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SPECIAL ISSUE PAPER

How regional economic structure matters in the era of COVID-19: resilience capacity of U.S. states

Ayoung Kim[1] · Jaewon Lim[2] · Aaron Colletta[2]

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Abstract
The COVID-19 pandemic is an unexpected-extreme event and has considerably impacted the national and regional economies. This paper emphasizes the importance of industrial structure for a region's resistance to the recessionary shock. Two significant factors that may determine the regional industrial structures in this ongoing recession include the relative composition of essential/non-essential sectors and the intensity of face-to-face interactions. Considering these factors, we focus on two groups of industries: essential industry with low interpersonal interactions and non-essential industry with high interpersonal interactions. The specialization in these industries is associated with the regional economic resistance to the COVID-19 induced recession. Estimation results from the ordinal logistic regression models show that essential industries with low interpersonal interactions, especially the retail and service sectors—for instance, non-store retailers and financial and professional service—are significantly related to regional economic resistance, and their relationship intensifies compared to other sectors during the COVID-19 pandemic. However, states specialized in the non-essential industries with high interpersonal interactions are less likely to resist economically during the lockdown-COVID and until the stabilizing-COVID period. In addition, a state that quickly recovered from the 2001 recession is more likely to resist the pandemic shock during early- and lockdown-COVID periods. Findings in this paper indicate the importance of regional industrial structure to determine the level of vulnerability to unexpected recessionary shocks. Additionally, identifying the vital factors to determine the industrial structure based on the type of shock is found to be crucial.

JEL classification R11 · R12 · P25 · L16 · L8

✉ Jaewon Lim
jaewon.lim@unlv.edu

Extended author information available on the last page of the article

1 Introduction

Since the outbreak of COVID-19 in December 2019, government restrictions amid the worldwide pandemic have slowed the flow of people across space and the flow of goods and services across countries and regions. By late March of 2022 in the USA, over 80 million cases and 970,000 deaths have been confirmed. This public health crisis has produced a significant shock to national and regional economies. Government directives for stay-home orders and business closures directly impacted economic activities while growing uncertainty and concerns associated with the COVID-19 pandemic discouraged economic activity indirectly. The negative shock on regional economies was widespread and extensive, though the magnitude of the shock varied by region. This was mainly due to regional economies' varying levels of resilience, which are largely dependent on their industrial structures.

Regions highly concentrated in service or manufacturing sectors that rely on intensive face-to-face interaction are more vulnerable to the economic shock from COVID-19. Businesses in those sectors, such as restaurants and bars, travel and transportation, entertainment (e.g., casinos and amusement parks), personal services (e.g., dentists, daycare providers, barbers), vulnerable retail (e.g., department stores and small retails), and vulnerable manufacturing (e.g., meat processing and packing), were directly and adversely affected by the shutdown orders. Conversely, regions highly specialized in industrial activities that are not necessarily prone to government shutdown orders are relatively less vulnerable to the economic shock from the pandemic. These industrial activities include but are not limited to: professional business services, information technology, financial activities, freight transportation, and warehousing and storage services. Martin and Sunley (2015) found that high-tech manufacturing and knowledge-led service industrial activities are vital for resilient regional structures, mainly thanks to innovative activities and a more adaptable labor market structure.

The economic shock from the worldwide pandemic is still ongoing and no one can accurately forecast when it will end due to existing uncertainty from COVID-19 variants even with widely available access to vaccines. In the first quarter of 2020, some U.S. regions started to show early signs of economic recession, but the shock to regional economies in the U.S. predominately started in the second quarter of 2020. With the recent release of state GDP in the U.S.,[1] empirical studies about the shock on regional economies in the U.S. have mainly focused on how regional economies react to shocks (resistance). This should be separated from the subsequent questions: how regional economics recover from shocks (recovery), and how regional economies grow in the post-recovery period by renewal and reorientation (realignment and adaptation). Martin (2012) provided an extensive discussion on a regional reaction to recessionary shocks, post-recession hysteresis, and the long-term trajectory of a regional economy facing recessionary shocks.

[1] Data for analysis are retrieved from U.S. Bureau of Economic Analysis in March, 2022.

Like many other recent studies on COVID-19 and its impact on regional economies, this study focuses on the question of how regional economies react to shocks (resistance) with the ongoing recession due to COVID-19. This paper emphasizes the importance of industrial structure for a region's reaction to a recessionary shock. This study employs two factors as the main determinants for the regional industrial structure during this ongoing recession. The first is if the economic activities have been determined as 'essential' by the federal government. The second is the level of interpersonal interactions for the economic activities. With these two factors under consideration, the industries of a region can be classified into four groups: (1) essential with high interpersonal interactions, (2) non-essential with high interpersonal interactions, (3) essential with low interpersonal interactions, and (4) non-essential with low interpersonal interactions. Specialization of re-classified industries is associated with the level of resistance to an extreme event, particularly an infectious disease outbreak, such as COVID-19. The two main research questions in this study are: 'does the industrial structure of a state differentiate the intensity of a negative economic impact from the COVID-19 shock?' Secondly, 'are states with highly specialized industries that are vulnerable to the pandemic disease more prone to the shock from COVID-19, as compared to other states?'.

Our study contributes to the evolving literature on the regional economic impact of COVID-19 by proposing an industrial taxonomy that allows us to investigate the extent to which regional industrial structure attributes to heterogeneous regional economic impacts in the U.S. The industrial structure is measured by the sectoral specialization and diversity for each state using employment and establishment data. The results enable us 1) to identify the states that are the most economically damaged (or benefitted) from the COVID-19 outbreak in terms of annual change in state GDP and resistance level, 2) to learn how regional industrial structure explains the variance in regional economic impacts, and 3) to draw policy implications to enhance economic resilience by restructuring regional industrial sectors. The following section summarizes the relevant literature and research, followed by the method and data in Sect. 3. Section 4 shares the findings from this study, and the last section concludes.

2 Literature review

The interest in ecological resilience as an academic concept started with Holling's (1973) seminal work in which he defined the term as a system's ability to absorb changes and shocks and still be able to persist in its function. In the last 50 years, an increased interest in resilience has led to a continually expanding list of definitions and applications. Norris et al. (2007) identify over twenty working definitions applying the concept of ecological resilience to cities, communities, social environments, and economies. Early work on economic resilience focused on natural disasters, which led Rose (2007) to define a static/dynamic framework that addressed the acute onset nature of economic shocks caused by natural disasters/hazards. Foster (2007) expanded the concept beyond natural disasters and defined the term as a region's ability to anticipate, prepare, respond, and recover from any economic disturbance.

Scholars have mainly focused on the response and recovery characteristics to a shock or disturbance, leading to a debate on how best to operationalize the concept. This debate centers around economic resilience being defined through an engineering equilibrist perspective or an evolutionary adaptive process (Simmie and Martin 2009). The engineering perspective refers to a system's ability to absorb a shock and return to an equilibrium point, a definition that is close to Holling's (1973) original ecological concept of resilience. The evolutionary, or adaptive, approach sees economies as having adaptive capacity where resilience is defined through its ability to successfully transform and generate a new long-run growth path; a view that incorporates punctuated equilibrium and accounts for hysteresis (Martin 2012; Simmie and Martin 2009).

