong edges	3	17
Number of weak edges	87	99
Number of reciprocated edges	20	40
Clustering coefficient	.238	.377
Number of (strong) components	4	2
Size of maximal (strong) component	19	21
Standard deviation of the diagonal of squared W	.0271	.0467
Node-level Statistics		
In-degree distribution	4.09 (1.74)	5.27 (2.07)
Out-degree distribution	4.09 (3.13)	5.27 (3.77)
Nodes with highest in-degree	BEL, JPN, PRT	NLD, AUT, DEU
Nodes with highest out-degree	ESP, ITA, USA	AUT, ESP, ITA
In-degree distribution (weighted)	.408 (.219)	.553 (.214)
Out-degree distribution (weighted)	.408 (.412)	.553 (.556)
Nodes with highest in-degree (weighted)	MEX, JPN, GRC	FIN, MEX, IRL
Nodes with highest out-degree (weighted)	IRL, ESP, USA	GBR, USA, AUT
Number of nodes	**22**	**22**
BIC($\hat{\mathbf{p}}$)	**14.4697**	**15.7761**
$\hat{\mathbf{p}} = (\hat{\mathbf{p}}_1, \hat{\mathbf{p}}_2, \hat{\mathbf{p}}_3)$	**(0, 0, 0.5)**	**(1, 0.001, 1.5)**

Notes: Network ties greater than or equal to .2 are identified as strong edges. Clustering coefficient indicates the ratio of the total weight of transitive triplets over the total weight of all non-vacuous triplets. The weight of an individual triplet is calculated as the geometric mean of the edges. (See Opsahl and Panzarasa, 2009) In-degree (out-degree) refers to the number of edges directed towards (originate from) the node. For the weighted case, in-degree (out-degree) refers to the total weight of the edges directed towards (originate from) the node. Standard deviations are in parentheses.

Evidence from empirical studies similarly suggest that the strength of interactions and clustering tendency across interdependence networks has grown over time.(Cooper, 1985; Kose et al., 2008; Doyle and Faust, 2005; Miśkiewicz and Ausloos, 2010; Antonakakis, 2012; Antonakakis and Scharler, 2012;Gomez et al., 2013) Paralleling these earlier findings, the results regarding the estimated network structures point to a trend of increased economic interdependence across countries over time.

5.2 Contemporaneous and Lagged Network Effects

Table 3 and 4 show the estimates and robust standard errors of autocorrelation coefficient $\hat{\beta}$, contemporaneous network effect $\hat{\rho}$ and lagged network effect $\hat{\gamma}$ respectively for the periods of 1960Q2-1988Q4 and 1990Q1-2019Q4. The results refer to the parameter estimates and statistics for the structural model in Equation 4. The model is estimated by substituting the unknown interactions matrix W_0 with the estimated network $\hat{W}$. *(ii) OLS* column shows the results from the parameters estimated directly from the model with the weighted average of peers' performance. *(iii) 2SLS I* and *(iv) 2SLS II* columns show the results for two-stage least squares (2SLS) estimation with the peers' (I) and peers-of-peers' (II) lagged economic growth used as instrumental variables. All model specifications include individual fixed-effect terms. Given that the model is a system of simultaneous equations and allows for lagged (exogenous) network effects[7], 2SLS with peers-of-peers as instruments is considered to provide the most accurate estimates.(De Paula et al., 2019)

As seen in Table 3, parameter estimates for the period of 1960Q2-1988Q4 indicate that, despite the negative initial estimate, there is no significant autocorrelation in economic growth. However, with $\hat{\gamma}_{OLS} = 1.33$, $\hat{\gamma}_{2SLSI} = 1.58$ and $\hat{\gamma}_{2SLSII} = 1.38$, the lagged network effect is strong and significantly positive, implying that the previous economic performance of peers have a considerable impact. On the other hand, the results reflect a mixed picture with respect to the contemporaneous network effect. While $\hat{\gamma}_{2SLSI} = -.189$ implies negative endogenous network effects, it is not significant. On the other hand, $\hat{\gamma}_{2SLSII} = .302$ indicates a moderately significant and positive network effect that is mildly lower than the initial guess. Given that the peers-of-peers perform best as instruments in this setting, the results suggest that both lagged and contemporaneous network effects exist for this period, while there is no significant autocorrelation.

