아태연구 제19권 제2호(2012)

Export Competitiveness and Technological Capability in Bioenergy Sector

Bong-Suk Sung*
Won-Guon Cho**

| 목 차 |

Ⅰ. Introduction
Ⅱ. Empirical methodology, model specification and data
Ⅲ. Empirical analysis
Ⅳ. Conclusion

| 논문요약 |

각국의 바이오에너지 산업의 성장과 수출은 주로 기술지향 및 수요견인 정책을 통해 유도되고 있다. 이들 정책의 주요 목표가 기술 혁신인 점을 감안하면 기술 역량은 곧 산업과 수출을 성장시키는 주요 요인이 된다. 이러한 사실에도 불구하고, 바이오에너지 산업에 있어서의 수출 경쟁력과 기술 역량 사이의 동태적 관계를 분석하고 있는 실증 연구는 없다. 이에 본 연구는 20개 OECD 국가에 대한 패널 자료를 구축하여 바이오에너지 산업에 있어서의 수출 경쟁력과 기술 역량 간 관계를 분석하였다. 먼저, 각 시계열에 있어서의 구조적 변화와 횡단면 사이의 상호의존성에 대한 검정을 실시하였으며, 이 결과에 기초하여 데이터의 정상성과 장기 균형의 존재 여부를 검정하였다. 패널 단위근 및 패널 공적분 검정 결과, 데이터가 안정적이지 않은 것으로 나타났으며, 시계열 사이에 공적분이 있는 것으로 나타났다. 이에 본 연구는 패널 VECM을 설정하고 1단계 차분 GMM 추정을 통해 양자간 관계를 분석하였다. 분석결과, 단기

* Department of International Management, Woosong University.
** Corresponding author. Department of Railroad and Business Management, Woosong University.

적으로 수출경쟁력은 기술역량에 정(+)의 영향을 미치고 있으며, 이들 양자는 오차수정항과 작용하여 상호 영향을 미치는 것으로 나타났다. 장기적으로는 기술역량의 강화가 오차수정항을 통해 수출경쟁력에 정(+)의 영향을 미치는 것으로 나타났다. 본 연구의 결과는 바이오에너지 공공정책의 입안과 수행이 수출경쟁력에 대한 긍정적인 정책탄력성을 유발할 수 있도록 장기적인 차원에서 접근해야할 필요성을 제기하고 있다.

▪ 주제어: 바이오에너지, 기술 특화, 무역 특화, 동태패널접근, 인과분석

I. Introduction

The market size and international trade volume of bioenergy have been substantially increased over the past two decades, which is attributed to each country's effort to perform the Kyoto Protocal and policy supports to promote innovation, solid expansion in demand of energy, abundance of biomass and so forth. Among them, technology-push and market-pull policy approaches carried out by each country around the world as part of efforts to create innovation have a key role in growing the market for renewable energy including bioenergy and the international trade. Despite the fact that each country has tried to promote bioenergy technology sector by encouraging cost-competitive technological innovation using various public policy measures, costs for most renewable energy technologies including bioenergy technology remain high compared to the fossil fuel alternative and many renewables technologies are relatively technically immature and are thus posed for further (and perhaps significant) cost and performance improvement(Arent et al., 2011). It indicates that governments will take various policy measures to promote technological capabilities related to bioenergy sector as part of effort to reduce the cost. Within the industrial growth context, the question of whether energy policies may succeed in the renewable energy technology industry, such as penetrating the market well and gaining lager market shares, relies entirely on creating the potential for technological innovation. It indicates that there is considerable relationship between a country's export competitiveness and the role played by technological innovation in creating and maintaining competitive advantage, especially in renewable energy technologies including bioenergy sector. Despite the importance of technological capability in enhancing the export specialization, no researches look into the dynamic relationship between the two factors.

In this context, this paper is to investigate the relationship between each country's export comparative advantage and technological capability in bioenergy technology sector, using panel data for OECD countries over the period from 1993 to 2008. Amendola et al.(1998), Laursen(2000), Uchida and Cook(2005), and so forth examined the linkage between a country's technological capacity and its ability to penetrate foreign market in manufacturing sector give a useful theoretical background to this paper. The notion of linkage between trade competitiveness and technological capability is that national system of innovation relates to the sector structural export performance, which is based on neo-Schumpeterian view that international trade specialization, as a measure of competitiveness, is the outcome of country- and sector-specific learning processes relating to technological capability. The mechanism linking the two leads to a stability of trade specialization, in which trade patterns are likely to be stable and changes in the pattern of technological specialization are cumulative or path dependent. These patterns are likely to be manifested through the path-dependency characteristics of the evolution of technological innovation(Dosi et al., 1990). Patterns of specialization over shorter time horizons are more likely to be susceptible to market and policy-induced influences relating to changes in exchange rates, factor prices and promotional policies (Grupp and Munt, 1998). In recent years, there has been mounting support from empirical studies, such Amable and Verspage(1995), Amendola et al.(1998), Dosi et al.(1990), Uchida and Cook(2005), Loiter and Norberg-Bohm(1999), to indicate that competitiveness in trade is indeed influenced by a country's technological capability.

The paper is structured as follows, Section Ⅱ provides the empirical methodology for analyzing the dynamic relationship between technological capability and trade competitiveness, and describes the data used in the empirical test. The empirical test results are presented and interpreted in Section Ⅲ. Section Ⅳ concludes and presents some policy implications based on the results from the paper.