Using the engineering framework, an economy's equilibrium point is measured as a return to a pre-shock growth path. Han and Goetz (2015) bifurcate this period into two different types of resilience measurements: absorption and rebound. Absorption measures the negative effects of the shock from an expected growth trend, while rebound measures the duration it takes for an economy to bounce back to the pre-shock growth levels. The other competing economic resilience perspective—evolutionary/adaptive—argues that economies are driven by knowledge and innovation and are never in a state of equilibrium (Ramlogan and Metcalfe 2006), thus economic resiliency must include an economy's ability to successfully adapt and improve its long-run growth path (Simmie and Martin 2009). Martin (2012) outlines a more comprehensive framework combining these two schools of thought and addresses the weakness of the bi-dimensional equilibrium framework popular with the engineering perspective. The author's model consists of four interrelated dimensions examining the characteristics of adaptive economic resiliency: (1) resistance, which indicates the severity of the shock; (2) recovery, which indicates how well/quickly an economy bounces back; (3) reorientation, which indicates the extent the industrial structure shifted during the recovery period; and (4) renewal, which is the resumption of normal economic activities redrawing long-run growth trends.

This paper looks specifically at the resistance dimension of economic resilience, which Martin (2012) further elaborates as the vulnerability or sensitivity of a region's economy to a disturbance or recessionary shock. Martin (2012) posits that industrial/economic structure, innovative propensity, entrepreneurial culture, workforce skills, and governance structure create a region's unique profile for resistance. It helps explain why recessionary shocks have regionally asymmetrical impacts (Fingleton et al. 2012). Even in the modern age of globalization, Stimson et al. (2006) assert that strategic planning for regional economies has embraced industrial specialization. Building on the advantages of industrial clusters first identified by Porter (1991), the authors highlight the competitive advantages of industrial specialization through efficiency generation and advancement in innovation and workforce competencies (Stimson et al. 2006). This strategic embrace of industrial specialization provides competitive economic advantages, but in return, it may diminish a region's economic resistance as recessionary shocks do not have a uniform impact on all industries. Empirical studies on regional resistance to the recessionary shock during the Great Recession found that sectoral labor composition (Faggian et al. 2018; Giannakis and Bruggeman 2017b), human capital (Crescenzi et al. 2016), and urbanization (Brakman et al. 2015; Giannakis and Bruggeman 2017a) are the major determinants causing regional variation in resistance. Yet, these studies might be insufficient in explaining regional economic resistance during recessionary shocks caused by pandemics. Rubin (2011) argues that global economic shocks caused by pandemics are uniquely different from other global shocks due to the added dynamics of global health concerns and the 'existential threat' posed by infectious diseases. This necessitates the need for studies focused on economic resistance during pandemic-initiated recessions.

While the COVID-19 global health crisis is a relatively recent phenomenon, preliminary studies have begun to investigate regional resistance to the economic shock it has created. Gong et al. (2020) looked at economic resistance in regional economies in China during the COVID-19 recession and found that asymmetric resistance to the recessionary shock was due to a complex combination of infection rate, pre-pandemic regional economic health, and industrial structure, while long-term economic resilience is affected by the level of government support measures/policies. Building on this, Hu et al. (2021) found that the higher resistant regional economies in Northeast China were positively impacted by lower infection rates, lower economic openness, and industrial specialization. Industrial specialization as a positive impact on resistance may appear contradictory, but the Northeast China regional economies specialize in industries that tend to be government-controlled and thus insulated from global supply chains issues (Hu et al. 2021). While government policy is treated as an input on economic resistance, the current literature lacks a comprehensive study on how government policy can directly influence which industrial structures generate positive or negative impacts on economic resistance to the COVID-19 recession.

Economic disruption and recessionary shock caused by natural disasters or financial institutions are assumed to be different from the recessionary shock caused by COVID-19. This difference is highlighted by the government's role in halting certain economic activities. To protect their citizens, governments instituted a wide range of prohibitory policies that included border closures, business closures, lockdowns, and social distancing measures. In the USA, state governments ordered business closures for all businesses not engaged in essential critical infrastructure (CDC 2020). Businesses deemed essential performed work in the following areas: healthcare, public safety, food and agriculture, energy, water, transportation and logistics, communication and information technology, and critical manufacturing and hazardous materials (CISA 2020). Non-essential industries that rely on social interactions—hospitality, food service, tourism, and leisure—were largely shuttered generating an economic disruption on both the supply-side and demand-side (Nicola et al. 2020). Based on the designation of essential and non-essential businesses mixed with myriad business closure orders for brick-and-mortar/ personal interaction reliant businesses, asymmetric shocks are expected based on the type of specialization of a region's industrial structure. Due to a culture of limited government and cooperative federalism, the USA developed a state decision-federal support model for all COVID-19 regulations and policies concerning travel and business activities (CISA 2020). This model allowed for each of the fifty states to generate their own policies creating a heterogeneous patchwork of regulations and enforcement mechanisms. The lack of a unified federal policy response is expected to compound asymmetric regional resistance to the COVID-19 caused recession.

3 Method and data

To figure out how resistant a regional economy is to the COVID-19 pandemic according to its industrial structure, we borrow indices to identify the regional economic resistance and measure industrial specialization and diversity. Researchers have developed various resistance/resilience indices to capture economic pattern changes to an economic shock (See pages 645–646 in Doran and Fingleton (2016)). Among the various resistance/resilience indices, we utilize the resistance index developed by Lagravinese (2015), which simultaneously measures regional resistance and sensitivity. The regional economic resistance index determines how a region is economically resistant compared to the national average by comparing annual growth in the gross regional domestic product (GRDP) and national GDP. The economic resistance at the state level (β_r) can be defined as follows:

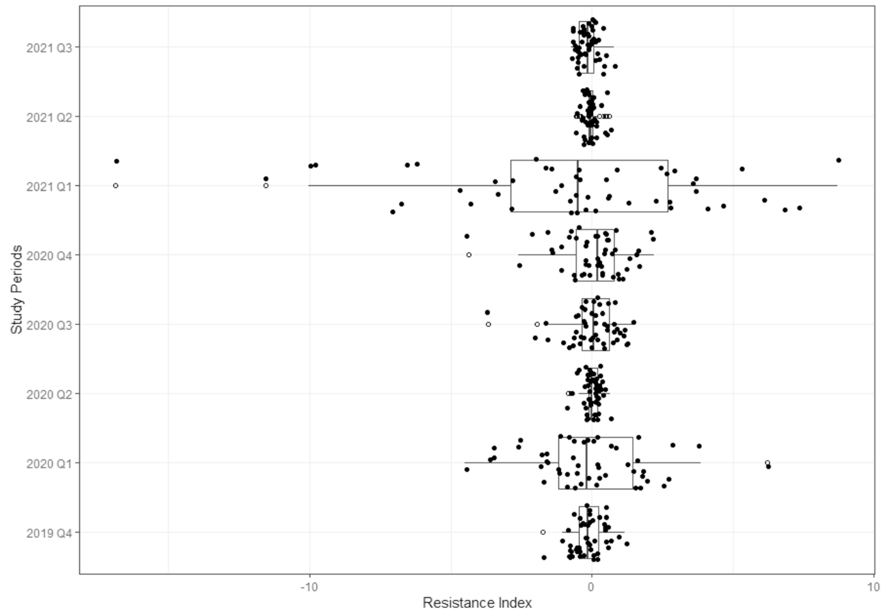
$$\beta_r = \left[\left(\frac{\Delta GSP_{r,t,t-1}}{GSP_{r,t-1}}\right) - \left(\frac{\Delta GDP_{t,t-1}}{GDP_{t-1}}\right)\right] / \left|\frac{\Delta GDP_{t,t-1}}{GDP_{t-1}}\right| \tag{1}$$

where $\Delta GSP_{r,t,t-1}/GSP_{r,t-1}$ and $\Delta GDP_{t,t-1}/GDP_{t-1}$ are the percentage change in the gross product at the state r (GSP_r) and national (GDP) levels between years $t-1$ and t.

