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A characterization of Colombian industries under Schumpeter's patterns of innovation

Progress Report

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1 Introduction and problem statement

Who drives innovation within an industry? Is it a small firm, or an established one? Is it an incumbent business or a novel startup? According to mainstream economics, several factors influx. For example, which market structure prevails may concentrate or disperse efforts, the existence of fierce entry barriers could dis-incentivize novel ideas in favour of established paradigms, specialization in certain activities could place industries at the source of a supply chain and dedicate all its efforts in supplying other sectors, or patents could motivate cooperation and foster the appropriation of an invention's gains.

This article will answer this question using Joseph Schumpeter's (1911;1942) Mark I and Mark II innovation patterns. Both archetypes assess a different market structure. While Mark I argues that novelty does not enter markets at the hand of incumbent firms but by entrant firms or new startups, Mark II appoints not the bold new enterprise or the brave startup but the large corporation as the driver of innovation.

As with every theory, its importance relies on its results when tested empirically. Fontana et al. (2012) pointed out an untapped potential for Mark I and Mark II patterns in this field. Moreover, existing characterizations for both Marks have "*been standing the test of time quite well*". There have been progress con characterizing industries with this pattern (Breschi et al., 2000; Castellaci and Zheng; 2010; Malerba and Orsenigo, 1996), which in turns gives a better insight of innovative activities in the countries where it takes place and serves as platform for policymakers to set up better guidelines for innovation-related policies.

But Fontana et al. overlook the concentration of this type of studies across the globe. Even though there are contributions to fill this gap worldwide, assessments in some countries are missing, with emphasis on countries outside the global north and core economies such as Colombia.

A gap in characterization eventually leads to a need for information. Hence, this document will employ information contained in DANE (2020) "*Encuesta de Desarrollo e innovación tecnológica*" (EDIT) survey and DANE (2019) "*Encuesta Anual Manufacturera*" (EAM) survey for manufacturers to characterize industries as Mark I or Mark II, according to their International Standard Industrial Classification code (ISIC, or CIIU in Spanish), emphasizing on Section C: Manufacturing. The EAM survey provides, with a yearly frequency, information on the manufacturing sector that allows a detailed understanding of its structure and evolution. EAM surveys hold variables related to sales, output, investment, export, number of employees, among others.

On the other hand, the EDIT survey tackles the need for information about the type of innovative activities (radical or incremental), and their effects in firm performance such as cost reductions or productivity enhancements. Moreover, there is data about sources of financing, information usage, human capital qualities, usage of patents, copyright, and other non-conventional protection methods. According to the DANE (2020) methodological overview, the EDIT survey preserves a theoretical framework that welcomes most of the methodological guidelines of the Organization for Economic Cooperation and Development (OECD), with emphasis on its innovation-tailored OSLO Manual.

This goal sets an intriguing task. First, there is novelty as earlier attempts to characterize all Colombian industries through Schumpeter patterns of innovation seem to be missing. Second, the characterization of industries yields useful information for future works and policymaking for one of the most important sectors in the country. Bear in mind that Colombian manufacturing has a 10% share on its GDP (Gross Domestic Product), but accounting for aggregated value chains, it composes more than one-third of the economy (Arbelaez et al., 2021).

2 Objective Setup

1 Characterize industries in the Colombian manufacturing sector based on the framework of Schumpeter's Mark I and II, aiming to supply a better insight on the differences between industries by finding out what type of firm drives innovation.

- 1.1 Utilize information from the EDIT and EAM surveys to set up a database about firm features in manufacturing industries.
- 1.2 Based on EDIT and EAM information, construct a quantitative analysis at the firm level that yields a result at the industry level, which in turn gives groundwork to create industry-level comparisons.
- 1.3 Employing a cluster algorithm, group industry-level data by common patterns and characterize them using Schumpeter's Mark I and II, which will give an insight into the drivers of innovation constrained to industrial structure and dynamics.

3 Theoretical Framework

The concept of innovation and its taxonomies

The base of innovation-related studies is to set up the concept of innovation and innovative activities. According to the OECD (2018), innovation is a "*New or improved product or process (or a combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)*" (p. 20).

Although the OSLO manual points out that innovation is inherently subjective, its practical application is objective if we consider shared grounds for novelty, utility, and the capacity to evidence significant differences. In that sense, the OSLO manual defines innovative activities as "*all developmental, financial and commercial activities undertaken by a firm that is intended to result in an innovation for the firm*" (p. 20). Despite being a firm-centric perspective, OECD's concept can also apply to markets and industries. Moreover, OECD nuances whether innovation tailors towards business practices, productive processes, goods, services, and marketing.

Innovation may have two taxonomies based on its novelty and impact. The efforts of Schumpeter (1942) focused on the nature of radical innovations as departing from known opportunities looking to forge something new at the expense of destroying something old. Schumpeter perspective of innovation would create the concept of creative destruction. On the other hand, Kirzner (1973) argued that human alertness to new opportunities yields more rents when channelled into incremental innovations, those who do not compromise the *status quo* and work under the realm of known opportunities.

In the case of the OSLO manual, two are identified. First, radical innovations, transform the *status quo.* The second, disruptive innovations, takes root in simple applications of niche markets and then diffuses throughout it; it does not immediately compromise the *status quo*, but eventually displaces established firms (OECD, 2018, p. 78). For this research, we will employ the concepts of radical innovations as those that alter the *status quo* and have the potential to displace established firms, and incremental innovations as those that stem from improvements to existing ideas that do not alter the current paradigm of the market.

