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Clusters and Resilience during the COVID-19 Crisis: Evidence from Colombian Exporting Firms*

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Abstract

In this paper, we characterize the geography of Colombian exporting clusters and analyze how the COVID-19 crisis has affected Colombian exporters. We contribute to the industrial clusters literature by defining exporting clusters with bipartite network analysis and community detection tools. The methodology allows us to empirically detect product clusters, which are compared with an alternative definition of industrial clusters, and to consider the centrality of firms within clusters. Then, we analyze the firms' trade margins during the COVID-19 crisis to evaluate whether belonging to an exporting cluster can be a source of resilience for firms. We find that clusters do not automatically lead to higher resilience and that there are differences in how firms react to a crisis within clusters. Identifying the relevant firms' characteristics can guide policymakers to activate the mechanisms that generate resilience.

Keywords: exporting clusters, margins of trade, resilience, COVID-19, bipartite networks, community detection

JEL Codes: F14, R12, L19

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1 Introduction

The COVID-19 pandemic has generated dramatic health and economic crises. In a highly interconnected world, the pandemic's impact on international trade has been fueled by national lockdowns, the adoption of trade and trade-related measures, and the temporary disruption of global value chains (Bonadio et al., 2020; Evenett, 2020). However, the effect is not evenly distributed across sectors, countries, and firms because idiosyncratic features can affect their capability to adapt to the crisis (Espitia et al., 2022). Therefore, strengthening the resilience of the economies to adverse exogenous shocks has become increasingly important.

Several studies have identified country- and region-specific patterns of related industries and trade composition as relevant factors for economic development (Hausmann and Klinger, 2006; Delgado et al., 2010). The presence of clusters—groups of closely related and complementary industries operating in a particular location—can play a role in the resilience of regional industry employment when faced with economic downturns. Thus, clusters could help to face the adverse effects of the COVID-19 crisis and improve firms' capabilities to survive in external markets, as recent studies have shown (for example, Dai et al., 2021; Delgado and Porter, 2021; Jun et al., 2021). However, clusters could also exacerbate existing vulnerabilities, facilitating the propagation of shocks across related industries and firms.

In this paper, we characterize the geography of Colombian exporting clusters and analyze how the COVID-19 crisis has affected exporting firms. First, we detect exporting clusters within Colombia using bipartite network analysis and community detection tools. Then, we use clusters-related measures to evaluate the effect of the crisis and whether belonging to an exporting cluster can be a source of resilience by analyzing firms' survival rates in the exporting market (the extensive margin) and export volumes (the intensive margin).

We argue that the structure of the product space of firms' exports should mirror the existence of industrial clusters. At the aggregate level, using country exports data, the product space has a triangular shape or a nested pattern (Hidalgo et al., 2007). However, this triangular shape disappears at the firm level, where a block-diagonal structure emerges (Bruno et al., 2018; Laudati et al., 2022). Each block relates to a subspace of products into which firms are likely to diversify. When analyzed separately, these subspaces reveal the great heterogeneity in the diversification patterns of firms (Bruno et al., 2018). Teece et al. (1994) show that existing capabilities constrain diversification opportunities of firms and that product portfolios are not random. They argue that more related activities will be more frequently combined within the same corporation. Therefore, a hierarchical structure might emerge in clusters (in-block nested structure): more competitive firms shall be more diversified. Consequently, competition and related diversification might be essential for the nested structure's emergence.

Our paper has a relevant methodological contribution to the literature on industrial clusters. Although bipartite network analysis and community detection tools have been increasingly used in economics, to our knowledge, they have not been applied to the detection and analysis of industrial clusters. These methods allow us to identify firms that share capabilities for exporting products and characterize them within the clusters.

We show that it is possible to apply these methods to detect product clusters and map them into a definition of industrial clusters. Empirically, we found that the product relatedness network is characterized by a highly modular structure, evidencing the existence of product communities, which are the inputs for our product clusters. Interestingly, there is a great correspondence between the empirically detected product clusters with those industrial clusters defined in Delgado et al. (2016). In addition, we use the centrality of firms to understand firms' heterogeneity and the roles they play within clusters.

Our analysis has implications in terms of diversification strategies. The detected modular structure reveals that firms' diversification occurs between relatively similar products. Conversely, the diversification in products with low relatedness is less frequent. However, this reveals connections between different industrial sectors and can indicate the diffusion of knowledge between them. We find that Colombia's larger departments enjoy greater diversification and more interconnections between their clusters. Conversely, smaller departments show great specialization in a few clusters and almost no between-cluster interconnections.

In addition, we contribute to the stream of literature that analyzes industrial clusters as a possible source of resilience when faced with a crisis. We find that, on average, global measures of competitiveness of the clusters do not provide an advantage for firms and do not significantly increase resilience during the crisis. However, cluster-related measures provide an advantage after the worst quarter of 2020, indicating greater resilience for firms in clusters, in particular for more central firms. Interestingly, the measures related to the competitiveness of the firms within clusters show statistically significant and robust positive effects on the intensive and extensive trade margins, on average, and after the COVID-19 shock. Products that belong to a cluster have higher survival probabilities and intensify their export volumes. Similarly, the centrality of firms within their clusters provides an advantage before and during the COVID-19 crisis. Diversifying exports beyond the main cluster also has a lower but still positive effect compared to between-cluster diversification, indicating that diversifying beyond the firms' core competencies can be an additional source of resilience. Therefore, we conclude that clusters do not automatically generate higher resilience, and there might be differences in how firms react to a crisis even within a cluster. Identifying the relevant firms' characteristics can guide policymakers to activate the mechanisms that generate resilience.

The rest of the paper is organized as follows. Section 2 presents a brief literature review. Section 3 explains the data and Section 4 discusses the methodology. Section 5 presents the results. Finally, Section 6 concludes and provides policy implications.

2 Clusters and Resilience

The origins of the notion of clusters can be traced back to the influential work of Alfred Marshall on industrial districts (Marshall, 1920). More recently, Porter (1990, 1998) introduced and defined the term "cluster" as a geographic concentration of interconnected firms and institutions in a particular field. Since then, clusters have been linked to the agglomeration of economic activities as a central feature of economic geography. In many studies, regional clusters refer to geographic concentrations of industries related by knowledge, skills, inputs-outputs, demand, or other linkages (Delgado et al., 2016).

Different ways of understanding the drivers of agglomerations may lead to different ways of identifying and measuring clusters. Marshall (1920) highlighted three distinct drivers: input-output linkages, labor market pooling, and knowledge spillovers, all of which are associated with cost or productivity advantages to firms. A vast amount of literature has broadened the agglomeration drivers, including local demand conditions, specialized institutions, the organizational structure of the regional business, and social networks (Porter, 1990; Saxenian, 1996; Storper, 1995; Markusen, 1996; Sorenson and Audia, 2000).

Following Marshall, location externalities and localized knowledge spillovers are highly relevant for the development of clusters. Vicente (2018) argues that although these conditions may be determining factors, there are still relevant microeconomic factors to be understood, such as the role that organizations play within clusters and why these organizations exchange cognitive resources and build knowledge collaborations. Many studies on knowledge networks explore this more deeply and provide relevant facts at the global and local levels (e.g., Giuliani, 2007; Vicente et al., 2011; Giuliani et al., 2019). At the global level, the structure of interactions of institutions related to knowledge flows explains the development and success of the clusters (Delgado et al., 2014). At the local level, there is a close relationship between the organization's performance and its centrality in the knowledge flow networks. Knowledge endowments determine the level of embeddedness or centrality, and the heterogeneity of these endowments prompts firms to establish collaborations to increase their knowledge stocks.

However, although geographic proximity facilitates interaction and cooperation for knowledge exchange, it is not a guarantee of knowledge diffusion (Breschi and Lissoni, 2001). There are some exceptions in which geographical proximity is less relevant. For instance, Ter Wal (2014) shows that in the biotechnology industry, the increasing codification of knowledge and the need to reach a phase of global market exploitation are making geographic proximity less relevant. For knowledge spillovers to emerge, it is necessary to consider other institutional dimensions. For instance, Boschma (2005) argues that geographic proximity combined with a certain level of cognitive proximity facilitates interactive learning. Two firms are cognitively close when they have accumulated similar forms of knowledge or possess similar capabilities. Firms' attributes, such as their products, markets, and patents, can capture the cognitive proximity between them. Nooteboom (2000) argues that this distance is key to facilitating communication and knowledge absorption and that the degree of novelty—for example, in an inter-firm alliance—is an inverse U-shaped function of the cognitive distance between the firms.

Accordingly, the clusters' attributes must also be related to the set of firms' capabilities in terms of the degree of technological variety and coordination. In other words, the cluster also acquires a cognitive profile. In this process, larger firms play a central role in the knowledge network and in coordinating the knowledge flows. For instance, Balland et al. (2013) highlights the importance of cooperating in R&D to achieve a common standard.

Similarly, the cluster life cycle approach has focused on explaining how clusters change and develop over time, arguing that their existence and structure can only be understood when studying their dynamics over time (Maggioni, 2002; Iammarino and McCann, 2006; Ter Wal and Boschma, 2011). In fact, Martin and Sunley (2006) argue that clusters may be best understood as products of a path-dependent process. In that context, scholars have described cluster development's main features over time and explored the driving forces behind its evolution. Menzel and Fornahl (2010) proposed a cluster life cycle model in which firms enter and exit the cluster, the capabilities of cluster firms develop and interact (and might converge), and interorganizational linkages within and beyond the cluster are established and dissolved along the cluster life cycle.

Nowadays, clusters are considered an essential part of regional development and innovation strategies in many parts of the world (Trippl et al., 2015). Industrial clusters might generate agglomeration and specialization economies in regions, boosting economic development. Clusters give rise to agglomeration economies among the related industries through input-output linkages, shared skills, knowledge linkages, and other links (Porter, 1990; Saxenian, 1996; Feldman and Audretsch, 1999; Delgado et al., 2010).

However, although the relevance of industrial clusters to promote regional innovation and economic development is widely recognized in theory, at the empirical level, the link between industrial clustering and regional economic outcomes is not always as expected (Martin and Sunley, 2003; Boschma and Kloosterman, 2005; Feser et al., 2008). Also, the effect of industrial clusters on exit, entry, and firm survival is mixed (see Frenken et al. (2015), for a review).

Clusters can play a role in the resilience of regional development to economic downturns. Following Simmie and Martin (2010) and Martin (2012), resilience could be regarded as lower vulnerability to shocks (relatively higher growth during a recession) and/or faster recovery (relatively higher growth post-recession). However, the effect and mechanisms are not completely clear. On the one hand, agglomeration and specialization economies and the close collaboration and trust among their firms within clusters could decrease their economic vulnerability and facilitate a faster recovery. Thus, agglomeration economies could mitigate the effects of recessions and the resulting increase in uncertainty.

On the other hand, cluster specialization could strengthen existing vulnerabilities, facilitating the propagation of shocks across related industries and firms. Therefore, clusters could amplify or increase the duration of adverse outcomes, intensifying the impact of recessions (Delgado and Porter, 2021). There is no consensus on which effect is stronger or whether certain conditions lead to one or the other outcome (Martin et al., 2017; Behrens et al., 2020).

Empirically, there are a few studies with mixed results. In recent work, Dai et al. (2021) show that the impact of the COVID-19 crisis on Chinese firms was significantly lower in counties and industries exhibiting a higher degree of clustering in terms of both entries of new firms and the performance of incumbents. Jun et al. (2021) identify spatial clusters of amenities and an amenity space in Seoul during 2016–2021 to examine the effect of relatedness on the resilience of each cluster. They find that businesses located in clusters of related amenities are more likely to survive. Delgado and Porter (2021) investigate the employment resilience of industries within clusters in the United States (U.S.) during the Great Recession. They show that larger regional industries experienced slower employment growth over the entire business cycle, and this convergence effect was greater during the financial crisis. However, those industries within a stronger or broader cluster experienced relatively higher annual growth, especially during the crisis.

