Chapter 1. A picture of the Italian manufacturing sectors as a first step to design proper industrial policies

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1.1 Introduction

The digital and green transitions are shaping new industrial policies. Simultaneously, the pandemic, energy crisis, war between Russia and Ukraine, shifting geopolitical balance, and high inflation have drastically altered the interactions between big and small companies and institutions, global value chains, and the relationship between Italy and other countries. Understanding these issues and in particular the reorganization of the production chains, the platform economy, the reshoring phenomenon, the new globalization, the right amplitude of reshoring across different economic areas (Europe, United States, and BRICS countries) requires various aspects to be analyzed in order to design proper industrial policies for pushing innovation, firms' growth and internationalization of companies. However, to address this issue, we must identify some priorities.

It is our belief that a preliminary starting point is to analyze the structure of the Italian manufacturing sectors before these crises. For this reason, we focus on the period between 2015 to 2019, a growth period for economic activity time of economic growth for Italy and other countries. Recently, companies have faced a lot of exogenous shocks, making it crucial to examine their strengths and weaknesses before the multiple crises to identify enduring characteristics. We use the Ateco sectors classification, even though one of the recent challenges in industrial economics and policy is identifying production chains without discretion. The state of the art in this area relies on the acquisition of electronic invoicing data, which requires more time. Thus, analyzing sectors remains the only available option.

The adoption of the classical standard ATECO classification serves as the best proxy for our analysis. Instead of focusing on production chains, we analyze ATECO sectors. Although the value chains approach is more compelling as it could help us to understand the linkages among companies within the same production chain, we use sector classifications as our starting point. This approach provides a snapshot of the Italian manufacturing sector, laying the groundwork for future analysis based on production chains. The structure of many sectors shapes the reaction to the conjectural crises (ISTAT, 2021). Therefore, understanding these structures, in particular with a good disaggregation, is crucial for designing effective economic policies for companies and for mitigating the spread of crises across sectors. As shown by the ISTAT Report on the competitiveness of productive sectors (ISTAT, 2021), small and medium-sized companies faced the greatest challenges during the Covid-19 crisis (Di Iorio and Giorgetti, 2020). Despite this, companies that demonstrated dynamic behaviour in the pre-pandemic phase, managed to counteract the effects of the crisis, a trend observed even among smaller units (Costa et al., 2021).

Thanks to a complex micro-sectorial database built by ISTAT, it is possible to carry out a classification analysis at a granular sectoral level (up to 5 digits of the ATECO classification). This analysis focuses on two main indicators: the number of enterprises and the degree of concentration within each sector. Although these indicators are straightforward, their combined analysis effectively characterizes the size distribution of companies within each industrial sector (Di Iorio and Giorgetti, 2022).

The technique used is Atheoretical Regression Trees (ART), first proposed by Cappelli et al., (2008) that exploits the recursive approach of Least Square Regression Trees (LSRT) (Breiman et al., 1984). The aim of this methodology is to partition a continuous variable, such as the number of enterprises and the degree of concentration in each sector, into groups the units by homogeneity with respect to the given considered variable. It is worth noticing that the procedure is data-driven as the number of subgroups is not predetermined. This makes it possible to create a cross-classification of industrial sectors into groups based on the combinations of the levels of the selected indicators.

Identifying the size distribution of firms within sectors can be a useful tool for mitigating the spread of negative effects during crises or to stimulate positive propulsive effects between firms of different sizes in the same sector or across related sectors. Understanding this distribution is essential for designing effective industrial policies or incentives to address potential crises and stimulate growth.

1.2 Theoretical references

As regards the market structure investigation, the Industrial Organization (IO) has evolved through several phases. From the Structure-Conduct-Performance literature to the Chicago School, the post-Chicago School, the New Empirical Industrial Organization (NEIO), the field has gone through several phases. Some phases have been more interested in recovering regularities among sectors, while others have been more focused on the analysis of specific sectors by adopting game theory. Sutton (1991, 1998), identified endogenous sunk costs as a criterion to group different sectors, revealing regularities regarding the level of concentration. In particular, seminal Sutton's (1998) contribution used the concentration ratio (CR1) in combination with the number of firms to explain the coexistence of different submarkets within the same sector. In this analysis, we use the Herfindahl index instead of concentration ratio and examine the number of firms in each sector to identify potential variations in firm size distribution.

