

TOTAL FACTOR PRODUCTIVITY AND ITS DETERMINANTS: AN ANALYSIS OF THE RELATIONSHIP AT FIRM LEVEL THROUGH UNSUPERVISED LEARNING TECHNIQUES

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Abstract. The paper is related to the identification of firm's features which serve as determinants for firm's total factor productivity through unsupervised learning techniques (principal component analysis, self organizing maps, clustering). This bottom-up approach can effectively manage the problem of the heterogeneity of the firms and provides new ways to look at firms' standard classifications. Using the large sample provided by the ORBIS database, the analyses covers the years before the outbreak of Covid-19 (2015-2019) and the immediate post-Covid period (year 2020). It has been shown that in both periods, the main determinants of productivity growth are related to profitability, credit/debts measures, cost and capital efficiency, and effort and outcome of the R&D activity conducted by the firms. Finally, a linear relationship between determinants and productivity growth has been found.

Keywords: Total Factor Productivity, Firm Characteristics, Industry Sectors.

JEL Classification: D2, L2, O3.

1. INTRODUCTION

1.1 Motivation

One of the big issues of economics is represented by the studying of the economic growth of countries, firms, and individuals, and by the understanding of the drivers which are related to.

There is a huge body of literature that contributes to the development of theories and models in this direction, starting from classical and neoclassical contributions. The crucial point from the first studies by these economists is related to the concept of productivity, in particular total factor productivity (TFP). More recent works, such as Cardona, Kretschmer and Strobel (2013), return on this point looking at productivity as the main driver of economic growth and on its impact the individuals (not casually they refer to productivity as the “wealth of nations”). But where does exactly productivity originate?

In this paper, I assume that the main source of productivity is given by the outcome of the research and development activity by the firms, measured in terms of intangible assets. This view is coherent with the Growth accounting literature (Solow, 1957; Romer, 1990), but also with many empirical studies. In this sense, the more efficient use of resources (a technological improvement) allows to obtain higher long-term economic growth.

The paper analyzes the relation between productivity and its determinants at the firm level. The aim consists of looking from a different perspective at this relation, since there is a huge heterogeneity in the data at the firm level that is only partially captured by neoclassical models and standard econometric techniques (Syverson 2004; Dosi, Grazzi, Tomasi and Zeli, 2012; Maue, Burke and Emerick, 2020).

1.2 Research questions

Overall, much work has been done on the link between TFP and some specific determinants (Melitz, 2003; Acemoglu, Aghion, & Zilibotti, 2006; Del Gatto, Ottaviano, & Pagnini, 2007; Melitz & Ottaviano, 2008; Aw, Roberts, & Yi Xu, 2008; Doraszelski & Jaumandreu, 2009; Faggio, Salvanes & Van Reenen, 2010; Syverson, 2011; Cardona, Kretschmer, & Strobel, 2013; Bottazzi, Grazzi, Secchi & Tamagni, 2017; Pieri, F., Vecchi, M. & Venturini, F., 2018).

Here, I provide a complementary approach in which I look at the association between TFP growth and a large set of accounting variables using unsupervised learning approaches (PCA, SOM and k-means clustering). These techniques allow indeed to consider firm heterogeneity working directly on firms' features as emerged by data analysis in two periods: pre and post-Covid.

Indeed, while most of the previous works in this field focus on understanding how one specific determinant impacts firms' productivity, this study provides new ways to look at the relationship between TFP growth and all the determinants. Thanks to this bottom-up approach, the paper tries to explain how firms' heterogeneity and thus firms' characteristics impact both firms' classification and the strength of the relation between TFP and determinants. Finally, the introduction of a principal component regression provides a way to evaluate potential patterns of TFP growth.

1.3 Content of this paper

The analysis follows several steps. At first, the paper considers two main issues widely discussed in the literature: measurement issues and applications. Attention has been given to the selection of the best possible methodology for estimating the total factor productivity.

Then, some accounting variables are considered for the aim of representing firms' characteristics. Some of them are directly referring to some determinants: capital efficiency (i.e. property, plant & equipment per worker), firms' profitability (i.e. net profit per worker), R&D effort and outcome (i.e. R&D expenditures and intangibles per worker), credit/debt measures (i.e. short-term debt per worker).

The result of the principal component analysis allowed the identification of 8 principal components (PCs) for the two periods which can represent better firms' characteristics. The first three PCs in both years are related to the same variables and may be interpreted as capital efficiency, profitability and cost management, and even effort in R&D activity.

After having discussed the main determinants through Self-Organizing Maps (SOM), the output of the SOM has been used as input for performing clustering. The clustering analysis has therefore allowed to group firms according to the principal components and the TFP growth estimates. Several groups have been found in this way in both periods and are mainly based on the average productivity growth. However, there is at least one group in both the pre- and post-Covid periods that shares the same average TFP growth, denoting a potential role for specific determinants.

Finally, the principal component regression results identify a linear relationship between PCs and productivity growth. This relation is checked also when sectorial and geographic controls are introduced. However, it does not hold if the principal component regression is performed within each cluster: PCs impact differently TFP growth. Lasso regression is implemented as robustness check on these results. The rest of the paper is organized as follows: section 2 is related to the literature review, both on measurement issues (2.1) and on applications (2.2); section 3 introduces the data description and the methodologies of the analysis (in particular, section 3.1 is related to data presentation; section 3.2 to the estimation of TFP growth; section 3.3 to PCA methodology; section 3.4 to self-organizing maps and cluster analysis methodology and section 3.5 to principal component regression and Lasso); section 4 discuss the empirical analysis both on TFP growth estimation (4.1), principal component analysis (4.2), SOM and clustering (4.3) and principal component regression and Lasso (4.4); finally, section 5 resumes the main results and concludes the paper.

2. PRODUCTIVITY: A LITERATURE REVIEW

For the aim of this paper, I refer to productivity using the concept of Total Factor Productivity (TFP).¹ TFP is mainly described in the literature as the ratio between economic output and the combination of inputs required for production. Intuitively this result is associated with the level of technology adopted by the unit of observation (firm, sector, or country). Indeed, as stated by Comin (2006):

Total Factor Productivity (TFP) is the portion of output not explained by the amount of inputs used in production. As such, its level is determined by how efficiently and intensely the inputs are utilized in production.

An alternative formulation of this concept is the one provided by Altomonte & Di Mauro (2022) which identifies total factor productivity (or “multi-factor productivity”) as the effectiveness of the production

¹ The notion of TFP differs from the one of Partial Factor Productivity which refers to a single factor of production (i.e. capital or labor). PFP may be general, as the output per unit of labor or capital, or specific, as the ratio between the economic output obtained by one single factor and the amount of that factor which is required for the production (Frigero, 1979).

process to bundle together several inputs (intermediates, energy, labour, capital, etc...) to produce an output. While the first definition by Comin (2006) focuses more on the existence of something that exceeds the strict combination of inputs as the output of the production process, Altomonte & Di Mauro (2022) rely more on the effectiveness of the process itself. Although these considerations, the two definitions are practically equivalent. Both are saying that the production process transforms inputs into outputs in such a way that a “value added” is produced.

However, the way in which this “value added” is measured differs in many authors works according to different approaches, methodologies, and fields of research (Del Gatto, Di Liberto, & Petraglia, 2009; Cardona, Kretschmer, & Strobel, 2013; Altomonte & Di Mauro, 2022).

2.1 Productivity: a literature review on measurement issues

The main line of distinction in measuring productivity is typically represented by the implementation of different groups of methodologies.

Considering that the list of methodologies may be quite large since there are also several ways to combine them in different research settings, here I am just providing the most used methods according to the well-established literature. Then, in the next paragraphs, many other settings may be discussed whenever they’re helpful in explaining in detail some determinants of productivity.

A first group of methods is given by the deterministic methodology, which is typically used for computing a deterministic measure of productivity through non-parametric techniques. The most popular and consolidated deterministic methodology is provided by the neoclassical approach on production theory and growth accounting techniques, whose Robert Solow’s paper on technical change and production function represents a first main contribution (Solow, 1957).

In this framework, the total factor productivity coincides with the Solow residual, whose growth rate is positive if the growth rate in output exceeds the growth rate of the combined input (Solow, 1957).

The interpretation of the TFP index as the “residual measure of our ignorance” has been later proposed by Hulten (2001) to describe the findings of two important contributions to the Solow theory. Indeed, several model specifications in the Solow setting, representing the first important linkage between production theory and growth accounting techniques. However, thanks to these specifications, they have found no residuals: specifying all the factors of the production function cleared the residuals. This last result has been contradicted by Denison (1972) who repeated the same procedure correcting some measurement issues (different time periods and capacity-utilisation adjustment by electricity use) and confirming the presence of non-zero residuals (Hulten, 2001).

The second important group of methodologies used for estimating productivity (in levels or growth rates) is given by the parametric or semi-parametric approaches through econometric techniques.

There are some advantages to following these approaches. The elasticities of output to input growth are directly estimated through the model and thus many neoclassical assumptions may be relaxed. In addition, the measure of productivity may be decomposed into trend and cyclical components, according to the business cycle literature (Cardona, Kretschmer, & Strobel, 2013).

In a parametric framework, the regression is obtained through the log-linearization of the production function where the coefficients are the output elasticities relative to the inputs and several control variables may be also included based on the level of the analysis. Also, in this case, productivity is measured as Solow residual. The results of the regression are then tested for statistical significance.

For studies conducted at the firm (or industry) level, it is important to introduce fixed effects since productivity may vary consistently across sectors due to unobserved heterogeneity in the data, as many factors correlated with productivity may have not been considered. In those cases, findings are related to intra-sectoral variation in productivity, allowing to compare firms that produce similar goods (Maué, Burke, & Emerick, 2020).