Conversely, Martin et al. (2017) show that French firms in clusters have higher survival probabilities on export markets and higher export growth rates. However, during the 2008-2009 crisis, French firms in clusters showed weaker resilience of competitiveness, probably because they were more dependent on the fate of the largest exporter in the cluster. Similarly, Acs et al. (2007) show that the expected positive relationship between regional human capital and new-firm survival in the U.S. is supported for 1993–1995 but is not as strong for the recession period 1990–1992.

The analysis of firm survival provides a complementary approach to understanding the role of clusters and localization economies during a crisis (see Frenken et al. (2015), for a review). Empirical studies only find evidence of localization economies for some industries. For example, Nyström (2007) shows that localization increases firm survival in 16 of 26 Swedish industries. On the other hand, several studies for different sectors and countries find no effects of clustering on firm survival (Wenting, 2008; Buenstorf and Klepper, 2009; Klepper, 2010). Moreover, other studies find negative effects of clusters on the survival of firms (Stuart and Sorenson, 2003; Acs et al., 2007; Boschma and Kloosterman, 2005).

3 Data

Exports

We use firm-level export data reported monthly to the Colombian Customs Office (DIAN) from 2017 to 2020. For each transaction, we use the exporter's tax identification number (NIT), the month, the Harmonized System (HS) 2017 product code at 6-digits, the department of origin of the product, the country of destination, the export volume, and the free-on-board value in U.S. dollars. We remove all transactions related to re-exports of products fabricated in other countries.

Table 1 shows several statistics of interest for our study including total exports, number

Table 1: Summary Statistics

Variable	2017	2018	2019	2020
Total exports (millions of current U.S. dollars)	22,944	24,196	23,526	20,383
Number of exporting firms	10,331	10,620	10,782	10,212
Number of products HS 6-digits	3,510	3,477	3,421	3,456
Number of firm-product pairs	44,391	44,841	45,620	44,035
Number of multi-department firms	4,780	4,909	4,994	4,584
Share of multi-department firms in total firms	0.46	0.46	0.46	0.45
Number of multi-product firms	5,325	5,399	5,572	5,200
Share of multi-product firms in total exports	0.49	0.50	0.59	0.58
Share of multi-product firms in total firms	0.52	0.51	0.52	0.51
Average number of products multi-product firms	7.40	7.34	7.25	7.50
Average number of destinations multi-product firms	3.78	3.76	3.73	3.81
Average number of destinations single-product firms	1.76	1.76	1.76	1.75

Note: We exclude exports with no department of origin identified. Thus, total exports are lower than those reported in the Colombian statistics. In most cases, exports with no departments are from Chapter 27 of the HS Code: "Mineral, fuels, mineral oils and products of their distillation; Bituminous substances; mineral waxes."

of exporting firms, number of products at the 6-digits level of the HS code classification, and the number of firm-product pairs (our unit of analysis). Depending on the year, there are around 10,000 exporting firms and 3,500 exported products, which total more than 44,000 product-firm pairs.

In addition, we define multi-department firms as those that export products from different departments. Around 46% of exporting firms are multi-department firms. For these cases, we consider each transaction separately because our observation unit is composed of products, firms, and departments. In the estimations, we include firms' fixed effects to consider common firms' effects.

Firms can be either single-product or multi-product (those that export only one product or more than one product, respectively). Multi-product firms make up around 50% in 2017 and 2018, increasing their share to around 59% in 2019 and 2020. The average number of exported products by multi-product firms is around 7.4. Finally, the average number of destinations of multi-product firms is around 3.7, while that of single-product firms is around 1.7.

The COVID-19 crisis had a substantial impact on Colombian exports. The left panel in Figure 1 shows the evolution of total monthly exports during 2018, 2019, and 2020. We observe a significant drop during the first months of 2020, reaching the lowest level in April, where the value is less than half (47%) of that observed in April 2019. Export volumes started recovering in May 2020, but the monthly values of exports in 2020 are significantly lower than those observed for the corresponding months in 2018 and 2019.

Although trade flows have decreased considerably during the COVID-19 crisis, there is heterogeneity across different types of firms and sectors. Dueñas et al. (2021) analyze

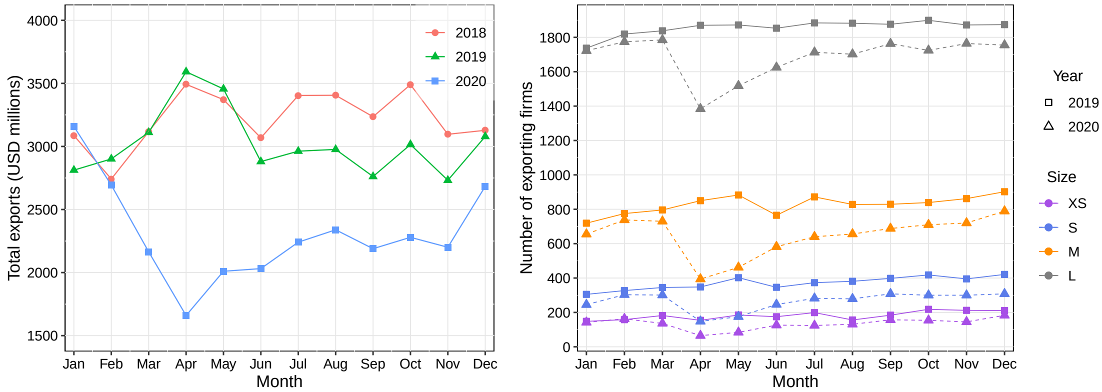

Figure 1: The evolution of total exports (left) and the number of surviving exporting firms within a size class (right). Firm size class derives from the firms' exports (in ln) distribution quartiles in a given year.

Colombian exporters' dynamics as a complex learning process, using different machine learning techniques to predict firms' trade status. They focus on the probability that Colombian firms survive in the export market under a COVID-19 setting and a non-COVID-19 counterfactual situation. They find that, in addition to the temporal dimension, the main factors predicting treatment heterogeneity are interactions between firm size and industry. Similarly, Benguria (2021) found that, during the COVID-19 shock, Colombian multinational affiliates experienced a better export performance, while firm size and indebtedness did not predict a differential growth in exports. Finally, producers of intermediate inputs and capital goods were more severely affected than producers of final consumer goods.

The right panel in Figure 1 shows the monthly number of exporting firms across four firm sizes in 2019 and 2020. We observe that the COVID-19 outbreak affected all firms regardless of their size, but larger firms were less affected than the rest of exporting firms.

Employment

We use information from DANE (2022) that provides annual data (for 2017 to 2020) of employment at the department and industry level at 4-digits of disaggregation of the ISIC Rev.4 code. These data are obtained from a survey using a representative sample.

Industrial Clusters Benchmark

As a benchmark to compare the empirically detected product clusters, we take advantage of the U.S. Benchmark Cluster Definitions (BCD) developed by Delgado et al. (2016) and presented in the U.S. Clusters Mapping Project.[1] The project includes 51 clusters, with 778 traded industries and 16 local traded clusters, including 310 industries (6-digits NAICS 2007) covering manufacturing and services. Table A.1 in the Appendix presents the clusters. We use these industrial clusters to map and compare the empirically detected product clusters.

[1] http://www.clustermapping.us/.

Concordance Tables

We use different concordance tables from the Statistics Division of the United Nations[2] to unify the codes of the different databases: Employment DANE (ISIC Rev.4), Exports DIAN (HS 2017), and U.S. Clusters Mapping (NAICS 2007). We aim to end up with information on exporters and their products to associate them with: (i) a given industry in the ISIC classification to know their employment levels, and (ii) a NAICS code to match product clusters and industrial clusters.

4 Methodology

We define the firm-exports matrix $\mathbf{X}^t_{F\times K}$, where rows represent the F firms, columns the K products, and non-zero entries X^t_{ik} indicate the total firm i exports of product k in time t. Here, K equals the total number of codes of the Harmonized System at 6-digits. Similarly, we define the bipartite firm-product matrix $\mathbf{M}^t_{F\times K}$ whose non-zero entries m^t_{ik} are equal to 1 when $X^t_{ik} > 0$; that is, whether firm i exports product k in time t.

Next, we describe the methodology that allows us to (i) study the product-product relatedness (or the product space of firms' exports) and the detection of product clusters, (ii) analyze the performance of the clusters at the department level and the local role of firms (i.e., their importance within the local clusters), and (iii) use this information to estimate the firms' survival rates in exporting markets and their trade volumes.

4.1 Product Clusters

Empirically, clusters can be defined by the observed linkages between industries and firms, which are expected to derive from spatial agglomerations. Besides, the linkages that define a cluster are related to capabilities as well as to knowledge creation and flows. Thus, to empirically detect exporting product clusters in Colombia, our methodology considers both spatial agglomerations and knowledge concentration.

Given that product relatedness captures dimensions of knowledge relatedness (Jun et al., 2020), and that skills, technology, and knowledge are spatially concentrated (Balland et al., 2020), we aim to detect the topology of product clusters within Colombia, assuming that some regions facilitate knowledge concentration, creation, and diffusion. Thus, we build the regional bipartite firm-product network averaging the period 2017-2020, restricting the products' origin department.

Identification of Relevant Exporters

In the bipartite firm-product matrix $\mathbf{M}_{F\times K}$, we only consider the products in which firms reveal a national comparative advantage. To do this, we compute the Revealed Comparative

[2]https://unstats.un.org/unsd/classifications/Econ

Advantage (RCA_{ik}) for firm i and product k using the Balassa index (Balassa, 1965) as:

$$RCA_{ik} = \frac{X_{ik}/\sum_{k'} X_{ik'}}{\sum_{i'} X_{i'k}/\sum_{i'}\sum_{k'} X_{i'k'}}; \tag{1}$$

For the sake of simplicity we have omitted the superscript t. We then obtain the RCA-filtered bipartite matrix $\mathbf{Y}_{F\times K}$ whose generic entry y_{ik} reads:

$$y_{ik} = \begin{cases} 0 \text{ if } RCA_{ik} < 1, \\ 1 \text{ if } RCA_{ik} \geq 1. \end{cases} \tag{2}$$

Considering relevant producers eliminates around 5% of the data because firms are generally very specialized in what they produce and export.[3]

Product Similarity

Next, we build the product space network as a network-based representation, where nodes are the exported products and ties among them indicate their degree of similarity, which derives from firms commonly exporting them together.

To compute the product-product similarity, we apply the Jaccard index (Jaccard, 1901) to all column couples in $\mathbf{Y}_{F\times K}$, which has been widely used as a relatedness measure to detect co-occurrences in data sets (see Leydesdorff, 2008; van Eck and Waltman, 2009; Boschma et al., 2014; Campi et al., 2021). The similarity $J_{kk'}$ between products k and k' reads:

$$J_{kk'} = \frac{\Lambda_{kk'}}{\Lambda_k + \Lambda_{k'} - \Lambda_{kk'}}, \tag{3}$$

where $\Lambda_{kk'} = \sum_i y_{ik} y_{ik'}$ is the number of times two different firms are relevant exporters of products k and k' together, and $\Lambda_k = \sum_i y_{ik}$ is the total number of firms that are relevant exporters of product k. The resulting matrix $\mathbf{J}_{K\times K}$ is used to define the product-product relatedness network, where nodes are products and weighted links $J_{kk'}$ measure similarity between them.

Community Structure Detection and Link-Weight Filtering

To measure modularity in matrix $\mathbf{J}$, we use the Louvain algorithm, which is a community-detection algorithm for large graphs that optimizes a function known as "modularity" over the possible partitions of a network (Blondel et al., 2008). The function aims to capture the degree to which a network can be partitioned into nodes, with higher interaction within groups than between them. We use the weighted version of the Louvain algorithm to consider link weights in the network.

[3]Countries can have a very high level of product and export diversification. Some countries can produce all types of products while observing a firm producing all possible products is implausible. A few recent studies discuss this (Bruno et al., 2018; Pugliese et al., 2019; Laudati et al., 2022).

