Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi • Cilt: 44 • Sayı: 1 • Haziran 2022, ISSN: 2587-2672, ss/pp. 20-35
DOI: 10.14780/muiibd.1135365

ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

THE NEXUS BETWEEN EMBODIED TECHNOLOGY DIFFUSION AND PRODUCTIVITY: KNOWLEDGE PRODUCTION*

ŞEKİLLENMİŞ TEKNOLOJİ YAYILIMI İLE VERİMLİLİK ARASINDAKİ BAĞLANTI: BİLGİ ÜRETİMİ

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Abstract

This study examines embodied technology flows through intermediate good transactions between industries in various economies and focuses on the ambiguity about their link to innovation. The model consists of two equations measuring labor productivity and knowledge production, and knowledge production is measured as the explanatory variable of productivity. We compare direct effect of embodied research transfer on labor productivity through intermediate good transactions between industries and its indirect effect via knowledge creation. We use input-output tables as a proximity mechanism for research capital and utilize production function approach. Simultaneous equations results support the system we introduce, indicating that both channels of embodied technology spillovers are significant. We observe that labor productivity soars with direct and indirect utilization of technology transfer via knowledge production.

Keywords: Technology Diffusion, Knowledge Production, Simultaneous Equations
JEL Classification: O31, O41, O47

Öz

Bu çalışma, çeşitli ekonomilerde sektörler arası ara mal işlemleri yoluyla şekillenmiş teknoloji akışlarını incelemekte ve bunların inovasyonla olan bağlantılarına ilişkin belirsizliğe odaklanmaktadır. Şekillenmiş araştırma transferi'nin endüstriler arasındaki ara mal işlemleri yoluyla emek verimliliği üzerindeki doğrudan etkisi ile bilgi yaratma yoluyla dolaylı etkisini karşılaştırıyoruz. Araştırma sermayesi için bir ağırlıklandırma yöntemi olarak girdi-çıktı tablolarını ve çoklu denklem GMM yaklaşımını kullanıyoruz. Model, emek verimliliğini ve bilgi üretimini ölçen iki denklemden oluşmakta, bilgi üretimi verimliliğin açıklayıcı değişkeni olarak ölçülmektedir. Eşzamanlı denklem sonuçlarımız, şekillenmiş teknoloji yayılmalarının her iki kanalının da anlamlı olduğunu göstererek, tanıttığımız sistemi desteklemektedir. Bilgi üretimi yoluyla teknoloji transferinin doğrudan ve dolaylı kullanımı aracılığıyla emek verimliliğinin arttığını gözlemliyoruz.

Anahtar Kelimeler: Teknoloji Yayılımı, Bilgi Üretimi, Eşzamanlı Denklemler
JEL Sınıflandırması: O31, O41, O47

* This paper was adapted from Cemil Faruk Durmaz's PhD thesis in preparation. Part of this study is funded by TUBITAK 2214-A scholarship for international research fellowship programme for PhD students.

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Makale Gönderim Tarihi: 03.02.2022
Yayına Kabul Tarihi: 22.06.2022

1. Introduction

Production process depends mainly on three inputs; capital, labor, and knowledge. Knowledge in the form of technological progress is considered as a commodity. However, unlike normal goods, knowledge is non-rival and partially excludable. These properties of knowledge give arise to externality.

Literature focuses on mainly two types of technology flows; knowledge embedded in patents and intermediate goods. Jaffe (1986) is a pioneer study on spillovers via patents in which he constructs a proximity matrix between firms via technology fields of patent applications and Bloom, Schankerman, & van Reene (2013) and Oikawa (2017) use researchers in the same field as a proxy. Aldieri (2013) and Hu & Jaffe (2003) show that Jaffe's method is also suitable for macroeconomics. Verspagen (1997) uses various methods to measure flows between sectors via patent documents with the emergence of the technology flow matrix.

Relation of intermediate goods with technology generation has an important place in endogenous growth models according to Romer (1990) and Grossman & Helpman (1991). Empirical literature adopts this approach and uses intermediate good transactions as a weighting scheme. Griliches (1976) defines spillovers that arise from good purchases from one firm (industry) to another as 'rent spillovers' and suggests that because of quality-price mismatch there is ambiguity about the occurrence of knowledge transfer. Los & Verspagen (2000) compare rent and pure knowledge spillovers and defines transfer via a transmission mechanism (intermediate goods or patents) as indirect R&D spillovers. Terleckyj (1980) and Aldieri, Sena, & Vinci (2018) are examples in the recent literature that compares pure and rent knowledge spillovers. They show that transfer via patents is stronger between agents close to the technology frontier with the same absorptive capacity and estimate that firms, which are further to high R&D intensity, receive knowledge transfer mostly from rent spillovers. Gonçalves & B. Ferreira Neto (2016) and Gonçalves, Perobelli, & Araújo (2017) also focus on the importance of indirect knowledge transfer in emerging countries and medium-level technology sectors.

