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글로벌 위기에서 산업 클러스터의 품질이 생산 탄력성에 미치는 영향

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The Impact of Industrial Clusters' Quality on the Production Resilience in the Global Crisis

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ABSTRACT

Purpose: This paper aims to verify the difference in production resilience between local clusters and regions without clusters before and after a major crisis. Furthermore, this paper aims to identify the clusters' quality factors that impact clusters' shock vulnerability and resilience.

Methods: Utilizing open-source data from the US Cluster Mapping platform, this paper compares regions with industrial clusters to those without using the Differences-in-Differences (DID) estimator. It considers the regions with industrial clusters as a treatment group and others as the control group, comparing the period before and after the pandemic. Additionally, the paper examines which cluster factors make a difference in economic resilience during the crisis using Regression Discontinuity Design (RDD).

Results: The study finds that regions with industrial clusters show higher production resilience compared to regions without clusters. Moreover, the number of establishments, annual payrolls, and employment can have a positive impact on resilience during the pandemic shock.

Conclusion: Though clusters could be vulnerable during the global crisis, industrial clusters can contribute to regional economic development and production resilience in the long-term aspect. Thus, it is required to construct a high-quality local cluster and support it during the economic crisis in the long-term aspect.

Key Words: Production Resilience, Industrial Cluster, Traded Cluster, Global Crisis, Cluster Quality, Industrial Policy

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1. Introduction

After the spread of the global pandemic, the world has faced extra-ordinal crises that severely affect the global economy. The prolonged COVID-19 caused long-term blockades in numerous nations and led to production deterioration by paralyzing the global supply chain. However, compared to the early stage of the global pandemic crisis, when the World Health Organization (WHO) declared a Public Health Emergency of International Concern (PHEIC) on January 30, 2020, as the fatality rate decreased, WHO declared the end of the PHEIC on May 5, 2023 (Schell et al., 2020; Burki, 2023). Likewise, as COVID-19 has been mitigated and society has recovered its normal life as before the emergence of COVID-19 corresponding to the governmental effort to re-activate the economy, the regional economy also has been restored gradually as the normal production and business activity has been re-operated (Quy and Dung, 2023; Park and Park, 2024). However, the global supply chain which is considered as transmuted into the recovery period encounters critical geopolitical threats evoked by the Ukraine crisis (Alam et al., 2023; Handfield et al., 2020; Panwar et al., 2022). Likewise, as the uncertainty of the global supply chain has increased, restoring global production is highlighted as an assignment to stimulate the depressed world economy. Strategies such as digitization, re-shoring, and others have been proposed through various studies for responding to external risks over the supply chain (Alam et al., 2023). Therefore, as one of the strategies to recover from the shock of the pandemic, developing a sustainable entrepreneurial ecosystem has been proposed (Meng et al., 2022). As these global crises impede the local industry and economy seriously, governments are struggling to overcome those external risks, and to overcome the crisis, the importance of industrial clusters increases as a method to enhance resilience.

The industrial cluster is the set of interconnected firms, suppliers, and institutions within a specific field. This geographical concentration of establishments is expected to have mutual beneficiary within the industry by improving productivity and performing as an entrepreneurial incubation through cooperation and knowledge sharing. Likewise, though industrial clusters can expect agglomeration advantages to enhance local competitiveness and shock resilience from the paralysis of the global supply chain, the study on the effect of the industrial cluster on production resilience during the global crisis is limited despite there are studies about enhancing industrial efficiency (Pai and Lim, 2023). Thus, this paper aims to examine the impact of the industrial cluster on local production resilience under the exogenous crisis focusing on the COVID-19 case. Thus the research questions of this paper are as follows.

RQ 1) Whether the industrial cluster denotes a difference in regional productivity when comparing before and after the global pandemic.

RQ 2) Which quality factors of cluster significantly impact the shock and resilience competence?

To verify those assumptions, this paper utilizes the open-source data published by the US Cluster Mapping platform supported by the United States Economic Development Administration and Harvard

Business School. Therefore, consider the regions obtaining industrial clusters as a treatment group and others as the control group, comparing the period before the pandemic and after the pandemic using the Differences-in-Differences (DID) estimator. After verifying whether the cluster contributes to production resilience, using the relatedness between clusters, this paper defines types of clusters based on the supply chain connectivity and identifies whether the types of the cluster and business make a difference in economic resilience under the crisis using Regression Discontinuity Design (RDD). Considering the recent dynamic industrial environment, this paper expects to provide significant implications on further cluster formation by identifying whether the cluster contributes to production resilience compared to the non-cluster area and which factors contribute to it.