Ⅱ. Model Specification, Empirical Methodology and Data

1. Model specification and empirical methodology

To investigate the bidirectional relationship between trade and technological specialization in bioenergy sector, the study considers the panel VAR model proposed by Holtz-Eakin et al.(1988), which can be expressed as

$$RSCA = \alpha_{1j} + \sum_{k=1}^{m+1} \beta_{11k} RSCA_{-k} + \sum_{k=1}^{m+1} \beta_{12k} TSCA_{-k} + \sum_{k=1}^{m+1} \beta_{13k} CO2PC_{-k} + \eta_{1i} + \mu_1 \qquad (1)$$

$$TSCA = \alpha_{2j} + \sum_{k=1}^{m+1} \beta_{21k} RSCA_{-k} + \sum_{k=1}^{m+1} \beta_{22k} TSCA_{-k} + \sum_{k=1}^{m+1} \beta_{23k} CO2PC_{-k} + \eta_{2i} + \mu_2 \qquad (2)$$

$$CO2PC = \alpha_{3j} + \sum_{k=1}^{m+1} \beta_{31k} RSCA_{-k} + \sum_{k=1}^{m+1} \beta_{32k} TSCA_{-k} + \sum_{k=1}^{m+1} \beta_{33k} CO2PC_{-k} + \eta_{3i} + \mu_3 \qquad (3)$$

where η_{1i}, η_{2i} and η_{3i} are country-specific effects for the ith individual in the panel, and μ_{1it}, μ_{2it} and μ_{3it} are the disturbance terms. RSCA is the trade specialization, TSCA stands for the technological specialization, and CO2PC, as a key social variable that has an effect on country's commitment to renewable, is to control the impact of political pressures to encourage society sustainability through renewable energy.

First of all, Jarque-Bera test for normality in each individual time series, to find whether or not structural breaks exist, is carried out. To diagnose for the presence of cross-section dependence, the study employs Frees(1995) and Pesaran(2004) tests used for $T < N$ (as is the case in this paper). Then, panel unit root tests for investigation of the order of integration of the series in the panel data are conducted, reflecting the results of the tests for structural breaks and for the presence of cross-section dependence. If the results of the panel unit root tests indicate that the series are non-stationary, the paper can confirm that a long run equilibrium relationship between the variables in question exists by performing panel cointegration tests based on Pedroni(1999; 2004), Westerlund(2007), or Banerjee and Carrion-i-Silvestre(2006), considering also the results of tests for structural break and cross-section dependence. In the last phase, the study sets empirical model based on the results of panel unit tests and panel cointegration tests, and perform panel causality tests.

2. Data sources and definition of variables

This study uses annual data on exports, patents related to bioenergy technologies sector, and carbon dioxide emissions per capita for each country. The balanced panel data set has 320 observations, representing 16 years of data (from 1993 to 2008) per country for each of the 20 OECD countries. The countries and the period have been selected on the ground of data availability. Data on bioenergy technology exports for each country were extracted from the UN COMTRADE database (UNCTAD), based on the Harmonized Commodity Description and Cording System(HS, 1996). The topologies of bioenergy technologies and components are well defined by Jha (2009), starting from the classification HS 1996. The HS codes of bioenergy technologies categorized by Jha(2009) are 220710, 220720, 380210, 382490, 730900, 741999, 761100, 840681, 840682, 841182, 841620, 841931, 841940, 841989, 842129, 842139, 847920, 847989. The trade data are calculated according to the 2009 constant price and the PPP international. Index measuring trade specialization was calculated on a country basis based on Balassa(1965), $RCA_{ij}=(X_{ij}/\sum_i X_{ij})/(\sum_j X_{ij}/\sum_i\sum_j X_{ij})$ where X_{ij} is exports of product j of country i, $\sum_i X_{ij}$ is world exports of product j, $\sum_j X_{ij}$ is total exports of country i and $\sum_i\sum_j X_{ij}$ stands for total world exports.

Data on the bioenergy patents for each country were obtained from the OECD database for science, technology and patents. Only patent applications deposited at the European Patent Office (EPO) were included, following Johnstone et al.(2010). Index measuring technology specialization, relative technological advantage (RTA) was calculated on a country basis based on patents data following Amendola et al.(1998), which has been calculated as follows: $RTA_{ij}=(P_{ij}/\sum_i P_{ij})/(\sum_j P_{ij}/\sum_i\sum_j P_{ij})$ where P_{ij} is the number of patents of country i in sector j, $\sum_i P_{ij}$ is the number of patents of world in sector j, $\sum_j P_{ij}$ is total number of patents in country i and $\sum_i \sum_j P_{ij}$ stands for the total number of patents in the world.

The paper is to minimize the possibility of adverse effects that the lack of normality in RCA and RTA index is not producing reliable t-satistics(Dalum et al., 1998; Larsen, 1998), by transforming the indices based on Larsen (1998), which has been calculated by $RSCA_t = (RCA_t - 1)/(RCA_t + 1)$ and $TSCA_t = (TCA_t - 1)/(TCA_t + 1)$. Accordingly, each value for RSCA or TSCA ranges from -1 to 1.

Data on carbon dioxide emissions per capita for each country were obtained from the World Development Indicators database of the World Bank. Higher levels of CO2PC create awareness in society about environment and sustainability, which results in political pressures to encourage the use of energy generated from renewable sources(Marques and Fuinhas, 2011). Such social sentiment encourages a greater number of stakeholders, such as investors and firms including government, to participate in various activities related to renewable energy sector including bioenergy technologies, for example R&D, investment and so forth, which is likely to result in higher specialization and production by helping component manufacture innovate in manufacturing of bioenergy technologies' components for export to foreign manufacturers of bioenergy systems as well as for the local. Hence, this paper controls the impact of political pressure to encourage society sustainability through renewable energy including bioenergy by putting the CO2PC into the model as a control variable.

Ⅲ. Empirical Analysis

1. Trend of export and technological competitiveness

<Table 1> reports the trend of export in each country. In terms of the average annual increase rate, Turkey secures the top spot. Hungary, Ireland Korea, Spain, Canada and the USA follows in the next six leading slots.

