UNIVERSITAT DE BARCELONA

Essays on industrial clusters: Smart Specialization Strategy and regional resilience

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Para mis padres
Conchita y Gerardo
De su xocoyota

Acknowledgements

First and foremost, I am extremely grateful to my primary supervisor, Dr. Rosina Moreno Serrano. There aren't enough words to express my gratitude for her advice, support, and patience. During the last few years, she has taught me how to carry out proper research work. Apart from being a great mentor and an excellent researcher, I admire Rosina as a person. It always amazes me how well she manages her time between research and her beautiful family. I hope that one day I will be able to acquire such superpowers. I am also indebted to Dr. Elisenda Paluzie I Hernàndez, my co-supervisor. I admire her not only as an economist but also as a great leader. A special mention goes to Dr. Fernando de Bulhões for being my mentor on this journey. I am immensely thankful for his help during my most challenging moments, always pointing me in the right direction. Hopefully, I will be able to rely on his wise insight for the next challenges to come in my life. In addition to my supervisors, I'd like to thank Dr. Elisabet Viladecans-Marsal, Ph.D., the Economics Director, for her dedication to improving the program and encouraging us to participate in research events. I couldn't forget to thank Jordi Roca Solanelles for his active support in all administrative issues. Without your efficient guidance, this department wouldn't exist.

The best part of this Ph.D. journey has been the time spent with my friends. I would like to thank all the guys from the "Ph.D. extracurricular group" for their support and friendship, which helped make my studies and life in Barcelona so memorable. I would especially like to thank my "comadris", Jessica Pesantez-Narvaez, for being so supportive during the COVID confinement. Your friendship helped me get through this tough time. We make the best friends during the most difficult times. I would also like to thank my friends from the dormitories, "Las Betanias" and "Niels," who have always been there to support me, listen to my complaints about the thesis, and spend some chill time with me.

In this acknowledgement, I would like to include the professors and friends who helped me during my research visits to Copenhagen Business School (CBS). First and foremost, I'd like to thank Dr. Mercedes Delgado for hosting me at the Department of Strategy and Innovation. Her advice assisted me in improving my research work. The academic discussions with Mona Reber, Anja Rösner, Sara Blasco, and Paul Hünermund were also useful, and apart from their academic support, their friendship made my days at CBS so much more enjoyable. ¡Don Julio team forever!

This Ph.D. journey would have been impossible without the support of two Mexican institutions: the National Council of Science (CONACYT) and UPAEP University. Thank you for believing in my ability to achieve this goal. Four professors from UPAEP University deserve a special mention. I am eternally grateful to Dr. Herberto Rodríguez Regordosa for encouraging me to pursue a Ph.D. I'd also like to thank Dr. Alfonso Mendoza Velázquez and Dr. Pablo Nuño de la Parra for introducing me to the study of clusters. Indeed, it was you who sparked my interest in researching clusters. Last but not least, I wanted to express my gratitude to Dr. Herminio Sánchez de la Barquera for all his support in the final stages of this journey.

Finalmente, pero no menos importante, quiero agradecer a mi familia. En primer lugar a mis padres, Conchita y Gerardo, por darme tanto amor y apoyo para estudiar este doctorado. A mis hermanas, Marisela y Gisela, gracias por apoyarme a la distancia y siempre cuidarme. No puedo olvidar mencionar a mis sobrinitas por contagiarme de su alegría.

Contents

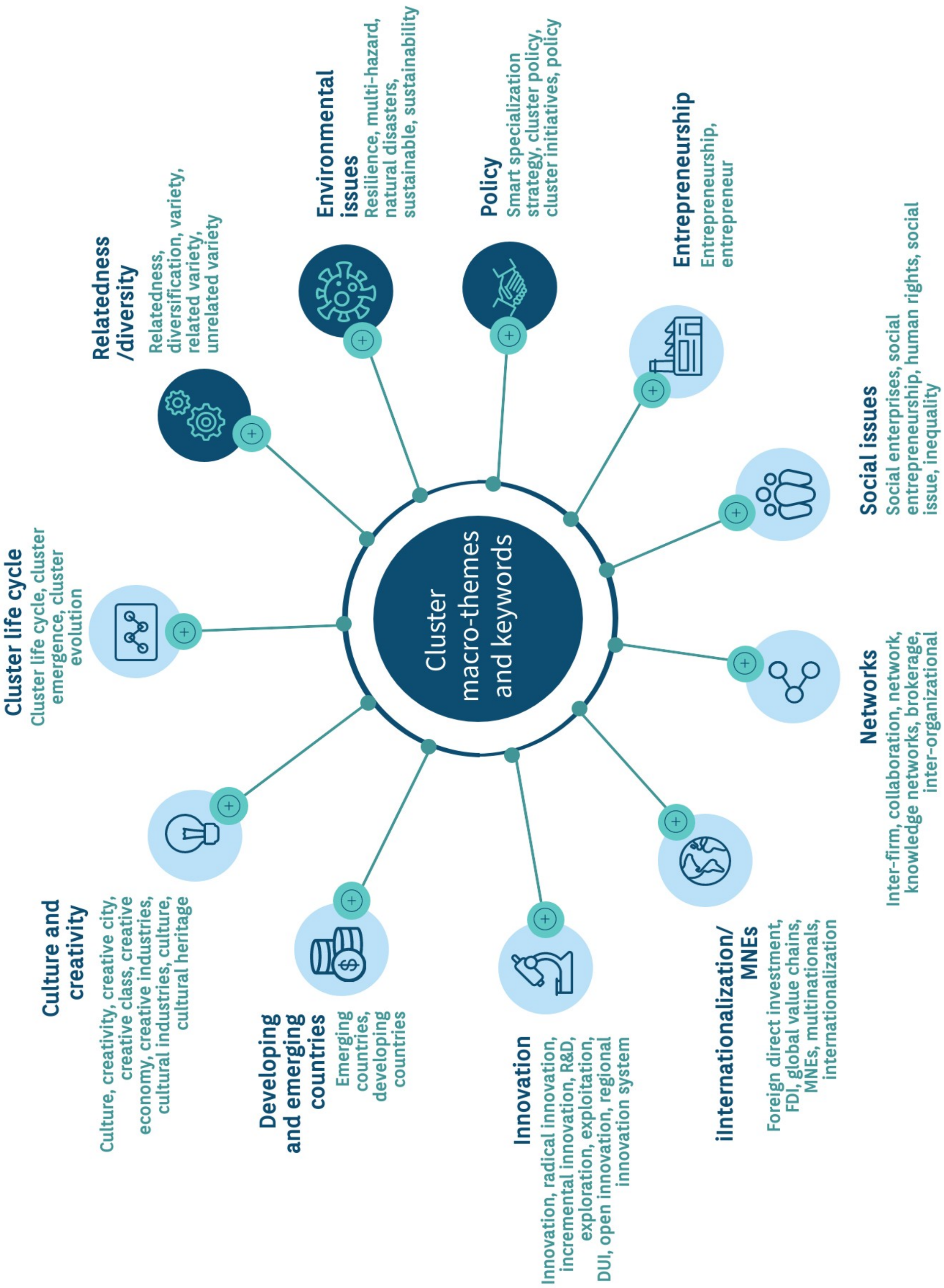
List of Figures

List of Tables

1 Introduction

After reading the title of this thesis, the first question that comes to mind is, *why write a Ph.D. thesis on the topic of clusters?* Clusters started to gain popularity around twenty years ago, mainly thanks to the contributions of Professor Porter (2003), who defined clusters as geographically proximate groups of interconnected companies, suppliers, service providers, and associated institutions in a particular field, linked by external factors of various types. The most well-known example is the Silicon Valley Cluster in California. The reason to devote this thesis to the study of clusters rests on the significant impact it has on the economy, which we can summarize in four main points (Harvard Business School, 2020): from a policy viewpoint, clusters are a powerful tool for policy action and economic development; for companies, clusters provide attractive opportunities for business investments, exports, and supply change assessments; from the territorial performance, clusters drive regional economic performance, from job growth to higher wages and innovation; and from the point of view of the profile, clusters are the building blocks of modern economies, as they profile the economy of a certain location. Besides, more recent literature has demonstrated that the presence of clusters can also influence economic prosperity (Ketels and Protsiv, 2020).

Figure 1.1: Cluster macro themes and keywords



SOURCE: *Own elaboration with information from Lazzeretti et al. (2019)*

Despite the vast amount of literature on clusters accumulated in the last two decades, there are still some unanswered questions and new ones being raised, making it necessary to place more attention on this topic. In this line, Lazzeretti et al. (2019) organized the new cluster research agenda in eleven macro themes: policy, environmental issues, relatedness/diversity, entrepreneurship, social issues, networks, internationalization/MNEs, innovation, developing and emerging countries, culture and creativity, and a cluster's life cycle. As we can observe in figure 1.1, each one of these macro themes represents a list of keywords. For instance, the macro themes for social issues include keywords such as social enterprise, social entrepreneurship, human rights, and inequality. This thesis aims to contribute to three of these eleven macro themes: policy, environmental issues, and relatedness/diversity. In the following paragraph, we briefly explain briefly the hypothesis presented in each chapter and how it relates to these cluster macro themes. Additionally, this section provides arguments for the countries selected as a case study in each chapter and briefly describes the cluster's classification methodology that was followed in this thesis.

The second chapter of this thesis, *The Impact of Smart Specialization Strategies (S3) on Sub-Cluster Efficiency: Simulation exercise for the case of Mexico*, aims to evaluate the cluster efficiency increase when they are complemented with the elements of the S3 policy. As we can observe in figure 1.1, S3 is one of the keywords in the cluster policy macro theme. S3 is an innovation policy implemented by the European Commission since 2013. This policy was born out of the necessity to close the productivity gap between the United States and Europe, which was clearly evident since 1995 (Ortega-Argilés, 2012). According to Foray et al. (2009), this strategy intends to reveal the most promising areas for innovation in a given region. In the most developed economies, the implementation of S3 should promote investment in creating activities with a strong component in science. Meanwhile, less developed economies should orient their R&D to areas where they already have some competitive advantage. Therefore, the regions should specialize in such identified activities to increase their efficiency, leading to higher productivity.

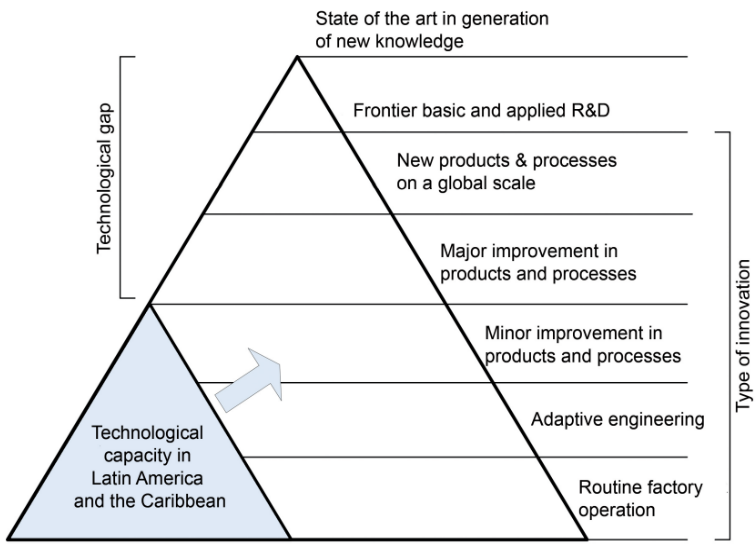
The S3 policy has two essential points in common with a cluster policy: 1) they both focus on productivity and innovation as key drivers of competitiveness; and 2) both argue that there are advantages to the proximity between industries (Pronestì, 2019). These common essential points make the researchers question the convenience to complement both policies in some regions (Aranguren and Wilson, 2013; Scutaru, 2015a; Bečić and Švarc, 2015) or for specific clusters (Todeva, 2015; Pronestì, 2019). The European Commission also questions the complementarity between these policies in the document "The role of clusters in Smart Specialization strategies (2013)," where it pointed out that the full potential of the clusters will be reached if it is integrated with S3 strategies. Despite the effort to figure out this issue, literature still presents a gap to evaluate the complementarity of both policies. Therefore, this chapter has three main assumptions to test: 1) to analyze the general effect of applying S3 across all sub-clusters; 2) to determine whether the effect of S3 varies according to the technological intensity of the sub-cluster; and 3) to determine which S3 element is more suitable for sub-clusters at different levels of technological intensity.

To test our assumptions, we selected a country from Latin America because these countries are in the process of adopting this policy. It is crucial to carry out research that contributes to the implementation of the S3 on them. Even though this policy was created for European countries, it has been an inspiration to promote innovation in other parts of the world, and "Latin America is undeniably one of the most dynamic places for Smart Specialisation outside Europe (Demblans et al., 2020)". The S3 argument is more relevant for intermediate regions than leading knowledge regions because of their growth potential and spatial structure between urban and rural areas (McCann and Ortega-Argilés, 2015).

The technological gap in Latin countries makes it urgent to implement a program like S3 to increase competitiveness. As we can observe in the figure 1.2, the technological capabilities in Latin American firms are focused on basic innovation, such as shop floor rutinary operations, adaptive engineering, and minor improvements in product and processes; leaving behind high technological capabilities like "major" improvements in products and processes, and develop new products and processes on a world scale. For this reason, in the past years, the European Commission has guided six Latin American countries in the process to adopt the S3 program: Mexico, Brazil, Colombia, Argentina, Chile and Peru.

Several projects and pilot initiatives have been tested to adapt S3 in these

Figure 1.2: Innovation type and technological gap in Latin American firms



SOURCE: *Barroeta et al. (2017)*

six Latin American countries. Table 1.1 summarizes such efforts in the adoption of this policy (Barroeta et al., 2017). We can observe that these pilot activities have counted on the participation of the federal government, the development of new governmental agencies, and the bilateral cooperation with some European countries. However, even though the S3 has gained traction in several Latin American countries, there is still a number of challenges in the S3 adaptation to the socio-economic and territorial contexts of these countries (Demblans et al., 2020). Therefore, our study contributes not only to the literature related to the joint implementation of clusters and S3 policy, but also to the adoption of the S3 policy in a Latin American country.

Among the six countries that have had pilot activities implemented to introduce the S3 policies, three have taken clusters as their base to implement this policy: Brazil, Colombia, and Mexico (Barroeta et al., 2017). We selected the Mexico case for two reasons. First, unlike the other two countries, Mexico benefits from the strong support of national policies and funding (Demblans et al., 2020, p. 7). Second, the Mexican industries are already classified into clusters following Delgado et al. (2016) methodology, which facilitates our analysis. This cluster database was built by UPAEP University in collaboration with Harvard Business School's Institute of Strategy and Competitiveness.

Table 1.1: Pilot activities introducing Smart Specialisation in Latin America and uptake at nation-wide level

Country	**Pilot activity**	**Empowerment and uptake at nation-wide level**
Chile	RED Project, 2011-2013	National programmes Transforma framework
Mexico	EU-Mexico cooperation on regional and urban policy, 2014	Federal and State framework for the implementation of Regional Innovation Agendas
Peru	Study of regional innovation systems in the regions of Cusco and Puno, 2013	Smart Specialisation as a working line in the constitution of 5 new Regional Development Agencies
Brazil	Study for a vision of the Smart Specialisation Strategy in the State of Pernambuco, 2017	Steps towards the adaptation of Smart Specialisation in Brazil and the creation of a dedicated Platform steered by the Brazilian Ministry of Science, Technology and Innovation.
	Sector Dialogues project: The customisation of the Smart Specialisation concept in Brazil, 2018.	
	INNOV-AL on regional bilateral cooperation between Pernambuco, Pará and Paraná with EU regions, 2018-2019.	
	INNOV-AL II on regional bilateral cooperation between Ceará and Santa Catarina with EU regions, 2019-2020.	
	Global Environment Facility-6 “Promoting Sustainable Cities in Brazil through Integrated Urban Planning and Innovative Technologies Investment”, supporting Smart Specialisation customisation and operationalisation in Brazil, 2018-2022.	

SOURCE: *Demblans et al. (2020)*

Continuation: Pilot activities introducing Smart Specialisation in Latin America and uptake at nation-wide level

Country	Pilot activity	Empowerment and uptake at nation-wide level
Colombia	Pilot call for projects on Smart Specialisation in the ICT sector in 7 Colombian regions, 2015	Articulation of the Smart Specialisation concept with a national policy of clusters.
Argentina	EU-Argentina Regional Policy Cooperation on Multi-Level Governance Systems, 2016	National Innovation Strategy identifying 12 priority axes as a response to innovation challenges

SOURCE: *Demblans et al. (2020)*

To evaluate our assumptions, we implemented the Data Envelopment Analysis (DEA) methodology, a nonparametric approach to measure the relative, rather than absolute efficiency of decision-making units (DMUs), where the DMUs are the sub-clusters. One of the main advantages of this methodology is that it allows the handling of multiple inputs and outputs. Furthermore, this methodology has been applied in some studies to compare the efficiency of manufacturing industries (Zhao et al., 2016; Chen and Jia, 2017). To check the robustness of any DEA to outliers, we estimate our results with super-efficient models that look for extreme points with a level of efficiency that can be unrealistic for the rest of the sub-clusters. Since we work with a sub-cluster classification at the national level, all the results are sectorial oriented instead of geographically-based.

The third chapter, *Regional Resilience and Cluster Strength: the case of the U.S. in the Great Recession*, evaluates the clusters' role on regional resilience. We evaluate whether the strength presence of clusters in the region is one determinant of regional resilience. Previous literature show us that industries that belong to strong clusters register a higher employment growth (Delgado et al., 2014) and higher resilience to economic shocks (Delgado and Porter, 2021). We expect that this effect can be translated into the regional level. In other words, we assume that the clusters' strength presence makes the regions more resilient.

As we can observe in figure 1.1, the keyword "resilience" is related to the "environmental issues" cluster macro theme. Resilience is a term implemented in many fields of study such as psychology, engineering, ecology, etc. In this case, we approach this term from the evolutionary perspective, which considers resilience the ability to adapt in the short run or to develop new growth patterns in the long run (Martin, 2012; Boschma, 2015). The interest in studying economic resilience increased after the Great Recession when regions showed an heterogeneous recovery. Some regions presented a rapid recovery meanwhile others lagged behind (Groot et al., 2011; Capello et al., 2015). Besides, the COVID-19 crisis makes the study of this topic even more relevant. In the last two years, regions have struggled to adapt their economies to the circumstance imposed by the pandemic.

The strength presence of clusters in the regions can significantly contribute to resilience for five main reasons. First, cluster strength is conceptually similar to a related variety (Delgado et al., 2016) since cluster strength reflects specialization in various related industries. Second, the cluster definition that we follow considers the traded industries which have a multiplier effect on the employment for nontradable sectors (Moretti, 2010). Third, Delgado et al. (2010) show evidence of the relationship between clusters and entrepreneurship, which is one of the crucial detrminance of resilience. Fourth, the cluster strength increases the productivity and competitiveness, which is another essential element in resilience (Martin and Sunley, 2015). Fifth, Boschma (2015) points out that resilience is related to industrial structures, networks, and institutions, which are elements that characterize clusters.

As in the second chapter, we follow Delgado et al. (2016) cluster's classification, but this time for the U.S. industries. If we aim to test the impact of clusters' presence on regional resilience, we must analyze a place with a strong cluster policy background. Since Mexico is still in an early stage of reinforcing its clusters, it is not an appropriate case to evaluate this hypothesis. On the other hand, the U.S. government has considered the cluster policy as one of the political agenda priorities. One of the most relevant initiatives was the launch of the cluster mapping project by the U.S. Economic Development Administration in 2014 to officially register all clusters in the country in different levels of analysis (county, state, and metropolitan). This national initiative allows unification of all efforts to develop clusters by business people, policymakers, and academics. In fact, the cluster classification that we follow in this thesis (Delgado et al., 2016) is part of this project. The third chapter provides more details about this national initiative and describes some graphics from the Cluster Mapping project in the U.S.

The Great Recession is the economic shock under study to evaluate our hypothesis. We compute three variables to proxy for different characteristics related to the strength of the cluster presence in various states of the U.S.: the overall clusters' strength in the region, the strength of the cluster portfolio in the region, and whether the cluster portfolio is biased toward clusters that tend to pay higher wages. With this variable, we run a regression analysis controlling for different fixed effects.

Once the third chapter demonstrates the significant impact of strong cluster presence on a state's resilience, the fourth chapter, *Cluster Composition and Regional Resilience*, goes deeper and evaluates the role of cluster composition on resilience. What we mean by composition is the cluster specialization and diversity in the state. We define cluster specialization as the strength of related industries inside a cluster, which resembles the related variety concept. Related variety refers to the necessary degree of cognitive complementarity between sectors for knowledge spillovers to take place Frenken et al. (2007). According to Delgado et al. (2016), "regional cluster strength is conceptually similar to the notion of 'related variety'". In both cases, we are talking about groups of different industries that are strongly linked and facilitate the creation of new processes and new products. The fact that the cluster specialization measure is similar to related variety has great implications on this study because recent literature has shown the significant impact of related variety on regional resilience (Cainelli et al., 2019a).

On the other hand, we refer to cluster diversity as the presence of many similar clusters in size, implying that not only a few of them dominate the region. A higher cluster diversity in the region suggests a lack of cognitive proximity that makes it costly for industries to collaborate in creating revolutionary technologies. This idea resembles the trouble for the innovation process among industries characterized by unrelated variety.

As mentioned above, cluster specialization and diversity resemble the related and unrelated variety concepts in the innovation process. Therefore, we formulate our hypotheses following the literature of related and unrelated varieties on resilience. We test the following six hypotheses: 1) Cluster specialization (related variety) is positively related to resilience in regions that show a high level of innovation; 2) Cluster specialization (related variety) is negatively related to resilience in regions that show a low level of innovation; 3) Cluster diversity (unrelated variety) is positively related to resilience in regions that show a low level of innovation; 4) Cluster diversity (unrelated variety) is negatively related to resilience in regions that show a high level of innovation; 5) Cluster specialization is related to resilience during the resistance stage, 6) Cluster diversity is related to resilience along the recoverability stage. The formulation of these hypotheses is described in detail in chapter four.

Given that this is an extension of the previous chapter, we also implement data from the states of the U.S. in the Great Recession. Cluster diversity is proxy with a Herfindahl index to indicate the extent to which employment is dispersed throughout clusters. Meanwhile, cluster specialization is measured with a location quotient index to proxy in which clusters the region is specialized. Considering these variables, we carry on a regression with panel data for 2006 – 2015, controlling for unobserved regional characteristics.

Finally, the fifth and last chapter summarizes the main findings in this thesis, discussing the policy implications, and provides some further research proposals. The information in this chapter is relevant to remind us of the main arguments presented in this thesis and reiterates the most important evidence supporting them.

As we can see from the brief description of each chapter, this thesis does not aim to develop a new methodology to group industries into clusters. Instead, this thesis pursues to test some hypotheses related to three macro themes in the cluster literature. Therefore, it is necessary to select a cluster classification that we can follow for our analysis. We can find two big groups of methodologies to identify industrial clusters: the region-specific cluster definitions, based on observed ties among industries or firms in a single region; and the comparable cluster definitions, based on inter-industry links inferred from multi-region analysis (Delgado et al., 2016).

Given the nature of this study, we need to select a methodology that belongs to the second group to compare clusters across regions. Three well-known representatives of these kinds of cluster classifications are: "knowledge clusters" that focus on a selected set of manufacturing industries with high technological intensity (Koo, 2005); "Input and output (IO) links" which define clusters according to the input-output link among the industries

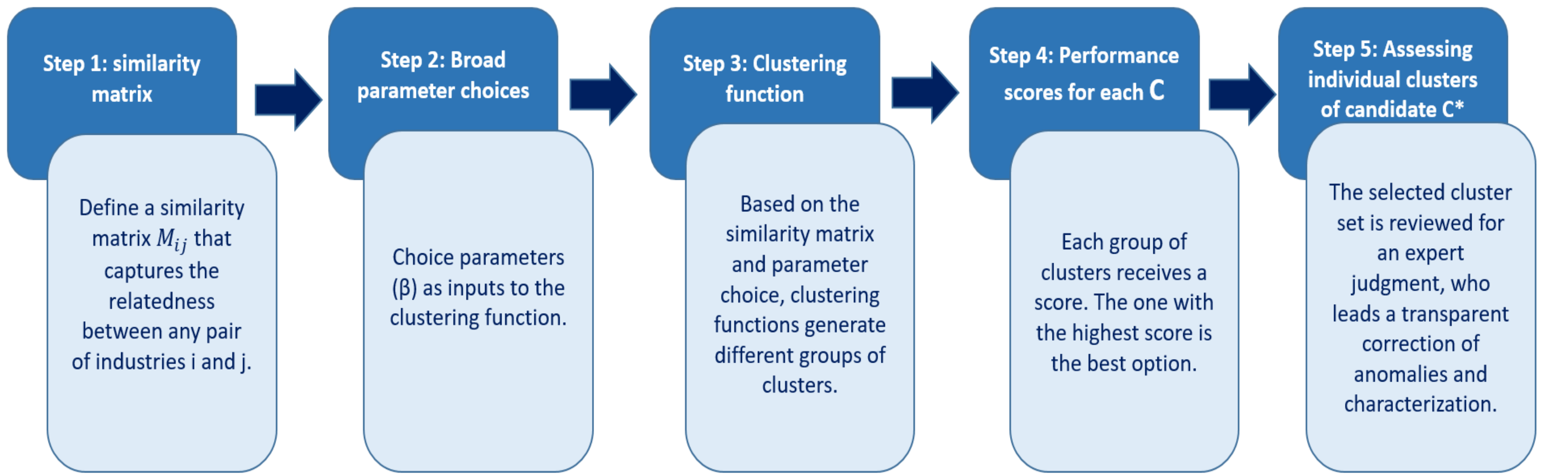
(Feser and Bergman, 2000; Feser, 2005); and "co-location" that captures the relatedness between a pair of industries based on the correlation or industry employment across states. In any of these options, by definition, clusters have a fixed set of industries to make them comparable across the regions. For the analysis of each chapter in this thesis, we follow the cluster classification by Delgado et al. (2016), who elaborated an algorithm that combines different methodologies of the comparable cluster definitions. Since our analysis is based on this cluster classification, it is necessary to explain the intuition behind its methodology.

Figure 1.3 summarizes the five steps that Delgado et al. (2016) follows to organize related industries into clusters. This methodology involves several key choices that compose a cluster algorithm. The first step consists on defining the degree to which each pair of industries are related. Three similarity matrix M_{ij} provide the relatedness between any pair of industries i and j (see figure 1.4): 1) the co-location patterns across many regions is represented with measures of locational correlation (Porter, 2003) and the co-agglomeration index (Ellison and Glaeser, 1997); 2) the National-level interindustry links are represented by measures of national input and output tables (Feser and Bergman, 2000; Feser, 2005; Ellison et al., 2010) and labor occupation connections (Glaeser and Kerr, 2009); 3) multidimensional matrices, that are the combination of the two previous ones.

Once the similarity matrices are defined, the second step (see figure 1.3) is to determine the starting values for the clustering function. The authors set the initial number of clusters between 30 and 60 since other references fix the number of clusters around this range. In the third step, the clustering function creates sets of clusters based on the similarity matrices and the selected parameters. Therefore, in the fourth step, the clustering functions assig a score to each group of clusters based on how strong the relatedness is among industries. The group of clusters with the highest score is the best cluster classification. This process is finalized with the expert validation of the selected group of clusters. A limitation in the data could occur that can create spurious industry relatedness location in the cluster that isn´t a best fit. This expert validation is completely transparent and it is available as an appendix in Delgado et al. (2016).

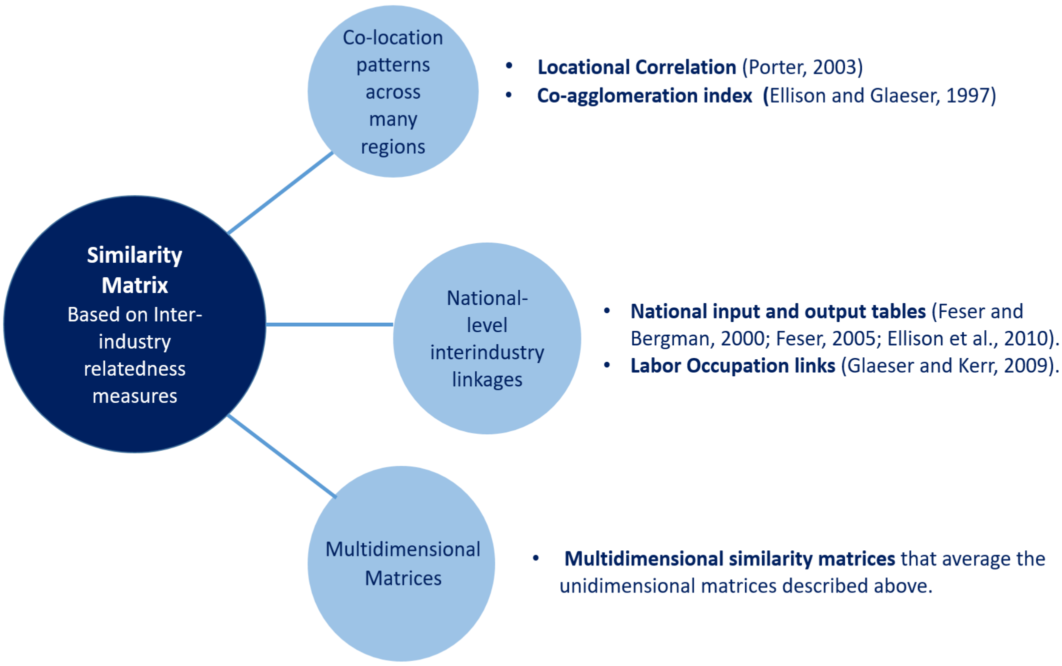
Another important fact about this methodology is that we just work with traded industries. Referring to Porter (2003), all the industries are distinguished between local and traded. The first ones are geographically dispersed and serve primarily the local markets. Meanwhile, traded industries are geographically concentrated and produce goods and services that are sold across regions and countries. For more indepth details on this cluster algorithm, see Delgado et al. (2016).

Figure 1.3: Clustering algorithm steps



SOURCE: *own elaboration with information from Delgado et al. (2016)*

Figure 1.4: Similarity matrix definition



SOURCE: *own elaboration with information from Delgado et al. (2016)*

2 The impact of Smart Specialization Strategies on Sub-Cluster Efficiency: Simulation exercise for the case of Mexico [§]

Introduction

In the past two decades, the cluster concept has become popular, but it represents the evolution of ideas that originated at the end of the 19th century (Vorley, 2008; Aranguren and Wilson, 2013). Cluster theory is rooted in Marshall (1890, 1919) work on "industrial districts" in the books *Principles of Economics and Industry and Trade*. Marshall defined an industrial district as an area with a high concentration of firms specializing in a main industry and auxiliary industries. Marshall observed that the co-location of firms in an industrial district has more advantages than aggregating activities within a single large firm. Although Marshall's work does not specifically refer to clusters, the empirical work established the fundamental ideas on which it is based.

Since Marshall's time, cluster theory has gone through several stages in its evolution (Vorley, 2008). The most recent conceptualization was presented by Porter in the middle and late 1990s. He popularized the concept of cluster theory through his textbook, *The Competitive Advantages of Nations* (Porter, 1990), and two articles that became the primary references in this academic field (Porter, 1998, 2000). Unlike Marshall, Porter did not just analyze the macroeconomic effects of localized industrial organizations, but

[§] The paper in this chapter is coauthored with Rosina Moreno Serrano also the microeconomic strategies of firms. The concept of cluster theory continued to evolve and new approaches were introduced. One of the new questions that have arisen is related to the recent innovation policy called "smart specialization strategies" (S3). The objective of this new policy is to build competitive advantages in research domains and sectors where regions have strengths.

S3 is related to cluster policy because both have essential points in common: they both focus on productivity and innovation as key drivers of competitiveness; both argue that there are advantages to proximity between industries (Pronestì, 2019). On the other hand, their differences can make them complementary to each other. "The full potential of clusters and cluster policies will be reached if: the Smart Specialization Strategies integrate cluster policies into a broader transformation agenda for the entire regional economy, and complement cluster policies with other cross-cutting and technology/knowledge domain specific activities (European Commission, 2013, p. 4)". Some authors talk about the possible complementarity between these two innovation policies (Aranguren and Wilson, 2013; Pronestì, 2019).

For this reason, our hypothesis is that the integration of S3 elements into clusters will increase their efficiency significantly. To assess the increment in efficiency through adopting this policy, we evaluate our hypothesis in a country that still does not implement the S3. The Mexican economy is a suitable case since this country is in the process of adopting this policy and already has its industries classified into Porter's clusters definition. This cluster classification has already been implemented in another study (Mendoza-Velázquez et al., 2018). Although the S3 has not been implemented in the Mexican economy, some variables could be used to represent the S3 elements to estimate their impact on clusters. The analysis of these variables could be used to support the design and implementation of the S3 strategy in Mexico. Furthermore, the answer to this research question will fill a gap in the literature that analyzes the joint application of clusters and S3 policy. The papers in this concern focus on specific clusters, like Benner (2017) with the tourism cluster and S3 policy analysis, or Todeva (2015), who analyze the health technology and S3 policy. Other studies consider all the clusters in the region for their analysis, like Aranguren and Wilson (2013) and Scutaru (2015a). Nevertheless, at the moment, the literature does not offer an analysis of the S3 elements by technological intensity.

The case of Mexico is interesting because of its stage of development. McCann and Ortega-Argilés (2015) pointed out that, in leading knowledge regions, the S3 argument will be less relevant as almost all sectors and technological fields will be present. On the other hand, S3 should be very well suited to intermediate regions because of their growth potential and the concentration of possibilities offered by their spatial structure (urban and rural areas). The Global Competitiveness Report (Schwab, 2018) classified countries into three categories according to their stage of development: 1) Factor-driven: natural resources and unskilled labor drive the economy; 2) Efficiency-driven: countries develop more efficient production processes; and 3) Innovation-driven: industry employs the most sophisticated production, and innovation processes. Mexico is classified as being in the second stage, so it offers an interesting opportunity to investigate whether the efficiency of clusters can be improved by applying S3 strategies in a country that is not a leader in the development of new technologies, and how S3 should be adapted to the technological level of such countries.

Given this background, the aims of this study were: to analyze the general effect of applying S3 across all sub-clusters; to determine whether the effect of S3 varies according to the technological intensity of the sub-cluster; and to determine which S3 is more suitable for sub-clusters at different levels of technological intensity. To achieve these goals, the paper is structured as follows. The next section summarizes the most important research on the joint application of S3 and clusters. Section 3 describes the method we used, the reasons for choosing this method, and the rationale for our estimation strategy. Section 4 presents the composition of the clusters and the variables that represent S3 strategies. In section 5, we discuss our findings on the above. Finally, section 6 presents the conclusions.

Literature Review

The European Commission implemented S3 as a tool for regional development in 2013. However, the development of Research and Innovation Strategies for Smart Specialization (RIS3) was initiated some years before. In 2009, Foray et al. (2009) stated that this strategy aims to reveal the most promising areas of innovation in a given region. In the most developed economies, the implementation of RIS3 should promote investment in creating new intensive activities with a strong science component. Meanwhile, less developed economies should direct their R&D to areas where they already have some advantage. In recent years, RIS3 literature has grown, allowing us to analyze and understand different approaches to this policy. Lopes et al. (2019) carried out a bibliometric analysis of these works, identifying four broad groups: Smart Specialization, innovation, and specialization; regional policies; regional development; and business discovery.

The first group of papers focuses on Smart Specialization, innovation, and specialization. Studies in this group deal with the identification of S3 areas, like Gulc (2015), who compare the methodological approaches to identify smart specialization at the regional level with the methods implemented for the identification of smart specialization areas in Polish regions. Their analysis reveals that the qualitative method is the most popular, but it is barely complemented by the quantitative ones. Gonzalez et al. (2017) propose the identification of industrial complexes based on the principles of related variety and S3 for the Mexican industries. Their analysis allows locating distinct complexes in particular portions of the country. The identification of these industrial complexes will benefit from more assertive policies that consider the regional differences in infrastructure and workforce. Radosevic and Stancova (2018) pointed out that, the identification of S3 areas should be considered as the internationalization component because s3 required not only endogenous knowledge and technology accumulation building but also coupling with international knowledge and production networks.

