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Supply Chain Resilience in California: Targeted-Efficient Spillover Methodology

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Abstract. The world has changed drastically in logistical and economic spheres as a result of the COVID-19 pandemic. This pandemic has caused a global crisis in supply-chain structures, creating regional, national and international impacts of unprecedented magnitude. Accordingly, this research develops a methodology to favour the logistics-resilience framework based on regional externalities and technical-efficiency analysis of the 51 US states, applying a Spatial Data Panel model and a Stochastic Frontier model in conjunction with graph theory (Ford–Fulkerson algorithm). The findings indicate that New York, West Virginia and North Dakota are vital external regions to support California's logistics resilience. We demonstrate that a region with high technical efficiency does not necessarily constitute a key logistics spillover for a target region. This study represents one of the first attempts to optimise and redirect externalities from one region to another using spatial and logistical mechanisms.
Keywords: logistics resilience, technical efficiency, Ford-Fulkerson algorithm, spillover, California.

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1 Introduction

Since September 2021, one of the most severe bottlenecks in supply-chain history has occurred, with significant global impacts centred on California's principal ports (Jarosz, 2021; Korber, 2021). Over 80 cargo ships remained anchored offshore, each waiting more than a month to unload thousands of tonnes of goods bound for the Americas. Owing to the gravity of the situation, California's federal representatives urged the US President to declare a state of emergency and requested direct support from the White House (Gallagher, 2021). This bottleneck has caused severe disruption: extensive delivery delays; high storage and customer costs; multimillion-dollar losses in global trade; and public-welfare grievances owing to shortages of medical supplies for treating COVID-19. Consequently, various urgent public policies have been introduced in California (Shilong et al., 2021; Silverthorn, 2021; Wan, 2021), and consumer prices have risen by 6.2 %, marking the highest inflation rate since 1990 (Lepore, 2021).

The problem facing ports in Latin America and the United States is so complex because it is a problem that encompasses not only one cause but multiple causes, such as shortages of transport workers (Vann, 2021) and low port logistics infrastructure (McCarthy, 2021), among others. Therefore, providing an integrative solution to such a logistical scenario represents an invaluable tool that would bring multiple benefits to the well-being of the regions and the entire global community. Therefore, this research aims to develop a proposal for economic-logistics resilience based on the logic of spillover to strengthen the logistics infrastructure of the United States and prevent and deal with supply chain crises. The research question that this research seeks to answer is: How to redirect the best logistical effects of each of the American states to strengthen its logistics infrastructure.

The focus of the present research is quantitative-deductive since it is predominantly applied mathematical deduction and inferences based on previously established theories within the economic and logistic field. The methodology in this research consists of a proposal based on optimizing the distribution of externalities by applying previous models proposed in the Spatial Data Panel, Stochastic Frontier Model, and use of logistic algorithms (Ford-Fulkerson algorithm). The results of this research dictate that the logistics public policy in California should integrate Wyoming and New Mexico as critical logistics pivots in its region; and New York, West Virginia, and North Dakota as external region support states. As an additional proposal, it should take action on the American states with low efficient usage of production resources (west region: California, Nevada; Midwest region: Minnesota, Michigan; South region: Delaware, Virginia; Northeast region: Vermont, Pennsylvania) and implant new public policy strategies to take advantages of the efficient states of every region (West region: Wyoming, New Mexico; Midwest region: Nebraska, Ohio; South region: Tennessee; West Virginia; Northeast region: New York, New Hampshire).

2 Literature review

As Pettit et al. (Pettit et al., 2010) point out, supply chain resilience (SCR) tries to make the given logistics system learn from the disruption suffered and achieve its improved reconfiguration. Pettit et al. make a taxonomic proposal of postulates under a qualitative approach to a strategic guide of factors to guide logistical resilience. Under this same qualitative-taxonomic line are the following researchers: Fiksel (2003); Tukamuhabwa et al. (2015); Kamalahmadi & Parast (2016); Ivanov (2018). Hosseini et al. (2019) conducted exhaustive research on the different quantitative techniques for evaluating and developing the SCR, which is evaluated below: Christopher & Rutherford (2004) exemplify and apply the Six Sigma technique to be able to develop the SCR as well as carry out. Hosseini & Barker (2016) use Bayesian networks to model the probability of geographically dispersed suppliers and thus develop resilience by applying supply dispersion strategies. Another type of approach is the optimization of multiple strategic supplies when risk and demand arise, and under this logic are the proposals of Namdar et al. (2017), Lucker & Seifert (2017), Yildiz et al. (2016), Yoon et al. (2016), Bicer (2015), Torabi et al. (2015), Peng et al. (2011); Sawik (2018), Meena & Sarmah (2013), Sadghiani et al. (2015); Zhang et al. (2015). Another type of approach to logistics resilience is based on inventory forecasting, as it can be anticipated in advance of disruption, the planned inventory can absorb the adverse effects. Under this approach in the research of Tomlin (2006), Turnquist & Vugrin (2013), Khalili et al. (2016), Spiegler et al. (2012).