2. Conceptual Background

2.1 Global Crisis and Global Value Chain

In December 2019, COVID-19 was first identified and rapidly spread throughout the world. Governments implemented global lockdowns to prevent the epidemic from spreading, which hampered the movement of people and goods. This restriction in the supply chain severely undermined productivity and deteriorated the economy of many regions.

In addition to COVID-19, other unpredictable geopolitical issues have arisen, such as the emergence of m-pox and the Russian-Ukraine war. The vulnerability of the hyper-connected global value chain, which developed during the globalization trend before COVID-19, has been proposed.

Likewise, as international threats such as the current prolonged trade war between the United States and China have increased, the recent business environment is represented as the Volatility, Uncertainty, Complexity, and Ambiguity (VUCA) era (Arunmozhi et al, 2021; Schell et al., 2020). Thus, referring to the current supply chain deterioration crisis caused by COVID-19, continuous studies are required to enhance resilience against further external threats.

Previous studies have studied the quality of the supply chain. Jeon and Yoo (2019) measured the efficiency of supply chain quality management using the Data Envelopment Analysis (DEA) model focusing on the domestic defense industry which should be inelastic from the externalities. Furthermore, Park, Soo, and Kim (2011) have examined that supply chain quality management with parent companies and cooperative companies can enhance the corporations' performance using the structural equation model. According to Park et al. (2011), the supply chain quality management infrastructural can impact pre-production and post-production processes, and the post-production process including production, storing, and service can lead to the performance of the business.

However, studies on industrial clusters and their performance measurement are limited and this causes skeptic concerns over the effectiveness of policies incubating the industrial clusters. Nonetheless, the role of industrial clusters and their supply chain within the local economy is expected as a method to mitigate the shock from the global crisis and enhance resilience from previous studies (Dai et al., 2021). Thus, this paper aims to measure the impact of the shock on the industrial cluster and its resilience.

2.2 Industrial Clusters

After Marshall insists on the agglomerate advantages of industrial concentration, to enhance industrial competitiveness, various types of clusters have emerged (Marshall, 2009; Gordon and McCann, 2000). Compared to the clusters formed by the physical proximity of the business, industrial clusters are generated by the conglomeration of interconnected businesses, suppliers, institutions, and others that are specialized in the specific industry.

U.S. Cluster Mapping categorizes the U.S. Clusters into traded and local clusters representatively, since balancing the traded and local clusters is significant to the policymaker as local clusters mitigate the external shock and intensify the local resilience, however, traded clusters improve local competitiveness and expand its economic size by serving several other markets (Delgado et al., 2014; Bell, 2005). Though, to mitigate the shock from the collapse of the global supply chain, the role of the local cluster has been highlighted as it has a short supply chain that serves the local market with less impact from external shock and responds promptly (Simmons et al., 2022; Hofe and Chen, 2006; Kim and Kim, 2019). However, despite its vulnerability to the effect of the supply chain, the traded clusters can also denote rapid resilience through active transactions with other clusters. However, in this paper, regarding that both types of clusters can contribute to regional economic development and production resilience by facilitating knowledge spillover, network effects, and other agglomeration effects, this paper verifies whether the region that has superior clusters has more resilience than other regions regardless of the type of the cluster.

Also, the study of Lu et al. (2013) has utilized R&D personnel, funds, institution, innovation consciousness, enterprise concentration, assets, technological purchase, digestion, and retrofit concentration with transportation conditions as quality factors of cluster explaining location quotient. However, the study of Slaper et al. (2018) utilizes population, wage, intensity, diversity, resource independence, education level, and others as quality factors that improve gross domestic production. Likewise, the cluster quality factor that can contribute to the performance of the cluster can be different, this paper adopts the indexes provided by the US Cluster Mapping data platform. Refer to the previous studies, this paper regards the industrial clusters' quality factors as the degree of industrial concentration index (QP), locational quotient (LQ) which refers to the distinctive industrial concentration to the national averages, number of establishments of the local clusters (EST), wage and annual payroll which implies the attractive work environment deriving employees can impact on the productivity resilience of clusters, specifically the GDP contribution of local cluster and its manufacturing sectors, exports, and employment performance of clusters.