While empirical literature of embodied knowledge flows focuses on the correlation between productivity and spillovers, we establish an indirect channel from embodied technology diffusion to labor productivity through innovations.

1.1 Main Proposition

In this subsection, we explain two main purposes of this study. First, we create 'a link' from knowledge production to the final product. We observe that empirical literature tends to regress embodied knowledge flow directly to productivity. Thus, we propose that technology spillover works through the knowledge production function in order to obtain a new patent then the new idea is utilized in good or service production. Our first hypothesis is as follows:

Hypothesis 1: Embodied technology flows might have an effect on a final good through knowledge production.

As an example, we assume that firm i operating in machinery sector producing hydraulic press buys a newly innovated metal component from firm j, which is operating in fabricated metals industry. The new component could be embodied with greater research intensity and enables firm i to produce with greater productivity. However, it does not necessarily mean that with the influx of external technology firm i also achieves innovation. We do not argue that so-called "direct effect" does not necessarily increase productivity of firm i's hydraulic press. However, we cannot simply conclude that R&D capital transfer which is weighted by transactions between industries causes an increase in firm i's productivity through its innovative performance. Griliches emphasizes a similar issue with a perspective in failure in price discrimination of firm j. We aim to isolate direct and indirect effects of externality on labor productivity. We summarize our second hypothesis below:

Hypothesis 2: Embodied technology flows might have a direct effect on a final good.

This paper is composed as follows; section two describes the model; section three presents descriptive statistics for the sample and methodology, section four presents results and section five concludes.

2. Model

The main aim of this paper is to examine inter-sectoral externalities and propose a new approach to embodied knowledge transfer. In the empirical literature, an intermediate good is treated as carrier of technology between units in an economy. Grilliches (1976) proposes a production function with externality between firms as follows where the first term is the constant, X_i is the conventional production factors, K_i is the firm's own resources of research and the last term is the knowledge pool comes from all other firms in a sector.

$$Y_i = BX_i^{1-\gamma}K_i^{\gamma}K_{\alpha}^{\mu} \tag{1}$$

Grilliches defines externality as follows;

$$\sum_i K_i = K_{\alpha} \tag{2}$$

Therefore, he aggregates all firm production functions to observe the overall elasticity of knowledge creation including externalities;

$$\sum_i Y_i = B\left(\sum_i X\right)^{1-\gamma}K_{\alpha}^{\gamma+\mu} \tag{3}$$

The last equation shows that coefficient of knowledge capital is greater than the individual production function in aggregated form. Based on Grilliches' function, we propose variations in twofold. First, we use sector production functions and secondly we treat each sector as producer of final output and knowledge.

The model consists of two endogenous equations. One is for the knowledge and the other is for the final good production.

We present the relationship with two equations; Equation 4 shows the final good production function where Y is the value of final goods produced in sector i and country c, X is a vector of conventional inputs such as physical capital stock and domestic inputs for each sector and A is the internal knowledge input. We present knowledge production in equation 5 where R stands for the internal R&D efforts, H is human capital in sector i, and T is the knowledge spillover from other sectors. Unlike Grilliches' model, our spillover term is inserted into both equations to represent two channels of transfer.

$$\mathrm{Y}_{\mathrm{ict}} = \mathrm{X}_{\mathrm{ict}}^{\alpha_1}\mathrm{A}_{\mathrm{ict}}^{\alpha_2}\mathrm{T}_{\mathrm{ict}}^{\alpha_3} \tag{4}$$

$$\mathrm{A}_{\mathrm{ict}} = \mathrm{R}_{\mathrm{ict}}^{\beta_1}\mathrm{H}_{\mathrm{ict}}^{\beta_2}\mathrm{T}_{\mathrm{ict}}^{\beta_3} \tag{5}$$