If $\beta_r > 0$, a state is considered resistant against a shock because the economic loss of the state is relatively smaller than the national average. On the other hand, if $\beta_r < 0$, a state is less (or not) resistant because the economic loss is relatively higher than the average national loss. The index with $\beta_r = 0$ indicates the state's GRDP change has the same pattern as the average national GDP change and does not determine whether the region is resistant. As the dependent variable in Eq. (4), we transform continuous index β_r in Eq. (1) into ordinal categories to make the marginal effects comparable across the study period. In the first quarter of 2020 and 2021 (2020:Q1 and 2021:Q1), the ranges of resistance index are significantly larger than other periods shown in Fig. 1. It can lead to exaggerating marginal effects of the interests in the first quarter of 2020 and 2021 due to the scale of the dependent variable. To avoid this, the economic resistance index, β_r, is grouped into four ordered categories: most-resistant, more-resistant, less-resistant, and least-resistant, according to their level.

Location quotient (LQ) is the most common measure of industrial specialization introduced by Florence (1939). It is the ratio of two shares: the employment shares of a particular industry at the regional level to the employment share of that industry at the national level. We calculate the LQs for the industries which are affected by COVID-19 in a particular state as:

$$LQ_{ir} = \left(E_{ir}/E_r\right)/\left(E_{in}/E_n\right) \times 100 \tag{2}$$



Periods	Mean	Median	Std. Dev.	Min	Max	Range
2019: Q4	-0.15	-0.14	0.55	-1.73	1.16	2.88
2020: Q1	-0.07	-0.19	2.01	-4.52	6.23	10.75
2020: Q2	0.02	0.01	0.28	-0.85	0.64	1.49
2020: Q3	0.01	0.07	0.92	-3.69	1.45	5.14
2020: Q4	0.04	0.22	1.19	-4.37	2.21	6.58
2021: Q1	-0.68	-0.50	5.02	-16.88	8.72	25.60
2021: Q2	-0.04	-0.06	0.24	-0.58	0.63	1.21
2021: Q3	-0.14	-0.15	0.35	-0.72	0.79	1.51

Figure 1 Box plot of Resistance Index, β_r

Fig. 1 Box plot of Resistance Index, β_r

where E_{ir} is the employment of industry i in a state r; E_n or E_r is total employment at the national level (n) or the state level (r), respectively; and, E_{in} is the national employment in the industry i. If the quotient is greater than 100 for an industry, then the region is more concentrated with the industry relative to the national average in terms of employment. Employment data from the Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labor Statistics (BLS) covers most industries to calculate the LQ. For some sectors, we use the secondary data provided by EMSI.[2]

The relative diversity index (Div_r), which corrects the inverse Herfindahl–Hirschman Index (HHI), is utilized to measure industrial diversity in each state:

[2] Employment data for 6-digit sectors from EMSI www.emsieconomicmodeling.com.

$$Div_r = 100/\sum_i |s_{ir} - s_i| \tag{3}$$

where s_{ir} is each industry i's share in the total establishments in the state r (i.e., $s_{ir} = Est_{ir}/\sum_i^N Est_{ir}$, where, Est_{ir} is the number of establishments of industry i in state r) and, s_i is the share of industry i's establishments in a nation among the total national establishments (i.e., $s_i = Est_i/\sum_i^N Est_i$). The index captures the relative diversity across 93 industry sectors, represented by the three-digit NAICS codes in a state. The index for a state r increases as the composition of industrial activities in state r increases, resembling the diversity of the national economy (Duranton and Puga 2000). Establishment data from the QCEW of BLS covers entire industries to calculate the diversity index. The spatial distribution of LQ and relative diversity among U.S. states can be found in Figures A.1. and A.2 of Online Appendix.

The two significant factors that may determine the regional industrial structure under the COVID-19 pandemic are the relative composition of essential/non-essential sectors and the intensity of face-to-face interactions. With these two factors under consideration, we classify industrial sectors into the four groups: (A) essential industry with high interpersonal interactions, (B) non-essential industry with high interpersonal interactions, (C) essential industry with low interpersonal interactions, and (D) non-essential industry with low interpersonal interactions. The non-essential industry with high interpersonal interactions (B) is more vulnerable to recessionary shocks during the pandemic due to governments' business closure orders or reduced demand for non-essential products and services. It would induce a negative impact on the state economy. On the other hand, the essential industry with low interpersonal interaction (C) is less likely to experience the negative shock. Other industries have a mixed impact. Thus, we focus on industry types (B) and (C) to investigate the relationship between industrial specialization and the impact of COVID-19 on state economies. The detailed sectors in industries (B) and (C) are listed in Table 1.

To account for the state economic resistance using the industrial structure and state's characteristics, we specify ordinal logistic regression model as follows:

$$log\frac{P(Y \le j)}{P(Y > j)} = logit(P(Y \le j)) = \alpha_{jo} - \sum_{n=1}^{n} \alpha_n x_n \tag{4}$$

where Y is an ordinal outcome with J categories (category $j = 1, \cdots, J$, where 1 = least-resistant, 2 = less-resistant, 3 = more-resistant, and 4 = most-resistant); and $P(Y \le j)$ denotes the cumulative probability of Y less than or equal to a specific category $j = 1, \cdots, J-1$. The dependent variable in Eq. (4) is the odds of being less than or equal to a particular category j in the ordered categories which are grouped according to the level of resistance β_r. The economic resistance index β_r in Eq. (1) is calculated with the annualized real GDP growth for four quarters, from the fourth quarter of 2018 to the third quarter of 2021, to examine whether COVID-19 affects the economy. The annualized growth for each quarter, i.e., percent change from the same quarter 1 year ago, enables us to compare each quarter's growth by controlling the seasonality in GDP. The resistance index β_r is used to place states in each category following conditions:

Table 1 Industry Reclassification

Industry B	Industry C
Non-essential sectors with high interpersonal interaction	Essential industries with low interpersonal interaction
Retail B	Retail C
448 Clothing and clothing accessories stores	441 Motor vehicle and parts dealers
451 Sports, hobby, music instrument, book stores	454 Nonstore retailers
452 General merchandise stores	
453 Miscellaneous store retailers	
Transportation and warehousing B	Transportation and warehousing C
481111 Scheduled passenger air transportation	481112 Scheduled freight air transportation
481211 Nonscheduled air passenger chartering	481212 Nonscheduled air freight chartering
483112 Deep sea passenger transportation	482 Rail transportation
483114 Coastal and great lakes passenger transport	
483212 Inland water passenger transportation	483111 Deep sea freight transportation
	483113 Coastal and great lakes freight transportation
487 Scenic and sightseeing transportation	483211 Inland water freight transportation
	484 Truck transportation
	488 Support activities for transportation
	491 Postal service
	492 Couriers and messengers
	493 Warehousing and storage
Service B	Service C
71 Arts, entertainment, and recreation	51 Information
72 Accommodation and food services	52 Finance and insurance
81 Other services, except public administration	54 Professional and technical services
	55 Management of companies and enterprises
	56 Administrative and waste services

†Authors-elaborated using NAICS 2017 code (2 to 6 digits in the table)

State r is included.
in the most-resistant group if $\beta_r \geq E\left[\beta_r \middle| \beta_r \rangle 0\right]$ (i).
in the more-resistant group if $\beta_r < E\left[\beta_r \middle| \beta_r \rangle 0\right]$ (ii).
in the less-resistant group if $\beta_r \geq E[\beta_r | \beta_r \leq 0]$ (iii).
in the least-resistant group if $\beta_r < E[\beta_r | \beta_r \leq 0]$ (iv).