2.3 Production Resilience

Resilience refers to the capacity of the system to withstand external shocks or stresses and recover from the pre-crisis level. Due to global crises such as COVID-19, various local economies have undertaken excessive damage and policymakers have struggled to explore ways to mitigate the damage and recover the local economy rapidly as Figure 1. Thus, the role of the industrial clusters is highlighted as a way to recover the economic level by recovering the production level. Production implies the overall creation of goods and services using the resources of capital, labor, materials, and others. Thus, though the definition or measurement to measure production or economic resilience varies, referring to the Mendoza-Velázquez and Rendón-Rojas' study on industrial resilience, this paper defines resilience as the inherent ability to withstand adverse shock and recover the pre-crisis status (2021). Also, to measure the resilience of the regional unit, Mardaneh, Jain, and Courvisanos (2016) and Mardaneh et al. (2020) utilize the production growth or employment before and after the unit-wide shock or treatment. Thus, this paper regards the gross domestic production (GDP) of regions and employment as an index of resilience.

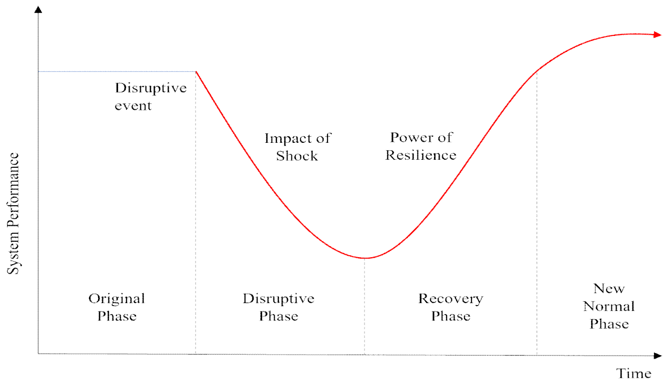


Figure 1. Scheme of Shock Impact and Recovery by Time

3. Methodology

3.1 Data Description

This study utilizes the open-source big data published by the US Cluster Mapping (USCM) platform supported by the United States Economic Development Administration and Harvard Business School. Since the global crisis from COVID-19 has been evoked in December 2019, its impact has been denoted after 2020. Thus, This paper regards 2020 to the present as the post-COVID era. However, as USCM provides data from 1998 to 2020, to measure the recent shock and resilience effect of regions, this paper retrieves the cluster feature from USCM, this study additionally collects GDP, GDP contribution of the manufacturing industry, location quotient (LQ), employment, export, and import data from Bureau of Economic Analysis (BEA) and BLS stands for the Bureau of Labor Statistics (BLS). These data sets from BEA and BLS are collected from 2015 to 2022 to measure the production resilience of the regions. However, this paper utilizes the time period from 2018 and 2020 to measure the shock of COVID-19 and 2020 to 2022 to measure resilience on the state level.

Table 1. Measurement Variables

Classification	Variable Name	Detail	Reference
Dependent Variable	GDP	Gross Domestic Product	BLS, 2023 BEA, 2023
	GDP	GDP of Manufacturing industry	
	Export	Export of Manufacturing industry	
	Import	Import of Manufacturing industry	
	Employment	Employment of regions	
Independent Variable	QP	Degree of industry concentration in a particular region	USCM, 2023
	LQ	Location quotient, the degree of industry concentration in the region differs from the national average	
	AP	Annual payroll	
	EST	Number of establishments	
	WAGE	The average annual wage for private employees	

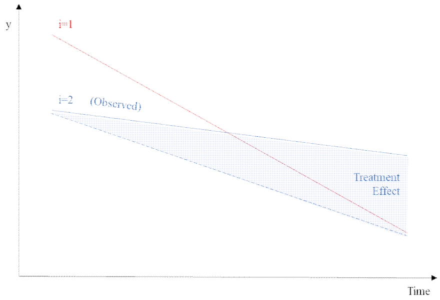
Table 2. Descriptive Statistics

Cluster		QP		LQ		AP		EST		Employment	
Count	60000	Count	60000	Count	60000	Count	60000	Count	60000	Count	60000
Count_ industry	67	Mean	104339.3	Mean	1.07	Mean	418224.55	Mean	510.66	Mean	2983.72
Count_ sub_ cluster	316	Median	9399.5	Median	0.79	Median	39836.50	Median	56	Median	1696.07
		STDEV	512563.8	STDEV	2.23	STDEV	1951622.59	STDEV	2283.39	STDEV	3418.84
Count_ state	32	Range	16367410	Range	121.56	Range	59745760	Range	78639	Range	17414.85
Count_ traded	40800	Min.	0	Min.	0	Min.	0	Min.	0	Min.	274.02
Count_ local	19200	Max.	16367410	Max.	121.56	Max.	59745760	Max.	78639	Max.	17688.87