The results in Table 4 indicate that there is a significant pattern of mean reversal during the period of 1990Q1-2019Q4. Although lower than the initial estimate, autocorrelation coefficient is negative and significant at 0.05 level for all specifications. Again lower than the initial estimate, lagged network effect is close to 1 for all specifications with the preferred estimate $\hat{\gamma}_{2SLSII} = .954$ which is obtained with of peers-of-peers as instruments. On the other hand, the initial guess of contemporaneous network effect is found to be lower than further specifications. With $\hat{\gamma}_{OLS} = .890$ and $\hat{\gamma}_{2SLSII} = .847$, OLS and peers-of-peers regression estimates are close and considerably greater than the initial estimate. With $\hat{\gamma}_{2SLSI} = .673$, 2SLS with peers as instruments appear to produce an estimate between the initial and $\hat{\gamma}_{2SLSII}$. Since the covariates underlying the lagged network effects and instruments are essentially same, this is an expected result as much

[7] The initial estimation procedure (outlined in Section 4.2) was also carried out without exogenous network effect $\hat{\gamma}$ restricted to be equal to zero. In neither period, $\hat{\rho}$ was found to satisfy the identification conditions outlined by De Paula et al., 2019). Specifically, assumption (A2) is violated since $\hat{\rho}$ was found to be greater than 1 for all cases.

Table 3: Estimation results for the period between 1960Q2 and 1988Q4

	1960Q2-1988Q4			
Parameter Estimates	(i) Initial	(ii) OLS	(iii) 2SLS I	(iv) 2SLS II
Autocorrelation coefficient: $\hat{\beta}$	-.024	.004	.022	.008
		(.031)	(.031)	(.031)
Contemporaneous network effect: $\hat{\rho}$	.450	.435***	-.189	.302*
		(.096)	(.218)	(.180)
Lagged network effect: $\hat{\gamma}$	1.43	1.33***	1.58***	1.38***
		(.104)	(.138)	(.131)
R-squared	.162	.167	.154	.166
F-statistic (First Stage)			5.214	3.388
Sum of squared resid.	4607.822	4626.762	4698.916	4629.072
Number of obs.	2508	2508	2508	2508

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. *(ii) OLS* column shows the results from the parameters estimated directly from the model with the weighted average of neighbours' performance. *(iii) 2SLS I* and *(iv) 2SLS II* columns show the results for two-stage least squares (2SLS) estimation with the neighbours' (I) and neighbours-of-neighbours' (II) lagged economic growth used as instrumental variables. All model specifications include individual fixed-effect terms. (See Section 4.2 for details.) Contemporaneous and lagged network effects and autocorrelation coefficient refer to the structural parameters ρ, γ, β respectively. Heteroskedasticity consistent (White) standard errors are in parentheses.

Table 4: Estimation results for the period between 1990Q1 and 2019Q4

	1990Q1-2019Q4			
Parameter Estimates	(i) Initial	(ii) OLS	(iii) 2SLS I	(iv) 2SLS II
Autocorrelation coefficient: $\hat{\beta}$	-.092	-0.069**	-.059**	-.066**
		(.027)	(.030)	(.028)
Contemporaneous network effect: $\hat{\rho}$	.508	.890***	.673***	.847***
		(.067)	(.186)	(.129)
Lagged network effect: $\hat{\gamma}$	1.20	.932***	1.05***	.954***
		(.073)	(.105)	(.087)
R-squared	.228	.235	.232	.235
F-statistic (First Stage)			8.629	4.684
Sum of squared resid.	3196.908	3166.157	3180.500	3167.918
Number of obs.	2618	2618	2618	2618

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. *(ii) OLS* column shows the results from the parameters estimated directly from the model with the weighted average of peers' performance. *(iii) 2SLS I* and *(iv) 2SLS II* columns show the results for two-stage least squares (2SLS) estimation with the peers' (I) and peers-of-peers' (II) lagged economic growth used as instrumental variables. All model specifications include individual fixed-effect terms. (See Section 4.2 for details.) Contemporaneous and lagged network effects and autocorrelation coefficient refer to the structural parameters ρ, γ, β respectively. Heteroskedasticity consistent (White) standard errors are in parentheses.

of the variation expressed through instruments is already captured by the exogenous effects. Considering the more accurate estimates from peers-of-peers as instruments, it is established that there are strong and significantly positive contemporaneous and lagged network effects as well as moderate but significant negative autocorrelation in economic growth across the panel over this period.