Two conditions are considered to assign states to groups. First, we determine whether a state has a resistance index (β_r) greater than zero or not, which means a state is resistant against a shock or not resistant. Among resistant states which have positive values of resistance index, a state is classified as the most-resistant state if a state's β_r is equal to or greater than the average of resistant states as (i). If a state's β_r

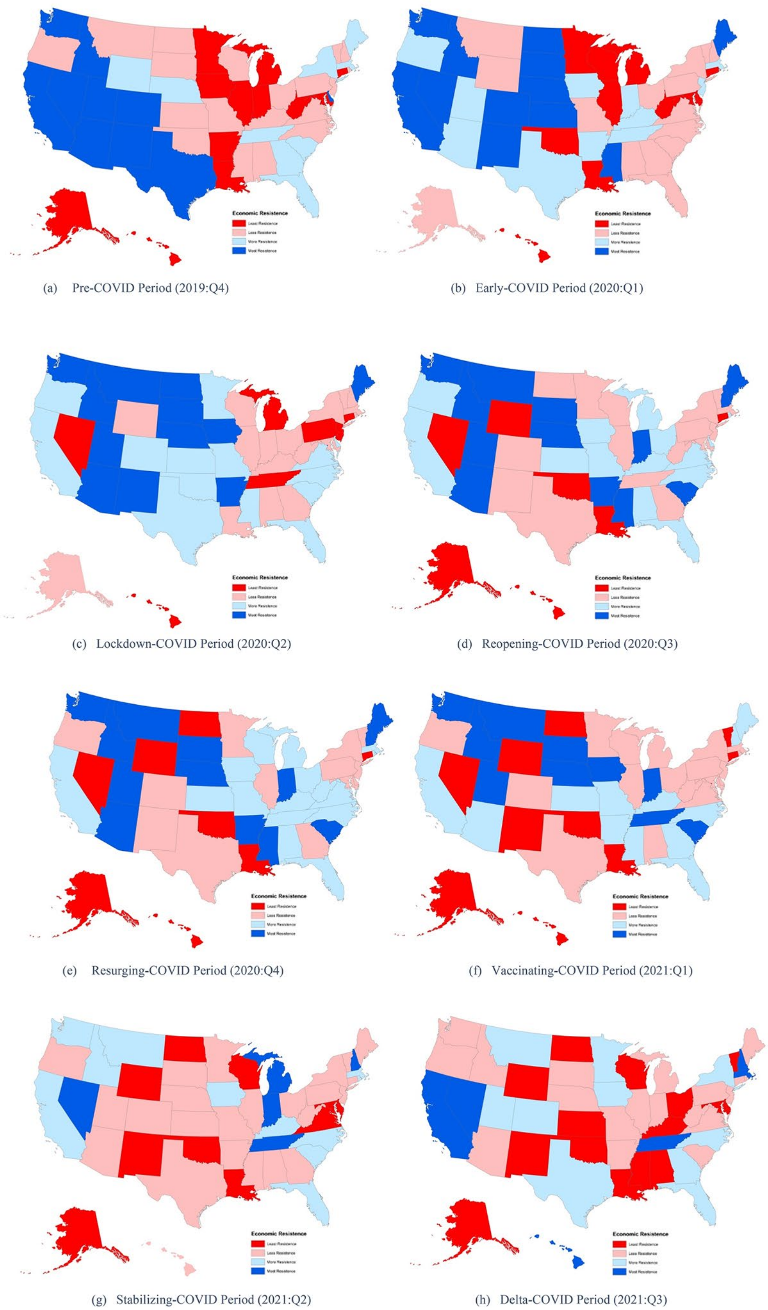
is below average among the resistant states as (ii), the state is assigned to the more-resistant group. Second, states with negative resistance index values are classified as the less- or least-resistant groups. If a state's β_r is equal to or greater than the average of states with negative β_r as (iii), the state is assigned to the less-resistant group. The remaining states that their β_r are below the average of states with negative β_r as (iv), are assigned to the least-resistant group.

Eight quarters of study periods in our study are defined as: 'pre-COVID' (2019:Q4), 'early-COVID' (2020:Q1), 'lockdown-COVID' (2020:Q2), 'reopening-COVID' (2020:Q3), 'resurging-COVID' (2020:Q4), 'vaccinating-COVID' (2021:Q1), 'stabilizing-COVID' (2021:Q2), and 'Delta-COVID' (2021:Q3). The spatial distribution of the resistance groups for each study period is shown in Fig. 2 of Sect. 4.1. LQ for two industry types (B and C) and their sub-sectors (retail, transportation and warehousing, and service for each industry) and diversity index (inverse HHI) are measured to describe state's industrial structure. Table 3 and Fig. 3 in Sect. 4.2. present industrial specialization and diversity. Additionally, the geographic distribution of LQ for each industry and diversity index can be found in Figures A.1. and A.2. of Online Appendix. Table 2 reports descriptive statistics of data used in our analysis.

4 Results

4.1 Economic resistance

Figure 2 shows the spatial pattern of economic resistance. Across the first six study periods, most states with higher resistance levels are clustered in the West. Since the resistance index is a comparative measure to the national average, pre-COVID resistance indices among the states have less variance than the pattern found during the early-COVID period, as shown in Fig. 1. During the early-COVID period, some states started to have net losses of GRDP due to the economic shocks mainly induced by government directives/orders. Still, the overall pattern is consistent with the previous period (pre-COVID) in that the majority of Western states had higher resistance levels than the national average, while most Midwestern and Northeastern states had lower resistance compared to the national average. During the lockdown-COVID period (second quarter of 2020), all fifty states and Washington D.C. reported 5–20% net GRDP losses. As a result, the regional variation in the comparative resistance index had significantly declined compared to the early-COVID period. This descriptive analysis on the spatial distribution can signal a link between government directives/orders and GRDP changes during the COVID-19 pandemic; however, a model specification is required to formally test if, and how much, industrial structure matters to determine the economic resistance level of a state. Spatial distribution patterns of resistance for the lockdown-COVID period (shown in Map (c) of Fig. 2) and for the reopening-COVID period (shown in Map (d) of Fig. 2) are also quite different. The resilience indices of Michigan, Indiana, Ohio, and Kentucky had improved, while six other states, Texas, Oklahoma, New Mexico, Colorado, North Dakota, and Minnesota experienced a drop in resilience indices.



(a) Pre-COVID Period (2019:Q4)

(b) Early-COVID Period (2020:Q1)

(c) Lockdown-COVID Period (2020:Q2)

(d) Reopening-COVID Period (2020:Q3)

(e) Resurging-COVID Period (2020:Q4)

(f) Vaccinating-COVID Period (2021:Q1)

(g) Stabilizing-COVID Period (2021:Q2)

(h) Delta-COVID Period (2021:Q3)

Fig. 2 Resistance Index over Eight Study Periods Maps present (1) the most-resistant states in blue; (2) the more-resistant states in light blue; (3) less-resistant states in light red; and (4) the least-resistant states in red.