WAGE		GDP		GDP_Manu		Export		Import	
Count	60000	Count	60000	Count	60000	Count	60000	Count	60000
Mean	42004.48	Mean	453626	Mean	45605.78	Mean	18767.38	Mean	45677.61
Median	41413.54	Median	222601.6	Median	25934	Median	9574.70	Median	15645.6
STDEV	31224.20	STDEV	611468	STDEV	65856.30	STDEV	22079.66	STDEV	74901.36
Range	394005.39	Range	3561772	Range	422377.3	Range	117445.2	Range	448517.30
Min.	0	Min.	36330.4	Min.	1321.30	Min.	282.90	Min.	424.40
Max.	394005.39	Max.	3598103	Max.	423698.6	Max.	117728.1	Max.	448941.70

3.2 Difference-in-Difference (DID)

Difference-in-differences (DID) is a statistical method to compare the difference in outcomes before and after the treatment (Callaway and Sant'Anna, 2021). Thus, DID can also be utilized in measuring the impact of the policy or events by comparing the control group and treatment group affected by events. In DID analysis, the Ordinary Least Squares (OLS) are used to estimate the causal effect by regressing the outcome variables on the dummy variables and their interaction term. of treatment and period as following equation 1. Referring to the OLS model, yit implies the dependent variable for individual i by time t. ɣs(i) denotes the vertical intercept of the DID graph as Figure 2 and λt indicates the time trend (Bertrand et al., 2004).



y_{it}	i=1	i=2	Difference
t=1	y_{11}	y_{21}	y_{11}-y_{21}
t=2	y_{12}	y_{22}	y_{12}-y_{22}
Change	y_{11}-y_{12}	y_{21}-y_{22}	(y_{11}-y_{21})-(y_{12}-y_{22})

Figure 2. Scheme of Difference-In-Difference Analysis

Thus, δ is the treatment effect and ε implies the residual term (Bertrand et al., 2004).

$$y_{it} = \gamma_{s(i)} + \lambda_t + \delta I(\ldots) + \varepsilon_{it} \qquad \text{(Equation 1)}$$

To measure the effect of COVID-19 on production resilience through DID methods, this paper mines data for three years before and after the starting year of the pandemic, 2019. Thus, From 2018 to 2020 becomes the pre-COVID era, and from 2020 to 2022 becomes the post-covid era. Also, Model 1 is for measuring the shock of the crisis which analyzes 2018 and 2020. In Model 2, 2020 and 2022 data sets are used to measure the recovery of the regions. In addition to the period, the type of clusters is considered as treatment which can cause differences in dependent variables as Figure 3.

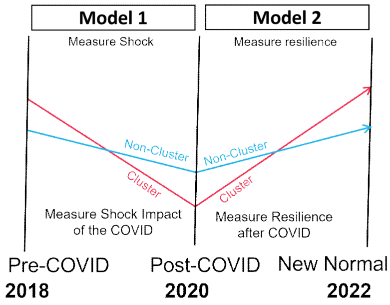


Figure 3. Scheme of Shock Impact and Recovery by Time

3.4 Regression Discontinuity Design (RDD)

The Regression Discontinuity Estimator (RDD) is a statistical method used to estimate causal effects in situations where treatment or intervention is assigned based on a continuous variable (Lee, 2016). It is similar to DID in the aspect of estimating casual effect, compared to DID which utilizes the binary or categorical variables, RDD can be applied to continuous variables. RDD compares the outcomes around the threshold value for continuous variables to measure the treatment and intervention effect (Hahn et al., 2001). To measure the impact of the test, the initial model of RDD can follow Equation 2.

$$y_i = \beta_0 + \beta_1 \widetilde{X}_i + \beta_2 Z_i + \beta_3 \widetilde{X}_i Z_i + \beta_4 \widetilde{X}_i^{2+} \beta_5 X_i^2 Z_i + \varepsilon_i \quad \text{(Equation 2)}$$

The outcome (yi) can be denoted through the sum of β coefficient, variable (X), and a dummy variable for treatment (Z). β1 implies the linear pretest coefficient, β2 mean difference for treatment, β3 linear interaction, β4 quadratic pretest coefficient, and β5 quadratic interaction. i denotes the control and treatment statements as 0 and 1. Thus, ε denotes the residual same as DID (Hahn et al., 2001).