The product-product relatedness network $\mathbf{J}$ is highly modular, characterized by a few partitions of great size. Despite this, a relevant statistical fact is that the modules include very close products. Note that if the partitions were perfect—that is, if there were full modularity—there would be a clear division of the diversification patterns of exports in specific sectors (product clusters).

Therefore, we apply a second link-weight filter to eliminate possibly noise-induced and irrelevant links for the network structure, applying the hypergeometric filter to detect more coherent product clusters. We adopt a null statistical model based on the hypergeometric filter to assess whether similarity links are statistically significant at the 1% level (Feller, 1968; Tumminello et al., 2011; Iori and Mantegna, 2018; Campi et al., 2020). Nevertheless, communities might include some products that are not necessarily strongly related. Different reasons can explain this, but the relevant issue is that the detected communities may not have an adequate resolution for the product-cluster analysis that we aim to develop (see Fortunato and Barthelemy (2007), for a discussion on the size of the detected communities). Then, we consider the detected communities with over 500 products and, again, we apply the methodology for link-weight filtering (hypergeometric filter) and community detection (Louvain algorithm).

In both steps, we control that the modularity is reasonably high. In the second step, we can obtain communities that are too small to be considered meaningful product clusters. Then, we move to the final step in analyzing whether we can regroup these apparently too-small communities as part of a larger community. We apply theoretical reasons and industrial classifications to determine whether these small communities were probably detached from a larger community after the application of the Louvain algorithm for the second time.

Finally, we end up with a set of C disjoint clusters of products $\Omega = \{\Omega_c\}_{c \in C}$. Therefore, for a given product cluster c in a department d, we define the local bipartite matrix $\mathbf{X}_{D_d \times \Omega_c}$, such that rows represent firms in department d and columns are products in Ω_c.

Product Clusters' Methodology: Summary

Table 2 summarizes the steps of the methodology that we implement for the empirical product clusters detection.

As a result of this methodology, we obtain communities of products, empirically defined by our data, which we define as *product clusters*. Afterwards, we use the benchmark definition of industrial clusters for the U.S. economy and match it with our product clusters.

Table 2: Summary of the Methodology for Empirically Detected Product Clusters

	Input: Bipartite firm-product matrix $M_{F\times K}$, rows are the F-firms and columns are the K-products
1.	Apply RCA to obtain the RCA-validated matrix Y
2.	Apply Jaccard index to obtain product-product similarity
3.	Apply hypergeometric filter to remove irrelevant links
4.	Apply Louvain algorithm to detect communities in the filtered RCA-validated network
	Output: Product network with high modularity and detected communities
	Input: Communities detected in steps 1 to 4
5.	On each detected community, repeat steps 3 and 4
	Output: New product network with higher modularity and probably a few small communities
	Input: Small communities
6.	Determine if small communities were detached from other relevant communities and regroup
	Output: We end up with a set of C clusters of products $\Omega = \{\Omega_c\}_{c\in C}$, which allows us to derive bipartite product matrices at department level

4.2 Agglomeration and Competitiveness

Global Measures

After having detected exporting product clusters, we compute measures that allow comparing spatial agglomerations and competitiveness of Colombian departments between each other. We use the Balassa index to measure departments and clusters exports' comparative advantages and department labor agglomeration.

First, we measure revealed comparative advantages of each department in each detected cluster RCA_{dc} as:

$$RCA_{dc} = \frac{X_{dc}/X_d}{X_c/X_{COL}}; \tag{4}$$

where X_{dc} are total exports of department d of the set of products Ω_c, X_d are the total exports of department d, X_c are the Colombian total exports of products in Ω_c, and X_{COL} are the total exports of Colombia.

Secondly, we estimate location quotients to determine spatial agglomerations at the department level. It is important to consider that employment data are aggregated at the industry level and that industrial sectors can have products distributed in different clusters (Ω_c).[4] Therefore, to assign an employment measure to a cluster c in a location d, we weight employment of the industries related to a cluster by the share of exports of the Ω_c products in each industry s exports in departments d (ω^d_{sc}), then $E_{dc} = \sum_s \omega^d_{sc} E_{ds}$. Therefore, the location quotient of cluster c in location d is defined as:

$$LQ_{dc} = \frac{E_{dc}/E_d}{E_c/E_{COL}}; \tag{5}$$

where E_d is the total employment of department d, E_c is the total employment of cluster c,

[4]Employment data are defined in the industrial classification ISIC Rev.4. To each product (HS 6-digits) we assign only one industrial sector (ISIC Rev.4, 4-digits).

and E_{COL} is the total employment in Colombia.

Considering that departments can be very heterogeneous, it might be difficult to compare the values of RCA and LQ between them. To facilitate this comparison, we use the normalized version of RCA, which we define as: $NRCA_{dc} = (RCA_{dc} - 1)/(RCA_{dc} + 1)$. An $NRCA \geq 0$ reveals a comparative advantage, and an $NRCA < 0$ the opposite. Similarly, the normalized location quotient is $NLQ_{dc} = (LQ_{dc} - 1)/(LQ_{dc} + 1)$, $NLQ \geq 0$ indicates an agglomeration of workers of cluster c in department d, and an $NLQ < 0$ no agglomeration of workers.

Thus, we define a measure that we call competitive cluster that combines two indicators:

$$CC_{dc} = \begin{cases} 1 \text{ if } NRCA_{dc} \geq 0 \text{ and } NLQ_{dc} \geq 0, \\ 0 \text{ otherwise.} \end{cases} \tag{6}$$

Firm-Specific Variables

We also consider a set of measures related to the competitiveness of the firms within clusters and departments. Firms can export only one product, several products from one cluster, or a more diversified basket of products belonging to different clusters. Thus, we first analyze the firm's basket of products over the period 2017–2020 to assign only one cluster to the firm according to the distribution of products and shares of volumes. Each firm will be in only one cluster and might, in addition, export products belonging to other clusters.

Then, for a given sub-partition $\mathbf{X}_{D_d \times \Omega_c}$, we compute bipartite network centrality of the firms using the BiRank algorithm (see He et al. (2016), for details on the methodology). Since we use the matrix $\mathbf{X}_{D_d \times \Omega_c}$ rather than $\mathbf{M}_{D_d \times \Omega_c}$, we are considering the weighted version of the BiRank algorithm.

An important attribute of this centrality measure is that it considers the number of products in addition to the volume of exports. Therefore, it reflects the position of exporting firms in each cluster. The motivation for using this indicator derives from the analysis of Bruno et al. (2018) who showed that within exporting clusters there is high heterogeneity in firms' diversification patterns.

To capture the fact that firms' diversification patterns can reach different clusters, we also compute the BiRank centrality outside the firm's cluster. We consider the outside cluster interactions to occur in the bipartite matrix $\mathbf{X}_{D_d \times \Omega \setminus \Omega_c}$, where $\Omega \setminus \Omega_c$ is the set difference of the universe of products minus those in cluster c. In addition, we include the age of the firm as a measure of its experience.[5] Finally, we consider the number of destinations because it can be a measure of the firm's size and we expect that those more diversified firms will be more central in the cluster.

[5]We used web-scraping to obtain the age from https://www.einforma.co/nit-empresas.

4.3 Resilience of Exporting Firms

The network analysis provides statistics to understand the network's topology and, therefore, the regional distribution of export capabilities. In particular, centrality measures allow understanding of the network's embeddedness and resilience. We argue that a cluster with strong cohesion should provide more resilience to firms during a crisis. After a shock, some firms are likely to exit the market and some other firms are likely to reduce their product scope. The resulting product relatedness network might be no more strongly connected, leading to a decrease in resilience.

To test these ideas, we analyze the impact of the crisis on the survival probability of exporting firms (extensive margin) and on the export volumes (intensive margin) at the product level. Our benchmark specification is:

$$y_{ikt} = \alpha\, C_{20} + \psi\, V_{d_i(t-t')} + \phi\, U_{ik(t-t')} + \nu\, C_{20} \times V_{d_i(t-t')} + \mu\, C_{20} \times U_{ik(t-t')} + \beta\, Y_{i(t-t')} + \varepsilon_{ikt}; \quad (7)$$

where y is the dependent variable, either the probability to remain in the export market for firm-product ik in year t (survival or extensive margin) or the value of exports of product k by firm i (intensive margin); C_{20} is a dummy variable for 2020 indicating the COVID-19 shock; $V_{d_i(t-t')}$ is a set of department cluster indicators to which firm i belongs: the NLQ_{dc}, the $NRCA_{dc}$ of a product in a department at the national level, and the competitive cluster indicator (CC_{dc}); $U_{ik(t-t')}$ is a set of firms' specific cluster statistics: Product^{in} that indicates if the exported product belongs to the cluster assigned to the firm, the weighted centrality measure inside and outside the cluster of the firms (WBiRank^{in} and WBiRank^{out}); $C_{20} \times V_{d_i(t-t')}$ and $C_{20} \times U_{ik(t-t')}$ are the same set of department and firm variables interacted by the dummy of the shock; $Y_{i(t-t')}$ is a set of firm level variables, the firm's age and the number of destinations, considering that more experienced exporters or firms with larger destination portfolios are probably more resilient to negative shocks; t' is a lag for the reference year; and ε_{ikt} is the estimation error.

We are mainly interested in the parameters ψ, ϕ, ν, and μ that relate to the importance of clusters. The first two parameters capture the contribution of industrial clusters to the probability of export survival, while the last two parameters measure the clusters' response to the shock and, therefore, allow us to understand their contribution to resilience.

When we focus on the extensive margin, we estimate Eq. (7) using a logit estimation method, including dummies for time, product (HS codes at 4-digits), cluster, department, and firm's ISIC section. However, when we consider the effect of clusters and the COVID-19 crisis on the intensive margin of trade, we use a Poisson Pseudo Maximum Likelihood (PPML) estimation method, and we include the same set of dummies and firm dummies.

5 Results

Correspondence between Product Clusters and Industrial Clusters

By applying network analysis and community detection methods to export data, we obtain 33 product clusters to which we simply assign numbers that allow for their identification. Each product cluster contains products with higher interaction between them than with any other product in the remaining clusters. In other words, products within a product cluster are more commonly exported together than any other pair of products from different clusters. Then, we match these "self-organized" or empirically detected product clusters with industrial clusters using a concordance table between products and industrial sectors, using the benchmark built for the U.S. economy by Delgado et al. (2016). We find 39 industrial clusters, given that some traded clusters of the benchmark definition are not present in Colombia. Next, we discuss the characteristics of the clusters, and we compare both types of definitions.

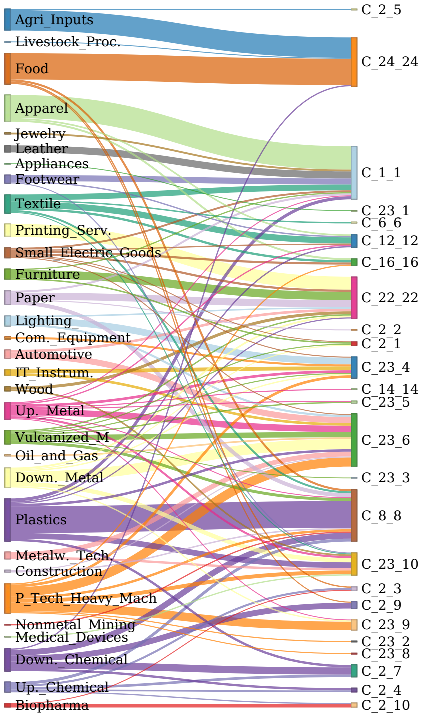

Figure 2: Correspondence between industrial clusters (left side) and product clusters (right side) for Colombia. Connections represent the shares of the number of firms. We consider connections between industrial and product clusters with at least 30 firms. On the right side, C corresponds to cluster, the first number corresponds to the clusters detected in the first round of cluster detection, and the second number identifies the clusters in the second round of cluster detection (see Table 2).