Another resilience approach in the SCR is through the construction of multiple distribution channels, in which the proposals of Khalili et al. (2016), Kamalahamadi & Parast (2016) are presented. Another focus is the strategic construction of backup providers Torabi et al. (2015), Ho et al. (2010), Chakraborty et al. (2016), Saghafian & Van Oyen (2016), Jabarzadeh et al. (2018), Turnquist & Vugrin (2013), Kamalahmadi & Parast (2016). Another approach strategy is by reinforcing routing (Liu& Lee Lam, 2013; Khaled et al., 2015; Hosseini & Khaled, 2016); another strategy is through the strengthening of communication and cooperation based on commercial interactivity between the agents of the supply chain, whose research for this approach is Scholten & Schilder (2015); Mandal et al. (2016); Wieland & Wallenburg (2013). Finally, there is also the resilience strategy through the ability to implement substitute products while the resilience period occurs (Mancheri et al., 2018), as well as the approach of implementing the capacity of restoration by suppliers so that they can be reinforced in the financial and technical aspect and in this current way agilely in the face of an adverse scenario (Hosseini & Barker, 2016; Sahebjamnia et al., 2018), (Turnquist & Vugrin, 2013). As can be seen, our research proposal is predominantly related to the resilience approach based on communication & cooperation. In this regard, there needs to be more research on this type of proposal where characteristics of spatial dependence and externalities are considered. The present research provides a proposal for this gap.

3 Methods & procedures

The proposal presented in this research is based on the Spillover Theory (Krugman, 1996; Maier & Sedlacek, 2005; Mancheri et al., 2018). The importance of spillover is that it represents the conduct to transmit the information and externalities (unplanned effects from a planned activity) despite the failures or asymmetries in the communication medium. To detect the spillover effect, we apply the techniques of the Spatial Data Panel to measure the Spatial Dependence of each of the American and world regions and thus understand the degree of externalities between the geographical spaces of the same concerning their aggregate production. Our methodological proposal uses spatial dependence and technical efficiency (applying both Stochastic Frontier Model and Spatial Error/Durbin Model) and each American state's market flow to detect which are the key States to influence logistics efficiency in California. To optimize this optimal distribution of information (spillover), we applied the Ford-Fulkerson algorithm (Kyi et al., 2019; MIT, 2012), (see Algorithm 1), applying our index proposal to verify the maximum flow of transmissibility to a target region, thus managing to detect those critical regions to support of the logistics resilience.

Algorithm 1 Ford-Fulkerson (G, s, t). Taken from Cormen et al., 2009

for each edge $(u, v) \in G.E$
    $(u, v).f = 0$
while there exists a path p from s to t in the residual network G_f
    $c_f\ (p) = \min\ \{c_f\ (u, v) : (u, v) \text{ is in } p\}$
    for each edge (u, v) in p
        if $(u, v) \in E$
            $(u, v).f = (u, v).f + c_f\ (p)$
        else $(v, u) = (u, v).f - c_f\ (p)$

Just as Cormen et al. (2009) explain about the Ford-Fulkerson algorithm, "*in each iteration of the Ford-Fulkerson method, we find some augmenting path p and increase the flow f on each edge of* p *by the residual capacity* c_f (p)*. The following implementation of the method computes the maximum flow in a graph* $G = (V, E)$ *by updating the flow* $(u, v).f$ *between each pair (u, v) of vertices connected by an edge. If u and v are not connected by an edge in either direction, we assume implicitly that* $(u, v).f = 0$*.*

The capacities $c(u, v)$ are assumed to be given along with the graph, and $c(u, v) = 0$ if (u, v) $\notin$ E. The expression c_f (p) in the code is just a temporary variable that stores the residual capacity of the path p.”