In this study, RDD can be used to estimate the causal effect of the cluster factors on production resilience for regions by the period, while DID could be used to estimate the causal effect of the pandemic on production resilience for regions that are assigned to different treatment groups.

4. Result

4.1 Shock Vulnerability of Cluster versus Non-cluster

To measure the shock effect of COVID-19 thoroughly, Model 1 compares 2018 and 2020 which are immediately before and after the emergence of the global pandemic. As Table 3, the pandemic has significant impacts on the overall GDP, export, import, and employment changes of the regions. To compare the non-cluster and regions with clusters, the shock effect is regarded as more significant than non-cluster regions and this paper assumes that the shock on the supply chain has spread by businesses and the physical concentration of the cluster can provide agglomerate advantages, however, it can also cause agglomerate damage. However, as in Table 3, since the adjusted R-squared value of GDP and Employment is higher than other models having 56% and 66.5% of explanation power, the model using the other performance index such as GDP of the manufacturing sector, export, and import denotes low explanation power by having 27.5%, 19%, and 17.8%.

Though the RDD model of Model 1 denotes low explanation power from 10.3% to 13% (Table 4), the establishment, annual payroll, and wage indicate a positive impact. However, the QP and LQ, implying the industrial concentration degree and differentiation indicate a negative impact on shock.

Table 3. DID Model and Result Summary

DID Model Summary					DID Result Summary				
Dependent	R^2	Adjusted R^2	F-stat	P	GDP	Coeff.	Std err	t value	p
GDP	0.560	0.560	8500	0.00	Intercept	0.070	0.002	40.170	0.00
GDP_manu	0.275	0.275	2530	0.00	Period	-0.033	0.002	-13.410	0.00
Export	0.190	0.190	156	0.00	Treatment	-0.034	0.002	-19.139	0.00
Import	0.179	0.178	1449	0.00	Interaction	-0.022	0.003	-8.868	0.00
Employment	0.667	0.655	53.70	0.00					

DID Result Summary									
GDP_manu	Coeff.	Std err	t value	p	Export	Coeff.	Std err	t value	p
Intercept	0.046	0.005	9.748	0.00	Intercept	-0.147	0.007	-20.380	0.00
Period	-0.038	0.007	-5.686	0.00	Period	0.139	0.010	13.610	0.00
Treatment	-0.020	0.005	-4.053	0.00	Treatment	0.137	0.007	18.827	0.00
Interaction	-0.045	0.007	-6.663	0.00	Interaction	-0.237	0.010	-23.053	0.00
Import	Coeff.	Std err	t value	p	Employment	Coeff.	Std err	t value	p
Intercept	-0.255	0.009	-29.089	0.00	Intercept	0.029	0.001	27.438	0.00
Period	0.327	0.012	26.407	0.00	Period	-0.036	0.002	-24.074	0.00
Treatment	0.288	0.009	32.593	0.00	Treatment	-0.018	0.001	-16.830	0.00
Interaction	-0.433	0.013	-34.606	0.00	Interaction	-0.036	0.002	-23.486	0.00

Table 4. RDD Model and Result Summary

RDD Model Summary					RDD Result Summary				
Dependent	R^2	Adjusted R^2	F-stat	P	GDP	Coeff.	std err	t value	p
GDP	0.127	0.127	484.3	0.00	Const	257100	6797.58	37.819	0.00
GDP_Manu	0.104	0.103	384.8	0.00	QP	-0.094	0.04	-2.337	0.02
Export	0.117	0.117	442.3	0.00	EST	36.261	2.763	13.123	0.00
Import	0.109	0.108	406.6	0.00	AP	0.067	0.012	5.482	0.00
Employment	0.130	0.130	498.1	0.00	WAGE	3.673	0.132	27.731	0.00
					LQ	-14390	1771.416	-8.124	0.00