Schumpeterian patterns of innovation

It was not the OECD that introduced innovative patterns. It was Schumpeter (1911; 1942) who explored these differences and pioneered on the proposal of differentiated archetypes for innovation. In his 1911 book "The Theory of Economic Development", he employs a metaphor that sums up his early thoughts on how new combinations enter the market: "*(...) in general it is not the owner of stagecoaches who builds railways*" (p. 66). The premise of Schumpeter implies that novelty does not enter the market at the hand of incumbent firms but by entrant firms. This idea would be coined as Schumpeter's Mark I, which places entrant firms as the drivers of innovation.

Schumpeter's ideas would change later in his 1942 book "*Capitalism, socialism and democracy": "(...) a shocking suspicion dawns upon us that big businesses may have had more to do with creating that standard of life than with keeping it down*" (p. 82). Such perspective departs from Mark I and will become Schumpeter's Mark II. In contrary to a Mark I market, Schumpeter appoints large, established firms as the driver of innovation. It is not the bold new enterprise or the brave startup that brings new goods or services but the tried and true stable, large corporation. Schumpeter would reinforce Mark II thereon in the book: "*Perfect competition is not only impossible but inferior and has no title to being set up as a model of ideal efficiency*" (p. 106).

Market structure and innovation

Mark I and II may seem exclusive. They are not *per se*, but the subjacent market structures they assess. According to Fontana et al. (2012), one may classify industries using Mark I and Mark II archetypes. Mark I industries are turbulent, with low entry barriers and fiercer competition. On the other hand, stable environments with large established firms and entry barriers characterize Mark II industries. In other terms, Schumpeter's Mark I and Mark II concede the existence of two fundamental market structures bonded to the concept of innovation. Mark I approach perfect competition, while Mark II appeals to a monopolistic (or oligopolistic) structure.

With an established framework using Schumpeter's contributions we can now add up its patterns with OECD's taxonomy. Considering Gilbert (2006) statement that the incentive to innovate is the difference in profits that a firm can earn if it decides to do so, which, according to Arrow (1962), is higher in perfect competition than in monopoly, because the existing monopoly power acts as a formidable disincentive to innovate, then perfect competition seems to have the suitable incentives to introduce breakthroughs in the market. Baumol (2004) reinforces this idea by saying: "*major breakthroughs have tended to come from small new enterprises*" (p. 10). In that sense, risky innovations that seek to disrupt the *status quo*, which OECD labels as radical innovations, seem to relate to perfect competition structures, which appeals to a Mark I pattern.

Baumol (2004) observation continues: "*(...) while the invaluable incremental contributions that multiply capacity and speed and increase reliability and user-friendliness have been the domain of the larger firms*" (p. 10). This allows us to construct the definition of the market structure related to OECD incremental innovations taxonomy. By considering Arrow's replacement effect and Gilbert statement on innovation incentives, we have strong signals that incremental innovations suit concentrated markets. Surely, entry barriers and high endowments of resources supply a deterrence to potential entrants, but when it comes to innovation, monopolies have less incentives to change the paradigm of their markets, as they can compromise existing gains. Therefore, incremental enhancements, as Baumol exemplifies, that increase reliability or user friendliness, characterize concentrated markets. In this case, the innovation pattern appeals to Mark II.

As an overlook of both Schumpeter's and Arrow's theories, Shapiro (2012) remarks that the unifying principle of both is that a contestable market and potential profits from sales spur innovation. Moreover, a firm that wants to maintain the *status quo* (I.e., Monopolies) has a smaller incentive than new entrants (let it be, a small startup) to disrupts said status by introducing radical innovations.

4 Literature Review

A first prominent characterization exercise comes from Malerba and Orsenigo (1996), who identified Schumpeter's Mark I and Mark II across 49 technological classes of six countries: the US, Japan, Germany, France, the UK, and Italy. The authors find Mark I as a widening pattern, where concentration of innovative activities is low, with small sized firms and low stability in the ranking of innovations. On the other hand, they find Mark II as a deepening pattern: high market concentration, larger firms, a stable ranking of innovators and deterrents to entry.

Further contributions by Breschi et al. (2000) suggest that better appropriability conditions work in the direction of Schumpeter's Mark II patter, while the opposite appeals to Schumpeter's Mark I. Their contributions do align with earlier results by Malerba and Orsenigo, reinforcing their findings. By principal component analysis, they found that the ability to employ protection mechanisms to protect innovation has a positive relation with Schumpeter Mark II. Moreover, low market concentration reinforces widening patterns (Mark I), and high stability appeals to Mark II.

Fontana et al. (2012) connects with Breschi et al. (2000) contributions. Moreover, Landström & Schön (2010) not only report similar findings, but also remark on similarities between patterns. For example, innovation is central to economic development and in both the capitalist assumes the risk.

However, Schumpeter marks are not alone in the literature. around the eighties, a new set of archetypes by Pavitt (1984) proposed an alternative to Schumpeter's Mark I and Mark II. Pavitt's (1984) taxonomy classifies industries based on the requirements of its users, the sources of its technologies, and the degree of appropriability. Pavitt finds four different patterns for industries: Supplier-dominated sectors; scale-intensive industries employing process and product innovation; specialized suppliers that market technology to other firms; finally, science-based, knowledge industries with a high degree of appropriability and tailored towards exploring innovative technological breakthroughs.

One may ask which framework is better. However, both appeal to distinct aspects of the same subject. In the case of Pavitt's taxonomy, Archibugi (2001) finds that each one closely ties with Kondratiev's long waves of capitalist development. On the other hand, Castellacci (2008) links its classification to the sectors that sustained the growth of advanced economies in the Fordist age. In contrast, Schumpeter's Mark I and II appeal to the dynamics of an industry life cycle. Mark I characterize the early stage of a firm, where turbulence in competition is common and there is no clear leader. On the other hand, Mark II refers to a more mature, late-stage phase of an industry that has large firms deeply rooted on the market (Malerba, 2005).