The main disadvantage is represented though by the endogeneity issue that arises when all the input factors are chosen by the firms: a problem that seems to be underestimated by the literature on the impact of IT on productivity (Draca, Sadun, & Van Reenen, 2006). Although the advantages of following a parametric approach may overcome the cons, any consideration on the causality of the relationships is avoided since the results are just establishing correlations between variables. For example, considering the role of the research and development activity by the firm, we can't determine exactly if the outcome of the R&D activity is a driver of productivity growth or vice versa.

These two groups of techniques have some predominant applications in the economic literature: macroeconomic studies follow mostly the growth accounting approach while microeconomic studies tend to use econometric approaches (Draca, Sadun, & Van Reenen, 2006). Despite that, there is not a strict rule, and both approaches may be used in different fields.

2.2 Productivity: a literature review on TFP studies

With respect to the same applications, as the empirical part of this paper will discuss productivity looking at microeconomic data, we are mostly interested in discussing microeconomic studies which thus deal with issues regarding the total factor productivity at an individual level (firm or plant).²

² For the sake of completeness, macroeconomic studies, instead, emphasize the role of total factor productivity on the dynamics of the economics growth at an aggregate level (country or sector). In addition to that, macroeconomists investigate the determinants of the economic growth with a particular attention to the differences that occur between countries. Originally strong related to growth accounting approaches, the neoclassical growth theory has been recently enriched by the development accounting decomposition (Caselli, 2005), which implies the use of TFP estimates in levels, and through the use of growth regressions for estimating TFP levels directly from aggregate data instead of looking at the residuals (Del Gatto, Di Liberto, & Petraglia, 2009).

Main methodologies

A lot of studies introduced semi-parametric methods to estimate productivity at a firm level. These methodologies are based on the use of proxy variables as dependant variables, once the TFP relation is inverted. This is the case of intermediate goods as a function of TFP and capital as reported by Levinsohn and Petrin (2003) or the use of investments as proposed in Olley and Pakes (1996) to deal with the “invertibility condition” of the TFP (Del Gatto, Di Liberto & Petraglia, 2009).

These methods allow to find evidence on firms’ productivity distribution and dispersion, which comes mainly from the heterogeneity of firms, but also from specific sectoral and industrial factors (Dosi, Grazzi, Tomasi and Zeli, 2012; Maue, Burke and Emerick, 2020), and even on which economic conditions may generate differences in productivity across firms.

On this point, Syverson (2011) provides a useful classification of TFP determinants, identifying two categories (internal and external drivers). Internal drivers are related to all the factors that are directly controlled by the firms, such as the presence of managerial practice or talent, higher quality in inputs (labour and capital), IT and R&D activity. External drivers, instead, are those that come from the operating environment which is not directly controlled by the firms, such as productivity spillovers, trade, market and intra-market competition.

The next sections provide a broad overview of the literature related to each productivity determinant according to Syverson’s (2011) classification. Although my empirical analysis won’t catch the role of all the determinants that are presented here, the aim is to present a quite exhausting literature review to make the reader understand the advantages and limitations of the implemented methodologies.

2.2.1 Internal drivers

Labour and Capital Misallocations

Looking at the two most important inputs of the production process, according to the production theory, labour and capital, there are many situations in which firms cannot perfectly allocate them.

According to Altomonte & Di Mauro (2022), there are three main business dynamics related to labour misallocation: the connection between job and worker reallocation; the heterogeneity of employment dynamics at the firm level; the cyclical behaviour of the labour market.

The continuous process of job creation and destruction, linked with firm exit/entrance in the market, was first discussed by Bartelsman and Doms (2000), based on Davis and Haltiwanger’s (1992) work on job flows across plants, and by Bartelsman et al. (2004) across several countries. Moreover, they found this process to affect productivity growth, reallocating resources from the less productive firms to the most productive ones. Other factors, like business dynamism, market regulation and restrictions on

foreign direct investments play a particular role in avoiding barriers to firm growth and resource allocation (Decker et al., 2014; Andrews and Cingano, 2014; Andrews et al., 2016).

Moving the attention to capital misallocation, one of the most important problems is represented by the presence of financial frictions. These frictions prevent firms from accessing external financial resources when they are requiring to, due to not enough internal funds.

Duval et al. (2017) analyse how firms' financial fragility and credit tightness at the country level may explain the slowdown of productivity growth in recent years (more financially constrained firms experienced the harder impact). Even Altomonte et al. (2018) find that a positive exogenous liquidity shock increases the overall amount of intangibles according to the data of French firms in the years of the financial crises. Financial constraints, thus, play an important role in this situation. These results are coherent with a successive study by Besley et al. (2020), that introduces a measure for credit frictions based on firms' default probability.

Innovation incentives and organizational framework

Moving to the contributions related to innovation incentives and organizational framework, Acemoglu, Aghion, & Zilibotti (2006) analyse the role of innovation and IT adoption. Innovation is favoured by the selection of high-skills managers and firms.³ But, more in general, firms introduce innovation mainly through the activity of R&D, while, in more recent years, the discussion on productivity has moved to the impact of Artificial Intelligence (A.I.) on economic activities (Aghion, Jones, & Jones, 2018; Brynjolfsson, Rock and Syverson, 2021).

Role of innovation and ICT capital

The contribution by Crepon, Duguet and Mairesse (1998) on research, innovation and productivity was among the first important contributions to develop a linkage between the internal activity of R&D conducted by the firm and productivity growth.

In particular, using micro data on French manufacturing firms they were able to derive a structural model that links productivity through innovation output and innovation output through R&D activity. In other words, firms invest in R&D expenditures as input for their innovation activity (two choices: investment decision, size), then the innovation process transforms inputs into outputs (measured as patents applications, matched to firm data) and, finally, innovation outputs contribute to firm's productivity.

³ Acemoglu, Aghion, & Zilibotti (2006) implement this assumption at a micro level for analyzing what happens at a macro level. In particular, they find that advanced economies pursue an innovation-based strategy with moderate investments and a good selection of firms and managers, while developing countries are typically maximizing investments at the cost of selection. The authors recommend the implementation of policies in case one emerging market countries switch out of the investment-based strategy too soon.

The results of the analysis show that only 11% of the firms in the sample are R&D investing firms, and almost the same percentage (12%) are patenting firms with the half of them that has two or less patents. Moreover, innovation firms seem to be larger, more productive, and more capital intensive. These results are in line with Cohen and Klepper's (1996) analysis of the relation between firm size and R&D innovation process by the firms. Larger firms have a higher probability to conduct R&D activities, while at the same time, their R&D intensity is not directly affected by. On the contrary, market shares, diversification, demand pull, and technology push indicators impact directly firms' R&D efforts. With respect to the patenting firms, firm size does not impact innovation output which is affected only by the research effort, demand pull and technology push indicators. As a final result, productivity is affected positively by higher innovation output (Crepon, Duguet and Mairesse, 1998).

Following another approach, a lot of studies introduce the role of innovation analysing information and communication technology as a new type of capital and its impact on productivity (Cardona, Kretschmer, & Strobel, 2013; Faggio, Salvanes & Van Reenen, 2010), while other authors are, instead, more sceptical of the role of information technology in reshaping the economy.⁴

At the firm level, however, the activity of R&D explains a good amount of productivity growth. As it happens with IT capital, this is also coupled with an increase in the uncertainty of its outcome (Doraszelski & Jaumandreu, 2009). The positive effect on firm's productivity by the R&D expenditures is confirmed also by Pieri, Vecchi & Venturini (2018).

Finally, considering other firms' characteristics, Bottazzi, Grazzi, Secchi and Tamagni (2017) analyse the relationship between productivity, profitability, and growth. In particular, they find that productivity and profitability seem to be not so strongly related.

2.2.2 External drivers

Trade competition

Looking at one of the most important external drivers, trade competition, there is a well-established literature related to the role of international trade in explaining productivity differences across countries, industries, and firms. Both the neoclassical trade and the new trade models rely on the assumption of representative firm, thus not considering specific differences in firms' performances that allow firms to achieve different levels of productivity (Melitz, 2003; Del Gatto, Ottaviano, & Pagnini, 2007; Melitz & Ottaviano, 2008; Berthou et al, 2016).

⁴ Carr (2003) have looked to IT as a commodity (with the economic implication that is more efficient to "spend less" on it), and Gordon (2010) have discussed the presence of a diminishing return's problem.

Market competition

The second important external driver that affects productivity at the firm level is market competition or, conversely, the presence of market power.

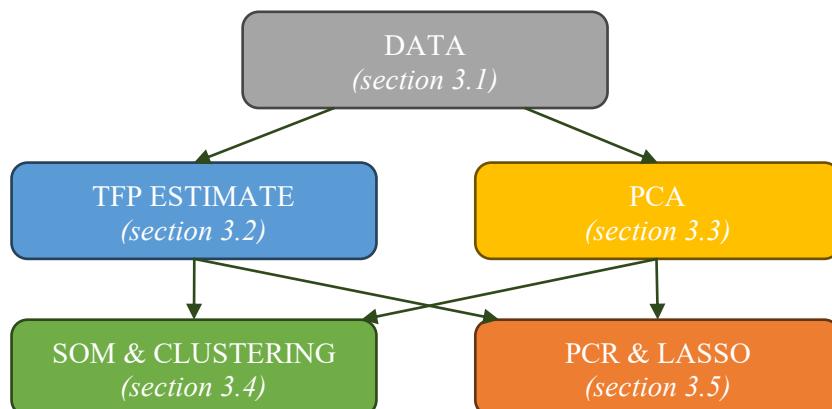
Market competition may impact firms' productivity through different channels, according to the market's economic and political environment. The most important characteristics that may influence firms' market power are demand-side features, international trade, and competition policies (Syverson, 2004; De Loecker, Eeckhout et al., 2018 & 2020; McAdam et al., 2019; Philippon, 2019; Gutierrez & Philippon, 2023; Bajgar et al., 2019; Covarrubias et al., 2020; Altomonte & Di Mauro, 2022).