We select the sample in accordance with available country-sector database from WIOD (World Input-Output Database) and OECD and match countries accessible in both sources. We create clusters for mean labor productivity for OECD economies and our sample consists of the cluster with Czech Republic, Lithuania, Poland, Portugal, Romania, Slovenia, and Turkey. Thus, there are 7 countries and 19 sectors (12 manufacturing and 7 service sectors) between 2009-2014. We have 456 observations with differenced logarithmic form and time lag. Time period is between 2009 and 2014 since R&D expenditure data causes missing observation problem before these dates. Hence, we examine whether two channels of embodied technology flows strengthens labor productivity in low productivity level countries during a post-crisis period. As a result, our sample is in a panel data structure with 7 countries and 19 sectors. We have 798 observations on the level and it reduces to 532 with first difference logarithmic form. Focus of this study is the first cluster with the lowest productivity levels. We choose to examine these countries in a post-crisis period to understand whether inter-sectoral spillovers generate new knowledge production, so that we aim to analyze that the internal innovative dynamics of countries with lower productivity benefits their labor productivity levels which were declined significantly after 2008.

Internal components of production function are calculated with a conventional approach. Physical capital is nominal capital stock and the number of employees in each sector stands for labor. Knowledge production function has three explanatory variables; R&D capital stock that is calculated via cumulative R&D expenditures with depreciation rate, human capital (number of researchers and R&D personnel) and technology spillover.

All variables are transformed into real terms with price indices in WIOD.[1] Gross output and physical capital are deflated via gross output prices when intermediate goods are deflated with intermediate goods price indices.[2] We use labor shares to overcome scale effects and estimate the system in differenced logarithmic forms.

We use number of patents as a proxy for knowledge output. Data for patent grants are obtained from WIPO (World International Patent Office). Patent grants are classified under IPC (International Patent Classification) and even though they are aggregated in NACE Rev 2. codes, each IPC code does not belong to only one sector. A patent grant under a certain technology field could be categorized under more than one NACE sector with two digits. Since there are no patent grants in each technology field[3] for every year in our sample, the following method enables us to overcome the missing data issue. We distribute each technology field code throughout the sectors with probabilistic concordance table (Neuhäusler, Frietsch, & Kroll, 2019). They use patent data for approximately 150 million companies under IPC classification and aggregate them on industry to generate a "technology profile" for each sector. Their data consists of largely with European and North American countries. The coverage of dataset is suitable for our sample. Even though it is not, they explain that their concordance scheme works with on country level with small discrepancies. Notation for each variable is presented in Table 1.

Table 1. List of Variables

Abbreviation	Variable	Source
Y/L	Labor Productivity	WIOD-SEA
K/L	Phsyical Capital Stock per employee	WIOD-SEA
M/L	Within Sector Inputs per labor	WIOD
A/L	# Patent Grants per labor	WIPO
H/L	Human Capital per labor	OECD-ANBERD
R/L	R&D Capital Stock per labor	OECD-ANBERD
T/L	Forward Embodied Technology flow per labor	Author`s calculation
B/L	Backward Embodied Technology flow per labor	Author's calculation

Embodied technology transfer for each sector is calculated as sum of number of patents in other sectors weighted by bilateral intermediate good transactions matrix. Matrix is calculated from input-output tables of each country for 19 sectors. W_{ijc} stands for IO table of each economy where i and j are sector indices and c is for the country. We measure expenditures between sectors by setting the diagonal of matrix W to zero. We name this matrix as $WX_{ijc.}$

1 WIOD presents national input-output tables as a result of project which is funded by European Comission as described by Timmer, Dietzenbacher, Los, Stehrer and Vries (2015).

2 Data collected from WIOD Socio Economic Accounts (SEA) are transformed from national currency to dollar values by using exchange rates of countries presented by WIOD. R&D expenditure is also transformed into in real terms from OECD database.

3 A technology field is an aggregated title for IPC codes with more digits.

$$WX_{ijc} = \begin{bmatrix} 0 & \cdots & n \\ \vdots & 0 & \vdots \\ n & \cdots & 0 \end{bmatrix} \tag{6}$$

Indirect technology spillover is calculated by multiplying WX_{ijc} by R&D intensity[4] of each sector in rows, so that spillover value for each sector is the sum of products between R&D intensity and each IO column. We calculate the variable for every year in the data in equation 7.

$$T_{ict} = \sum_{i=1}^{n} \frac{R_{jct}}{Y_{jct}} WX_{ijct} \tag{7}$$

We calculate backward linkage by simply transposing WX matrix in eq. 8.