The question revolves not around which framework is better but on when and how to use these frameworks. In the literature, authors like Fontana et al. (2021), Breschi et al. (2000), Castellaci and Zheng (2010), Malerba and Orsenigo (1996), Corrocher et al. (2007), among others focused their efforts on Schumpeter's patterns. In contrast, Landström & Schön (2010), Marsili and Verspagen (2002), and Leiponen and Drejer (2007) preferred an approach using Pavitt's taxonomy.

The selection of either Schumpeter's or Pavitt's framework relies usually on the scope and objectives of the research. For example, Breschi et al. (2000) wanted to test Schumpeter's hypotheses through quantitative analysis, Corrocher et al. (2007) aimed to create a distinction for ICT sectors based on Schumpeter's work, proving a coexistence of both Marks in some cases, and Castellaci and Zheng (2010) deployed an industry-level productivity growth characterization using Schumpeterian patterns. However, the literature has found that sometimes Schumpeter's pattern may offer a narrow view of an industry, which makes them employ Pavitt's taxonomy. Such is the case of Van Dijk (2000), who showed how some groups among Dutch manufacture do not fit easily into either group of Schumpeter's Marks, or Leiponen and Drejer (2007) with a similar phenomenon on Danish industries.

Characterizing exercises yields information on how their industries work and what environment they enclose. Policymaking can borrow elements from these studies. However, as we stated previously, tension builds in countries or regions where this exercise does not exist. With the emphasis on Colombia, Schumpeter's theory is known, as some articles appeal to its contributions to their study (Umaña-Aponte et al., 2013; Marroquín, 2010; Arroyo-Mina & Guerrero, 2018; Langebaek-Rueda & Vásquez, 2007). Nonetheless, it is not used for characterization of industries but for impact evaluation, behavioral economics, and case analysis.

There are attempts to build sector-specific entrepreneurship profiles (Cerón et al. 2010), and innovative profiles (Ovallos-Gazabón & Amar-Sepúlveda, 2014), but they do not employ Schumpeterian patterns of innovation. With that in mind, this article will join the academic dialogue about innovation patterns in Colombia by characterizing industries in the manufacturing sector. I intend to reach this goal by characterization Colombian manufacturing industries using Schumpeter's framework, which will supply insight into how firms behave toward innovation, based on industrial life cycle and dynamics.

5 Methodology

This research employs a cross-section hybrid of DANE (2020) "*Encuesta de Desarrollo e innovación tecnológica*" (EDIT) survey and DANE (2019) "*Encuesta Anual Manufacturera*" (EAM) survey. Both surveys differentiate firms by a "*Numero de Orden*" (NORDEMP) registration, which makes it easier to identify common patterns and merge them in one single database.

EAM is a census of all manufacturing industries in Colombia that fulfils its classification criterion of at least ten employees and sales greater than 517 million pesos. If a firm fulfil the sales requirement but not the employees one, it is also included in the census. This implies that the EAM by itself is a population database, not a sample. Moreover, given the sales and employment thresholds, the informal economy, small and micro firms end up excluded from the survey. As Annex 1 illustrates, the selection at the four-level ISIC digits is based on the following three digits industries [1][2].

Given the fact that EDIT samples EAM sectors, instead of firms, not every industry in EAM is present in the EDIT. By using statistical software like R, I solve this problem through an inner join of both databases by their common ISIC code and NORDEMP

[1]Source: Own elaboration based on DANE's Methodology (2018, p. 7)

[2]As an exception, ISIC codes 202 and 210 select specific four-digit industries within them

registrations. Thus, the yielding database reduced the number of observations from almost 8000 to 6405.

From this database, I will employ some of the variables that approach Breschi et al. (2000), and Malerba & Orsenigo (1996) dimensions: market concentration, stability and technological opportunities, an. Based on these dimensions the relevant variables found on the EDIT/EAM cross are:

Table 1: Relevant variables for the study

Dimension	**Concepts**	**Variables (by DANE's code)**
Stability	Amount of radical innovations	I1R4C2N
	Amount of incremental innovations	I1R4C2M
Concentration	Total sales	I3R2C1
	Total spending on innovative activities	II1R10C2
	Total Employees	PERTOTAL
	Total Output	PRODBIND
Technological Opportunities	Possession of conventional protection mechanisms valid until 2018 (Patents, IP, Copyright, Trademarks)	VI1R8C2
	Obtention of conventional protection mechanisms between 2017-2018	VI2R8C2
	Usage of non-conventional protection mechanisms (NDA, industrial secrets, high complexity on designs)	VI3R5C2

Source: Own elaboration based on DANE's surveys (2019;2020)

By making use of these variables in R, I construct 3 dimensions at the industry level: Concentration (CON), Technological Opportunities (TO) and Stability (STA). The way to measure these variables adopts the following forms:

1 CON: Based on the works of Malerba and Orsenigo (1996), it is a measure of concentration of innovative activities and firm size. At the firm level, I employ these variables, but also extend the measure to include market share in number of employees and total output. Variations between these shares are smoothened by

using a geometrical mean such that the industry-level measure adopts the form:

$$CON = (HH_{ms} * HH_{msa} * HH_{lsd} * HH_{ss})^{1/4} \tag{1}$$

Where HH is a Herfindahl-Hirschman index, and the subindex represent each measure of interest. In that sense, ms means Market Share, msa means Innovative Activities, lds stands for Labour Demand Share, and ss for Supply Share. Per our established conceptual review, we expect that low values of the CON measure will relate to Mark I industries, while large coefficients would appeal to Mark II industries.