3. METHODOLOGY AND DATA DESCRIPTION

This section is related to the presentation of the dataset used for the empirical analysis and to the description of the implemented methodologies.

After having provided a discussion on the accounting variables that are selected for the next steps, a framework that connects the deterministic models to the semiparametric techniques is introduced for the productivity growth estimation. Further on, unsupervised machine learning techniques are implemented: principal component analysis (PCA) is required to reduce the number of accounting variables that are considered, while self-organizing maps (SOM) and clustering analysis are used for developing new ways to look at firms' heterogeneity accordingly to firms' micro characteristics and their TFP growth. Finally, PCSs and TFP growth estimates are linked using Principal Component Regression (PCR) to provide further economic interpretation of the results in terms of TFP determinants (a comparison with the Lasso is included). The different steps of the analysis and their order are shown in Figure 1.

Figure 1 - Steps of the empirical analysis.



3.1 Data Description

The analysis is conducted at the firm level and considers the large sample provided by the database of ORBIS, which includes the data for the balance sheets of over 41 million firms. The final sample is obtained considering only the corporate firms with any ownership, from any country and sector with the availability of data for gross sales, R&D expenses, and number of employees for at least the last two years under consideration (2019 and 2020). The data of 19.852 firms are then collected and reported in the following tables.

The economic variables used for obtaining productivity growth estimates are described in Tables 1 and 2 for the years before the outbreak of Covid-19 (the averages between 2015 and 2019) and for the post-Covid period (year 2020).

Table 1 – Descriptive stats for main variables (USD), averages 2015-2019.

Variable	N	Mean	Pctl. 85	Max	Std. Dev.
<i>final goods</i>	14302	98282.55	72698.49	34739997.41	620897.91
<i>workers</i>	19852	4319.31	4107.35	670682.50	21029.44
<i>fixed assets</i>	19852	1380157.85	768210.47	305091875	9085822.87
<i>short-term investments</i>	8878	145921.15	70226.88	113345800	1865081.49
<i>investments</i>	11530	115261.65	44944.38	161069800	1981840.01
<i>intermediate goods</i>	10482	55406.11	31675.89	66119091.52	750283.98

Table 2 – Descriptive statistics for main variables (USD), year 2020.

Variable	N	Mean	Pctl. 85	Max	Std. Dev.
<i>final goods</i>	12959	111431.87	84308.02	33382009.34	697831.20
<i>workers</i>	19852	4501.41	4221.35	1298000	22955.57
<i>fixed assets</i>	19852	1675396.88	962330.21	370792595.31	10770286.26
<i>short-term investments</i>	5815	241349.25	108701.77	122951000	2683990.49
<i>investments</i>	7832	133480.78	56017.74	126809189.53	2011527.72
<i>intermediate goods</i>	9434	70103.97	37858.59	126749624.68	1361964.96

We may have an idea of the size of the firms in the sample by looking at the “workers” variable, which denotes the number of employers hired by each firm.⁵

⁵ According to the EU standard classification for small and medium-sized enterprises (SMEs) micro firms have fewer than 10 workers, small firms have from 10 up to 50 workers, while medium firms have from 50 up to 250 workers. SMEs represent 99% of all the business in the US and in the EU (EU recommendation 2003/361).

Our sample is quite heterogeneous in size: even large firms (more than 250 workers) are distributed over a large interval. Moreover, the sample average is slightly greater than the 85th percentile, which means that the sample average is strongly influenced by values from very large firms.

All the other variables are represented by final goods (the output of the production by firms), intermediate goods, but also fixed assets, as a measure of the stock of capital owned by the firms, and short-term and long-term investments. All these variables show mean values greater than the 85th percentile of their distributions which means that larger firms have huge amounts of resources with respect to the “average” firm.

Figures 2 and 3 show densities and boxplots for some of the main variables (workers, final goods, fixed assets, investments) in both the pre and the post- Covid period. There are no significant changes in the densities, while means and the 85 percentile are slightly bigger than in the pre-Covid period.

Figure 2 – Densities and boxplots, pre-Covid period.

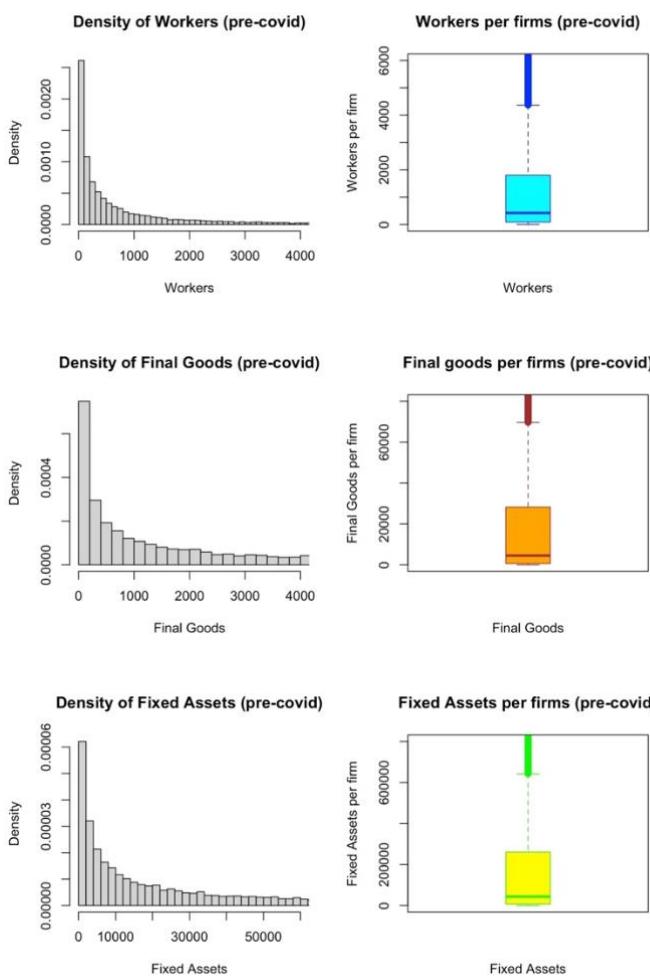
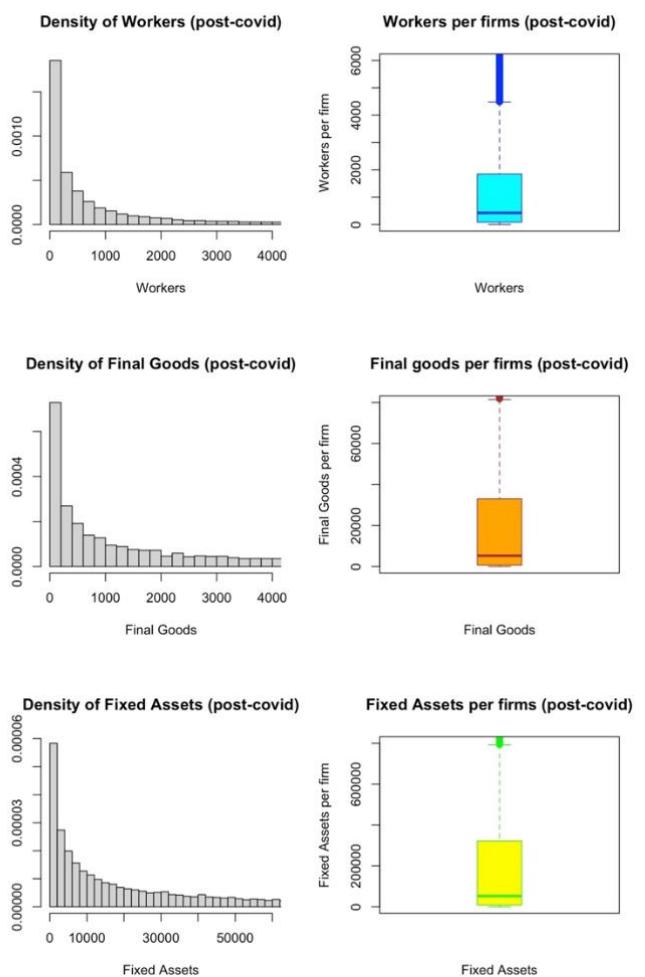


Figure 3 – Densities and boxplots, post-Covid period.



The descriptive statistics of the accounting variables included in the balance sheet of the firms with more than 16.000 observations are reported in the appendix (Tables A.1 and A.2).

The first group of variables is related to the assets section of the balance sheet which includes current assets (total value, inventories, account receivables, cash and other current assets) and long-term assets (net property, plant and equipment, goodwill and intangibles assets and other fixed and long-term assets). Another group of variables consider current liabilities as their total value, account and notes payables to creditors and other short-term debt, and long-term liabilities (in particular, interests and stock of total long-term debt).

The last group is then related to the stockholder's equity, an accounting measure of the firm's net worth (Berk & DeMarzo, 2017), and to the total enterprise value.

All these variables are characterized by positive values and basically express the financial position of the firms in terms of investments, debts and cash reserves and thus they are impacted over time by firm's decisions. To compare mean values with the 85th percentiles of the distributions shows that for all the variables the size of the firms is relevant: for this reason, variables are then considered in per worker terms.

In the appendix (Tables A.3 and A.4) are reported even the accounting variables related to the income statement, which considers firm's revenues and expenses over time. In this direction, many variables may take negative values (cost of sales, research and development expenditures, selling, general and administrative expenses, depreciation and amortization, financial expenses, tax and dividends), or positive values (total revenues, gross sales, net sales and all the measures of earnings and incomes).