In the second group, regional policy, papers address some important issues in the design of an S3 policy. Some of them emphasize the role of stakeholders, like Lopes et al. (2018), who study the case of the S3 policy in Portuguese regions. Their findings show the relevance of considering stakeholder perceptions for the success of the S3 policy. McCann and Ortega-Argilés (2015) argue that the design of S3 should be shaped by the institutional and governance context, as well as the regional economic specifics. There is not a single S3 plan that should be transplanted to every region. Kroll (2015) evaluates the S3 policy in the Southern and Eastern European regions. He concludes that one of the main S3 policy challenges is government capacity, which is at least as important as techno-economic potential. Other studies emphasize that S3 policies should consider the special characteristics of less developed regions. For instance, Capello and Lenzi (2016) criticized the lack of reference to the regional context in evaluating the technological development and innovation funds spent. Barzotto et al. (2019) study how S3 should be adapted to lagging regions since they lack the technological capabilities and networks to benefit fully from S3. They point out that extra-regional collaboration is an opportunity to overcome this problem. Lagging regions that carry out extra-regional collaboration raise innovation. However, such collaboration should be in cooperation with advanced regionsCarayannis and Grigoroudis (2016) describe the six major steps that every nation or region should follow to establish S3. One special contribution of this last paper is to consider society as a critical factor in innovation processes.

The third group of papers explores the relationship between S3 and development. For instance, Healy (2016) analyzes the implementation of S3 in one of the less developed regions in Europe, North-East Romania. Even when Romania launched a national RIS3, this region developed its RIS3 policy. The main finding from this paper is that S3 will support the development of lagging regions if the regions count on supporting institutional structures. Another relevant work in this group is the one by Krammer (2017). Based on their analysis of the case of Bulgaria, he affirms that for a successful implementation of the S3 policy in less developing countries, particular characteristics such as low entrepreneurship rates and limited technological opportunities should be considered.

The fourth group of RIS3 papers is Business Discovery. As the title indicates, this group of papers study the application of S3 in relation to business. For instance, Gheorghiu et al. (2016) detect the lack of foresight based toolkit for smart specialization and entrepreneurial discovery. Their work provides some useful advice in this respect, based on their experience with the Romanian strategy-building process. Another representative work in this group is presented by Mieszkowski and Kardas (2015). They evaluate some initiatives that facilitate the entrepreneurial discovery process for Smart Specialization, such as foresight programs, strategic research and development programs, and sectoral research programs.

The brief literature on S3 contains just a few papers on the integration of S3 and the cluster concept. The first reference is a document produced by a group of experts in clusters and published by the European Commission

(2013), which identifies the commonalities and differences between them in order to determine the potential contribution of clusters to the design and implementation of S3. This report makes clear, however, that a deeper analysis is required: "since both are policy approaches with a place-based dimension that aim at economic growth and competitiveness, the question of the differences, similarities, and contributions of one approach to the other is highly relevant (European Commission, 2013, p. 7)." Another publication by the European Commission, *The Smart Guide to Cluster Policy* 2016, asseverates S3 is the transition toward modern cluster policy. The systemic and strategic vision needed for modern cluster policies can be provided by the concept of Smart Specialization.

Through the study of cases, we can find in the literature some papers supporting the idea of integrating S3. Aranguren and Wilson (2013) presented the case of the Basque Country, which has two decades of experience in the design of cluster policies. Aranguren and Wilson carried out a qualitative analysis to identify the differences and similarities between their mapping cluster and the S3 characteristics mentioned in Foray et al. (2012) document. As a result, they identified the specific points of S3 that contribute to their cluster classification: forms of cooperation among firms and a range of other agents that are developing related or complementary economic activities; processes of prioritization and selection that combine top-down and bottom-up forces; and building from existing place-based assets and capabilities. Scutaru (2015b) presented a case study of Romania in which clusters were evaluated to determine which had the most potential for the development of an S3 plan. The main criterion was the availability of sufficient specialized human capital to support innovation. Bečić and Švarc (2015) analyzed Croatia's clusters and concluded that S3 is better suited to developed countries than developing ones due to the technological backwardness and lack of resources for R&D and advanced technologies. Finally, Todeva (2015) also analyzed the integration of these clusters and S3 policies based on a study of the specific cluster of health technology in the Greater South East of England. This author focuses on a specific characteristic of S3: the combining of the efforts of public administration agencies, business leaders and university establishments. The interaction between these organizations is referred in the literature as the *Triple Helix*. Then, the location of the best health technology cluster for S3 is the most prominent in terms of Triple Helix.

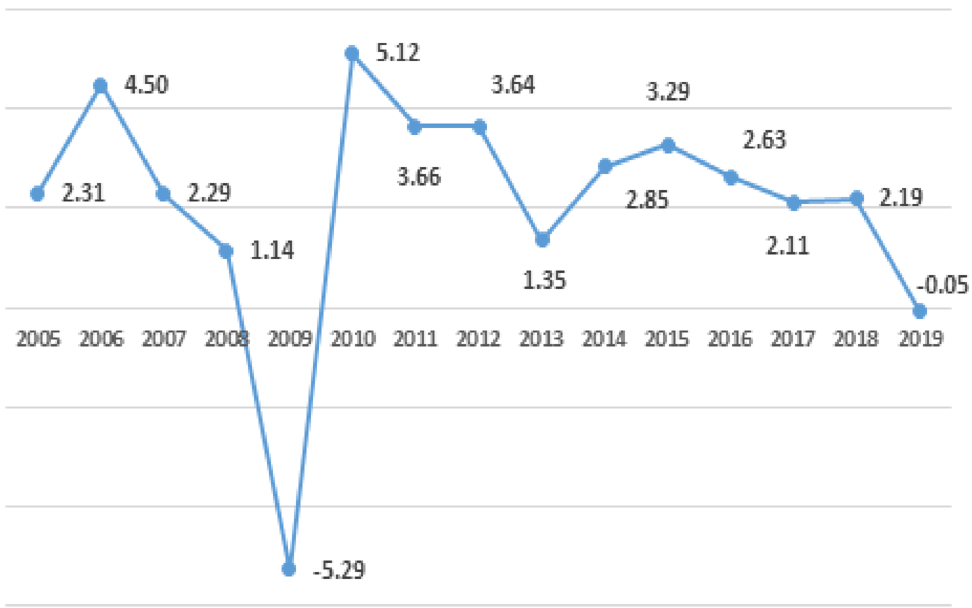
The book, entitled, *The Life Cycle of Clusters in Designing Smart Specialization Policies* (Pronestì, 2019), explores a new perspective on the role of clusters in catalyzing the effective design and implementation of S3. It explains how the different phases of the cluster life cycle (CLC) can help to identify a region's potential to specialize in new domains. Different phases of the CLC have different roles in S3 policymaking. This research showed that a cluster in the stage of emergence, development, and transformation offers the best conditions for the entrepreneurial discovery process necessary for S3. To sum up, Pronestì (2019) shows that clusters are useful in the implementation of S3 depending on its life cycle stage.

Despite the valuable contribution of these authors to our understanding of the relationship between clusters and S3, the academic debates about the effective integration of these policies continue. There is a great need for research on this topic. It is fundamental to get estimates that demonstrate the relationships between the two approaches. We aimed to go one step further and investigate whether S3 affects clusters' efficiency, and if so, whether the influence varies according to the technological intensity of the cluster.

Empirical Method

We consider the Mexican economy to test our hypotheses because this country has already classified its industries in Porter's cluster definition. Furthermore, this country is in the process of developing an S3 policy. So, the findings from this work will be crucial for the design of such a policy. Figure 2.1 shows the annual GDP growth in Mexico. We can observe that this economy was in a growth period for the year that this analysis takes place, 2013. In the period 2014 to 2018, annual growth hovering around the range of 2 and 4%. After 2018, the economy shows a decreasing tendency that should be more pronounced in 2020 for the COVID19-crisis. Figure 2.2 compares Mexico with other countries for the Global Innovation Index (GII). This index provides detailed metrics about the innovation performance of 131 countries around the world. From this graphic, it is clear that the Mexican economy is not a leader in developing breakthrough innovations. As we specified in the introduction, this country specializes in creating a more efficient production process.

Figure 2.1: GDP growth (annual %)
Constant 2010 US$



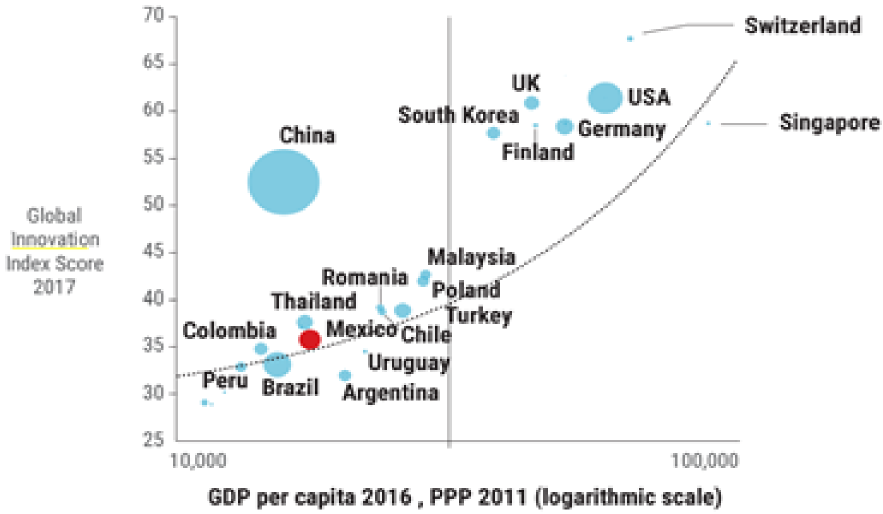
SOURCE: *Own elaboration with data from World Bank Group (2021)*

Methodology

To obtain a measure of efficiency it is necessary to compare actual performance with optimal performance, but as it is not possible to know what constitutes optimal performance it is approximated by the "best practice frontier." There are two methods to estimate efficiency: the econometric approach and mathematical programming techniques. The econometric approach is stochastic; it can be implemented using maximum likelihood estimation or corrected OLS (COLS) (Rogers and Rogers, 1998). On the other hand, the programming approach is nonparametric. Data envelopment analysis (DEA)is the representing methodology in this category.

All the methods have advantages and disadvantages. The choice depends on the research objective and characteristics of the data. One of the main advantages of DEA is that it can handle multiple inputs and outputs (denominated in different units) in a non complex way (Diaz-Balteiro et al., 2006). Furthermore, Costa et al. (2015) showed that DEA estimate of efficiency scores (non-parametric) are more accurate than OLS estimates

Figure 2.2: Global innovation index



SOURCE: *World Bank Group (2019)*

(parametric). They evaluated the operational efficiency of power distribution companies in Brazil through these methods. After a statistical comparison of the results in both cases, they concluded that the COLS Cobb-Douglas model has major deficiencies as a method of estimating efficiency scores.

Many studies have applied DEA to compare the efficiencies of manufacturing industries. For instance, Zhao et al. (2016) and Chen and Jia (2017) evaluated the efficiency of industries with respect to environmental issues. They included two kinds of variables: those representing the production function and those related to the environment and pollution. Both models include the fundamental inputs to a production function (labor and capital). The output is represented by the value of production or the gross domestic product. DEA has also been used to evaluate innovation in firms and industries (Si and Qiao, 2017; Suh and Kim, 2012; Zhang et al., 2019). In these cases, patents represent the desirable output variable. These examples are relevant to our study because S3 are, in essence, innovation actions directed at specific objectives.

S3 is one of the new topics on the cluster research agenda, (Lazzeretti et al., 2019). Therefore, there is a great area for contributions but a shortage of references that support the analysis. As far as we know, this is the first study that aims to estimate the change in all clusters' efficiency for the integration of S3 strategies. However, even though this is the first time tackling this estimation, a group of studies supports the approach that we follow. This group of studies implements DEA to evaluate the increment of industrial efficiency given by incorporating innovation inputs. They can support our decision to follow DEA because S3 is basically a group of innovation strategies. As these studies indicate, DEA is a very convenient methodology in this kind of analysis because the innovation variables can be correlated, and this methodology is not affected by them. Table 2.1 summarizes the innovation inputs and outputs from some of these studies. As we will notice later, some of these variables are the same or equivalent to the ones in this study. For instance, the outputs variables of patents and value added, and the inputs variables of employment, capital, R&D expenditure, R&D internal expenditure, and projects for innovation.

We used DEA, which is a non-parametric technique, to measure the relative rather than absolute efficiencies of decision-making units (DMUs). DMUs can be firms, industries or countries. It does not require any functional form. Although DMUs on the efficient frontier have a 100% efficiency score they could improve their productivity further (Huguenin, 2012). Linear programming methods are used to compute the efficient frontier from inputs and outputs. There are two main DEA approaches: the Charnes et al. (1978) approach (CCR) assumes constant returns to scale (CRS) in order to estimate a global efficiency score, which is appropriate when all firms operate at the optimal scale; the Banker et al. (1984) approach (BCC) uses variable returns to scale (VRS) to estimate a pure technical efficiency score. Both approaches can be implemented in output-oriented models or input-oriented models. The former maximize the output for a fixed input, whereas the latter minimize inputs whilst holding output constant (Banker et al., 1984). The choice depends on the variables (inputs or outputs) over which the decision-maker has most control or on the objectives of the analysis (Yang, 2006).

To demonstrate the rationale underlying DEA analysis, Figure 2.3 shows a simple example of efficiency score estimation with just one input and one output (Huguenin, 2012). The input is represented by axis "x," and the output is represented by axis "y". Each point in the figure 2.3 represents one DMU with a different combination of input and output. The line 0B represents the efficient frontier for the CCR model under CRS. Meanwhile, the line

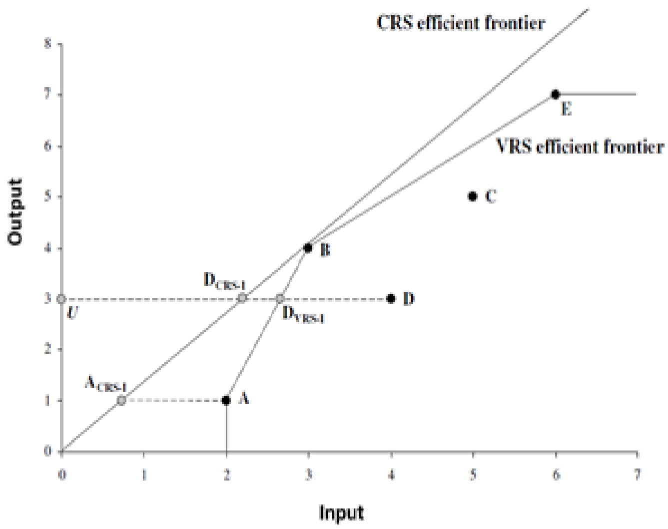
Table 2.1: Studies that implement DEA for the analysis of industrial efficiency by innovation

Authors	**Inputs**	**Outputs**
Ge and Yang (2017)	(i) R&D institutions; (ii) R&D personnel; (iii) new product R&D expenses	(iv) new product sales revenue; (v) number of patent application
Han et al. (2017)	(i) R&D expenditure; (ii) R&D personnel; (iii) accumulated patents stock	(iv) patent applications; (v) value-added; (vi) sale revenue
Jang et al. (2016)	(i) R&D expenditures; (ii) R&D personnel; (iii) number of papers published	(iv) number of patents granted; (v) net sales
Li et al. (2017)	(i) employment; (ii) fixed assets' capital stock; (iii) R&D cost;	(iv) gross output value (v) exports
Guan and Chen (2010)	(i) R&D internal expenditure; (ii) R&D personnel; (iii) patents stock	(iv) applied patents; (v) taxes and profits; (vi) value-added; (vii) export value; (viii) sale revenue
Jianfeng (2015)	(i) R&D internal expenditure; (ii) R&D personnel; (iii) expenditure on new products development; (iv) the projects for new products	(v) patents in force; (vi) gross industrial output value of new products
Chen et al. (2018)	(i) R&D personnel; (ii) R&D internal expenditure; (iii) expenditure on new product development; (iv) expenditure for technical renovation; (v) employed personnel; (vi) fixed assets	(vii) patent applications; (viii) new product development

SOURCE: *Wang et al. (2020)*

ABE is the efficient frontier for the BCC model assuming VRS. A DMU is considered efficient if it lies on the efficient frontier. In the case of the CCR model, point B is globally efficient both in terms of management (as signalled by the VRS efficient frontier) and scale (as signalled by the CRS efficient frontier). On the other hand, ABEs are efficient DMUs for the BCC model. The rest of the DMUs (C and D) are inefficient in both cases.

Figure 2.3: DEA model with one input and one output variable



SOURCE: *Data envelopment analysis Huguenin (2012)*

The gap between the CCR (CRS) and the BCC (VRS) frontiers is due to a problem of scale. For instance, A needs to modify its scale (size) to become CRS-efficient. D not only has a problem of scale; it is also poorly managed. First D has to move to the point DVRS-1 to eliminate the inefficiency due to poor management. These two movements represent the components of efficiency: technical (due to management efficiency) and allocative (due to scale efficiency) (Diewert et al., 1999). Then, D has to move to point DCRS-I to eliminate the inefficiency due to a problem of scale. Observe that, even when D reduces its level of inputs, it still gets the same level of output. The objective of a DEA is to minimize the number of inputs required to maintain a fixed level of output.

The previous example is the simplest way to understand how DEA works.

However, in a model with multiple inputs and outputs, the solution to this problem is formulated like a linear programming problem. Equations 2.1 to 2.4 represent the input-oriented model for the CCR model (Huguenin, 2012), where s is the number of outputs; m is the number of inputs; n is the number of units to be evaluated (DMUs); x_{ik} represents the amount of input i consumed by the unit that is evaluated, unit k; x_{ij} represents the input quantities i ($i = 1, 2, \ldots, m$) consumed by the *j*th unit (notice that this element is next to a summation operator); y_{ik} is the quantity of output i produced by the unit k; y_{ij} represents the observed quantities of output r ($r = 1, 2, \ldots, s$) produced for the *j*th unit (this element also goes with a summation operator); θ_k is the relative technical efficiency score of the *k*th unit; λ_j expresses the weight that each DMU has within the comparison group; ϵ is a non-negative infinitesimal number for keeping coefficients of input and output variables positive; s_r^- and s_r^+ are non-negative slack variables for input and output constraints.

More details are needed to understand the meaning of the weights and slacks. This last one is the amount of deviation from the efficient frontier. The terms $\sum_{j=1}^{n} \lambda_j x_{ij}$ and $\sum_{j=1}^{n} \lambda_j x_{rj}$ are called input virtual and output virtual respectively. These values express information about the importance that a unit attributes to specific inputs and outputs in order to obtain its maximum efficiency score. It is possible to determine the importance (contribution) of each input to the total as well as the contribution of each output to the efficiency score. On the other hand, the slack variables represent potential improvements. They relate to the further increases in output (s_r^+) or reductions in input (s_r^-) that would be needed to reach the efficiency frontier. In other words, the slack variables can be interpreted as the output shortfall and input overconsumption relative to the efficient frontier. A unit is considered technically efficient if and only if $\theta^* = 1$ and all the slacks are null ($s_r^- = 0$, $s_r^+ = 0$). This means the unit is efficient in relation to the others since it is not possible to find another unit that obtains the same or greater output of that unit using fewer factors. In all other cases a unit is classified as inefficient.

$$Minimize \theta_k - \epsilon \sum_{r=1}^{s} s_r^+ - \epsilon \sum_{i=1}^{m} s_i^- \tag{2.1}$$

subject to

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_{rk}^{+} = 0, r = 1, ..., s \tag{2.2}$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} + s_i k^{-} = 0, i = 1, ..., m \tag{2.3}$$

$$\lambda_j, s_r^{+}, s_i^{-} \geq 0 \, \forall \, j = 1, ..., n; r = 1, ..., s; i = 1, ..., m \tag{2.4}$$

The CCR model implies the existence of constant returns to scale. It means that all units are compared and their differences in operational scale are not taken into consideration. It can, however, be used to obtain a model with variable returns to scale. Equations 2.5 to 2.9 present the BCC input-oriented model (Huguenin, 2012). Compared with the CCR model, it has an extra constraint $\sum_{j=1}^{n} \lambda_j = 1$, which is a convexity constraint (Figure 2.3 makes clear the need for this condition). It tells the model that each unit has to be compared with those of the same size rather than with all the units present in the problem. The solution of this system gives, as a result, the pure technical efficiency score of the *k*th unit (ϕ_k). Compared with using technical efficiency (θ_k), l it is possible to get a higher number of efficient units using the BCC model, because units are compared only with those of the same size.

$$Minimize \phi_k - \epsilon \sum_{r=1}^{s} s_r^{+} - \epsilon \sum_{i=1}^{m} s_i^{-} \tag{2.5}$$

subject to

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_{rk}^{+} = 0, r = 1, ..., s \tag{2.6}$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} + s_{ik}^{-} = 0, i = 1, ..., m \tag{2.7}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2.8}$$

$$\lambda_j, s_r^{+}, s_i^{-} \geq 0 \, \forall \, j = 1, ..., n; r = 1, ..., s; i = 1, ..., m \tag{2.9}$$

The results of this minimization problem can be classified into two groups: DMUs with an efficiency score equal to 1 (100%) that are located at the frontier and inefficient DMUs whose score is less than one (less than 100%) that are located below the efficient frontier. The magnitude of the inefficiency depends on how far the DMU observation is from the efficient frontier (Charnes et al., 1994). It is necessary to check the robustness of any DEA to outliers. To do this we used a computational approach to detect outliers. It is based on the concept of leverage. Leverage for a single DMU is a measure of the impact that removing one of the DMUs has on the efficiency scores of all the other DMUs (Zhu et al., 2001). A super-efficient model looks for extreme points with a level of efficiency that can be unrealistic for the rest of the DMUs. The leverage of the *j*th DMU is defined as a standard deviation (Martínez-Núñez and Pérez-Aguiar, 2014), see equation 2.10. First, the DEA model is estimated from the complete database to obtain the efficient DMUs $\theta_k | k = 1, 2, \ldots, K$. Then, DMUs are removed from the data in turn to generate the new set of efficient DMUs $\{\theta_k^* | k = 1, 2, \ldots, K;\ k \neq j\}$.

$$l_j = \sqrt{\frac{\sum_{k=1 k \neq j}^{K} (\theta_{kj}^* - \theta_k)^2}{k-1}} \tag{2.10}$$

This estimation allows us to get efficiency scores higher than one. For this reason, it is called a "super-efficient model". As a rule of thumb, DMUs that get efficiency scores greater than two are excluded from the estimations (Avkiran, 2007).

Data

Data source and clusters

The data source for this study was the National Institute of Statistics and Geography (INEGI) in Mexico.We took data from the 2014 Economic Census, which included an exclusive survey of “Science, Technology, and Innovation” for that specific edition. We consider this source because, at the moment, it is the only one that provides this kind of data at the six-digit industry NAICS code, which is the necessary desegregated level to classify industries into clusters. Even when it is not recent data, this study is relevant to the current situation in Mexico for two reasons. First, the national innovation system in Mexico does not demonstrate a significant change in recent years as the number of patent applications show. In 2013 the number of patent applications by Mexicans that reside in this country was 7.4%, meanwhile, this number slightly changed to 7.6% in 2019 (see figure 2.4 in the Appendix section). Second, since Mexico is designing its S3 policy, the results from this analysis are relevant to provide some guidance in this objective.

The variables were obtained at the national industry level at the most disaggregated level, six digits in the North American Industry Classification System (NAICS). However, to answer the research questions in this paper, we need to classify the industrial observations into clusters. As mentioned in the Introduction we follow the cluster definition suggested by Delgado et al. (2016). This methodology takes all traded industries at the six-digit NAICS code and classified them into clusters. Traded industries are the ones whose localization depends on issues of competitiveness. Delgado et al. (2016) algorithm generates clusters based on occupation links, input-output links, and inter-industry measures of co-location patterns of employment and the number of establishments. For instance, the automotive cluster is composed 26 industries such as motor vehicle body manufacturing, light truck and utility manufacturing, gasoline engine, etc. Their work provides a full list of industries that belong to each cluster.

As Mexican industries are classified with the NAICS code, Porter’s cluster definition can be applied for this country. In fact, Mendoza-Velázquez et al. (2018) follow this definition for their analysis of Mexican clusters. Similarly, we group the industrial data obtained from the Economic Census according to the list from Porter's work, which generates 51 clusters and 182 sub-clusters. The models reported in this paper were estimated at the sub-cluster level to maximize the number of observations, so the DMU was the sub-cluster. The total number of firms was 657, 973 classified in 551 industries, 182 sub-clusters, and 51 clusters. The average number of firms in each sub-cluster was 3,654. It is essential to point out that the cluster's classification and the consequent analysis are sectorial oriented instead of geographically based.

Input/Output Selection

We used the Pastor test (Pastor et al., 2002) to determine whether introducing new inputs or outputs to a model contributes significantly to efficiency. Models are estimated twice, first with the variable of interest included (total model), and second, when it has been excluded (reduced model). The variable is considered relevant if more than a certain share (*P*) of DMUs have an associated change in efficiency greater than ρ. Following Pastor et al. (2002), the values selected are $P = 15\%$ and $\rho = 10\%$. The null hypothesis is that excluding the variable will lead to a random improvement in the total model. It is evaluated with a binomial statistical test (Nataraja et al., 2011). The candidate variable is not included in the model if the test statistic leads to the rejection of the null hypothesis. The Pastor test can be used to evaluate the contribution of a single variable or a group of variables and Nataraja et al. (2011) demonstrated that it performs moderately well under both scenarios. Studies that have applied the Pastor test include Lovell and Pastor (1997), Mancebon and Molinero (2000), Matthews (2013) and Martínez-Núñez and Pérez-Aguiar (2014).

Our data set included seven input variables: (1) employees, (2) capital, (3) presence of collaborative innovation initiatives involving universities and research centers, (4) presence of collaborative innovation activities involving companies without productive relationship, (5) presence of innovation activities in partnership with customers or suppliers, (6) presence of innovation activities in collaboration with the government and (7) investment in research and development for innovation. All variables were measured at the sub-cluster level. Table 2.2 presents the summary statistics for all of them [1]. There are various rules for determining the minimum number

[1]Some sub-clusters register zero values for some variables because they do not have

of observations required for a DEA model. In this case, the number of observations (185) was much higher than the minimum number suggested by all of them.[2]. All S3 input variables were introduced with a one-year lag because the outcome of innovation activities is not immediately observed.[3] Table 2.2 shows that some of the variables had a widely scattered distribution (large standard deviation). This is why it is important to carry out super efficiency estimates to check the robustness of the results in the presence of outliers.

intensive innovation activities. Since DEA does not work with negative or zero values, we substitute the observations of these variables for a very low value (0.01) following (Huguenin, 2012).

[2]The rules of thumb for the minimum number of observations required for a DEA model with 7 inputs and 2 outputs are: a) At least twice the number of inputs and outputs (Golany and Roll, 1989). According to this rule, we would need 18 DMUs; b) Three times as many DMUs as there are input and output variables, (Sinuany-Stern and Friedman, 1998), DMU=27; c) Twice the product of the number of input and output variables (Dyson et al., 2001), DMU=28

[3]Wang et al. (2016) test the time lags effects of innovation input on output in the national innovation systems in China. They demonstrate that it is not just necessary to lag those variables, but also that the distribution of time lags varies according to the characteristics of the innovation input and influencing factors in the internal transformation. The variables included in their study are industry-academy research collaboration, R&D expenditure, and researchers in R&D and are lagged differently. Their variables are quite similar to the ones included in this analysis. Unlike their work, the available database for our study allows only lagging each innovation variable by just one year.

Table 2.2: Summary statistics of outputs and inputs
(Data correspond to the 185 sub-clusters)

Variable	Descriptive Statistics	Unit of measurement	Mean	Minimum	Maximum	Standard Deviation
y1	Value added, 2013	Thousands of dollars	1,759,004.75	456.07	70,159,482.93	5,752,917.77
y2	Subcluster patents[a], 2013	Number of patents	15.73	0	115.00	21.96
x1	Employment, 2013	Persons	50,040.25	127.00	946,966.00	95,047.49
x2	Capital, 2013	Thousands of dollars	2,521,926.37	387.86	133,840,417.38	11,370,636.40
z1	Innovation universities[b], 2012	Number of firms	8.38	0	222.00	18.50
z2	Innovation firms[c], 2012	Number of firms	7.01	0	198.00	16.64
z3	Innovation clients[d], 2012	Number of fimrs	14.08	0	139.00	23.10
z4	Goverment innovation[e], 2012	Projects #	2.62	0	24.00	3.13
z5	Innovation investment[f], 2012	Thousands of dollars	5,850.57	0	116,501.41	13,408.14

NOTE: a. Number of firms in the sub-cluster that register patents. b. Number of firms in the sub-cluster that register innovation activities in collaboration with universities, 2012 c. Number of firms in the sub-cluster that register innovation activities in collaboration with other firms, 2012 d. Number of firms in the sub-cluster that register innovation activities in collaboration with clients, 2012 e. Number of firms in the sub-cluster that register innovation activities in collaboration with the Government, 2012 f. Investment in research and development for innovation, 2012.

The first two inputs were the traditional ones in a production function. The variable "employees" is the number of people working in each sub-cluster. Business Support Services is the sub-cluster with the highest number of employees, at 946,966, which is equivalent to 10.2% of the total labor force in the clusters. Forestry had the fewest employees, with 127. Capital was measured in thousands of dollars. It is interesting to notice that the three sub-clusters with the highest levels of capital are related to the production of energy: Electric Power Generation and Transmission, Oil, and Gas Extraction and Petroleum Processing. Together they account for 49% of the total capital.

The rest of the input variables represent the S3 elements. Table 2.3 summarizes the S3 elements and the way that they are represented in the model. The first element aims to get stakeholders involved in innovation activities and it is captured by three input variables: the number of firms in the cluster that carry out innovation activities in collaboration with 1) universities and research centers (innovation with universities); 2) other companies without a productive relationship (innovation with firms); 3) with customers or suppliers (innovation with clients). These three variables can be highly correlated, but this tends not to affect the average efficiency score in DEA (López et al., 2016). As expected, the sub-cluster Colleges, Universities, and Professional Schools had the greatest number of firms carrying out innovation activities in collaboration with others, 9.8% of the total projects. The Construction sub-cluster was in second place, with 4.5% of firms collaborating with other organization on innovation activities.

According to the European Commission (2013), the range of stakeholders to be involved in the implementation of S3 is potentially very wide. However, it is typically focused on the Triple Helix members (Etzkowitz and Leydesdorff, 1995), which refers to the relationship between universities, private industry, and government. For this reason, we represent the first S3 element with the number of firms in the sub-cluster that register innovation activities in collaboration with universities, research centers, and other firms. The government was not included because, by itself, it represents the following component.

Turning back to Table 2.3, the second key element is the implementation of a policy that supports and invests in national/regional priorities, challenges and needs for knowledge-based development. This element is captured as the number of firms in the cluster that have received government funding for a specific project or for innovation activities (government innovation). The government invested in innovation projects in 484 firms in 2012. The three sub-clusters with the highest number of firms that had received funding were Automotive Parts (24), Bus Transportation (21) and Biopharmaceutical Products (14). We can conclude that these sectors are the government's priority when it comes to innovation. The role of the government in the S3 context is to provide incentives and encourage entrepreneurs and other organizations to be involved in identifying the regions' specializations, supported through a targeted investment agenda (European Commission, 2016). During the period 2000-2012, the Mexican government significantly increased its investment in Science and Technology. The public-private partnership was being encouraged by Strategic Alliances and Innovation Networks for Competitiveness (AERIs) (OECD, 2012). Therefore, this variable represents the public-private partnership envisaged in the S3 strategy.

The third key element of S3 is the stimulation of private sector investment to support technology and innovation. This element is represented in the model by the amount invested in innovation in each sub-cluster (investment in innovation). The sub-clusters with the greatest investment in innovation were automotive parts (10.1%), motor vehicles (8.5%) and biopharmaceutical products (4.4%). Although Mexico has not developed an S3 strategy, this variable helps to approximate the effect of investment on innovation.

The data set includes two outputs: (1) value-added and (3) patents. As mentioned in the methodological section, output can be measured as gross output or value added. However, value-added is mainly used in analyses at the industry or firm level (OECD Manual, 2001). "Value-added is a net measure in the sense that it includes the value of depreciation or consumption of fixed capital (OECD Manual, 2001, p. 24)". Value added was measured in thousands of dollars.

The fourth element in Table 2.3 points to the need for an evidence-based, monitoring and evaluation system for the S3 innovation strategies. We attempted to create a proxy for this element in the form of an additional output, the number of firms in a cluster that have registered patents. In our dataset there were 2,910 firms that had registered patents, which is equivalent to 0.43% of the total. Considering that the Mexican government incentivized public-private partnership for innovation, and given the insignificance of private investment on innovation in the Mexican case (OECD, 2008), the number of patents that are registered by sub-clusters must very likely be the result of the public economic support.

Following the Guide to Research and Innovation Strategies for S3 (European Commission, 2012), there is no single standardized approach for developing an evaluation system for S3, since it needs to be tailored to each specific region. In general, the evaluation should measure a change in the region towards globally competitive activities or with potential for value-added. For more specific objectives, it should be evaluated with different variables in the short and long term. For instance, when the objective for the S3 strategy is an increase in the research activity in a region, which is the case for this study, we can use the number of patents as an intermediate indicator. In the long term, the evaluation should be made based on improving innovation performance and enhancing reputation. Therefore, the information from this guide supports considering the value-added and the number of patents registered as variables for evaluation. The last S3 key element in Table2.3 is building on each country or region's strengths, competitive advantages and potential for excellence. This characteristic is already included in the definition of the clusters. It was mentioned above that Porter's methodology just considers traded industries, whose localization depends on factors relevant to competitiveness (Delgado et al., 2016).

Results

This section is divided into two parts. The first describes the testing of the different sets of models to find the most appropriate ones. The second takes the selected set of models to estimate CCR and BCC models in order to provide evidence relevant to our main objective. As previously stated, given that the cluster classification was made at the national level, all the results presented in this section are sectoral oriented instead of geographically-based.

Sensitivity Analysis

Table 2.4 shows the results of the first set of models [4]. Model 1 is the basic production function with two inputs (labor and capital) and one output

[4] We implement the MATLAB program to obtain the estimations, which count with a special package for this methodology, "Data Envelopment Analysis Toolbox".

Table 2.3: Variables representing the S3 key elements

Key elements of S3	Representative variable	Measure
1. Getting stakeholders fully involved and encouraging innovation and experimentation	Innovation activities in coordination with universities and research centers.	Number of firms in the sub-cluster that register innovation activities in collaboration with universities, 2012
	Innovation activities in collaboration with companies without productive relationship	Number of firms in the sub-cluster that register innovation activities in collaboration with other firms, 2012.
	Innovation activities in partnership with customers or suppliers.	Number of firms in the sub-cluster that register innovation activities in collaboration with clients, 2012
2. Policy support and investments are focused on key national/regional priorities, challenges and needs for knowledge-based development	Innovation activities in collaboration with the Government	Number of firms in the sub-cluster that register innovation activities in collaboration with the Government, 2012
3. There is support for technological as well as practice-based innovation and efforts to stimulate private sector investment	Investment in research and development for innovation	Thousands of dollars of private investment in each sub-cluster, 2012
4. Policies are evidence-based and include provision for sound monitoring and evaluation systems	Industries that register patents	Number of firms in the sub-cluster that register patents.
5. Policies build on each country or region's strengths, competitive advantages and potential for excellence.	This characteristic is already include in the Porter's cluster definition because it consider just traded industries.	Traded industries are classified in 51 clusters and 185 sub-clusters.

SOURCE: *Own elaboration with information from European Commission (2013) and the analysis from this research.*

(value added). This model was extended with the addition of universities (model 2). The Pastor test showed that the extra variable contributed to the explanation of sub-cluster efficiency. Similarly, the input variables, other firms and government, which were added in model 3 and 5 respectively, were also shown to contribute to variance in sub-cluster efficiency (all p-values significant at the 1% level). These variables were therefore retained in the model. On the other hand, the clients variable (model 4) and investment in innovation (model 6) did not contribute to variance in efficiency.

Results for the second set of models are presented in Table 2.5. In this set of models patents were treated as the output variable. Once again the variables universities, other firms, and government contributed to variance in sub-cluster efficiency. Unlike the previous set of models, innovation activities with clients also contributed to sub-cluster efficiency, possibly because output is related to innovation, although investment in innovation did not contribute to efficiency.

Previous tables show that most of the inputs have an impact on both output variables. Table 2.6 considers the two outputs, value-added and patents together. All the inputs contributed to efficiency in this case, except for investment in innovation. This variable was therefore not included in the final model. Consequently, the model selected to test the hypothesis was model 22. The variable investment in innovation does not significantly contribute to our model's efficiency because of Mexico's lack of private investment in innovation. In 2008, the OECD Review of Innovation Policy indicated that the ratio of R&D expenditures to GDP in Mexico was the second-lowest among OECD countries. Furthermore, despite increasing RD investment by industry, the public sector performed the majority of RD. Therefore, it seems that in the sensitivity analysis, the variable government has a significant contribution, whereas this is not the case for the variable innovation investment.