2 TO: I employ Maleki et al. (2018) approach, where Technological Opportunities are measured by the growth rate of patents. However, growth rate requires a comparable measure for 2017. I do not possess this data as EDIT surveys are non-comparable. Thus, I employ the proportion of new protection mechanism relative to registered mechanisms. In this case, we can employ the following formula at the industry level:

$$TO = \frac{PM_{1718} + NCPM_{1718}}{PM} \tag{2}$$

Where PM_{1718} captures the industry aggregate of all protection mechanisms obtained between 2017 and 2018, $NCPM_{1718}$ follows the same mechanism, but with emphasis on non-conventional protection mechanisms (e.g., Non-Disclosure Agreements, Industrial Secrets and Complex Design). Finally, PM contains all protection mechanisms valid until the end of the year of interest (2018). Considering Breschi et al (2000) distinction, Mark I industries have low appropriability for their inventions, while Mark II tend to appropriate knowledge better and possess more technological opportunities. Thus, we may speculate in favour of an inclination towards Mark II on industries with high TO values.

3 STA: Since stability has close ties with firms entering and exiting the market of innovation, it demands a dynamic analysis. Bear in mind that DANE's EDIT methodology states that EDIT 2018 is non-comparable with its predecessors. Thus, we need to employ a different approach.

To solve this setback, I borrow theoretical concepts from the literature. Specifically, I rely on Baumol (2004, p. 10) observation that "major breakthroughs have tended to come from small new enterprises, while the invaluable incremental contributions (...) have been the domain of the larger firms.". Baumol proposition, coupled with the relationship between firm size and Schumpeterian patterns established in the literature review, provides a stability approach that could be classified under either Mark I or II. Hence, to quantify that stability approach, I propose the following mathematical form:

$$STA = Sr - Si \tag{3}$$

Where Sr is the share of radical innovations over the total amount of innovations in the industry, and Si the share of incremental innovations. Based on Baumol's proposition and reviewed theory, we shall expect a high share of radical innovations to have a relation with turbulent Mark I industries, while incremental innovations to the Mark II archetype.

Considering the nature of these three dimensions, I had to filter the database further, as some industries, for example, reported an aggregate of zero on innovation activities spending. Therefore, the concentration measure would result in zero, even though the other components do report values greater than zero. This began to be a problem on industries with less than 20 observations. Hence, I establish 20 as the minimum number of observations in my study. Results are reported on Annex 2.

The information is then clustered using a k-means method for 2 groups, employing a Lloyd algorithm and 10 repetitions. Following MacKay (2003) explanation, k-means calculates a mean for each group and assigns a data point (in this case, industry) to said group by the following mechanism:

1 *Assignation phase*: Each observation gets assigned to the group with the closest mean (by Euclidean distance). Each generated group is composed by a centroid that serves as reference point for the following steps.

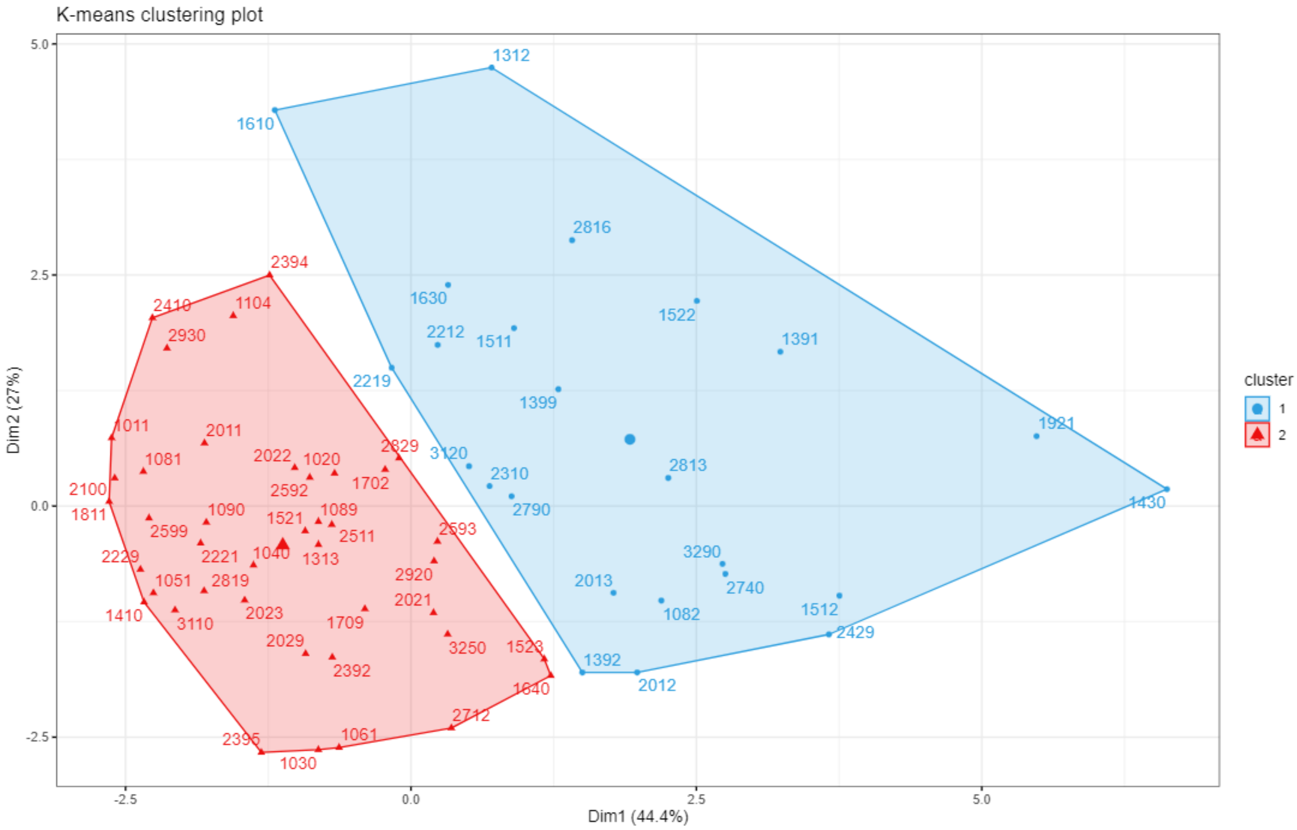
2 *Update phase*: Group parameters adjust to match the means of the data points.