As regards the sub-sectors, from a theoretical perspective, the combination of these two indicators, mentioned above (the number of companies and the level of concentration), identifies the following clusters of interest with regard to the size distribution of companies within a sector (see Table 1.1):

CASE A) Sectors characterized by the prevalence of a reduced number of small companies. Low concentration and a small number of companies.

CASE B) Sectors characterized by a large number of small companies. Low concentration and a high number of companies.

CASE C) Sectors characterized by a small number of large firms. High concentration and a low number of companies.

CASE D) sectors characterized by one or a few dominant firms and many small firms. High concentration and high number of firms.

Table 1.1: Size and concentration

	Number of Competing companies	
Herfindahl	LOW	HIGH
LOW	Case A: small number of small firms	Case B: many small firms
HIGH	Case C: small number of large firms	Case D: One or very few dominant firms and many small firms

The joint classification by concentration and the number of firms allows us to make further analysis on the potential firm size distribution in each sub-sector. The primary aim of this analysis is to provide insights that can inform the development of effective industrial policies[1].

In recent years, there has been growing consensus in the literature on the need for explicit industrial policies (Criscuolo and Lalanne, 2023; Giorgetti and Anderloni, 2022), starting from the seminal work of Aghion et al. (2015), which highlights the synergies between competition policies and industrial policies. Recent developments, such as the USA Inflation Reduction Act 2022[2], which provided considerable support for US companies, have sparked a lively debate - both in the world of research and in policy-making - on how to deal effectively with ways to offer incentives and support for businesses.

Building on this contribution, we analyse the entire manufacturing sector with a granular disaggregation, thanks to a rich database provided by the Italian National Statistical Office (ISTAT).

1.3 Data

The database is based on the ISTAT Extended Statistical Business Performance Register (Frame-SBS), which contains individual data on all industrial and service companies in Italy (approximately 4.4 millions of units). This database is linked to official statistical registers providing detailed information on employment characteristics, primarily sourced from INPS (National

1 A next step could be the transition from the ATECO classification of sectors to the identification of production chains, but this will be a further step when data will be available.

2 17th Congress (2021-2022): Inflation Reduction Act of 2022. (2022, 16th august). https://www.congress.gov/bill/117th-congress/house-bill/5376. The Inflation Reduction Act of 2022 will make a down payment on deficit reduction to fight inflation, invest in domestic energy production and manufacturing, and reduce carbon emissions by roughly 40 percent by 2030. The bill will also finally allow Medicare to negotiate for prescription drug prices and extend the expanded Affordable Care Act program for three years, through 2025.

Institute for Social Security)[3]. The sectorial database is further enriched by a wide range of economic aggregates and indicators, coming from National Accounts, able to measure the structure, the performance and the role of each sector within the production system. The main variables are: number of firms by subsector, number of employed, turnover, production, value added, wage, gross operating margin, imports and exports, concentration (Herfindahl index based on turnover).

The structure and economic variables (at national and sub-national level), as well as those concerning internationalization are obtained for each economic sector (up to 5-digit ATECO) from individual company data. Information on the number of enterprises, the employed, the self-employed and the total number of employed were extracted from the ISTAT statistical archive of active enterprises (Archivio Statistico delle Imprese Attive, ASIA) with reference year 2017.

Based on this initial framework, ISTAT has developed similar databases for the period 2015 to 2019. As first step, we don't use all this information.

The aim of this paper is to provide an overview of the manufacturing sector's structure, at two different levels of disaggregation: the 3-digit and 5-digit ATECO breakdown. To achieve this, in light of the motivation section, we focus on classifying sectors by combining data on concentration levels and the number of incumbent companies within each sector.

The Herfindahl index is widely recognized as a key tool for analyzing market concentration. Usually the concentration classes are defined using specific thresholds. The usual Herfindahl thresholds, elaborated in an antitrust framework, identifies 4 groups: first group with an index below 0.01, that indicates a highly competitive industry; a level between 0.01 and 0.15 indicates an unconcentrated industry; a level between 0.15 and 0.25 that indicates moderate concentration while a level above 0.25 indicates high concentration[4].

However, using predefined thresholds for classification may lead to the creation of groups that are not necessarily homogeneous, especially when these thresholds are defined in a broad or generalized context. For this reason, we elaborate this data-driven approach using Atheoretical Regression Trees (ART). This method generates homogeneous groups driven by data i.e. not fixing their number in advance.