These results establish that network effects are present, implying that economic interdependence is palpable across the set of countries during both periods. On the other hand, R-squared is higher for all specifications in the later period. In fact, with an R-squared of .235, the model explains a substantial fraction of the total variation in the period of 1990Q1-2019Q4. This indicates that the fraction of the variation in economic growth explained by network interactions has grown over time. Similar to the prevalent findings in the literature regarding economic interdependence and integration, the results show that economic interdependence and its impact has increased over time.

5.3 Regression Results

Table 5 depicts the results from regressions of network links against different model specifications. A number of other specifications with different control variables were also included. However, only the distance between country i and country j, denoted by DIST_{ij}, and logarithm of the time-averaged GDP of country j, denoted by $\log(\text{GDP}_j)$, were found to have significant explanatory power. Yet, these two variables explain a larger share of the variation compared to the international trade and FDI indicators.

The coefficient estimates on the 2nd and 6th columns in Table 5 indicate that, regardless of whether or not FDI flows are included in the regression, volume of exports from country i to country j, denoted by $\text{TRADE}_{export,ij}$ significantly correlate with the link directed from j to i. On the other hand, volume of goods and services imported from country j to country i do not correlate with the the link directed from j to i. These results are consistent with the implications of the empirical evidence on the relationship between trade and income as various studies found export volume to have a positive impact on economic growth. On the other hand, positive correlation between network links and export volume confirms the hypothesis that the degree of economic influence and trade positively correlates. Considering that the coefficient is negative and not significant for imports, it is likely that economic conditions and exogenous shocks on j have an impact on i partially because aggregate demand in j is a substantial determinant of the exports from i to j, which constitutes an important fraction of the economy in i. Thus, these findings can be interpreted as pointing to a demand-side effect underlying the impact which economic shocks in j have on i through trade.

Inward FDI flows are also found to be positively correlated with link strength. FDI flows from j to i as fraction of the GDP of i significantly correlate with the economic influence of j has over i. The coefficient estimates for $\text{FDI}_{flow,ji}$ are respectively 9.950 and 9.620 for both specifications including FDI flows. Similarly, with a coefficient estimate of 0.633, correlation between accumulated FDI stocks invested from j to i and the strength of the link from j to i have a positive and significant correlation. On the other hand, neither FDI flows nor stock were found to correlate with link strength if the investing country is at the receiving end of the link. These results confirm the hypothesis that inward FDI flows correlate with economic interdependence and also indicate that existing foreign investment stocks correlate positively

Table 5: Network links versus international trade and FDI levels

	Dependent Variable: $\hat{W}_{ij}$					
DIST_{ij}	$-.017^{**}$	-0.012^{*}	-0.016^{***}	-0.016^{***}	-0.015^{**}	-0.011^{*}
	(.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
$\log(\mathrm{GDP}_j)$	0.010^{***}	0.008^{***}	0.009^{***}	0.009^{***}	0.009^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathrm{TRADE}_{export,ij}$		0.292^{***}				0.286^{***}
		(0.109)				(0.108)
$\mathrm{TRADE}_{import,ij}$		-0.188				-0.186
		(0.124)				(0.124)
$\mathrm{FDI}_{flow,ij}$			0.817			0.757
			(0.962)			(0.956)
$\mathrm{FDI}_{flow,ji}$			9.950^{***}			9.620^{***}
			(4.291)			(4.261)
$\mathrm{FDI}_{stock,ij}$					-0.022	
					(0.055)	
$\mathrm{FDI}_{stock,ji}$					0.633^{***}	
					(0.229)	
constant	-0.031^{**}	-0.0215	-0.029^{**}	-0.025^{*}	-0.026^{*}	-0.020
	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
R^2	0.057	0.075	0.070	0.071	0.072	0.088
N	462	462	462	462	462	462