Figure 2 illustrates the correspondence between industrial clusters (left) and product clusters (right). The number of firms exporting the products classified in the corresponding cluster determines the size of the clusters (nodes in the figure). These two types of clusters show different aggregations and different processes: one is based on industrial sectors and the other one is based on products. However, in general, they have a relatively high correspondence, especially when we look at the correspondence in the departments, as we will discuss.

In the left part of Figure 2, we observe that clusters such as Apparel, Plastics, Production Technology and Heavy Machinery, Food, Agri Inputs, and Downstream Chemicals concentrate a higher number of firms. Conversely, other clusters are very small as they include a low number of firms (e.g., Oil and Gas, Medical Devices, and Construction). The higher correspondence between product clusters and industrial clusters in some cases, such as Food and Agri Inputs, reveals higher specialization of these activities and products.

The fact that there is no perfect match between the clusters' definitions is interesting because it shows that firm's capabilities transcend to different industrial sectors. In other words, this evidence reveals that some firms have export baskets that are diversified enough to include products from different industrial clusters of the benchmark.

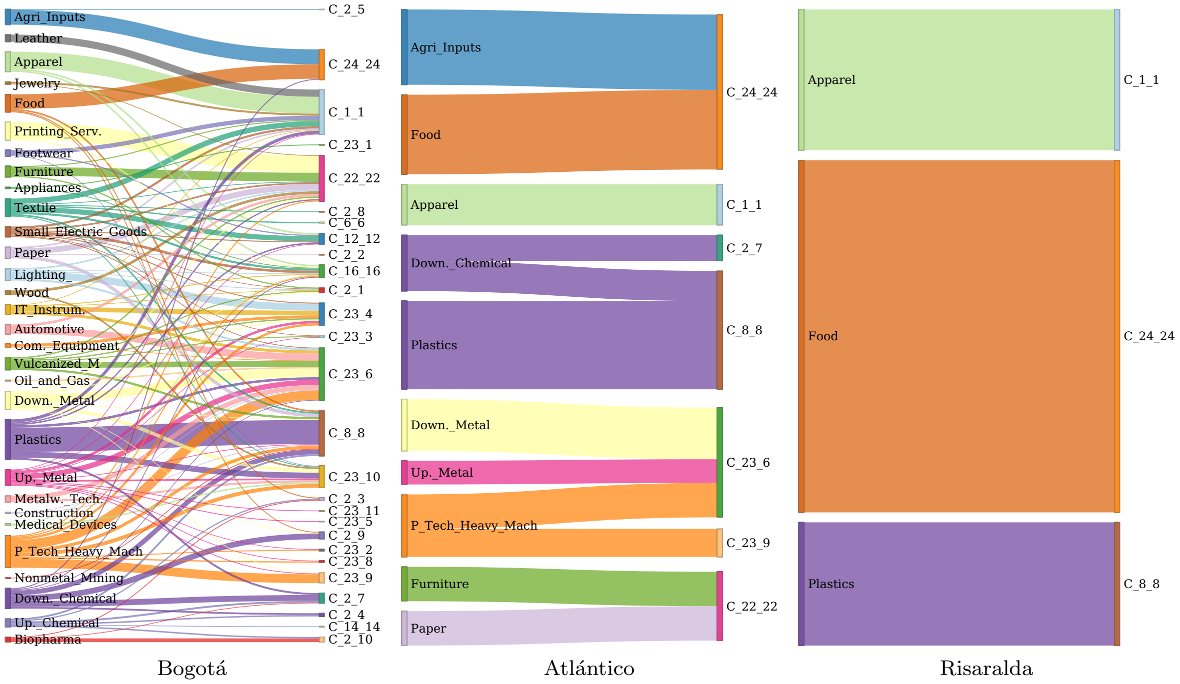

Figure 3: Correspondence between industrial clusters (left side) and product clusters (right side) for Bogotá, Atlántico, and Risaralda. Connections represent the shares of the number of firms. We consider connections between industrial and product clusters with at least 10 firms. In the right side of the graphs, C corresponds to cluster, the first number corresponds to the clusters detected in the first round of cluster detection, and the second number identifies the clusters in the second round of cluster detection (see Table 2).

Figure 3 compares the correspondence between the two definitions of clusters for three departments of different sizes. Bogotá agglomerates many different activities and the matching pattern of clusters is quite similar to the one observed at the national level. However, when we look at smaller departments such as Atlántico and Risaralda, a surjective pattern emerges between both sets of clusters, meaning that exports baskets in those departments tend to be more specialized in specific clusters.

Clusters' Connectivity

Now, we analyze how firms' export patterns map inside their own cluster and outside in other clusters. Figure 4 shows chord diagrams for the two sets of clusters.

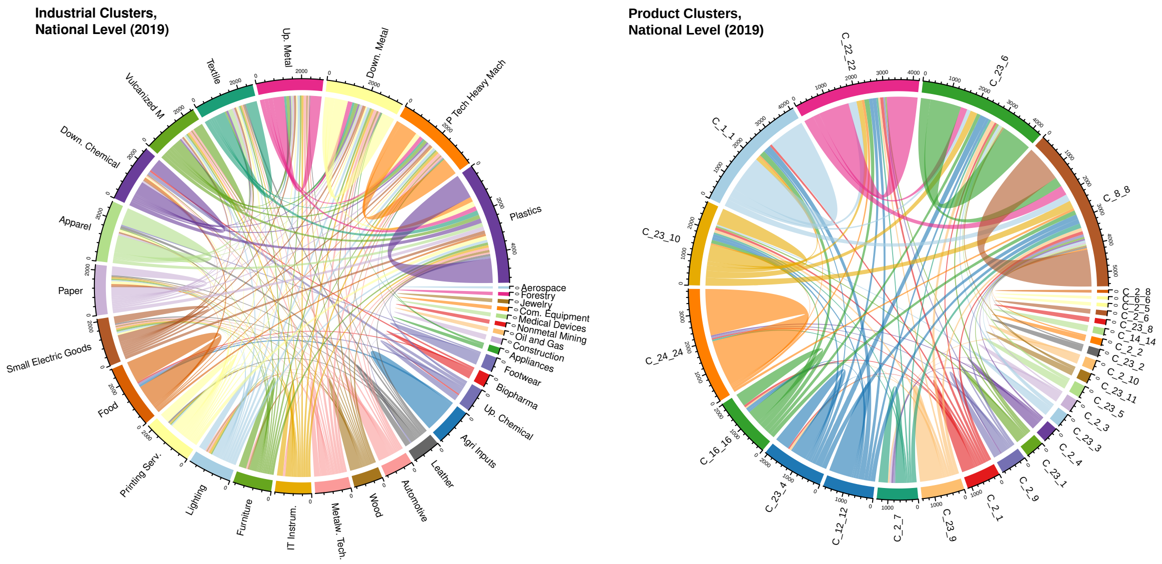

Figure 4: Number of firms in industrial clusters (left) and product clusters (right) for Colombia, 2019. Both product and industrial clusters have at least 10 firms. In the product clusters, C corresponds to cluster, the first number corresponds to the clusters detected in the first round of cluster detection, and the second number identifies the clusters in the second round of cluster detection (see Table 2).

Clusters are represented as nodes around the circle diagram, and links are the number of firms shared by two clusters. The higher the participation in the perimeter of the circumference, the greater the number of firms participating in this cluster. The thicker the link, the greater the number of firms that are shared by a pair of clusters.

As expected, both sets of clusters exhibit high inner activity, which implies that many firms have export baskets whose products belong to a specific cluster. However, a non-negligible number of firms have export baskets that map into different industrial clusters. The clusters' connectivity might indicate spillovers or knowledge flows between different industries and clusters, which might be relevant for economic development and resilience.

The degree of clusters' relatedness is correlated with the economic size of the departments, as observed in Figure 5, which shows the chord diagram for three different departments. In departments such as Risaralda, firms are very specialized and the connectivity between clusters is very low, while larger departments such as Bogotá or even Atlántico show more connectivity between clusters, considering both definitions.

In essence, clusters enable interaction channels for actors who bring together different knowledge, leading to the emergence and development of innovation, products, and new industries. Thus, the structure and effectiveness of these channels depend on the clusters' stage of development. Our analysis reveals that firms located in regions with low economic

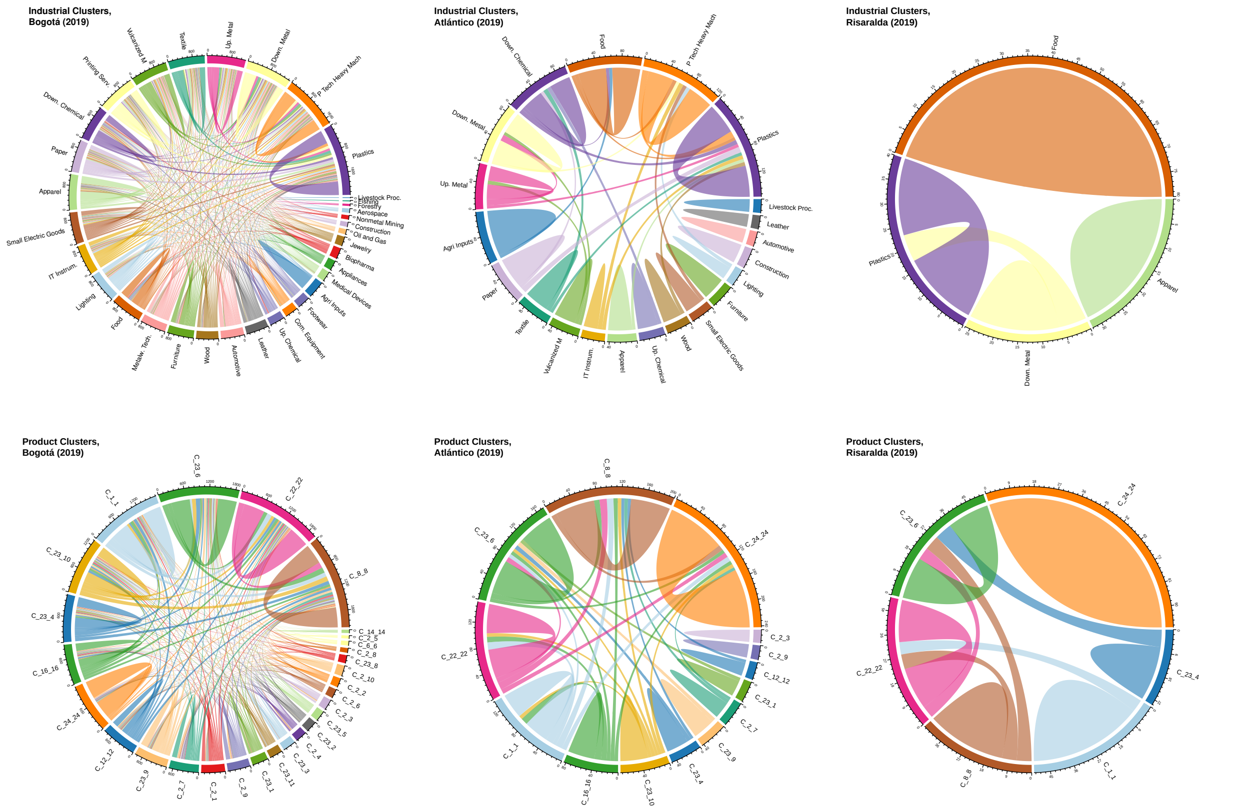

Figure 5: Number of firms in the industrial clusters (upper panel) and the product clusters (lower panel) for selected Colombian departments: Bogotá, Atlántico, and Risaralda, 2019. Both product and industrial clusters have at least 10 firms. In the product clusters, C corresponds to cluster, the first number corresponds to the clusters detected in the first round of cluster detection, and the second number identifies the clusters in the second round of cluster detection (see Table 2).

activity or low industrial concentration and diversity are characterized by a high product specialization and low local competition. Therefore, in those regions, the probability of finding industrial clusters in Marshall's sense is very low. In regions with greater economic activity and concentration of diverse industries, firms have more heterogeneous diversification patterns, which reveals a greater accumulation of knowledge and capabilities and, therefore, a higher probability of finding industrial clusters.