Comparison of data envelopment analysis results

Model 15 was taken as the base case in the comparison of CCR and BCC results. It includes two inputs (employment and capital) and two outputs (value-added and registered patents). Table 2.7 shows the results for the CCR and BCC models. In these models the Mexican sub-clusters had an

Table 2.4: Results of Pastor et al. model selection procedure I

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
y1	Value added	x	x	x	x	x	x	x
y2	Registered patents							
x1	Employment	x	x	x	x	x	x	x
x3	Capital	x	x	x	x	x	x	x
z1	Universities		x					x
z2	Other firms			x				x
z3	Clients				x			x
z4	Government					x		x
z5	Innovation investment						x	x
B			120	128	98	163	102	170
T			64.9%	69.2%	53.0%	88.1%	55.1%	91.9%
p-value			0.000***	0.000***	0.462	0.000***	0.186	0.000***

NOTE: B= Number of sub-clusters whose efficiency changes by at least 10% in the new model. T= Percentage of sub-clusters whose efficiency changes by at least 10% in the new model. * Significant at the 10%; ** Significant at the 5%; *** Significant at the 1%

Table 2.5: Results of Pastor et al. model selection procedure II

		Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
y1	Value added							
y2	Registered patents	x	x	x	x	x	x	x
x1	Employment	x	x	x	x	x	x	x
x3	Capital	x	x	x	x	x	x	x
z1	Universities		x					x
z2	Other firms			x				x
z3	Clients				x			x
z4	Government					x		x
z5	Innovation investment						x	x
B			156	155	165	164	104	174
T			84.3%	83.8%	89.2%	88.6%	56.2%	94.1%
p value			0.000***	0.000***	0.000***	0.000***	0.106	0.000***

NOTE: B= Number of sub-clusters whose efficiency changes by at least 10% in the new model. T= Percentage of sub-clusters whose efficiency changes by at least 10% in the new model. * Significant at the 10%; ** Significant at the 5%; *** Significant at the 1%

Table 2.6: Results of Pastor et al. model selection procedure III

		Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
y1	Value added	x	x	x	x	x	x	x	x
y2	Registered patents	x	x	x	x	x	x	x	x
x1	Employment	x	x	x	x	x	x	x	x
x3	Capital	x	x	x	x	x	x	x	x
z1	Universities		x					x	x
z2	Other firms			x				x	x
z3	Clients				x			x	x
z4	Government					x		x	x
z5	Innovation investment						x	x	
B			134	137	141	151	100	166	163
T			72.4%	74.1%	76.2%	81.6%	54.1%	89.7%	87.6%
p-value			0.000***	0.000***	0.000***	0.000***	0.303	0.000***	0.000***

NOTE: B= Number of sub-clusters whose efficiency changes by at least 10% in the new model. T= Percentage of sub-clusters whose efficiency changes by at least 10% in the new model. * Significant at the 10%; ** Significant at the 5%; *** Significant at the 1%

average efficiency of 24.22% or 35.59%[5], depending on whether the model considered was CRS or VRS. These numbers indicate that sub-clusters could achieve the same output, in terms of value added or patents, whilst making input savings of 75.78% and 64.41% respectively. Seven of the 185 sub-clusters in the sample were deemed efficient by the CCR model (CRS), and 16 by the BCC model (VRS). In other words, seven sub-clusters are globally efficient and 16 are technically efficient. That implies that there are nine sub-clusters that become globally efficient by scaling up their activity. The percentage of sub-clusters deemed efficient was 3.79% and 8.65% in the CCR model and BCC model respectively, indicating very high levels of global and operational or management inefficiency in the sub-clusters.

Table 2.7: Original DEA Efficiency coefficients (model 15)

	CCR	BBC	Scale
# efficient DMUs (Sub-clusters)	7	16	7
% Efficient DMUs (Sub-clusters)	3.79%	8.65%	3.79%
Average Efficiency	24.22	35.59	75.92
Standard deviation	21.14	28.44	23.48
Maximum	100	100	100
Minimum	4.31	4.34	14.79

Table 2.8 presents the CCR results for models 15 to 22. These results are provided for comparison purposes, because CCR represents global efficiency (in management and scale). The CCR approach, using CRS, provides more conservative estimates of efficiency than the BCC approach, which uses VRS (Cantos et al., 2000). In order to get robust results we used the super-efficiency approach to detect and exclude outliers from the data used for the CCR analysis. The first row of Table 2.8 shows the outliers removed in each model. A trend can be seen towards an association between efficiency and the use of S3 in the sub-clusters. It is evident that average efficiency is higher in the extended models than in the base model (15). The highest average

[5] In DEA analysis, the maximum magnitude obtained for efficiency is 1 (100%), which corresponds to the units of analysis that reach the frontier. In other words, the unit that registered the most efficient use of their inputs compared to others. An efficiency lower than 100% implies that the unit is inefficient, being below the frontier.

Table 2.8: DEA results applying Super Efficiency

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed[a]	2	3	3	3	3	4	8	4
# efficient DMUs (Sub-clusters)	7	16	18	17	20	23	57	38
% Efficient DMUs (Sub-clusters)	3.83%	8.79%	9.89%	9.34%	10.99%	12.71%	32.20%	20.99%
Average Efficiency	27.25	45.59	46.05	45.54	46.16	41.82	70.25	59.49
Potential input savings (respect to model 15)		18.34	18.80	18.29	18.91	14.57	43.00	32.24
Average Efficiency score of inefficient DMUs	24.36	40.35	40.13	39.93	39.52	33.36	56.11	48.73
Standard deviation	21.52	26.22	25.90	25.15	27.41	28.78	25.95	27.50
Maximum	100	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	4.62	7.60	7.58	7.80	7.18	8.46	16.66	9.08

NOTE: a. Outliers from the supper-efficiencies.

efficiency score was obtained when all the S3 elements were included; this raised average efficiency from 27.25% to 59.49%. When the production process included collaborative innovation activities with universities, the potential input saving was 18.34%, which corresponds to the average efficiency increment from Model 15 to Model 16. Similar percentages were obtained when production included collaborative innovation activities with other firms (18.80%) and clients (18.29%). The highest input saving was observed with the industries in the sub-clusters carrying out innovation activities in collaboration with the government (18.91%). The smallest input saving was for investment in innovation, but this result was expected since this variable failed the Pastor Test.

Based on the Pastor test, the final model selected was model 22, which included all the proposed variables except for investment in innovation. In this model the potential input saving was 32.24%. In other words, the performance of its inputs improves by this ratio. In this case, the average inefficiencies are reduced by 24.4% (average efficiency increase of model 21 with respect to 15). This means that when all S3 variables are included in the production process, the average inefficiency of sub-clusters is reduced by 24.4%. Furthermore, including S3 variables also increased the number of sub-clusters that reach global efficiency (in management and scale) from 7 to 38. More sub-clusters make optimal use of their inputs.

Results by Technological Intensity

So far, we have not considered how the different technological intensities of sub-clusters could affect the impact of the S3 variables. For that reason, this section presents the results by groups of sub-clusters. First, we separate them according to the classification scheme for technological intensity of manufacturing industries by Eurostat Statistics Explained (2018), which defines four groups of manufacturing industries: high-tech, medium high-tech, medium low-tech and low tech. Services are classified into two groups: knowledge-intensive and less knowledge-intensive. The sub-clusters were assigned to one of these categories based on the kind of industries they contained. For instance, since the pharmaceutical industry is classified as high-tech, the biopharmaceutical products sub-cluster was assigned to that category. Other examples include motor vehicles industries and the motor vehicles sub-cluster in the medium high-tech category; rubber and plastic product industries and Plastic products cluster in the medium low-tech group; textile industries and textile and fabric-finishing sub-cluster in the low-tech category; air transport services and air transportation sub-cluster in the knowledge-intensive services; and business support activities and business support services sub-cluster in the less knowledge-intensive services. To sum up, this process identified 8 high-tech sub-clusters, 34 medium high-tech sub-clusters, 26 medium low-tech sub-clusters, 43 low-tech sub-clusters, 35 knowledge-intensive services sub-clusters and 39 less knowledge-intensive services sub-clusters. For a full list of this classification see Table 2.10 in the Appendix.

We obtained DEA results for all groups by applying the super efficiency approach. The high-tech and medium high-tech were treated as a single group because high-tech contained just eight sub-clusters, and it is not possible to get DEA results with this number of DMUs. Tables 2.11 to 2.15 in the Appendix present the estimations by group. In this section, Table 2.9 summarizes the results just for models 15 and 22. Remember that model 15 includes the essential inputs in a production function (labor and capital) whilst model 22 also includes the variables that represent S3 strategies.

The results in Table 2.9 make it clear that S3 strategies have the highest impact on the efficiency of the medium low-tech group: the percentage of sub-clusters that reach global efficiency (in management and scale) increases from 24% to 65.2%. This group also has the highest average efficiency (91.25%). Furthermore, even the inefficient sub-clusters comprising medium low-tech industries obtained the greatest average efficiency score (74.85%). On the other hand, with respect to input saving, S3 had the most impact on the high-tech and medium high-tech groups, the performance of their inputs improving by a ratio of 32.35%. Nevertheless, despite the high input saving, the average efficiency and the percentage of efficient sub-clusters were still higher in the medium low-tech group. This can be attributed to the fact the industries in Mexico's high-tech sub-clusters are still developing (which is reflected in the fact that this group was represented by just 8 sub-clusters).

Table 2.9: DEA results applying Super Efficiency: Sub-clusters groups by technological intensity

	High-tech and Medium High-tech		Medium low-tech		Low-tech		knowledge-intensive services		Less knowledge-Less intensive services	
	Model 15	Model 22	Model 15	Model 22	Model 15	Model 22	Model 15	Model 22	Model 15	Model 22
# Sub-clusters	42	42	26	26	43	43	35	35	39	39
# outlier removed	1	4	1	3	3	5	1	4	1	5
# efficient DMUs (Sub-clusters)	3	12	6	15	5	14	7	8	8	13
% Efficient DMUs (Sub-clusters)	7.3%	31.6%	24.0%	65.2%	12.5%	36.8%	20.6%	25.8%	21.1%	38.2%
Average Efficiency	47.32	79.67	71.01	91.25	54.80	74.81	53.52	75.48	56.85	76.11
Potential input savings (respect to model 15)		32.35		20.24		20.01		21.96		19.26
Average Efficiency score of inefficient DMUs	43.17	70.29	61.85	74.85	48.34	60.11	41.47	66.95	45.34	61.32
Standard deviation	20.96	21.63	21.80	17.37	28.48	25.74	31.74	25.33	30.89	24.55
Maximum	100	100	100	100	100	100	100.00	100	100	100
Minimum	11.32	25.5	18.64	27.17	17.28	24.54	8.79	16.63	11.85	27.94

Service sub-clusters present similar results to manufacturing; S3 converted a higher percentage of sub-clusters to efficiency in the case of less knowledge-intensive services (38.2%) than the knowledge-intensive service sector (25.8%). It seems that the implementation of S3 offers more advantages in industries and services that have a medium dependence on technology and are less knowledge-intensive.

Tables 2.11 to2.15 (see Appendix section) present other important results, such as the most effective S3 strategy for each kind of sub-cluster group. For the high-tech and medium high-tech group, the highest increment in the percentage of efficient sub-clusters (from 7.32% to 26.83%) was observed when the variable innovation activities in coordination with universities and research centers (model 16) was added to the model. This is because only high-tech firms can absorb the knowledge provided by the universities, which is of a more fundamental nature and needs to be developed into new processes or new products. In the case of the medium low-tech group, investment in research and development for innovation had the highest impact on efficiency (model 20). The percentage of efficient sub-clusters doubled from 24% to 48%. Firms with this level of technology need to adopt and adapt technology to their production process, making it necessary for them to invest in innovation. In the case of the low-tech group the greatest impact came from the inclusion of innovation activities in collaboration with the government (model 19), which increased the percentage of efficient sub-clusters from 12.5% to 28.21%. Investment in innovation is not one of the main priorities for firms in this group, so perhaps government investment enables them to become involved in innovation activities.

Service sub-clusters present similar results to those of the last two manufacturing groups. For knowledge-intensive services, the most critical S3 element was investment in research and development for innovation, which increased the percentage of efficient sub-clusters from 20.59% to 38.71%. As in the manufacturing group, this S3 is crucial because firms have to adapt and adopt knowledge. For less knowledge-intensive services, however, the most influential variable was innovation activities in collaboration with the government, which increased the percentage of efficient sub-clusters from 21.05% to 31.58%. The development of new knowledge does not occur to a meaningful extent in this group, so it is possible that government resources are required to enable it to innovate.

Conclusions

The results above allow us to test the main objective of this work: sub-cluster average efficiency shows a significant increment when we integrate the variables that represent the S3 elements. Furthermore, we observe an increment in the number of sub-clusters that reach global efficiency. The sensitivity analysis confirms the significant contribution of each S3 component to the model efficiency. It is of special interest to observe that the significant variables imply innovation activities in collaboration with other agents like clients, universities, or government. This result makes sense since one of the main mechanisms of innovation is knowledge spillover. The innovation effort in collaboration with other agents should produce better results than the individual efforts.

Our results are in line with the DEA model estimates for the Mexican industries. As we explained above, no study estimates the change in all clusters' efficiency for integrating S3 strategies, so we followed the DEA models that evaluate the increment of industrial efficiency given by innovation inputs. Therefore, we compare our results with the study carried on by Mateo et al. (2014), who estimate efficiency for Mexican manufacturing industries through DEA. Our results for the base model (Model 15) correlate with their results. They also consider the Economic Census as a data source, but their analysis corresponds to the year 2008. The inputs considered are labor and capital, while the output is gross production. The results are presented by groups of technological intensity: low tech, medium low-tech, and high-tech. This study can be considered a point of reference.

According to Mateo et al. (2014) the average efficiency of manufacturing industries in Mexico was 49.78 [6] in 2008. Meanwhile, in our study, the average cluster efficiency is 57.71 [7]. The disparity in these values could be attributed to the differences in specifications in each model as well as the different economic situations in 2008 and 2014. For instance, their research

[6] Mateo et al. (2014) present the efficiency estimations according to the size of the firms (micro, small, medium, and large). The average efficiency mentioned (49.78) considers all of them except for micro firms. We compare our result with this average because we also did not take into account this firm's size.

[7] In order to compare our results with the ones in Mateo et al. (2014), the average of 57.71 considers just the estimations for high-tech and medium high-tech (47.32), medium low-tech (71.01) and low-tech (54.8)

analyzes data before the great recession (2008), and our analysis after the downturn (2014). By technological intensity, the estimations for low-tech manufacturing are very similar in both cases. We obtain an average efficiency of 54.8; meanwhile, this value corresponds to 56.33 in the other study. The medium high-tech group shows the highest difference: 71.01 in our study and 34.67 in the other one. In the case of high tech manufacturing, we estimate the average efficiency at 47.32, compared with 58.33.

Therefore, the significant impact of innovation variables on the base model could be explained by the strategy for science and technology implemented in Mexico. The Mexican government carried out the Special Programme for Science, Technology, and Innovation (PECiTI) in the period 2008–2012. This strategy had an ambitious set of objectives with a greater emphasis on innovation carried out by enterprises and, in particular, small- and medium-sized enterprises (SMEs) (OECD, 2012). Apart from this program, the stage of development in Mexico could explain the higher impact of the innovation variables on the medium high-tech clusters. This stage of development is characterized by some gaps in physical infrastructure, restrictive regulations, and low levels of human capital. Therefore, Mexican firms have a preference for imported technologies over the development of domestic capacity (OECD, 2012). They prefer to adopt and adapt those high-tech technologies that already exist, which gives rise to the fact that the high-tech and not the medium high-tech manufacturers are the ones making the innovation effort.

This research aimed to provide empirical evidence relevant to the discussion about whether S3 can be considered as a new step in the evolution of the cluster concept. We therefore evaluated, through a simulation exercise, the impact of the different strategies envisaged in S3 on the efficiency of 185 sub-clusters in Mexico using DEA. The results confirmed our hypothesis that the integration of S3-type policies increases sub-cluster efficiency. This indicates that policies directed at clusters should be complemented with S3 strategies to enable themto make more efficient use of their inputs.

Although the policies envisaged in S3 had a general positive influence, it should be remembered that the effects varied with the technological intensity of sub-clusters. We found that S3 had the most impact on the medium low-tech group, producing the greatest increment in the percentage of efficient sub-clusters in this group. This result makes sense in the case of Mexico, a country that is not a leader in the development of new technologies. This finding also contributes to the debate on whether S3 implementation should be different in developed and developing countries. Another important observation is that, although S3 had the most impact on the percentage of efficient sub-clusters in the medium low-tech group they produced the greatest input saving in high-tech industries.

This study has provided an in-depth analysis of which specific S3 elements are most effective for industries at each technological intensity. These findings are crucial in the design of an S3 policy in Mexico. They guide the selection of the S3 areas that Mexico should adopt according to the technological intensity of the sub-clusters to develop. The high-tech and medium high-tech subclusters benefit most from innovation activities in collaboration between firms and universities and research centers. This makes sense, since the most revolutionary innovation depends on highly specialized research. For the medium low-tech group, the most effective S3 was internal investment in research and development for innovation. The main reason could be that firms with this level of technology need to adopt and adapt technology to their production process. Meanwhile, for the subcluster groups of low-tech, the key S3 element was innovation activities in collaboration with the government, perhaps because development of new technology is not a priority for this group and is only possible with financial support from the government. The results for service swere similar to those for the last two manufacturing groups. For knowledge-intensive services, the most important strategy was internal investment in research and development for innovation, whereas for the less knowledge-intensive services it was innovation activities in collaboration with the government. Similar reasons to those given above with reference to the manufacturing groups may apply. The main message is that the technological intensity of sub-clusters should be considered in the design and implementation of an S3 initiative.

The results of this paper contribute to the cluster and S3 literature. In the case of cluster, results demonstrate that S3 could be considered one step in the evolution of cluster concept. As Aranguren and Wilson (2013) noted, many countries already use clusters to guide regional development, so they could easily be used to facilitate the design and implementation of S3. In this study, we analyzed clusters using Porter's classification, which is amongst the most widely adopted by policymakers. In the case of S3 literature, the results of this paper contribute to two of the four RIS3 research lines identified in the bibliometric analysis by Lopes et al. (2019). First, this study contributes to the group of studies that analyze the effect of S3 on regional development. The findings demonstrate how the S3 policy must be tailored to the characteristics of Mexican development. Second, this work contributes to the group of papers that study the design of the S3 policy. Results show the appropriate S3 element that should be implemented for each sub-cluster technological intensity.

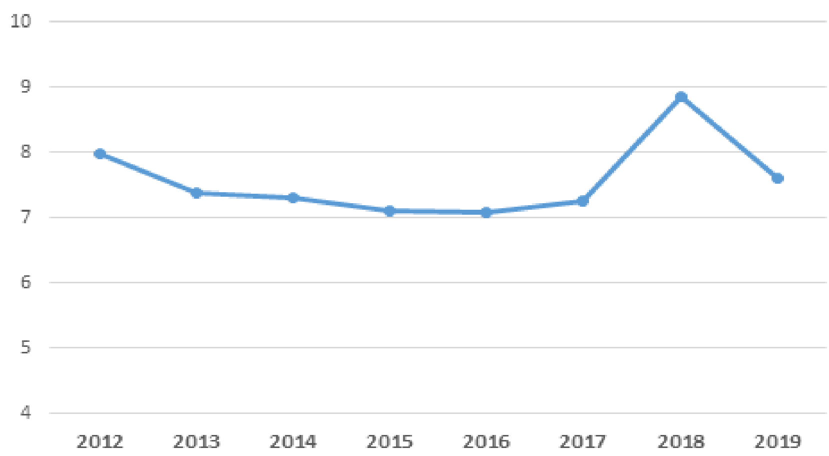
As well as contributing to the academic literature this study has important implications for public policy in Mexico. As Mexico has not implemented any overall strategy for S3, the results could be used to support the design and implementation of such a strategy. We have shown that application of S3 produces a general increase in sub-cluster efficiency, which is one of the main issues on Mexico's political agenda. In recent decades Mexico's growth in productivity has been modest, leading to low and volatile economic growth (Padilla-Pérez and Villarreal, 2017). For the Mexican government, this topic is so important that some actions have already been implemented, for example, a National Commission on Productivity was established in 2013.

The application of S3 in Mexico should focus on the medium low-tech industries. This group includes sub-clusters like metal containers, jewelry, and precious metal products, glass products, and rubber products, among others. It should be remembered that the most effective S3 in this group is investment by firms in research and development for innovation. The design of the S3 policy should include mechanisms to encourage such investment, for example tax rebates for firms that invest in innovation projects. Finally, if Mexico were to adopt an S3-based innovation policy the effects of the variables that represent S3 might become more prominent. We have used some variables from the Economic Census to represent the S3 and shown that they have a positive impact on efficiency.

Even with the practical and theoretical contributions of these findings, its main limitation is the lack of more recent technological data for all industries at the six-digits American Industry Classification System (NAICS), which is the disaggregate level necessary to classify the industries into clusters. The Mexican Economic Census is the only source in the country that provides some technological and innovation data at this disaggregated level in the special survey included in the 2014 Census.

Appendix

Figure 2.4: Percentage of the patent applications by Mexicans that reside in the country



SOURCE: *Own elaboration with data from World Intellectual Property Organization (2021)*

Table 2.10: Technical and scale efficiencies for model 22

Cluster		Subcluster	Technological Intensity	# Industry	# Firms	Model 22			
#	Name					CRSTE	VRSTE	SCALE	RTS
1	Aerospace Vehicles and Defense	Aircraft	High-tech	1	94	0.42	0.50	0.85	irs
2	Agricultural Inputs and Services	Agricultural Services	LKI-services[c]	6	971	0.29	1.00	0.29	irs
2	Agricultural Inputs and Services	Fertilizers	KI-services[d]	1	170	0.46	0.50	0.93	irs
3	Apparel	Accessories and Specialty Apparel	Low-Tech	3	1,192	0.74	1.00	0.74	irs
3	Apparel	Clothing	Low-Tech	7	25,735	1.00	1.00	1.00	crs
4	Automotive	Automotive Parts	Medium High-tech	6	1,051	0.41	0.46	0.88	drs
4	Automotive	Gasoline Engines and Engine Parts	Medium High-tech	1	98	0.28	0.28	1.00	irs
4	Automotive	Motor Vehicles	Medium High-tech	4	963	1.00	1.00	1.00	crs
4	Automotive	Small Vehicles	Medium High-tech	1	35	1.00	1.00	1.00	crs
4	Automotive	Metal Mills and Foundries	Medium High-tech	2	326	0.20	0.50	0.40	irs
5	Biopharmaceuticals	Biopharmaceutical Products	High-tech	2	686	0.80	1.00	0.80	drs
6	Business Services	Corporate Headquarters	KI-services[d]	2	357	1.00	1.00	1.00	crs
6	Business Services	Consulting Services	KI-services[d]	2	4,688	0.59	0.60	0.99	drs
6	Business Services	Business Support Services	LKI-services[c]	11	11,637	1.00	1.00	1.00	crs
6	Business Services	Computer Services	LKI-services[c]	2	3,082	0.46	0.50	0.92	irs
6	Business Services	Employment Placement Services	LKI-services[c]	1	1,774	1.00	1.00	1.00	crs
6	Business Services	Engineering Services	KI-services[d]	1	1,690	0.67	0.67	1.00	drs
6	Business Services	Architectural and Drafting Services	KI-services[d]	3	3,123	0.43	1.00	0.43	irs
6	Business Services	Ground Passenger Transportation	LKI-services[c]	2	296	0.17	1.00	0.17	irs
7	Coal Mining	Coal Mining	Medium Low-tech	1	47	0.27	1.00	0.27	irs
8	Communications Equipment and Services	Communications Services	LKI-services[c]	4	3,733	1.00	1.00	1.00	crs
8	Communications Equipment and Services	Communications Equipment	KI-services[d]	3	104	0.49	0.51	0.95	irs
9	Construction Products and Services	Construction	KI-services[d]	13	4,659	0.31	0.42	0.74	drs
9	Construction Products and Services	Construction Products	KI-services[d]	2	238	0.19	0.50	0.38	irs
9	Construction Products and Services	Construction Components	KI-services[d]	7	10,106	0.47	0.51	0.92	irs
9	Construction Products and Services	Construction Materials	KI-services[d]	1	98	1.00	1.00	1.00	crs

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Continuation: Technical and scale efficiencies for model 22

Cluster		Subcluster	Technological Intensity	# Industry	# Firms	Model 22			
#	Name					CRSTE	VRSTE	SCALE	RTS
10	Distribution and Electronic Commerce	Warehousing and Storage	LKI-services [c]	4	1,055	0.22	1.00	0.22	irs
10	Distribution and Electronic Commerce	Electronic and Catalog Shopping	LKI-services[c]	2	1,062	0.53	1.00	0.53	irs
10	Distribution and Electronic Commerce	Support Services	LKI-services[c]	1	284	0.27	0.50	0.54	irs
10	Distribution and Electronic Commerce	Wholesale of Apparel and Accessories	LKI-services[c]	2	3,029	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Books, Periodicals, and Newspapers	LKI-services[c]	2	444	0.60	1.00	0.60	irs
10	Distribution and Electronic Commerce	Wholesale of Chemical and Allied Products	LKI-services[c]	1	2,668	0.62	1.00	0.62	irs
10	Distribution and Electronic Commerce	Wholesale of Drugs and Druggists' Sundries	LKI-services[c]	2	2,876	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Farm Products and Supplies	LKI-services[c]	4	18,454	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Food Products	LKI-services[c]	7	9,377	0.61	0.62	0.98	drs
10	Distribution and Electronic Commerce	Wholesale of Furniture and Home Furnishing	LKI-services[c]	2	726	0.67	1.00	0.67	irs
10	Distribution and Electronic Commerce	Wholesale of Jewelry, Watches, Precious Stones, and Precious Metals	LKI-services[c]	1	900	0.50	1.00	0.50	irs
10	Distribution and Electronic Commerce	Wholesale of Paper and Paper Products	LKI-services[c]	2	3,721	0.90	0.90	1.00	irs
10	Distribution and Electronic Commerce	Wholesale of Sporting and Recreatiol Goods and Supplies	LKI-services[c]	1	372	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Toy and Hobby Goods and Supplies	LKI-services[c]	1	431	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Other Merchandise	LKI-services[c]	2	4,994	0.62	1.00	0.62	irs
10	Distribution and Electronic Commerce	Wholesale of Farm and Garden Machinery and Equipment	LKI-services[c]	2	2,705	0.60	1.00	0.60	irs
10	Distribution and Electronic Commerce	Wholesale of Construction and Mining Machinery and Equipment	LKI-services[c]	1	659	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Industrial Machinery, Equipment, and Supplies	LKI-services[c]	3	6,397	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Wholesale of Professiol and Commercial Equipment and Supplies	LKI-services[c]	5	6,962	0.90	1.00	0.90	drs
10	Distribution and Electronic Commerce	Wholesale of Electrical and Electronic Goods	LKI-services[c]	2	5,270	0.32	0.50	0.65	irs
10	Distribution and Electronic Commerce	Wholesale of Metals and Minerals (except Petroleum)	LKI-services[c]	1	3,829	1.00	1.00	1.00	crs
10	Distribution and Electronic Commerce	Rental and Leasing	LKI-services[c]	6	5,856	0.81	1.00	0.81	irs
11	Downstream Chemical Products	Persol Care and Cleaning Products	Medium High-tech	2	1,299	0.95	0.95	1.00	irs
11	Downstream Chemical Products	Processed Chemical Products	Medium High-tech	5	1,141	0.63	0.64	0.98	drs
11	Downstream Chemical Products	Dyes, Pigments and Coating	Medium High-tech	2	514	0.86	1.00	0.86	irs
11	Downstream Chemical Products	Explosives	Medium High-tech	1	12	0.69	1.00	0.69	irs
11	Downstream Chemical Products	Lubricating Oils and Greases	Medium High-tech	1	-a	1.00	1.00	1.00	crs

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Continuation: Technical and scale efficiencies for model 22

Cluster		Subcluster	Technological Intensity	# Industry	# Firms	Model 22			
#	Name					CRSTE	VRSTE	SCALE	RTS
12	Downstream Metal Products	Metal Products	Medium Low-tech	6	57,510	0.35	0.35	0.99	drs
12	Downstream Metal Products	Fabricated Metal Structures	Medium Low-tech	1	1,413	0.38	0.38	0.98	irs
12	Downstream Metal Products	Metal Containers	Medium Low-tech	1	116	0.45	1.00	0.45	irs
13	Education and Knowledge Creation	Training Programs	KI-services^{d}	6	7,793	0.73	0.74	0.98	irs
13	Education and Knowledge Creation	Colleges, Universities, and Professiol Schools	KI-services^{d}	2	3,424	0.49	1.00	0.49	drs
13	Education and Knowledge Creation	Educatiol Support Services	LKI-services^{c}	1	166	0.58	1.00	0.58	irs
13	Education and Knowledge Creation	Research Organizations	KI-services^{d}	2	239	0.25	0.50	0.49	irs
13	Education and Knowledge Creation	Professiol Organizations	KI-services^{d}	1	594	0.14	1.00	0.14	irs
14	Electric Power Generation and Transmission	Electric Power Generation and Transmission	KI-services^{d}	1	18	1.00	1.00	1.00	crs
15	Environmental Services	Waste Collection	LKI-services^{c}	1	150	0.36	1.00	0.36	irs
16	Fincial Services	Fincial Investment Activities	KI-services^{d}	4	3,090	1.00	1.00	1.00	crs
16	Fincial Services	Credit Intermediation	KI-services^{d}	7	7,681	b	b	b	
16	Fincial Services	Credit Bureaus	KI-services^{d}	1	32	0.36	1.00	0.36	irs
16	Fincial Services	Securities Brokers, Dealers, and Exchanges	KI-services^{d}	3	137	1.00	1.00	1.00	crs
17	Fishing and Fishing Products	Fishing and Fishing Products	Medium Low-tech	7	19,757	0.61	0.63	0.97	irs
18	Food Processing and Manufacturing	Specialty Foods and Ingredients	Low-Tech	8	1,258	0.59	0.63	0.93	drs
18	Food Processing and Manufacturing	Baked Goods	Low-Tech	7	94,232	0.57	0.57	1.00	irs
18	Food Processing and Manufacturing	Candy and Chocolate	Low-Tech	2	2,532	1.00	1.00	1.00	crs
18	Food Processing and Manufacturing	Coffee and Tea	Low-Tech	4	488	1.00	1.00	1.00	crs
18	Food Processing and Manufacturing	Packaged Fruit and Vegetables	Low-Tech	4	5,886	1.00	1.00	1.00	crs
18	Food Processing and Manufacturing	Dairy Products	Low-Tech	4	12,375	0.88	1.00	0.88	drs
18	Food Processing and Manufacturing	Animal Foods	Low-Tech	1	512	1.00	1.00	1.00	crs
18	Food Processing and Manufacturing	Soft Drinks and Ice	Low-Tech	4	20,629	1.00	1.00	1.00	crs
18	Food Processing and Manufacturing	Malt Beverages	Low-Tech	2	62	0.53	0.57	0.94	drs
18	Food Processing and Manufacturing	Distilleries	Low-Tech	3	696	1.00	1.00	1.00	crs
18	Food Processing and Manufacturing	Wineries	Low-Tech	2	75	0.81	1.00	0.81	irs

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Continuation: Technical and scale efficiencies for model 22

Cluster		Subcluster	Technological Intensity	# Industry	# Firms	Model 22			
#	Name					CRSTE	VRSTE	SCALE	RTS
18	Food Processing and Manufacturing	Milling and Refining of Cereals and Oilseeds	Low-Tech	3	134	0.71	0.77	0.93	drs
18	Food Processing and Manufacturing	Milling and Refining of Sugar	Low-Tech	2	163	0.21	0.33	0.63	irs
18	Food Processing and Manufacturing	Farm Wholesalers	Low-Tech	1	1,956	0.53	0.53	1.00	drs
18	Food Processing and Manufacturing	Glass Containers	Low-Tech	1	42	0.16	0.50	0.32	irs
19	Footwear	Footwear	Low-Tech	4	3,499	b	b	b	
19	Footwear	Footwear Components	Low-Tech	2	4,831	1.00	1.00	1.00	crs
20	Forestry	Forestry	Low-Tech	1	14	b	b	b	
21	Furniture	Household Furniture	Low-Tech	2	27,319	0.58	0.60	0.96	irs
21	Furniture	Institutiol Furniture	Low-Tech	1	1,665	0.73	1.00	0.73	irs
21	Furniture	Office Furniture	Low-Tech	1	1,129	0.67	0.68	0.99	drs
21	Furniture	Wood Cabinets and Woodwork	Low-Tech	1	3,110	0.58	1.00	0.58	irs
21	Furniture	Mobile Homes	Low-Tech	1	2,964	1.00	1.00	1.00	crs
22	Hospitality and Tourism	Spectator Sports	KI-services^{d}	3	151	0.29	1.00	0.29	irs
22	Hospitality and Tourism	Amusement Parks and Arcades	KI-services^{d}	2	14,452	0.19	1.00	0.19	irs
22	Hospitality and Tourism	Cultural and Educatiol Entertainment	KI-services^{d}	4	1,038	0.10	0.50	0.20	irs
22	Hospitality and Tourism	Gambling Facilities	KI-services^{d}	2	5,149	0.43	1.00	0.43	irs
22	Hospitality and Tourism	Other Tourism Attractions	LKI-services^{c}	2	991	0.17	1.00	0.17	irs
22	Hospitality and Tourism	Accommodations and Related Services	LKI-services^{c}	7	23,332	0.27	0.34	0.78	drs
22	Hospitality and Tourism	Tourism Related Services	LKI-services^{c}	7	7,105	0.37	1.00	0.37	irs
23	Information Technology and Alytical Instruments	Electronic Components	High-tech	1	373	0.62	0.62	0.99	drs
23	Information Technology and Alytical Instruments	Computers and Peripherals	High-tech	2	51	0.35	0.50	0.70	irs
23	Information Technology and Alytical Instruments	Software Publishers	High-tech	1	51	1.00	1.00	1.00	crs
23	Information Technology and Alytical Instruments	Software Reproducing	High-tech	1	21	0.16	1.00	0.16	irs
23	Information Technology and Alytical Instruments	Process and Laboratory Instruments	High-tech	2	119	0.53	1.00	0.53	irs
23	Information Technology and Alytical Instruments	Audio and Video Equipment	High-tech	1	77	0.57	1.00	0.57	irs
24	Insurance Services	Insurance Carriers	Services	2	120	1.00	1.00	1.00	crs
25	Jewelry and Precious Metals	Jewelry and Precious Metals Products	Medium Low-tech	4	3,957	0.36	1.00	0.36	irs

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Continuation: Technical and scale efficiencies for model 22

Cluster		Subcluster	Technological Intensity	# Industry	# Firms	Model 22			
#	Name					CRSTE	VRSTE	SCALE	RTS
26	Leather and Related Products	Persol Leather Goods and Luggage	Low-Tech	2	2,492	0.63	1.00	0.63	irs
26	Leather and Related Products	Textile Bags and Canvas Products	Low-Tech	2	501	0.32	1.00	0.32	irs
27	Lighting and Electrical Equipment	Lighting Fixtures and Parts	Medium High-tech	2	321	0.77	0.77	0.99	drs
27	Lighting and Electrical Equipment	Electrical Equipment	Medium High-tech	2	328	0.43	0.43	1.00	drs
27	Lighting and Electrical Equipment	Electrical Components	Medium High-tech	4	289	0.67	0.68	0.99	irs
27	Lighting and Electrical Equipment	Storage Batteries	Medium High-tech	1	22	0.61	1.00	0.61	irs
28	Livestock Processing	Meat Processing	Low-Tech	4	3,144	0.57	0.61	0.94	drs
28	Livestock Processing	Livestock Merchant Wholesalers	Low-Tech	1	861	0.23	1.00	0.23	irs
29	Marketing, Design, and Publishing	Advertising Related Services	KI-services[d]	5	6,964	0.56	0.56	1.00	drs
29	Marketing, Design, and Publishing	Other Marketing Related Services	LKI-services[c]	4	652	0.69	0.85	0.82	drs
29	Marketing, Design, and Publishing	Design Services	KI-services[d]	4	2,234	1.00	1.00	1.00	crs
29	Marketing, Design, and Publishing	Publishing	KI-services[d]	13	1,917	1.00	1.00	1.00	crs
30	Medical Devices	Optical Instruments and Ophthalmic Goods	Medium High-tech	1	283	0.46	1.00	0.46	irs
30	Medical Devices	Surgical and Dental Instruments and Supplies	Medium High-tech	1	181	0.42	0.50	0.83	irs
31	Metal Mining	Metal Mining	Medium Low-tech	7	303	0.61	0.62	0.99	irs
32	Metalworking Technology	Metalworking Machinery	Medium Low-tech	2	243	0.60	1.00	0.60	irs
32	Metalworking Technology	Fasteners	Medium Low-tech	1	212	0.39	0.54	0.72	irs
32	Metalworking Technology	Metal Processing	Medium Low-tech	2	701	0.48	1.00	0.48	irs
33	Music and Sound Recording	Music and Sound Recording	Medium Low-tech	5	134	0.39	1.00	0.39	irs
34	Nonmetal Mining	Nonmetal Mining	Medium Low-tech	16	2,592	0.31	0.31	1.00	drs
35	Oil and Gas Production and Transportation	Petroleum Processing	Medium Low-tech	2	7	1.00	1.00	1.00	crs
35	Oil and Gas Production and Transportation	Support Activities for Oil and Gas Operations	Medium Low-tech	1	49	0.09	1.00	0.09	irs
35	Oil and Gas Production and Transportation	Drilling Wells	Medium Low-tech	1	12	0.49	1.00	0.49	irs
35	Oil and Gas Production and Transportation	Oil and Gas Extraction	Medium Low-tech	1	66	b	b	b	
35	Oil and Gas Production and Transportation	Pipeline Transportation	Medium Low-tech	1	25	0.42	1.00	0.42	irs
36	Paper and Packaging	Paper Mills	Low-Tech	2	42	0.22	0.26	0.87	irs