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. DIST_{ij} is the distance between country i and country j. $\log(\mathrm{GDP}_j)$ is the logarithm of the time-averaged GDP of country j. $\mathrm{TRADE}_{export,ij}$ and $\mathrm{TRADE}_{import,ij}$ denotes the time-averaged volume of exports from i to j and imports from j to i respectively. $\mathrm{FDI}_{flow,ij}$ denotes the average size of FDI flows from j to i with respect to the GDP of i. $\mathrm{FDI}_{income,ij}$ denotes the average size of payments from j to i due to the income from FDI in j with respect to the GDP of i. $\mathrm{FDI}_{flow,ij}$ denotes the average size of FDI stocks invested by j in i with respect to the GDP of i.

with interdependence. In consistence with the finding that inward FDI flows stimulate economic growth, it is found that country i is impacted by the economic shocks (e.g. innovation) in country j to a larger extent if the flow of investments from j into i are and have been sizable.

On the other hand, with an R-squared value of 0.088, the last column on Table 5 appears to be strongest specification. Given that the first specification, only with control variables distance and log GDP, already accounts for 0.057 of the total variation in link strength, the results indicate that differences in export volume and FDI flows across countries account for only limited a fraction of the total variation.

6 Conclusion

In this paper, the relationship between international trade, FDI flows and economic interdependence was examined and found to be significant. To measure of economic interdependence, I proposed model within the social network framework which accounts for the possibility of asymmetrical influence within an interdependent relationship. The estimated network ties between countries were obtained with this model and were used to test the hypothesis that economic influence correlates with trade volume and FDI flows between countries. In line with the literature on economic interdependence, differences between the network structures and effects estimated over the earlier and later periods point to an increase in economic interdependence across countries. Regression analysis shows that there is a significant and positive relationship between the economic influence of a country over its trade partner and the degree to which its partner relies on the exports to that country. The results also indicate that there is a significant and positive relationship between an investing country's economic influence over the host country and the FDI flows as well as the accumulated FDI stocks. These findings confirm the hypothesis that inward FDI flows and reliance on trade exposes countries to the economic developments experienced by its investors and export partners. Thus, the results of this paper indicate that international trade and FDI are considerable sources of economic interdependence.

An important limitation of this study is that the number of countries and observations included in the analysis is limited. A number of other countries with a potentially substantial place in the underlying network, such as China, were not included due to unavailability of data. On the other hand, the full network could not be retrieved due to the relatively small number of observations relative to degrees of freedom inherent to the model. The derivative nature of the measure of economic interdependence proposed in this study also implies a limited generalizability of the conclusions drawn from the analysis. Nevertheless, this study makes a valuable contribution to the literature on economic interdependence by providing a reliable framework to estimate and examine the asymmetrical formations of economic interdependence across a set of countries. A potential direction for future research is to test the validity and universality of the relationship implied in this study with a larger set of countries. Given that international trade and FDI are possibly endogenous to economic interdependence, another direction for further research is to employ a more refined analytical strategy to examine the direction of causality and assess the impact as the results may have specific policy implications.

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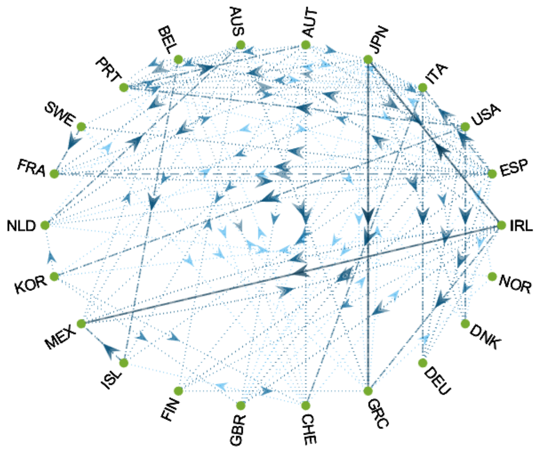
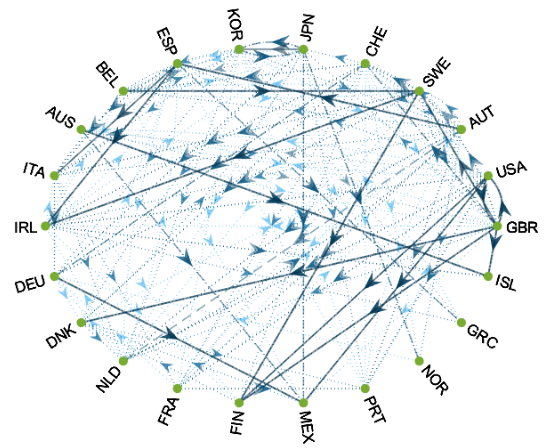
Appendix A: Visualized Networks