Global Variables of Competitiveness and Agglomerations

Considering measures of competitiveness and spatial agglomerations of employment allows us to understand the concentration and the distribution of capabilities, knowledge, employment, and resources in general, which can be heterogeneous between Colombian departments (Smits and Permanyer, 2019; Campi et al., 2022). See Table A.2 in the Appendix.

Figure 6 shows the distribution of exporting firms (left), the revealed comparative advantages (middle), and the employment location quotients (right) for all Colombian departments and industrial clusters in 2019. The analysis with product clusters provides similar conclusions. Departments (from bottom to top) and industrial clusters (from left to right) are organized

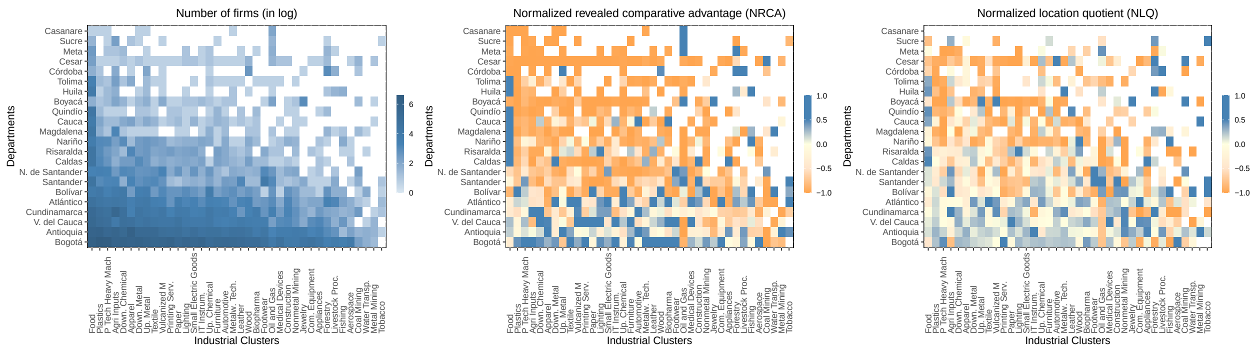

Figure 6: Distribution of capabilities within industrial clusters and Colombian departments, 2019. Departments and clusters are organized by the total number of firms from bottom to top and from left to right. Left: distribution of exporting firms (in log). Middle: normalized revealed comparative advantages (NRCA). Right: normalized location quotients (NLQ).

by the total number of exporting firms in the three matrices. Thus, the largest agglomeration of exporting firms is in Bogotá and Antioquia. The clusters that agglomerate more exporting firms are Food and Plastics. In general, the departments that agglomerate a higher number of firms are also those that reveal more comparative advantages and agglomerate most economic activities. The larger departments have capabilities for developing most economic activities, which is reflected in the agglomeration of employment and revealed comparative advantages for exporting.

However, spatial agglomerations of employment do not necessarily reveal comparative advantages for exports. Figure 7 shows the geographical distribution of employment and exports for some of the largest clusters in Colombia: Apparel, Food Processing and Manufacturing, Agricultural Products and Inputs, Plastics, Production Technology and Heavy Machinery, and Downstream Chemical Products.

An interesting fact is that some departments have spatial agglomerations of employment but do not export or have low comparative advantages for exporting. For example, we observe this situation in the Apparel cluster in Córdoba, Sucre, Magdalena, Cesar, and Bolívar; the cluster of Agricultural Products and Inputs in the departments of Sucre and Córdoba, or Downstream Chemical Products in Quindío. This evidence might indicate that spatial agglomerations alone do not necessarily lead to export competitiveness. However, this possibly indicates that there might be opportunities in those locations for export development.

Econometric Model

We now study if clusters provide an advantage to exporting firms and, particularly, if this advantage remains during the COVID-19 crisis. Firstly, we estimate the survival probability of product firm exports (extensive margin of trade) using a logit estimation method. Table 3 presents the estimation results. Models (1) to (3) use product clusters, and models (4) to (6) use industrial clusters. Comparing the alternative definitions of clusters, the results are robust and lead to similar conclusions in most cases, although we discuss some differences.

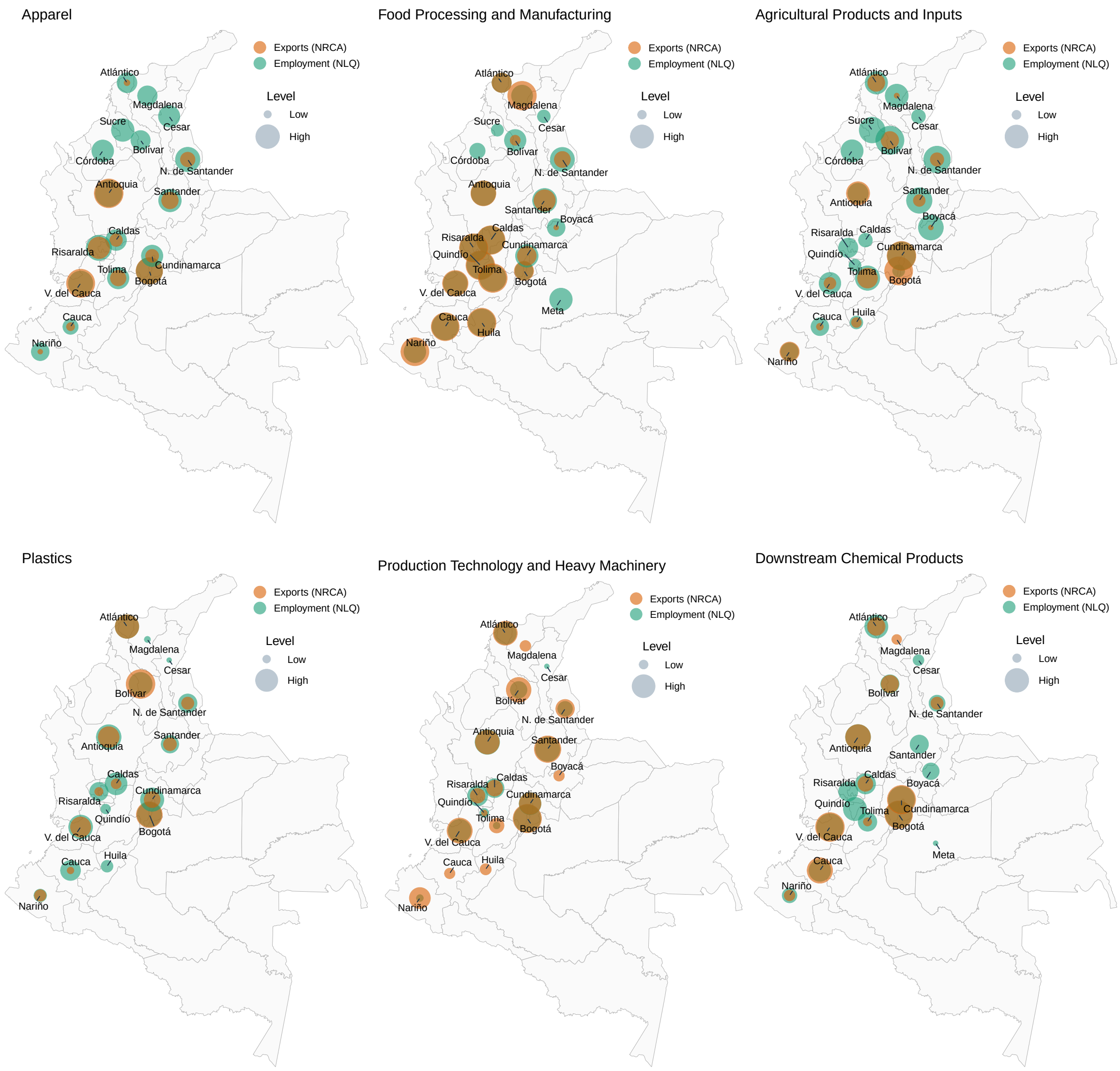

Figure 7: Distribution of employment and exports of selected industrial clusters within Colombian departments. Dots represent values of the normalized location quotients (NLQ) and the normalized revealed comparative advantages (NRCA). "Low" denotes a value less than 0 (no concentration or no specialization). "High" denotes a value greater than 0, which indicates a comparative advantage or employment agglomeration.

Models (1) and (4) analyze the effect of clusters on exporting firms' survival probabilities. We estimate that belonging to a competitive cluster has a not significant effect (model 1) or a statistically significant but negative effect (model 4) on the survival probabilities, as indicated by the competitive cluster dummy. All the remaining measures related to clusters and competitiveness increase the survival probabilities. We observe that products that belong to the cluster assigned to the firm have a higher survival probability (Product^{in}). Firms and products that are central inside the cluster of the firm have a higher survival probability (WBiRank^{in}). Those exported products that are central in clusters outside the firms' cluster (WBiRank^{out}) also have a higher survival probability, although the effect is lower. This might indicate that central products and firms in a cluster with diversified product baskets are likely to be central or at least relevant in other clusters. This is a piece of interesting evidence

Table 3: Product Firm Survival Probability (Extensive Margin of Trade): Logit Estimations

	Cluster definition					
	Product clusters			Industrial clusters		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Competitive cluster dummy	0.029	-0.120**		-0.075***	-0.229***	
	(0.018)	(0.055)		(0.017)	(0.040)	
Competitive cluster dummy × COVID		-0.087***			-0.036	
		(0.028)			(0.030)	
NLQ_{dc}			0.006			-0.073*
			(0.041)			(0.039)
NLQ_{dc} × COVID			0.068			0.241***
			(0.060)			(0.059)
NRCA_{dc}			0.130***			0.029
			(0.030)			(0.026)
NRCA_{dc} × COVID			-0.183***			-0.218***
			(0.038)			(0.039)
Product^{in} dummy	0.760***	0.759***	0.762***	0.819***	0.807***	0.795***
	(0.018)	(0.021)	(0.021)	(0.018)	(0.021)	(0.021)
Product^{in} dummy × COVID		0.005	-0.008		0.072**	0.068**
		(0.034)	(0.034)		(0.033)	(0.033)
Weighted BiRank^{in}	0.074***	0.074***	0.066***	0.077***	0.083***	0.073***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Weighted BiRank^{in}× COVID		0.021***	0.023***		0.006	0.012**
		(0.006)	(0.006)		(0.006)	(0.006)
Weighted BiRank^{out}	0.028***	0.026***	0.026***	0.033***	0.029***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Weighted BiRank^{out}× COVID		0.005	0.004		0.013***	0.013***
		(0.003)	(0.003)		(0.003)	(0.003)
Age (ln)	0.072***	0.072***	0.073***	0.073***	0.076***	0.074***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Number destinations (ln)	0.429***	0.420***	0.429***	0.435***	0.421***	0.435***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Constant	-1.332***	-1.087***	-1.242***	-1.944***	-1.385***	-1.901***
	(0.304)	(0.311)	(0.305)	(0.355)	(0.317)	(0.359)
Observations	125,275	125,275	125,275	123,361	123,361	123,361

Notes: The dependent variable is Y_{ikt}, which indicates whether firm i exports product k at time t. Products are at 6 digit level of the HS code classification. All the estimations include dummies for: time, product (HS codes at 4-digits), cluster definition, department, and firm's ISIC section dummies. Robust standard errors are in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.10.

because those central firms that perform better in their clusters can help diffuse knowledge to other clusters when they diversify their exports and interact with firms in other clusters.

Models (2) and (5) interact the independent variables with a dummy of the year 2020 that aims to capture the effect of the COVID-19 crisis. The competitive cluster dummy results are negative and statistically significant. Moreover, belonging to a competitive cluster seems to reduce the survival probabilities of exports during the COVID-19 period in both models. This can derive from the fact that firms in more competitive clusters are exporting more and, therefore, are more affected by the crisis.