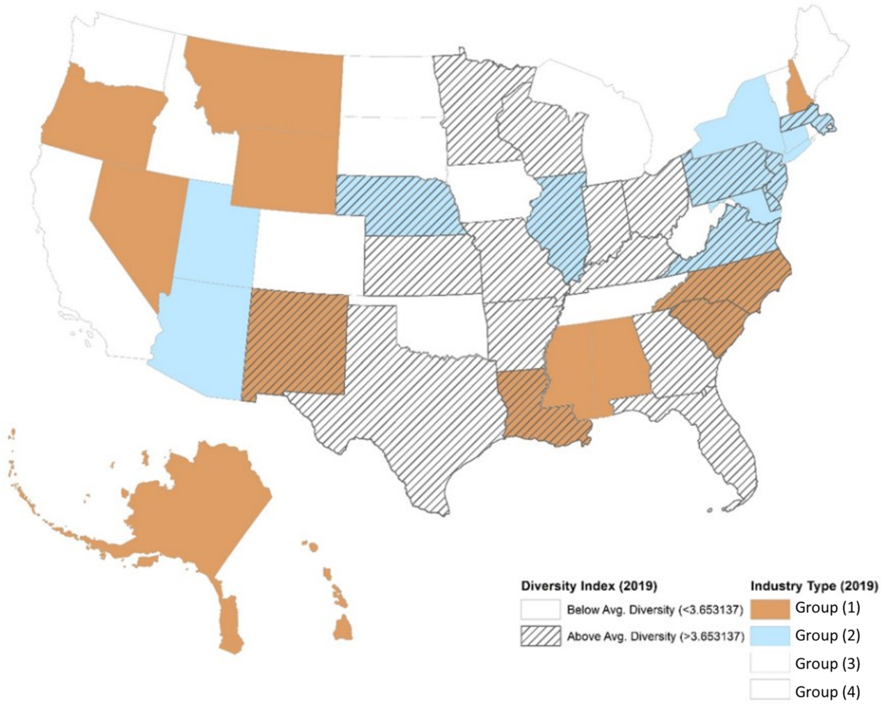


Fig. 3 COVID-19 Related Industry Types & Industrial Diversity The states in brown color are the Group (1) states in Table 3, specialized in industry B and not specialized in industry C (more vulnerable during a pandemic), whereas the states in light blue color are the Group (2) states in Table 3, not specialized in Industry B and specialized in industry C (less vulnerable during a pandemic)

The spatial pattern of the resistance index had been similar and persistent across the three study periods, from the third quarter of 2020 (reopening-COVID period) to the first quarter of 2021 (vaccinating-COVID period). A noticeable change was found between the first two quarters of 2021 (from the vaccinating-COVID period to the stabilizing-COVID period) which many internal states had experienced drops in their resistance levels. These states are mainly located in the western part of the Midwest and the eastern part of the Mountain West. Facing the widespread Delta variant during the third quarter of 2021, the spatial variation of economic resistence had increased from the second quarter of 2021.

4.2 Industry structure

In order to analyze the industrial concentration of re-classifying industries B and C, we create four groups according to the level of specialization: (1) states specialized in industry B ($LQ_{B,r} \geq 100$) but not in industry C ($LQ_{C,r} < 100$) in the bottom-left corner in Table 3; (2) states not-specialized in industry B ($LQ_{B,r} < 100$) but specialized in industry C ($LQ_{C,r} \geq 100$) in the top-right corner in Table 3; (3) states

Table 2 Summary Statistics

Study period	2019: Q4Pre- COVID		2020: Q1 Early- COVID		2020: Q2 Lockdown-COVID		2020: Q3 Reopening-COVID	
Variables	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Resistance Index	−0.15	0.55	−0.07	2.01	0.02	0.28	0.01	0.92
Number of States								
(Least resistant)	12		12		7		7	
(Less resistant)	19		15		17		16	
(More resistant)	9		11		14		14	
(Most resistant)	10		12		12		13	
Covid-19 (per 100 k pop)								
New Death			0.93	1.61	30.81	37.62	19.60	15.02
Study period	**2020: Q4 Resurging-COVID**		**2021: Q1 Vaccinating-COVID**		**2021: Q2 Stabilizing-COVID**		**2021: Q3 Delta-COVID**	
Variables	**Mean**	**S.D**	**Mean**	**S.D**	**Mean**	**S.D**	**Mean**	**S.D**
Resistance Index	0.04	1.19	−0.68	5.02	−0.04	0.24	−0.14	0.35
Number of States								
(Least resistant)	8		10		10		15	
(Less resistant)	13		18		24		19	
(More resistant)	16		12		11		10	
(Most resistant)	13		10		5		6	
Covid-19 (per 100 k pop)								
New Death	49.02	26.78	54.57	23.75	14.71	8.95	27.59	18.53

Table 2 (continued)

Study period	2020: Q4 Resurging-COVID		2021: Q1 Vaccinating-COVID		2021: Q2 Stabilizing-COVID		2021: Q3 Delta-COVID	
Variables	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Pre-existing Attributes (2019)								
Industry B* (LQ)	100.14	14.15						
- Retail	101.96	12.34						
- Transportation	87.94	115.22						
- Service	100.00	15.20						
Industry C* (LQ)	92.94	13.09						
- Retail	104.90	19.44						
- Transportation	100.26	29.87						
- Service	90.84	16.57						
Diversity (relative HHI)	369.96	87.58						
Ln (Population)	8.30	1.03						
Months to recover								
from 911 recession	13.04	6.95						
from 2008–9 recession	24.74	9.74						
Observation	50							

† Data Source: The COVID Tracking Project by The Atlantic Monthly Group; Gross Domestic Product by State, BEA; Current Employment Statistics (ECS) and Quarterly Census of Employment and Wages (QCEW), BLS; EMSI 2020.3. * Industry B: Non-essential sectors with high personal interaction; Industry C: Essential sectors with low personal interaction

Table 3 COVID-19 Related industry types & industrial diversity

	Specialized in industry type B	Not specialized in industry type B
Specialized in industry type C	Group (3) states: California, Colorado **Florida, Georgia Tennessee, Texas**	Group (2) states: Arizona, Connecticut, **Delaware, Illinois,** Maryland, **Massachusetts Nebraska, New Jersey,** New York, **Pennsylvania,** Utah, **Virginia**
Not specialized In industry type C	Group (1) states: Alabama, Alaska, Hawaii, **Louisiana** Mississippi, Montana, Nevada, New Hampshire, **New Mexico, North Carolina,** Oregon, **South Carolina** Wyoming	Group (4) states: **Arkansas,** Idaho, **Indiana, Iowa Kansas, Kentucky,** Maine, Michigan **Minnesota, Missouri,** North Dakota, **Ohio,** Oklahoma, **Rhode Island** South Dakota, Vermont, Washington, West Virginia, **Wisconsin**

†Bold text presents states above average in industrial diversity level

specialized in both industries, and (4) states not-specialized neither in industry B nor industry C. In terms of industrial diversity, we regroup states into two categories: above and below the average in diversity index ($Div_r = 365$).

States in group (1) in Table 3 are expected to be relatively less economically resistant to COVID-19, while the states in group (2) in Table 3 are expected to be more resistant. From the literature, researchers found that diversity plays a major role in regional economic (productivity) growth through inter-regional knowledge spillover (Beaudry and Schiffauerova 2009; Melo et al. 2009). The states in the bold text in the table have a diverse industrial structure that may be more economically resistant. Figure 3 presents the spatial distribution of the industrial structure. States in group (1), which are specialized in industry B and not in industry C, are mostly shown in West and South. States in group (2), which are assumed to be more resistant under the pandemic, are clustered in the Northeast region. Illinois and Nebraska in Midwest and Utah and Arizona in the West are also specialized in industry C but not in industry B. Except for New Mexico, Western states are less likely to have diverse industry structures than other states.