(a) Circular graph of the network for the period of 1960Q2-1988Q4.



(b) Circular graph of the network for the period of 1990Q1-2019Q4.



Notes: Stronger edges between nodes are indicated with darker lines. Abbreviations denote the following list of countries: Australia (AUS), Austria (AUT), Belgium (BEL), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Ireland (IRL), Iceland (ISL), Italy (ITA), Japan (JPN), South Korea (KOR), Mexico (MEX), Netherlands (NLD), Norway (NOR), Portugal (PRT), Sweden (SWE) and the United States (USA).

Appendix B: MATLAB Code for Network Estimation

```
clear

rng 'default' % For reproducibility
w = warning ('off','all');

[X,Y] = data();

[X,Y,colmean,colstd] = normalize(X,Y);

T = size(X,1);
N = size(X,2);

I = eye(N);

nvars = (1)+(1)+(1)+(N^2);

XX = multiX(X,N,T);

L1 = [0.1 0;
      0.1 0.001;
      0.1 0.01;
      0.1 0.1;
      0.5 0;
      0.5 0.001;
      0.5 0.01;
      0.5 0.1;
      1 0;
      1 0.001;
      1 0.01;
      1 0.1;];

L2 = [0; 0.25; 0.5; 1; 1.5];

for i=1:size(L1,1)
    lambda = [L1(i,:) 0]
    [obj,G,W,p0,b0,g0,M] = step1(X,Y,XX,N,T,nvars,colmean,colstd,
        lambda);

    for j=1:size(L2,1)
        lambda = [L1(i,:) L2(j)]
        step2(X,Y,XX,N,T,nvars,colmean,colstd,lambda,W)
    end
end

function [obj,G,W,p0,b0,g0,M] = step1(X,Y,XX,N,T,nvars,colmean,colstd
    ,lambda)