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Continuation: Technical and scale efficiencies for model 22

Cluster		Subcluster	Technological Intensity	# Industry	# Firms	Model 22			
#	Name					CRSTE	VRSTE	SCALE	RTS
36	Paper and Packaging	Packaging	Low-Tech	2	1,119	0.36	0.51	0.71	irs
36	Paper and Packaging	Paper Products	Low-Tech	3	2,769	0.43	1.00	0.43	irs
37	Performing Arts	Performing Artists	KI-services[d]	5	3,860	0.49	1.00	0.49	irs
37	Performing Arts	Promoters and Magers	KI-services[d]	3	1,130	0.24	0.50	0.49	irs
38	Plastics	Plastic Products	Medium Low-tech	12	5,100	0.33	1.00	0.33	drs
38	Plastics	Plastic Materials and Resins	Medium Low-tech	2	253	0.35	0.50	0.69	irs
39	Printing Services	Printing Inputs	KI-services[d]	1	38	0.42	1.00	0.42	irs
39	Printing Services	Support Activities for Printing	LKI-services[c]	1	604	0.37	1.00	0.37	irs
39	Printing Services	Printing Services	LKI-services[c]	2	19,326	0.75	1.00	0.75	irs
40	Production Technology and Heavy Machinery	Industrial Machinery	Medium High-tech	12	932	0.35	0.38	0.93	irs
40	Production Technology and Heavy Machinery	Agricultural and Construction Machinery and Components	Medium High-tech	3	271	0.54	1.00	0.54	irs
40	Production Technology and Heavy Machinery	Air Handling Equipment	Medium High-tech	2	319	0.43	0.43	1.00	drs
40	Production Technology and Heavy Machinery	Commercial and Service Industry Machinery	Medium High-tech	1	-a	0.81	1.00	0.81	irs
40	Production Technology and Heavy Machinery	Moving and Material Handling Equipment	Medium High-tech	1	170	0.36	1.00	0.36	irs
40	Production Technology and Heavy Machinery	Process Equipment and Components	Medium High-tech	4	339	0.62	1.00	0.62	irs
41	Recreatiol and Small Electric Goods	Recreatiol and Decorative Goods	Medium High-tech	5	7,558	0.76	0.76	1.00	drs
41	Recreatiol and Small Electric Goods	Games, Toys, and Children's Vehicles	Medium High-tech	1	917	0.49	1.00	0.49	irs
41	Recreatiol and Small Electric Goods	Motorcycles and Bicycles	Medium High-tech	2	72	0.40	1.00	0.40	irs
41	Recreatiol and Small Electric Goods	Sporting and Athletic Goods	Medium High-tech	1	1,367	1.00	1.00	1.00	crs
41	Recreatiol and Small Electric Goods	Office Supplies	Medium High-tech	1	271	0.36	1.00	0.36	irs
41	Recreatiol and Small Electric Goods	Electric Housewares	Medium High-tech	1	79	0.51	1.00	0.51	irs
42	Textile Manufacturing	Yarn and Thread Mills	Low-Tech	3	14,048	0.59	1.00	0.59	irs
42	Textile Manufacturing	Fabric Mills	Low-Tech	4	747	0.43	0.47	0.92	irs
42	Textile Manufacturing	Textile and Fabric Finishing	Low-Tech	2	255	0.40	0.50	0.79	irs
42	Textile Manufacturing	Knitting Mills	Low-Tech	3	1,913	0.97	1.00	0.97	irs
42	Textile Manufacturing	Household Textile Products	Low-Tech	3	2,387	0.82	1.00	0.82	irs
42	Textile Manufacturing	Other Textile Products	Low-Tech	2	25,579	0.35	1.00	0.35	irs
42	Textile Manufacturing	Fibers	Low-Tech	1	14	0.35	1.00	0.35	irs

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Continuation: Technical and scale efficiencies for model 22

Cluster #	Cluster Name	Subcluster	Technological Intensity	# Industry	# Firms	Model 22 CRSTE	Model 22 VRSTE	Model 22 SCALE	Model 22 RTS
43	Tobacco	Tobacco	Low-Tech	3	49	1.00	1.00	1.00	crs
44	Trailers, Motor Homes, and Appliances	Burial Caskets	Medium High-tech	1	305	0.65	1.00	0.65	irs
44	Trailers, Motor Homes, and Appliances	Household Appliances	Medium High-tech	1	174	0.34	1.00	0.34	irs
45	Transportation and Logistics	Air Transportation	KI-services[d]	5	277	0.88	1.00	0.88	irs
45	Transportation and Logistics	Specialty Air Transportation	KI-services[d]	1	28	0.30	1.00	0.30	irs
45	Transportation and Logistics	Ground Transportation Support Activities	LKI-services[c]	7	4,387	0.77	1.00	0.77	irs
45	Transportation and Logistics	Trucking	LKI-services[c]	7	4,113	0.20	0.20	0.98	irs
45	Transportation and Logistics	Bus Transportation	LKI-services[c]	2	1,716	0.19	0.20	0.95	drs
46	Upstream Chemical Products	Organic Chemicals	Medium High-tech	3	181	1.00	1.00	1.00	crs
46	Upstream Chemical Products	Inorganic Chemicals	Medium High-tech	1	116	0.44	1.00	0.44	irs
46	Upstream Chemical Products	Industrial Gas	Medium High-tech	1	41	0.90	1.00	0.90	irs
46	Upstream Chemical Products	Agricultural Chemicals	Medium High-tech	1	111	1.00	1.00	1.00	crs
47	Upstream Metal Manufacturing	Iron and Steel Mills and Forging	Medium Low-tech	3	338	0.76	0.81	0.94	irs
47	Upstream Metal Manufacturing	Metal Processing	Medium Low-tech	6	378	0.62	0.69	0.89	irs
47	Upstream Metal Manufacturing	Metal Products	Medium Low-tech	1	104	1.00	1.00	1.00	crs
48	Video Production and Distribution	Video Production and Distribution	KI-services[d]	5	369	0.55	1.00	0.55	irs
49	Vulcanized and Fired Materials	Clay Products and Refractories	Medium Low-tech	5	18,853	0.47	0.56	0.85	irs
49	Vulcanized and Fired Materials	Glass Products	Medium Low-tech	6	870	0.31	0.31	0.99	drs
49	Vulcanized and Fired Materials	Rubber Products	Medium Low-tech	4	1,045	0.78	0.82	0.95	irs
50	Water Transportation	Water Passenger Transportation	KI-services[d]	1	11	0.49	1.00	0.49	irs
50	Water Transportation	Marine Transportation Services	KI-services[d]	7	474	0.52	1.00	0.52	irs
50	Water Transportation	Boat Building and Repairing	Medium Low-tech	1	48	0.28	1.00	0.28	irs
51	Wood Products	Wood Processing	Low-Tech	3	552	0.27	1.00	0.27	irs
51	Wood Products	Wood Components and Products	Low-Tech	3	2,483	0.38	0.50	0.76	irs
51	Wood Products	Prefabricated Wood Building	Low-Tech	3	16,270	0.36	1.00	0.36	irs
		Total		551.0	675,973.0	107.7	152.1	132.0	
		Average		3.0	3,653.9	0.6	0.8	0.7	
		Standard deviation		2.6	9,409.1	0.3	0.2	0.3	
		Maximum		16	94,232	1	1	1	
		Minimum		1	7	0.0908	0.1965	0.0908	

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Table 2.11: High-tech and Medium high-tech Sub-clusters

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed	1	1	3	1	1	3	8	4
# efficient DMUs (Sub-clusters)	3	11	9	6	9	8	23	12
% Efficient DMUs (Sub-clusters)	7.32%	26.83%	23.08%	14.63%	21.95%	20.51%	67.65%	31.58%
Average Efficiency	47.32	71.09	69.67	60.34	74.02	71.08	93.89	79.67
Potential input savings (respect to model 15)		23.77	22.34	13.02	26.70	23.76	46.56	32.35
Average Efficiency score of inefficient DMUs	43.17	60.49	60.57	53.54	66.71	63.62	81.11	70.29
Standard deviation	20.96	24.01	23.40	24.18	22.11	21.82	11.95	21.63
Maximum	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Minimum	11.32	20.86	18.23	14.29	16.80	16.92	60.25	25.50

Table 2.12: Medium low-tech sub-clusters

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed	1	2	1	2	1	1	6	3
# efficient DMUs (Sub-clusters)	6	11	8	10	8	12	18	15
% Efficient DMUs (Sub-clusters)	24.00%	45.83%	32.00%	41.67%	32.00%	48.00%	90.00%	65.22%
Average Efficiency	71.01	85.56	78.64	81.86	82.31	81.57	98.34	91.25
Potential input savings (respect to model 15)		14.55	7.63	10.85	11.30	10.56	27.33	20.24
Average Efficiency score of inefficient DMUs	61.85	73.34	68.59	68.91	73.98	64.55	83.41	74.85
Standard deviation	21.80	19.43	20.03	20.01	19.46	19.70	4.99	17.37
Maximum	100	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	18.64	26.69	18.64	18.64	22.57	44.41	82.10	27.17

Table 2.13: Low-tech sub-clusters

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed	3	3	3	4	4	3	6	5
# efficient DMUs (Sub-clusters)	5	7	7	9	11	8	18	14
% Efficient DMUs (Sub-clusters)	12.50%	17.50%	17.50%	23.08%	28.21%	20.00%	48.65%	36.84%
Average Efficiency	54.80	64.21	61.43	64.75	65.25	63.77	82.85	74.81
Potential input savings (respect to model 15)		9.42	6.63	9.96	10.45	8.97	28.06	20.01
Average Efficiency score of inefficient DMUs	48.34	56.62	53.25	54.18	51.60	54.71	66.61	60.11
Standard deviation	28.48	27.14	27.07	26.67	29.34	26.43	20.69	25.74
Maximum	100	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	17.28	21.67	19.74	24.13	21.05	23.99	40.08	24.54

Table 2.14: Knowledge-intensive services sub-clusters

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed	1	3	3	4	2	4	9	4
# efficient DMUs (Sub-clusters)	7	7	7	7	7	12	18	8
% Efficient DMUs (Sub-clusters)	20.59%	21.88%	21.88%	22.58%	21.21%	38.71%	69.23%	25.81%
Average Efficiency	53.52	65.47	61.40	69.41	57.75	70.75	91.50	75.48
Potential input savings (respect to model 15)		11.95	7.88	15.89	4.23	17.23	37.98	21.96
Average Efficiency score of inefficient DMUs	41.47	55.80	50.59	60.48	46.37	52.28	72.38	66.95
Standard deviation	31.74	26.73	28.29	26.97	30.25	28.56	17.85	25.33
Maximum	100	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	8.79	11.13	11.13	16.63	10.79	16.95	42.36	16.63

Table 2.15: Less knowledge-intensive services sub-clusters

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed	1	2	3	2	1	3	8	5
# efficient DMUs (Sub-clusters)	8	10	8	10	12	10	20	13
% Efficient DMUs (Sub-clusters)	21.05%	27.03%	22.22%	27.03%	31.58%	27.78%	64.52%	38.24%
Average Efficiency	56.85	63.15	63.33	65.44	64.93	70.16	90.35	76.11
Potential input savings (respect to model 15)		6.30	6.48	8.59	8.08	13.31	33.50	19.26
Average Efficiency score of inefficient DMUs	45.34	49.50	52.85	52.64	48.74	58.68	72.81	61.32
Standard deviation	30.89	29.34	29.14	28.25	30.66	27.29	15.70	24.55
Maximum	100	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	11.85	19.06	16.15	18.17	14.71	22.57	41.70	27.94

3 Regional resilience and cluster strength: The case of the U.S. in the Great Recession[§]

Introduction

The interest in regional resilience has increased in the last decade, mainly influenced by the heterogeneous effects of the Great Recession across regions and countries (Groot et al., 2011; Capello et al., 2015). Additionally, the COVID-19 crisis has intensified the enthusiasm for the study of this topic. It is crucial to figure out the mechanisms and determinants that make regions resilient. The concept of resilience has a well-established tradition in fields like engineering, ecology, and evolution (Holling, 1973; Pimm, 1984; Martin, 2012; Martin and Sunley, 2015). Regardless of its definition, the interest in regional economics lies in understanding how regional economies react to and recover from recessionary shocks (Crescenzi et al., 2016; Lagravinese, 2015).

Among the different determinants of regional resilience, the recent discussion in this matter revolves around the impact of the industrial composition of the region. The main question is whether regional resilience is enhanced by sectoral diversity, specialization or even the more elaborated concept of related variety introduced by Frenken et al. (2007). It assumes that some degree of cognitive complementarity between sectors should exist for knowledge spillovers to happen. Cainelli et al. (2019a) provide empirical evidence that positions this variable as a relevant determinant of regional resilience. In this sense, the introduction of the concept of clusters can contribute to this recent literature because it is conceptually similar to the notion of related variety (Delgado et al., 2016, p. 5), but its definition is more

[§]The paper in this chapter is coauthored with Rosina Moreno Serrano elaborated. Indeed, clusters include the participation of other agents that support their performance, such as financial institutions and governments. As far as we know, cluster strength has not been tested as a determinant of resilience, contributing this way to the cluster literature too (Delgado and Porter, 2021).

Back into 2003, Porter defined clusters as a geographically proximate group of interconnected companies, suppliers, service providers, and associated institutions in a particular field, linked by externalities of various types. A well-known example of a cluster is Silicon Valley. This California area concentrates many technological firms that serve as a center for innovation. A cluster's strong connections amongst the industries, generates agglomeration forces that benefit their individual performances. Industries participating in strong clusters register higher employment growth as well as higher growth in wages (Delgado et al., 2014). Apart from the higher performance, the industries that belong to strong clusters show higher resilience to economic shocks (Delgado and Porter, 2021). According to this previous literature, prior to the economic shock, the industries belonging to a cluster develop some mechanisms that mitigate the negative effect of a downturn. Some of these mechanisms can be long contracts, collaboration with institutions, trust with clients, and institutions that facilitate credit.

In the present paper we transfer these ideas to the regional level and try to analyse how a strong cluster presence might explain overall regional resilience. In previous literature, Delgado et al. (2014) show how strong clusters in a region enhance growth opportunities not only in the corresponding industries but also in other industries and clusters in a multiplicative way. Consequently, we presume that regions with a strong cluster presence may show less vulnerability to economic shocks. However, at the same time, sectoral linkages and interrelatedness may increase the diffusion of the shock from one sector to the others, amplifying the negative impact (Acemoglu et al., 2013; Giannakis and Bruggeman, 2017; Martin, 2012). In our paper we aim to check whether one of these two forces dominates. In order to do this, we contribute in several ways. First, to measure the strength of the clusters' presence in a region, we follow the US cluster mapping project by Delgado et al. (2016) [1], which groups industries based on an empirical analysis of co-location patterns, similarities

[1] www.clustermapping.us

in skill needs, and input-output relationships. One of the main advantages of this cluster definition is the possibility to compare clusters across regions. Second, based on this cluster definition, we compute different indicators that proxy for the strength of the region's cluster portfolio as well as the mix of clusters in which the region has a robust importance, specifically the bias of the region towards high wage clusters following Ketels and Protsiv (2020). Third, since resilience is a process with different stages (risk, resistance, reorientation, and recovery, as in Martin et al. (2016),we want to scrutinize how cluster strength affects this process. Our analysis focuses on the Great Recession in the US.

The remainder of the paper is organized as follows. The second section summarizes the regional resilience literature, while the third describes the U.S. cluster mapping project. The fourth section shows the empirical model implemented to test our hypothesis. The fifth section introduces the data used to measure the dependent and independent variables and their descriptive statistics. The sixth section discusses the main findings on the role of cluster strength on regional resilience. Finally, the concluding section presents the policy implications of these findings.

Literature Review

Recent literature in regional economics shows an increasing interest in identifying the determinants of regional resilience. Despite the outstanding progress in this area, the academic discussion on the topic continues. This section reviews the main findings on this matter and provides the reasons justifying the inclusion of cluster strength in this academic discussion.

Some works aiming to shape the determinants of regional resilience find industrial composition as a critical element. For instance, Eraydin (2016) classified the attributes of resilience in two paths. First, several components can be grouped under the title of "resources and vulnerability", determining the region's ability to respond to a crisis. Some of these components are location, trade openness, a skilled workforce, and public and private infrastructure. Second, several determinants related to "industrial diversity and specialization" guide the adaptive capacity to an economic shock, making this an essential issue for higher resilience. In the same line, Breathnach et al. (2015) find that sectoral composition has an important impact on regional resilience for the Irish regions during the great recession. Also, in this downturn, Cainelli et al. (2019a) identify industrial relatedness as the critical element for the most resilient regions in Europe.

Similarly, Martin and Sunley (2015) highlight the relevance of labor market conditions, financial arrangements, government arrangements, and industrial and business structure to shape regional resilience. Except for the last one, the authors describe all these elements as institutional since they are durable patterns of organizing economic activity. In other words, they are related to long-run regional development rather than responses to adverse shocks. Whereas industrial and business structure would be the fundamental determinant of regional resilience. In the same line, while analyzing the determinants of regional resilience to employment displacement, Nyström (2018) identified five elements (regional closures, skills and human capital of the labor force, local conditions that affect the job-search process of displaced workers, regional attractiveness and regional industry), obtaining that the regional industry, related to the knowledge spillover as a result of agglomeration economies, is a real driver of resilience.

According to the above references, the industrial composition of a region is a key driver in entangling resilience, and agglomeration forces are the argument behind this effect. The firms' geographical proximity allows them to benefit from agglomeration drivers such as knowledge spillovers, labor market pooling, and input-output linkage (Marshall, 1920). These mechanisms produce increasing returns that lead the firms to become more resilient. A secondary question is which kinds of industrial agglomerations benefit resilience more: a group of industries working in the same sector (specialization) or a group of diversified industries (diversity) (Boschma et al., 2012; Frenken et al., 2007). In other words, the discussion is whether firms learn more from others in the same industry or from firms in other sectors.

Existing literature shows a contradiction between the consequences of diversity and specialization on resilience Martin and Sunley (2015). On the one hand, the diversity of economic activities reduces the risk in a downturn (Crescenzi et al., 2016). In case the downturn affects specific industries, there are still others supporting the economy. On the other hand, regions specializing in highly productive sectors are more resilient to recessions (DiCaro, 2017). However, the strong linkages among the industries may increase the diffusion of the economic shock. This discussion has evolved to include the analysis of related and unrelated varieties.

Related variety assumes that some degree of cognitive complementarity between sectors should exist for the knowledge spillover to happen, whereas the unrelated variety concept corresponds to industries that do not share complementary competencies (Frenken et al., 2007; Boschma and Iammarino, 2009). Cainelli et al. (2019a) present empirical evidence that regions with a higher level of related variety are better able to weather economic downturns. Two reasons make the related variety a shock absorber. First, redundant employees can more easily find jobs since the industries require workers with similar skills (Diodato and Weterings, 2015). Second, related variety increases the likelihood of producing technological breakthroughs that are more likely to generate innovation (Boschma, 2015), allowing for recoverability.

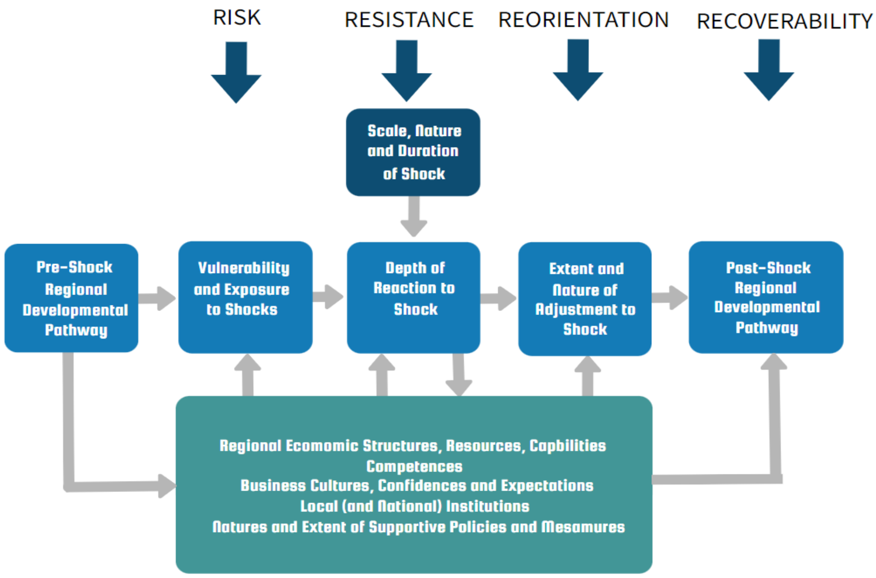
Despite our interest in the industrial composition of a region and the concept of related variety, entrepreneurship and innovation are other determinants identified as relevant for resilience. Eraydin (2016) provides empirical evidence that the share of entrepreneurs in total employment is one of the most important assets of shock- resistant areas. The ability of entrepreneurs to be adaptable is crucial to the region's ability to absorb and respond to external shocks. On the other hand, Bristow and Healy (2018) found that European regions identified as innovation leaders at the time of the Great Recession were significantly more likely to show resistance to the crisis or quickly recoverability. Additionally, Martin and Sunley (2015) claim that there exists a "region-specific" component when explaining regional resilience, in the sense that firms in a given sector in a given region grow more quickly (or more slowly) than their counterparts in the same industry nationally. Among other reasons, the authors highlight those of the region's productivity and competitiveness. Fratesi and Rodríguez-Pose (2016) reached a similar conclusion, affirming that the most resilient regions in times of crisis turned out to be those that before the crisis, were alredy more competitive. DiCaro and Fratesi (2018) also highlight regional competitiveness as a factor that contributes to economic performance, not just in normal times but also during and after economic shocks.

Clusters and Resilience

This paper focuses on the strength of the clusters located in a region as one of the determinants for its resilience, making agglomeration economies the main reason behind Marshall (1920). The close interaction among the industries in a cluster allows them to share similar skills, technology, input and output links, and social capital. Those elements allow them to mitigate the effect of an economic shock through long-term contracts with clients, more efficient labor markets, trust and altruism, and institutions for collaboration that may facilitate credit (Delgado and Porter, 2021). However, it is possible to observe the opposite effect: the strong linkages and interrelatedness among the industries could easily propagate the economic shock amplifying the negative impact and prolonging the recession (Giannakis and Bruggeman, 2017; Martin, 2012). Acemoglu et al. (2013)develop a theoretical model that shows how the input-output linkages between different sectors could increase an economic downturn.

Five additional reasons support clusters as determinants of resilience. First, the notion of cluster strength is conceptually similar to the concept of "related variety," which is one variable that previous research has identified as driving resilience (Cainelli et al., 2019a). Indeed, cluster strength reflects specialization in various related industries, not specialization in a narrowly defined single industry (Delgado et al., 2014), so that the same reasoning behind the influence of related variety on resilience would apply. Second, there is significant evidence of the relationship between clusters and entrepreneurship (Delgado et al., 2010), another crucial resilience determinant mentioned in the literature. Industries located in regions with strong clusters experience more growth in new business formation and start-up employment, which would affect resilience. Third, cluster strength is characterized by high productivity and competitiveness, both of them representing the “region-specific component” highlighted by Martin and Sunley (2015) as determinants of resilience. Fourth, the cluster definition that we follow in this study only considers traded industries, which tend to be geographically concentrated and produce goods and services sold across regions and countries. When employment increases in these kinds of industries, it causes a multiplier effect on employment in nontradable sectors (Moretti, 2010) because the demand for local goods and services

Figure 3.1: Regional resilience to recession



SOURCE: *Martin et al. (2016)*

increases: "adding one additional skilled job in the tradable sector generates 2.5 jobs in local goods and services" (Moretti, 2010, p. 373). For all these reasons, we argue that the presence, strength, and mix of the clusters in a region should be taken into account as drivers of resilience in such a region. Fifth, Boschma (2015) discusses how an evolutionary approach to regional resilience is linked to industrial structure (both related and unrelated variety), networks, and institutions. Clusters are characterized by representing all of these three dimensions.

Finally, it is important to note that the effect of cluster presence on regional resilience may vary depending on the stage of the resilience process (Martin et al. 2016, see figure 3.1): 1) the risk that firms, industries, and institutions face during the economic shock; 2) the resistance that those economic actors show to the downturn; 3) the reorientation of the economic actors to the new conditions to recover their performance; and 4) the recoverability that they show from the economic shock. The sequential aspect from one stage to another depends on the depth, nature, and duration of the recession process. Based on the agglomeration argument, we expect that the cluster strength in a region presents a higher impact on resilience during the resistance period. Delgado and Porter (2021) find that industries located in a strong cluster were

Figure 3.2: Why are clusters important for the U.S. economy?

SOURCE: *Harvard Business School (2020).*

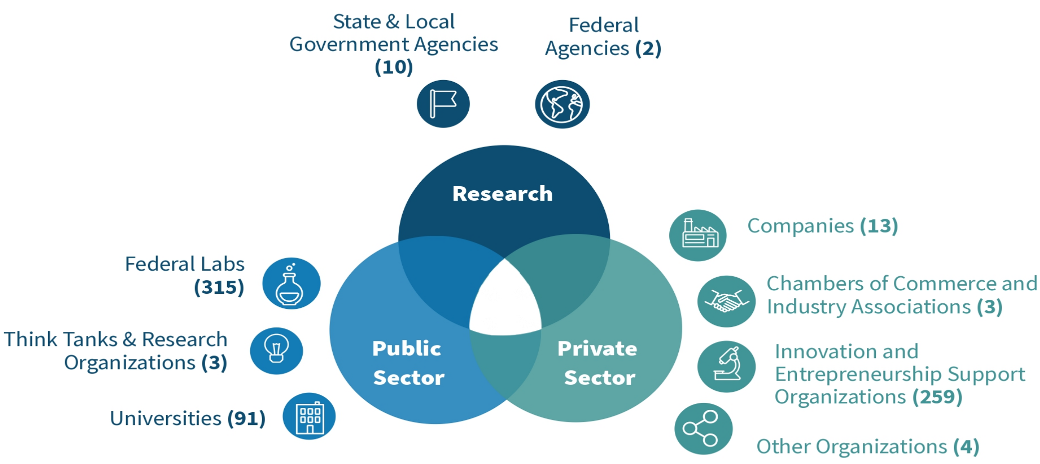
especially resilient during the Great Recession years.

Clusters Policy in the U.S.

The development of a cluster policy in the U.S. has been one of the main issues on the political agenda, given its importance to the U.S. economy (see figure 3.2). For instance, during the administration of President Obama, one of the objectives of the "Strategy for American Innovation, 2009" was the promotion of regional innovation clusters (European Cluster Collaboration Platform, 2022). To achieve this goal, the U.S. government provides funding to the clusters through different agencies like the Economic Development Administration, the Small Business Administration, the Department of Labor, the Department of Education, and the Department of Energy (Farrell and Kalil, 2010).

One of the most ambitious initiatives to support cluster development has been the U.S. Cluster Mapping Project. This project was launched in 2014 by the U.S. Secretary of Commerce, Penny Pritzker (Harvard Business School, 2020). Its purpose is to identify and provide data for all the clusters located at the state, metropolitan, and county levels. To have a formal cluster registration consulted by economic developers, policymakers, researchers, and members of the private sector to coordinate in the same direction all the efforts to support cluster development. This project offers an accessible tool

Figure 3.3: Cluster Mapping Project Community in the U.S.



SOURCE: *Own elaboration with data from the Cluster mapping project (Harvard Business School, 2020).*

on its website (www.clustermapping.us) to elaborate on the cluster mapping of any geographical area in the U.S., which is a helpful instrument to shape the competitiveness of the regions. Additionally, this platform enables the community network to learn about some cluster initiatives and share their best practices.

The cluster mapping project is financed by the U.S. Department of Commerce and the U.S. Economic Development Administration and led by Harvard Business School's Institute for Strategy and Competitiveness. Professor Michael Porter, who heads this institute, is well-known for his significant contribution to the cluster and competitiveness literature. Professor Porter and his research team developed an algorithm that groups industries into clusters, as briefly described in the introduction of this work. For more details about this methodology, see Delgado et al. (2016).

Apart from being a cluster data supplier, this national initiative is implemented as a networking tool where any participant in the cluster initiatives can interact with others. This is a unique opportunity to share experiences or learn from others how they use the information obtained through this project to improve cluster performance. The number of registered participants on this platform gives us an idea of the significant impact this initiative has had on the country. As you can observe in figure 3.3, the participants are classified into three main groups. First, the private sector is represented by companies (13), the Chamber of Commerce and Industry Association (3), Innovation and Entrepreneurship support organizations (259), and other organizations (4). Second, the public sector includes state and local government agencies (10) and federal agencies (2). Finally, the research group is composed of federal labs (315), think tanks and research organizations (3), and universities (91). The joint effort of all these participants gives, as a result, 126 cluster organizations and initiatives listed in table 3.5 in the appendix section.

As mentioned above, the vast community registered at the cluster website can share their experience using the data provided by this initiative to develop policies, projects, or businesses. Here we briefly mention two successful cases for clusters at the state level, which is the geographic unit of analysis in this work. The Director of Business and Industrial Development for the state of West Virginia, Kris Hopkins, aimed to grow existing companies in that region and attract new ones in 2015. The information provided by the cluster mapping project allows him to identify West Virginia's key clusters, a list of cluster organizations, and chambers of commerce, making it possible to elaborate suitable cluster initiatives for that state. The second case is when the president and CEO of the South Carolina Council on Competitiveness, Ann Marie Stieritz, elaborated a strategy to increase the state's competitiveness. Using the information provided by the cluster mapping project, she identified the most competitive cluster compared to the other states in the country and worked to strengthen them. As a result, she produced a framework to improve the competitive position of South Carolina in the United States. It is possible to consult these cases and more on the Cluster Mapping Project website. There is no doubt that this national initiative has a significant impact on cluster development, economic growth, and national competitiveness.

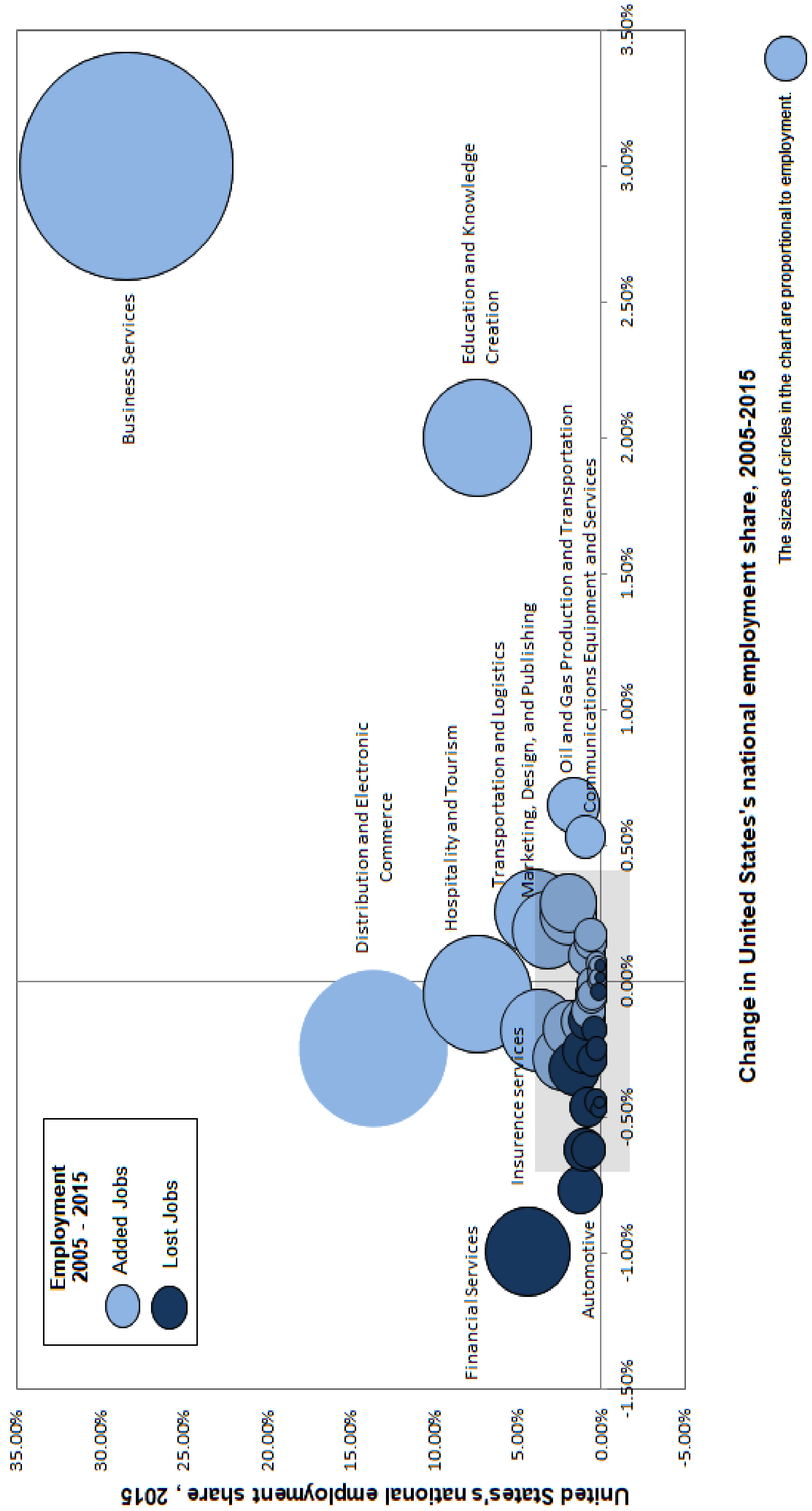
The U.S. Cluster mapping

Figure 3.4, similar to the ones provided by the cluster mapping project, gives a general idea of the U.S. national cluster composition and its change in the period 2005 to 2015, which corresponds to the analysis period for this study. Each bubble in the graphic represents one cluster, and its size is proportional to the number of employees. As expected, the Business services cluster employs the highest number of employees in the country, followed by the clusters Distribution and Electronic Commerce, Education and Knowledge Creation, and Hospitality and Tourism. We can notice an accumulation of bubbles near the origin axes marked off by the gray area. To better appreciate those clusters, figure 3.5 represents a zoom of this gray area. This new graphic allows us to identify the little clusters in the U.S. like music and recording, forestry, and metal mining.

Besides their size, the bubble colors provide information about the change in the number of employees for a specific period. In this way, the bubbles in light blue indicate the number of employees in that cluster increased from 2005 to 2015. In the opposite case, the dark blue bubbles imply that the cluster decreased its number of employees in that period. This detail is relevant for a cluster mapping analysis because, even when two clusters had the same size in 2015, one was creating new job opening, while the second was losing them. For instance, in figure 3.5, Aerospace Vehicles (in light blue) and Downstream Metal Products (in dark blue) have similar sizes but opposite changes in the number of job positions for this period.