4.3 COVID-19, economy structure and economy resistance

Our empirical analysis investigates whether states' industrial structures are associated with regional economic resistance to the COVID-19 pandemic as an external shock. Results from the ordered logistic regression models in Tables 4 and 5 show that industry C is positively correlated with the odds of having higher regional economic resistance, particularly, retail or service in essential sectors with low personal interaction—for instance, non-store retailers and financial, professional, and business services. It reveals that the concentration of those sectors has a statistically significant and positive relationship with regional economic resistance over study periods except the early-COVID and lockdown-COVID periods.

Table 4 Estimation Results of Ordinal Logistic Regression with Industry B and C

Estimate (Standard Error)	2019: Q4 Pre-COVID	2020: Q1 Early-COVID	2020: Q2 Lockdown-COVID	2020: Q3 Reopening-COVID	2020: Q4 Resurging-COVID	2021: Q1 Vaccinating-COVID	2021: Q2 Stabilizing-COVID	2021: Q3 Delta-COVID
Specialization								
Industry B†	0.016 (0.025)	−0.019 (0.028)	−0.092*** (0.031)	−0.076*** (0.028)	−0.054** (0.027)	−0.047* (0.027)	0.053** (0.025)	0.137*** (0.043)
Industry C††	0.103*** (0.033)	0.006 (0.029)	0.053 (0.033)	0.034 (0.030)	0.017 (0.030)	0.030 (0.028)	0.011 (0.032)	0.068* (0.036)
Diversity	−0.003 (0.004)	−0.002 (0.004)	−0.001 (0.004)	−0.003 (0.003)	−0.002 (0.003)	−0.002 (0.003)	−0.003 (0.004)	−0.006 (0.004)
Recovery Experience								
911 Recession	−0.091* (0.053)	−0.036 (0.049)	−0.097* (0.052)	0.011 (0.050)	−0.001 (0.047)	−0.013 (0.046)	0.109** (0.052)	0.068 (0.059)
2008 Recession	−0.013 (0.032)	−0.003 (0.031)	−0.013 (0.033)	0.066* (0.035)	0.065* (0.033)	0.019 (0.033)	0.028 (0.031)	−0.053 (0.033)
Population	−0.259 (0.402)	0.117 (0.403)	−0.181 (0.369)	−0.539 (0.401)	−0.047 (0.371)	0.113 (0.371)	0.177 (0.413)	0.327 (0.476)
Covid-19 Death†††		−0.134 (0.162)	−0.036*** (0.011)	0.049** (0.024)	0.008 (0.012)	0.002 (0.012)	−0.036 (0.035)	−0.035* (0.020)
Cut 1 (1|2) ††††	4.942 (3.282)	−3.012 (3.527)	−11.743*** (4.005)	−9.587*** (3.711)	−5.022 (3.874)	−2.848 (3.618)	6.582* (3.427)	17.609*** (4.838)
Cut 2 (2|3) ††††	6.979** (3.345)	−1.656 (3.510)	−8.988** (3.856)	−7.466** (3.638)	−3.404 (3.852)	−1.005 (3.626)	9.152*** (3.536)***	20.051*** (5.044)
Cut 3 (3|4) ††††	8.179** (3.419)	−0.635 (3.495)	−7.298* (3.814)	−6.039 (3.596)	−1.924 (3.831)	0.154 (3.617)	10.761 (3.617)	22.127*** (5.228)
Model Statistics								
Obs	50	50	50	50	50	50	50	50

Table 4 (continued)

Estimate (Standard Error)	2019: Q4 Pre-COVID	2020: Q1 Early-COVID	2020: Q2 Lockdown-COVID	2020: Q3 Reopening-COVID	2020: Q4 Resurging-COVID	2021: Q1 Vaccinating-COVID	2021: Q2 Stabilizing-COVID	2021: Q3 Delta-COVID
Residual Deviance (− 2*LL)	118.13	136.11	105.58	118.43	126.17	128.24	109.76	97.30
AIC	136.13	156.11	125.58	138.43	146.17	148.24	129.76	117.30

$*p<0.1$, $**<0.05$, $***<0.01$

†Industry B: Non-essential sectors with high personal interaction; ††Industry C: Essential sectors with low personal interaction; ††† COVID-19 Death per 100 K population Industry; †††† Cut-point coefficients in our models reflect the natural logarithm of the ratio of the predicted fraction of states above the cut-point to the fraction of states below the cut-point. We have three cut-points (Cut 1, 2, and 3) to divide the distribution of Y (in Eq. (4)) into four groups

Table 5 Estimation Results of Ordinal Logistic Regression with Disaggregate Sectors

Estimate (Standard Error)	2019: Q4 Pre- COVID	2020: Q1 Early-COVID	2020: Q2 Lockdown-COVID	2020: Q3 Reopening-COVID	2020: Q4 Resurging-COVID	2021: Q1 Vaccinating-COVID	2021: Q2 Stabilizing-COVID	2021: Q3 Delta-COVID
Specialization								
Industry B[†]								
Retail B	−0.008 (0.029)	−0.010 (0.027)	0.048 (0.032)	0.049 (0.034)	0.042 (0.032)	0.030 (0.03)	−0.008 (0.034)	0.016 (0.039)
Transportation B	−0.007 (0.005)	−0.002 (0.003)	−0.010** (0.004)	−0.012** (0.006)	−0.018** (0.007)	−0.012** (0.006)	−0.005 (0.004)	−0.001 (0.004)
Service B	0.063** (0.029)	0.010 (0.023)	−0.099*** (0.034)	−0.060* (0.032)	−0.022 (0.027)	−0.029 (0.026)	0.129*** (0.034)	0.189*** (0.034)
Industry C[††]								
Retail C	0.050*** (0.015)	0.025 (0.016)	0.007 (0.016)	0.074*** (0.02)	0.096*** (0.019)	0.061*** (0.017)	0.039*** (0.014)	0.032** (0.014)
Transportation C	0.011 (0.011)	0.021* (0.012)	−0.021* (0.013)	0.004 (0.012)	0.002 (0.012)	0.034*** (0.012)	0.015 (0.012)	0.016 (0.013)
Service C	0.088*** (0.027)	0.000 (0.026)	0.049* (0.028)	0.046* (0.027)	0.054* (0.03)	0.052** (0.026)	0.006 (0.028)	0.055* (0.03)
Diversity	−0.003 (0.004)	−0.004 (0.004)	0.000 (0.004)	−0.003 (0.004)	−0.003 (0.004)	−0.005 (0.004)	−0.004 (0.004)	−0.007 (0.005)
Recovery Experience								
911 Recession	−0.113* (0.061)	−0.039 (0.053)	−0.128** (0.058)	−0.003 (0.053)	0.014 (0.051)	−0.034 (0.048)	0.145*** (0.054)	0.088 (0.062)
2008–9 Recession	−0.056 (0.035)	−0.017 (0.035)	−0.057 (0.038)	0.014 (0.038)	0.015 (0.04)	−0.028 (0.037)	0.006 (0.035)	−0.077** (0.036)
Population	0.175 (0.441)	0.228 (0.421)	0.046 (0.406)	−0.063 (0.451)	0.538 (0.467)	0.587 (0.406)	0.428 (0.441)	0.542 (0.479)

Table 5 (continued)