$$B_{ict} = \sum_{i=1}^{n} \frac{R_{jct}}{Y_{jct}} \left(WX_{ijct}\right)^{T} \tag{8}$$

We also use domestic inputs of each sector as variable M. We obtain this variable by multiplying W with an identity matrix and extracting the diagonal.

$$WD_{ijc} = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & 1 & \vdots \\ 0 & \cdots & 1 \end{bmatrix} W_{ijc} \tag{9}$$

We divide all variables to number of employees in each industry. Final good product turns into labor productivity and conventional sector inputs are fixed capital stock and inputs. Finally, all variables are transformed into logarithmic forms in differences with additional control variables. We also utilize dummy for manufacturing industries in equation 10 and a dummy for high and medium-high technology level sectors in eq. 11 and 12 to control for sector heterogeneity. [5] We also consider backward link of spillovers in knowledge production where sectors adjust their innovative efforts in accordance with their buyers' research capital stocks in equation 12.

$$\triangle \log Y/L_{ict} = C_{ic} + \alpha_0 \triangle \log K/L_{ict} + \alpha_1 \triangle \log M/L_{ict} + \alpha_2 \triangle \log A/L_{ict} + \alpha_3 \triangle \log T_{ict} + \alpha_4 D_i^1 + \epsilon_t \tag{10}$$

$$\triangle \log A/L_{ict} = C_{ic} + \beta_0 \triangle \log R/L_{ic(t-1)} + \beta_1 \triangle \log H/L_{ic(t-1)} + \beta_2 \triangle \log T/L_{ic(t-1)} + \beta_3 D_i^2 + \epsilon_t \tag{11}$$

4 We calculate R&D intensity by dividing R&D capital stock to final output for each sector.

5 First dummy variable takes the value of 1 if there is a manufacturing industries and 0 otherwise. Dummy variables in knowledge production function are constructed as follows; dummy for high-medium-high technology industries takes the value of 1 for manufacture of chemicals and chemical products; computer, electronic and optical products, electrical equipment, machinery and equipment n.e.c., motor vehicles, trailers and semi-trailers, other transport equipment, Information and communication (except computer programming, consultancy and related activities) services, computer programming, consultancy and related activities; information service activities.

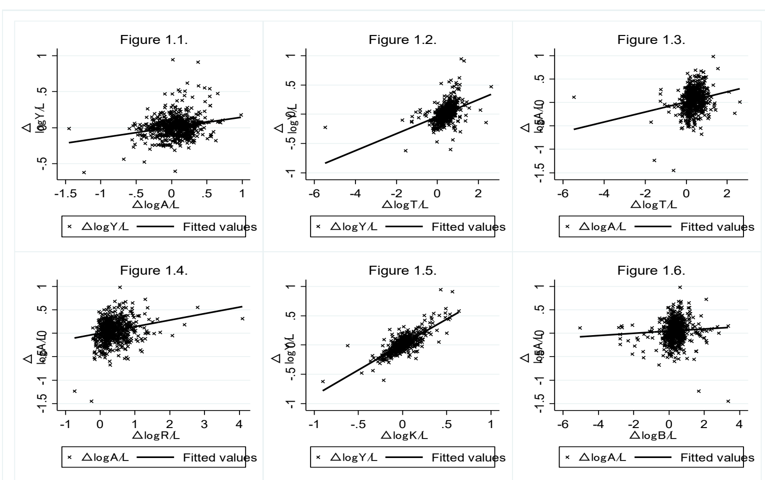
$$\triangle \log A/L_{ict} = C_{ic} + \beta_0 \triangle \log R/L_{ic(t-1)} + \beta_1 \triangle \log H/L_{ic(t-1)} + \beta_2 \triangle \log T/L_{ic(t-1)} + \beta_3 \triangle \log B/L_{ic(t-1)} + \beta_4 D_i^2 + \epsilon_t \quad (12)$$

3. Methodology

Figure 1.1 shows the qualitative relationship between labor productivity and knowledge creation. We examine a possible positive relationship between new ideas and productivity. Thus, patent grants are utilized in good/service production. We also observe a relationship between final goods and external R&D capital stock as positive. In figures 1.3 and 1.4, comparison between external and internal R&D capital stock can be found. We expect contribution from both domestic and inter-industry R&D efforts to knowledge creation. In Figure 1.5. and 1.6., we present physical capital stock and backward embodied technology transfer. These two graphs indicate that they also have a positive relationship between labor productivity and patent grants when the latter is of relatively low magnitude.