3 *Repetition phase*: Assignation and Update phases repeat until they do not change anymore, that is, data points do not change their position in the groups.

6 The Cluster

6.1 Preliminary Results

Figure 1: Preliminary characterization of Colombian Manufacture using a two groups k-means clustering method



Source: Own elaboration based on DANE (2019;2020) databases.

Figure 1 shows the resulting cluster from the k-means algorithm. Before evaluating both groups, bear in mind that the X and Y axis are in function of "Dim1" and "Dim2" variables, instead of our initial measures. This change obeys to the fact that the k-cluster method in R employs a principal component analysis (PCA) dimensional reduction algorithm. PCA operates our three dimensions (*STA, TO, CON*) and creates "shadow" variables "Dim1" and "Dim2". These variables capture a certain amount of the variation contained in the original dataset. In this case, Dim1 and Dim2 find components of 44.4% and 27% respectively.

In our 2 groups k-means clustering exercise, we find that Cluster Group 2 (CG2), colored red, has 5192 observations and is denser than Cluster Group 1 (CG1), colored blue, which has 794 observations. On the other hand, red group industries are closer between them than those in the blue group. Initial descriptive statistics for both groups are shown in the following table.

Table 2: Initial descriptive statistics of the two groups k-means clustering

	Cluster Group 2			*Cluster Group 1*		
	TO	*CON*	*STA*	*TO*	*CON*	*STA*
Max	3.500	1023.11	0.586	6.000	2702.96	1.000
Min	0	160.28	-1.000	0.047	1068.11	-1.000
Mean	0.522	572.22	-0.294	0.983	1507.72	-0.345
Std Dev	0.651	262.98	0.414	1.496	416.08	0.550

Source: Own elaboration

Initial differences arise on the preliminary descriptive statistics, which may aid in our characterization purpose. In the case of CG2, Technological Opportunities oscillate between a growth rate of 350% and no growth at all, with a representative value of 0.52 and a standard deviation of 0.65. Concentration values in CG2 tend to be smaller, oscillating between 1023 and 160 on the Herfindahl-Hirschman index and reporting a representative value of 1507. Standard deviation across concentration stands at 262 index points. Finally, Stability reports values between 0.586 and –1 with a standard deviation of 0.414 and a mean of –0.294

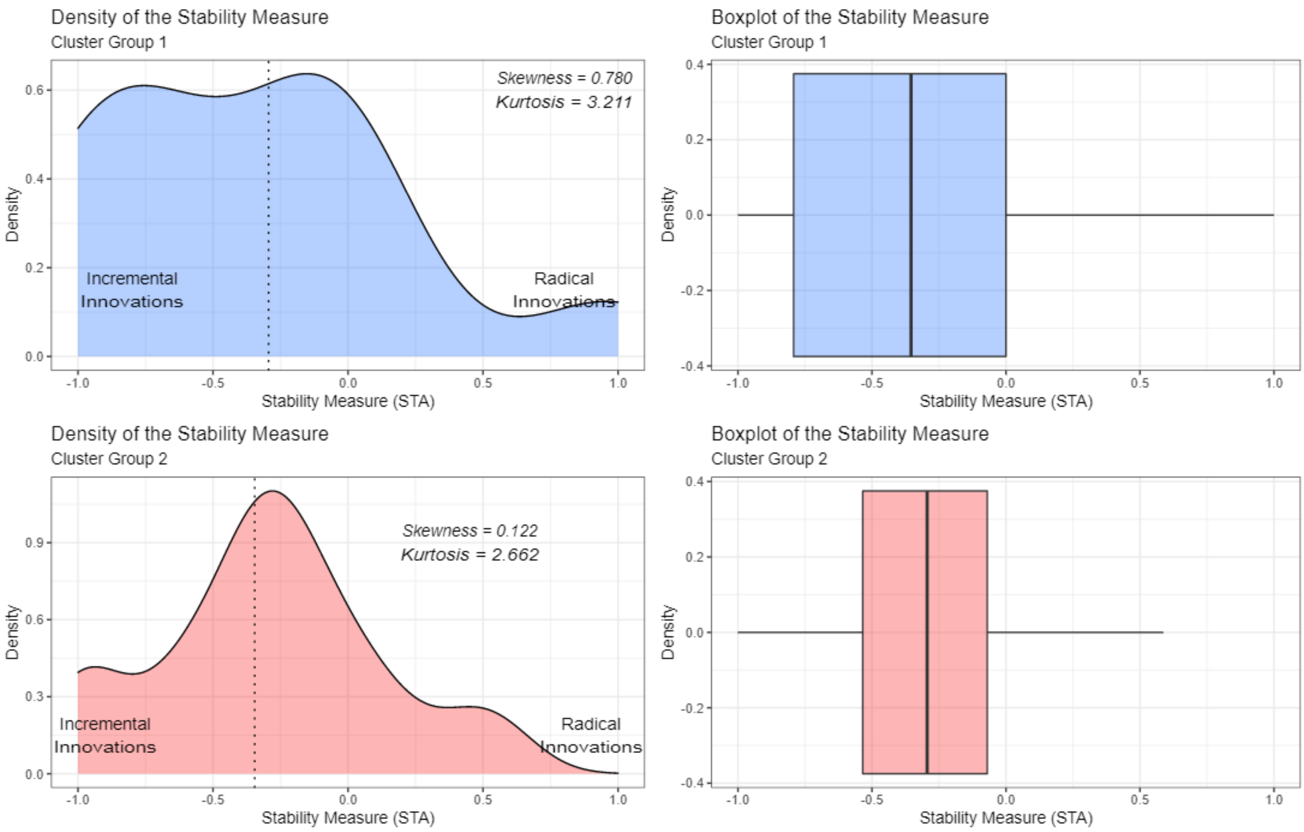
In the case of CG1, we find a large value of Technological Opportunities, with industries reporting a growth rate of 600% relative to existing protection mechanisms. The mean of this group stands near 1 with a standard deviation of 1.496, telling us about an overall feature in this group to grow their protection mechanism registries more than their CG2 counterparts. Concentration index in CG2 also reports a significant deviation from CG1 results. While the former oscillates between 2702 and 1068, with a representative value of 1507, the latter passes maximum 1000 index points. Finally, Stability reports in average slightly higher values towards incremental innovations when compared to CG1.