Estimate (Standard Error)	2019: Q4 Pre- COVID	2020: Q1 Early-COVID	2020: Q2 Lockdown-COVID	2020: Q3 Reopening-COVID	2020: Q4 Resurging-COVID	2021: Q1 Vaccinating-COVID	2021: Q2 Stabilizing-COVID	2021: Q3 Delta-COVID
Covid-19 Death[†††]		−0.001 (0.182)	−0.038*** (0.012)	0.028 (0.025)	0.027** (0.013)	−0.007 (0.015)	−0.040 (0.038)	−0.053** (0.023)
Cut 1 (1|2) [††††]	14.946*** (0.009)	2.725*** (4.244)	−9.964*** (0.003)	6.675*** (0.011)	18.606*** (0.012)	13.168*** (0.014)	19.356*** (0.005)	28.408*** (0.009)
Cut 2 (2|3) [††††]	17.366*** (0.492)	4.260*** (4.28)	−6.680*** (0.8)	9.299*** (0.621)	20.751*** (0.545)	15.706*** (0.544)	22.248*** (0.515)	31.099*** (0.529)
Cut 3 (3|4) [††††]	18.749*** (0.618)	5.380*** (4.294)	−4.806*** (0.911)	11.200*** (0.759)	22.976*** (0.699)	17.311*** (0.661)	24.173*** (0.705)	33.355*** (0.767)
Model Statistics								
Obs	50	50	50	50	50	50	50	50
Residual Deviance (−2*LL)	104.45	128.72	96.19	97.83	98.78	105.04	98.27	91.42
AIC	130.45	156.72	124.19	125.83	126.78	133.04	126.27	119.42

*$p < 0.1$, ** < 0.05, *** < 0.01

[†]Industry B: Non-essential sectors with high personal interaction; ††Industry C: Essential sectors with low personal interaction; ††† COVID-19 Death per 100 K population Industry; [††††] Cut-point coefficients in our models reflect the natural logarithm of the ratio of the predicted fraction of states above the cut-point to the fraction of states below the cut-point. We have three cut-points (Cut 1, 2, and 3) to divide the distribution of Y (in Eq. (4)) into four groups

Industry B, non-essential sectors with high personal interaction, is negatively associated with the odds of being resistant for almost 1 year since the early-COVID period. The service or transportation sectors in industry B—for instance, passenger transportation, entertainment-related and accommodation, and food services—are statistically significant over the lockdown-COVID and reopening-COVID. Interestingly, industry B, especially the service sector, turns to a positive relationship during the second quarter of 2021 with the stabilized COVID-19 due to the widely available and rapidly growing vaccination across the country since the first quarter of 2021. During this period, vaccinated people restarted traveling with growing confidence. Recovery experience, measured by months taken of recovering from economic recession, presents states that quickly recovered from 911 recession are more likely to be economically resistant against the COVID shock.

Using variables in Table 4, we examine Spearman's correlation coefficient between each pair of variables and the variance inflation factor (VIF) of each variable (See Table A.1. and A.2. of Online Appendix). Variables *Specialization in industry C* and *Population* have the highest VIF values around 2.0; however, multicollinearity does not appear to be a problem in the analysis following the general rule that VIF less than 10 indicates serious multicollinearity. We also perform robustness checks by omitting industry structure in the proposed model specifications and find that the results are robust. Inclusion of industry (or detailed) structure improves goodness-of-fit of models except for the Early-COVID period (See Table A.3. of Online Appendix). Additionally, Table 6 summarizes the estimated odd ratios of being more economically resistant relative to less resistant. The coefficients in Tables 4 and 5 are used to calculate those odds ratios to interpret logistic regression.

We find that the probability of economic resistance is higher for the regions with specialized industry C than for those with less specialization during the pandemic. In other words, if a state is concentrated in industry C, the state's resistance to the recessionary shock from the COVID-19 pandemic tends to increase. Especially, the odds of being more resistance versus less resistance is 1.06 times higher for regions more specialized in industry C during lockdown-COVID, as presented in Table 6. From a different angle, a state lacking in industry C specialization is more likely to experience a dramatic decrease in economic performance. Specialization in industry B tends to lower the probability of economic resistance to the COVID shock during Lockdown-COVID, Reopening-COVID, Resurging-COVID, and Vaccinating-COVID periods, while specialization in industry C tends to increase the economic resistance. Regions with industry B's specialization are less likely to be resistant. The odds of being more resistant drop to 0.91 during lockdown-COVID but slightly up to 0.95 after reopening-COVID. However, it still lowers the regional economic resistance during the pandemic until the second quarter of 2021.

Even though the most direct shock affects industry type B in the first two quarters of 2020, the indirect impact has spread into other industrial activities through the inter-industrial linkages. Therefore, the odds from industry C are reduced after COVID broke out but are still positively related even though they are not statistically significant. For the lockdown-COVID period, the direct negative shock in industry B is more noticeable with the significant and negative coefficient (in Table 4),

Table 6 Estimated Regional Economic Resistance Odds-Ratio

	2019: Q4	2020: Q1	2020: Q2	2020: Q3	2020: Q4	2021: Q1	2021: Q2	2021: Q3
Specialization								
Industry B	1.02	0.98	0.91***	0.93***	0.95**	0.95*	1.05**	1.15***
Industry C	1.11***	1.01	1.06	1.04	1.02	1.03	1.01	1.07*
Diversity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99
Recovery Experience								
911 Recession	0.91*	0.96	0.91*	1.01	1.00	0.99	1.12**	1.07
2008 Recession	0.99	1.00	0.99	1.07*	1.07*	1.02	1.03	0.95
Population	0.77	1.13	0.83	0.58	0.95	1.12	1.19	1.39
Covid-19 Death†		0.88	0.97***	1.05**	1.01	1.00	0.97	0.97*
	2019: Q4	2020: Q1	2020: Q2	2020: Q3	2020: Q4	2021: Q1	2021: Q2	2021: Q3
Specialization								
Industry B								
Retail B	0.99	0.99	1.05	1.05	1.04	1.03	0.99	1.02
Transportation B	0.99	1.00	0.99**	0.99**	0.98**	0.99**	1.00	1.00
Service B	1.06**	1.01	0.91***	0.94*	0.98	0.97	1.14***	1.21***
Industry C								
Retail C	1.05***	1.03	1.01	1.08***	1.10***	1.06***	1.04***	1.03**
Transportation C	1.01	1.02*	0.98*	1.00	1.00	1.04***	1.02	1.02
Service C	1.09***	1.00	1.05*	1.05*	1.06*	1.05**	1.01	1.06*
Diversity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99
Recovery Experience								
911 Recession	0.89*	0.96	0.88**	1.00	1.01	0.97	1.16***	1.09
2008 Recession	0.95	0.98	0.95	1.01	1.02	0.97	1.01	0.93**
Population	1.19	1.26	1.05	0.94	1.71	1.80	1.53	1.72
Covid-19 Death†		1.00	0.96**	1.03	1.03**	0.99	0.96	0.95**

*$p < 0.1$, ** < 0.05, *** < 0.01

Odds ratios are calculated using the coefficients from Tables 4 and 5

especially in the transportation and service sectors of industry B (in Table 5). During lockdown-COVID, states highly specialized in the service sector in industry B are less likely to have economic resistance with considerably low odds of 0.91. A state specialized in industry B started to experience a more severe negative shock in its economic performance, inducing a decline in the resistance level of the state to the recessionary shocks.

The results from the disaggregated sector models in Tables 5 and 6 tell us which sector mainly delivered the effects on the resistance levels. Specialization in industry B and its sectors do not significantly correlate with economic resistance during the pre- and the early-COVID pandemic periods. However, with more restrictive government directives/orders facing the rapidly growing pandemic during the lockdown-COVID period, states specializing in industry B (non-essential and involving higher interpersonal interactions) tend to have lower economic resistance for 1 year after the lockdown-COVID. The major carriers of the negative correlation are transportation and service sectors of industry B. Businesses in passenger transportation, art, entertainment, recreation, accommodation, and food services are directly damaged by government orders for non-essential business closure and significantly diminishing demand due to growing health concerns associated with high interpersonal interactions. After COVID-19 vaccines had been available everywhere by the end of the first quarter of 2021, the states specialized in the service sector of industry B, such as entertainment, accommodations, and food services, rebounded significantly with the growing confidence among vaccinated people. This is still persistent with the newly emerging Delta variant in the third quarter of 2021.