We also present weighted network graphs for WX_{ijc} matrix of economies as the average of all years in figures in Appendix. These networks show input-output transactions between sectors in each economy without a self-loop. Thicker edges indicate a relatively higher weight between two nodes. Thus, network graphs show that there is a heterogeneous structure between sectors in absolute values which points out that some sectors have a more prominent role in the economy. We observe that service sectors have relatively higher interactions among each other in all countries. Additionally, manufacturing industries also establish relatively stronger links to service sectors in Poland and Turkey.

Figure 1. All Sample Scatter Plots



3.1. Diagnostics

We present diagnostic test results for data in this section and Table 2 shows descriptive statistics for the sample in logarithmic differences. Industries' R&D capital stock and both types of spillovers have the highest mean which are the focal variables for our purpose.

In Table 3, we present Breusch-Pagan / Cook-Weisberg test values and first-order autocorrelation test results for the same equations. Null hypothesis for no heteroscedasticity is accepted by p values higher than 0.05 for all equations. Wooldridge test for autocorrelation indicates the presence of first-order autocorrelation in equation 10. We also do not observe any significant multi-collinearity.

Table 2. Sample Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
$\triangle$ **logY/L**	0.010028	0.070763	-0.21516	0.257038
$\triangle$ **logK/L**	0.002217	0.065521	-0.21802	0.18365
$\triangle$ **logM/L**	-0.06587	0.222068	-1.0899	0.58546
$\triangle$ **logA/L**	0.052897	0.102682	-0.51277	0.411917
$\triangle$ **logR/L**	0.374576	0.164647	-0.00432	1.0725
$\triangle$ **logH/L**	0.081257	0.1637	-0.51674	0.713787
$\triangle$ **logT/L**	0.347283	0.144444	-0.38604	0.599241
$\triangle$ **logB/L**	0.323911	0.188204	-0.43203	0.692523

Table 3. Heteroscedasticity – First Order Autocorrelation Test Results

Equation 10	Equation 11	Equation 12
Breusch-Pagan / Cook-Weisberg test for heteroscedasticity		
Prob > chi2 = 0.1197	Prob > chi2 = 0.3474	Prob > chi2 = 0.0768
Wooldridge test for autocorrelation in panel data		
Prob > F = 0.0003	Prob > F = 0.0533	Prob > F = 0.0542
Mean VIF = 1.1	Mean VIF = 1.23	Mean VIF = 1.23

3.2. Estimation Strategy

We utilize Generalized Method of Moments-3 Stages Least Squares (GMM-3SLS) method. Wooldridge (2002) argues that GMM-3SLS is consistent and asymptotically normal. 3 stages least squares uses all exogenous determinants as instruments for each equation.

We use a weight matrix up to two lags with Bartlett Kernel that allows for autocorrelation and heteroscedasticity. Band-with is determined as one addition to the lag structure. Significance of our results do not vary depending on band-with used in the weight matrix. We also obtain robust clustered standard errors and use twostep GMM estimator. Additionally, we use an identity weight matrix for the first step parameter estimates. Finally, Hansen's J test result shows that system is over-identified.

4. Results

Results for final good production function in third column indicate that physical capital has the largest impact on labor productivity in Table 4. Patent to labor ratio has the second largest effect on labor productivity and our dummy variable for manufacturing industries is significant and positive. Our spillover term has a significant impact on knowledge production. We should also note that the impact of indirect R&D spillover is higher more than the direct effect. If we had regressed our technology spillover variable to labor productivity function, results would be misleading and we would not know whether R&D inflow actually turns into inventions and through that process productivity in final good soars. In our model, we try to isolate "direct" and "indirect" effects of intermediate good transactions.

Our empirical results support the system we have introduced where both indirect knowledge spillovers are effective through knowledge production and direct flow from other industries increases labor productivity of receiving sector. Thus, we create a 'link' via knowledge creation from spillovers to final good production that would be missing otherwise. Finally, backward linkage falls short in its impact on knowledge creation. Therefore, forward spillover comes forward as the prominent source of externality for our sample.

5. Conclusion

This paper presents a production function approach to simultaneously analyze different roles of embodied technology transfer through intermediate goods between industries. First, we measure direct impact of diffusion on labor productivity. Second, we propose an indirect effect of technology transfer on productivity through knowledge creation. Therefore, the receiver sector of research diffusion uses higher external research intensity to produce a more efficient final output when it also uses it to produce new ideas in knowledge production part of the sector. We also introduce research flows to R&D department as backward link where supplier industries adapt their research efforts to their customers'.