<Table 1> Status of export by countries

(Unit: export, million dollar; net export: ratio)

Country	Export			Net export	
	1993	2008	average annual increase rate ('93-'08)	1993	2008
Australia	108.9	364.6	7.84%	0.28	0.21
Canada	496.4	2,904.7	11.67%	0.40	0.84
Czech	503.9	503.9	0.00%	0.75	0.75
Denmark	821.2	9,146.8	16.26%	0.69	2.06
Finland	243.4	1,334.2	11.22%	1.03	1.64
France	2,970.0	2,352.6	-1.45%	1.27	1.80
Germany	5,304.5	24,290.5	9.98%	2.62	2.33
Hungary	7.4	456.0	29.39%	0.26	0.50
Ireland	92.2	3,321.4	25.11%	0.43	8.74
Korea	268.6	5,484.2	20.75%	0.20	0.45
Netherlands	1,014.5	9,699.5	15.15%	1.40	1.99
New Zealand	20.3	83.2	9.21%	0.33	0.34
Norway	151.5	1,356.8	14.68%	0.71	1.01
Portugal	0.5	0.4	-0.95%	0.47	0.40
Spain	236.9	1,613.7	12.74%	0.49	0.48
Sweden	511.1	1,914.8	8.61%	1.30	1.22
Switzerland	1,070.1	2,831.5	6.27%	1.57	1.51
Turkey	0.1	407.2	70.52%	0.04	0.22
Uk	1,650.2	3,925.6	5.57%	1.35	1.02
USA	4,460.3	22,643.3	10.69%	1.76	1.43

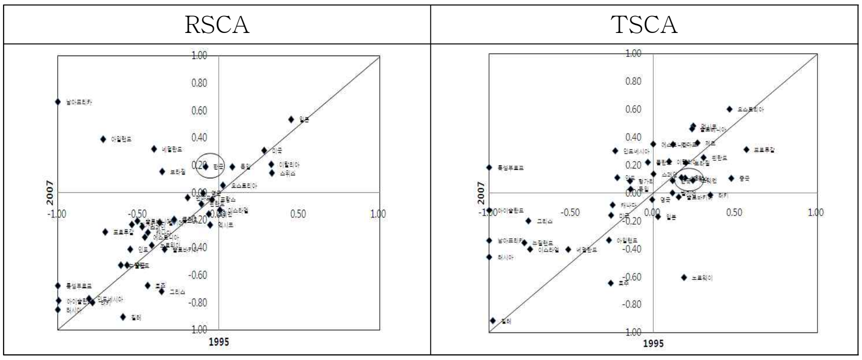
Source: The figures are calculated based on the data analyzed in the study.
Notes: Net export stands for the share of export relative to import.

As of 2008, Germany ranks first, exporting the amount of about US$ 24 billion, and the USA, the Netherlands, Denmark and Korea rank second, third, fourth and fifth, respectively. In terms of the net export, Germany, Denmark, the Netherlands, the USA and so fourth are ordered as of 2008 in which over 1 means the net exporter that its export exceeds the import in bioenergy technologies sector.

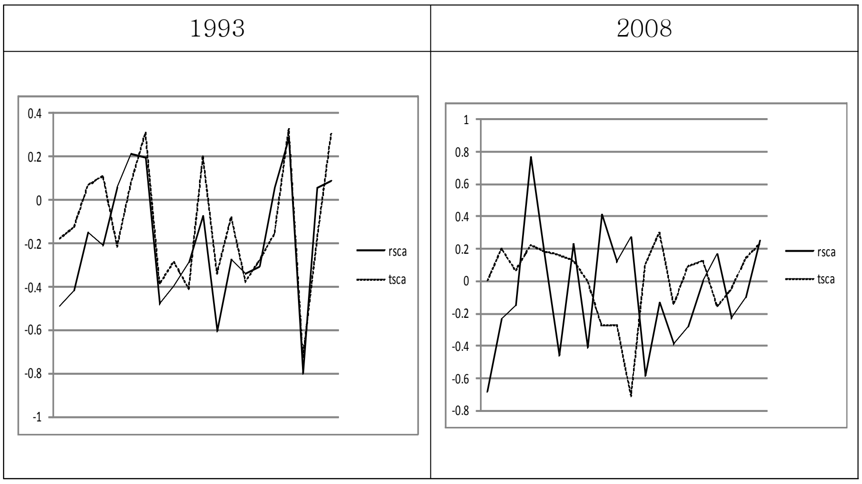
<Figure 1> shows that each country's competitive position in trade and technology between 1993 and 2008. The results presented in <Figure 1> imply that the country with a positive RSCA index has a comparative advantage compared to other countries, while the country with a negative RSCA index has a comparative disadvantage compared to other countries. It also shows, between the two periods, 1993 and 2008, that first quadrant represents keeping its comparative advantage, second quadrant describes change its competitive position from comparative disadvantage to comparative advantage, third quadrant indicates keeping its comparative disadvantage, and fourth quadrant implies changes its competitive position from comparative advantage to comparative disadvantage. The upper or lower part of a slope of forty-five degrees indicates the direction of change in its comparative competitiveness in terms of trade and technology capability. For example, the countries on the upper part of a slope of forty-five degrees can be interpreted as their competitiveness increased (improvement of the degree of its comparative advantage or disadvantage), and the countries on the lower part of a slope of forty degrees can be interpreted as their competitiveness decreased. According to <Figure 1>, Korea in second quadrant and on the upper part of a slope of forty-five degree has changed its competitiveness in trade from comparative disadvantage in 1993 to comparative advantage in 2008. The countries, such as Finland, Germany and Switzerland, have kept their comparative advantage in trade, being on first

quadrant. Denmark, the Netherlands, Ireland including Korea are on second quadrant. The countries kept being in a comparative disadvantage position locared third quadrant are Australia, Canada, Czech, Hungary, New Zealand, Norway, Portugal, Spain and Turkey.

In terms of the technological capability changes based on <Figure 1>, Korea in first quadrant and on the lower part of a slope of forty-five degrees has kept staying in a comparative advantage position between the two periods, decreasing the degree of its comparative advantage in technological capability. Most of the countries except Germany, the Netherlandes, Switzerland and USA are on the upper part of a slope of forty-five degrees, suggesting that their technological competitiveness have been increased, improvement of the degree of its comparative advantage or disadvantage. Canada, Finland, New Zealand, Norway, Spain and Sweden have kept their comparative advantage in technology capability, being on second quadrant.



<Figure 1> Changes in the competitiveness of trade and technology



<Figure 2> Correlation between trade and technological specialization

<Figure 2> shows correlation between trade and technological specialization index, RSCA and TSCA, on a country basis in 1993 and 2008. As <Figure 2> presents, the RSCA index correlates almost perfectly to the TSCA index in 1993, while the RSCA index correlates less strongly to the TSCA index in 2008 compared to that of 1993.