Similarly, but in the opposite direction, the service sector in industry C (information, finance and insurance, professional and technical services, management of companies and enterprises, and administrative and waste services) carries out a significant positive impact across all study periods except the early-COVID. The retail sector in industry C, including non-store retailers such as online shops and other e-commerce businesses, also has a positive and statistically significant impact on the resistance of a state economy except for early- and lockdown-COVID. Table 7 presents states by regrouping according to the level of specialization in service sectors in each industry.

Previous studies found that industrial diversity is one of the key players to increase regional productivity and economic performance (Beaudry and Schiffauerova 2009; Melo et al. 2009). However, our results statistically fail to present that industrial diversity is positively associated with the regional economic resistance shown in Tables 4 and 6. Instead, we find states' past recovery experience is associated with economic resistance in the early stage of shock. We test two different types of economic shocks: the 911 recession in 2001 as a relatively short-term shock and the great recession of 2008 as a long-term shock. The recovery experience from the 911 recession in 2001 has negative correlations for most study periods until the stabilizing-COVID period. It presents that a state with a longer recovery time from the 911 recession tends to have lower resistance to COVID-19 pandemic shocks, while a state that experienced a shorter recovery path from the 911 recession tends to have a higher resistance to the ongoing pandemic shock. The recovery path from the great recession of 2008 was not found to impact resistance to COVID-19 significantly. Figure A.3. summarizes the estimated odds ratios of being more economically resistant relative to less resistant during the pandemic for an industrial structure that significantly addresses the regional economic resistance.

Table 7 COVID-19 Related industry types & industrial diversity (Service Sector Activities)

	Specialized in service sector of industry type B	Not specialized in service sector of industry type B
Specialized in service sector of industry type C	California, Colorado, Florida Rhode Island	Arizona, Connecticut, Delaware, Georgia, Illinois, Maryland, Massachusetts, New Jersey, New York, Utah, Virginia
Not specialized in service sector of industry type C	Hawaii, Louisiana, Mississippi, Montana, Nevada, New Mexico North Carolina, Oregon, South Carolina, Tennessee, Wyoming	Alabama, Alaska, Arkansas, Idaho, Indiana, Iowa, Kansas, Kentucky, Maine, Michigan, Minnesota, Missouri, Nebraska, New Hampshire, North Dakota, Ohio, Oklahoma, Pennsylvania, South Dakota, Texas, Vermont, Washington, West Virginia, Wisconsin

5 Conclusion

Facing the unexpected worldwide pandemic, global communities experienced a recessionary shock to various economic activities. Disrupted human interactions in space are major causes of the shock during the COVID-19 pandemic. The U.S. has recorded over 18% of the total confirmed cases and around 15% of COVID-19 deaths in the world. Unlike many other countries with a stronger central government, such as China, Russia, and Japan, public health policies in the U.S. are mainly designed and implemented at state and local levels. This can partly explain the discrepancies in COVID-19 cases and the related public health issues among the U.S. states. In 2020, some states like New York, New Jersey, and Massachusetts in the Northeast region had experienced an early surge in COVID-19 cases, mainly in late March through early April, while some states like California, Arizona, Nevada, and Florida, had experienced a surge in the middle of the summer. States with more restrictive 'stay-home' and 'business closure' government directives/orders had better controlled the public health issues; however, many of these states have suffered from the economic shocks from the restrictive government directives/orders, at least temporarily. Every state has different industrial compositions (structures) and the vulnerability to pandemic shocks in each state varies depending on the industrial structure.

This study employed the two characteristics of industrial activities: essential and intensity of interpersonal interaction. These two factors can determine the level of vulnerability to COVID-19 pandemic shocks considering the restrictive government measures to fight against COVID-19. The two research questions in this study are: (1) does the industrial structure differentiate the intensity of negative economic impacts from the COVID-19 shocks? And (2) are states with highly specialized industries that are more vulnerable to the pandemic more prone to the shock from COVID-19 as compared to the other states?

Major findings in our model indicate that the industrial structure of a state matters in determining the level of resistance of a state economy. A state more specialized in essential industries with limited interpersonal interactions (industry C) successfully maintained a higher resistance level during most pandemic periods. Conversely, a state more specialized in non-essential industries with intensive interpersonal interactions (industry B) diminished its resistance to shocks from the lockdown-COVID to vaccinating-COVID periods. For the early-COVID period, we were not able to confirm the direct impact of industries B and C on the resistance to recessionary shock.

Among the sectors of industry C, essential retail and service sectors with limited (relatively low levels of) interpersonal interactions serve as a buffer to downward pressure on the resistance level in a state. These sectors include 'non-store retailers,' 'information,' 'finance and insurance,' and 'professional and technical services.' States specialized in these sectors had successfully maintained a higher resistance to recessionary shocks than the national average during the pandemic. Among the sectors of industry B, non-essential transportation and service sectors with intensive human interactions most significantly reduced the level of resistance to COVID-19 shocks in the lockdown-COVID period and following periods until the stabilizing-COVID period. These sectors include 'passenger transportation,' 'sightseeing transportation,' 'arts, entertainment, and recreation,' and 'accommodation and food services.' States highly specialized in these sectors experienced larger losses in resistance levels than the national average in the lockdown, but the situation improved with lower negative impacts with the reopening of the economy.

Since the great recession of 2008, many state and local governments in regions that are highly specialized in low-skilled service industries have been working diligently to diversify their regional economic structure by promoting high-skilled service industries that may serve as a buffer to external shocks. Some states have been successful, while others are still struggling with high concentrations in low-skilled service industries (service in industry B). For the ongoing recession caused by the COVID-19 pandemic, earlier efforts to reduce concentration in low-skilled service industries partly helped states by easing the downward pressure on their resistance levels to external shocks. At the same time, investment to promote high-skilled service industries (service in industry C) also helped states by reducing downward pressure on the resistance level. Our study focuses on the resistance of a state economy considering industrial structure. However, during the upcoming recovery period, states that are highly specialized in low-skilled service sectors that experienced significant economic shocks may have faster recovery periods, while states that are highly specialized in high-skilled service sectors may experience slower recovery periods since the shock was milder in these states. The unprecedented recessionary shock from the worldwide pandemic provides policymakers opportunities to revisit the link between industrial specialization and resistance level. There will not be a one-size-fits-all model. However, policymakers in states that endured significant economic shocks can learn from other states with less severe shocks in developing strategies to be less vulnerable and more resistant to external shocks considering their industrial development strategies.

Our paper employs state and national GDP as a measure of economic performance. More direct impact can be felt in state and local labor market conditions. Future studies should include a comparison between two sets of models: one with GDP and the other with labor market conditions, which would reveal how industrial composition matters to the state labor market and how that link determines the resistance level of a state's labor market.

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Authors and Affiliations

Ayoung Kim[1] · Jaewon Lim[2] · Aaron Colletta[2]

Ayoung Kim
a.kim@msstate.edu

Aaron Colletta
aaron.colletta@unlv.edu

[1] Department of Agricultural Economics, Mississippi State University, 317 Lloyd-Ricks-Watson Bldg., Mississippi State, MS 39762, USA

[2] School of Public Policy and Leadership, University of Nevada Las Vegas, 4505 S Maryland Pkwy, Box 454030, Las Vegas, NV 89154-4030, USA