As a first step, we constructed a modified model of the Cobb-Douglas function (Ioan & Ioan, 2015) that represents the current aggregate economic reality of the study regions (1):

$$Y= K^{\alpha 1}L^{\alpha 2}H^{\alpha 3}V^{\alpha 4}P^{\alpha 5}S^{\alpha 6}R^{\alpha 7}D_1{}^{\alpha 8}D_2{}^{\alpha 9}e^{\lambda} \qquad (1)$$

where Y is aggregate production; K is the capital stock, composed of fixed capital formation undertaken in previous periods (OECD, 2021); L is the workforce; H is human capital; V is the average container vessel dwell time (ACVDT), which means “Within port terminal boundaries limited to terminals servicing container vessels” (Bicer, 2015); P is the percentage of transport workers about the economically active population; S is the amount of CO2 emissions (carbon dioxide) from the given region, expressed in millions of metric tons; R is the percentage of acceptability of the road infrastructure of the given region; D_1 is the dichotomous variable that represents the two most notable economic contractions of recent years (corresponding to the year 2009 and the year 2020); D_2 is the dichotomous variable that represents the most critical year of the current COVID-19 pandemic (the year 2020); λ is technological change and α_n are the respective regressors of each of our variables. For the present research, note that we do not apply any restriction concerning the sum of the exponents of each variable of the equation (1) to obtain in the results the best significant representation and that it is these who decide if the economic scenario represents an approach of increasing economic returns, constant or decreasing. Additionally, a second model was designed below that aims to represent the force of spatial transmissibility from one entity to another (2):

$$I_{ij}=\psi_r F_{ij} T_i \qquad (2)$$

where I is the redirected force of spatial resilience between a supplying State (i) to another receiving State (j), which in our case j represents the target region of California; ψ is the Spatial Dependency of positive externalities of a r given region by applying the Spatial Error/Durbin Model (Sarrias, 2020), using inverse matrix of spectral type (STATA, 2021) (the median centroid technique was applied to obtain the geographical coordinates of each entity applying ArcMap 10.3); F is the existing trade flow between given regional entities; T is the technical efficiency of the American states concerning the use of its resources used in its aggregate production. To apply this second model, we applied the Ford-Fulkerson algorithm proposed in 1955 (Kyi et al., 2019). With this strategy, we optimize the capacity of externality transmission of resilience information added to a given state (California), thus detecting the key American entities to be considered in the logistics resilience of the State of California (see Fig. 1).

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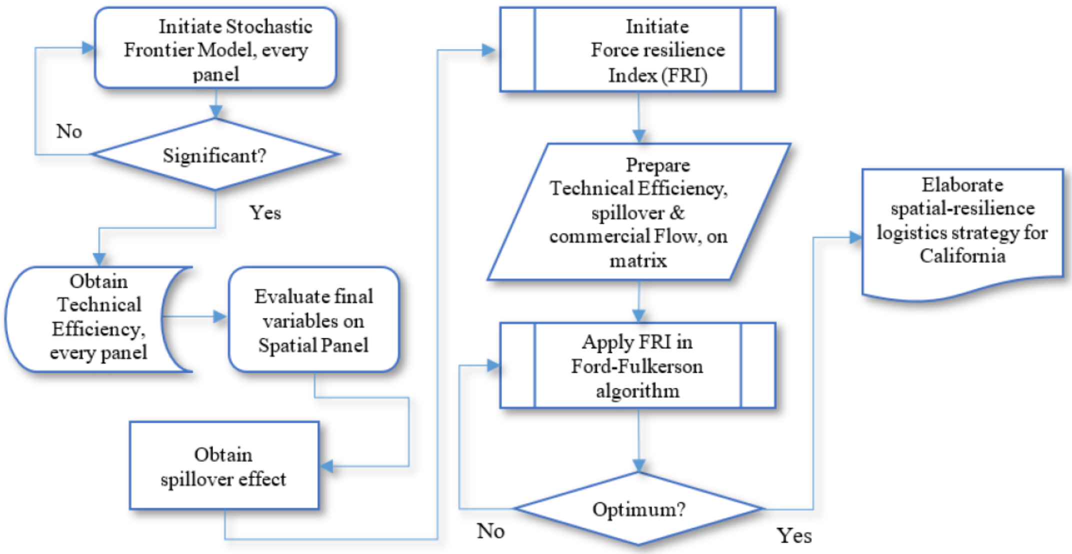