Finally, just a short comparison between the two periods considered in the tables in terms of firms' dimensions. The average number of workers has increased (+182) from the pre-Covid period to the post-Covid period and also the 85% of the firms now have more workers on average (+114).

3.2 First step: TFP estimation

3.2.1 Model Description

The starting point for deriving a useful relation for the TFP is to consider the neoclassical production function where output is a function of observable inputs (labor, physical capital, and intermediate goods) and a Hicks neutral technology.⁶

At time t the production function for any firm i is defined as

⁶ The derivation is based on Solow (1957) and slightly different from Draca, Sadun and Van Reenen (2006) as it includes only intermediates as additional input.

$$Y_{it} = A_{it} F(L_{it}, K_{it}, M_{it}) \quad (1)$$

where A_{it} is the level of technology, L_{it} is the labor input (number of workers), K_{it} is the physical capital and M_{it} is the stock of intermediate goods.

Moreover, assuming a Cobb-Douglas specification form

$$Y_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} M_{it}^{\alpha_m} \quad (2)$$

it is also possible to consider the production function in natural logarithm

$$\ln(Y_{it}) = \alpha_0 + \alpha_l \ln(L_{it}) + \alpha_k \ln(K_{it}) + \alpha_m \ln(M_{it}) \quad (3)$$

and taking the first difference the relation finally becomes

$$\Delta \ln(Y_{it}) = \Delta \alpha_0 + \alpha_l \Delta \ln(L_{it}) + \alpha_k \Delta \ln(K_{it}) + \alpha_m \Delta \ln(M_{it}) \quad (4)$$

where $\Delta \alpha_0$ is the TFP growth and the other terms are in growth rates.

This is equivalent to the econometric specification (in logs):

$$output_{it} = \alpha_1 labor_{it} + \alpha_2 capital_{it} + \alpha_3 interm_goods_{it} + \varepsilon_{it} \quad (5)$$

where the residuals catch the productivity growth as Solow residuals.

Although this specification may be quite intuitive for representing our setting, it doesn't consider several issues, such as the selection and simultaneity problems.⁷ Indeed, estimating the production function with standard econometric techniques (O.L.S., panel regressions) when firms' choices on serving the market and on input quantities are based on their productivity may generate biases (Olley and Pakes, 1996). As we want to deal with those issues to obtain consistent estimates, these methods are then discussed and implemented.

3.2.2 Semi-parametric methods

The first method to be presented is the one provided by Olley and Pakes (1996, OP from now on). They introduced an algorithm that considers the self-selection problem caused by the shutdown decision and the simultaneity problem caused by input decisions. Instead of using a traditional balanced panel regression, which does not solve the selection bias, the main assumption of the OP model is based on the existence of one unobserved state variable – firm's productivity – which describes firm's behaviour over time allowing for idiosyncratic changes. Moreover, profits are determined by a function of firms' state variables (age, physical capital and efficiency index, ω_{it}) and factor prices.

⁷ Firstly described by Marschak and Andrews (1944).

At the beginning of every period, each firm decides to remain or leave the market. If it remains then it chooses labor input and investments, which are used to determine the level of capital in the next period as

$$k_{t+1} = (1 - \delta)k_t + i_t . \quad (6)$$

Most importantly OP model assumes that the firm's efficiency index ω_t is known by the firm, and it evolves over time following an exogenous first-order Markov process. Since firms are supposed to maximize the expected discounted value of their future net cash flow, then investment and shutdown decisions should be generated by the perceived distribution of future market structures. Investment is described by the function

$$i_t = i_t(\omega_t, a_t, k_t) \quad (7)$$

and is increasing in ω_t (at least when $i_t < 0$, Pakes, 1994).

This allows to obtain

$$\omega_t = h_t(i_t, a_t, k_t) . \quad (8)$$

Let us consider the OP basic econometric specification (in logs) as

$$output_{it} = \beta_0 + \beta_a age_{it} + \beta_k capital_{it} + \beta_l labor_{it} + \omega_{it} + \eta_{it} \quad (9)$$

where ω_{it} is the unobserved productivity and η_{it} is the unobserved and unpredictable shock to productivity.

Now, the OP estimation algorithm assumes labor as the only variable factor (free variable), while capital and age are fixed (state variables) and affected by the distribution of ω_t conditional on the information at the previous period and on the values of ω_{t-1} .

Thanks to the invertibility of the investment function (which serves as a proxy variable⁸), the unobserved productivity variable is indeed a function of observables and the specification may be rewritten as a semiparametric regression model (in logs):

$$output_{it} = \beta_l labor_{it} + \phi_t(i_t, a_t, k_t) + \eta_{it} \quad (10)$$

where

$$\phi_t(i_t, a_t, k_t) = \beta_0 + \beta_a age_{it} + \beta_k capital_{it} + h_t(i_t, a_t, k_t) . \quad (11)$$

⁸ The use of proxy variables is aimed to control for the error component correlated with inputs (Levinsohn and Petrin, 2003).

The algorithm proceeds in two steps: at first, the partial linear model allows us to obtain the estimates of the freely variable inputs, β_l and ϕ_t ; then, these estimates and the survival probabilities are used to compute β_a and β_k . Please note that residuals η_{it} are computed in the first stage and they're not a state variable (as ω_{it}), thus they are not affecting firms' decisions.

The second method that is considered is the one by Levinsohn and Petrin (2003, LP from now on). In particular, they try to deal with the same issues – simultaneity and selection biases in the production function estimation – but using intermediate inputs as a proxy variable instead of investments as Olley and Pakes (1996) did.⁹

Even the LP algorithm is characterized by the two-step approach used by OP. However, in this case, the first step determines the coefficients of β_l and ϕ_t (but not the one related to intermediates), while the second step is required to compute both β_m and β_k (while in OP investments are not part of the production function).

3.2.3 Further developments

Ackerberg, Caves, and Frazer (2015, ACF from now on) underline several identification problems that arise when OP and LP methods are used. In particular, with respect to the first stage of the algorithms, the labour coefficient can be estimated consistently if and only if the variability of the free variables is independent of the proxy variable. Otherwise, the coefficients estimated in the first stage would be perfectly collinear (Rovigatti and Mollisi, 2018). The ACF method introduces corrections for the functional dependence problem.

OP and LP methods can correctly identify β_l just under very specific DGPs (their estimates may be quite precise although not consistent), while a consistent estimate can be obtained through the ACF method with less restrictive assumptions. For these reasons, I consider ACF as the main method for conducting the analysis, using OP and LP methods as further checks on the results.

3.3 Second step: unsupervised learning approach - PCA

The second step of the empirical analysis is related to the implementation of the principal component analysis (PCA), whose aim is to identify new variables able to better represent the firms' heterogeneity in data.

PCA allows data visualization in low dimensions with the highest possible variation given all the observations included in the dataset on the main firms' features (the original regressors).

⁹ Intermediates are a valid proxy when several conditions are satisfied: the monotonicity condition must be satisfied, which means intermediates must be increasing in ω_t conditional on capital; markets must be perfectly competitive; the production technology used for intermediate inputs must be separable.

PCA, in fact, finds the first principal component (PC) as the normalized linear combination of the features with the largest variance as

$$Z_1 = \phi_{11}X_1 + \phi_{21}X_2 + \dots + \phi_{p1}X_p \quad (12)$$

where the sum of the square of the loadings $\phi_{11}^2 + \phi_{21}^2 + \dots + \phi_{p1}^2$ is equal to 1.

Then, the second principal component is found by the normalized linear combination with the highest variance among all the linear combinations uncorrelated with Z_1 such that the loading vector ϕ_2 is orthogonal to the loading vector ϕ_1 , and so on and so forth.¹⁰

3.4 Third step: unsupervised learning approach - SOM & clustering

After the principal component analysis, self-organizing maps (SOM) are introduced to identify potential clusters and to discuss their interpretation. They consist of several maps that allow to synthesize and better visualize a dataset with multiple dimensions in a two dimensional plane.

Afterward, the output of the SOM is collected for the clustering analysis. In particular, the K-Means algorithm is implemented to split the observation sample into several subgroups according to the SOM. These subgroups also represent a new way to look at firms' classification, according to firms' heterogeneous characteristics and the TFP growth estimates obtained in the previous steps of the analysis. Indeed, elements within each group are expected to be the most like each other, while they are expected to be the most different among groups.¹¹

3.5 Fourth step: PC and Lasso regression

The last step of the analysis corresponds to a further look at the relation between firm's total factor productivity, as estimated according to the semi-parametric techniques, and the principal components. In particular, the principal component regression can be used to identify the relationship between firms' productivity and the related predictors (in other words, its determinants). A robustness check is performed using the original variables as regressors in a shrinkage method, Lasso regression¹².

¹⁰ Scree plots help in deciding how many principal components are computed according to the proportion of the variance explained.

¹¹ The number of clusters is pre-defined: the problem consists of minimizing the within-cluster variation $W(C_k)$ where the functional of W is chosen to be the Euclidean distance. In practice, each observation is randomly assigned to a cluster, then centroids are computed, and observations are redistributed to the nearest centroid, centroids are re-computed, and so on.

¹² As other shrinkage methods, like the ridge regression, Lasso shrinks the coefficient estimates towards zero. In addition, a penalty term is introduced for forcing some estimates to be exactly zero and thus performing variable selection and enhancing the interpretability of the results (James, Witten, Hastie & Tibshirani, 2017).

4. EMPIRICAL ANALYSIS

This section relates to the implementation of the methodologies discussed in the previous paragraphs. The structure reflects the one of Section 3: the stages of the analysis are presented in depth and then the results are discussed. In the illustration of the results, particular attention is given to the economic meanings and interpretations of the different stages.

4.1 First step: TFP estimation

In the first step of the analysis, the production coefficient estimates are estimated according to the semi-parametric methods of OP, LP and ACF (Table A.5 in the appendix).