2. The testing frameworks

<Table 2> summarizes the basic statistics of the variables during the research period. The Jarque-Bera test results show that almost all of these series do not deviate substantially from normal distribution, demonstrating that the null hypothesis of normality cannot be rejected at 1% and 5% level of significance in almost all individual time series. This implies that almost all of the series are stable over time.

<Table 2> Descriptive statistics

Industry	Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Jarque -Bera
Australia	RSCA	−0.510	0.112	−0.681	−0.239	0.681	3.161	1.256
	TSCA	0.063	0.192	−0.203	0.365	−0.070	1.748	1.057
	CO2PC	−0.338	0.286	−0.737	0.101	0.093	1.581	1.363
Canada	RSCA	−0.356	0.081	−0.493	−0.237	−0.281	1.923	0.984
	TSCA	0.207	0.224	−0.176	0.436	−0.790	2.066	2.247
	CO2PC	0.643	0.145	−0.420	0.925	0.196	2.206	0.521
Czech	RSCA	−0.250	0.110	−0.378	0.061	1.398	4.931	7.699
	TSCA	−0.220	0.304	−0.507	0.195	0.270	1.122	2.544
	CO2PC	−0.045	0.401	−0.531	0.590	0.283	1.499	1.521
Denmark	RSCA	0.255	0.274	−0.221	0.789	0.270	3.025	0.195
	TSCA	0.284	0.174	−0.180	0.446	−1.282	4.020	5.078**
	CO2PC	0.111	0.598	−1.548	0.614	−1.796	4.971	11.200*
Finland	RSCA	0.018	0.070	−0.098	0.137	−0.189	2.123	0.608
	TSCA	0.147	0.206	−0.218	0.424	−0.788	2.245	2.037
	CO2PC	0.474	0.122	0.280	0.686	0.280	1.956	0.935
France	RSCA	0.010	0.155	−0.461	0.213	−1.727	6.440	15.850*
	TSCA	0.125	0.089	−0.960	0.252	−0.963	3.592	2.707
	CO2PC	0.264	0.062	0.171	0.368	0.167	1.750	1.115
Germany	RSCA	0.212	0.028	0.161	0.264	0.079	2.177	0.467
	TSCA	0.180	0.054	0.109	0.308	0.621	2.838	1.048
	CO2PC	0.398	0.092	0.257	0.555	0.128	1.852	0.921
Hungary	RSCA	−0.338	0.102	−0.527	−0.157	−0.309	2.193	0.688
	TSCA	−0.347	0.249	−0.534	0.148	1.149	2.512	3.681
	CO2PC	0.406	0.295	−0.182	1.056	0.080	3.495	0.180
Ireland	RSCA	0.196	0.307	−0.447	0.473	−1.248	2.972	4.160
	TSCA	−0.125	0.238	−0.286	0.359	1.230	2.667	4.109
	CO2PC	−0.221	0.483	−0.970	0.342	−0.137	1.468	1.614
Korea	RSCA	−0.041	0.137	0.291	0.174	−0.062	2.107	0.541
	TSCA	−0.277	0.145	0.426	0.024	−0.990	2.774	2.649
	CO2PC	−0.011	0.463	0.916	0.562	−0.288	1.959	0.943
Netherlands	RSCA	−0.036	0.131	0.153	0.295	1.827	5.010	11.600*
	TSCA	−0.088	0.430	−0.808	0.382	−0.686	1.684	2.409
	CO2PC	−0.065	0.841	−1.390	0.652	−0.781	1.695	2.762
New Zealand	RSCA	−0.522	0.090	−0.634	−0.317	0.900	2.940	2.166
	TSCA	−0.215	0.196	−0.353	0.168	1.240	2.730	4.154
	CO2PC	0.283	0.356	−0.627	0.525	−2.035	5.566	15.440*

<표 계속>

Industry	Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Norway	RSCA	−0.294	0.137	−0.550	−0.030	0.013	2.524	0.151
	TSCA	0.057	0.213	−0.125	0.474	0.711	2.835	2.256
	CO2PC	0.270	0.072	−0.173	0.397	0.168	2.743	1.129
Portugal	RSCA	−0.274	0.099	−0.500	−0.130	−0.324	2.963	0.282
	TSCA	−0.200	0.269	−0.419	0.279	0.744	1.747	2.524
	CO2PC	0.358	0.086	−0.209	0.491	−0.166	1.959	0.796
Spain	RSCA	−0.307	0.037	−0.345	−0.208	1.095	3.912	3.755
	TSCA	−0.029	0.217	−0.298	0.250	−0.130	1.303	1.965
	CO2PC	0.379	0.093	0.217	0.516	−0.045	1.933	0.764
Sweden	RSCA	−0.038	0.076	−0.175	0.084	−0.126	1.988	0.725
	TSCA	0.037	0.172	−0.190	0.310	0.110	1.534	1.465
	CO2PC	0.226	0.062	0.135	0.325	0.201	1.869	0.960
Switzerland	RSCA	0.286	0.073	0.140	0.388	−0.470	2.345	0.876
	TSCA	0.091	0.187	−0.261	0.456	0.019	2.112	0.526
	CO2PC	0.170	0.032	0.113	0.217	−0.243	2.079	0.723
Turkey	RSCA	−0.685	0.152	−0.827	−0.230	1.755	5.933	13.950*
	TSCA	−0.516	0.179	−0.726	−0.048	0.952	3.961	3.035
	CO2PC	1.845	2.043	−1.282	0.754	0.808	3.137	1.758
UK	RSCA	−0.031	0.052	−0.110	0.052	0.109	1.818	0.962
	TSCA	0.101	0.143	−0.182	0.230	−1.187	2.876	3.773
	CO2PC	0.301	0.477	−1.428	0.652	−3.208	12.328	85.460*
USA	RSCA	−0.202	0.054	−0.086	0.291	−0.442	3.129	0.532
	TSCA	−0.266	0.046	−0.170	0.352	−0.278	2.662	0.283
	CO2PC	−0.623	0.076	0.383	0.933	0.313	1.822	1.187

Notes: ** and * denotes significance at the 1% and 10% levels, respectively. The Jarque-Bera statistic is used to determine whether the data come from a normal distribution. The null hypothesis is normality.