Fig. 1. Flow Diagram of research´s logic

The data sources used for our variables, along with their respective processing techniques and characteristics, are as follows: GDP (Y): State GDP (BEA, 2021); Capital stock (K) (Gupta et al., 2011): Durable capital goods, stock (FRED, 2021); Human Capital (H): Subnational Human Development Index (GlobalDataLab, 2021); Labor (L): Civilian Labor Force by State, Persons (FRED, 2021); State geographic coordinates: Geographic files in SHP format (Census, 2021); Interstate trade flow (F): Freight flows by State. Inbound & Outbound types, all commodities, Value (millions) (U.S. Department of Transportation, 2020), (BTS, 2021); The American States by region: Census regions and divisions of the United States (Census, 2021); average container vessel dwell time (V), (BTS, 2021); % of Transport Workers (P) (BTS, 2021); CO2 pollution level (S) (BTS, 2021); Level of state acceptability of roads (R) (BTS, 2021); liner shipping connectivity index (World Bank, 2022).

We apply the logarithmic transformation to all our time series to be able to handle the regressors practically, thus leaving our model as follows (3):

$$lnY = c + \alpha_1 lnK + \alpha_2 lnL + \alpha_3 lnH + \alpha_4 lnV + \alpha_5 lnP + \alpha_6 lnS + \alpha_7 lnR + \alpha_8 D_1 + \alpha_9 D_2 + \varepsilon \qquad (3)$$

Moreover, we apply a battery of unit roots for data panels such as the Levin-Lin-Chu test and Hadri LM Stationary test (Levin et al., 2002; Hadri, 2000), to our logarithmic series to ensure that our results are not spurious concluded by most tests that our variables are stationary (See Appendix 1). Additionally, to verify that our data panels are valid in their results in long-term projections, we perform a battery of Cointegration tests such as Kao test, Pedroni test, Westerlund test (Kao, 1999; Pedroni, 1999; Westerlund, 2013; Doornik & Hansen, 2008), whose results indicate their predominant acceptability of the value of less than 0.05 P-value to reject the null hypothesis that the variables do not cointegrate over time (see Appendix 1). Therefore, we can confirm that the Stochastic Frontier Model technique to represent the American regions' economic reality is wisely applied since it is designed to work with variables that have truncated normal distribution.

4 Results & discussion

Applying the STATA 15.0 software, using both the Stochastic Frontier Model, the results of our regressors are as follows (Table 1):

Table 1. Obtained results using Stochastic Frontier Model data panel, regions of United States. Standard errors are in parentheses. ***: p<.01, **: p<.05; *: p<.1. ---: discarded.

Variable	West Region	Midwest Region	South Region	Northeast Region
lnK	.046497***	0.0421802***	.0296157***	.0384048***
	(0.013495)	(0.013531)	(0.010217)	(0.010259)
lnH	9.2494***	9.761799***	7.025086***	10.29487***
	(1.225882)	(1.151157)	(0.868602)	(0.974122)
lnL	1.145245***	1.107944***	1.08667***	1.148758***
	(0.060498)	(0.025918)	(0.018052)	(0.066449)
lnV	-0.13381	0.104109	-0.08794	-.2683055**
	(0.099155)	(0.081116)	(0.061825)	(0.116681)
lnP	.5610719***	.477419***	.4052202***	.5371065***
	(0.050775)	(0.040892)	(0.029785)	(0.0765)
lnS	.1110817*	-0.06057	-.1525545***	-.200898***
	(0.057916)	(0.049235)	(0.030262)	(0.063033)
lnR	-.2198263***	-0.02442	0.02393	.1224705***
	(0.074625)	(0.062596)	(0.026004)	(0.044392)
D_1	-.0432268***	-.0460405***	-.037036***	-.052498***
	(0.013902)	(0.013056)	(0.00976)	(0.017594)
D_2	0.031114	0.017659	-0.00705	0.040307
	(0.019363)	(0.019049)	(0.014751)	(0.025246)
c	-1.810594***	-1.72435***	---	-0.33205
	(0.730096)	(0.269246)		(0.924344)