We observe that the positive effects remain and increase for the remaining variables related to clusters' competitiveness. For products in the cluster of the firm, the advantage during COVID-19 increases, but it is close to 0, indicating that all products and firms are, on average, similarly affected. Conversely, the centrality of the products and firms within the cluster of the firm actually increases the survival probability even more during the COVID-19 crisis.

The effect for those central products and firms outside the firm's cluster is still positive but lower and increases with the shock.

Given that the indicator of competitive clusters includes two different indicators, models (3) and (6) independently analyze those indicators' effects. In model (3), the normalized location quotient (NLQ_{dc} index) shows a not significant effect before and during the crisis. In model (6), the estimated effect is negative and significant but small, and it becomes positive during the crisis.

The effect estimated for the normalized indicator of revealed comparative advantages (NRCA_{dc}) is positive and significant in model (3) but not statistically significant in model (6). However, in both models, the estimated effect becomes negative during the COVID-19 crisis. This implies that clusters with larger revealed comparative advantages were more affected by the shock.

The competitiveness indicators at the firm and product level are again significant and positively related to the extensive trade margins before and during the COVID-19 shock. Products belonging to the firm's cluster have an advantage that remains during the COVID-19 crisis. Being central in the firm's cluster has a positive and large impact on the survival probability, which increases during the crisis. Products-firms that are central in a cluster outside that of the firm have higher survival probabilities and a small plus during the COVID-19 shock.

In all the specifications, the firm's age and the number of destinations are positive and statistically significant, indicating that more experienced and larger exporters (in terms of destinations) have a higher probability of exporting. Next, we estimate the effect on the intensive margins of exports. Table 4 presents the estimation results. Again, in models (1) to (3) we use product clusters, and in models (4) to (6) we use industrial clusters.

In models (1) to (2) and (4) to (5), we estimate that being in a competitive cluster has no statistically significant impact on the volume of exports before and during the COVID-19 crisis.

In models (3) and (6), we use the two independent indicators of spatial agglomerations and competitiveness. We estimate that the indicator of spatial agglomerations has a not significant effect (or negative effect in model 6) on exports, and during the COVID-19 crisis the effect remains similar. This is not surprising because several departments reveal spatial agglomerations in some sectors but do not export. Conversely, the indicator of revealed comparative advantages at the cluster level has a positive and relatively large effect on the volume of exports, which slightly increases during the crisis.

The indicators of the centrality of the product (Product^{in}) and of the centrality of the firm within the cluster (Weighted BiRank^{in}) are statistically significant and positive in all the specifications. The effect of the centrality of the product is slightly reduced during the crisis. In contrast, the effect of the centrality of the firm within its cluster slightly increases during the COVID-19 period. The indicator of the centrality of the product-firm outside the firm's cluster (Weighted BiRank^{out}) is negative and significant in some specifications, indicating

Table 4: Effect on the Intensive Margin of Exported Products: PPML Estimations

	Cluster definition					
	Product clusters			Industrial clusters		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Competitive cluster dummy	0.108	0.123		0.126	0.080	
	(0.092)	(0.099)		(0.093)	(0.097)	
Competitive cluster dummy × COVID		-0.041			0.161	
		(0.101)			(0.101)	
NLQ_{dc}			-0.039			-0.210*
			(0.178)			(0.122)
NLQ_{dc} × COVID			-0.267			-0.077
			(0.198)			(0.159)
$NRCA_{dc}$			0.586***			0.775***
			(0.140)			(0.139)
$NRCA_{dc}$ × COVID			0.211			0.127
			(0.147)			(0.145)
$Product^{in}$ dummy	2.389***	2.407***	2.407***	2.608***	2.646***	2.652***
	(0.079)	(0.087)	(0.087)	(0.070)	(0.081)	(0.081)
$Product^{in}$ dummy × COVID		-0.062	-0.062		-0.126	-0.142
		(0.137)	(0.135)		(0.133)	(0.132)
Weighted $BiRank^{in}$	0.201***	0.195***	0.186***	0.143*	0.139*	0.119*
	(0.048)	(0.049)	(0.048)	(0.076)	(0.072)	(0.062)
Weighted $BiRank^{in}$× COVID		0.021	0.008		0.021	0.024
		(0.028)	(0.028)		(0.029)	(0.030)
Weighted $BiRank^{out}$	-0.011	-0.010	-0.014	0.001	-0.001	-0.002
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Weighted $BiRank^{out}$× COVID		-0.002	0.002		0.005	0.005
		(0.008)	(0.007)		(0.009)	(0.008)
Age (*ln*)	-0.539	-0.533	-0.738**	-0.320	-0.220	-0.251
	(0.342)	(0.342)	(0.330)	(0.375)	(0.390)	(0.370)
Number destinations (*ln*)	0.935***	0.933***	0.933***	0.991***	0.994***	0.985***
	(0.089)	(0.088)	(0.084)	(0.115)	(0.110)	(0.098)
Constant	9.957***	9.927***	10.720***	9.791***	9.424***	9.674***
	(1.252)	(1.244)	(1.214)	(1.400)	(1.383)	(1.311)
Observations	110,102	110,102	110,102	108,472	108,472	108,472

Notes: The dependent variable is the value of exports of product k of firm i at time t. All the estimations include dummies for: firms, time, product (HS codes at 4-digits), cluster definition, and department. Robust standard errors are in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.10.

that diversifying beyond the core competencies of the firm can negatively impact the intensive margin of exports. This negative effect remains during the crisis.

In all the specifications, the number of destinations is positive and statistically significant, indicating that larger or more diversified firms in terms of export destinations increase their volume of exports. Conversely, the firm's age has a negative effect when it turns out significant. This could probably reflect a non-linear impact of the age of the firms.

Finally, we estimate the effect of the COVID-19 crisis during the four quartiles of 2020 to consider possibly different reactions, taking into account what we observed in Figure 1. Figure 8 presents the estimated net marginal effects of our variables of interest related to clusters using the two alternative cluster definitions. Table A.3 in the Appendix presents the estimation results.

The blue dashed line shows the average estimated marginal effect of the variables. We

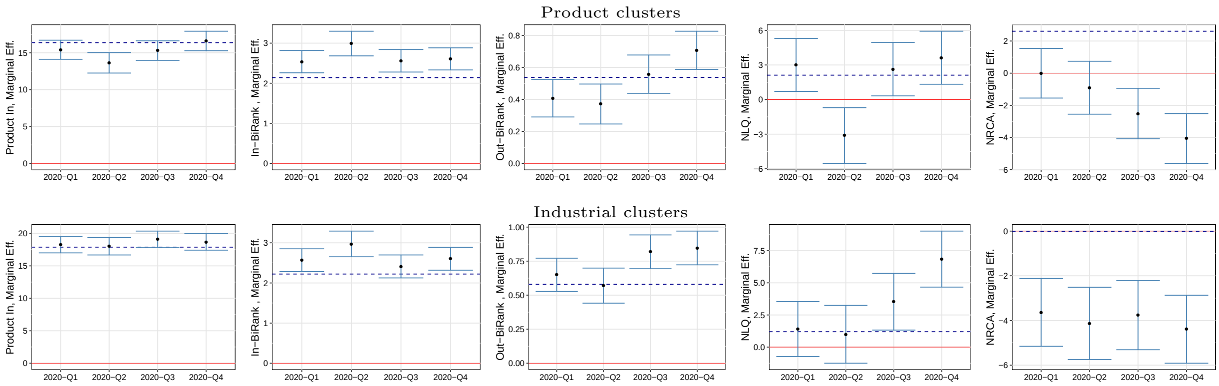

Figure 8: Estimated net marginal effects (×100) of the variables related to the effect of clusters in Eq. (7). Computed by the delta method at averages for 2020 considering the net effect of each variable in each quarter. Dots represent the point estimate of net marginal effects and bars are 95% confidence intervals. The blue dashed lines are the average estimated marginal effects. All differences are computed in absolute values.

observe that all the variables provide an advantage for the survival probability, except for revealed comparative advantages when we use the definition of industrial clusters. In other words, the cluster-related measures increase the extensive margin of trade or the export survival probability.

If the product belongs to the firm's core capabilities, survival probabilities increase by around 16% (using both definitions of clusters). The net estimated effect of this variable during the 2020 quartiles (presented in the dots for each quartile) does not significantly increase, and it ranges between 14% in the second quarter and 16% in the fourth quarter (for the product clusters). Similarly, in the case of industrial clusters, we observe a similar but higher impact of this variable (around 17 and 18%).

For firm's centrality in its cluster, we estimate that, on average, it has an advantage of over 2% in its survival probabilities for both definitions of clusters. This effect increases during the COVID-19 shock, in particular during the second quartile when the effect of the crisis was stronger.

The centrality of the firm outside its main cluster has a positive but relatively small effect on the survival probabilities of firms (above 0.5% in both product and industrial clusters). This advantage slightly decreases during the first two quartiles of 2020 and slightly increases during the second two quartiles of 2020. However, the net positive effect remains, and the differences between quartiles are very small.

The global indicators of cluster competitiveness (location quotients and revealed comparative advantages) show larger differences. We estimate a positive and significant average effect of the employment agglomerations of above 2% in the case of product clusters and above 1% in the case of industrial clusters. During the 2020 quartiles, the estimated effect of spatial agglomerations remains similar, except that it decreases in the second quartile (in the product clusters) and increases in the fourth quartile (in the industrial clusters). We observe more differences for the revealed comparative advantages when comparing the average effect and the impact during the quartiles and when comparing the effect for the two definitions of clusters. In the case of product clusters, we estimate a positive effect above 2%, which decreases during the four quartiles of 2020. In the case of industrial clusters, we estimate no significant effects of revealed comparative advantages that become significant and negative during the COVID-19 shock (between -3 and -4%).

6 Discussion and Policy Implications

Our study characterizes the geography and topology of Colombian exporting clusters, studying the distribution of comparative advantages for exports and employment spatial agglomerations, and using bipartite network analysis and community detection tools. These methods, which are increasingly used in economics, provide opportunities for analysis in other dimensions within the field of industrial clusters. In particular, we used this methodology to analyze exporting product clusters and the role of firms within clusters.

We derive exporting product clusters and compare them with a benchmark definition of industrial clusters obtained with other methods in Delgado et al. (2016). Although both methods result in different sets of clusters that are likely to reflect different processes, they lead to similar results when we use them to measure their impact on firm trade margins.

The analysis reflects the uneven distribution of employment and capabilities within the Colombian territory. Only a few departments have a large diversity of exporting clusters (Bogotá, Antioquia, Cundinamarca, and Valle del Cauca) while smaller departments are much less diversified, with most exporting firms specialized in only one cluster. In general, departments become more and more specialized as their size in terms of GDP decreases.

Some clusters are located in most departments and are central because they have many connections with other clusters and they include the most diversified firms (such as plastics, apparel, production technology and heavy machinery, and downstream metal products), indicating the possibility of spillovers to several other clusters. Conversely, although most departments export products from the food processing and manufacturing cluster, we do not observe a large extent of firms exporting products from this cluster and other clusters simultaneously. In other words, firms in the food processing and manufacturing cluster are in general specialized in that cluster, which might provide low probabilities of knowledge exchange and spillovers. Of course, this analysis is not considering other types of spillovers, for example, those that might arise from the interactions with other clusters or sectors in value chains.

The detection and characterization of exporting product clusters provide policy design tools for regional development. For example, some departments with relatively large employment agglomerations are unable to export. Understanding the reasons behind this behavior requires further analysis, but it also indicates a possibility for public policy to develop export capabilities, taking advantage of the employment spatial agglomerations. Moreover, another example that provides space for policy intervention derives from the possibility of classifying clusters according to their potential spillovers derived from whether they include diversified firms.

In addition, the analysis of spatial agglomeration and product relatedness indicates a possible export development trajectory. The results can be used to predict outcomes depending on the characteristics of the department and firms and develop policies guiding them to follow certain development trajectories.