<Table 3> Correlation matrix of residuals from pesaran (2004) test.

	AUS	CAN	CZ	DEN	FIN	FRA	GER	GRE	IRL	KOR	NED	NZL	NOR	POR	ESP	SUI	SWI	TUR	UK	USA
AUS	1																			
CAN	−0.573	1																		
CZ	0.077	−0.330	1																	
DEN	−0.672	0.766	−0.276	1																
FIN	0.026	−0.044	0.164	−0.069	1															
FRA	0.459	−0.419	0.115	−0.712	−0.292	1														
GER	−0.042	0.489	0.132	0.249	0.202	−0.062	1													
GRE	−0.070	0.108	−0.554	0.193	0.128	−0.060	0.070	1												
IRL	−0.473	0.764	−0.297	0.793	−0.183	−0.427	0.591	0.049	1											
KOR	−0.570	0.680	−0.071	0.840	−0.230	−0.399	0.365	0.128	0.802	1										
NED	−0.548	0.431	0.053	0.691	0.249	−0.662	−0.010	−0.016	0.290	0.553	1									
NZL	−0.015	0.323	0.178	0.294	−0.328	0.134	0.689	−0.102	0.655	0.608	−0.055	1								
NOR	0.403	−0.269	−0.186	−0.127	0.289	−0.374	0.022	0.081	−0.169	−0.347	0.118	−0.266	1							
POR	0.459	−0.173	−0.648	−0.189	−0.046	0.174	−0.231	0.339	−0.088	−0.239	−0.308	−0.084	0.263	1						
ESP	−0.108	0.237	−0.010	0.475	0.338	−0.388	0.219	0.137	0.328	0.438	0.622	0.182	0.227	−0.124	1					
SUI	−0.337	0.550	0.092	0.113	−0.116	0.249	0.426	−0.255	0.238	0.250	0.146	0.333	−0.348	−0.297	−0.144	1				
SWI	0.555	−0.403	−0.326	−0.541	−0.001	0.307	−0.087	0.070	−0.261	−0.708	−0.799	−0.223	0.299	0.454	−0.381	−0.368	1			
TUR	−0.428	0.481	0.180	0.532	0.389	−0.687	0.319	−0.136	0.398	0.557	0.717	0.134	0.212	−0.348	0.454	0.245	−0.654	1		
UK	−0.502	0.443	−0.269	0.761	−0.199	−0.620	−0.034	0.296	0.579	0.647	0.339	0.092	−0.165	−0.202	0.361	−0.354	−0.243	0.264	1	
USA	0.293	−0.123	0.103	−0.423	−0.299	0.788	0.139	−0.356	−0.145	−0.263	−0.384	0.263	−0.245	0.034	−0.209	0.552	0.209	−0.485	−0.636	1

Notes: The correlation matrix of residuals between the countries is based on fixed effect model. The country codes, AUS. CZ, CAN, DEN, FIN, FRA, GER, GRE, IRL, KOR, NED, NZL, NOR, POR, ESP, SUI, SWI, TUR, UK and USA, denote Australia, Canada, Czech, Denmark, Finland, France, Germany, Greece, Ireland, Korea, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States of America, respectively.

The correlation matrix of residuals from the test for the presence of cross-section dependence is presented in <Table 3>. The test statistic is 1.920, revealing that the null hypothesis of cross-section independence is rejected at the 5% significance level. Average absolute value of the off-diagonal elements from Pesaran (2004) is 0.319. The result of Free (1995) test also shows that there is cross-sectional dependence in the panel.

Having established that the series are cross-sectionally correlated, the next step is to implement a panel unit root test that take account of the presence of cross-section dependence. Cross-sectional dependence biases the panel data unit root tests towards the alternative hypothesis (Banejee et al., 2004). The occurrence of cross-sectional dependence may reflect the mixed results observed over the different panel unit root tests.

<Table 4> Panel unit root tests

Variables	RSCA	$\Delta RSCA$	TSCA	$\Delta TSCA$	CO2PC	$\Delta CO2PC$
(A) Pesaran CADF test $z[t$-bar]sta.	1.028	−2.155*	0.343	−4.235**	1.287	−8.080**
(B) Pesaran CADF test $z[t$-bar]sta.	3.347	−3.541**	1.761	−1.807*	−1.305	−6.359**

Notes: Individual intercept and time trend included in (A) and individual intercept in (B). The test of the null hypothesis of non-stationarity is based on the mean of individual DF (or ADF) t-statistics of each unit in the panel. To remove the cross-sectional dependence, the standard DF (or ADF) regressions are augmented with the cross-section average of lagged levels and first-differences of the individual series (CADF statistics). The lag lengths for the panel test are based on those employed in the univariate ADF test. The normalized z test statistic is computed by using the t-bar statistics. ** and * denote significance at the 1% and 5%, respectively.

One of such tests is the presence of cross-sectionally augmented version of the Im et al. (2003), test proposed by Pesaran (2007). Pesaran's test is favored over of all others for its simplicity and clarity. The results of Pesaran (2007) test reported in <Table 4> show that the hypothesis that the series contain a unit root is confirmed at the 1% or 5% significance level. This implies that the series are non-stationary.

<Table 5> Panel cointegration tests

Statistics	With trend				Without trend			
	value	Z	*p*-value	Robust *p*-value	value	Z	*p*-value	Robust *p*-value
Gt	−1.191	7.111	1.000	0.476	−1.825	1.017	0.845	0.474
Ga	−0.358	8.098	1.000	0.048	−0.804	5.933	1.000	0.002
Pt	−3.007	8.008	1.000	0.014	−3.581	3.951	1.000	0.016
Pa	−0.336	6.716	1.000	0.103	−0.559	4.244	1.000	0.179

Notes: All of these statistics distributed are standard normal. The lag and lead lengths are set to one, respectively. Choosing too many lags and leads can result in a deterioration of the small-sample properties of the test. To control for cross-sectional dependence, robust critical values are obtained through 5,000 bootstrap replications.