6.2 Preliminary Analysis

In this section, I put the results in context with Schumpeterian patterns of innovation by employing further data visualization and inferences. To begin with, results report lower Stability in CG2 when compared to CG1. Even though the mean difference fin both groups is not large, data distribution as per the Figure 2 shows that the density plot for CG1 has a prominent number of observations between 0 and -1, which in turn means, by the nature of the measure employed, that CG1 has many industries with a predominance of incremental innovations in their aggregates. This remark is reinforced by a high positive skew of the distribution.

In the case of CG2, the next figure shows that it distributes mostly below 0, but its differentiating factor is its lower density when compared to CG1 across said interval. Skewness and kurtosis measures support this idea. The main insight to draw from this analysis is that CG1 industries tend to be dominated by larger shares of incremental innovations in their aggregate, while industries in CG2 do not show this tendency, instead, they have smaller differences between radical and incremental shares rather than disproportions towards one of the two types. Box plots support this conclusion, considering that CG1 left box is much wider than its CG2 equivalent.

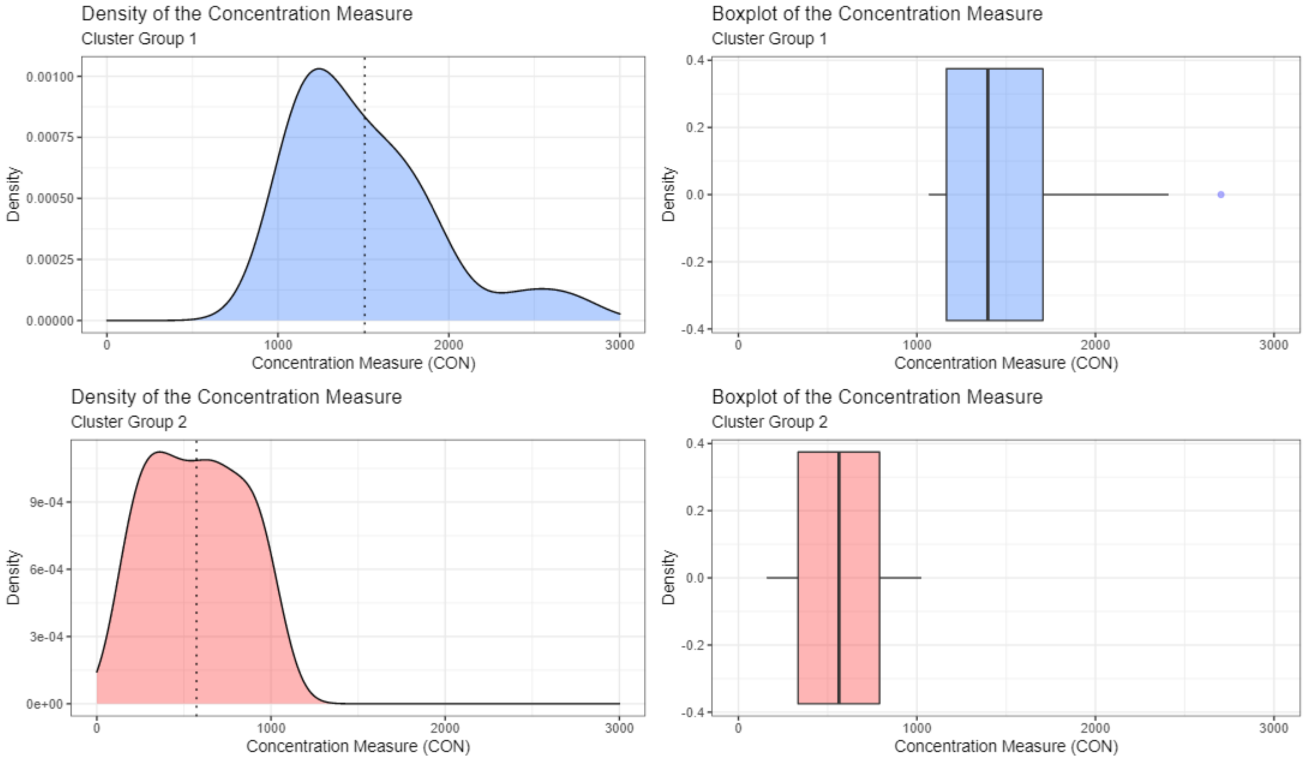
Figure 2: Density and box plots of both Groups in the Stability dimension.



Source: Own elaboration

Within the Concentration measure, density plots in the next figure show a clear difference between both groups. While CG2 distribution finds its peak near 500 and reaches 1000 concentration points at most, CG1 reports values above 1000, with a long-tailed right side until 2700. Boxplot of both datasets provides a different visualization of this phenomenon, but confirms that CG1 market concentration is, on average, much larger than industries on CG2. All this statistical insight points out to one conclusion: CG1 industries are highly concentrated, and, dominated by larger firms.