In particular, the sample using the OP methodology is smaller than the one used for the other two methodologies. Despite that, estimates using OP and ACF for β_l and estimates using OP and LP of ϕ_t (*first stage coefficients*) are not so different: it seems that the use of different samples has just affected the estimation of β_l for LP. Slightly different estimates are obtained for β_k (*second stage coefficient*). In our analysis the benchmark estimation method to be used is represented by ACF since the coefficient for β_l is quite like the one obtained with OP, and β_k estimate is slightly higher than the other two methodologies.

However, these differences in partial productivity estimates should not influence the relation between TFP estimates and the other economic variables: the residuals collected at the end of the first stage are, indeed, strongly positively related and serve as alternative TFP growth measures for implementing the next stages (clustering in particular)¹³.

4.2 Principal Component Analysis

The economic intuition underlying the use of the principal component analysis lies in finding new variables (the principal components) that can describe the characteristics of heterogeneous firms better than the original features. Both the balance sheet and income statement variables, provided by the ORBIS dataset (see paragraph 3.1), are useful indicators of the way in which firms manage their productivity given financial and input constraints. Thus, PCA considers all those variables except the input and proxy variables used for performing the estimates of the TFP.

Since the number of observations among variables is different, a strategy to cope with missing values is required. In the literature there are several studies on the proportion of missing data that may be problematic for statistical analysis. Schafer (1999) evaluated as likely biased an analysis with more than

¹³ Results of the analysis using OP and LP methods for estimating TFP growth are available upon request.

a missing rate of 5%, while Bennett (2001) established a level of 10% of data missing. Tabachnick and Fidell (2012) stressed instead the role of missing data mechanisms and missing data patterns.

Instead of removing a substantial amount of data (and thus information) from the dataset, an approach based on imputation is considered just for PCA. Imputation may be problematic when the number of observations to be estimated is quite high. For this reason, we have considered just the variables that present a number of observations at least close to 85% of the total number (17.000 over 19.852).

Before imputation, all the firms' variables are transformed in per worker term and the sample is normalized. Then, an iterative regularized PCA algorithm¹⁴ is used for imputing data using initial values as the mean of the variables. Finally, the imputed sample is used for performing the PCA.

Looking at the results, as shown in Tables 3 and 4, in both periods the first principal components explain more than 26% of the variance of the original variables. The second principal components explain more than 12% of the variance, while the third PCs are about 10% (higher in the post-Covid period). All the other principal components are almost or less than 8%.

Each principal component exhibits positive and negative correlations with the original features. In particular, the first three principal components capture almost the same key variables in the two periods. The first principal component is strongly associated with property, plant and equipment (net and other measures, positively), depreciation and amortization (negatively) and it may be seen as a proxy for the efficiency in the use of fixed assets in the production process. It may be interpreted as a measure of the optimal allocation of capital resources in the long run by firms.

The second principal component is positively related again to property, plant and equipment measures, denoting a particular role for capital efficiency. But it is associated negatively with net profits and earnings after tax in both periods. Therefore, it may be seen as a measure of firm's profitability (inverse relation) and secondarily as efficiency in cost management (both related to fixed assets, and goods sold). Finally, the third principal component is positively related to different credit/debt measures in the two periods (other short-term debt in the pre-Covid period and accounts receivable in the post-Covid period). Moreover, it's negatively associated with research and development expenditures and on property, plant and equipment. It measures different credit/debit measures in the two periods, but it can be used commonly as a proxy for firm's R&D effort and efficiency.

The other principal components are more heterogeneous in the two periods. In the pre-Covid period, the fourth principal component is positively related to R&D expenditures (and intangibles) and negatively to other financial flows. In the post-Covid period, the fourth principal component is strongly positively related only to intangibles. The other PCs are related to capital efficiency measures, debts/credits and efficiency in sales.

¹⁴ The algorithm is available in the R package "missMDA".

Table 3 – correlations between principal components and features, pre-Covid period.

(pre-Covid)	Var. Explained	Top Positive Correlated Variables	Top Negative Correlated Variables
PC 1	26.1%	<i>property_plant_equipment_other_tot</i> <i>property_plant_equipment_net</i> <i>property_plant_equipment_other_net</i>	<i>depreciation_amortization</i> <i>depreciation</i> <i>amortization</i>
PC 2	16.4%	<i>property_plant_equipment_other_tot</i> <i>property_plant_equipment_other_net</i> <i>intangibles_other</i>	<i>financial_flow_other</i> <i>earnings_after_tax</i> <i>profit_net</i>
PC 3	9.5%	<i>debt_short_term_other</i> <i>intangibles</i> <i>intangibles_other</i>	<i>rd_expenses</i> <i>property_plant_equipment_other_tot</i> <i>property_plant_equipment_other_net</i>
PC 4	7.6%	<i>rd_expenses, intangibles_other</i> <i>debt_short_term_other</i>	<i>financial_flow_other</i>
PC 5	5.5%	<i>amortization</i>	<i>financial_flow_other</i> <i>intangibles_other</i>
PC 6	4.7%	<i>interest_minority</i>	<i>dividends</i>
PC 7	4.3%	<i>dividends</i>	<i>debt_short_term_other</i>
PC 8	3.3%	<i>interest_minority</i>	<i>accounts_receivable</i>

Table 4 – correlations between principal components and features, post-Covid period.

(post-Covid)	Var. Explained	Top Positive Correlated Variables	Top Negative Correlated Variables
PC 1	27.7%	<i>property_plant_equipment_other_tot</i> <i>property_plant_equipment_other_net</i> <i>property_plant_equipment_net</i>	<i>depreciation_amortization</i> <i>depreciation</i> <i>amortization</i>
PC 2	12.7%	<i>property_plant_equipment_other_tot</i> <i>goods_sold_cost</i> <i>earnings_tax</i>	<i>amortization</i> <i>profit_net</i> <i>earnings_after_tax</i>
PC 3	11.9%	<i>accounts_receivable</i> <i>accounts_receivable_net</i>	<i>property_plant_equipment_other_tot</i> <i>rd_expenses</i>
PC 4	8.3%	<i>intangibles_other</i> <i>intangibles</i>	<i>amortization</i>
PC 5	6.6%	<i>rd_expenses</i>	<i>depreciation</i>
PC 6	5.2%	<i>amortization</i> <i>goods_sold_cost</i>	<i>rd_expenses</i>
PC 7	3.8%	<i>property_plant_equipment_net</i>	<i>depreciation</i>
PC 8	3.4%	<i>sales_net</i>	<i>goods_sold_cost</i>

4.3 Cluster Analysis

This section shows the results from the cluster analysis conducted combining firms' characteristics (the principal components) and TFP growth estimates (according to the ACF method) for both the pre and the post-Covid periods. The point is indeed to find a new way to manage the heterogeneity of the firms that should be more accurate in both representing firms' characteristics and serving as a classifier for in depth studies on the relation between TFP and its determinants.

In particular, TFP growth estimates and principal components are combined through the k-means clustering algorithm in such a way that the difference among groups is maximized and the difference within each group is minimized. In other words, all the elements that belong to a specific group are expected to be the most like each other and the most different to the elements of the other groups. This (dis)similarity is measured according to the standard setting that considers Euclidean distance and complete linkage (James, Witten, Hastie, & Tibshirani, 2017).

4.3.1 Self-Organizing Maps

Self-organizing maps (SOM) are introduced before the k-means clustering to give a better interpretation of clusters and their proximity. These maps allow to visualise the entire dataset in a two dimensional grid made by nodes ordered on the basis of the input variables (the firm's characteristics and the TFP growth estimates).

Figures 4 and 5 show several heatmaps for the two periods. Heatmaps represent how nodes are distributed across the SOM grid in terms of node counts, neighbour distances and input variables. Note that the grids in the two periods are not directly comparable. However, they show some common patterns.

The original observations are allocated to nodes according to their proximity and in both cases they assume a "U"-shape (reversed in the post-Covid period). The distances from neighbour nodes are then greater for at least one region: the north in the pre-Covid period and the south in the post-Covid period (other "sparse" nodes are at the corners).

Then, the TFP growth estimates represent the most important variable for discussing the proximity of nodes: in both cases, negative values for TFP growth are located in the western part of the grid, while positive values are located in the eastern part of the map. In particular, nodes reach maximum and minimum productivity growth at the corner of the U-shaped distributions. Principal components are, instead, more heterogeneous in their distributions across the maps.

The output of the SOM models is, thus, used for performing the k-means algorithm, while a direct application of the k-means on the dataset is used as robustness check.¹⁵

¹⁵ These results, obtained for every TFP growth estimation methods, are available upon request.

Figure 4 – Nodes distribution, pre-Covid period.