As regards an analysis of sectors by the number of incumbent companies, there is no universally accepted threshold for grouping. Therefore, we will try

3 The National Institute for Social Security (Italian: Istituto Nazionale della Previdenza Sociale) is the main entity of the Italian public retirement system. All waged labourers and most of self-employed, without a proper autonomous social security fund, must be subscribed to INPS.

4 U.S. Justice Department. "Horizontal Merger Guidelines," Select "5.3 Market Concentration." https://www.justice.gov/atr/horizontal-merger-guidelines-08192010

to cluster sectors using the data-driven procedure aiming to create the most homogeneous groups possible.

We focus our analysis on the years 2015 and 2019. Tables 1.2 and 1.3 present the main characteristics of the 1-digit ATECO sectors for these years.

Table 1.2: Number on firms, number of employees, and degree of turnover concentration (Herfindahl)
at 1 digit ATECO, 2015

1 DG ATECO	N. firms	N. employees	% firms.	% empl	HClas.
Mining	2186	30245	0.05	0.19	hconc
Industry	389317	3619121	9.18	23.02	hcomp
Energy	10775	89108	0.25	0.57	unconc.
Water	9231	186988	0.22	1.19	hcomp
Construction	511405	1323554	12.06	8.42	hcomp
Retail trade	1105227	3302193	26.05	21.01	hcomp
Transport	123625	1089419	2.91	6.93	hcomp
Accom.& food	315464	1323345	7.44	8.42	hcomp
Inform.& communication	98381	541978	2.32	3.45	unconc.
Real estate	238273	298553	5.62	1.90	Hcomp
Professional activities	714934	1211338	16.85	7.71	Hcomp
Rent, travel agency	139595	1165287	3.29	7.41	Hcomp
Education	29566	96649	0.70	0.61	Hcomp
Human health	285231	824530	6.72	5.25	Hcomp
Arts, recreation	65022	164032	1.53	1.04	Hcomp
Other services	203680	452496	4.80	2.88	Hcomp
Total	4241912	15718834	100.00	100.00	

Legend: high competitive (hcomp), high concentrated (hconc), unconcentrated (uncon)

Table 1.3: Number of firms, number of employees, and degree of turnover concentration (Herfindahl)
at 1 digit ATECO, 2019

1 DG ATECO	N. firms	N. employees	% firms.	% empl	HClas.
Mining	1971	27744	0.05	0.16	hconc
Industry	372343	3755625	8.70	22.24	hcomp
Energy	12443	84112	0.29	0.50	un-conc
Water sewerage and waste management	9598	209213	0.22	1.24	hcomp
Construction	487266	1319484	11.39	7.82	hcomp
Retail trade	1068883	3442212	24.98	20.39	hcomp
Transport	119550	1142580	2.79	6.77	hcomp
Accom.& food	335140	1592737	7.83	9.43	hcomp
Inform.& communication	108531	586405	2.54	3.47	un-conc
Real estate	236477	309075	5.53	1.83	hcomp
Professional activites	750117	1294996	17.53	7.67	hcomp
Rent, travel agency	157076	1392278	3.67	8.25	hcomp
Education	36510	117679	0.85	0.70	hcomp
Human health	303498	939221	7.09	5.56	hcomp
Arts, recreation	73559	189771	1.72	1.12	un-conc
Other services	205784	480203	4.81	2.84	hcomp
Total	Total	4278746	16883337	100.00	100.00

Legend: high competitive (hcomp), high concentrated (hconc), unconcentrated (uncon)

1.4 Methodology

As mentioned before, the technique applied to classify the industry sub-sectors is Atheoretical Regression Trees (ART). This method, introduced by Cappelli et al. (2008) exploits the recursive partitioning approach of Least Squares Regression Trees (LSRT) (Breiman et al., 1984). LSRT express the relationship between a response variable and a set of covariates in the form of a binary tree. This tree is generated by recursively splitting, i.e. dividing, the data into two subgroups increasingly homogeneous with respect to the response variable.

Specifically, tree growing relies on a data driven top-down algorithm known as recursive partitioning. This method evaluates all potential splits of a current node using a splitting criterion. The best split is selected based on a goodness-of-split measure, which reflects how effectively the split divides the node into two mutually exclusive subsets that are as homogeneous as possible with respect to the given response variable.