RDD Model Summary									
GDP_Manu	Coeff.	std err	t value	p	Export	Coeff.	std err	t value	p
Const	26120	739.507	35.324	0.00	Const	15260	360.819	42.284	0.00
QP	-0.027	0.004	-6.229	0.00	QP	-0.009	0.002	-4.176	0.00
EST	3.025	0.301	10.062	0.00	EST	1.7156	0.147	11.697	0.00
AP	0.012	0.001	8.769	0.00	AP	0.0044	0.001	6.809	0.00
WAGE	0.354	0.014	24.591	0.00	WAGE	0.1916	0.007	27.251	0.00
LQ	-15,700	1,943.579	-8.078	0.00	LQ	-691.429	94.028	-7.353	0.00
Import	Coeff.	Std err	t value	p	Employment	Coeff.	Std err	t value	p
Const	26030	878.33	29.638	0.00	Const	1863.395	38.68	48.175	0.00
QP	-0.022	0.005	-4.162	0.00	QP	-0.006	0	-2.481	0.01
EST	4.065	0.357	11.385	0.00	EST	0.204	0.016	12.977	0.00
AP	0.011	0.002	7.121	0.00	AP	0.003	0.069	5.045	0.00
WAGE	0.423	0.017	24.739	0.00	WAGE	0.0219	0.001	29.048	0.00
LQ	-1509	228.889	-6.591	0.00	LQ	-88	10.08	-8.726	0.00

4.3 Production Resilience of Cluster versus Non-cluster

For production resilience, it indicates superior explanatory power near 70% to 97%. Though import of the region is not significantly influenced by the interaction of type of cluster and COVID impact under the 95% confidence level, COVID-19 itself and whether it is a cluster or not have an impact on import. Thus, for all GDP, GDP, export, and employment of the manufacturing sector denote significant impact. As Table 5, the treatment which implies whether it is a cluster or not has a negative impact on resilience, however, as indicated on interaction, under the global crisis, the cluster can have a significantly positive impact on resilience. Thus, it implies that the regions with clusters have a significant impact on the index related to production resilience, especially during the global crisis and a paralyzed value chain like COVID-19. Furthermore, rather than employment, in various dependent variables the amount of establishment of the business, average payroll level, and the location quotients which imply the comparative competitiveness with other clusters tend to influence production resilience on the confidence level of 95%. However, rather than the qp and lq which denote the distinctive competitiveness or concentration intensity of the industry, the index related to the working environment such as wage and annual payroll has a positive impact on resilience (Table 6). Thus, since the number of established companies denotes a positive impact on resilience, this paper assumes that the variety and amount of the company can enhance the quality of the cluster by enhancing resilience. However, instead, the lq and qp which have a negative impact on both shock and resilience can imply that clusters with high lq and qp are less vulnerable to shock but can be also slow to recover from the shock.

Table 5. DID Model and Result Summary

DID Model Summary					DID Result Summary				
Dependent	R^2	Adjusted R^2	F-stat	P	GDP	Coeff.	Std err	t value	p
GDP	0.843	0.843	35780	0.00	Intercept	0.037	0.002	21.098	0.00
GDP_manu	0.704	0.704	15850	0.00	Period	0.101	0.002	40.351	0.00
Export	0.970	0.97	216700	0.00	Treatment	-0.056	0.002	-31.520	0.00
Import	0.972	0.972	233300	0.00	Interaction	0.016	0.003	6.179	0.00
Employment	0.892	0.892	54850	0.00					

DID Result Summary									
GDP_manu	Coeff.	Std err	t value	p	Export	Coeff.	Std err	t value	p
Intercept	0.008	0.004	1.922	0.06	Intercept	-0.008	0.005	-1.647	0.10
Period	0.131	0.006	21.890	0.00	Period	-0.907	0.007	-129.49	0.00
Treatment	-0.065	0.004	-15.181	0.00	Treatment	-0.100	0.005	-20.020	0.00
Interaction	0.056	0.006	9.272	0.00	Interaction	0.102	0.007	14.519	0.00
Import	Coeff.	Std err	t value	p	Employment	Coeff.	Std err	t value	p
Intercept	0.072	0.070	1.027	0.30	Intercept	-0.007	0.001	-5.914	0.00
Period	11.817	0.100	118.723	0.00	Period	0.045	0.002	26.631	0.00
Treatment	-0.145	0.071	-2.034	0.04	Treatment	-0.054	0.001	-44.791	0.00
Interaction	0.078	0.101	0.775	0.44	Interaction	0.053	0.002	31.272	0.00