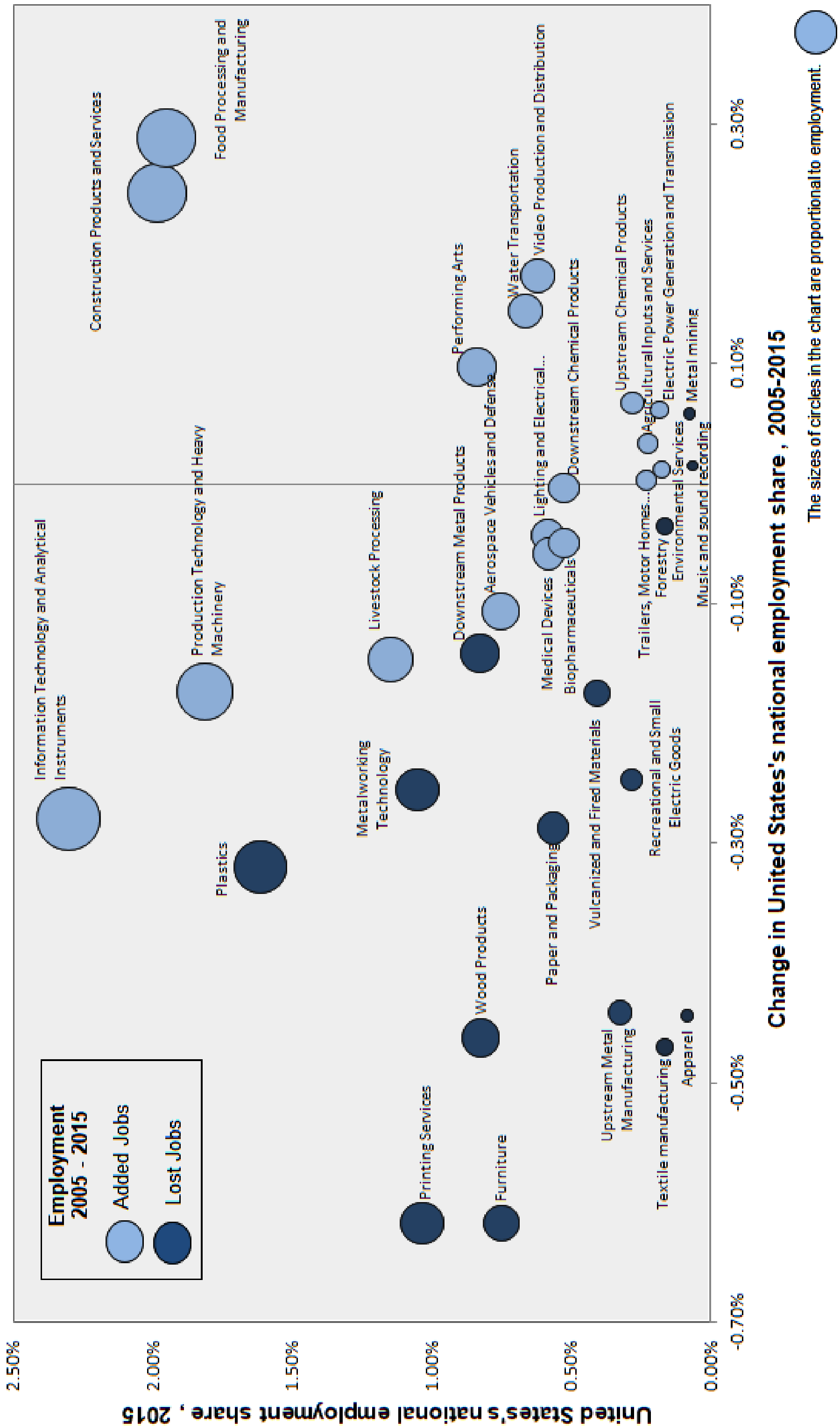
The y axis of these graphs shows the percentage by which each cluster contributes to the national employment generated by all traded clusters. As mentioned above, traded clusters are concentrated in regions that afford specific competitive advantages and serve markets in other regions or nations. These are the kind of clusters that concern the cluster mapping analysis because of their contribution to competitiveness. Back to the "y" axis in the graph, it is evident that the higher the bubble’s position in the graph, the higher its contribution to national employment. For instance, in figure 3.5, Distribution and Electronic Commerce contribute 13.6% to the total employment generated by traded clusters, one of the highest percentages in the U.S.

Figure 3.4: United States Clusters
2005 to 2015



SOURCE: *Own elaboration with data from the Cluster mapping project (Harvard Business School, 2020)*

Figure 3.5: Continuation. United States Clusters 2005 to 2015



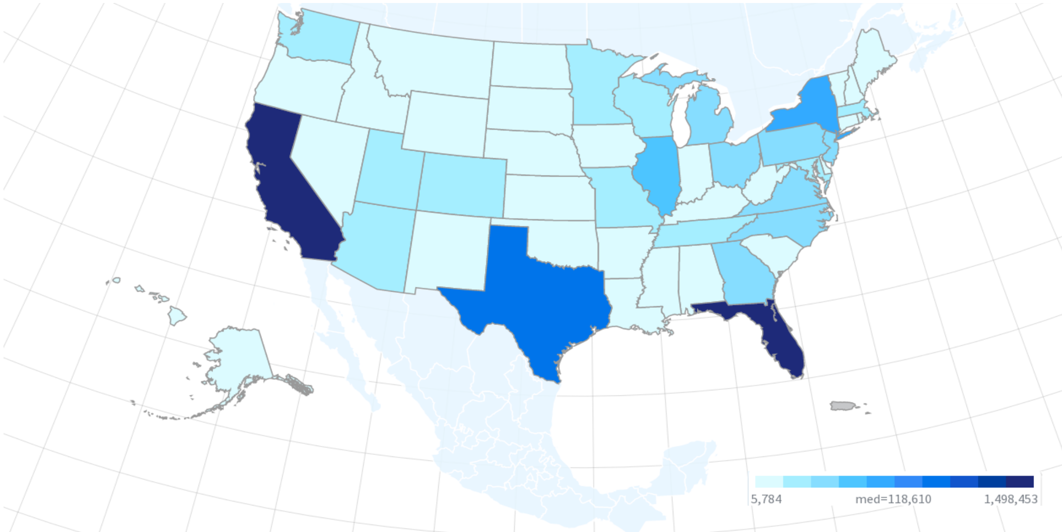
SOURCE: *Own elaboration with data from the Cluster mapping project (Harvard Business School, 2020)*

On the other hand, the "x" axis shows the percentage change in the contribution to national employment for a specific period. In other words, it compares the Y axis's measure against two different years, in this case, 2005 and 2015. This information is relevant because, even when two clusters have a similar size and contribution to national employment for a given year, the share can decrease or increase along that period. For instance, in figure 3.5, the Production Technology and Heavy Machinery, and the Food Processing and Manufacturing clusters have a similar size and share contribution to the national employment but, compared to the year 2005, the Production technology and Heavy Machinery cluster is decreasing its contribution to the national employment (-0.17%). Meanwhile, the Food Processing and Manufacturing cluster employs a greater proportion of the national workforce (0.024%). [2] It is possible to build this kind of chart for other variables like value-added, wages, innovation, etc. However, here we focus on employment because this is the variable that concerns our analysis.

In addition to the national clusters' charts, we can analyze maps for specific clusters across the regions. For instance, figure 3.6 exhibits the presence of the Business Service cluster in each state. The darker the color of the state on the map, the higher the number of employees in this cluster. Furthermore, this map can be built for other variables like in figure 3.7. Once again, this map focuses on the Business Service cluster but this time it shows the growth of employment. When we compare both maps, we can notice the states that generate the highest number of employees for the Business Service cluster, like California and Florida, which do not necessarily show the highest employment growth rate.

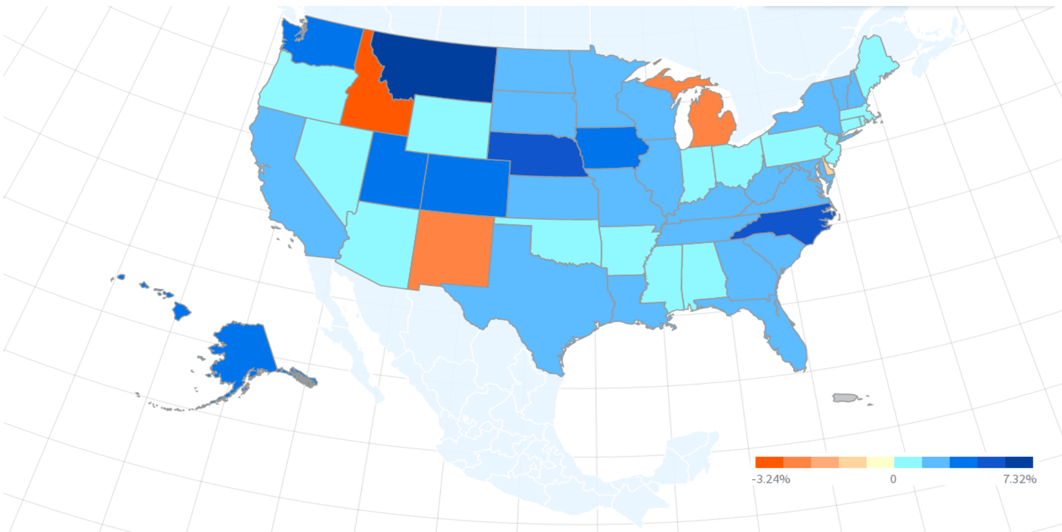
[2] With the information from the cluster mapping, it is possible to build a similar graph for lower geographic units. In that case, the graphics will identify the potential clusters in that specific state or metropolitan region.

Figure 3.6: Employment in Business Services Cluster by State, 2015



SOURCE: *The U.S. Cluster Mapping Project (Harvard Business School, 2020).*

Figure 3.7: Employment Growth Rate in Business Services Cluster by State, 2005 - 2015



SOURCE: *The U.S. Cluster Mapping Project (Harvard Business School, 2020).*

Empirical Model

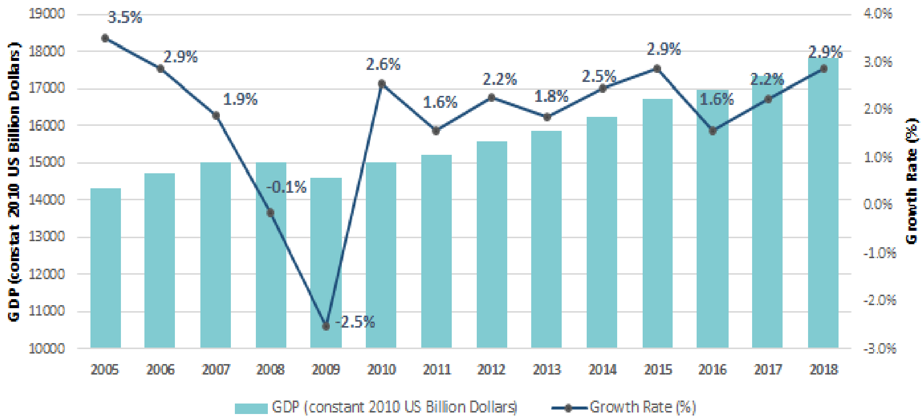
To test our hypothesis, we need to select an economic shock to which regions must show their resilience. The COVID-19 pandemic produced the most recent downturn that hit the world economy. However, given that it is still a recent event, there is not enough data to analyze the different stages of the resilience process. We refer mainly to the recovery stage, for which it is necessary to have data some years after the economic shock took place. For the cluster classification that this work follows, the year 2019 is the most recent data available. Therefore, it is necessary to select another economic shock apart from the COVID-19 downturn, and the Great Recession has been considered the most prolonged downturn since the Great Depression of the 1930s (Grusky et al., 2011).

The Great Recession had its roots in the U.S. economy with the housing bubble's collapse and the excessive expansion of credit. This financial collapse started in December 2007, and growth did not return to the economy until the summer of 2009 (see figure 3.8). However, even when production started its recovery, the most severe effect was evident in employment. It was also a Great Recession from the point of view of the labor market, which lost over 7.5 million jobs from May 2007 to October 2009 (Grusky et al., 2011). Meanwhile, the unemployment rate increased by 5.7 percentage points from the pre-recession to October 2009 (see figure 3.9). The negative effect of the Great Recession was severe, not just in the U.S. This downturn affected Europe more severely than any other crisis since the end of the Second World War (Capello and Caragliu, 2016).

For the above reasons, many researchers consider the Great Recession as the downturn to evaluate regional resilience in studies for Europe and the U.S. (Ringwood et al., 2019; Han and Goetz, 2015; Giannakis and Bruggeman, 2017; Ezcurra and Rios, 2019; Brakman et al., 2015; Arbolino and Di Caro, 2021; Cainelli et al., 2019b; Davies, 2011; Rios and Gianmoena, 2020). Among these references, we can find the study by Delgado and Porter (2021), which evaluates whether strong clusters are resilient to the Great Recession, measuring resilience with employment. This reference is relevant because those authors implement the same cluster classification as in this study. What is more, they developed this cluster classification.

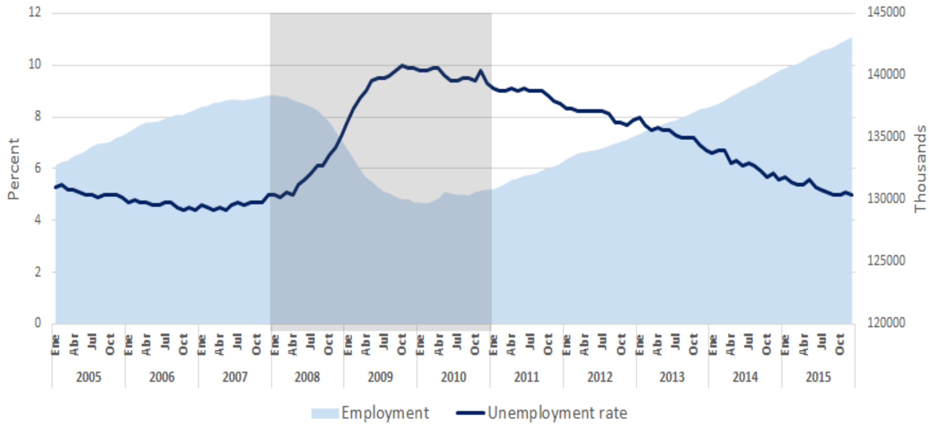
Given that the Great Recession had its roots in the U.S. economy, it seems

Figure 3.8: American GDP dynamics



SOURCE: *Own elaboration with data from World Bank Group (2021)*

Figure 3.9: Unemployment rate and total employment in the U.S.



SOURCE: *Own elaboration with data from the U.S. Bureau of Labor Statistics (2021).*

the most appropriate country to test our hypothesis. According to data from the World Bank, the U.S. economy is ranked as a high-income economy, boasting a per capita GDP of $58,559 in 2020. This number positioned the country in eighth place among those with the highest per capita GDP. Additionally, this country has one of the most technologically advanced economies globally. The U.S. registered 285,113 patent applications in 2019, which was second only to China. In 2020, 19.5% of its manufactured exports corresponded to high-technology products, similar to countries like Japan (18.6%), Germany (15.5%), and the United Kingdom (22.9%). Aside from this, in 2018, it expended 2.8% of its Gross Domestic Product on Research and Development. Even when this percentage is inferior to other countries like Denmark (3.03%) and Germany (3.1%), it is still one of the highest registered in the world.

Our empirical model to test the relationship between cluster presence and resilience is drawn from Delgado and Porter (2021). They evaluate the role of strong clusters in the resilience of regional industry employment to the Great Recession. In their model, they represent strong clusters with a variable of *cluster specialization*, which they want to vary yearly to test precisely in which years cluster strength facilitates resilience. Consequently, they include the *cluster specialization* variable as an interaction term with the dummy of the years in the same way we introduce the *cluster presence* variable in our model. This interaction term allows them to evaluate in which precise year the presence of strong clusters benefits mostly the regional industries' employment. Results reveal that industries located within a strong cluster experienced relatively higher employment growth during the analysis period. What is more relevant is that such a positive effect is stronger in the year when the Great Recession started, 2008. On the other hand, industries located in weak clusters were more vulnerable to the Great Recession. The authors explain this effect by arguing that regions specialized in particular clusters enjoy agglomeration economies that could mitigate the impact of recessions and the resulting increase in uncertainty.

The empirical model of Delgado and Porter (2021) is the inspiration for our analysis, given the similarities between both studies. They evaluate the impact of clusters' strength on the resilience of regional industry employment; meanwhile, we analyze the effect of clusters' strength on the resilience of state employment. In other words, both aim to evaluate a strong cluster's presence on resilience but at a different aggregate level. They analyze their effect on industrial employment, and we assess their impact on state employment. Furthermore, we follow the same cluster classification for the U.S. industries as these authors. In fact, they designed this cluster definition (Delgado et al., 2016) for the U.S. cluster mapping project. This point has great implications because the results of our analysis will be of interest to the policymakers involved in this project. Additionally, both studies consider the Great Recession as the economic shock to evaluate resilience. For these reasons, in our analysis we decided to draw from the model of those authors and include the interaction term between cluster strength and year. This term will allow us to compare if the positive effect of strong clusters is more intense in the critical year of the Great Recession as in the referred work. In that case, cluster strength mitigates the effect of the economic shock not only at the industrial but at the state level.

$$\begin{aligned} Resilience_{rt} = \alpha + \beta_1 Year_t * Cluster\,presence_{r,t} + \\ \beta_2 X_{rt} + \mu_r + \varepsilon_{rt} \end{aligned} \tag{3.1}$$

The dependent variable is resilience in region r and year t (*Resilience*$_{r,t}$), where the spatial unit of analysis is the state. The main independent variable is an interaction term between the proxy for the cluster presence and each year. The coefficients of this interaction term will allow us to observe how the effect of the clusters' strength changes over the period. The cluster presence is proxied with three variables, each one tested in an individual regression. The first measure captures the strength of the regional cluster portfolio (*Portfolio*), measuring the share of payroll from traded clusters in every state that is accounted for by strong clusters. A second measure represents the overall cluster strength in a region based on four dimensions: size, specialization, productivity, and growth (*Hotspots*). The third measure represents whether the cluster portfolio in a region is biased toward clusters that tend to pay higher wages (*Mix*). All these variables account for agglomeration forces, and we have two expectations about their effect: 1) agglomeration economies within the cluster have a positive impact on regional resilience; 2) they propagate the negative impact of the economic shock more easily. The objective of this work is to verify which of these two forces predominates when explaining regional resilience. Apart from these variables, we also include a set of control variables that tend to be included in previous literature on regional resilience (X). Finally, our model includes a term for unobserved or omitted heterogeneity across regions that do not vary over time (μ_{r}) and the error time variant component ($\varepsilon_{\mathrm{r,t}}$).

Data description

The data comes from two sources. First, the U.S. Bureau of Labor Statistics provides information on the number of employees in each state for the period 2005-2015. Second, the County Business Patterns (CBP) supply the employment data at the industry level, which is coded into the Benchmark Cluster Definition (BCD) developed by Delgado et al. (2016). The BCD groups 778 traded industries (six-digit NAICS) into 51 mutually exclusive clusters. The BCD's algorithm generates clusters by using input-output links, labor occupation links, and inter-industry measures of co-location patterns of employment and the number of establishments. We can compare clusters across regions since they include the same industries across the regions. Table 3.6 in the appendix section provides a complete list of the clusters and the number of clusters that each one includes.

The 51 clusters we consider in this analysis are composed of traded industries exclusively. This kind of industry is geographically concentrated and produces goods and services sold across regions and countries (Delgado et al., 2016). The regions presenting stronger clusters benefit from the demand that traded clusters create for local industries (Porter, 2003). Due to their high competitiveness, these kinds of clusters generate 96.5% of the patents in the U.S.

Cluster analysis at the state level

We selected state as the geographic unit of analysis because it influenced the U.S. cluster development. The main duties of the federal government are to conduct monetary, trade, and regulatory policies and to support basic infrastructure. When the federal government supports industries, most of the time it is for industries related to defense and nation security technology projects, sponsored by the Department of Defense, Energy, and Homeland Security. Therefore, it is the commitment of the sub-national government, and mainly the states, to support industrial development mainly through innovation initiatives.

In recent decades, innovation initiatives have moved to the center of state and local efforts. Their actions are effective since they can control factors of production such as land use, infrastructure water, and waste disposal. However, the state has greater effectiveness than the local government in innovation. “In the United States, a number of academic studies have concluded that in the development of technology pioneering firms, state support has played a key role in pooling multiple external public and private funding sources, including federal funds and venture capital, and directing them to private firms (Wessner, 2013).” Every state supports a system of public universities with the largest proportion of their operating budgets, which allows the state to encourage them to align their priorities with local economic development. This action is essential because, over the last few decades, universities and their private counterparts have led the way in terms of innovation progress.

Therefore, the state government must support the development of all industries in general and, consequently, the development of clusters. “The states have been the primary movers in the widespread and growing practice of fostering innovation clusters as an economic development tool (Wessner, 2013)." We do not argue that local cluster analysis is unnecessary, but, given the organization of the U.S. government, state analysis is also an interesting level of analysis as the first step in a cluster policy design, given its key position interacting with the federal and local government.

Dependent variable

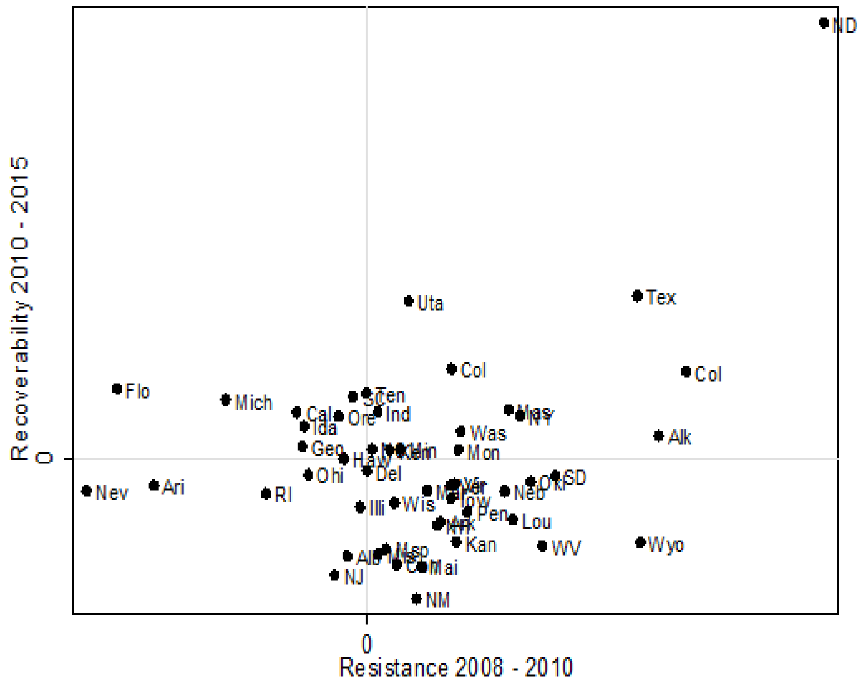
Literature does not show agreement on the best resilience measure due to the different perspectives on how to approach this concept (Martin and Sunley, 2015). We can classify the methods used to measure resilience into four main groups (Bristow and Healy, 2020): i) *the case study base* implies simple descriptive data and interviews with key actors (Evans and Karecha, 2014; Cowell, 2013; Lyon, 2014); ii) *the resilience indices* group the comparative measures of (relative) resistance and recovery (Martin, 2012; Augustine et al., 2013); iii) *the statistical time series models* estimate how long it takes for the impact of a shock to dissipate (Fingleton et al., 2012); iv) and *the* *causal structural models* embedding resilience in regional economic models try to estimate where the economy would have been in the absence of the downturn (Doran and Fingleton, 2018; Sensier et al., 2016). As we can see, these methods to measure resilience range from descriptive interpretation to sophisticated models, and each one has its merits and limitations.

The convenience of using one of these measures or another depends on the objective of the analysis. In our case, we need a measure that corresponds to the *resilience indices group* because we pretend to compare resilience among the states. We do not aim to analyze the case of a natural disaster for a specific region, a localized financial crisis, or the collapse of a local major employer. The Great Recession was a common shock that impacted all regions. Therefore, we need a relative rather than an absolute measure of resilience to compare different regions' behavior. In this sense, the index developed by Lagravinese (2015) to compare resilience for the major UK regions is the mostly followed by other authors. Cainelli et al. (2019a) implement this index to compare the resilience of Italian regions, while Giannakis and Bruggeman (2017) and Rios and Gianmoena (2020) use it to compare the resilience of European regions during the Great Recession. Such resilience index is specified as follows:

$$Resilience_{rt} = \frac{\left(\frac{E_{rt} - E_{rt-1}}{E_{rt-1}}\right) - \left(\frac{\sum_{r=1}^{s} E_{rt} - \sum_{r=1}^{s} E_{rt-1}}{\sum_{r=1}^{s} E_{rt-1}}\right)}{\left|\frac{\sum_{r=1}^{s} E_{rt} - \sum_{r=1}^{s} E_{rt-1}}{\sum_{r=1}^{s} E_{rt-1}}\right|} \tag{3.2}$$

Where E_r represents employment in region r and s is the total number of regions. In this case the regions are the states. As we can see, this measure corresponds to the growth rate of employment for a specific region standardized by the growth rate in other regions. If the region experiences a larger proportional fall in employment than the national economy, it indicates the region has a relatively low resistance to the economic shock ($Resilience_{rt}$ < 0). In the opposite case, when the region shows a lower proportional fall in employment than the national economy, the region is relatively more resilient than its counterparts ($Resilience_{rt}$ > 0).

Figure 3.10: Regional Resilience
(Average resilience by periods)



The reason for measuring resilience based on employment instead of production output is that the cyclical movements in employment tend to be more pronounced than those in production (Martin et al., 2016). When an economic shock strikes the economy, a region's workforce bears the brunt of adjustment in recessionary contractions. Even when the demand for the region's products and services begin to recover, the workers laid off during a recession cannot be hired again. Some of them are forced to find jobs in other regions or simply drop out of the labor force. Employment better reflects the social impact of a recession (Fratesi and Rodríguez-Pose, 2016).

Figure 3.10 provides a general view of the resilience variable that we measure for the U.S. states, similarly to the charts that Martin et al. (2016) elaborate on for this resilience measure. The x axis shows the average for the resilience measure in the period 2008-2010, which is called the resistance period. Meanwhile, the y axis presents the resilience average for 2010–2015, which is identified as the recoverability stage. We follow these periods similar to Martin et al. (2016), who analyze how employment in the major UK regions reacted to the four major recessions of the last 40 years, including the Great Recession. Besides, the unemployment change in the U.S. supports this delimitation for each period. In figure 3.9, the abrupt unemployment increment in 2008 is clearly visible and continues into 2009. In 2010, some ups and downs in unemployment took place. Until 2011, we can observe a significant downward trend in the unemployment rate.

Figure 3.10 reveals a number of features. The most obvious is that the resilience in North Dakota is much superior to the rest of the regions. This exceptional employment recovery is due to the extraordinary development of the oil and gas industry. Then, North Dakota is an outlier in regional and national trends, which we drop from our analysis. Apart from this outlier, the axes of this graph delimit four groups. In the first quadrant, we can find the states that show high resistance when the downturn strikes the economy and high recoverability in later year. Some of the states that belong to this privileged group are Texas, Colorado, and Utah. On the opposite side (third quadrant), the states with low resistance and low recoverability including Nevada, Arizona, and Rhode Island can be found. In the intermediate position are the groups of states that show low resistance but high recoverability (second quadrant) such as Florida, Michigan, and California, or high resistance but low recoverability (fourth quadrant) like West Virginia, Wyoming, and Louisiana. To sum up, this graphic brings a general view of the resilience in the U.S. states, explained by their resistance and recoverability.

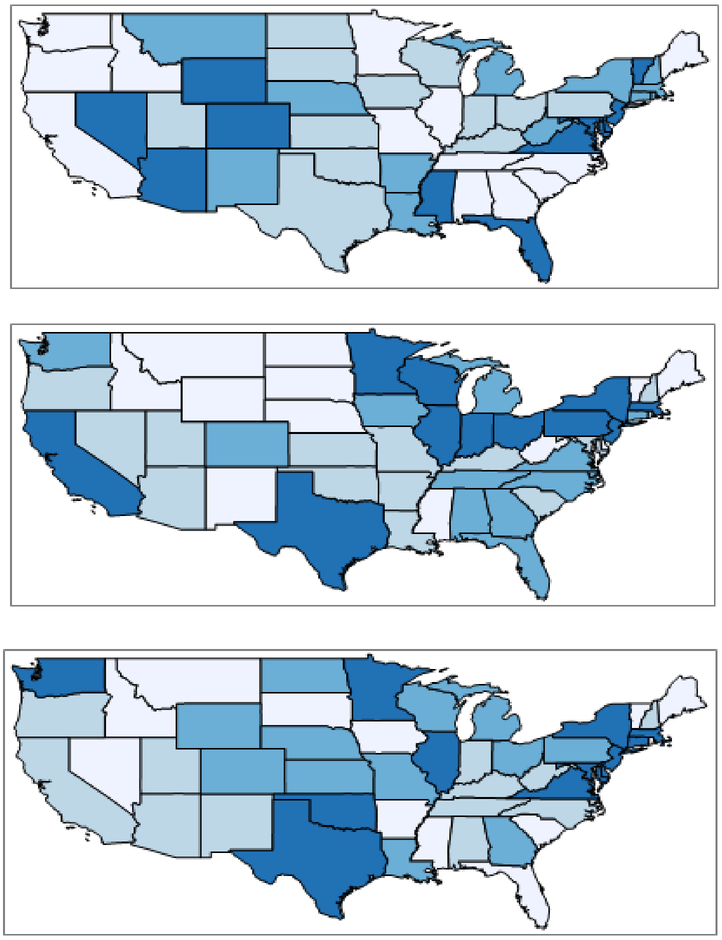
Key Independent variables

We proxy the main independent variables with three different indicators of clusters' strength in the region:

• *Portfolio strength.* This variable represents the strength of the regional cluster portfolio, and for its construction, we follow Ketels and Protsiv (2020). First, we identify strong clusters in each region, which correspond to the top 20% ranked by a Location Quotient (LQ) of employment [3]. Afterwards, as a second condition, these top clusters should also be in the

[3] LQ = (e_c/e) / (E_c/ E) Where e $_c$ is the employment in the cluster c in region r; e is the regional employment; E_c is the national employment in cluster c; E is the national employment

Figure 3.11: Indicators of cluster strength



Note: Indicators of cluster strength: (top) cluster portfolio strength (share of payroll accounted by strong clusters) across the U.S. regions; (medium) cluster hotspots (overall clusters' strength in the region) across the U.S. regions; and (bottom) cluster mix (bias towards cluster categories with higher wages) across the U.S. regions. Colours refer to quartiles of the corresponding variables such that darker colours indicate higher values.

top 80% of all clusters ranked by employment, with the objective of avoiding very small clusters. Finally, the Portfolio strength is the share of employment from traded clusters in every region accounted for strong clusters [4]. Figure 3.11 (top) shows the portfolio variable's average for the period 2006-2015. Some of the states with the strongest cluster portfolio are Florida, New York, New Jersey, and Arizona. Their cluster portfolio contributes the highest proportion to the total number of traded cluster employees.

. *Hotspots.* This variable captures overall clusters' strength in the region and is obtained from the Cluster Observatory by the European Cluster Collaboration Platform [5] To compute it, we assign one star to those clusters that are in the top 20% along each of the four dimensions at the national level: size (total number of employees), specialization (location quotient applied to employment), productivity (wages and salaries per worker as a proxy), and growth (growth rate in the number of employees). Therefore, the hotspot variable is the total number of stars in a region. Figure 3.11 (medium) shows the average of the Hotspots variable across the US states in the period of our analysis. Compared to the portfolio indicator, this variable takes into account a broader cluster measure considering different strength indicators. Some of the states with the highest values are California, Texas, Pennsylvania, and New York.

• *Mix variable.* This variable represents whether the cluster portfolio is biased toward clusters that tend to pay higher wages across regions, following Ketels and Protsiv (2020). When we observe clusters with high wages, it is not evident if this variation corresponds to productivity differences or that clusters tend to be located in regions that pay higher salaries. To clarify this effect, we regress the log of wages for regional industries on industry and region fixed effects [6]. Then, we take the beta coefficient of each industry as an indicator of how "well-paid" the workers are. Later, we get the cluster Mix variable by weighing the industry-specific wage by the number of employees in each region [7]. We must remember that we are working with the industries

[4]Cluster Portfolio = (Employment from strong clusters) / (Employment in all clusters in the region)

[5]https://www.clustercollaboration.eu/cluster-mapping

[6]Log wages = $\beta_i + \alpha_r + u_{irt}$ where wage is approximate by the payroll divided by the number of employees

[7]Mix cluster = ($\sum \beta_i * L_{ir}$) / $\sum L_{ir}$ where L_{ir} is the number of employees in industry i in region r

that belong to the region's cluster portfolio. Thus, high values of this variable indicate that the state is relatively more specialized in clusters that pay high wages, which as shown in Figure 3.11 (bottom), correspond to Texas, New York, Minnesota, Illinois, Massachusetts, and New Jersey. These states not only have strong clusters, but they also pay the highest wages across the regions. Table 3.7 in the appendix section shows the descriptive statistics of the key variables for this analysis.

Control variables

In addition to the variables that proxy for clusters' strength in the region, we also include some variables usually included in regional resilience analyses. Eraydin (2016) classified these determinants into four categories: vulnerability, resources, adaptive capacity, and policies/measures of support. The vulnerability to economic shocks is proxied by exports per capita and consumer credit per capita. The first one evaluates the openness of a regional economy to external threats and global economic volatilities, while the second one measures the financial dependence of a region on financial markets. Within the resources category, we include a proxy for entrepreneurs and the infrastructure in the region, as these available resources should facilitate overcoming the downturn. Entrepreneurs are measured by the share of the population that starts a new business, and infrastructure is the percent share of roads that are in acceptable condition. The category of adaptive capacity is evaluated by innovation, which is determined as the number of patents per 1,000 inhabitants, and the startup early survival which is measured through the share of startups that are still active after one year. Finally, government policies and support are proxied with the amount of federal investment in research and development per capita, which are important resources to increase regional resilience. Table 3.8 in the Appendix section presents the descriptive statistics of these variables, and Table 3.9 provides the correlation matrix.

Results

Table 3.1 shows the results for each one of the variables proxying for the regional clusters' strength. We can observe that the Portfolio and Mix variables do not contribute to the resilience for the U.S. states in the period

2006–2015. On the other hand, the positive coefficient of the Hotspot variable on resilience is persistent with the inclusion of different control fixed effects. Unlike the Portfolio and Mix variables, the Hotspot captures the overall clusters' strength in the region and not just the clusters portfolios' strength. This reason can be behind the significant impact of this variable and not the others for the whole period under analysis.

Tables 3.2 to 3.4 show the results when we include the interaction term between the key variables for the regional clusters' strength and the year dummies. The inclusion of these terms will allow observing the precise year when the cluster strength impacts resilience. The first column in table 3.2 shows that a strong cluster Portfolio reduced regional resilience in 2008, which was the most struggling year for the Great Recession. However, the estimation of this coefficient does not consider the control variables described above (Eraydin, 2016). To reveal the proper coefficient, the last column in this table includes these other variables that the literature considers as determinants for resilience and control for a set of year*region fixed effects. These last results indicate that regions with strong cluster portfolios show higher resilience during the period 2006–2009. Agglomeration forces in strong clusters may be creating mechanisms that make them less vulnerable to downturns, as argued by Delgado and Porter (2021). Consequently, regions with strong cluster portfolios are expected to be associated with higher resilience. Specifically, as observed in our estimation, a strong cluster portfolio plays a more relevant role in the risk and resistance period, that is, a couple of years before the downturn hit the economy and during the years when it took place.

On the other hand, it seems that this relationship changes in later stages, with a strong cluster Portfolio showing a negative effect on resilience for the last year of our analysis (2015), which corresponds to the recovery period. This finding could be related to the fact that strong industrial linkages propagate the economic shock easily among the industries, an issue that was anticipated in the model by Acemoglu et al. (2013). Additionally, according to Diodato and Weterings (2015), once a downturn hits an economy, the recovery speed depends on how fast laid-off workers can be reabsorbed into the labor market. Since services have the highest skill-relatedness, regions specializing in services show higher resilience in the recoverability stage. We must remember that we are working with traded clusters composed mainly of manufacturing industries instead of services, which could be behind the negative coefficient observed in the recovery period.

Table 3.3 shows the positive impact the overall cluster strength has had on regional resilience from 2007 to 2015, pointing to the fact that such strength makes the regional economy less vulnerable to the four resilience stages: risk, resistance, reorientation, and recoverability. Our findings are similar to the ones by Cainelli et al. (2019a) for related variety showing that regions characterized by a higher level of related variety show a higher capacity to overcome economic downturns. Compared to the results for the Portfolio variable, the Hotspot does not present any negative effect on resilience during the recovery period. Even more, its positive impact persists for all the years after the great recession. However, we have to mention that the hotspot's positive influence varies between the resilience stages according to the fixed effect included in the model. First, hotspot increases the regional resilience for the risk and resistance period when we include the set of year*region fixed effects, which control change in resilience, derived from region-specific factors each year. Whereas hotspot is significant for the reorientation and recovery period, when we separately control for year and region-fixed effects.