ART are an adaptation of LSRT that aim to partition a response variable y while preserving some internal ordering. To achieve this goal, the response variable is tree regressed using a single artificial covariate given by an arbitrary sequence of strictly increasing numbers $K=1,2,\ldots,i,\ldots,n$, hence the name Atheoretical.

A successful application of this method regards the determination of multiple level shifts occurring at unknown dates in various types of time series (see among the others Rea et al. 2010, Cappelli et al 2013) as well as to classify financial institutions by risk (Cappelli et al., 2021).

In this study, the ART framework has been applied to classify sub-sectors either with respect to the degree of turnover concentration or to the number of companies within each sub-sector.

Formally, let y_i, with $i=1,\ldots,n$, be a target variable, characterized by an internal order, that we want to partition into by G a priori unknown groups identified by G-1 thresholds. The objective is to estimates the set of thresholds or cut points that define the partition of the variable

$$P(G) = \{(y_1, \ldots, y_{n_1}), \ldots, \left(y_{n_{g-1}+1}, \ldots, y_{n_g}\right), \ldots, (y_{n_{G-1}+1}, \ldots, y_n)\}$$

into subgroups such as the target variable is homogeneous with respect to some statistical feature. In case the feature of interest is the average, the groups will be such that $\mu_g \neq \mu_{g+1}$ and, in order to identify the cut points and consequently the groups, the estimation criterion is based on the least squares principle that selects the split of a current node h that maximizes the sum of square reduction i.e. the difference:

$$SS(h)\text{-}[SS(h_l)\text{-}SS(h_r)] \qquad (1.1)$$

where $SS(h)=\sum_{y_i\in h}(y_i - \hat{\mu}(h))^2$, is the sum of squares of the father node h, $\hat{\mu}(h)$ is the mean of the y values in node h and $SS(h_l)$ and $SS(h_r)$ are the corresponding quantity computed for the left and right descendants, respectively. Note that, since h_l and h_r are an exhaustive partition of node h, $SS(h)$ represents the total sum of squares whereas $[SS(h_l)+SS(h_r)]$ is the within-group sum of squares. Therefore, the splitting criterion stated in equation 1.1 is equivalent to maximize the between-group sum of squares and that for a binary partition resorts to search for the child nodes that are as far as possible, in terms of squared distance between their means. Figure 1.1 graphically displays and explains the splitting of a node h into its child nodes h_l and h_r.

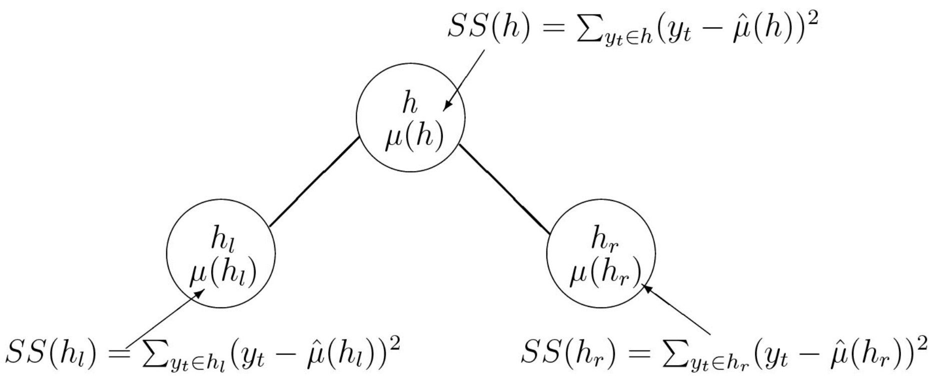

Figure 1.1 Split of a node based on the least squares principle in a Tree diagram

Once a node is partitioned, the process is applied recursively to each child node until a minimum size within a node is reached or the homogeneity cannot be further increased. The resulting tree, known as the maximal tree, is then pruned to generate a sequence of nested subtrees. Among these, the final subtree, which represents the final partition, is selected.

As previously mentioned, within ART, the target variable is partitioned while preserving its internal order. In this case, the two variables considered have been sorted in increasing order. Consequently, the final partition provides groups consisting of sub-sectors characterized by an increasing number of enterprises or degree of concentration.

Specifically, with respect the number of enterprises, ART identifies 4 classes labelled as low, medium, high and very high. For the level of concentration, the procedure defines 4 classes: highly unconcentrated, unconcentrated, medium concentrated, highly concentrated. It's worth noticing that, as the thresholds are estimated on the data at hand, although the number of groups corresponds to the literature, the thresholds of the Herfindahl index are rather different.