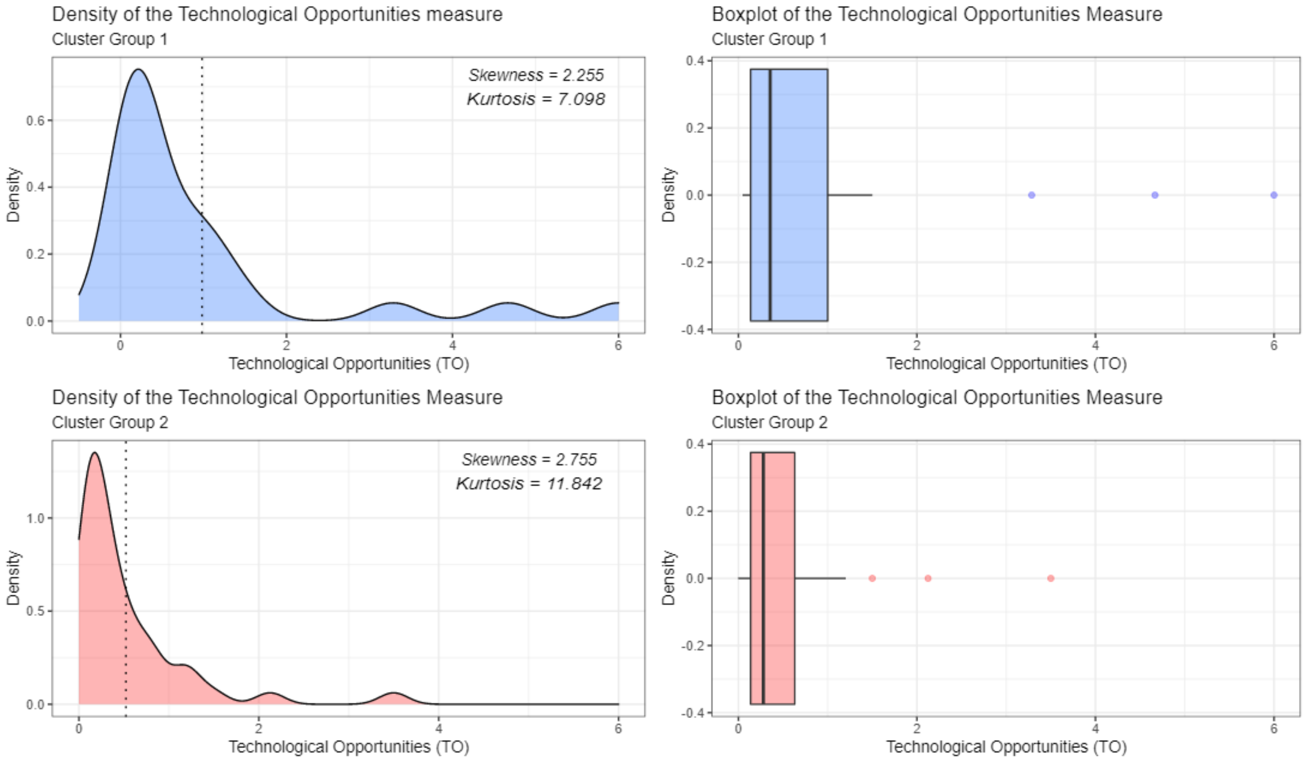
Figure 3: Density and box plots of both Groups in the Concentration dimension.



Source: Own elaboration

Finally, the behaviour of technological opportunities shows that both groups distribute mostly near zero. However, as shown in the next figure, skewness in CG2 is larger than CG1, which may lead us to infer that their registry of new protection mechanisms relative to the existing ones is low, which in turn may indicate low appropriability. Kurtosis in CG2 is also higher, which indicates that the TO measure industries classified on CG2 is highly concentrated around its mean. In the case of CG1, both moments are lower. Thus, CG1 industries do register a higher proportion of protection mechanisms relative to the existing ones compared to CG2, which may indicate an overall higher level of appropriability in this group. Box plots reinforce this idea, as CG1 right box is wider.

Figure 4: Density and box plots of both Groups in the Technological Opportunities dimension.



Source: Own elaboration

By evaluating these three dimensions, let us go over again our most important discoveries. First, we found a tendency in CG1 towards high shares of incremental innovations, while CG2 tends to be more balanced between shares. Second, CG1 market concentration is clearly larger in average than CG2, which in turn gives us reasons to argue in favour of large firms as the dominant agents of these industries. Finally, we found that CG1 industries register more protection mechanisms relative to the existing ones compared to CG2, which appeals to higher levels of appropriability as there are formal methods to secure benefits from innovation (I.e., Patents, IPs, Copyrights, et cetera).

Per this inferential analysis, and based on reviewed theory, we can provide a preliminary characterization of CG1 industries under the Mark II pattern, while features of CG2 industries gravitate towards the Mark I Archetype.

7 Preliminary Conclusions

Our preliminary conclusions revolve around three ideas. First, we have been able to characterize Colombian industries under Schumpeterian patterns of innovation. Even without the dynamic component of previous characterization exercises, statistical analysis and inference show clear differences, proper of Schumpeterian patterns.

Second, we found what type of firm drives innovation on each industry. CG1, the less dense group, has been labeled as Mark II, thus, larger firms drive innovation within this group. On the other hand, CG2, the densest group, gravitates toward Mark I, placing startups and small firms as the drivers of I innovation. This difference in amount shows us that Colombian manufacture is more of a Mark I than Mark II sector, as the largest group of industries is the Mark I group.

Third, concentration is the spearhead of innovation pattern analysis in Colombia, as the most prominent differences came from its measure. It is true that the Stability and Technological Opportunities measures yielded relevant results, but its analysis required further statistical tools to produce a formidable conclusion.