Finally, table 3.4 shows that states with a cluster portfolio with high wages present less vulnerability in the Great Recession's first year. As expected, a regional cluster mix biased towards higher wages is associated with higher resilience, probably due to their higher productivity, which makes these regions specialized in highly productive activities more resilient to recessions (DiCaro, 2017). When we control for region and year fixed effects instead of the year*region set, the Mix variable has a positive effect on resilience, in contrast to the Portfolio. This fact demonstrates that, no matter the fixed effect that we include, regional cluster strength is critical for resilience in the most complicated year of this downturn.

All in all, our results point to the fact that the strength and composition of the clusters in a region are associated with its resilience. States in the US with stronger cluster portfolios and a cluster mix biased towards higher wage clusters tend to be more resilient, in the sense of having had a lower economic vulnerability in the Great Recession. Like Delgado and Porter (2021) argue, these variables show that the agglomeration forces that characterize strong clusters make the regions more resilient. Furthermore, regions with high overall cluster strength present lower vulnerability not just for the risk and resistance stages, but also during the reorientation and recoverability phases.

Our results are in line with those of Delgado and Porter (2021), whose analysis was the basic for developing our own model, as we explained in the empirical model section. Meanwhile they evaluate the role of strong clusters in the resilience of regional industry employment to the Great Recession, we assess the effect of strong clusters on the resilience of state employment. They found that industries within strong clusters experienced relatively higher employment growth during the analysis period. In other words, cluster strength makes industries less vulnerable to an economic shock. More importantly is the fact that cluster strength had a higher impact on industrial employment resilience in 2008, the year when the Great Recession hit the economy and the most critical drop in employment, as we describe in figure 3.9. The findings of this research ran along the same line as Portfolio and Hotspot, in the sense that the variables *Portfolio* and *Hotspot* showed that a strong cluster presence significantly increases the employment resilience in the state for the years around the Great Recession. In the same way, we can observe that this positive effect is higher for 2008. To sum up, these results suggest that cluster strength mitigates the impact of the economic shock both at the industrial and state levels.

Table 3.1: Dependent variable: regional resilience

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Cluster Strength												
Portfolio	-0.391	-0.794	0.589	0.599								
Hotspots					0.018	0.026**	0.026	0.026*				
Mix									-0.508	-0.467	-0.373	-0.409
Year Fixed Effects	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Year - Region Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.04	0.204	0.062	0.175	0.043	0.208	0.067	0.179	0.041	0.203	0.061	0.174
Obs.	500	500	500	500	500	500	500	500	500	500	500	500

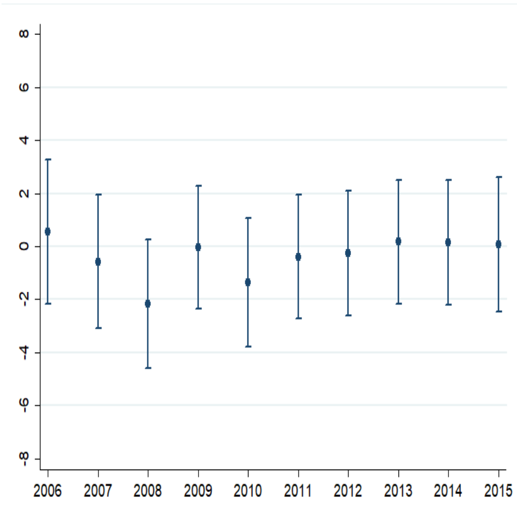
***p < 0.01, **p < 0.05, *p < 0.1

Table 3.2: The role of the strenght of the regional cluster portfolio on regional resilience

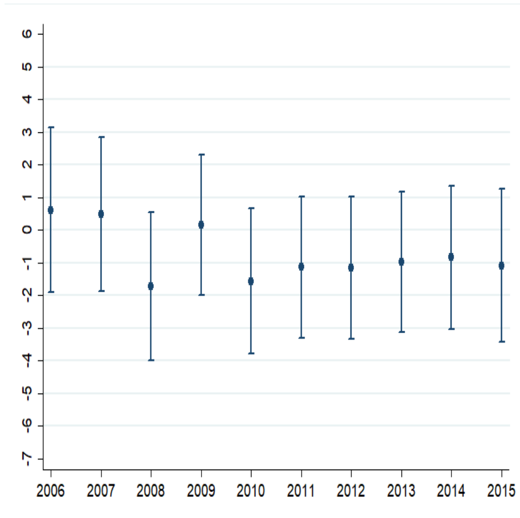
	Model 13	**Model 14**	**Model 15**	**Model 16**
Year2006*Portfolio$_t$	0.54	0.614	3.692*	5.800***
Year2007*Portfolio$_t$	-0.574	0.482	0.455	1.697*
Year2008*Portfolio$_t$	-2.169*	-1.714	1.304	2.365**
Year2009*Portfolio$_t$	-0.036	0.16	0.523	1.706*
Year2010*Portfolio$_t$	-1.365	-1.571	0.195	0.472
Year2011*Portfolio$_t$	-0.386	-1.141	-0.007	-0.504
Year2012*Portfolio$_t$	-0.252	-1.158	0.031	-0.816
Year2013*Portfolio$_t$	0.167	-0.969	0.03	-1.400
Year2014*Portfolio$_t$	0.149	-0.837	0.021	-1.599
Year2015*Portfolio$_t$	0.062	-1.084	-0.002	-1.657*
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year-Region Fixed Effects	No	No	Yes	Yes
R-squared	0.053	0.217	0.079	0.26
Obs.	500	500	500	500

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

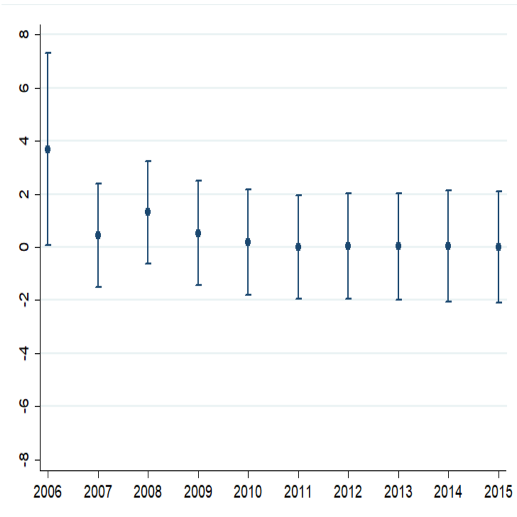
Figure 3.12: Estimated effect of regional cluster portfolio on regional resilience



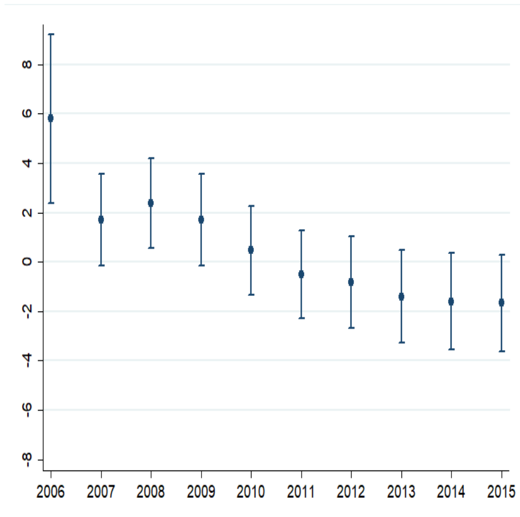
(a) Coef. Portfolio (Model 13)



(b) Coef. Portfolio (Model 14)



(c) Coef. Portfolio (Model 15)



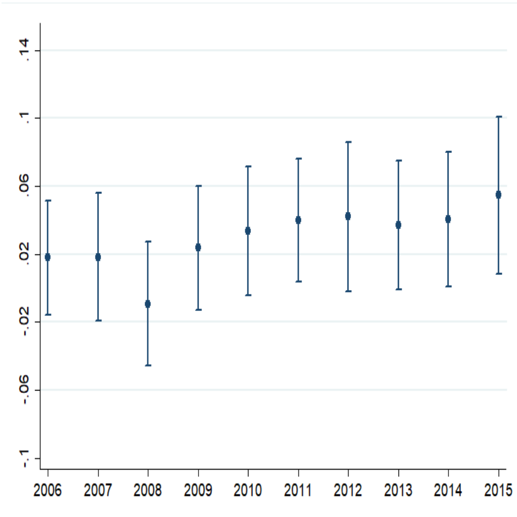
(d) Coef. Portfolio (Model 16)

Table 3.3: The role of the overall clusters strenght on regional resilience

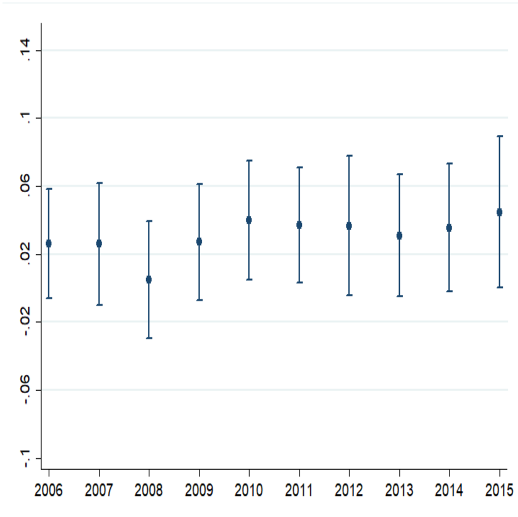
	Model 17	**Model 18**	**Model 19**	**Model 20**
Year2006*Hotspots$_t$	0.018	0.026	0.023	0.035
Year2007*Hotspots$_t$	0.018	0.026	0.021	0.033**
Year2008*Hotspots$_t$	-0.009	0.005	0.029*	0.042***
Year2009*Hotspots$_t$	0.024	0.027	0.020	0.035**
Year2010*Hotspots$_t$	0.033*	0.040**	0.021	0.025
Year2011*Hotspots$_t$	0.040**	0.037**	0.017	0.014
Year2012*Hotspots$_t$	0.042*	0.037*	0.018	0.010
Year2013*Hotspots$_t$	0.037*	0.031*	0.017	0.003
Year2014*Hotspots$_t$	0.040**	0.036*	0.017	0.002
Year2015*Hotspots$_t$	0.055**	0.045**	0.017	0.003
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year -Region Fixed Effects	No	No	Yes	Yes
R-squared	0.077	0.220	0.081	0.240
Obs.	500	500	500	500

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

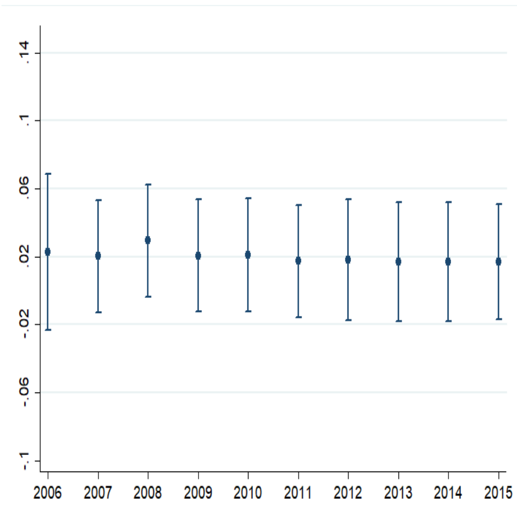
Figure 3.13: Estimated effect of overall cluster strenght on regional resilience



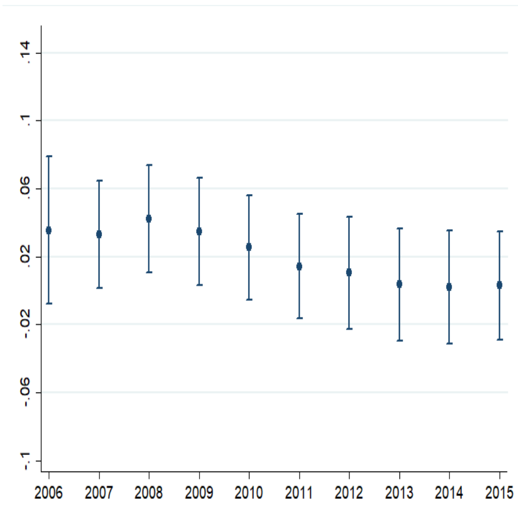
(a) Coef. Hotspots (Model 17)



(b) Coef. Hotspots (Model 18)



(c) Coef. Hotspots (Model 19)



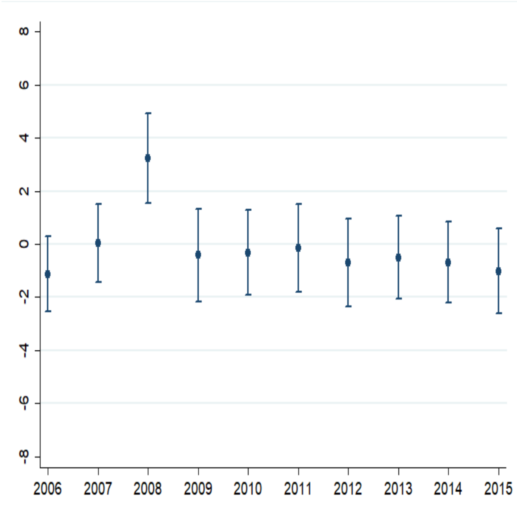
(d) Coef. Hotspots (Model 20)

Table 3.4: The role of the strenght of clusters with high wages on regional resilience

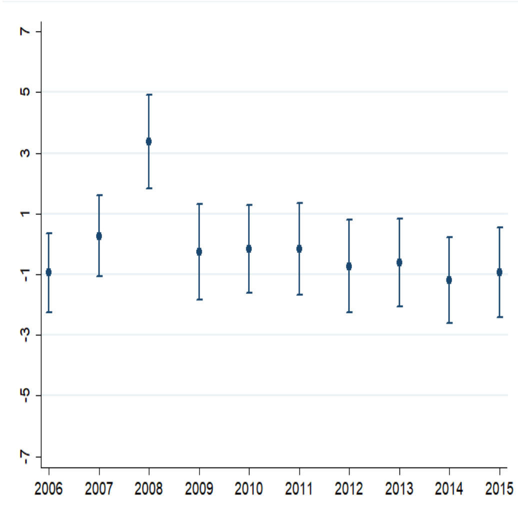
	Model 21	**Model 22**	**Model 23**	**Model 24**
Year2006*Mix$_t$	-1.13	-0.946	-1.19	-0.634
Year2007*Mix$_t$	0.028	0.268	-0.260	-0.511
Year2008*Mix$_t$	3.239***	3.383***	1.544	1.493
Year2009*Mix$_t$	-0.413	-0.258	-0.689	-1.078
Year2010*Mix$_t$	-0.326	-0.172	-0.542	-0.963
Year2011*Mix$_t$	-0.157	-0.168	-0.166	-0.117
Year2012*Mix$_t$	-0.704	-0.726	-0.631	-0.467
Year2013*Mix$_t$	-0.500	-0.618	-0.358	-0.186
Year2014*Mix$_t$	-0.687	-1.183	-0.555	-0.556
Year2015*Mix$_t$	-1.016	-0.931	-0.893	-0.394
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year -Region Fixed Effects	No	No	Yes	Yes
R-squared	0.114	0.282	0.087	0.201
Obs.	500	500	500	500

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

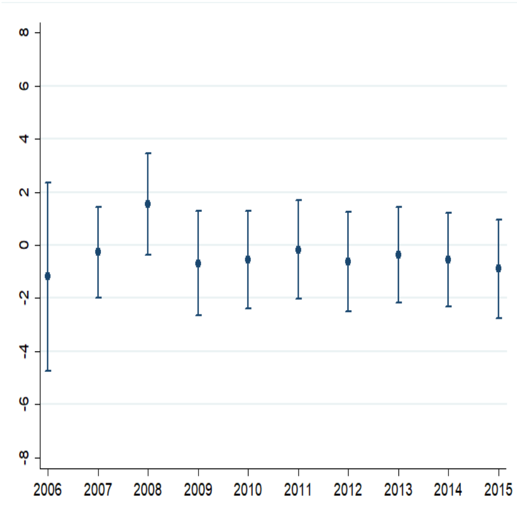
Figure 3.14: Estimated effect of clusters with high wages on regional resilience



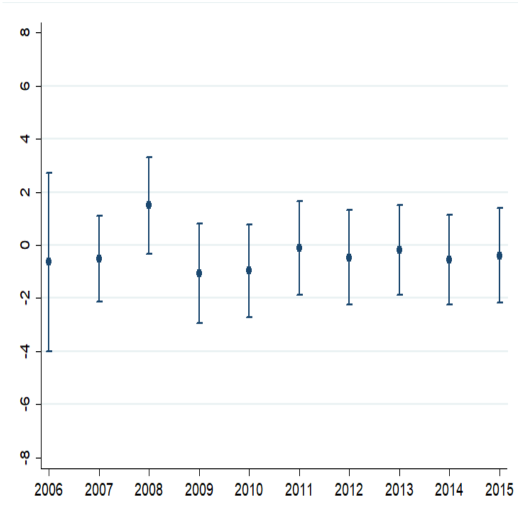
(a) Coef. Mix (Model 21)



(b) Coef. Mix (Model 22)



(c) Coef. Mix (Model 23)



(d) Coef. Mix (Model 24)

Conclusion

This research aimed to provide empirical evidence in the role of regional cluster strength on the resilience of the US states during the Great Recession. Our findings confirm the expected hypothesis that regions with strong cluster portfolios and with a regional cluster mix biased towards higher wage clusters are associated with greater resilience during the years of this downturn. These findings imply that the agglomeration forces within a cluster made its industries less vulnerable to the economic shock. Furthermore, regional clusters' strength contributes to regional resilience in the years after the economic shock occurs, that is, the reorientation and recoverability stages of resilience. These results support the strength of regional clusters as a crucial element in the whole process of resilience of regions confronting an economic shock.

An intriguing finding is that, while the various proxies we use to measure the presence of strong clusters in a regional economy, as well as the mix of clusters in which the region has a robust importance, all contribute to less regional vulnerability during economic shocks, only overall cluster strength (Hotspot variable) is significant for the years following the Great Recession. As argued by Boschma (2015), the resilience process implies adaptation, which concerns changes within preconceived paths, and adaptability, which is about developing new pathways from existing ones. Diversified regions should present better adaptability performance since they have more potential to make new recombination across local industries to develop new growth paths (Jacob's externalities). And adaptability is characterized as a long-term process because it requires the recombination of industries that may have low cognitive complementarity. This way, high values of the overall strength of all clusters in a region (hotspot variable) and not just the strength of a select group of these clusters (portfolio) would contribute to the adaptability process, explaining the significant impact of this variable in the long term. At the same time, this argument could justify the portfolio's negative effect in the recoverability period since the specialization in a few clusters does not allow for increased adaptability. To sum up, a strong cluster portfolio influences the regional adaptation and the overall cluster strength's impact on the adaptability process.

These findings are relevant for policy-makers. The development of a cluster portfolio turned out to be beneficial not only for the economic prosperity of the regions (as obtained in Ketels and Protsiv 2020), but also for their resilience. When an economic shock strikes the economy, the agglomeration forces built within the strong clusters help mitigate the adverse effects of the downturn. Therefore, providing incentives to develop strong cluster portfolios in regions can be considered as a mechanism to overcome a potential future economic shock. Indeed, during the last decade, some governments have prioritized the development of cluster portfolios in their territory. The findings in this paper give additional arguments to continue with their efforts.

The findings from this work have direct implications for the U.S. cluster policy. Earlier, we explained that the cluster classification followed in this work belongs to the U.S. Cluster Mapping Project, a national initiative financed by the U.S. Economic Development Administration and led by Harvard Business School's Institute of Strategy and Competitiveness. In this project, the government and academia join efforts to reinforce the cluster's development in the country, providing an official cluster registration to be consulted by policymakers, business people, and researchers. As a result, all the efforts to contribute to the cluster's growth lead in the same direction. This project has registered 126 cluster organizations and initiatives that have used the provided data.

As we mentioned above, apart from providing official cluster data, the cluster mapping project aims to be a platform where policymakers, business people, and researchers can share their successful experiences with the cluster data. In fact, above we referred to a couple of those successful experiences with cluster analysis at the state level. Therefore, the finding of this study can be of high interest to the participants in this initiative who are familiar with this cluster classification.

Our findings are helpful for cluster policy at the state level. As described above, the state has a privileged position in leading cluster policy in the U.S. It has an intermediate role between the federal and lower levels of government. It manages most of the funding for innovation and research, which are crucial elements for cluster development. "The states have been the primary movers in this widespread and growing practice of fostering innovation clusters as an economic development tool" (Wessner, 2013). Many cluster initiatives have been launched through the U.S. cluster mapping project and can be easily enriched with these findings since we implement the same cluster classification.

Our study can take some future directions for a more in-depth analysis on this topic. While we focus our study on the Great Recession years, these estimations should be tested for other economic shocks like the COVID-19 crisis. Also, it would be desirable to carry out these estimations at a more disaggregated analysis level such as the county. It is possible to build the clusters at this level since the Country Business Patterns provide the industrial information at the six-digit NAICS code.

Acknowledgements
The authors would like to thank Dr. Rich Bryden of the ISC-Harvard, Dr. Pablo Nuño of Sintonía-UPAEP, Dr. Herberto Rodríguez of CIIE-UPAEP, and Dr. Alfonso Mendoza of CIIE-UPAEP, for the access to the database for the Cluster Mapping Project in Mexico, which was one of the references in the construction of the data base for the U.S. Financial support for this research was provided by CONACYT and UPAEP University, Mexico.

Appendix

Table 3.5: Cluster Organizations and Initiatives

No.	Cluster organization or initiative	Primary activity
1	Cluster for Unmanned Vehicles and Robotics	Technology R& D
2	Advanced Cyber Security Center	N.A.
3	The Berkeley Startup Cluster	Networking
4	Wisconsin Wind Works	Initiative management
5	Creative Alliance Milwaukee	Regional Promotion
6	Advanced Manufacturing in Thermal and Environmental Controls	Business development
7	Agile Innovation in Manufacturing	Technology R&D
8	Interoperability & Integration Innovation Lab (I3L)	Networking
9	Roane State Community College	Training and education
10	InnoState Regional	Promotion
11	Advanced Manufacturing Institute	Business development
12	Mi-Light	Networking
13	LAEDC Cleantech Cluster Project	Regional Promotion
14	Enterprise for Innovative Geospatial Solutions	Regional promotion
15	Northeast Electrochemical Energy Storage	Cluster Networking
16	Mass Technology Leadership Council, Inc.	Networking
17	NorTech	Initiative management
18	EngenuitySC	Regional promotion
19	Oregon Business Council	Public policy advocacy
20	The Water Council	Initiative management
21	Nashville Health Care Council	Networking
22	Consortium for Building Energy Innovation	Regional promotion
23	MAGNET	Regional promotion
24	Confluence Water Technology Innovation Cluster	Regional promotion
25	Finger Lakes Food Processing Cluster Initiative	Regional promotion
26	LifeScience Alley	Business development
27	BioBusiness Alliance of Minnesota	Business development
28	Upper Michigan Green Aviation Coalition	Business development
29	Maine Food Producers Alliance	Regional promotion
30	Massachusetts High Technology Council	N.A.
31	NECEC Institute	Business development
32	New England Clean Energy Council	Networking
33	Massachusetts Biotechnology Council	Regional promotion
34	Colorado Space Coalition	Networking
35	massPLASTICS Medical Device Connection	Networking
36	Massachusetts Medical Device Industry Council	Networking
37	Massachusetts Life Sciences Center	Business development
38	Network for Excellence in Health Innovation	Networking
39	Colorado Clean Energy Cluster	N.A.
40	San Diego Advanced Defense Technology Cluster	N.A.

SOURCE: *Own elaboration with data from Harvard Business School (2020)*

Continuation: Cluster Organizations and Initiatives

No.	Cluster organization or initiative	Primary activity
41	Center for Commercialization of Advanced Technology San Diego	Technology R&D
42	OSTIM Medical Industry Cluster	N.A.
43	Huntsville Advance Defense Technology Cluster Initiative	Business development
44	Ketchikan Marine Industry Council	Business development
45	Space Coast Energy Consortium	Networking
46	Food Resource and Agribusiness Network	Regional promotion
47	MiKE - Innovation in Milwaukee	Business development
48	Greater Waco Aviation Alliance	Networking
49	Milwaukee Water Council	Networking
50	San Diego Film Commission	Regional promotion
51	Columbia River Gorge Technology Alliance	Networking
52	Carolinas MicroOptics Triangle	N.A.
53	Washington Technology Industry Association	Public policy advocacy
54	Washington Clean Technology Alliance	Initiative management
55	Vermont Cheese Council	Networking
56	The Solar Energy Consortium	Business development
57	The Hosiery Association	N.A.
58	Technology and Education Center for Renewable Energy	Networking
59	Supplier Excellence Alliance	Networking
60	Technology Association of Oregon	Networking
61	South Carolina Council on Competitiveness	Economic analysis
62	Software San Diego	Networking
63	Professional Aerospace Contractors Association	Networking
64	Portland Development Commission - Green Development	Networking
65	Pacific Northwest Defense Coalition	Networking
66	Oregon Tourism & Hospitality Industry Consortium	Regional promotion
67	Oregon Solar Energy Industries Association	Networking
68	Oregon Manufacturing Extension Partnership	Networking
69	Oregon Creative Industries	Networking
70	Oregon Association of Nurseries	Networking
71	Ohio Aerospace Institute	Networking
72	Northwest Environmental Business Council	Networking
73	Northwest North Carolina Advanced Materials Cluster	Networking
74	Northwest Education Cluster	Networking
75	Monterey County Tourism Cluster	Regional promotion
76	North Carolina Biotechnology Center	Networking
77	New Mexico Optics Industry Association	Networking
78	New York Photonics	Networking
79	New York Battery and Energy Storage Technology Consortium, Inc	Networking
80	Nevada Institute for Renewable Energy Commercialization	Networking
81	New Mexico Book Association	Networking
82	National Center for Simulations	Networking
83	Mid-Oregon Production Arts Network	Regional promotion
84	MdBio Division of Tech Council of Maryland	Networking
85	Massachusetts Technology Collaborative	Initiative management
86	ITFlorida	N.A.
87	International Association of Nanotechnology	Networking
88	Illinois Science and Technology Coalition	Networking
89	Florida Photonics Cluster	Networking
90	Florida Medical Manufacturers Consortium	Networking

SOURCE: *Own elaboration with data from Harvard Business School (2020)*

Continuation: Cluster Organizations and Initiatives

No.	Cluster organization or initiative	Primary activity
91	Florida High Tech Corridor	Regional promotion
92	Florida Biomedical Society	Regional promotion
93	Florida Aviation Aerospace Alliance	Regional promotion
94	Environmental Technology Industry Cluster	Business development
95	Connecticut United for Research Excellence, Inc.	Regional promotion
96	Connecticut Tourism Division	Regional promotion
97	Colorado Photonics Industry Association	Networking
98	Citizens for Sound Conservation Business development	N.A.
99	Catskill WoodNet	Networking
100	BioFlorida	Business development
101	BIOCOM	Business development
102	Automation Alley	Business development
103	Arizona Bioindustry Association	Business development
104	Agri-Business Council of Oregon	Business development
105	China Partnership of Greater Philadelphia	International trade promotion
106	Minnesota Forest Industries	Regional promotion
107	Wisconsin Energy Research Consortium	Regional promotion
108	Communications and Information Technology of Mississippi	Networking Regional promotion
109	Puerto Rico Construction Cluster	Networking
110	Advanced Materials Processing and Analysis Center	Technology R&D
111	New Mexico Biotechnology and Biomedical Association	Networking
112	Space Florida	Business development
113	CleanTECH San Diego	Business development
114	Connecticut Maritime Coalition	Regional promotion
115	Next Energy	Networking
116	Monterey Bay Higher Education & Research	Networking
117	Monterey County Agricultural Cluster	Networking
118	Connecticut Technology Council	Regional promotion
119	Northwest Food Processors Association	Networking
120	Oregon Bioscience Association	Networking
121	Commonwealth Center for Advanced Manufacturing	Regional promotion
122	Colorado Association For Manufacturing And Technology	Networking
123	Aerospace Components Manufacturers	Networking
124	Intermountain Roundwood Association	Regional promotion
125	CALSTART	Business development
126	Arizona Optics Industry Association	Networking

SOURCE: *Own elaboration with data from Harvard Business School (2020)*

Table 3.6: List of traded clusters

Cluster code	**Cluster name**	**Number of industries**
1	Aerospace Vehicles and Defense	7
2	Agricultural Inputs and Services	9
3	Apparel	21
4	Automotive	26
5	Biopharmaceuticals	4
6	Business Services	33
7	Coal Mining	4
8	Communications Equipment and Services	8
9	Construction Products and Services	20
10	Distribution and Electronic Commerce	62
11	Downstream Chemical Products	13
12	Downstream Metal Products	16
13	Education and Knowledge Creation	15
14	Electric Power Generation and Transmission	5
15	Environmental Services	7
16	Financial Services	26
17	Fishing and Fishing Products	5
18	Food Processing and Manufacturing	47
19	Footwear	6
20	Forestry	4
21	Furniture	12
22	Hospitality and Tourism	31
23	Information Technology and Analytical Instruments	27
24	Insurance Services	8
25	Jewelry and Precious Metals	4
26	Leather and Related Products	6
27	Lighting and Electrical Equipment	15
28	Livestock Processing	5
29	Marketing, Design, and Publishing	22
30	Medical Devices	5
31	Metal Mining	8
32	Metalworking Technology	17
33	Music and Sound Recording	5
34	Nonmetal Mining	13
35	Oil and Gas Production and Transportation	12
36	Paper and Packaging	20
37	Performing Arts	8
38	Plastics	15
39	Printing Services	13
40	Production Technology and Heavy Machinery	41
41	Recreational and Small Electric Goods	15
42	Textile Manufacturing	23
43	Tobacco	3
44	Trailers, Motor Homes, and Appliances	9
45	Transportation and Logistics	17
46	Upstream Chemical Products	12
47	Upstream Metal Manufacturing	26
48	Video Production and Distribution	6
49	Vulcanized and Fired Materials	17
50	Water Transportation	12
51	Wood Products	13

SOURCE: *Own elaboration with data from Delgado et al. (2016)*

Table 3.7: Definition and Descriptive Statistics of the variables

Variable	Definition	Source	Min	Max	Mean	SD
Resilience	Employment resilience in the state	Own elaboration with data from the U.S. Bureau of labor statistics.	-5.497	6.814	0.087	1.018
Portfolio	Strength of the regional cluster portfolio	Own elaboration with data from the County Business Patterns(CBP)	0.058	0.853	0.323	0.177
Hotspots	Overall cluster strength in a region	Own elaboration with data from the County Business Patterns(CBP)	10.000	76.000	33.027	12.285
Mix	Cluster portfolio biased toward clusters that tend to pay higher wages across regions	Own elaboration with data from the County Business Patterns(CBP)	-0.754	0.577	-0.100	0.257

Table 3.8: Descriptive Statistics of Control Variables

Attributes	Definition	Variables	Source	Minimum	Maximum	Mean	SD
Vulnerability	Exports	Export per capita (US$)*	U.S. Census	182.34	5,978.48	1,615.92	902.82
	Debt	Consumer credit per capita (US$)*	Federal Reserve Bank of New York	9,462.40	41,456.80	20,228.59	5,874.73
Resources	Entrepreneurs	Percent of population that starts a new business	Kauffman indicators of entrepreneurship	0.151	0.603	0.303	0.076
	Infrastructure	Porcentage of road in acceptable conditions	Bureau of Economic Analysis	0.030	1.000	0.806	0.159
Adaptive capacity	Innovativeness	Number of patents per 1,000 inhabitants	United States Patent and Trademark Office	0.000	1.132	0.257	0.221
	Startup Early Survival	Percent of startups that are still active after one year	Kauffman indicators of entrepreneurship	66.99	91.58	78.30	2.68
Policies and measures of support	Investment in R&D	Federal investment in Research and Development per capita (US$)*	National Center for Science and Engineering Statistics	0.035	32.197	0.545	1.619

*Variables in constant (real) dollars

Table 3.9: Correlation Matrix (N=510)

Variable	**Cluster Strength Portfolio**	**Cluster Stars**	**Cluster Mix**	**Exports per capita**	**R&D per capita**	**Road**	**Patent**	**Debt**	**RNE**	**SSR**
Cluster Strength Portfolio	1.000									
Cluster stars	-0.327	1.000								
Cluster Mix	-0.092	0.295	1.000							
Exports per capita	-0.211	0.248	0.395	1.000						
R&D per capita	0.163	-0.125	0.000	-0.125	1.000					
Road	-0.147	0.073	-0.004	0.092	-0.522	1.000				
Patent	-0.067	0.313	0.120	0.285	-0.040	-0.081	1.000			
Debt	0.360	0.151	0.111	-0.103	0.362	-0.395	0.351	1.000		
RNE	0.146	-0.179	-0.145	-0.033	0.005	0.107	0.008	0.080	1.000	
SSR	-0.160	0.156	0.022	0.001	-0.114	-0.012	0.123	-0.163	-0.107	1.000

4 Cluster composition and regional resilience: The case of the U.S. in the Great Recession [§]

Introduction

Resilience has become one of the most crucial topics in regional literature. The interest in this topic gained a special momentum after the Great Recession, when a heterogeneous economic recovery was observed among regions. This downturn made it evident that regions have different capacities to overcome economic shocks, and it is necessary to find the mechanisms that explain such a process (Martin and Sunley, 2015). Recently, the enthusiasm for this topic has gained a higher proportion with the COVID-19 crisis. Regions around the world have been seriously affected by the consequences that this pandemic has had on economic activity. More than ever, it is necessary to figure out the mechanisms that increase the regional ability to overcome economic shocks.

Literature on this topic presents three main definitions of resilience. Firstly, the ecological approach, which assumes that the regional economy will reach a new steady–state while maintaining its structure, identity or function (Holling, 1973; Reggiani et al., 2002). Secondly, from the engineering perspective, resilience is the region's capacity to return to a persistent steady-state equilibrium after a shock (Fingleton et al., 2012; Pimm, 1984; Rose, 2004). Finally, the evolutionary approach defines resilience as the ability to adapt in the short run or to develop new growth paths in the long run (Martin, 2012; Boschma, 2015). For this last definition, we must consider resilience as a process of stages, as Martin et al. (2016) describe: risk, resistance, reorientation, and recoverability. In terms of the evolutionary

[§] The paper in this chapter is coauthored with Rosina Moreno Serrano definition, the resistance and recoverability phases are of particular interest because it is in these stages that adaptation take place in the short run and new growth paths take place, respectively. Literature related to the evolutionary definition deems industrial composition as one of the main determinants of a region's capacity to react positively to economic shocks (Boschma, 2015; Breathnach et al., 2015; Martin and Sunley, 2015; Eraydin, 2016; Nyström, 2018; Cainelli et al., 2019a).

The discussion on industrial composition goes around the issue of whether industrial specialization (when few sectors account for a relatively large share of the region's GDP or employment) or industrial diversity (each of a wide range of industries accounts for a relatively small share of it) enhance regional resilience (Martin and Sunley, 2015). On one hand, regions specialized in highly productive activities have been found to be more resilient to recessions (DiCaro, 2015) because specialization is associated with productivity growth (Van Oort et al., 2015). However, if the economic shock affects particularly the industries in which the regions are specialized, the sectoral linkages and interrelatedness among them may increase the diffusion of the shock from one sector to the rest. In this sense, Brown and Greenbaum (2017) find that more concentrated industry structures face a greater risk of economic growth subsequent to experiencing economic shocks. On the other hand, diversity can benefit regional resilience in the short and long term. In the short term, industrial diversity can spread the risk when a specific sector is affected by an economic shock (Boschma, 2015; Brown and Greenbaum, 2017; Crescenzi et al., 2016). In this line, DiCaro (2017) provides evidence that the most resilient Italian regions have the highest level of industrial diversification. In the long term, sectoral heterogeneity generates externalities à la Jacobs (1961, 1969) that influence the regional capacity for adaptive resilience (Martin, 2012; Martin and Sunley, 2015). In other words, knowledge spillovers between different industries create innovation that benefits resilience.

On the issue of diversification, one step forward is the one given by Frenken et al. (2007), who consider that a key point is the degree of diversification or variety. They define "related variety" as the presence of a variety of industries within a region that are cognitively related, and "unrelated variety" as the existence of a variety of industries that do not share complementary competencies. In this sense, the question is which kind of diversity has a higher impact on resilience: a group of diversified industries with certain cognitive proximity between them, or a group without any proximity. According to some empirical works, these concepts are determinants of regional resilience (Holm and Østergaard, 2015; Sedita et al., 2017; Cainelli et al., 2019b).