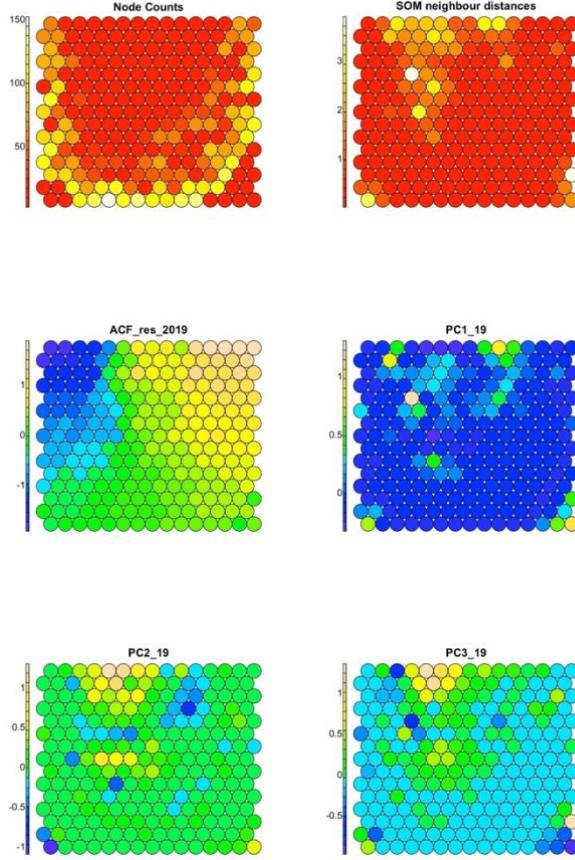
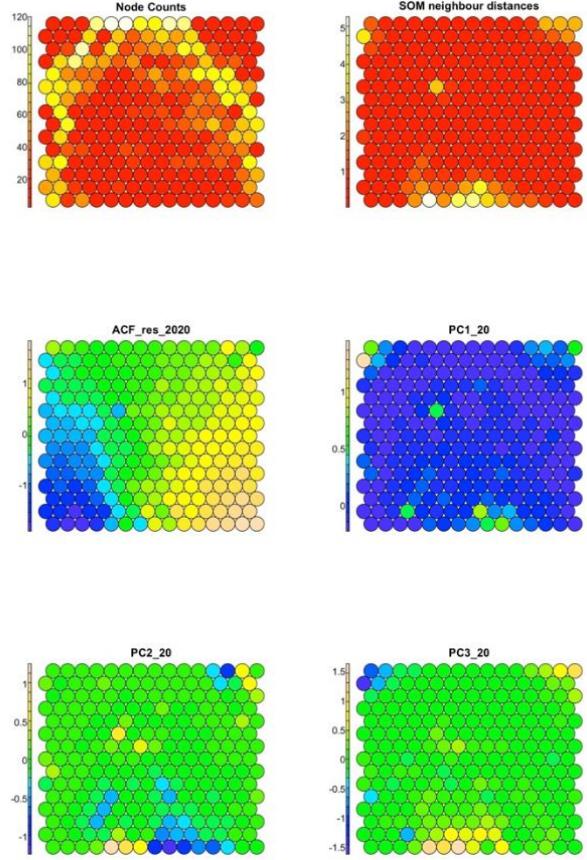


Figure 5 – Nodes distribution, post-Covid period.



According to both the Elbow method¹⁶ and the gap statistics¹⁷ up to 5 clusters and 6 clusters are identified respectively in the pre-Covid period and in the post-Covid period, as shown in Figures A.1 and A.2, in the appendix.

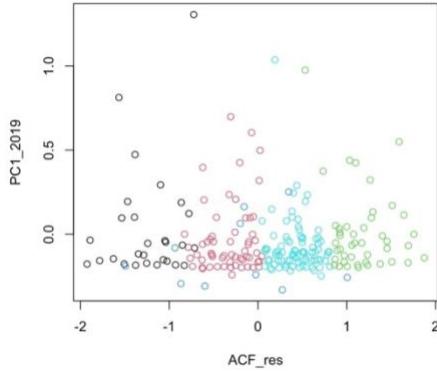
4.3.2 Firms groups in the pre-Covid period

According to the results of the k-means, SOM nodes are allocated into five different groups, shown in Figure 6. Four clusters are distributed according to productivity growth: very low productive growth, low productive growth, medium productive growth, very high productive growth, while the fifth group (medium TFP growth) is more related to specific principal component measures. The results for the firms' sample are shown in Table 5.

¹⁶ According to the Elbow method, the number of clusters is selected at the point in which the drop in the WSS is the largest, excluding the first one (results in the appendix).

¹⁷ The optimal number of clusters according to the Gap statistic corresponds to reaching maximum Gap. In our case, local maxima are selected in presence of a reduction in the growth of the Gap (results in the appendix).

Figure 6 – K-means clustering using SOM nodes (pre-Covid period).



The first group is characterized to have very low values for productivity growth, which means that firms' productivity grows at a slower rate than the average firm. Looking at the principal components, this group has negative values for PC1 (-0.13), PC2 (-0.04), PC3 (-0.12) and positive values for PC4 (0.13). Even the second group has low productivity growth, associated with negative values for PC1 (-0.22). However, it relates negatively to PC4 (-0.999) and PC6 (-0.11) and positively to PC2 (0.79), PC3 (0.75) and PC5 (0.21). In this context firms' productivity grows faster than that of the first group, but the number of firms is quite limited (71 vs 1623). Values for the other principal components are almost zero. At this point, we may say that low productivity growth seems to be associated with low capital efficiency (property, plant, equipment per worker), while the role of R&D activity must be discussed more in detail. Group 2 has, indeed, positive values for the second and third principal components, indicating that these firms perform better costs and debit/credits management (cost of goods sold and accounts receivable/short term debt per workers) than group 1, but fails in R&D effort and outcome (PC4 is indeed positively related to R&D expenditures and it's very low).

Moving up to the third and fourth groups we have slightly positive values for productivity growth (almost the same, firms' productivity grows slightly faster than the average firm), while there are differences in the capital efficiency (property, plant, equipment per worker) and R&D effort (R&D expenditures per worker): group 3 has positive values for PC1 (on average 0.88), while group 4 has negative values (on average -0.14). Moreover, group 3 is the only group with positive values for PC1, meaning that it benefits from a stronger role of property, plant and equipment (capital efficiency), and high values for the last three principal components. Group 4 is instead characterized by negative values for PC3 (-0.11), denoting a positive association with R&D expenditures per worker (the relation is inverse). Even in this case, group 3 is largely smaller than group 4 (18 vs 4826 observations).

Finally, group 5 is characterized by the largest average TFP growth, slightly negative values for the first three principal components and positive values for the fourth principal component. This group may take advantage from higher net profits (inverse relation to PC2) and it shows important contributions of the

principal components related to R&D expenditures and intangibles, interpretable as R&D effort (PC3) and R&D outcome (PC4).

Table 5 – Groups' characteristics according to PCs, pre-Covid period.

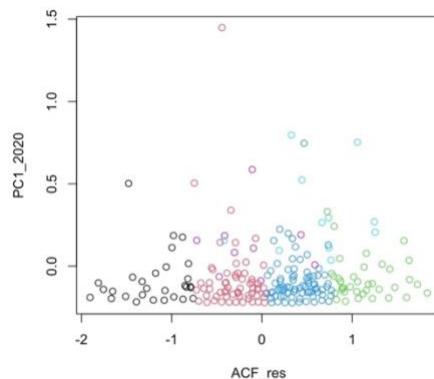
Groups	G1	G2	G3	G4	G5
N	1623	71	18	4826	2141
ACF_res	-1.02268	-0.4624	0.0757	0.12276	1.02226
PC1	-0.12946	-0.2193	0.8797	-0.14369	-0.11875
PC2	-0.03971	0.7850	0.0154	-0.04299	-0.06330
PC3	-0.12137	0.7429	0.0122	-0.10695	-0.09738
PC4	0.12860	-0.9987	0.0372	0.09993	0.10684
PC5	-0.03154	0.2135	0.4587	-0.02405	0.01788
PC6	-0.00321	-0.1130	-0.5153	0.00426	-0.00202
PC7	-0.01072	-0.0673	-0.4532	-0.02211	0.00346
PC8	0.00348	-0.0517	0.5555	-0.01223	-0.05811

4.3.3 Firms groups in the post-Covid period

We should observe even in the post-Covid period at least four groups related to the intensity of TFP growth, as shown in Figure 7. The results for the firms' sample are shown in Table 6.

However, the main differences here are represented by the presence of six groups instead of five and by the different combinations of the principal components. For these reasons, we cannot compare directly all the clusters in the two periods, but we may look at the determinants that emerge from each analysis.

Figure 7 – K-means clustering using SOM nodes (post-Covid period).



Groups 1 and 2 are again associated with negative values of ACF residuals (TFP grows slower than the average), non-positive values for PC1 (-0.6 and 0), while they both have positive values for PC2 (0.05 and 0.24). It seems that on average these groups experienced an increase in the average TFP growth, probably due to a larger number of firms classified in group 1 in the post-Covid period, and a convergence in the relation with the second principal component, associated negatively to profitability (net profit per workers). Even the values for the third principal component are quite similar. Note that group 2 is instead hugely affected by the last three principal components denoting an increase in the heterogeneity of that group.

Groups 3 and 4 stay instead on their medium productivity growth (TFP grows only slightly faster than the average). Both groups are positively related to PC1 (1.03, 0.55) and negatively to PC4 and PC5. Moreover, group 3 is positively related to PC2 and negatively to PC3 while group 4 is the reverse. Capital efficiency (property, plant, equipment per worker) plays again a major role in both groups, with opposite dynamics in the other components. In particular, Group 3 is characterized by high coefficients associated with R&D effort, but not with R&D outcome, while Group 4 seems to have low levels of R&D efforts but potential outcome.

Finally, group 5 in the post-Covid period is almost peculiar to the corresponding group in the pre-Covid period, but it doubles the number of observations (4518 from the 2141 of the pre-Covid period). This implies a drop in the average TFP of the group, which remains at a high level, while the other components seem to be less affected. Group 6 is, instead, the one with the best performance in terms of TFP growth although the scarce numerosity (just 13 observations).

Table 6 – Groups' characteristics according to PCs, post-Covid period.