The results of the panel unit root tests displayed in <Table 4> indicate that there can be a long run equilibrium relationship between the variables. Hence, the study implements heterogeneous panel cointegration tests by Westerlund(2007), allowing for cross-sectional dependence. Since Westerlund(2007) tests are based on structural rather than residual dynamics, there is no one common factor restriction. The panel tests denoted by Gt and Ga(using the nomenclature in Westerlund, 2007) are performed under the assumption that the panel is entirely cointegrated, while the other two tests, Pt and Pa, are designed under the assumption that at least one element of the panel is cointegrated. In all cases, the null hypothesis of no cointegration, which infers whether the error-correction term in a conditional error-correction model is equal to zero, is tested. If the null hypothesis of no error-correction is accepted, then the null hypothesis of no cointegration is also accepted. These tests have limiting normal distributions and are consistent. <Table 5> shows the results of the Westerlund(2007) panel cointegration tests which include and intercept and an intercept and a linear trend. The results indicate that there is evidence of cointegration among the variable.

3. Model specicification and causality test

In the last phase, the study employs the dynamic panel causality tests based on the vector error correction model (VECM) to evaluate the short-run and long-run directions of causality between the variables.

After having established a cointegrating relationship, estimating the long-run equilibrium relationship given by the error correction term is required. The long-run equilibrium coefficients can be estimated by using various single equation estimators, such as the fully modified OLS procedures (FMOLS) proposed by Pedroni(2000), the dynamic OLS (DOLS) estimator from Saikkonen (1991) and Kao and Chiang (2000), the pooled mean group estimator (PMG) proposed in Pesaran, Shin, and Smith(1999), or by using system estimators as panel VARs, estimated with the Generalized Method of Moments (GMM) or the Quasi Maximum Likelihood (QML). Single equation approaches assume homogeneity between cross-section units for the long-run relationship whereas short-run dynamics are allowed to be panel-specific across cross-sections. Although this restriction may seem too severe for some variables, allowing all parameters to be panel-specific would reduce the appeal of the panel data approach considerably(Breitung and Pesaran, 2008). The FMOLS estimator is consistent and efficient in estimating long-run cointegrating coefficients. It also allows for endogenous regressors and serial correlation. As demonstrated by Kao and Chiang (2000), the DOLS outperforms the FMOLS estimator in terms of mean biases. Despite the differences between the two methods, the estimates from both the FMOLS and DOLS are asymptotically equivalent for more than 60 observations (Banerjee, 1999). Hence, to determine the long-run equilibrium relationship among the variables in question, the present study performs the DOLS procedures developed by Kao and Chiang(2000). The DOLS estimators allow control of possible cross-sectional dependence by including common time dummies. The estimators allow heterogeneous cointegrating vectors for each cross-section member and, therefore, provide interpretable results when cointegrating vectors are believed to be heterogeneous, as is very likely the case in the present analysis.

The DOLS results can be interpreted as long-run coefficients, which express as the following equation:

$$RSCA - 0.43\,TSCA + 0.11\,CO2PC = 0 \tag{4}$$

According to the equation (4), the technological specialization is positively correlated with the trade specialization while that is negatively correlated with carbon dioxide emissions at 1% significant level. It implies that technological capacity has an impact on trade competitiveness in bioenergy technologies sector. Specially, the results show that there is a unique cointegrating vector among the variables in question.

Heterogeneous panel cointegration tests indicate only the presence or absence of a long-run relationship between the variables; they do not indicate the direction of causality when the variables are cointegrated. Hence, causality tests are needed. To infer a causal relationship among the variables, the panel VECM set in Eqs. (5) - (7) is estimated.

$$\Delta RSCA = \sum_{k=1}^{m}\beta_{11k}\Delta RSCA_{-k} + \sum_{k=1}^{m}\beta_{12k}\Delta TSCA_{-k} + \sum_{k=1}^{m}\beta_{13k}\Delta CO2PC_{-k} + \gamma_{1i}ECT_{-1} + \Delta\mu_1 \quad (5)$$

$$\Delta TSCA = \sum_{k=1}^{m}\beta_{21k}\Delta RSCA_{-k} + \sum_{k=1}^{m}\beta_{22k}\Delta TSCA_{-k} + \sum_{k=1}^{m}\beta_{23k}\Delta CO2PC_{-k} + \gamma_{2i}ECT_{-1} + \Delta\mu_2 \quad (6)$$

$$\Delta CO2PC = \sum_{k=1}^{m}\beta_{31k}\Delta RSCA_{-k} + \sum_{k=1}^{m}\beta_{32k}\Delta tSCA_{-k} + \sum_{k=1}^{m}\beta_{33k}\Delta CO2PC_{-k} + \gamma_{3i}ECT_{-1} + + \Delta\mu_3 \quad (7)$$

where Δ is the first difference operators, β_{ij}s are the short-run adjustment coefficients, and μ_{it}s are disturbance terms assumed to be uncorrelated with mean zero. ECT is the error correction term lagged one period that are the lagged residuals derived from the long-run cointegrating relationship.

To infer a causal relationship among the variables, the panel VAR in first difference set in Eqs. (4)-(6) is estimated. The fixed effects in Eqs. (1)-(3) are eliminated by differencing. To deal with the correlation between the lagged endogenous variables on the right-hand side and the new differenced error term that introduced by differencing and existence of heteroscedasticity in the genuine errors across countries, Arellano and Bond(1991) have proposed a difference-GMM approach, where the lags in the explanatory variables at different levels are used as instruments. For the instruments to be valid, no serial correlation must exist among the error terms. The optimal lag length, m, is likewise selected until no serial correlation is observed in the residuals. This assumption may be tested taking into account the fact that, if the disturbances are not serially correlated, there should be evidence of significant negative first-order serial correlation and no evidence of second-order serial correlation in the differenced residuals. Arellano and Bond's(1991) statistic is used to test the null hypothesis of no jth-order correlation in the differenced residuals. For the overidentifying restrictions, both Hansen's (1982) J test and Sargan's (1958) test are conducted and an inference is made, chiefly by analyzing the Hansen test results because the Sargan test is not robust against heteroscedasticity or autocorrelation. The Hansen test, which gives the minimized value of the value of the GMM criterion function, is robust.