This paper contributes to the discussion of industrial composition as a determinant of resilience by analyzing cluster composition. A cluster is a geographically proximate group of interconnected companies, suppliers, service providers, and associated institutions in a particular field, linked by externalities of various types (Porter, 2012). For instance, the automotive cluster is composed of 26 industries like motor vehicle body manufacturing, light truck and utility manufacturing, gasoline engine manufacturing, etc. Consequently, clusters represent an aggregate level to organize and analyze the industries in a region. Recent evidence shows that cluster presence in a region matters for economic performance (Ketels and Protsiv, 2020). This finding leads to the issue of the role of clusters' presence in a region on regional resilience. Reminiscent of the industry level analysis, we question whether it is cluster specialization or cluster diversity that matters for resilience.

To be more precise, we refer to "cluster diversity" as the presence of many clusters similar in size, which implies the region is not only dominated by a few clusters. The cognitive proximity among the industries inside a cluster (related variety) is evident, but this relationship is weak between clusters. However, it does not imply that they never collaborate. Clusters can work together to create revolutionary technologies, but the lack of cognitive proximity complicates this process making it risky and implying high switching cost. This concept resembles the one driving the innovation process in industries characterized by unrelated variety. Therefore, we proximate a high degree of cluster diversity with the concept of unrelated variety.

Similarly, we refer to "cluster specialization" as the strength of the related industries inside a cluster, not the specialization of a narrowly defined single industry. Such strength can be proxied by quantifying how concentrated that cluster is in the region as compared to the nation. Since industries inside a cluster are connected by linkages of skilled workers, supply, and technology, these factors imply a cognitive proximity among them, facilitating the creation of new processes and new products. In this sense, cluster strength would be conceptually similar to the notion of "related variety" developed by Frenken et al. (2007).

Given the similitude between these concepts, we formulate our hypotheses for clusters following the evidence for related and unrelated variety on resilience. Evidence shows that related and unrelated variety have different impacts on resilience according to the knowledge-based in the region (Sedita et al., 2017). Therefore, we consider this matter to set the following six hypotheses that we describe in detail in the next section: 1) Cluster specialization (related variety) is positively related to resilience in regions that show a high level of innovation; 2) Cluster specialization (related variety) is negatively related to resilience in regions that show a low level of innovation; 3) Cluster diversity (unrelated variety) is positively related to resilience in regions that show a low level of innovation; 4) Cluster diversity (unrelated variety) is negatively related to resilience in regions that show a high level of innovation; 5) Cluster specialization is related to resilience during the resistance stage, 6) Cluster diversity is related to resilience along the recoverability stage.

The paper is organized as follows. The next section reviews the literature associated with the impact of related and unrelated variety on resilience, which upholds our hypotheses. Section 3 explains the model to test our hypotheses. Section 4 describes the implemented data, the computation of the main variables, and presents their descriptive statistics. Section 5 shows the main findings and finally, the conclusion presents the policy implications of the findings.

Literature Review

As we point out in the introduction, our hypotheses are based on the empirical evidence for related and unrelated variety. Therefore, this section reviews the evidence, analysing its impact on resilience. Related variety refers to a variety of industries within a region that are cognitively related. Their relatively diversified structure allows them to share, modify and recombine ideas to develop new products and services. Boschma (2015) claimed that related variety benefits resilience by facilitating the adaptation and adaptability processes, which, according to the evolutionary perspective, are two components of resilience. The first one refers to changes within preconceived paths, while the second one is about developing new pathways. Related variety guarantees adaptation because the local presence of a high number of related industries provides a supportive local environment. Additionally, it promotes adaptability because related variety is a crucial factor in developing new growth paths. On the other hand, unrelated variety measures the extent to which a region is diversified in activities that share low cognitive proximity. Boschma (2015)argued that unrelated variety enhances adaptability because it increases the potential to make new recombinations that lead to new growth paths.

Some studies provide empirical evidence for the Boschma assumption. According to Holm and Østergaard (2015) related variety influenced the resilience of the information and communication technology (ICT) sector in Denmark, which had previously been shocked by the dot.com bubble and the economic recession in 2000-2001. The diversity within the ICT sector creates a greater variety in the knowledge base and thus a greater source of cross-subsector knowledge spillovers and an opportunity for the emergence of new activities, leading to higher resilience. Sedita et al. (2017) found that after the Great Recession in Italy, the impact of related and unrelated variety differs according to the region's knowledge base. They differentiate three knowledge bases: analytical (which requires scientific knowledge to generate radical innovation), synthetic (innovation that depends on new combinations of existing knowledge), and symbolic (more related to design elements in innovation). Their results show that related variety enhances regional resilience capacity when it is complemented with analytical knowledge. Since this kind of knowledge concerns a very specialized group of industries, they benefit more from higher cognitive proximity (related variety). Meanwhile, unrelated, more than related variety, benefits from the impact of synthetic knowledge on resilience. This kind of knowledge is required for a larger number of industries rather than using other knowledge bases, so that a broader diversity among industries improves their performance. Finally, related variety supports a region's resilience capacity when linked to symbolic knowledge because there is a large relatedness across creative services. To sum up, the impact of related and unrelated variety depends on the region's knowledge based specialization.

We combine two arguments in related and unrelated variety literature to set up our hypotheses. Firstly, Boschma (2015) argues that a high related variety, which implies a high cognitive proximity, allows industries to generate changes in the short term to confront economic shocks. In other words, they generate the changes within the preconceived paths to increase the adaptability resilience process. Second Castaldi et al. (2015) and Miguelez and Moreno (2018) find that high cognitive proximity among industries increases the general innovation in the region. Therefore, a general high innovation level in the regions can be considered as a sign that related variety mechanism is working properly. In the opposite case, we expect that low innovation indicates the regions have not benefited from the related variety mechanism. Considering these arguments, we therefore put forward the following hypotheses:

H1. Cluster specialization is positively related to resilience in regions that show a high level of innovation.

H2. Cluster specialization is negatively related to resilience in regions that show a low level of innovation.

We follow similar arguments to set up hypothesis 3 and 4. Boschma (2015) assumes that unrelated variety increases resilience because it guarantees adaptability, that is, it increases the potential to make a new recombination of preexisting knowledge. In this line, Castaldi et al. (2015) and Miguelez and Moreno (2018) show that unrelated variety raises the likelihood of breakthrough innovations. This recombination between unrelated knowledge domains implies more risk and higher switching costs, making this breakthrough rare. Therefore, the innovation arising when the knowledge base consists of unrelated technologies is less frequent than the innovation produced in a knowledge base consisting of related technologies. Considering these arguments, we therefore put forward the following hypotheses:

H3. A presence of a diversity of Clusters in a region is positively related to resilience in regions that show a low level of innovation.

H4. A presence of a diversity of Clusters in a region is negatively related to resilience in regions that show a high level of innovation.

A higher presence of related and unrelated variety should have a beneficial effect on regional resilience. Boschma (2015) points out that related variety (within each knowledge domain) secures adaptation, while unrelated variety (unrelated knowledge domains) guarantees adaptability. This may imply that related variety would affect resilience during the years of the downturn, and unrelated variety would have a more prolonged effect during the resilience stage. Similarly, Wagner and Deller (1998) expect that industrial specialization is beneficial for comparative advantages as a short-run growth strategy and diversity for long-run stability. This information implies that we expect to observe a greater effect of cluster specialization in the moment of the economic shock and a more important role of cluster diversity for a more prolonged period. If we translate these effects to the resilience multi-phase process (Martin et al., 2016), we may think that cluster specialization would impact resilience during the resistance period and cluster diversity on the recoverability. Therefore, we may put forward the following hypotheses:

H5. Cluster specialization is related to resilience during the resistance stage, that is, higher cluster specialization increase resilience.

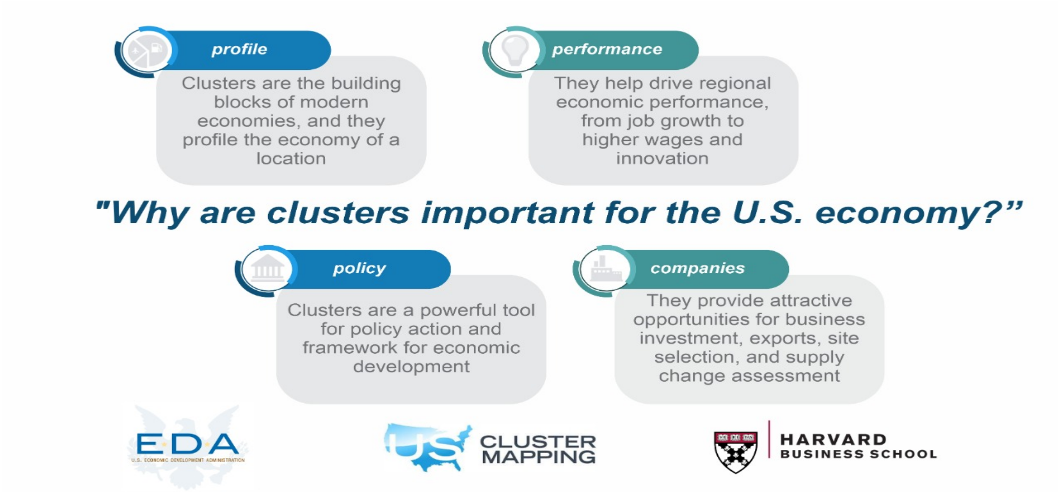
H6. Cluster diversity is related to resilience along the recoverability stage, that is, higher cluster diversity increase resilience.

Cluster Policy in the U.S.

One of the main issues on the political agenda has been the development of a cluster policy in the U.S., in reference to its importance to the U.S. economy (see figure 4.1). An example of this is during the Obama administration, where the "Strategy for American Innovation, 2009" was the promotion of regional innovational clusters (European Cluster Collaboration Platform, 2022). The U.S. government provided funding for the clusters through different agencies to reach the goal. The funding agencies were the Economic Development Administration, the Small Business Administration, the Department of Labor, the Department of Education, and the Department of Energy (Farrell and Kalil, 2010).

The U.S. Cluster Mapping Project has been one of the most ambitious initiatives to support cluster developments. The U.S. Secretary of Commerce, Penny Pritzker, launched the project in 2014 (Harvard Business School,

Figure 4.1: Why are clusters important for the U.S. economy?



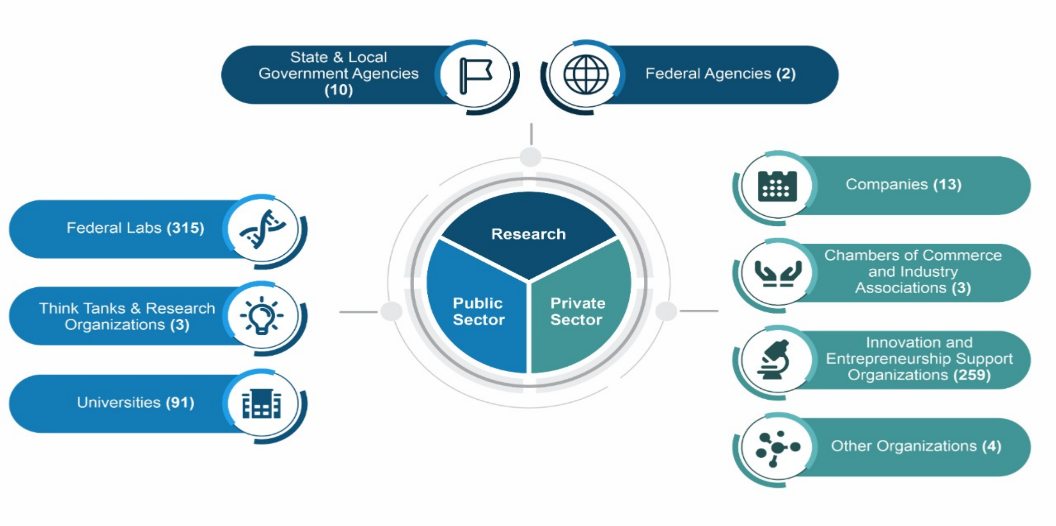
SOURCE: *Harvard Business School (2020).*

2020). Its primary goal was to identify and provide data for all clusters located in the state, the metropolitan, and at the county level. You need to coordinate clusters in the same direction to support a cluster development in order to have a formal registration that can be consulted by economic developers, policymakers, researchers, and members of the private sector. There is an accessible tool on the project´s website (www.clustermapping.us) where you can access cluster mapping in any geographical area in the U.S.. This is a helpful instrument in shaping the competiveness of all areas.

Financed by the U.S. Department of Commerce and the U.S. Economic Development Administration, the cluster mapping project is led by the Institute for Strategy and Competitiveness at Harvard Business School. Professor Micheal Porter, head of this institute, is well known for his significant contributions to the clusters and literature on competitiveness. Algorithms were developed that grouped industries into clusters by Professor Porter and his research team. For more information, refer to the brief description in the introduction of this paper, also see Delgado et al. (2016) to learn more about the methodology.

This national initiative (a cluster data supplier) is carried out as a networking tool where participants in the initiative can interact with each other. Improving the cluster performance is achieved through this unique opportunity to share experiences and learn from others on how to use the

Figure 4.2: Cluster Mapping Project Community in the U.S.



SOURCE: *Own elaboration with data from the Cluster mapping project (Harvard Business School, 2020).*

information. This initiative has had a significant impact on the country by the number of participants who have registered on the platform. Refer to figure 4.2 to see the three main group classifications of participants. The first group (The Private Sector) is represented by companies (13), the Chamber of Commerce and the Industry Association (3), Innovation and Entrepreneurship support organizations (259), and other organizations (4). In the second group (The Public Sector) it includes the state and local government agencies (10) and federal agencies (2). And the last group (The Research Sector) is composed of federal labs (315), think tanks, research organizations (3), and universities (91). The joint effort of all these participants provides, as a result, 126 cluster organizations and initiatives.

The cluster website community that is registered with them are able to share their experiences to create policies, projects, or businesses using the data provided. The geographic unit of analysis in this work will be based on two successful cases for state level clusters that will be mentioned briefly below (Harvard Business School, 2020). The first case was on growing existing companies in the region of West Virginia and attracting new ones which was the aim for the Director of Business and Industrial Development for the state of West Virginia, Kris Hopkins,in 2015. It was possible to expand suited cluster programs for West Virginia through the information offered by the Cluster Mapping Project which Hopkins used to identify the region´s key clusters, a list of cluster organizations and chambers of commerce. The second success was when a strategy to increase the state´s competitiveness was presented by the president and CEO of the South Carolina Council on Competitiveness, Ann Marie Stieritz, in which she identified the most competitive cluster compared to the other states in the country to strengthen them, using the information on the Cluster Mapping Project. She was able to produce a framework to improve the competitive ground of South Carolina in the U.S. The Cluster Mapping Project has a significant impact on cluster development, economic growth, and national competitiveness which can all be found on their website.

Clusters and innovation

To support the main argument in this study, it is necessary to clarify the relevance of traded clusters for innovation in the U.S. Porter (2003) distinguished all industries into two groups: the local and traded. The first ones are geographically dispersed and serve primarily the local markets, like physician offices. Meanwhile, traded industries are geographically concentrated and produce goods and services that are sold across regions and countries, like aircraft manufacturing. In the same way, they classify clusters as either local or traded. Local clusters sell products and services primarily for the local market, and the traded clusters are concentrated in regions that afford specific competitive advantages, exporting their products to other areas (see figure 4.3).

For the U.S. Cluster Mapping Project, Delgado et al. (2016) implement just the traded cluster since they are the engines of the regional economies. Figure 4.4 shows the significant impact of this kind of cluster on creating innovation in the U.S. economy. Meanwhile, 3.5% of the patents registered in the country are generated by industries belonging to the local clusters, while 96.5% of the patents created in the country take place in the traded cluster. This fact clarifies why this kind of cluster is called "the engine of the regional economies." The three clusters with the highest number of patents awarded in 2015 are Information Technology and Analytical Instruments (42,481), Communications Equipment and Services (15,865), and Production Technology and Heavy Machinery (11,837). Additionally, traded clusters

Figure 4.3: Traded clusters vs Local clusters

SOURCE: *Cluster mapping project (Harvard Business School, 2020).*

Figure 4.4: Patents in traded and local clusters

SOURCE: *Own elaboration with data from the Cluster mapping project (Harvard Business School, 2020).*

have great importance in the creation of new job positions because the increment of employment in traded industries has a multiplier effect on nontradable sectors (Moretti, 2010).

Empirical Model

To test our hypothesis, an economic shock needs to be selected in which it demonstrates regional resilience. The world economy was hit by the COVID-19 pandemic, which caused the most recent downturn. Unfortunately, not enough data was able to be collected to analyze the different stages of resilience due to it still being a recent event. It is necessary to have data some years after the economic shock has taken place. This is referred to as the recovery stage. 2019 is the year the most recent data was available for the cluster classification that this work follows. Another economic shock such as the Great Recession is an excellent selection apart from the COVID-19 downturn, mostly due to its prolonged downturn since the Great Depression of the 1930s (Grusky et al., 2011).

The U.S. economy's housing bubble´s collapse and the excessive expansion of credit were rooted from the Great Recession. In December 2007, when this financial collapse commenced, growth didn´t recover until the summer of 2009. Employment was the most severely affected even with production beginning to recover. From the point of view of the labour market, it was considered a "Great Recession", which had losses of over 7.5 million jobs dating from May 2007 to October 2009 (Grusky et al., 2011). The severe negative effects of the Great Recession in the United States increased the unemployment rate by 5.7 percent between the pre-recession period and October 2009. Not only did it have an ill effect on the U.S. but it severely affected Europe more so than the end of World War II (Capello and Caragliu, 2016).

For these reasons, the Great Recession has been considered by researchers as the downturn for further research and evaluation for European and U.S. studies on regional resilience (Ringwood et al., 2019; Han and Goetz, 2015; Giannakis and Bruggeman, 2017; Ezcurra and Rios, 2019; Brakman et al., 2015; Arbolino and Di Caro, 2021; Cainelli et al., 2019b; Davies, 2011; Rios and Gianmoena, 2020). The Delgado and Porter studies measured resilience with employment using evaluations from strong clusters and their resilience in the Great Recession. They developed the cluster classification which is the same classification used in the study above, which is a very relevant reference.

We refer to Delgado and Porter (2021) studies on the relationship between cluster presence and resilience in our empirical model, which evaluated the role of strong clusters in the resilience of regional industry employment to the Great Recession. The model by Delgado and Porter shows strong clusters using the cluster specialization variable, which they want to vary every year to test and see what precise years have cluster strengths allowed resilience. Our cluster presence variable is used in the same way as their cluster specialization variable as an interaction term with the years. During this analysis, this term allows them to assess in what precise year the presence of strong clusters would benefit the regional clusters that would experience fairly higher employment growth. Interestingly, this positive effect was stronger at the beginning of 2008, the start of the Great Recession. On the other end of the spectrum, industries that were located in weak clusters were more vulnerable to the effects of the Great Recession. The authors discuss mitigation of the impact of recessions and the resulting uncertainty that increases with regions specialized in particular agglomeration economies.

Our analysis was inspired by the empirical model of Delgado and Porter (2021), as there were a lot of similarities in the results of the studies. In our analysis we looked at the effect of the clusters' strength on the resilience of state employment, while their evaluation was on the impact of clusters' strength on the resilience of regional industry employment. In both evaluations there was a focus on looking at a strong cluster presence on resilience but on contrasting aggregate levels, as theirs was on industrial employment and ours was on state employment. We followed the exact cluster classification for the U.S. industries as the authors did, and curiously enough, the cluster definition (Delgado et al., 2016) was designed by them for the U.S. Cluster Mapping Project. According to the above mentioned, the results of our analysis will be of great interest to the policymakers involved in this project. As both studies examined the Great Recession as the economic shock to evaluate resilience, we decided to create a model of our analysis with the influence of the authors and include cluster strength and year as the interaction terms. The term helps us to see if the positive effect of strong clusters is stronger during the year of the Great Recession than in other years, as demonstrated in our work. If this is the case, the clusters strength has a lower severity on the effect of the economic shock at both industrial and state levels. Please refer to the following model:

We specify the following empirical model to test the relationship between cluster composition and resilience at the regional level:

$$\begin{aligned} Resilience_{rt} = \alpha + \beta_1 Year_t * ln(Cluster\,Spec_{r,t-1}) + \\ \beta_2 Year_t * ln(Cluster\,diver_{r,t-1}) + ln\,\rho_5 x_{rt} + \mu_r + \varepsilon_{rt} \end{aligned} \tag{4.1}$$

The dependent variable refers to the resilience in region *r* in time *t*. The main independent variables appear as an interaction term between the proxy for the cluster presence and each year. The coefficients of these interaction terms will allow us to observe how the effect of the cluster's composition changes over the period, especially in the years of the great recession. Furthermore, because the results of innovation activities are not immediately visible, we introduce these variables late in one period. $Cluster\ Spec_{r,t-1}$ describes how specialized clusters are in region *r* for time *t-1*. Meanwhile, $Cluster\ diversity_{r,t-1}$ represents the heterogeneity in the set of clusters in region *r* for time t-1. In addition to the cluster composition, we include a vector of control variables $x_{r,t-1}$ as well as the term that accounts for unobserved or omitted heterogeneity across regions that do not vary over time μ_r and the time variant component of the error ε_{rt}.

Data description

To measure our independent variables, we need to identify the clusters in a region. To accomplish this goal, we follow the cluster definition by Delgado et al. (2016). Their algorithm generates clusters based on occupation links, input-output links and inter-industry measures of co-location patterns of employment and the number of establishments. This methodology takes 778 (six-digit NAICS) U.S. industries and classifies them into 51 mutually exclusive clusters. This classification is implemented for the industries in each region. For instance, the automotive cluster, which is composed of 26 industries is present in each one of the U.S. states. Table 4.5 in the appendix section shows a full list of these clusters as well as the number of industries that each one includes.

Some relevant reasons justify following this cluster definition. First, we can compare the same cluster across the regions because the industries that integrate a cluster are always the same. Second, these cluster definitions have served as the foundation for other research works that evaluate regional prosperity (Ketels and Protsiv, 2020), innovation in clusters (Delgado, 2020), and cluster resilience (Delgado and Porter, 2021). Third, this cluster definition has been implemented not just in research, but also in the elaboration of some policies. It is the base data for the U.S. cluster mapping project, which aims to strengthen U.S. competitiveness by helping regions understand and improve their economic composition and performance. Finally, it is relevant to mention that this cluster definition only considers traded industries characterized for being geographically concentrated and producing goods and services sold across regions and countries (Delgado et al., 2016).

Until now, we have grouped industries into clusters, but we ignore the number of employees in them. We obtain the employment data for the 778 industries in the 51 U.S. states from the County Business Patterns (CBP), which is an annual series that provides subnational economic data by industry. Once we know the number of employees in each industry, we can obtain the corresponding number at the cluster level and consequently, we can measure our independent variables. Employment data at the state level is also necessary to measure the dependent variable, which we obtained from the U.S. Bureau of Labor Statistics. All these information sources allow us to build panel data for the period 2005–2015.

Cluster analysis at the state level

We chose the state as our geographic unit of selection in our analysis due to its influence on the U.S. cluster development. The conduct of currency, trade, and regulatory policies and the support of basic infrastructure is the main duty of the federal government. The federal government supports industries, but mainly those related to defense and national security technology projects which are sponsored by the Departments of Defense, Energy, and Homeland Security. So the commitment of the subnational government and the states is to back up industrial development, mainly through innovation initiatives.

In recent years, innovation initiatives have transitioned to the center of state and local efforts. The control of factors of production such as land use, water infrastructure, and waste disposal makes them very effective actions. Refer to the following statement: “In the United States, a number of academic studies have concluded that in the development of technology pioneering firms, state support has played a key role in pooling multiple external public and private funding sources, including federal funds and venture capital, and directing them to private firms (Wessner, 2013)”. This proves that the state has greater effectiveness than the local government in regards to innovation. Every state supports a system of public universities with the largest proportion of their operating budgets. This allows the state to encourage them to prioritize local economic development, which is a crucial step as in the past ten years, universities and their private partners have led the advances in innovation.

For this reason, it is important to have support for the development of all industries in general and the development of clusters as a consequence of this support by the state government. “The states have been the primary movers in the widespread and growing practice of fostering innovation clusters as an economic development tool (Wessner, 2013)." The local cluster analysis is an unessential analysis, yet, on the other hand, the state analysis is an interesting level of analysis in taking a first step towards creating a cluster policy design, with key interactions with the federal and local government.

Dependent variable

As mentioned in the literature (Martin and Sunley, 2015), there are different perspectives in approaching the concept of a resilience measure. The methods used to measure resilience can be classified into four main groups (Bristow and Healy, 2020). The first group, called the case study base, talks about simple descriptive data and interviews with key actors (Evans and Karecha, 2014; Cowell, 2013; Lyon, 2014). The second, the resilience indices group, expresses the comparative measures of resistance and recovery (Martin, 2012; Augustine et al., 2013). The third group, the statistical time series model, offers an approximate time for the impact of shock to dissipate. And lastly, the causal structural models, embed resilience in regional economic models to estimate where the economy would be in the absence of the downturn (Doran and Fingleton, 2018; Sensier et al., 2016). As you have just read, each method of measuring resilience has its advantages and disadvantages in its differing ranges of models.

The analysis objective is dependent on the convenience of using one of these measures. We need a measure that can be compared with the resilience indices group due to the desire to compare resilience among the states. There is no need for analysis of the case of a natural disaster in a specified region, a localized financial crisis, or the collapse of a major local employer. A common shock that impacted all the regions was the Great Recession. There is a need for a relative instead of an absolute measure of resilience to compare the behaviors of the different regions. It is very useful to cite the following indexes for the comparison of resilience in various regions, such as the UK (Lagravinese, 2015), the Italian regions (Cainelli et al. 2019), and lastly, the varying regions in Europe, Giannakis and Bruggeman (2017) and Rios and Gianmoena (2020), to study the various effects of the Great Recession. See the resilience index that follows:

$$Resilience_{rt} = \frac{\left(\frac{E_{rt} - E_{rt-1}}{E_{rt-1}}\right) - \left(\frac{\sum_{r=1}^{s} E_{rt} - \sum_{r=1}^{s} E_{rt-1}}{\sum_{r=1}^{s} E_{rt-1}}\right)}{\left|\frac{\sum_{r=1}^{s} E_{rt} - \sum_{r=1}^{s} E_{rt-1}}{\sum_{r=1}^{s} E_{rt-1}}\right|} \tag{4.2}$$

where E_r denotes employment in region *r* during period *t* and s denotes the total number of regions.

where E_{rt} represents employment in region *r* in period *t*; s is the total number of regions. These equations are regional growth rates standardized by the growth rate in all other regions for the same year. By definition, these measures are centered at zero. We have three possible interpretations for this index: 1) $Resilience_{rt} > 0$ indicates that the region shows less vulnerability to an adverse shock compared with the national effect, which means the region is resilient; 2) $Resilience_{rt} < 0$ reveals that the region is more vulnerable than the nation, implying the region is not resilient; 3) $Resilience_{rt} = 0$ means there is no difference with the rest of the country.

To provide a general view of the resilience variable, figure 4.6 in the appendix section shows the average resilience for each state in 2008-2010 (resistance) and 2010-2015 (recoverability). We follow these periods similar to Martin et al. (2016), who analyze how employment in the major UK regions reacted to the four major recessions of the last 40 years, including the Great Recession. This graphic shows that North Dakota's recoverability is much superior to the rest of the states. The extraordinary development of its oil and gas industry turned this observation into an outlier. Therefore, we dropped it from our analysis.

Key Independent variables

To proxy the regional cluster specialization, we use a location quotient (LQ) representing how concentrated a particular cluster is in the region compared with the nation. Some previous studies proxy cluster specialization with LQ measures (Delgado et al., 2010, 2014), such as follows:

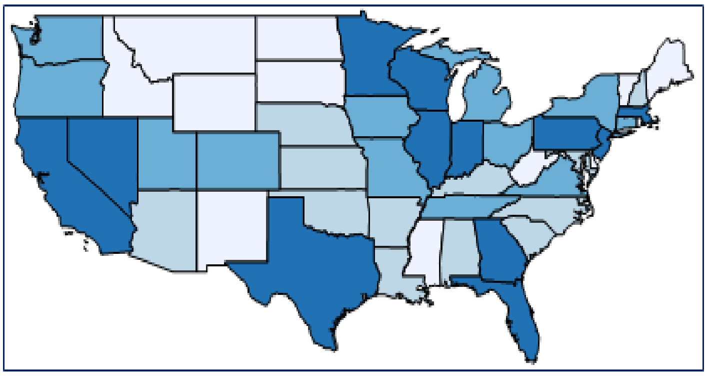
$$Cluster\,Location\,Quotient_{c,r,t} = \frac{E_{c,r,t}/E_{r,t}}{E_{c,US,t}/E_{US,t}} \tag{4.3}$$

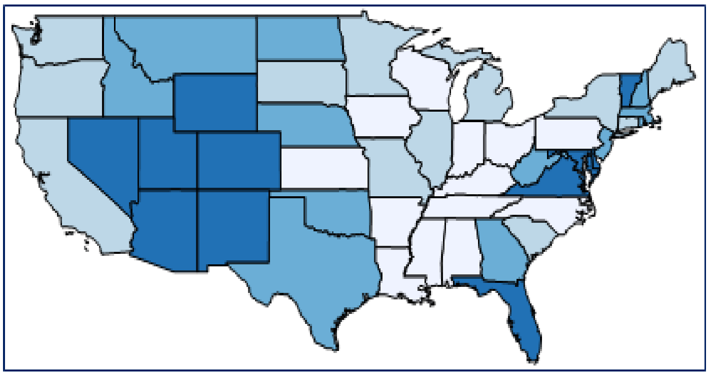
where *c* describes each cluster; *r* is the region; U.S. is the country. In order to know if the LQ of a specific cluster is high or low, we must compare it with the rest of the clusters. Once we get the LQ for each cluster in a region, their average represents the cluster specialization for that region. If this value is high, it means the region is accounted for by clusters that are highly concentrated in that region compared with the rest of the country. Some of the U.S. regions with the highest cluster specialization are California, Texas, Massachusetts, Florida, and Pennsylvania (figure 4.5, top).

We proxy cluster diversity based on measures of the Herfindahl index. Recent studies of regional resilience include this index to proxy the diversity of industries (Eraydin, 2016; Giannakis and Bruggeman, 2017). Similarly to these studies, we implement this index to measure the diversity of regional clusters. This index indicates the extent to which employment is dispersed throughout clusters.

$$Cluster\,Diversity_{r,t} = \sum_{c=1}^{S} \left(\frac{E_{crt}}{E_{rt}}\right)^2 \tag{4.4}$$

Figure 4.5: Indicators of cluster composition





Indicators of cluster composition: (top) cluster specialization (average of cluster location quotient) across the U.S. regions; and (bottom) cluster diversity (extent to which employment is dispersed throughout clusters) across the U.S. regions.
Note: Colours refer to quartiles of the corresponding variables such that darker colours indicate higher values. For cluster diversity, higher value means less diversity.

where E_{crt} is the employment in cluster c in the region r for the year t; E_{rt} is the total employment of clusters in region r for the year t; S refers to the total number of clusters. The closer to zero the value of this index, the higher the diversity within the clusters in the region. For that reason, the U.S. states with the highest diversity are the brightest ones in figure 4.5 (bottom), like Indiana, Ohio, Tennessee, Alabama, and Kentucky. As we can see from this map, the regions with the highest diversity are concentrated in the western part of the country.

Control variables

Apart from the main independent variables described above, we also include other variables considered as determinants of regional resilience in our analysis. We follow the analysis by Eraydin (2016), who classified the variables that could explain regional resilience into four groups: vulnerability, resources, adaptive capacity, and policies and measures of support.

We proxy the regional vulnerability by the variables' exports and debt. A high number of exports represents a source of vulnerability because a more open region to the international market will be more negatively affected by external economic conditions. Meanwhile, a region with a high dependency on the financial market could be more vulnerable when an economic shock takes place because, most of the time, governments drop the total volume of credits as an austerity measure.

The resources attributed to them include the variables entrepreneurs and infrastructure. Entrepreneurs is a measure of the share of the population that starts a new business, which proxies the capabilities and skills in the regions essential to overcome a downturn. Meanwhile, infrastructure is a measure of the share of roads in acceptable conditions representing the availability of resources that should facilitate the recovery of the region.

The adaptive capacity of regions is proxied by the share of startups that are still active after one year. It proxies the resistance of new businesses. Our independent variables, cluster specialization and cluster diversity, belong to the adaptive capacity group. We mention above that they are positive assets of a region resisting crises and recovering in the post-recession period.

Finally, we proxy the last resilience attribute with measures for the federal investment in research and development (R&D). Investment in this R&D is relevant since innovative regions are more resilient during and after economic shocks (Bristow and Healy, 2018; Filippetti et al., 2020). Table 4.7 in the Appendix section presents the descriptive statistics of these variables, and Table 4.8 provides their correlation matrix.

Results

We built a series of regression models with resilience as the dependent variable and cluster specialization and cluster diversity as the main independent variables. We controlled factors such as region and year fixed effects as well as the interaction term between region and year effects. The region fixed effects observe all region-specific factors beyond cluster composition, which were not specifically included in our model. Year fixed effects capture the differences across years driven by specific events. The interaction term, region-year fixed effects, controls for changes in resilience derived from region-specific factors each year. Tables 4.2 and 4.4 show the results of the estimation of the model by groups of regions with low or high innovation. The group of highly innovative regions is composed of those that register a higher number of patents than the national average. Otherwise, they are included in the group of regions with a low innovation level.

Table 4.1 shows the impact of cluster composition on resilience for the whole period 2006–2015. Results suggest that regions characterized by a high cluster diversity are more vulnerable to downturns than the rest of the country. However, cluster diversity turned into one of the resilience determinants when we ran the same model just for regions with low innovation activity (table 4.2), which is fully in line with hypothesis 3. The low cognitive proximity among the clusters makes the emergence of new technology less frequent, but when it does take place, such innovation is a breakthrough. On the other hand, when we run the model for regions with high innovation, cluster diversity has the same negative effect as in table 4.1, confirming hypothesis 4. Additionally, table 4.2 provides evidence for the cluster specialization variable, which is significant for regions with high innovation. Strong cluster specialization in the regions implies high cognitive proximity between their industries, leading them to the creation of paths in the short term and thus to their adaptation. The positive influence of cluster specialization on resilience supports hypothesis 1. These first tables demonstrate the necessity of differentiating regions by innovation intensities to capture the effect of the cluster composition variables.

Table 4.3 introduces the interaction term between the main independent variables and each year, which are necessary terms to examine the impact of cluster composition over the period. Results show that higher cluster specialization makes the regions more vulnerable in the Great Recession years (2008–2010). The coefficients corresponding to these years are the only significant ones throughout our period of analysis. However, like in the previous tables, we can observe how cluster composition variables change their effects when we obtain the results by innovation intensity. In table 4.4, columns that correspond to high innovation indicate that strong clusters contribute positively to overcoming economic shocks, supporting the argument for hypothesis 1. On the other hand, coefficients in columns for low innovation suggest that regions with strong clusters will be less resilient than the rest of the country, evidence that confirms our hypothesis 2. It is relevant to mention that coefficients in the Great Recession years increased their proportion two or five times compared with coefficients one year before. The magnitude of these coefficients confirms the relevant influence of cluster specialization on resilience. Nevertheless, the high proportion of these coefficients can work in both directions, making the regions more or less vulnerable according to their innovation intensity.

With respect to cluster diversity, almost all coefficients are significant throughout the period, supporting the impact of these variables in the long term. However, similar to cluster specialization, this variable effect can benefit or harm resilience according to the regional innovation level. Columns that correspond to low innovation show clearly that high cluster diversity will increase resilience, supporting hypothesis 3. On the other hand, the corresponding columns for high innovation demonstrate that cluster diversity makes the regional recovery more vulnerable to an economic shock, confirming hypothesis 4.

So far, we have not commented on the effect of cluster composition in the short and long term. We can observe in Table 4.4 that cluster specialization coefficients are significant in 2008, the year when the Great Recession hit the economy. There are also other significant coefficients in 2010, one year after this downturn took place. We mentioned above that adaptation is the resilience stage that occurs in the years following the economic shock, which corresponds to the short-term reaction of the economy towards the downturn. Therefore, we can conclude that cluster specialization impacts the adaptation stage of resilience, confirming hypothesis 5. Furthermore, cluster specialization coefficients show their highest values in the year in which the Great Recession started. In 2008, the coefficients are between two and five times higher than in the previous year, 2007. All these facts support the hypothesis that high cluster specialization impacts the adaptation process of resilience. On the other hand, coefficients for cluster diversity are significant in the long term. They are significant for almost every year analyzed (in our model). Furthermore, they reach their highest values after 2012, years considered a part of the adaptability period, when the economy develops new growth paths to recovery, confirming hypothesis 6. These results are consistent with the Boschma (2015) assumptions explained above. The appendix section shows the result without lagging the independent variables, and the same conclusion remains (Tables 4.9 to 4.12).