We create a sample with 7 economies and 19 sectors between 2009 and 2014. We also utilize multiple equation GMM to simultaneously estimate a two-equation system; final good and knowledge production. Results indicate that both channels of embodied technology flow are significant indicators of labor productivity. We also conclude that indirect impact of research transfer is greater than its direct effect when backward linkage on knowledge creation has no significant influence.

Overall, this paper argues the literature by emphasizing that a direct correlation of embodied technology flow via intermediate goods to the productivity of industries is not sufficient to analyze whether there is room for creation of new ideas as a result of externalities. Thus, we create a link between embodied research transfer and labor productivity through knowledge creation along with the direct impact of spillovers.

We suggest that policymakers consider these two channels jointly in order to examine inter-sectoral transactions in an economy in the framework of research diffusion. Thus, stimulation of externalities as result of R&D subsidies would be analyzed in terms of not only direct link to productivity levels but also as a nexus between final good and embodied technology transfer via knowledge creation.

Table 4. Estimation Results

	No Externalities		**Externalities**			
	Eq. 10	**Eq. 11**	**Eq. 10 Eq. 11**		**Eq. 10 Eq. 12**	
VARIABLES	**$\triangle logY/L_{ict}$**	**$\triangle logA/L_{ict}$**	**$\triangle logY/L_{ict}$**	**$\triangle logA/L_{ict}$**	**$\triangle logY/L_{ict}$**	**$\triangle logA/L_{ict}$**
$\triangle$ logK/L$_{ict}$	0.824***		0.801***		0.800***	
	(0.0608)		(0.0589)		(0.0559)	
$\triangle$ logM/L$_{ict}$	0.0192**		0.0199***		0.0196**	
	(0.00787)		(0.00768)		(0.00767)	
$\triangle$ logA/L$_{ict}$	0.265**		0.250*		0.228*	
	(0.127)		(0.140)		(0.127)	
$\triangle$ logT/L$_{ict}$			0.0275**		0.0284**	
			(0.0118)		(0.0111)	
D^1	0.0324***		0.0313***		0.0314***	
	(0.00682)		(0.00668)		(0.00660)	
$\triangle$ logH/L$_{ic(t-1)}$		0.00604		0.00231		0.00274
		(0.0164)		(0.0166)		(0.0170)
$\triangle$ logR/L$_{ic(t-1)}$		0.107***		0.0953***		0.0948***
		(0.0293)		(0.0306)		(0.0312)
$\triangle$ logT/L$_{ic(t-1)}$				0.0385*		0.0381*
				(0.0211)		(0.0218)
D^2		-0.0132		-0.0133		-0.0128
		(0.0153)		(0.0154)		(0.0158)
$\triangle$ logB/L$_{ic(t-1)}$						0.00730
						(0.0145)
Constant	-0.0374***	0.00898	-0.0436***	-0.00164	-0.0426***	-0.00495
	(0.00890)	(0.0175)	(0.00820)	(0.0181)	(0.00802)	(0.0182)
Hansen's J	0.2201		0.2395		0.3004	
Observations	532		532		532	

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Acknowledgements

Special thanks to my thesis supervisor Dr. Burcu Düzgün Öncel of Marmara University for her valuable contributions and to Dr. M. Nedim Sualp for all of his advices.

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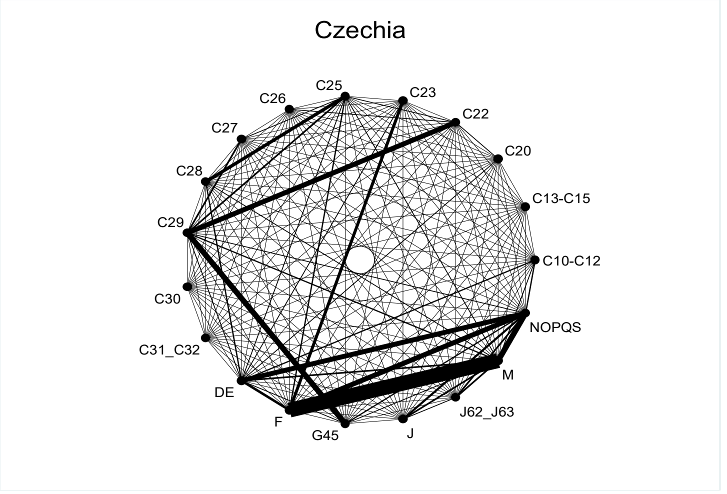
Appendix