Groups	G1	G2	G3	G4	G5	G6
N	3073	145	27	18	4518	13
ACF_res	-0.59862	-0.04649	0.1289	0.234	0.5984	1.055
PC1	-0.16036	0.00162	1.0284	0.553	-0.1505	0.334
PC2	0.04671	0.24017	0.1290	-0.789	0.0134	-0.680
PC3	-0.10376	0.55838	-1.2222	0.349	-0.0803	0.275
PC4	0.00572	0.10467	-0.5709	-0.433	-0.0269	-0.470
PC5	0.02325	-0.42859	-0.3963	-0.522	0.0285	0.122
PC6	-0.01660	0.33233	0.3983	-0.717	-0.0669	-1.036
PC7	-0.00267	0.41359	-0.0403	0.364	0.0120	0.545
PC8	-0.08936	0.64535	0.3148	-0.816	-0.0809	1.019

4.3.4 More on clusters' characteristics: main sectors and taxonomies

An important point of the cluster analysis consists of identifying groups that are better representative of firm productive behavior than the original sectors as well as other classifications known in the literature. In the pre-Covid period, the most representative sector was Industrial, Electric & Electronic Machinery (between 10 and 15% in all the five groups), followed by Chemicals, Petroleum, Rubber & Plastic (about 10% in all the groups). At this point, the structure of the clusters seems to be quite similar.

However, things become different when looking at the third most important sector. Groups 1, 2, 4 and 5 are characterized by a relevant share of Business services (about 7%), while group 3 firms share the frequency of this sector with many others, representing a quite heterogeneous group. Moreover, high-productive growth groups present larger shares of the Wholesale sector with respect to the others.

The findings for the clusters in the post-Covid period are not so different but consist of some changes. Industrial, Electric & Electronic Machinery (between 10 and 25%) is confirmed to be the most representative sector in all groups, except for group 4 where it is absent at all. Even Chemicals, Petroleum, Rubber & Plastic (between 10 and 12%) remain the second most representative sector for all the clusters with the exception of group 6. In this group, the property services sector is the one that emerges with a high frequency. Groups 3 and 4 are (again) more uniform in their distributions, while the others (1, 2 and 5) remain the most heterogeneous.

Looking at the classification of sectors based on the Schumpeterian patterns of innovation¹⁸ for all the clusters and in both periods, Schumpeter mark I is the most representative with more than the 60% of the observations. This result is reasonable, since Schumpeter mark II firms are mostly characterized to be persistent innovators, while Schumpeter mark I firms are more heterogeneous.

Things are slightly different when looking at the distributions of the firm's sectors according to the Pavitt taxonomy.¹⁹ In almost all the clusters specialised suppliers are the most relevant category, followed by the suppliers dominated. It's interesting to notice that suppliers dominated firms prevail in group 3 pre-Covid and in group 4 post-Covid, both characterized by a slightly positive level of total factor productivity growth. Science-based is about 10% with a larger presence in cluster 2 pre-Covid and cluster 4 post-Covid.

In general, it seems that original sectors and classic taxonomies cannot express differences in terms of productivity growth, while the new clusters can. Despite that, there are some groups that are quite similar in terms of average TFP growth. It's thus necessary to look more in depth at clusters' characteristics to better understand the differences between these groups.

¹⁸ Based on these classification, original sectors are identified as Schumpeter mark I, Schumpeter mark II or Public service, according to their characteristics (Malerba & Orsenigo, 1995).

¹⁹ According to Pavitt, firms are classified as supplier dominated, specialized suppliers, scale intensive or science based (Pavitt, 1984). Moreover, a category for public services has been added.

4.3.5 More on clusters' characteristics: clusters' dissimilarity

At first, we aim to verify if the average productivity growth of each cluster is statistically different from the ones of the other clusters. Then, the mean values of the original variables within each cluster (both in absolute values and per worker) are discussed to identify the most prominent directions of the principal components. Average productivity estimates are tested to be statistically different two at a time using the student-t test for the comparison of two sample means. The results, using ACF residuals, are shown in Tables 7 and 8 for both the pre and the post-Covid periods.

Table 7 – stud. t tests for the comparison of average TFPs (pre-Covid).

Groups	G1	G2	G3	G4	G5
G1	-	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16
G2	< 2.2e-16	-	0.001	< 2.2e-16	< 2.2e-16
G3	< 2.2e-16	0.001	-	0.6	< 2.2e-16
G4	< 2.2e-16	< 2.2e-16	0.6	-	< 2.2e-16
G5	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	-

As shown, the average productivity growth of groups 3 and 4 is not statistically different in the pre-Covid period. According to the estimation using ACF, both medium productive groups share the same (average) TFP growth. However, group 3 is characterized to be assigned to unique characteristics of the principal components more than on a particular level of TFP growth.

Table 8 – stud. t tests for the comparison of average TFPs (post-Covid).

Groups	G1	G2	G3	G4	G5	G6
G1	-	< 2.2e-16	0.0000005	< 2.2e-16	< 2.2e-16	< 2.2e-16
G2	< 2.2e-16	-	0.2	0.03	< 2.2e-16	< 2.2e-16
G3	0.0000005	0.2	-	0.6	0.00007	0.000004
G4	< 2.2e-16	0.03	0.6	-	0.0003	0.000002
G5	< 2.2e-16	< 2.2e-16	0.00007	0.0003	-	< 2.2e-8
G6	< 2.2e-16	< 2.2e-16	0.000004	0.000002	< 2.2e-8	-

Looking at the results with respect to the post-Covid period, the average productivity growth of groups 3 and 4 (associated with medium productivity growth) is again not statistically different. Moreover, in this case also the average TFP growth of groups 2 and 3 is quite similar.

Since the numerosity of the clusters changes drastically in the two periods, it doesn't make any sense to compare the absolute values of the average TFP growth without considering how many firms have been classified differently in the two periods. But, before moving into this point, it is important to understand better which variables explain the differences among groups and, in particular, between the groups that share the same (average) value for productivity growth.

According to the results using ACF residuals discussed in the previous paragraph, the only groups with positive values associated with the first principal component are group 3 pre-Covid and groups 3, 4 and 6 post-Covid. As reported in Tables A.8, A.9, A.12 and A.13 in the appendix (related to balance sheet variables within each cluster), these groups have the lowest absolute and relative values for property, plant & equipment measures, the first loadings of PC1. Firms belonging to these clusters are not particularly efficient in the use of fixed assets in the long run and they just reach medium levels of productivity growth in both periods. The only exception is represented by cluster 6 post-Covid (this may be an effect of the pandemic on particular firms).

Other important considerations are related to the dimensions of the second principal component, which is strongly negative only for groups 5 pre-Covid and 4 and 6 post-Covid. As shown in tables A.10, A.11, A.14 and A.15 (related to income statement measures within each cluster), these groups collected the largest amount of net profits among all the groups in absolute values in both periods. However, looking at the profitability (net profit per worker) only group 5 pre-Covid confirms this result. Groups 4 and 6 of the post-Covid period are, instead, not doing particularly well in profitability, but they realize a good performance in the efficiency of cost management (cost of goods sold per worker is the lowest among all the groups).

The fact that all these groups reach high levels of productivity growth proves that both profitability and efficiency in cost management are important determinants of TFP growth. The fact that the second one prevails after the outbreak of Covid pandemic may represent a direct consequence of the reaction of the firms to the pandemic shock.

While the dimensions of the third principal components are quite heterogeneous in the two periods, it's important to look at the values of R&D expenditures and intangibles in both absolute and relative terms. R&D expenditures are larger in groups 1, 4 and 5 pre-Covid and in groups 1 and 5 post-Covid. All these groups, indeed, related negatively to PC3 and positively to PC4 in the pre-Covid setting and positively to PC5 in the post-Covid setting. Per worker's values confirm this result only in the post-Covid setting, while in the pre-Covid the distribution of R&D expenditures is more homogeneous. The interpretation

is quite intuitive: in a situation of economic stability firms sustain on average the same effort in the R&D activity, while the pandemic shock affected firms in different ways changing their choices.

Looking at the values of the output of the R&D activity, as proxied by the intangibles per workers variable (R&D intensity), groups 4 and 5 pre-Covid and groups 1 and 5 post-Covid are the ones with the highest values. Not surprisingly in both periods group 5 firms, the ones with high productivity growth, conduct the R&D activity efficiently. Less clear is the result of group 1 post-Covid: it seems that TFP growth has slowed for this group despite a good efficiency of the R&D activity.

4.3.6 Changes in clusters membership (pre- and post-Covid)

An important way to evaluate better how the Covid pandemic affected firms is to consider the changes in the cluster membership between the two periods of the analysis.

In particular, Table 9 shows that the largest changes are coming from the largest groups: 756 firms belong to group 5 in the pre-Covid period and to group 1 in the post-Covid period, while 839 firms are in group 1 in the pre-Covid period and in group 5 in the post-Covid period. Moreover, group 5 in the post-Covid period (high productivity growth) seems to capture most of the observations from group 4 in the pre-Covid period (2522), denoting a potential increase in the aggregate productivity growth of these firms.

Table 9 - Changes in the cluster membership between pre- and post-Covid.

ACF		Post-Covid					
		Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Pre-Covid	Group 1	-	24	2	3	839	4
	Group 2	-	1	0	0	41	0
	Group 3	9	-	-	0	8	0
	Group 4	16	82	-	-	2522	14
	Group 5	756	38	4	3	-	-

Data associated with groups with similar TFP growth are omitted.

As general pattern, firms seem to move to higher productive growth groups, meaning that the Covid pandemic has worsened the economic conditions of some firms only, while the others have potentially improved theirs. Furthermore, the large size of group 5 in the post-Covid period can be explained by the different classifications of group 1 and 4 firms in the pre-Covid period. Although the average TFP growth of this group remains one of the highest, it drops significantly if we consider group 5 of the pre-Covid period as a benchmark. On the contrary, the reclassification of several firms from this last group

to group 1 in the post-Covid period makes the average TFP growth of this group to increase slightly. A trend of convergence in the average TFP growth is therefore observed because of the Covid pandemic. Interestingly, the size of the movements of firms between groups 1 and 5 in the two periods is almost the same. All these groups show efficiency in conducting their R&D activity. We can just conclude that the pandemic affected more the other TFP determinants than the R&D effort and outcome.