In this context, the different sources of causation can be identified by testing, $H_0 : \beta_{12k} = 0, \forall k = 1,....m$ and $H_0 : \beta_{13k} = 0, \forall k = 1,....m$ in Eq. (5) or $H_0 : \beta_{21k} = 0, \forall k = 1,....m$, $H_0 : \beta_{23k} = 0, \forall k = 1,....m$ in Eq. (6) or $H_0 : \beta_{31k} = 0, \forall k = 1,....m$, $H_0 : \beta_{32k} = 0, \forall k = 1,....m$ in Eq (7). Finally, strong causality is evaluated by checking whether or not the sources of causation are jointly significant. On the basis of the difference-GMM estimation results, causality is determined by running Wald tests on the coefficients of variables. The test statistics follow a chi-squared distribution with $k-m$ degrees of freedom. <Table 6> reports the Wald test for the null hypothesis of no causality. As the Sargan and Hansen test results, the m_1 and m_2 statistics, show, the selection of 1 lag is needed in Eq. (5) to have no serial correlation in the disturbance μ_{1it}. 1 lag and 4 lags are needed in Eqs. (6) and (7), respectively, to have no serial correlation in the disturbances μ_{2it} and μ_{2it}.

There is evidence of a positive short-run and strong linear causal relation running from RSCA to TSCA. There is evidence of a positive strong linear causal relation running from TSCA to RSCA, and a negative strong linear causal relation running from CO2PC to RSCA and running from RSCA to CO2PC. This indicates that there is no evidence of a short-run bidirectional causality between RSCA and TSCA, but there is a strong linear bidirectional relation running between the two. The coefficients of ECT are significant in Eqs. (5) and (7), indicating that RSCA and CO2PC respond to a deviation from the long-run equilibrium in the previous period, while TSCA does not.

<Table 6> Statistic values for panel causality tests

Independent variables (sources of causation)		Dependent variable		
		$\Delta RSCA$	$\Delta TSCA$	$\Delta CO2PC$
Short-run	$\Delta RSCA$	-	7.94***	2.27
	$\Delta TSCA$	0.24	-	1.75
	$\Delta CO2PC$	1.03	0.00	-
Long-run	ECT	14.57***	1.00	2.64*
Strong (Joint)	$\Delta RSCA$ ECT	-	3.00*	6.57**
	$\Delta TSCA$ ECT	10.84***	-	2.08
	$\Delta CO2PC$ ECT	14.45***	0.99	-
Sargan test		203.14[0.000]	266.76[0.000]	286.13[0.000]
Hansen test		18.32[1.000]	14.35[1.000]	21.22[1.000]
m_1		-2.82[0.005]	-3.23[0.001]	-2.83[0.005]
m_2		-0.59[0.555]	-1.26[0.206]	1.24[0.214]

Notes: The tests are based on one-step robust difference GMM estimates. The explanatory variables are assumed to be endogenous and are instrumented in GMM style (Roodman, 2009). p-values are in square brackets. χ^2-statistics. ***, ** and * denote that the null hypothesis of no causation is rejected at the 1%, 5%, and 10% significance levels, respectively.

IV. Conclusions

This study tests the dynamic relationship between each country's export comparative advantage and technological capability in bioenergy technology sector. The study uses panel data to avoid problems associated with standard econometric methods applied to short-time series. The study implements heterogeneous panel unit root tests and cointegration tests, taking into account of the results of the normality test for each individual time series and the test for the presence of cross-section dependence in the panel. The study finds evidence that there is co-movement among the series. Thus, the empirical model to test the casual relationship among the variables in question is based on the panel VECM. And the study implements panel GMM estimation to determine the dynamic relationship between the series to deal with a simultaneity problem introduced by difference and existence of heteroscedasticity in the genuine error cross countries.

The panel data tests reveal a long-run relationship between trade and technological specialization. The long-run relationship emerging from the DOLS results inticates that one unit increase in technological capability beefs up the trade comparative advantage by some 2.3 unit. The RSCA and CO2PC variables respond to a deviation from the long-run equilibrium in the previous period. In the causality results, this study finds evidence of a positive short-run and strong linear casual relation running from RSCA to TSCA, and a positive strong linear causal relation running from TSCA to RSCA. Based on these results, the following implications can be presented. The results indicate that there is no evidence of a short-run bidirectional causality between the two. It implies that technological capability may be important to comparative advantage in trade of bioenergy sector, especially when it comes to long-term period. Hence, reliable long-run public policy elasticity estimates of trade competitiveness are important input in the development of bioenergy technologies sector related policy. However, it means that government needs to study that how and how much policy measure, technology-push or demand-pull, affects the technological innovation. That is because the two policy measures can be very different from each other in terms of policy-induced effects(Lund, 2009) through technological innovation and diffusion.

It should be pointed out that these findings are based on only bioenergy technologies for each country. However, the relationship between technological and trade specialization largely depends on the kind of renewable energy source at issue. Hence, further investigation should be conducted using data of different sectors of the renewable energy technology fields, especially the public policy sensitivity to trade competitiveness in other sector, such as sola, wind, geothermal, hydro and ocean including bioenergy technologies.

| 참고문헌 |

Amable, B. and Verspagen, B.(1995). “The role of technology in market shares dynamics.” *Applied Economics*. Vol. 27, pp. 197-204.

Amendola, G., Guerrieri, P. and Padoan, P. C.(1998). “International patterns of technological accumulation and trade.” Archibugi, D. and Michie, J.(ed.). *Trade, growth and technological change*. Cambridge: Cambridge University Press, pp. 141-167.

Arellano, M. and Bond, S.(1991). “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations.” *Review of Economic Studies*. Vol. 58, pp. 277-297.

Arent, D. J., Wise, A. and Gelman, R.(2011). “The status and prospects of renewable energy for combating global warming.” *Energy Economics*. Vol. 33, pp. 584-593.

Dalum, B., Laursen, K. and Villumsen, G.(1998). “Structural changed in OECD export specializations: de-specialization and ‘stickiness’.” *International Review of Applied Economics*. Vol. 12, pp. 423-443.

Banerjee, A. and Carrion-i-Silvestre, J. L.(2006). “Cointegration in panel data with breaks and cross-section dependence.” *Working Paper 591*. European Central Bank.