The results of our regressors are as follows (Table 1): In this table, we can see a low capitalization in the South regions (0.0296) which means these regions have trouble adding formation of capital stock and, therefore, low investment in the infrastructure. The regions with the higher capital stock (West and Midwest regions) show low values on this variable, considering that traditional ones range from 10 to 20 %. Additionally, we can see that the Northeast region has the best human capital regressor (10.2948). This region has a solid performance on education and health systems for its inhabitants; nevertheless, the lowest value on this one is presented in the South region (7.025). On the other part, the *lnL* variable (labor force) has an outstanding performance in the West and Northeast regions (1.1452 and 1.1487, respectively) which means that these regions have high productivity from their workers; meanwhile, the Northeast region´s average container vessel dwell time is undermining its aggregated production (-.2683) so it´s recommended to improve conditions for agile the dwell time on its ports. We can see that Transport workers (*P*) are scarce in the South Region (0.4052).

The variable of CO2 contamination (*S*) has its highest regressor in the West region, which means that there are regions that have an economic production that is directly proportional to pollution; conversely, the other regions show the lowest values on their regressors, which means these regions are successfully applying sustainable mechanism for this issue. We can see that the variable *R* is significant only in the West and Northeast regions; the West region is taking poor productivity on it because there are backward road conditions for every step forward in its production. This issue is an opportunity to consider public policy for the supply chain in the West Region. The dicotomical variable D_1 (economic contraction) shows that the Northeast region is the most sensitive one to the economic contraction effect (years 2009 and 2020); the dicotomical variable D_2 (year of the pandemic COVID-19) shows South Region was the most affected region for this phenomenon. Finally, West Region has weaker regional resilience (-2.30629).

According to the Hausman test, all our spatial panels were random except type, indicating that most of the positive externalities of each region do not tend to clusters but are generated by random regional shocks. This issue makes our additional proposal to locate the entities closest to the weakest interstate trade flows highly necessary since they would serve as resilient supports to strengthen the Californian logistics development. The logic of the Maximum Flow of the Ford-Fulkerson algorithm (see figure 1) applied in our proposal of externalities lies in the fact that each region has a limited capacity for unique absorption of externalities if its commercial influence channels (serve as means of communication or cooperation) are smaller to receive such influence they would be saturated even when the influence comes from a high and technically efficient entity. This is based on the Economic Bifurcation Theory (Krugman, 2001) and the Spillover Theory (Keller, 2004). Therefore, obtaining the maximum flow of externalities which strengthen the logistics of California would indicate ideal states/regions which should take into account public policy for the supply chain in California.

As additional observations resulting from Table 1: the negative effect of the ACVDT is most substantial in the Northeast region; the effect of transport workers into aggregated production is most notable in the West; the west region hurt its economic performance because of the conditions of their road structure (-.2198); in all regions of our study, the economic contractions of 2008 and 2020 adversely affected, which corroborates the empirical effectiveness of our proposed model. Additionally, we can observe that COVID-19 was not significant enough to undermine the American regions during the start year of the pandemic. The next step is to obtain every American state´s Technical efficiency (T), from our stochastic frontier model results. By way of summary, we show in Fig.2, the two higher T´s of American states from every American region and the two lower ones:

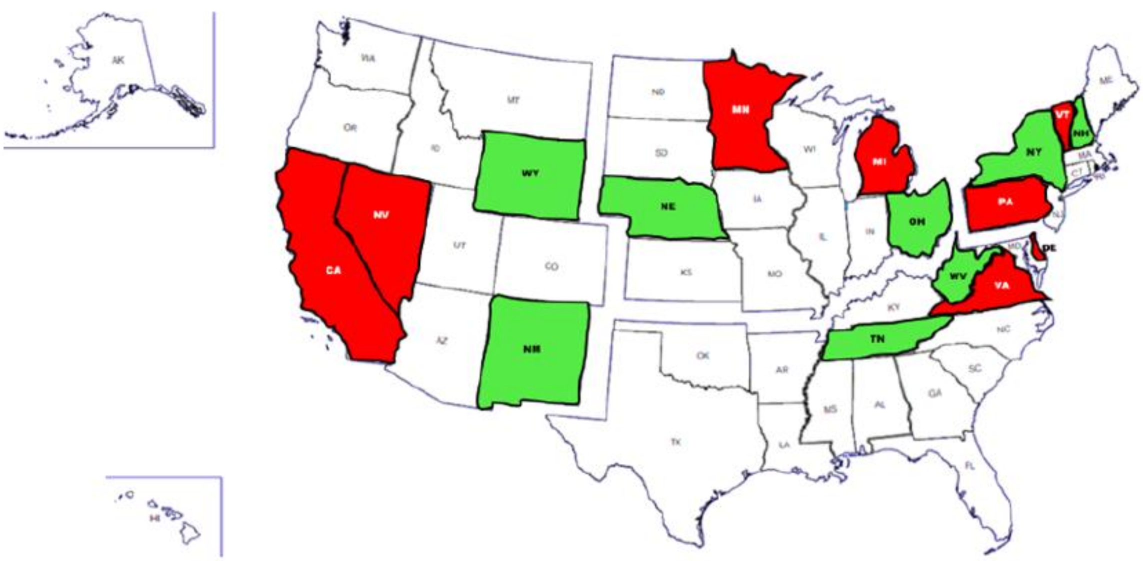

Fig. 2. Higher (green) and lower (red) Technical efficiencies

In Fig. 2, we can observe that California is one of the lower *T* in the West region. This issue shows that California is vulnerable to a logistics bottleneck because its resource usage is inefficient. That represents the necessity of applying our proposed model to redirect the logistics spillover from other American states. This issue represents an alert point: the most important maritime ports of the United States rely on a state (California). Unfortunately, it has less efficient usage of its resources, representing an undermining point of logistics bottleneck recovery. The next step of our methodology is to obtain the spillover effects from every American region. Therefore, we applied a battery of spatial models, with finally the spatial error/Durbin model being the most significative one (see Table 2):

Table 2. Direct and Spillover effect results. ***: p<.01, **: p<.05; *: p<.1.

	Variable	Direct Effect	Spillover Effect	Net influence	Significative Spatial model	Significance components spatial model
West Region	*lnK*	.0450534***	---	.0450534***	Spatial Error Durbin Model	Error *Y*= 0.018; Lagged X´s = *H*: 0.024, *P*: 0.000, *S*: 0.000
	lnH	14.01838***	-2.927099**	11.09128***		
	lnL	.8777859***	---	.8777859***		
	lnV	-0.05376	---	-0.0537586		
	lnP	.2757404***	.6366899***	.9124303***		
	lnS	.1533346***	.443118***	.5964525***		
	lnR	-.3047475***	---	-.3047475***		
	D_1	-0.01505	---	-0.0150458		
	D_2	-0.01234	---	-0.0123389		
Midwest Region	*lnK*	.0174405**	.0261234**	.0435639**	Spatial Durbin Model	*Y* = 0.000; Lagged X´s = H:.000, L: .000, V: .006, D1: .006
	lnH	8.490053***	2.810077*	11.30013***		
	lnL	.9241126***	.1651277*	1.08924***		
	lnV	.1802833**	-.3422084**	-0.1619251		
	lnP	.434305***	.6505266***	1.084832***		
	lnS	-0.01632	-0.02445	-0.0407697		
	lnR	-0.03243	-0.04858	-0.0810086		
	D_1	-.0540702***	.0424019*	-0.0116682		
	D_2	-.0235555**	-.0352827**	-.0588381**		
South Region	*lnK*	-0.00954	.0460242***	.0364806***		*Y*= .021; Lagged X´s = *K*: .001, *H*: .000, *M*: .091, *P*: .000, D_1: .018
	lnH	9.746734***	-3.586804***	6.15993***		
	lnL	.9178633***	0.029398	.9472617***		
	lnV	-0.02079	-0.00405	-0.0248435		
	lnP	.2419373***	.366882***	.6088194***		
	lnS	-.05090611*	-0.00991	-.060817*		
	lnR	-.0501292**	-0.00976	-.0598894**		
	D_1	-.0503392***	.0319877**	-.0183515*		
	D_2	-.0317558**	-.0061829*	-.0379387**		
Northeast Region	*lnK*	.0392592***	.0246749*	.0639341***	Spatial Error Durbin Model	Error *Y*: 0.000; *Y*: .008; Lagged X´s = *K*:.022, *L*: .000, *P*: .000, *S*: .023, *R*: .020
	lnH	7.411273***	-2.318809***	5.092463***		
	lnL	1.211708***	.0820954*	1.293803***		
	lnV	-0.08566	0.026802	-0.0588603		
	lnP	.1782686**	.6018219***	.7800904***		
	lnS	-.1562755***	-0.09884	-.255111***		
	lnR	.1180347***	.1947189*	.3127536***		
	D_1	-.0606765**	.0189842*	-.0416923**		
	D_2	.0638007*	-0.01996	.043839*		