Table A.1. List of Sectors

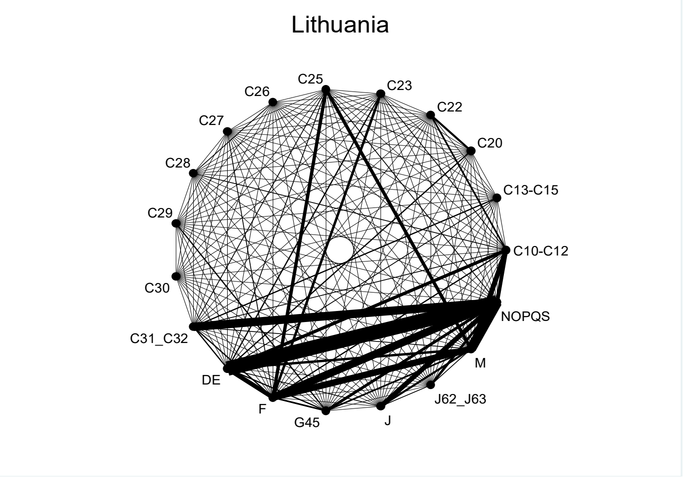
NACE Rev. 2.	Sector
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C20	Manufacture of chemicals and chemical products
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31_C32	Manufacture of furniture; other manufacturing
DE	Electricity, Gas And Water Supply; Sewerage, Waste Management And Remediation Activities
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
J	Information and communication (except Computer programming, consultancy and related activities)
J62_J63	Computer programming, consultancy and related activities; information service activities
M	Professional, scientific and technical activities (with scientific research and development)
NOPQS	Community, Social And Personal Services

Figure A.1. Czech Republic Input-Output Network



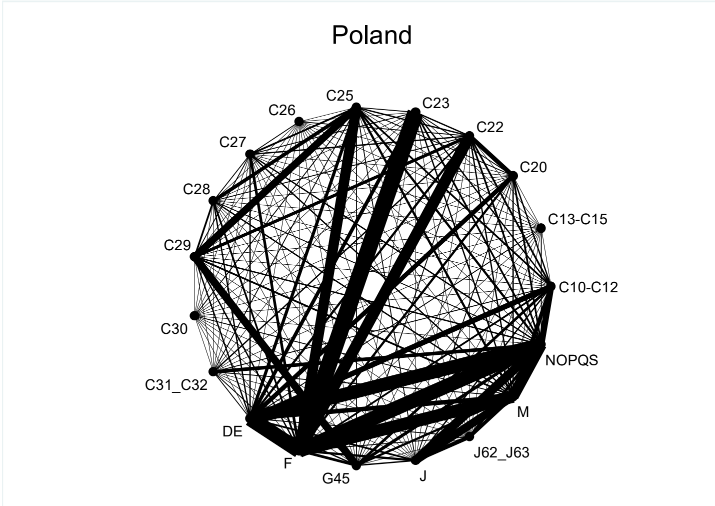
Source: Author's calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)

Figure A.2. Lithuania Input-Output Network



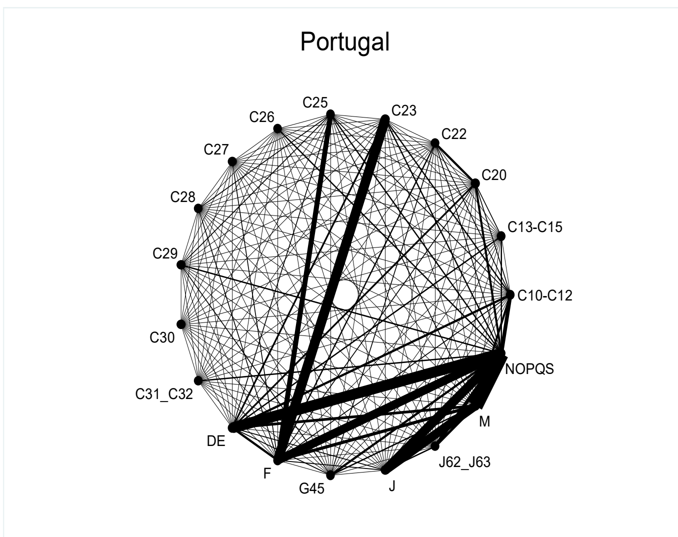
Source: Author's calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)