Our results are in line with Sedita et al. (2017), and Boschma (2015), who were our primary references to set our hypotheses in the literature section. We agree with Sedita et al. (2017) in the sense that related and unrelated variety, equivalent to our measure of cluster specialization and cluster diversity, can be determinants of regional resilience depending on specific characteristics of the region. In their study, one such characteristic is the knowledge-base of the regions, which, in this study, is the innovation level. These two concepts are closely linked since the innovation processes of firms are strongly shaped by their specific knowledge base (Asheim and Coenen, 2005). Therefore, our results support Sedita et al. (2017) findings, but on a more aggregate scale, they measure related and unrelated variety at the industry level, whereas, our work did so at the cluster level. Furthermore, our findings are consistent with Boschma (2015) in that related and unrelated variety is significant at different stages of the resilience process. Related variety, cluster specialization in our case, influences the resistance process, and the unrelated variety, cluster diversity in our case, contributes to the recoverability stage of resilience.

Table 4.1: The role of regional cluster composition on resilience (all regions)

	All regions	**All regions**	**All regions**	**All regions**
Ln(Traded Cluster Specialization)$_{t-1}$	-1.08	-0.136	-1.175	-0.662
Ln(Traded Cluster Diversity)$_{t-1}$	0.701	0.567	-1.096*	-1.498**
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year – Region Fixed Effects	No	No	Yes	Yes
R-squared	0.094	0.273	0.088	0.172
Obs.	500	500	500	500

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

Table 4.2: The role of regional cluster composition on resilience (innovation level)

	Low innovation	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**
Ln(Traded Cluster Specialization)$_{t-1}$	-1.134	0.027	-0.696	2.14*	-1.487	0.075	-0.955	1.252
Ln(Traded Cluster Diversity)$_{t-1}$	1.959**	-1.54*	1.585**	-1.248	-0.742	-1.896**	-1.013	-3.086***
Control variables	No	No	Yes	Yes	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Region Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Year – Region Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.153	0.064	0.295	0.335	0.074	0.144	0.158	0.268
Obs.	311	189	311	189	311	189	311	189

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

Table 4.3: The role of regional cluster composition on resilience (all regions and interaction terms)

	All regions	**All regions**	**All regions**	**All regions**
Year2006*Ln(Traded Cluster Spec)$_{t-1}$	-0.779	0.609	-2.131	-1.392
Year2007*Ln(Traded Cluster Spec)$_{t-1}$	-1.269	0.184	-1.282	-0.874
Year2008*Ln(Traded Cluster Spec)$_{t-1}$	-4.892***	-3.231***	-4.667***	-4.380***
Year2009*Ln(Traded Cluster Spec)$_{t-1}$	-1.972*	-0.447	-1.945*	-1.874*
Year2010*Ln(Traded Cluster Spec)$_{t-1}$	-2.383**	-1.495	-2.370**	-2.701***
Year2011*Ln(Traded Cluster Spec)$_{t-1}$	-0.496	-0.062	-0.549	-1.281
Year2012*Ln(Traded Cluster Spec)$_{t-1}$	-0.645	-0.831	-0.704	-1.825*
Year2013*Ln(Traded Cluster Spec)$_{t-1}$	-0.46	-0.852	-0.492	-1.890*
Year2014*Ln(Traded Cluster Spec)$_{t-1}$	-0.298	-0.898	-0.312	-1.903*
Year2015*Ln(Traded Cluster Spec)$_{t-1}$	-0.403	-1.081	-0.463	-2.062*
Year2006*Ln(Traded Cluster Div)$_{t-1}$	1.278**	1.509**	0.558	0.937
Year2007*Ln(Traded Cluster Div)$_{t-1}$	0.547	0.993*	0.449	0.642
Year2008*Ln(Traded Cluster Div)$_{t-1}$	-0.215	0.474	0.327	0.308
Year2009*Ln(Traded Cluster Div)$_{t-1}$	0.453	1.015	0.489	0.455
Year2010*Ln(Traded Cluster Div)$_{t-1}$	0.359	0.726	0.394	0.528
Year2011*Ln(Traded Cluster Div)$_{t-1}$	0.649	0.806	0.476	0.814
Year2012*Ln(Traded Cluster Div)$_{t-1}$	0.686	0.505	0.499	0.864
Year2013*Ln(Traded Cluster Div)$_{t-1}$	0.941	0.648	0.505	0.972
Year2014*Ln(Traded Cluster Div)$_{t-1}$	0.734	0.379	0.498	1.125*
Year2015*Ln(Traded Cluster Div)$_{t-1}$	1.003	0.51	0.531	1.185*
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year -Region Fixed Effects	No	No	Yes	Yes
R-squared	0.212	0.342	0.265	0.416
Obs.	500	500	500	500

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

Table 4.4: The role of regional cluster composition on resilience (innovation level and interaction terms)

	Low innovation	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**
Year2006*Ln(Traded Cluster Spec)$_{t-1}$	-0.741	0.728	-0.022	3.386**	-1.960	0.000	-1.862	0.000
Year2007*Ln(Traded Cluster Spec)$_{t-1}$	-1.427	1.061	-0.428	2.934*	-1.077	-0.782	-1.295	0.540
Year2008*Ln(Traded Cluster Spec)$_{t-1}$	-6.688***	2.799	-5.528***	4.263**	-6.082***	1.489	-6.609***	2.297
Year2009*Ln(Traded Cluster Spec)$_{t-1}$	-2.137	1.366	-1.061	3.005	-1.751	-0.255	-2.409*	0.392
Year2010*Ln(Traded Cluster Spec)$_{t-1}$	-2.747**	1.648	-2.165*	2.633	-2.386*	0.162	-3.249**	0.694
Year2011*Ln(Traded Cluster Spec)$_{t-1}$	-0.542	1.094	-0.327	1.938	-0.216	-0.437	-1.410	0.194
Year2012*Ln(Traded Cluster Spec)$_{t-1}$	-0.91	2.234	-1.149	2.909	-0.557	0.389	-2.131	0.531
Year2013*Ln(Traded Cluster Spec)$_{t-1}$	-0.775	2.182	-1.167	2.351	-0.401	0.687	-2.214	0.406
Year2014*Ln(Traded Cluster Spec)$_{t-1}$	-0.387	1.863	-1.141	2.117	-0.002	0.339	-2.056	0.197
Year2015*Ln(Traded Cluster Spec)$_{t-1}$	-0.539	1.59	-1.174	1.958	-0.172	-0.069	-2.136	0.064
Year2006*Ln(Traded Cluster Div)$_{t-1}$	2.467***	-1.442	2.275***	-0.152	1.980**	-2.834**	1.784**	-2.107**
Year2007*Ln(Traded Cluster Div)$_{t-1}$	1.697**	-2.072	1.653**	-0.962	1.781**	-2.982**	1.490*	-2.395**
Year2008*Ln(Traded Cluster Div)$_{t-1}$	1.306	-3.449***	1.438*	-2.154*	1.819**	-3.290**	1.333*	-2.969***
Year2009*Ln(Traded Cluster Div)$_{t-1}$	1.819**	-2.757**	1.829**	-1.292	1.802**	-2.920**	1.318	-2.640***
Year2010*Ln(Traded Cluster Div)$_{t-1}$	1.822**	-3.238**	1.605*	-2.163*	1.748**	-3.072**	1.381*	-2.552**
Year2011*Ln(Traded Cluster Div)$_{t-1}$	2.060**	-3.203**	1.608*	-2.252*	1.848**	-3.096**	1.635**	-2.257**
Year2012*Ln(Traded Cluster Div)$_{t-1}$	1.969**	-2.423	1.198	-1.293	1.885**	-3.040**	1.686**	-2.159**
Year2013*Ln(Traded Cluster Div)$_{t-1}$	2.314**	-2.458*	-1.325	1.964**	-3.159**	1.834**	-2.139**	
		1.425						
Year2014*Ln(Traded Cluster Div)$_{t-1}$	2.042**	-2.817**	1.216	-1.846	1.913**	-3.155**	1.968**	-1.903*
Year2015*Ln(Traded Cluster Div)$_{t-1}$	2.395**	-2.462*	1.297	-1.600	1.973**	-3.134**	2.019**	-1.830*
Control variables	No	No	Yes	Yes	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Region Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Year - Region Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.337	0.124	0.422	0.385	0.374	0.212	0.481	0.471
Obs.	311	189	311	189	311	189	311	189

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

Conclusions

The purpose of this paper is to contribute to current literature already available on regional resilience. The analysis contributes in particular to disentangling industrial composition as one of the main determinants for resilience. Existing literature has focused on variables like industrial specialization, industrial diversity, related variety, and unrelated variety. In this work, we analyze the industrial composition of clusters, which are groups of interconnected industries linked by externalities of various types. We describe the cluster composition via cluster specialization, a measure of cluster strength in the region, and cluster diversity, a measure of how diversified the presence of clusters is within the region.

We assume that the impact of cluster specialization and cluster diversity on resilience is similar to the effect of related and unrelated variety. We make this assumption since the innovation process between these concepts is analogous. Similar to related variety, high cluster specialization implies strong cognitive proximity between the industries which facilitate the emergence of new technology to increase regional adaptation to economic shocks. Meanwhile, high cluster diversity implies low cognitive proximity among the clusters, which scarcely generates the emergence of new innovation. However, when they collaborate, they produce breakthrough innovations that lead to new growth paths for resilience adaptability, resembling the process for unrelated variety. In our view, testing the cluster composition variables is like evaluating related and unrelated variety at a more aggregated level. To test our assumptions, we follow the cluster methodology by Delgado et al. (2016), which groups 775 U.S. industries into 51 clusters for each of the 51 states in 2005-2015. In general, we find that cluster specialization and cluster diversity resemble the effects that current literature has shown for related and unrelated variety on resilience.

We find that the U.S. regions characterized by strong clusters and high innovation before the Great Recession present less vulnerability than the rest of the country in the years of this downturn. The common technological base makes it easier for the reallocation of skills, technology, and workers from one industry to the other, allowing the economy to adjust to the new conditions in the short run. We observe the opposite effect when the region is identified with a low innovation level. Even when there is a great cluster specialization (related variety) in the region, a low innovation level indicates that short-term adjustment mechanisms do not work properly. This situation could be explained by a recent increment in the regional cluster specialization that requires a longer time to make the adaptation mechanisms visible.

We also find that U.S. regions with high cluster diversity and low innovation levels show higher adaptability in the years after the Great Recession. The lack of cognitive proximity among the clusters increases the collaboration cost, making the innovation that works between them less frequent. However, when this innovation process takes place, it results in breakthrough innovations that lead to the creation of new growth paths. Since the creation of these breakthrough innovations requires a long time, cluster diversity affects resilience in its adaptability period in the long run. On the other hand, when a high cluster diversity is combined with a high innovation level, the region is less resilient than the rest of the country. Even with high cluster diversity, the regions are more vulnerable to the downturn.

These findings are relevant to policy-makers. Firstly, many regions worldwide have already implemented a cluster policy, and therefore, these findings contribute to improving a policy that they have already carried out. Secondly, if policy-makers want to implement cluster policy as a tool to reinforce regional resilience, they must consider the innovation level in the region. Our results show that cluster specialization and cluster diversity can benefit or damage resilience depending on the innovation intensity in the region. Thirdly, these findings come at a moment where policymakers are especially needed for regional resilience guidance. The COVID-19 crisis is producing straggles in all regional economies around the world. Recently, a considerable amount of funding has been made available to research projects that can provide clues in disentangling the resilience determinants. These findings contribute to the necessity of the cluster approach. However, it is still necessary to elaborate more on how clusters can contribute to resilience. Fourthly, the findings of this paper are of particular interest for the design of cluster policies in the U.S. We follow the cluster definition by Delgado et al. (2016), which is the same implemented for the U.S. cluster mapping project. This project is a platform that provides cluster information for business design, cluster projects, and cluster policies in the U.S. Our findings have a direct implication for these regions.

Acknowledgements
The authors would like to thank Dr. Rich Bryden of the ISC-Harvard, Dr. Pablo Nuño of Sintonía-UPAEP, Dr. Herberto Rodríguez of CIIE-UPAEP, and Dr. Alfonso Mendoza of CIIE-UPAEP, for the access to the database for the Cluster Mapping Project in Mexico, which was one of the references in the construction of the data base for the U.S. Financial support for this research was provided by CONACYT and UPAEP University, Mexico.

Appendix

Table 4.5: List of traded clusters

Cluster code	Cluster name	Number of industries
1	Aerospace Vehicles and Defense	7
2	Agricultural Inputs and Services	9
3	Apparel	21
4	Automotive	26
5	Biopharmaceuticals	4
6	Business Services	33
7	Coal Mining	4
8	Communications Equipment and Services	8
9	Construction Products and Services	20
10	Distribution and Electronic Commerce	62
11	Downstream Chemical Products	13
12	Downstream Metal Products	16
13	Education and Knowledge Creation	15
14	Electric Power Generation and Transmission	5
15	Environmental Services	7
16	Financial Services	26
17	Fishing and Fishing Products	5
18	Food Processing and Manufacturing	47
19	Footwear	6
20	Forestry	4
21	Furniture	12
22	Hospitality and Tourism	31
23	Information Technology and Analytical Instruments	27
24	Insurance Services	8
25	Jewelry and Precious Metals	4
26	Leather and Related Products	6
27	Lighting and Electrical Equipment	15
28	Livestock Processing	5
29	Marketing, Design, and Publishing	22
30	Medical Devices	5
31	Metal Mining	8
32	Metalworking Technology	17
33	Music and Sound Recording	5
34	Nonmetal Mining	13
35	Oil and Gas Production and Transportation	12
36	Paper and Packaging	20
37	Performing Arts	8
38	Plastics	15
39	Printing Services	13
40	Production Technology and Heavy Machinery	41
41	Recreational and Small Electric Goods	15
42	Textile Manufacturing	23
43	Tobacco	3
44	Trailers, Motor Homes, and Appliances	9
45	Transportation and Logistics	17
46	Upstream Chemical Products	12
47	Upstream Metal Manufacturing	26
48	Video Production and Distribution	6
49	Vulcanized and Fired Materials	17
50	Water Transportation	12
51	Wood Products	13

SOURCE: *Own elaboration with data from Delgado et al. (2016)*

Table 4.6: Definition and Descriptive Statistics of the variables

Variable	Definition	Source	Min	Max	Mean	SD
Resilience	Employment resilience in the state	Owe elaboration with data from the U.S. Bureau of labor statistics.	-5.497	6.814	0.087	1.018
Cluster Specialization	See equation (2) in the paper	Own elaboration with data from the County Business Patterns(CBP)	0.426	1.288	0.881	0.173
Cluster Diversity	See equation (3) in the paper	Own elaboration with data from the County Business Patterns(CBP)	0.064	0.363	0.139	0.054

Figure 4.6: Regional Resilience
(Average resilience by periods)

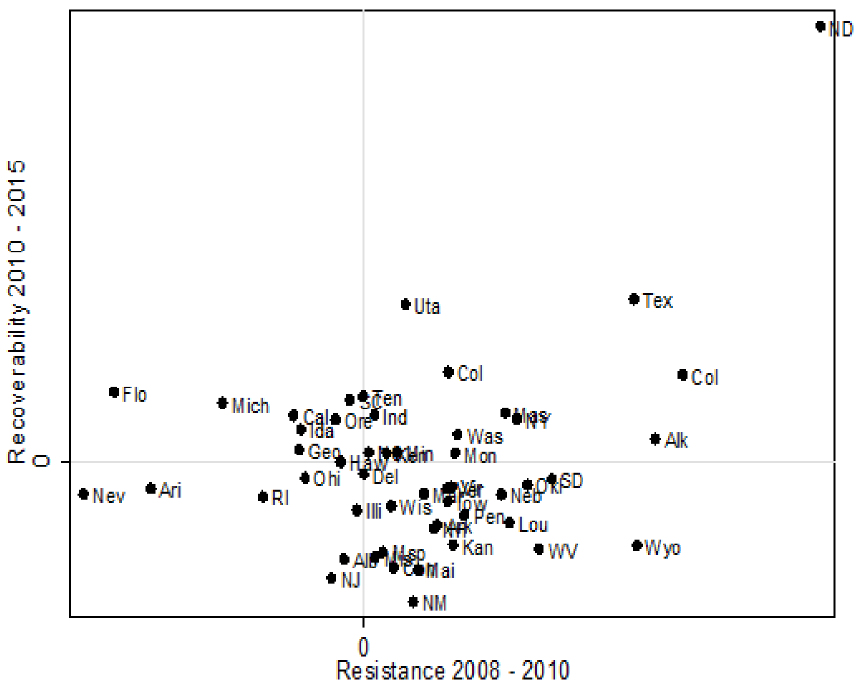


Table 4.7: Descriptive Statistics of Control Variables

Attributes	Definition	Variables	Source	Minimum	Maximum	Mean	SD
Vulnerability	Exports	Exports per capita (US$)*	U.S. Census	182.34	5,978.48	1,615.92	902.82
	Debt	Cosumer credit per capita (US$)*	Federal Reserve Bank of New York	9,462.40	41,456.80	20,228.59	5,874.73
Resources	Entrepreneurs	Share of population that starts a new business	Kauffman indicators of entrepreneurship	0.151	0.603	0.303	0.076
	Infrastructure	Share of road in acceptable conditions	Bureau of Economic Analysis	0.030	1.000	0.806	0.159
Adaptive capacity	Startup Early Survival	Share of startups that are still active after one year	Kauffman indicators of entrepreneurship	66.99	91.58	78.30	2.68
Policies and measures of support	Investment in R&D	Federal investment in Research and Development per capita (US$)*	National Center for Science and Engineering Statistics	0.035	32.197	0.545	1.619

*All monetary variables are in constant (real) dollars

Table 4.8: Correlation Matrix (N=510)

Variable	Cluster special-ization	Cluster Diversity	Exports pc	R&D pc	Road	Debt pc	RNE	SSR
Cluster Specialization	1.000							
Cluster Diversity	0.048	1.000						
Exports pc	0.203	-0.229	1.000					
R&D pc	-0.105	0.297	-0.125	1.000				
Road	0.102	-0.255	0.092	-0.522	1.000			
Debt pc	0.261	0.516	-0.103	0.362	-0.395	1.000		
RNE	-0.128	0.220	-0.033	0.005	0.107	0.080	1.000	
SSR	0.126	-0.208	0.001	-0.114	-0.012	-0.163	-0.107	1.000

Table 4.9: The role of regional cluster composition on resilience (all regions)

	All regions	**All regions**	**All regions**	**All regions**
Ln(Traded Cluster Specialization)	-0.674	0.466	-1.410	-1.532
Ln(Traded Cluster Diversity)	0.353	0.412	-1.688***	-1.911***
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year – Region Fixed Effects	No	No	Yes	Yes
R-squared	0.089	0.272	0.096	0.182
Obs.	500	500	500	500

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

Table 4.10: The role of regional cluster composition on resilience (innovation level)

	Low innovation	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**
Ln(Traded Cluster Specialization)	-0.727	0.741	-0.428	2.359*	-2.553*	1.240	-2.843*	1.601
Ln(Traded Cluster Diversity)	1.778**	-2.208**	1.715**	-2.026**	-1.288	-2.576***	-1.428	-3.009***
Control variables	No	No	Yes	Yes	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Region Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Year – Region Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.143	0.079	0.293	0.349	0.083	0.166	0.173	0.276
Obs.	311	189	311	189	311	189	311	189

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

Table 4.11: The role of regional cluster composition on resilience (all regions and interaction terms)

	All regions	**All regions**	**All regions**	**All regions**
Year2006*Ln(Traded Cluster Spec)	-0.207	1.117	-0.420	-0.060
Year2007*Ln(Traded Cluster Spec)	-0.95	0.947	-1.238	-0.170
Year2008*Ln(Traded Cluster Spec)	-4.168***	-2.344**	-4.196***	-3.275***
Year2009*Ln(Traded Cluster Spec)	-1.188	0.399	-1.464	-0.746
Year2010*Ln(Traded Cluster Spec)	-1.658	-0.631	-1.908	-1.629
Year2011*Ln(Traded Cluster Spec)	0.378	0.985	0.031	-0.025
Year2012*Ln(Traded Cluster Spec)	0.18	0.237	-0.077	-0.607
Year2013*Ln(Traded Cluster Spec)	0.544	0.286	0.266	-0.550
Year2014*Ln(Traded Cluster Spec)	0.588	0.100	0.290	-0.679
Year2015*Ln(Traded Cluster Spec)	0.789	0.171	0.449	-0.757
Year2006*Ln(Traded Cluster Div)	0.357	0.726	-0.629	0.056
Year2007*Ln(Traded Cluster Div)	-0.405	0.300	-0.804	-0.253
Year2008*Ln(Traded Cluster Div)	-1.314*	-0.440	-0.905	-0.571
Year2009*Ln(Traded Cluster Div)	-0.549	0.243	-0.770	-0.441
Year2010*Ln(Traded Cluster Div)	-0.769	-0.171	-0.889	-0.386
Year2011*Ln(Traded Cluster Div)	-0.416	-0.017	-0.815	-0.112
Year2012*Ln(Traded Cluster Div)	-0.409	-0.335	-0.812	-0.059
Year2013*Ln(Traded Cluster Div)	-0.184	-0.194	-0.830	0.017
Year2014*Ln(Traded Cluster Div)	-0.288	-0.451	-0.835	0.174
Year2015*Ln(Traded Cluster Div)	-0.133	-0.348	-0.799	0.193
Control variables	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	No	No
Region Fixed Effects	Yes	Yes	No	No
Year –Region Fixed Effects	No	No	Yes	Yes
R-squared	0.213	0.337	0.267	0.411
Obs.	500	500	500	500

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

Table 4.12: The role of regional cluster composition on resilience (innovation level and interaction terms)

	Low innovation	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**	**Low innovation**	**High innovation**
Year2006*Ln(Traded Cluster Spec)	-0.087	0.190	0.615	2.736	-0.972	0.000	-0.976	0.000
Year2007*Ln(Traded Cluster Spec)	-1.448	2.471	-0.043	4.407**	-1.871	1.481	-1.349	2.496
Year2008*Ln(Traded Cluster Spec)	-5.913***	2.847	-4.703***	4.627**	-6.138***	2.577	-5.887***	2.975*
Year2009*Ln(Traded Cluster Spec)	-1.407	1.476	-0.284	2.916	-1.880	1.166	-1.721	1.496
Year2010*Ln(Traded Cluster Spec)	-2.151	1.246	-1.543	2.593	-2.623*	1.348	-2.784*	1.690
Year2011*Ln(Traded Cluster Spec)	0.201	1.281	0.47	2.316	-0.308	1.317	-0.717	1.524
Year2012*Ln(Traded Cluster Spec)	-0.278	2.923	-0.343	3.355*	-0.729	2.411	-1.547	1.962
Year2013*Ln(Traded Cluster Spec)	0.158	2.332	-0.203	2.568	-0.285	1.814	-1.405	1.257
Year2014*Ln(Traded Cluster Spec)	0.423	1.879	-0.288	2.092	-0.031	1.314	-1.332	0.953
Year2015*Ln(Traded Cluster Spec)	0.676	2.226	-0.093	2.817	0.106	1.665	-1.271	1.322
Year2006*Ln(Traded Cluster Div)	1.587**	-2.490**	1.686**	-1.81	0.896	-2.852**	1.169	-1.962*
Year2007*Ln(Traded Cluster Div)	0.918	-2.534**	1.199	-1.518	0.669	-3.025***	0.865	-2.257**
Year2008*Ln(Traded Cluster Div)	0.305	-3.919***	0.749	-2.821**	0.709	-3.267***	0.719	-2.796***
Year2009*Ln(Traded Cluster Div)	0.946	-3.746***	1.297	-2.535**	0.690	-2.974***	0.705	-2.537**
Year2010*Ln(Traded Cluster Div)	0.843	-4.265***	0.95	-3.252**	0.616	-3.158***	0.751	-2.482**
Year2011*Ln(Traded Cluster Div)	1.043	-4.095***	0.953	-3.089**	0.694	-3.087***	0.994	-2.104**
Year2012*Ln(Traded Cluster Div)	1.017	-3.344**	0.587	-2.367*	0.741	-3.141***	1.080	-2.072**
Year2013*Ln(Traded Cluster Div)	1.198	-3.284**	0.742	-2.318*	0.757	-3.178***	1.170	-2.002*
Year2014*Ln(Traded Cluster Div)	1.173	-3.327**	0.643	-2.737**	0.732	-3.171***	1.314	-1.774*
Year2015*Ln(Traded Cluster Div)	1.347	-3.421**	0.620	-2.581**	0.706	-3.054***	1.254	-1.636
Control variables	No	No	Yes	Yes	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Region Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
Year –Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.327	0.147	0.414	0.394	0.364	0.219	0.471	0.474
Obs.	311	189	311	189	311	189	311	189

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

5 Conclusions

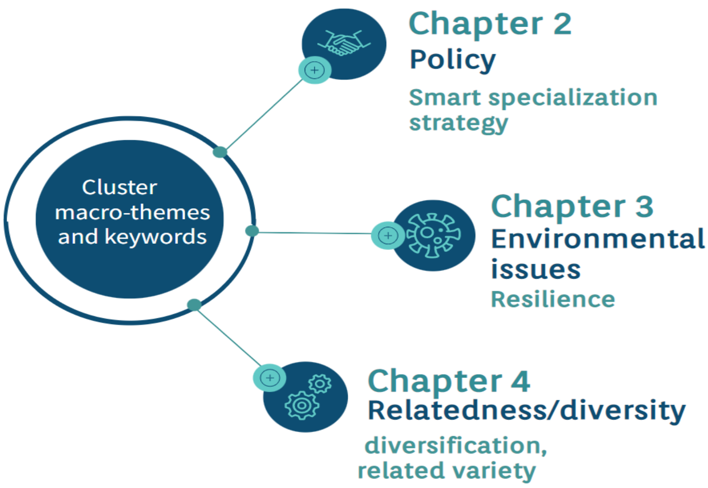
As mentioned in the introductory chapter, despite the vast amount of literature on clusters, there still exists some unanswered questions and new ones raising. Given the necessity to rethink this topic, Lazzeretti et al. (2019) organized the new cluster's research agenda in eleven macro themes, through which this thesis has contributed to the literature on three of them (see figure 5.1). The second chapter was associated with the macro theme on policy by studying the convenience of joint implementation of clusters and the S3 policies for higher efficiency. Meanwhile, the third chapter was related to the macro theme on environmental issues, evaluating the impact of clusters' strength on regional resilience. Finally, the fourth chapter deals with the macro theme on relatedness by analyzing how cluster specialization and diversity impacts resilience according to the innovation levels in the state. In the following paragraphs, we sum up the main findings of each chapter and their implications for the design of cluster policies. Furthermore, at the end of this section, we comment on the limitation of this thesis and how future research could address it them.

Related to clusters and S3, chapter two presents the findings to three main issues. First, results show that the efficiency of the sub-clusters increases when they are complemented with variables that represent the S3 elements. Furthermore, the S3 variables increase the number of sub-clusters that reach global efficiency. To sum it up, S3 has a positive impact on sub-cluster efficiency in general.

Second, the findings demonstrate that the impact of the S3 variables change according to the technological intensity of the sub-clusters. Results show that S3 has the highest impact on the efficiency of the medium low-tech group for the Mexican case. The reason is that Mexico specializes in improving production processes and not developing breakthrough innovations.

In about the third objective of this chapter, results show which S3 strategy is more suitable for sub-cluster at different levels of technological

Figure 5.1: Cluster macro themes to which this thesis contributes



SOURCE: *Own elaboration based on the Cluster macro themes defined by Lazzeretti et al. (2019).*

intensity. For the sub-clusters classified in the high-tech and medium high-tech group, the S3 strategy that mostly increases efficiency are the innovation activities carried out in coordination with universities and research centers. In the medium low-tech sub-clusters, the most effective S3 element is the investment in research and development for innovation. We observe the highest increment in efficiency for the low-tech group when they include innovation activities in collaboration with the government. In general, the findings of this chapter demonstrate the convenience of complementing clusters with the S3 policy for more efficient use of their inputs since both policies pursue increasing regional productivity. In a way, S3 can be considered a new step in cluster evolution.

The findings in the second chapter are of interest to policymakers in Mexico and other countries. As mentioned in the introduction section, in the last years, the European Commission has guided six Latin American countries in the process to adopt the S3 program: Mexico, Brazil, Colombia, Argentina, Chile, and Peru. Table 1.1 in the introductory chapter summarizes the S3 pilot activities carried out by these countries. Consequently, the findings from the second chapter are of great interest for those countries, whose implications are very similar to their economies, considering that Latin American countries generally suffer from a lack of new innovations and technologies. However, these findings are of the most significant interest to Brazil and Colombia because these countries, as in the Mexico case, take clusters as the base to implement their S3 pilot activities. Additionally, even when the findings of the second chapter are of genuine interest for Latin American countries, they can also be significant for countries with similar economic and innovation backgrounds to that of Mexico's.

Therefore, the findings from the second chapter contribute to the cluster and S3 literature. The cluster concept is an evolutionary collection of ideas since the concept of the industrial district by Marshall (1919). It could be a new level in its evolution to complement it with the ideas of this innovation policy. Furthermore, our findings contribute to the literature that analyzes the design of the S3 policy. Since many regions have already developed clusters, they can be considered as the foundation to carry out S3.

Findings in chapter three indicate that regions with the presence of strong clusters show higher resilience to economic shocks than the rest of the regions. However, the effect of such influences change for different moments of the resilience mechanism. According to Martin et al. (2016), resilience is a process of four stages: risk, resistance, reorientation, and recoverability. Based on these stages, we got two main conclusions. Firstly, regions with strong portfolios and portfolios that tend to pay higher wages across regions will be less vulnerable in the years when the economic shock hits the economy. In other words, these regions will be less resilient for the resistance stage. Secondly, regions with an overall cluster strength are resilient in the year after the economic shock corresponding to the recoverability phase.

Chapter three demonstrates that the presence of strong clusters matters for regional resilience, chapter four goes into deeper analysis and shows us which cluster composition is more convenient to resilience according to the innovation level in the region. We characterize such cluster compositions by cluster specialization or cluster diversity. We assume that the effect of these variables resembles the impact of related and unrelated varieties on resilience. We find that cluster specialization makes regions less vulnerable to downturns when the region is characterized by high innovation. Whereas a high cluster specialization will complicate resilience for a region with low innovation. In the case of cluster diversity, it positively influences economic recovery for regions with low innovation.

Cluster specialization and diversity are crucial for different phases in the resilience process. Strong cluster specializations improve the regional adaptations during the years of a downturn. The reason is the strong cognitive proximity between the industries, facilitating the reallocation of workers and technology as well as the emergence of new technology to increase regional adaptation to new circumstances. This reason explains why strong cluster specializations positively impact resilience in regions with high innovation levels. Meanwhile, high cluster diversity supports the region's adaptability, that is, the resilience response in the long term. The high cluster diversity implies low cognitive proximity that complicates reallocating production inputs or responding to innovation with new economic circumstances in the short term. Nevertheless, in the long term, these diversified clusters collaborate to create breakthrough innovations, that can lead to new growth paths of resilience.

Findings from chapters three and four have relevant implications for policies oriented to improve regional resilience. Furthermore, these findings are of particular relevance given the economic challenges that regions confronted with the COVID-19 crisis. It is crucial to find the determinants that can help support overcoming these difficult economic circumstances. Chapter three indicates that the development of strong clusters can be considered a tool to make the regions less vulnerable to economic shocks. Many regions worldwide have already developed their cluster portfolios, and other regions are in the process of defining them. Its positive influence on resilience is another reason that supports the development of such portfolios.

Findings from the third and fourth chapters have direct implications for the state cluster policy in the U.S. To understand the reasons, we need to mention the National Governors Association (NGA). It is an American political organization whose members are the governors of the fifty U.S. states and five U.S. territories (American Samoa, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands). This association serves as a public policy liaison between the state government and the federal government, where governors receive advice on issues like health, environment, education, technology, etc. To fulfill its duties, the NGA has the Center for Best Practices, which is in charge of developing innovative solutions to today's most pressing public policy challenges (National Governors Association, 2022).

In 2012, the NGA Center for Best Practices published the article "Redesigning State Economic Development Agencies," written by its

Figure 5.2: Fundamental strategies to increase the effectiveness of state economic development agencies

SOURCE: *Own elaboration with information from Sparks and Pappas (2012)*

advisors Sparks and Pappas (2012). In this document, they indicate to the governors the three foundational strategies to increase the effectiveness of their state economic development agencies, which we summarize in figure 5.2. As we can observe, one of these three foundational strategies is creating mechanisms to encourage collaboration among industry clusters and government agencies. We emphasize this point to clarify the relevance that clusters have for state policies in the U.S. Such a recommendation was supported by the launch of the U.S. Cluster Mapping Project in 2014, described in the third chapter. As mentioned above, this national initiative provides cluster data to policymakers, business people, and academics to guide all the efforts for cluster development into the same direction. The findings from the third and fourth chapters can contribute to this huge effort to enhance the cluster policy in the U.S. Additionally, these findings are helpful for other countries where the state government has an essential role in the design of a cluster policy.

Based on the results from these chapters, a cluster policy could be designed to make the regions less vulnerable in different moments of the resilience process. Suppose that the objective is to make the region less vulnerable during the downturn. In that case, the cluster policy should focus on building a strong cluster portfolio. However, if the objective is to make the region less vulnerable in the years of recoverability, the cluster policy should enhance the general cluster growth in the region. Cluster composition has another essential role in the design of cluster policies. Cluster specialization and diversity have different effects on resilience, and differ also according to the innovation level in the regions. For regions that produce a high number of patents it is recommended to improve cluster specialization. It will enforce regional resistance to an economic shock. The opposite happens for regions with low innovation; their cluster policy should promote the cluster diversity for a greater regional recoverability to downturns.

This thesis has some limitations that set the lines for future research. Concerning chapter two, *The Impact of Smart Specialization on Sub-cluster Efficiency*, our analysis could be carried out at a more disaggregated level. This chapter evaluates the effects of S3 at the national level, which is relevant for the national objectives of the S3 policy. However, it would be interesting to carry out an analysis at the regional level, given the remarkable economic difference in the North and the South part of the country. The North is more specialized in manufacturing industries, and the South is more focused on services (Juárez and Campos Benítez, 2010; Arévalo and Peláez Herreros, 2015). Therefore, the recommendations for the S3 policy should be different for those two big regions in the country and a separated analysis would be worth doing. Another limitation in this chapter is the year for the analysis, 2013. At the moment of developing this research, it was the most recent data on innovation at the industry level provided by the Economic Census of 2013. However, such data was not included again for the census that followed this one. Even though our results can still be considered valid as the number of patent applications, Mexico's national innovation system has not demonstrated a significant change in the past years. In 2013, the number of patent applications by Mexicans that reside in this country was 7.4%, a number that slightly changed to 7.6% in 2019 (World Intellectual Property Organization, 2021).

In chapter three, *Regional Resilience and Cluster Strength*, our analysis is drawn from the model by Delgado and Porter (2021) given the points in common for both studies and the convenience to set our research to the U.S. Cluster Mapping Project. However, we could test our hypothesis with the models proposed by other authors to compare results. For instance, Giannakis and Bruggeman (2017) have analyzed data over a period of several years for the European regions, while our data is year by year. On the same line, we

Figure 5.3: Keywords in this thesis

SOURCE: *Own elaboration*

develop our analysis at the state level, given the way the cluster policy is managed in the U.S., but we can elaborate on a more desegregated geographic unit of analysis to compare our results with authors that lead their studies at the metropolitan or county level. Another possibility to extend this research is to address this analysis for other economic shocks like the one caused by the COVID-19 pandemic. At the moment of closing this dissertation, cluster data was not available for the years of the pandemic. Nonetheless, it would be interesting to determine if the same conclusions hold for this downturn.

Chapter four, *Cluster Composition and Regional Resilience*, is an extension of chapter three, so the same future lines of research mentioned above apply to this case too. However, there is a point that is specific to this chapter. It classified regions into a group of either low or high levels of innovation according to the number of patents registered, which is not an incorrect procedure, but we could try a more advanced method. For instance, Szopik-Depczyńska et al. (2020) assessed the innovation level for the European regions using the results obtained for a group of indicators in different areas like framework conditions, intellectual activities, innovation activities, etc.

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