In Table 2, we show the Direct Effect (generated externalities that affect inner American states in a region), the Spillover effect (generated externalities that affect external American states to a different region), and Net influence (the net difference between the Direct and Spillover effect). As we can observe, our results are significative: finally, we can be applied our second model (2) using and, by way of summary, the obtained results for the implementation of California resilience based on our methodology are presented below (Table 3):

Table 3. Results of our proposal index of resilience logistics

Midwest region	To California	South Region	To California	Northeast Region	To California
Kansas	116.9603	Texas	130.5295	Massachusetts	194.5519
Illinois	109.9145	South Carolina	126.8895	New Hampshire	192.5755
Missouri	108.755	Oklahoma	110.9701	Rhode Island	178.0586
Michigan	105.5942	North Carolina	105.5092	Vermont	159.8075
South Dakota	104.8108	Virginia	105.1406	Connecticut	0
Indiana	101.8785	Georgia	103.4147		
Iowa	100.305	Louisiana	97.5415		
Minnesota	94.7293	Kentucky	95.3674		
		Mississippi	94.1701		
		Alabama	93.2622		
		Arkansas	93.1568		
		Delaware	82.9803		
		District of Columbia	78.1471		

In Table 3, we can observe North Dakota (West Region), West Virginia (South Region), and New York (Northeast Region). These have the higher I_{sj} values, representing the key American states with the maximum flow of logistics spillover with high benefits to California. Therefore, these American states have aggregated production and infrastructure, contributing to California's resilience in logistics and economic matters. So, it should be taken into account to improve public policy for California's growing logistics and economy. In Figure 3, by way of summary, we represent these key American states which function as a logistics influencers States to California:

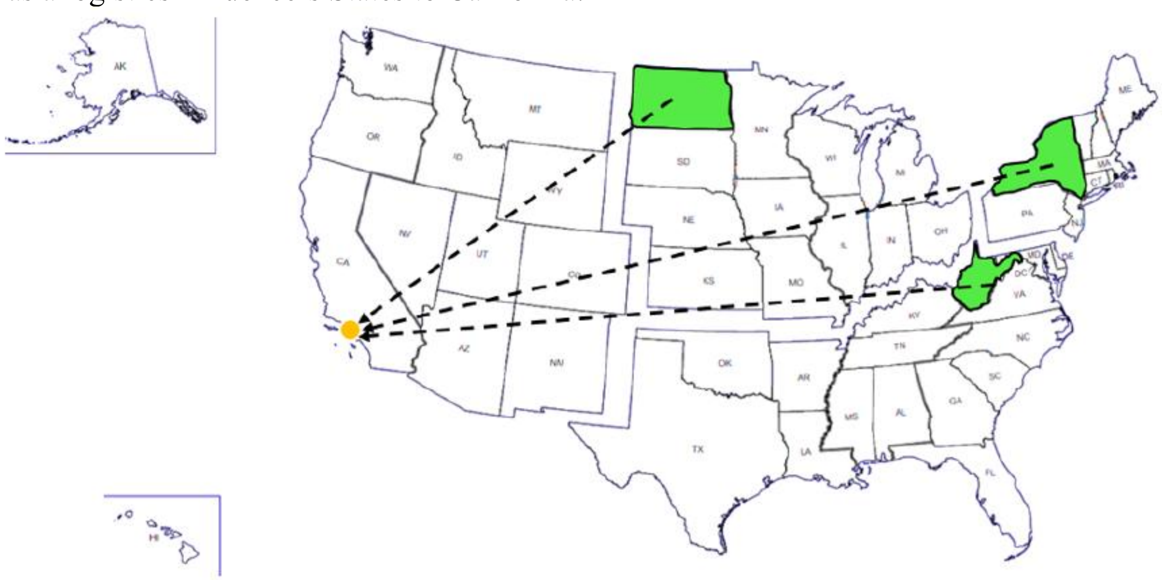

Fig. 3. Logistics influencers States to California

With the results obtained, it is indispensable to strengthen the resilience of the logistics infrastructure in all American regions. By doing so, the key states detected for the resilience of California will contribute to the logistical strengthening of that region in the face of bottlenecks in supply chains. Current public policies must consider the strengths and weaknesses detected in the spatial economic plane, such as those detected in this research, to face integrally the crisis of supply chains such as those currently facing California.