Figure A.3. Poland Input-Output Network



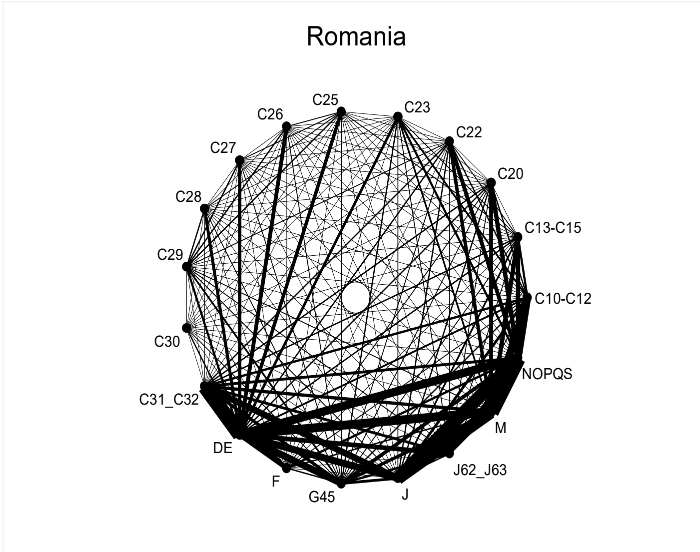
Source: Author’s calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)

Figure A.4. Portugal Input-Output Network



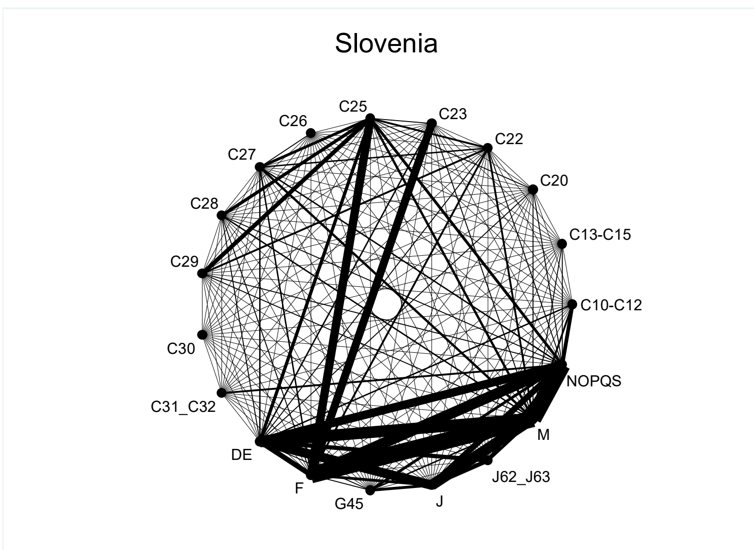
Source: Author’s calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)

Figure A.5. Romania Input-Output Network



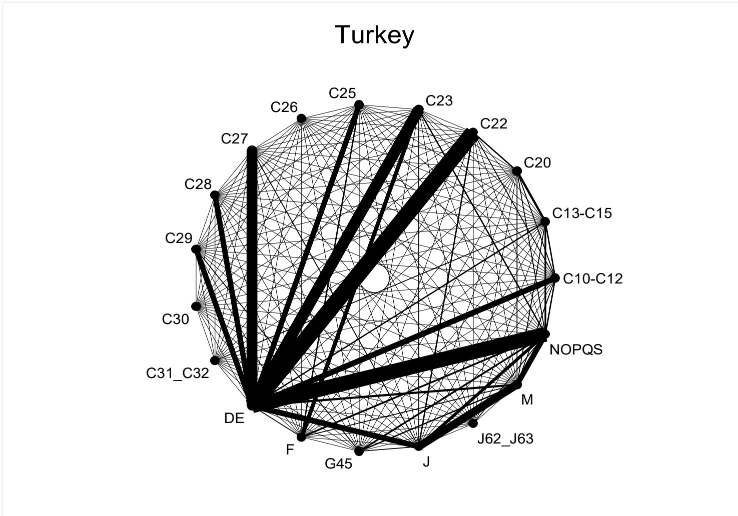
Source: Author's calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)

Figure A.6. Slovenia Input-Output Network



Source: Author's calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)

Figure A.7. Turkey Input-Output Network



Source: Author's calculations based on WIOD, Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)