```

```
    hybridopt = optimoptions(@fmincon,'Display','iter');
    opt = optimoptions(@particleswarm, ...
    'Display','iter', ...
    'SwarmSize',100,...
    'InitialSwarmSpan',1.5*ones(nvars,1) ,...
    'MinNeighborsFraction',0.1,...
    'UseParallel',true,...
    'UseVectorized',true);

    lb = [];
    ub = [];

    fun = @(theta)(network(theta,lambda,X,Y,XX,N,T,colstd));
    theta = particleswarm(fun,nvars,lb,ub,opt);

    [obj,G,W,p0,b0,g0,M] = network(theta,lambda,X,Y,XX,N,T,colstd);
end

function step2(X,Y,XX,N,T,nvars,colmean,colstd,lambda,W)

    hybridopt = optimoptions(@fmincon,'Display','iter');
    opt = optimoptions(@particleswarm, ...
    'Display','iter', ...
    'SwarmSize',100,...
    'InitialSwarmSpan',1*ones(nvars,1) ,...
    'MinNeighborsFraction',0.1,...
    'UseParallel',true,...
    'UseVectorized',true);

    p1 = lambda(1);
    p2 = lambda(2);
    p3 = lambda(3);

   W = round(W,3);
   W(W>0) = Inf;
    W_hat = (1+p2/T).*W;

    lb = [-Inf*ones(3,1);-W_hat'];
    ub = [Inf*ones(3,1);W_hat'];

    fun = @(theta)(adaptive(theta,lambda,X,Y,XX,N,T,W_hat,colstd));
    theta = particleswarm(fun,nvars,lb,ub,opt);

    [obj,G,W,p0,b0,g0,M] = adaptive(theta,lambda,X,Y,XX,N,T,W_hat,
        colstd);

   W = (1+p2/T).*reshape(round(W,3),N,N);

    coeff = (1+p2/T).*[p0,b0,g0]
```

```

    log(G)

    criterion = bic(G,W,T)

    strid = strcat(string(p1),'_',string(p2),'_',string(p3),'_',string(criterion));

    writematrix(W,strcat('W_vecc_',strid,'.csv'));
    writematrix(coeff,strcat('coeff_vecc_',strid,'.csv'));

    Y_hat = (M*X')' + colmean;
    Y_hat = Y_hat.*colstd;

    writematrix(Y_hat,strcat('Y_hat_vecc_',strid,'.csv'));

    nnz(W)
end

function [obj,G,W,p0,b0,g0,M] = network(theta,lambda,X,Y,XX,N,T,colstd)
    [G,W,p0,b0,g0,M] = GMM(theta,X,Y,XX,N,T,colstd);

    Wnorm(:,1) = sum(abs(W),2); % Calculating the L1-norm of elements of W
    Wnorm(:,2) = sum(W.^2,2); % Calculating the L2-norm of elements of W

    p1 = lambda(1);
    p2 = lambda(2);

    obj=penalty(G,p1,p2,Wnorm);
end

function [obj,G,W,p0,b0,g0,M] = adaptive(theta,lambda,X,Y,XX,N,T,W_hat,colstd)
    [G,W,p0,b0,g0,M] = GMM(theta,X,Y,XX,N,T,colstd);

    W_hat(W_hat==0) = 1;

    Wnorm(:,1) = sum(abs(W)./(abs(W_hat).^2.5),2); % Calculating the L1-norm of elements of W
    Wnorm(:,2) = sum(W.^2,2); % Calculating the L2-norm of elements of W

    p3 = lambda(3);
    p2 = lambda(2);

    obj=penalty(G,p3,p2,Wnorm);
```

```
end

function obj = penalty(val,p1,p2,Wnorm)
    obj = val + p1*Wnorm(:,1)+ p2*Wnorm(:,2);
end

function [G,W,p0,b0,g0,M] = GMM(theta,X,Y,XX,N,T,colstd)
    K = size(theta,1);

    I = eye(N);
    S = diag(1./colstd);

    n = 0;

    p0 = theta(:,n+1);
    n = n + 1;

    b0 = theta(:,n+1);
    n = n + 1;

    g0 = theta(:,n+1);
    n = n + 1;

    ERR = zeros(N*T,K);
    W = zeros(K,N^2);

    for k = 1:K
        w = reshape(theta(k,n+1:n+N^2).^2,N,N);
        w = w - diag(diag(w));
        rowsum = sum(w,2);
        w = w./max(rowsum); % Scaling ==> at least one row-sum == 1
            and all row-sums <= 1

        W(k,:) = w(:)';

        M = (I-p0(k,1)*w)\(diag(b0(k,:))*I+g0(k,1)*w);

        err = (Y' - S*M*inv(S)*X');
        ERR(:,k) = err(:);
    end

    G = gMg(XX,ERR);
end


function obj = bic(G,W,T)
    obj = log(G) + nnz(W)*(log(T)/T);
end
```

```
function G = gMg(XX,ERR)
    gNT = XX*ERR;
    G = sum(gNT.*gNT,1)';
end

function XX = multiX(X,N,T)
    XX = [];
    for n=1:N
        XXt = [];
        for t=1:T
            XXt = [XXt X(t,n).*eye(N)];
        end
        XX = [XX;XXt];
    end
end

function [X,Y] = data()
    Y = readmatrix('g_rate.csv');
    Y = Y(:,2:size(Y,2));

    X = circshift(Y,1,1);

    Y = Y(2:size(X,1),:);
    X = X(2:size(X,1),:);
end

function [X,Y,colmean,colstd] = normalize(X,Y)
    colstd = std(Y,0);
    Y = Y./colstd;
    X = X./colstd;

    colmean = mean(Y,1);
    Y =  Y - colmean;
    X = X - mean(X,1);
end
```