5 Conclusions & future research

This research provides a methodological contribution for optimising the directed transmission spillover from one region to a specified target region through the application of two Cobb–Douglas models, which represent economic and spatial dependence alongside regional technical efficiency and interstate commercial flow behaviours. We employ a Spatial Data Panel model (spatial error/Durbin), a Stochastic Frontier model, and graph theory via the Ford–Fulkerson algorithm. The results indicate that California's logistics public policy should integrate Wyoming and New Mexico as critical regional pivots, with New York, West Virginia and North Dakota serving as external support states. Additionally, it recommends intervention in American states with low technical resource efficiency—California and Nevada in the West; Minnesota and Michigan in the Midwest; Delaware and Virginia in the South; and Vermont and Pennsylvania in the Northeast—and the implementation of new policy strategies to leverage the most efficient states in each region: Wyoming and New Mexico in the West; Nebraska and Ohio in the Midwest; Tennessee and West Virginia in the South; and New York and New Hampshire in the Northeast. Moreover, we find that states with high technical efficiency are not always those with the strongest economic performance: California, for instance, leads economically in its region while ranking among the least efficient in resource use. We also observe that the proportion of transport workers is most pronounced in the Midwest, while the West and South suffer economically due to their road infrastructure. Regarding indirect spillover effects, the Midwest exerts the most significant negative influence on ACVDT, yet also the greatest positive influence in terms of transport-worker percentage. Regional road conditions exhibit no significant indirect effects between regions.

This research's approach combines spatial analysis and graph-theory techniques to develop a comprehensive methodology for enhancing logistics resilience and addressing California's supply-chain bottleneck. Future research lines include conducting sensitivity analyses by commodity type within the United States to assess spatial influences and technical efficiency in the proposed framework and provide strategic spatial solutions per commodity category, as well as applying the methodology at municipal and county levels.

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Appendix 1

Unit roots test for time series

Panel	Variables	Levin-Lin-Chu	P-value
West Region	lnY	-5.0428	0
	lnK	-10.4849	0
	lnH	-6.5323	0
	lnM	-2.9508	0.0016
	lnV	-5.2817 **	0
	lnP	-6.8429 **	0
	lnS	-6.8471	0
	lnR	-5.6402	0
Midwest Region	lnY	-3.9999	0
	lnK	-12.8783	0
	lnH	-7.9331	0
	lnM	-2.7175	0.0033
	lnV	-2.7175	0.0033
	lnP	-3.3326	0.0004
South Region	lnY	-7.0759	0
	lnK	-13.9787	0
	lnH	-10.4449	0
	lnM	-5.7874	0
	lnV	-6.0399**	0
	lnP	-4.4155	0
	lnS	-7.3731	0
Northeast Region	lnY	-3.2993	0.0005
	lnK	-4.3799	0
	lnH	-4.8067	0
	lnM	-4.5974	0
	lnV	-4.3946**	0
	lnP	-3.1989	0.0007
	lnS	-4.4808	0
	lnR	-4.4062	0

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

Results of Cointegration Test for Data Panel

Kao test*	Unadjusted Modified Dickey-Fuller t		Unadjusted Dickey-Fuller t	
Panels	Statistic	P-value	Statistic	P-value
West Region	-3.8787	0.0001	-3.5048	0.0002
Midwest Region	-2.8692	0.0021	-2.117	0.0171
South Region	-1.9487	0.0257	-0.9915	0.1607
Northeast Region	1.0444	0.1481	0.3169	0.3756

Pedroni	Modified Phillips-Perron t		Phillips-Perron t		Augmented Dickey-Fuller t	
Panels	Statistic	P-value	Statistic	P-value	Statistic	P-value
West Region	3.7427	0.0001	-2.4553	0.007	-3.9076	0
Midwest Region	4.0414	0	3.8731	0.0001	4.0102	0
South Region	4.748	0	-1.0132	0.1555	-1.4605	0.0721
Northeast Region	3.254	0.0001	2.7453	0.0006	1.4085	0.0795

Westerlund	Statistic	P-value
West Region	1.809	0.0352
Midwest Region	2.9585	0.0015
South Region	3.3421	0.0004
Northeast Region	0.4432	0.3288