Besides our data-driven conclusions, this characterization exercise provides an input for future works and serves as a groundwork for public policy recommendations. In the former, as every industry is now classified under a Schumpeterian pattern of innovation, it may serve as the starting point for a probabilistic exercise, in the latter, as we found who drives innovation within each industry, it may aid in future policies or reforms that tackle, for example, innovative activities or research incentives.

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A Annex 1: Universe of study for the EDIT survey.

ISIC code	Economic activity
101	Processing and preservation of meat and fish
102	Processing and preservation of fruits, vegetables and tubers
103	Production of oils and fats
104	Dairy Processing
105	Production of milling products, starches and their derivatives
106	Elaboration of coffee products
107	Sugar and panela processing
108	Manufacture of other foodstuffs
109	Preparation of prepared feedingstufss for animals
110	Beverage production
131	Spinning, weaving and finishing of textiles
139	Manufacture of other textiles
141	Manufacture of clothing
143	Manufacture of knitted and crocheted articles
151	Tanning and retanning of hides and manufacture of travel goods
152	Footwear manufacturing
161	Sawing, waxing and impregnation of wood
162	Manufacture of sheets of wood for plating, boards and panels
163	Manufacture of wooden parts and pieces
164	Manufacture of wooden containers
169	Manufacture of other wood products
170	Manufacture of paper and cardboard
181	Printing activities and related services
190	Coking, oil refining and fuel mixing
201	Manufacture of basic chemicals and their products
203	Manufacture of synthetic and artificial fibres
221	Manufacture of rubber products
222	Manufacture of plastic products
231	Manufacture of glass and glass products
239	Manufacture of non-metallic mineral products
242	Basic precious and non-ferrous metal industries
251	Manufacture of metal products for structural use
259	Manufacture of other products made of metal

260	Manufacture of computer, electronic and optical products
270	Manufacture of electrical appliances and equipment
281	Manufacture of machinery and equipment for general use
282	Manufacture of machinery and equipment for special use
291	Manufacture of motor engines and their engines
292	Manufacture of bodies for motor vehicles
293	Manufacture of parts, auto parts and vehicle accessories
300	Manufacture of other types of transport equipment
311	Furniture manufacturing
312	Manufacture of mattresses and box springs
321	Manufacture of jewellery and related articles
323	Manufacture of articles and equipment for the practice of sport
324	Manufacture of games, toys and headbutts
325	Manufacture of medical and dental instruments, apparatus and materials
329	Other manufacturing industries
330	Maintenance and repair of metal products, machinery and equipment
2021	Manufacture of pesticides or chemicals for agricultural use
2022	Manufacture of paints, varnishes and similar coatings
2023	Manufacture of soaps, detergents and perfume
2029	Manufacture of other chemicals
2100	Manufacture of pharmaceutical products and medicinal chemicals
241 & 243	Metal foundry

B Annex 2: Industry-level results

Three-Digit ISIC	Four-Digit ISIC	TO	CON	STA
101	1011	0.157	305.89	0.234
102	1020	0.353	815.72	-0.111
103	1030	0.121	396.99	-0.933
104	1040	0.136	488.88	-0.294
105	1051	0.094	198.09	-0.279
106	1061	1.192	412.75	-1.000
108	1081	0.136	334.15	0.099
	1082	0.062	1389.42	-0.784
	1089	0.172	674.37	-0.217
109	1090	0.140	423.24	-0.120

110	1104	0.109	790.62	0.467
131	1312	0.308	1753.45	0.926
	1313	0.818	656.25	-0.333
139	1391	0.500	1904.26	-0.143
	1392	0.404	1156.52	-1.000
	1399	0.102	1504.79	-0.077
141	1410	0.252	160.28	-0.313
143	1430	0.048	2702.96	-1.000
151	1511	1.500	1291.60	0.000
	1512	0.158	1847.33	-1.000
152	1521	0.092	651.43	-0.250
	1522	0.211	1913.61	0.000
	1523	1.500	1017.81	-1.000
161	1610	1.000	1093.55	1.000
163	1630	6.000	1105.45	0.000
163	1640	0.000	1023.11	-1.000
170	1702	0.766	933.74	-0.176
	1709	0.054	716.54	-0.534
181	1811	0.866	193.94	0.000
192	1921	1.250	2407.87	-0.667
201	2011	0.425	528.27	0.091
	2012	0.195	1316.55	-1.000
	2013	0.138	1281.94	-0.692
202	2021	0.086	866.59	-0.613
	2022	0.114	740.74	-0.048
	2023	0.324	414.61	-0.402
	2029	0.205	499.38	-0.622
210	2100	0.100	259.39	0.107
221	2212	3.286	1068.11	0.000
	2219	1.000	1081.54	0.111
222	2221	0.160	386.37	-0.190
	2229	1.179	164.87	-0.258
231	2310	0.283	1186.85	-0.333
239	2392	0.280	544.95	-0.647
	2394	0.129	919.09	0.586

	2395	0.585	231.47	-0.905
241	2410	0.165	583.96	0.545
242	2429	0.133	1690.52	-1.000
251	2511	1.200	628.54	-0.371
259	2592	2.125	693.44	-0.200
	2593	0.299	974.42	-0.440
	2599	0.448	285.49	-0.070
271	2712	0.408	750.81	-1.000
274	2740	0.920	1626.86	-0.818
279	2790	0.821	1168.34	-0.375
281	2813	0.429	1633.96	-0.500
	2816	4.667	1405.11	0.000
	2819	0.505	317.84	-0.353
282	2829	3.500	886.41	-0.333
292	2920	0.804	920.49	-0.500
293	2930	0.632	563.31	0.412
311	3110	0.531	219.11	-0.382
312	3120	0.099	1125.81	-0.273
325	3250	0.256	887.84	-0.714
	3290	0.066	1528.87	-0.667