1.5 Results

As mentioned in Section 1.2, our aim is to provide an overview of the structure of the Italian manufacturing sectors by leveraging a data-driven approach. The main characteristic of a data-driven classification method is the evaluation of mutual position of different observations instead of their absolute position in relation to a fixed threshold. In other words, groups are formed when the "distance" (measured with respect to a given objective function) between the units in the same group is minimized or when the "distance" among groups is maximized.

Finally, in the light of what was discussed in the motivation section (see Table 1.1), since our aim to capture the firms size distribution for all the manufacturing sub-sectors, in Tables 1.4 and 1.5 we present the classification at 5-digits level obtained by the ART procedure for the number of companies and the level of concentration jointly. We do not present the three-digit classification. By analyzing these two tables we observe that the number of sub-sectors fitting Case D, that is one or very few dominant firms and small firms (see Table 1.1) are close to zero. Some changes happen from 2015 to 2019, but these are not referred to situations with high number of companies and highly concentrated sectors. The changes involve a shift and increase of sub-sectors from a highly competitive classification to unconcentrated sectors classification and the shift from a low number of companies to a medium number of companies. From 2015 to 2019 we observe a slight tendency of 5 digit sectors to be less fragmented, although the manufacturing structure and firms size distribution seem to maintain their main characteristics.

Table 1.4: Sub-sector classification by number of companies and Herfindahl index, 5 digits, 2015

	num. of companies				
Herfindahl	Low	Medium	High	Very High	Total
Highly competitive	177	46	7	4	234
Unconcentrated	43	2	0	0	45
Moderate concentration	25	1	0	0	26
High concentration	10	0	0	0	10
Total	255	49	7	4	315

Table 1.5: Sub-sector classification by number of companies and Herfindahl index, 5 digits, 2019

	num. of companies				
Herfindahl	Low	Medium	High	Very High	Total
Highly competitive	154	33	7	2	196
Unconcentrated	80	2	0	0	82
Moderate concentration	27	1	0	0	28
High concentration	9	0	0	0	9
Total	270	36	7	2	315

1.6 Conclusions

This paper, focusing on the years 2015 and 2019, demonstrates a data-driven methodology for classifying Italian manufacturing sectors based on the firm size distribution. This classification is determined by two simple indicators: the number of companies and the level of concentration within each specific sector.

The main finding is that the majority of sectors, both at 3 and 5-digit levels, continue to be characterized by a remarkable level of small/medium companies. This persists despite the contributions in the literature and public debates about the necessity to strengthen our industrial system by adopting policies able to increase the companies' average size. The analysis conducted provides an important, updated snapshot that can be the starting point for many policy design and evaluation.

Indeed, analyzing the size distribution of firms within sectors can be a useful tool for identifying ways to mitigate the spread of negative effects, as occur in crisis situations, or to stimulate positive propulsive effects between firms of different sizes in the same sector or in related sectors.

We observe some changes regarding the numbers of sectors in 2015 and in 2019 but these are not referred to the case D (see Section 1.2), which is characterized by high number of companies and highly concentrated sectors.

The changes concern the increase of sectors from a highly competitive classification to unconcentrated sectors classification (as regards concentration) and the shift from a low number of companies to a medium number of companies. Between 2015 and 2019 we observe a slight tendency of 5-digit sectors to be less fragmented, even though the manufacturing structure and firms size distribution does not lose its main feature: the presence of too many small companies. Thus, if we want to design policy such that companies help each other in the sense that bigger companies push smaller ones, we have to take into account three important conclusions from our analysis:

1) Sectors with a few dominant companies and many small companies are nearly non-existent (see Table 1.1, Case D). Consequently, within each sector, it is difficult to define actions where big companies can support small and medium size companies in the process of digital and green transitions.

2) We have to investigate linkages among sectors in Italy in order to see if there are asymmetric firms size distributions across sectors, and the successive step is the identification of the value chains.

3) A further step is to identify the same linkages where parts of the production chains are located in other European countries. If the head of the value chain is outside the national borders, the identification of the other players within Europe becomes crucial for developing a cohesive industrial policy.

This is crucial for accurately understanding the situation and for dealing with acquisition and change of company ownership within Europe where the state aids regime has been suspended. This presents a challenge for a common industrial policy. States with better financial resources across Europe can more effectively help their companies, by increasing the inequalities among economies inside Europe.

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