Banerjee, A., Marcellino, M. and Osbat, C.(2004). “Some cautions of the use of panel methods for integrated series of macro-economic data.” *Econometrics Journal*. Vol. 7. No. 2, pp. 322-340.

Breitung, J. and Pesaran, M. H.(2008). “Unit roots and cointegration in panels.” Matyas, L. and Sevestre, P.(ed.). *The econometrics of panel data: Fundamentals and recent developments in theory and practice*. USA: Kluwer Academic Publishers, pp. 297-322.

Dosi, G., Pavitt, K. and Soete, L.(1990). *The economics of technological change and international trade*. Hemel Hempstead: Harvester Wheatsheaf.

Frees, E. W.(1995). "Assessing cross-sectional correlation in panel data." *Journal of Econometrics*. Vol. 69, pp. 393-414.

Grupp, H. and Munt, G.(1998). "Trade on high-technology markets and patent statistics-leading-edge versus high-level technology." Archibugi, D. and Michie, J.(ed.). *Trade, growth and technological change*. Cambridge: Cambridge University Press, pp. 168-187.

Hansen, L.(1982). "Large sample properties of generalized method of moment estimators." *Econometrica*. Vol. 50, pp. 1029-1054.

Holtz-Eakin, D., Newey, W. and Rosen, H.(1998). "Estimating vector autoregressions with panel data." *Econometrica*. Vol. 56, pp. 1371-1395.

Im, K. S., Persaran, M. H. and Shin, Y.(2003). "Testing for unit roots in heterogeneous panels." *Econometrica*. Vol. 115, pp. 53-74.

Jha, V.(2009). "Trade flows, barriers and market drivers in renewable energy supply goods: The need to level the playing field." *ICTSD Trade and Environment Issue Pape 10*. International Centre for Trade and Sustainable Development: Geneva, Switzerland.

Johnstone, N., Haščič, I. and Popp, D.(2010). "Renewable energy policies and technological innovation: Evidence based on patent counts." *Environmental and Resource Economics*. Vol. 45, pp. 133-155.

Kao, C. and Chiang, M.(2000). "On the estimation and inference of a cointegrated regression in panel data." *Advances in Econometrics*. Vol. 15, pp. 179-222.

Larsen, K.(1998). "Revealed comparative advantage and alternatives as measures of specialization." *Danish Research Unit for Industrial Dynamics Working Paper*. No. 98-30.

Laursen, K.(2000). "Do export and technological specialization patterns co-evolve in terms of convergence or divergence? Evidence from 19 OECD countries, 1971-991." *Journal of Evolutionary Economics*. Vol. 10, pp. 415-436.

Lund, P. D.(2009). "Effects of energy policies on industry expansion in renewable energy." *Renewable Energy*. Vol. 34, pp. 53-64.

Pedroni, P.(1999). "Critical values for cointegration tests in heterogeneous panels with multiple regressors." *Oxford Bulletin of Economics and Statistics*. Vol. 61 (Special Issue, 1999), pp. 653-678.

Pedroni, P.(2000). "Fully modified OLS for the heterogeneous cointegrated panels." *Advances in Econometrics*. Vol. 15, pp. 93-130.

Pedroni, P.(2004). "Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis." *Econometric Theory*. Vol. 20, pp. 597-625.

Pesaran, H. M.(2007). "A simple panel unit root test in the presence of cross-section dependence." *Journal of Applied Econometrics*. Vol. 22, pp. 265-312.

Pesaran, M. H.(2004). "General diagnostic tests for cross section dependence in panels." *Cambridge Working Papers in Economics*. No. 0435. University of Cambridge.

Pesaran, M. H., Shin, Y. and Smith, R. P.(1999). "Pooled mean group estimation of dynamic heterogeneous panels." *Journal of the American Statistical Association*. Vol. 94. No. 446, pp. 621-634.

Roodman, D.(2009). "How to extabond 2: An introduction to difference and system GMM in Stata." *The Stata Journal*. Vol. 9, pp. 86-136.

Saikkonen, P.(1991). "Asymptotically efficient estimation of cointegration regressions." *Econometric Theory*. Vol. 12. No. 1, pp. 1-21.

Sargan, J.(1958). "The estimation of economic relationships using instrumental variable," *Econometrica*. Vol. 26, pp. 393-415.
Uchida, Y. and Cook, P.(2005). "The transformation of competitive advantage in East Asia: An analysis of technological and trade specialization." *World Development*. Vol. 33, pp. 701-728.
Westerlund, J.(2007). "Testing for error correction in panel data." *Oxford Bulletin of Economics and Statistics*. Vol. 69, pp. 709-748.

| **논문투고일** : 2012년 05월 16일 |
| **논문심사일** : 2012년 07월 18일 |
| **게재확정일** : 2012년 07월 31일 |

ABSTRACT
Journal of Asia-Pacific Studies Vol. 19. No. 2 (2012)

Export Competitiveness and Technological Capability in Bioenergy Sector

Bong-Suk Sung
(Dept. of International Management, Woosong University)
Won-Guon Cho
(Dept. of Railroad and Business Management, Woosong University)

This paper tests the dynamic relationship between each country's export comparative advantage and technological capability in bioenergy technology sector using panel data from 20 OECD countries over the period from 1993 to 2008. The study implements heterogeneous panel unit root tests and cointegration tests, taking the normality and cross-section dependence test into account. The study finds evidence that there is co-movement among the series. Thus, the empirical model to test the casual relationship among the variables in question is based on the panel VECM model and implements panel GMM estimation to determine the dynamic relationships between the series to deal with a simultaneity problem introduced by difference and existence of heteroscedasticity in the genuine errors across industries. The long-run relationship emerging from the DOLS results indicates that 1 unit increase in technological capability increases trade comparative advantage by some 2.3 unit. The RSCA and CO2PC variables respond to a deviation from the long-run equilibrium in the previous period. In the causality results, this study finds evidence of a positive short-run and strong linear causal relation running from RSCA to TSCA, and a positive strong linear causal relation running for TSCA to RSCA.

Key words : Bioenergy, Technological Specialization, Trade Specialization, Dynamic Panel Approach, Causality Analysis