The econometric analysis provides new evidence on the role of clusters in fostering resilience for exporting firms. We do not identify a clear and strong effect of the global indicators of competitiveness of clusters on generating resilience during the COVID-19 crisis. This can be due to the emergence of opposite effects for different types of firms within clusters when facing a shock, which depends on several mechanisms. While some firms might be severely affected by the shock, which reduces the extensive and intensive margins, some other firms can increase their exports by taking advantage, for example, of a reduction in competition. These opposite effects are more likely to be observed in more dense clusters, which concentrate more firms.

All this is linked with another finding of our analysis. We observe robust, strong, and significant positive effects of the product-firm-cluster competitiveness indicators on average and during the crisis period. For example, products that belong to the cluster in which the firm has the larger participation have higher survival probabilities and increase their exported volumes after a shock compared to those that do not belong to the firm's cluster. The centrality of firms within their clusters provides an advantage before and during the COVID-19 crisis. Similarly, although less relevant, the centrality of firms outside their main cluster has a positive impact on the survival probability and export volumes.

These results imply that the heterogeneity of firms and their idiosyncratic components are relevant for generating resilience. This poses challenges in terms of policies, which should target firms considering their heterogeneity. For example, depending on the different needs, policy responses might take forms, such as grants and loans, production subsidies, infrastructure investments, deregulation, tax cuts, interest rate cuts, or increases in funding for training (WTO, 2021).

More specifically, policies aiming to encourage the generation of more local value chains could benefit and magnify the positive effect of larger, more diversified, and more central firms in clusters, which play a role in generating knowledge spillovers between clusters.

Policies aiming to strengthen core capabilities could target, especially, small and medium-sized exporters or less central firms, which might need to strengthen their capabilities, generate economies of scale, or intensify their exports. Policy instruments for this aim include tools that can help firms overcome trade barriers to other export destinations, reduce or eliminate non-tariff barriers, and other instruments that allow them to diversify their export markets.

Theoretically, firms tend to specialize in sets of related products that are linked to their core capabilities, following a coherent diversification (Penrose, 1959; Teece et al., 1994). In this sense, this paper presents a relevant contribution: the existence of exporting clusters provides empirical evidence that the diversification patterns of firms are not random. In general, digging deeper into the relevance of the coherence of export baskets and the relations with firms' performance can provide additional tools for policy design.

Promoting firms' export diversification might be a relevant policy for at least two reasons. First, it might increase firms' centrality within their cluster, which contributes to enhancing resilience. Second, diversifying beyond firms' core competencies might also enhance regional resilience by creating positive externalities, for example through knowledge flows via interconnections of different economic sectors.

To conclude, our evidence points that we need a more detailed discussion on the role of clusters in generating resilience and understanding the channels that could provide resilience. The results indicate that there are differences in how firms react to a crisis even within clusters. Therefore, identifying firm characteristics linked to higher resilience can guide policymakers. In other words, clusters do not automatically generate higher resilience for their members, but there could be opportunities for active policies in that direction.

References

Acs, Z., C. Armington, and T. Zhang (2007). The determinants of new-firm survival across regional economies: The role of human capital stock and knowledge spillover. *Papers in Regional Science 86*(3), 367–391.

Balassa, B. (1965). Trade liberalization and 'revealed' comparative advantage. *The Manchester School 33*(2), 99–123.

Balland, P.-A., C. Jara-Figueroa, S. G. Petralia, M. P. Steijn, D. L. Rigby, and C. A. Hidalgo (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour 4*(3), 248–254.

Balland, P. A., R. Suire, and J. Vicente (2013). Structural and geographical patterns of knowledge networks in emerging technological standards: evidence from the European GNSS industry. *Economics of Innovation and New Technology 22*(1), 47–72.

Behrens, K., B. Boualam, and J. Martin (2020). Are clusters resilient? Evidence from Canadian textile industries. *Journal of Economic Geography 20*(1), 1–36.

Benguria, F. (2021). The 2020 trade collapse: Exporters amid the pandemic. *Economics Letters 205*, 109961.

Blondel, V. D., J.-L. Guillaume, R. Lambiotte, and E. Lefebvre (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment 2008*(10), P10008.

Bonadio, B., Z. Huo, A. A. Levchenko, and N. Pandalai-Nayar (2020). Global supply chains in the pandemic. NBER Working Paper 27224. Available at: https://www.nber.org/papers/w27224.

Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional Studies 39*(1), 61–74.

Boschma, R., G. Heimeriks, and P. A. Balland (2014). Scientific knowledge dynamics and relatedness in biotech cities. *Research Policy 43*(1), 107–114.

Boschma, R. A. and R. C. Kloosterman (2005). Clustering, learning and regional development. In R. A. Boschma and R. C. Kloosterman (Eds.), *Learning from Clusters. A Critical Assessment from an Economic-Geographical Perspective*, pp. 1–15. Dordrecht: Springer.

Breschi, S. and F. Lissoni (2001). Knowledge spillovers and local innovation systems: a critical survey. *Industrial and Corporate Change 10*(4), 975–1005.

Bruno, M., F. Saracco, T. Squartini, and M. Dueñas (2018). Colombian export capabilities: building the firms-products network. *Entropy 20*(10), 785.

Buenstorf, G. and S. Klepper (2009). Heritage and agglomeration: the Akron tyre cluster revisited. *The Economic Journal 119*(537), 705–733.

Campi, M., M. Dueñas, and G. Fagiolo (2020). How do countries specialize in agricultural production? A complex network analysis of the global agricultural product space. *Environmental Research Letters 15*(12), 124006.

Campi, M., M. Dueñas, and G. Fagiolo (2021). Specialization in food production affects global food security and food systems sustainability. *World Development 141*, 105411.

Campi, M., M. Dueñas, and T. Ciarli (2022). Do Creative Industries Enhance Employment Growth? Regional Evidence from Colombia. IDB Working Papers Series No. IDB-WP-1279. Available at: http://dx.doi.org/10.18235/0003993.

Dai, R., D. Mookherjee, Y. Quan, and X. Zhang (2021). Industrial clusters, networks and resilience to the Covid-19 shock in China. *Journal of Economic Behavior & Organization 183*, 433–455.

DANE (2019). Great integrated household survey. Several editions. DANE.

DANE (2022). Gran Encuesta Integrada de Hogares (GEIH)-DANE. Gerencia de Inteligencia Competitiva. Colombia Productiva. Available at: https://www.maro.com.co/departamento/bienes/25.

Delgado, M. and M. Porter (2021). Clusters and the great recession. Available at: http://dx.doi.org/10.2139/ssrn.3819293.

Delgado, M., M. Porter, and S. Stern (2010). Clusters and entrepreneurship. *Journal of Economic Geography 10*(4), 495–518.

Delgado, M., M. Porter, and S. Stern (2014). Clusters, convergence, and economic performance. *Research Policy 43*(10), 1785–1799.

Delgado, M., M. Porter, and S. Stern (2016). Defining clusters of related industries. *Journal of Economic Geography 16*(1), 1–38.

Dueñas, M., V. Ortiz, M. Riccaboni, and F. Serti (2021). Assessing the impact of COVID-19 on trade: a machine learning counterfactual analysis. Available at: https://arxiv.org/abs/2104.04570.

Espitia, A., A. Mattoo, N. Rocha, M. Ruta, and D. Winkler (2022). Pandemic trade: COVID-19, remote work and global value chains. *The World Economy 45*(2), 561–589.

Evenett, S. (2020). Sicken thy neighbour: The initial trade policy response to COVID-19. *The World Economy 43*(4), 828–839.

Feldman, M. and D. Audretsch (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review 43*(2), 409–429.

Feller, W. (1968). *An introduction to probability theory and its applications*, Volume 1. New York: John Wiley & Sons, Inc.

Feser, E., H. Renski, and H. Goldstein (2008). Clusters and economic development outcomes: An analysis of the link between clustering and industry growth. *Economic Development Quarterly 22*(4), 324–344.

Fortunato, S. and M. Barthelemy (2007). Resolution limit in community detection. *Proceedings of the National Academy of Sciences 104*(1), 36–41.

Frenken, K., E. Cefis, and E. Stam (2015). Industrial dynamics and clusters: a survey. *Regional Studies 49*(1), 10–27.

Giuliani, E. (2007). The selective nature of knowledge networks in clusters: evidence from the wine industry. *Journal of Economic Geography 7*(2), 139–168.

Giuliani, E., P.-A. Balland, and A. Matta (2019). Straining but not thriving: understanding network dynamics in underperforming industrial clusters. *Journal of Economic Geography 19*(1), 147–172.

Hausmann, R. and B. Klinger (2006). The evolution of comparative advantage: the impact of the structure of the product space. Center for International Development and Kennedy School of Government, Harvard University.

He, X., M. Gao, M. Y. Kan, and D. Wang (2016). Birank: Towards ranking on bipartite graphs. *IEEE Transactions on Knowledge and Data Engineering 29*(1), 57–71.

Hidalgo, C. A., B. Klinger, A. Barabási, and R. Hausmann (2007). The product space conditions the development of nations. *Science 317*(5837), 482–487.

Iammarino, S. and P. McCann (2006). The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. *Research Policy 35*(7), 1018–1036.

Iori, G. and R. N. Mantegna (2018). Empirical analyses of networks in finance. In C. Hommes and B. LeBaron (Eds.), *Handbook of Computational Economics*, Volume 4, pp. 637–685. Amsterdam: Elsevier.

Jaccard, P. (1901). Étude comparative de la distribution florale dans une portion des alpes et des jura. *Bulletin del la Société Vaudoise des Sciences Naturelles 37*, 547–579.

Jun, B., A. Alshamsi, J. Gao, and C. A. Hidalgo (2020). Bilateral relatedness: knowledge diffusion and the evolution of bilateral trade. *Journal of Evolutionary Economics* (30), 247–277.

Jun, B., C. J. Figueroa, and D. Yu (2021). The economic resilience of amenity cluster in the post-Covid city: the effect of relatedness on the survival of amenity shops. SocArXiv. Available at: https://osf.io/preprints/socarxiv/v6wjp/.

Klepper, S. (2010). The origin and growth of industry clusters: The making of Silicon Valley and Detroit. *Journal of Urban Economics 67*(1), 15–32.

Laudati, D., M. S. Mariani, L. Pietronero, and A. Zaccaria (2022). The different structure of economic ecosystems at the scales of companies and countries. Available at: https://doi.org/10.48550/arXiv.2202.01804.

Leydesdorff, L. (2008). On the normalization and visualization of author co-citation data: Salton's Cosine versus the Jaccard index. *Journal of the American Society for Information Science and Technology 59*(1), 77–85.

Maggioni, M. A. (2002). *Clustering dynamics and the location of high-tech-firms*. Heidelberg: Springer.

Markusen, A. (1996). Sticky places in slippery space: a typology of industrial districts. *Economic Geography 72*(3), 293–313.

Marshall, A. (1920). *Principles of Economics*. London: Macmillan and Co.

Martin, P., T. Mayer, and F. Mayneris (2017). Are clusters more resilient in crises? Evidence from French exporters in 2008–2009. In L. Fontagné and A. Harrison (Eds.), *The Factory-Free Economy: Outsourcing, Servitization, and the Future of Industry*. Oxford: Oxford Scholarship Online.

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography 12*(1), 1–32.

Martin, R. and P. Sunley (2003). Deconstructing clusters: chaotic concept or policy panacea? *Journal of Economic Geography 3*(1), 5–35.

Martin, R. and P. Sunley (2006). Path dependence and regional economic evolution. *Journal of Economic Geography 6*(4), 395–437.

Menzel, M.-P. and D. Fornahl (2010). Cluster life cycles—dimensions and rationales of cluster evolution. *Industrial and Corporate Change 19*(1), 205–238.

Nooteboom, B. (2000). *Learning and innovation in organizations and economies*. Oxford: Oxford University Press.

Nyström, K. (2007). An industry disaggregated analysis of the determinants of regional entry and exit. *The Annals of Regional Science 41*(4), 877–896.