Table 6. RDD Model and Result Summary

RDD Model Summary					RDD Result Summary				
Dependent	R^2	Adjusted R^2	F-stat	P	GDP	Coeff.	std err	t value	p
GDP	0.125	0.125	477.4	0.00	Const	281,700	7,458.236	37.766	0.00
GDP_Manu	0.102	0.102	377.6	0.00	QP	-0.106	0.044	-2.394	0.02
Export	0.116	0.116	438.4	0.00	EST	39.610	3.032	13.065	0.00
Import	0.108	0.108	403.2	0.00	AP	0.073	0.013	5.498	0.00
Employment	0.130	0.129	496.0	0.00	WAGE	3.991	0.145	27.465	0.00
					LQ	-15,700	1,943.579	-8.078	0.00

RDD Model Summary									
GDP_Manu	Coeff.	std err	t value	p	Export	Coeff.	Std err	t value	p
Const	28,670	811.015	35.355	0.00	Const	7,868.08	275.901	28.518	0.00
QP	-0.030	0.005	-6.221	0.00	QP	-0.005	0.002	-2.877	0.00
EST	3.291	0.330	9.984	0.00	EST	0.884	0.112	7.882	0.00
AP	0.013	0.001	8.729	0.00	AP	0.002	0.000	4.660	0.00
WAGE	0.383	0.016	24.249	0.00	WAGE	0.099	0.005	18.483	0.00
LQ	-1,277.8	211.347	-6.046	0.00	LQ	-360.47	71.899	-5.014	0.00
Import	Coeff.	std err	t value	p	Employment	Coeff.	Std err	t value	p
Const	29,940	1,002.9	29.848	0.00	Const	1,871.722	38.923	48.088	0.00
QP	-0.024	0.006	-3.967	0.00	QP	-0.001	0.000	-2.571	0.01
EST	4.649	0.408	11.402	0.00	EST	0.205	0.016	12.984	0.00
AP	0.012	0.002	6.894	0.00	AP	0.000	0.000	5.113	0.00
WAGE	0.484	0.020	24.769	0.00	WAGE	0.022	0.001	28.915	0.00
LQ	-1,741.09	261.362	-6.662	0.00	LQ	-88.542	10.143	-8.729	0.00

5. Conclusion

This paper aims to analyze the impact of global crises on the production resilience of industrial clusters. Furthermore, this paper aims to provide insights into components of industrial clusters that can have a positive impact on regional productivity and economy. Based on the study, this paper expects to provide useful insights for policymakers and researchers.

Referring to the results, industrial clusters are more affected by global crises than non-clustered regions, however, they also have a more positive impact on production resilience. This is assumed that the cluster promotes interaction and collaboration among industries, and facilitates knowledge and technology sharing, performing as a factor in promoting economic recovery and growth.

These results suggest that industrial clusters provide effective production resilience, however, also vulnerable to external crises. Thus, this study has implications for verifying the shock and resilience of the clusters quantitatively, and though it is limited to the quantitative cluster features in USCM, it identifies which components significantly influence the production indicators.

Considering the results of this study, it is important for the government and businesses to actively promote the formation of clusters, and effectively manage, and support them. Though clusters seem vulnerable and ineffective to the crisis, industrial clusters can contribute to regional economic development and production resilience in the long-term aspect, which can strengthen the sustainability and competitiveness of the local economy. Thus, while constructing the cluster, it is important to consider the method to attract company and employees to the cluster as it on the RDD result. Furthermore, based on the cluster strategy of the policy decision-maker maker whether to form an elastic cluster that can recover from the shock rapidly or form an inelastic cluster that can mitigate the external shock, the policymakers can support expanding the size of the cluster by forming superior work environment or specializing cluster by enhancing concentration of industry and competitive differences with other clusters.

Also, this paper has implications for examining the impact of the cluster under the global crisis. Though this paper focuses on the pandemic issue caused by COVID-19, under a similar situation that paralyzed the supply chain, the cluster that has high lq and qp can mitigate the impact of the shock, or conversely, a cluster that has a large cluster with lots of establishment and employees but has low lq and qp can be vulnerable to the shock but recover faster than other regions. Thus, supporting clusters during the crisis situation can prevent the collapse of the regional economy of the cluster and recover from the shock rapidly.

Thus, through additional research, policymakers can form and support the Korean industrial cluster. In particular, by presenting specific measures such as improving the employment environment, attracting companies, and strengthening industrial concentration, the resilience of domestic industrial clusters could be increased and the sustainability and competitiveness of the local economy could be intensified.

However, due to the limitations of the data and analysis methods used in this paper, the generalization of the research results can be restricted. Primarily, research methodology using secondary data is very useful in terms of reducing research costs and time efficiency, but it must be used carefully considering the limitations and accuracy of the data. This study reflects these aspects and suggests that future research requires in-depth analysis using more diverse data sources. Additionally, as this paper presents the analysis results for specific industries and regions, extensive study is required to generalize the results for other industries and regions. To expand this study to the Korean industrial cluster, since the data used in this study is focused on clusters in the United States, and there are limitations in generalizing it to domestic industrial complexes. Therefore, additional research tailored to domestic industrial complexes is needed. For example, in Korea, there is a need to collect and analyze similar data from specific industrial complexes to examine the impact of cluster qualitative factors on production resilience.

Also, though the analysis denotes that there is no significant difference between traded and local clusters, however, this result should be re-analyzed since this paper utilizes the secondary dataset and the types of the cluster are pre-defined. Thus, to attain thorough insight, it is required to pre-defined the features of the traded and local cluster through the statistical standards such as the amount of the transaction with other locals or nations and re-conduct the analysis. Furthermore, this paper only focuses on each index of the cluster and its impact on productivity. Among the dependent variables, Gross Domestic Product (GDP) can be used as an indicator of a region's overall economic performance, but it may not be the best indicator to measure production resilience specifically. GDP measures the total value of goods and services produced in a region over a specific time period. While it can be influenced by a region's ability to maintain or recover production capacity, it is also influenced by other factors such as consumption, investment, and government spending. Therefore, while GDP can provide some insight into a region's economic health, it may not capture the specific factors that contribute to production resilience. However, due to the limitation of the dataset which makes it hard to measure the total production and its sales by cluster unit, this paper utilizes GDP which reflects the production of local partially. Thus, future studies on other types of clusters, not only the innovative or cooperative clusters but also the traded and local clusters reflecting more performance indexes that can have a significant impact on productivity, should be continued.

Furthermore, to enhance the practical implication of this study, future studies could be conducted on the Korean industry to diagnose the quality of the cluster, collecting data considering the characteristics of domestic industrial clusters should be a prerequisite. For example, factors of a cluster can be evaluated using data such as the number of companies in an industrial complex, number of employees, and annual salary. Additionally, regional GDP and manufacturing GDP data can be used to analyze the impact of clusters on regional economic recovery as it is collected in USCM.

Applying this study to the Korean case is significant since Korea attains various and superior industrial clusters such as the Seoul Digital Industrial Cluster, Daegu Seongseo Industrial Cluster, and others, which have become the base of a variety of companies and have a positive impact on the local economy through geographical advantages and network effects, it is hard to measure the resilience and economic effect of the cluster in a simple and efficient way. Though RDD and DID are simple analyzing methods, they can provide the effectiveness of clusters and provide insights to policymakers to design policies to enhance the local economy and clusters. Thus, as it is on USCM, constructing a database that can track the economic status based on the economic statistical area can activate studies on incubating and accelerating Korean industrial clusters and local clusters.

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저자소개

조영주 네브라스카 주립대에서 경영학사와 데이터 분석 석사 과정 졸업 후, 연세대학교 산업공학 박사과정에 재학 중이다. 주요 관심분야는 기술경영, 조직관리이다.

이창근 육군사관학교 경영학과를 졸업하고, 연세대학교 일반대학원 산업공학과에서 석사과정에 재학 중이다. 주요 관심분야는 기술경영, 품질경영이다.

유준영 인천대학교 산업경영공학과를 졸업 후, 연세대학교 일반대학원 산업공학과에서 석박사 통합과정에 재학 중이다. 주요 관심분야는 기술경영, 마케팅 전략이다.

김소영 아주대학교 산업공학과 학사를 졸업하고, 연세대학교 일반대학원 산업공학과에서 석사과정에 재학 중이다. 주요 관심분야는 특허분석, 기술경영이다.

박희준 George Washington University에서 공학경영 전공으로 박사학위를 취득하고 Marymount University 경영학과에 재직하였으며, 현재 연세대학교 산업공학과에 재직 중이다. 주요 관심 분야는 플랫폼 기반의 혁신 전략, 비즈니스 모델 개발, 전략 수립 및 성과평가 방법론 개발 등이다.