Penrose, E. (1959). *The Theory of the Growth of the Firm*. Oxford: Oxford University Press.

Porter, M. (1990). *The Competitive Advantage of Nations*. New York: The Free Press.

Porter, M. (1998). Clusters and the new economics of competition. *Harvard Business Review 76*(6), 77–90.

Pugliese, E., L. Napolitano, A. Zaccaria, and L. Pietronero (2019). Coherent diversification in corporate technological portfolios. *PloS one 14*(10), e0223403.

Saxenian, A. (1996). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Cambridge, MA: Harvard University Press.

Simmie, J. and R. Martin (2010). The economic resilience of regions: towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society 3*(1), 27–43.

Smits, J. and I. Permanyer (2019). The subnational human development database. *Scientific Data 6*, 190038.

Sorenson, O. and P. G. Audia (2000). The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States, 1940–1989. *American Journal of Sociology 106*(2), 424–462.

Storper, M. (1995). The resurgence of regional economies, ten years later: the region as a nexus of untraded interdependencies. *European Urban and Regional Studies 2*(3), 191–221.

Stuart, T. and O. Sorenson (2003). The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy 32*(2), 229–253.

Teece, D., R. Rumelt, G. Dosi, and S. Winter (1994). Understanding corporate coherence: Theory and evidence. *Journal of Economic Behavior & Organization 23*(1), 1–30.

Ter Wal, A. L. (2014). The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure. *Journal of Economic Geography 14*(3), 589–620.

Ter Wal, A. L. and R. Boschma (2011). Co-evolution of firms, industries and networks in space. *Regional Studies 45*(7), 919–933.

Trippl, M., M. Grillitsch, A. Isaksen, and T. Sinozic (2015). Perspectives on cluster evolution: critical review and future research issues. *European Planning Studies 23*(10), 2028–2044.

Tumminello, M., S. Micciche, F. Lillo, J. Piilo, and R. N. Mantegna (2011). Statistically validated networks in bipartite complex systems. *PloS one 6*(3), e17994.

van Eck, N. J. and L. Waltman (2009). How to normalize cooccurrence data? An analysis of some well-known similarity measures. *Journal of the American Society for Information Science and Technology 60*(8), 1635–1651.

Vicente, J. (2018). *Economics of clusters: A brief history of cluster theories and policy*. Cham, Switzerland: Springer.

Vicente, J., P. A. Balland, and O. Brossard (2011). Getting into networks and clusters: evidence from the Midi-Pyrenean Global Navigation Satellite Systems (GNSS) collaboration network. *Regional Studies 45*(8), 1059–1078.

Wenting, R. (2008). Spinoff dynamics and the spatial formation of the fashion design industry, 1858–2005. *Journal of Economic Geography 8*(5), 593–614.

WTO (2021). World Trade Report. Economic Resilience and Trade. Geneva: World Trade Organization.

Appendix

Table A.1: Traded and Local Industrial Clusters Defined for the U.S. Economy

Code	Cluster name	Code	Cluster name
		Traded Clusters	
1	Aerospace Vehicles and Defense	27	Lighting and Electrical Equipment
2	Agricultural Inputs and Services	28	Livestock Processing
3	Apparel	29	Marketing, Design, and Publishing
4	Automotive	30	Medical Devices
5	Biopharmaceuticals	31	Metal Mining
6	Business Services	32	Metalworking Technology
7	Coal Mining	33	Music and Sound Recording
8	Communications Equipment and Services	34	Nonmetal Mining
9	Construction Products and Services	35	Oil and Gas Production and Transportation
10	Distribution and Electronic Commerce	36	Paper and Packaging
11	Downstream Chemical Products	37	Performing Arts
12	Downstream Metal Products	38	Plastics
13	Education and Knowledge Creation	39	Printing Services
14	Electric Power Generation and Transmission	40	Production Technology and Heavy Machinery
15	Environmental Services	41	Recreational and Small Electric Goods
16	Financial Services	42	Textile Manufacturing
17	Fishing and Fishing Products	43	Tobacco
18	Food Processing and Manufacturing	44	Trailers, Motor Homes, and Appliances
19	Footwear	45	Transportation and Logistics
20	Forestry	46	Upstream Chemical Products
21	Furniture	47	Upstream Metal Manufacturing
22	Hospitality and Tourism	48	Video Production and Distribution
23	Information Technology and Analytical Instruments	49	Vulcanized and Fired Materials
24	Insurance Services	50	Water Transportation
25	Jewelry and Precious Metals	51	Wood Products
26	Leather and Related Products		
		Local Clusters	
101	Local Food and Beverage Processing and Distribution	109	Local Retailing of Clothing and General Merchandise
102	Local Personal Services (Non-Medical)	110	Local Entertainment and Media
103	Local Health Services	111	Local Hospitality Establishments
104	Local Utilities	112	Local Commercial Services
105	Local Logistical Services	113	Local Education and Training
106	Local Household Goods and Services	114	Local Community and Civic Organizations
107	Local Financial Services	115	Local Real Estate, Construction, and Development
108	Local Motor Vehicle Products and Services	116	Local Industrial Products and Services

Source: Delgado et al. (2016).

Table A.2: Economic and Social Indicators: Colombian Departments, 2017

Department	GDP	Population	Subnational Human Development Index
Bogotá	236,786	8,080.73	0.792
Antioquia	132,369	6,613.12	0.752
Valle del Cauca	89,766	4,708.26	0.727
Santander	59,463	2,080.94	0.770
Cundinamarca	55,731	2,762.78	0.699
Atlántico	40,875	2,517.90	0.766
Bolívar	33,394	2,146.70	0.736
Meta	30,239	998.16	0.709
Boyacá	24,782	1,279.96	0.740
Tolima	19,988	1,416.12	0.725
Cesar	19,551	1,053.48	0.712
Cauca	16,739	1,404.21	0.702
Córdoba	15,793	1,762.53	0.748
Huila	15,222	1,182.94	0.737
Risaralda	14,922	962.53	0.765
Caldas	14,749	991.86	0.757
Norte de Santander	14,445	1,379.53	0.758
Nariño	14,062	1,787.55	0.730
Casanare	13,145	368.99	0.730
Magdalena	12,422	1,285.38	0.678
La Guajira	10,785	1,012.93	0.709
Sucre	7,702	868.44	0.758
Quindío	7,633	571.73	0.699
Arauca	4,367	267.99	0.722
Chocó	3,958	510.05	0.679
Caquetá	3,866	490.06	0.701
Putumayo	3,613	354.09	0.704
San Andrés y Providencia	1,439	77.76	0.742
Guaviare	758	114.21	0.654
Amazonas	710	77.95	0.701
Vichada	597	75.47	0.624
Guainía	339	42.78	0.754
Vaupés	263	44.50	0.771

Notes: Departments are ordered by their GDP. GDP (in billions of Colombian pesos) and Population (in thousands) are from DANE (2019). Subnational Human Development Index from Smits and Permanyer (2019).

Table A.3: Estimations of the Effect of Clusters on Generating Resilience during the Four Quarters of 2020

	Product clusters		Industrial clusters	
Model	(1)	(2)	(3)	(4)
Method	Logit	PPML	Logit	PPML
NLQ$_{dc}$	0.106***	-0.040	0.059***	-0.210***
	(0.022)	(0.105)	(0.020)	(0.072)
NRCA$_{dc}$	0.130***	0.587***	-0.000	0.775***
	(0.016)	(0.079)	(0.014)	(0.076)
NLQ$_{dc}\times$ 2020-Q1	0.044	0.122	0.010	0.127
	(0.054)	(0.145)	(0.050)	(0.162)
NLQ$_{dc}\times$ 2020-Q2	-0.262***	-0.398**	-0.010	-0.275*
	(0.058)	(0.174)	(0.053)	(0.155)
NLQ$_{dc}\times$ 2020-Q3	0.026	-0.364**	0.116**	-0.061
	(0.055)	(0.170)	(0.052)	(0.151)
NLQ$_{dc}\times$ 2020-Q4	0.075	-0.413**	0.280***	-0.112
	(0.054)	(0.207)	(0.051)	(0.145)
NRCA$_{dc}\times$ 2020-Q1	-0.131***	-0.102	-0.180***	-0.144
	(0.036)	(0.139)	(0.036)	(0.137)
NRCA$_{dc}\times$ 2020-Q2	-0.176***	0.302**	-0.204***	0.251*
	(0.039)	(0.134)	(0.038)	(0.143)
NRCA$_{dc}\times$ 2020-Q3	-0.256***	0.347**	-0.186***	0.210
	(0.037)	(0.142)	(0.036)	(0.143)
NRCA$_{dc}\times$ 2020-Q4	-0.333***	0.311**	-0.217***	0.199
	(0.036)	(0.153)	(0.036)	(0.145)
Product^{in} dummy	0.818***	2.408***	0.887***	2.652***
	(0.011)	(0.048)	(0.011)	(0.047)
Product$^{in}\times$ 2020-Q1	-0.048	-0.040	0.018	-0.071
	(0.031)	(0.127)	(0.030)	(0.113)
Product$^{in}\times$ 2020-Q2	-0.137***	-0.048	0.007	-0.139
	(0.034)	(0.129)	(0.032)	(0.153)
Product$^{in}\times$ 2020-Q3	-0.054*	-0.095	0.059*	-0.202
	(0.032)	(0.122)	(0.030)	(0.145)
Product$^{in}\times$ 2020-Q4	0.012	-0.065	0.040	-0.152
	(0.032)	(0.117)	(0.030)	(0.116)
WBiRank^{in}	0.107***	0.185***	0.110***	0.119***
	(0.003)	(0.025)	(0.003)	(0.032)
WBiRank^{out}	0.027***	-0.014**	0.029***	-0.002
	(0.001)	(0.006)	(0.001)	(0.006)
WBiRank$^{in}\times$ 2020-Q1	0.020***	0.024	0.017***	0.044*
	(0.007)	(0.025)	(0.007)	(0.025)
WBiRank$^{in}\times$ 2020-Q2	0.042***	0.012	0.037***	0.037
	(0.007)	(0.029)	(0.008)	(0.030)
WBiRank$^{in}\times$ 2020-Q3	0.021***	-0.005	0.009	0.005
	(0.007)	(0.024)	(0.007)	(0.028)
WBiRank$^{in}\times$ 2020-Q4	0.023***	0.002	0.019***	0.014
	(0.006)	(0.030)	(0.007)	(0.032)
WBiRank$^{out}\times$ 2020-Q1	-0.006**	-0.001	0.003	0.006
	(0.003)	(0.006)	(0.003)	(0.007)
WBiRank$^{out}\times$ 2020-Q2	-0.008***	0.003	-0.000	0.008
	(0.003)	(0.007)	(0.003)	(0.008)
WBiRank$^{out}\times$ 2020-Q3	0.001	0.003	0.012***	0.004
	(0.003)	(0.007)	(0.003)	(0.008)
WBiRank$^{out}\times$ 2020-Q4	0.008***	0.002	0.013***	0.003
	(0.003)	(0.007)	(0.003)	(0.009)
Age	0.073***	-0.739***	0.074***	-0.249
	(0.004)	(0.194)	(0.004)	(0.223)
Number destinations	0.392***	0.933***	0.404***	0.984***
	(0.005)	(0.048)	(0.005)	(0.055)
Constant	-2.430***	9.346***	-3.064***	8.295***
	(0.169)	(0.695)	(0.208)	(0.776)
Observations	501,100	441,528	493,444	434,992

Notes: The dependent variable in the logit estimations is Y_{ikt}, which indicates whether firm i exports product k at time t; and in the PPML estimations is the the value of exports of product k of firm i. Logit estimations include dummies for: time, product (HS codes, 4-digits), department, cluster definition, and firm's ISIC section. Robust standard errors are in parentheses. PPML estimations include dummies for: firms, time, product (HS codes, four digits), cluster definition, and department. Significance level: *** p<0.01, ** p<0.05, * p<0.10.