4.4 Principal Component Regression

If the presence of different clusters allows us to deal with heterogeneity in firm characteristics, the point now is to consider how and if principal components may be good proxies in explaining the relation between TFP growth estimates and its determinants. Moreover, thanks to the results of the cluster analysis it is possible to check if this relation changes within each different group.

The way in which this is implemented is through the principal component regression that implies the presence of a linear relationship between TFP and principal components.

Figure 8 shows the results of the PCR for both the pre-Covid and post-Covid periods using the estimate of the productivity growth (ACF method) as the response variable, the principal components as explanatory variables and considering the entire sample of firms.

Figure 8 – PC regression results for both periods.

(ACF)	FULL SAMPLE					
	pre-Covid period		post-Covid period		estimate	p-value
	estimate	p-value	estimate	p-value		
PC1	-0.5230	0.00	***		-0.5650	0.00
PC2	-0.4141	0.00	***		-0.2117	0.0049
PC3	0.2125	0.0024	**		0.2550	0.00
PC4	0.1649	0.0156	*		-0.5044	0.00
PC5	0.3998	0.00	***		-0.0144	0.8499
PC6	0.2644	0.00	**		-0.9647	0.00
PC7	0.0553	0.4559			-0.1409	0.0453
PC8	-0.9173	0.00	***		0.3719	0.00

In the pre-Covid period, significant coefficients are associated with seven principal components, since only PC7 exhibits coefficient estimates almost equal to zero. In particular, the PC3, PC4, PC5 and PC6 have positive coefficients, while PC1, PC2 and PC8 have negative. These denote negative relationships between TFP growth and property, plant, equipment, dividends and interest minority, and positive

relationships between TFP growth and net profits, short term debt, R&D expenditures and amortization (all these variables are in per workers terms).

Although the variance explained by the principal components is different, results seem to be quite similar moving at the post-Covid period. In particular, significant coefficients are associated (again) with seven principal components: PC3 and PC8 have positive coefficients, while PC1, PC2, PC4, PC6 and PC7 are negative. That confirms the results obtained for the first three principal components in the pre-Covid period. Since PC4 is negatively affecting TFP growth, it seems that other loadings prevail on intangibles in this setting.

In general, it emerges a positive relationship between TFP growth and profitability (net profits per worker), short term debt and account receivables per worker and a negative relationship between TFP growth and property plant equipment per worker (capital efficiency). R&D activity in terms of efforts affects TFP growth only in the pre-Covid period, while its outcome (intangibles per worker) seems to be negatively related to TFP in the post-Covid period, potentially due to the Covid shock.

Moreover, introducing geographic and sectorial control variables (Table A.16) does not impact significantly the results at this level.

Looking at the principal component regression conducted by restricting the sample to the observations of each cluster separately in both periods with and without controls (Tables A.17-A.27 in the appendix), the situation is heterogeneous. In general, introducing controls is not always possible due to the lack of data on specific clusters (3 in the pre-Covid period and 3, 4 and 6 in the post-Covid period), but when it is possible it affects slightly the within sample results.

In the pre-Covid period, except for cluster 2, all the others have significant coefficients that link the principal components with TFP growth. The situation is slightly worse in the post-Covid period when only clusters 1 and 5 have significant coefficients. This confirms the results of the previous steps of the analysis: groups that are efficient in conducting the R&D activity show that a relation between PCs and TFP growth is true even after the Covid shock.

4.4.1 LASSO Regression

Finally, this section is related to the implementation of the Lasso regression, a shrinkage method useful to obtain significant estimates of the coefficients of the original variables that are related to TFP growth. As shown in Table 10, the significant coefficients that are found correspond to the main loadings of the principal components: property, plant, equipment (PC1), cost of goods sold (PC2) and other intangibles (PC4). Moreover, it's interesting to notice that the coefficients obtained for the post-Covid period are just a few with respect to those obtained for the pre-Covid period.

The presence of property, plant and equipment coefficient is particularly relevant since confirms the negative coefficient associated with PC1 in the principal component regression. The main interpretation

of this result is that the efficiency in the use of fixed assets, in the long run, may reduce productivity growth in the short run due to the limited amounts of available resources. This is confirmed also by a particular role of debt which emerges for the principal component regression. Firms with additional resources present indeed larger values of productivity growth.

Table 10 – Lasso regression, significant coefficients (full sample)

Variables	pre-Covid period	post-Covid period
inventory	13.6241	5.0104
assets_other	-1.1347	.
property_plant_equipment_net	-0.5146	-0.3269
intangibles_other	-0.0223	.
liabilities_current_other	-1.1864	.
liabilities_non_current	-0.2847	.
debt_interest_long_term	-0.2243	.
liabilities_non_current_other	-0.7077	.
sales_gross	3.0183	0.0628
share_reserves	-0.2813	.
goods_sold_cost	.	-0.9998

5. MAIN RESULTS AND CONCLUSIONS

The aim of this paper was to investigate better the relation between the total factor productivity and its determinants for providing a new way to look at how firms' characteristics can affect the pattern of productivity and, thus, the technological progress. In particular, using a bottom-up approach we have found that the TFP, estimated as Solow residuals through semi-parametric techniques, is in general positively related to profitability measures (net profits per workers), credit/debts measures (account receivables and short-term debt per workers) and negatively related to cost and capital efficiency measures (property, plant, equipment and cost of goods per workers). In the pre-Covid period, there is evidence also of a significant positive relation between TFP growth and R&D activity by the firms (R&D expenditures per worker).

The fact that firm's profitability, efficiency (in cost reduction) and the presence of credit/debt measures may affect the total factor productivity is certainly not new. However, these results seem to be quite different from the ones obtained by Bottazzi, Grazzi, Secchi and Tamagni (2017) who have found a weak relation between productivity and profitability.

Moreover, this paper has provided a further classification, different from the original sectors and other taxonomies present in the literature. Indeed, the cluster analysis allowed us to identify at least five

clusters according to the average levels of TFP growth: from very low to very high TFP growth firms. In particular, five clusters have been found in the pre-Covid period and six in the post-Covid period with some of them that share the same average TFP growth.

Some clusters are characterized by similar features as measured by the principal components. The first principal component is related to the efficiency in the use of fixed assets in the long run (property, plant, equipment per worker), or capital efficiency, and it is positive for group 3 pre-Covid and groups 3, 4 and 6 post-Covid. It is negative for all the other groups. The second principal component, associated positively with the efficiency in cost management (cost of goods sold per worker) and negatively with profitability (net profit per worker) is always non-positive for all the groups in the pre-Covid period and it is positive only for groups 2 and 3 in the post-Covid period.

Considering groups 3 in pre-Covid period and groups 3, 4 and 6 in the post-Covid period, these groups have some common features. They are characterized to have the smallest samples among all the groups, and they share their average TFP growth with other groups. We can conclude that for these groups the features expressed by principal components prevail on TFP growth in expressing firms' heterogeneity. The other groups, especially the ones with the largest samples (groups 1 and 4 in the pre-Covid period and groups 1 and 5 in the post-Covid period), relate in the same manner with the TFP determinants. This proves that the difference in TFP growth levels is mainly given by the way in which firms can better exploit their opportunities and make decisions (productivity decisions, investment decisions, managerial practice and organizational framework all have impacted output levels and thus the way in which each firm uses efficiently inputs). The fact that the TFP growth is lower in some groups comes not only from profitability and efficiency in the use of resources, which are observable but also by the outcome of the decision made by the firms.

Not surprisingly, in both periods there are several principal components that refer to firms' R&D activity in terms of effort (R&D expenditures per worker) and outcomes (intangibles per worker). The difference observed with respect to these determinants between the two periods confirms the impact of the Covid pandemic in increasing uncertainty and in disrupting the R&D activity conducted by the firms.

Our methodology, and the resulting taxonomy based on largely available accounting data, can also be valuable for policy. Indeed, classifying firms, and identifying some characteristics typically associated with each group, allows policymakers to pinpoint where resources and interventions are most needed, whether it is in boosting lagging firms or supporting high-performing ones. For instance, high-productivity firms may benefit from policies that encourage cutting-edge research and development, while lower-productivity firms might need assistance with technology adoption or skills training. By understanding the distinct characteristics and challenges of each group, policies can be tailored to foster innovation, enhance competitiveness, and ultimately promote economic growth. In addition, the proposed approach can help in monitoring policy outcomes and adjusting strategies as needed.

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APPENDIX

Table A.1 – Descriptive stats for the balance sheet (USD), averages 2015-2019.

Variable	N	Mean	Pctl. 85	Max	Std. Dev.
assets_current	19852	792949.70	590540.38	196541906.32	4944837.03
inventory	17412	163675.80	119623.82	66442324.95	1143767.68
accounts_receivable_net	19415	185304.88	147655.51	77314091.41	1096161.51
accounts_receivable	18370	194685.68	159638.91	77675039.09	1130381.33
assets_other	19852	475614.07	291247.18	192678588.58	3659333.10
assets_current_other	19439	195712.67	64584.36	140614302.20	2181400.50
cash_short_term_investment	19846	248943.24	179369.07	121959800	1906118.49
cash	19843	189148.85	149513.83	55929431.13	1093198.82
property_plant_equipment_net	19726	622546.05	305044.18	258285075.03	4956379.46
property_plant_equipment_oth_tot	17870	344011.42	84421.06	337561000	5269791.33
property_plant_equipment_oth_net	17808	173668.89	45457.34	158245900.90	2243213.73
intangibles	17056	430470.50	125855.85	162182600	3309060.29
intangibles_other	17019	185106.03	51864.34	59808256.69	1550084.96
assets_fixed_other	19313	404439.62	165193.91	223296400	3782568.43
assets_long_term_other	18690	183164.37	76935.45	149199496.93	1923786.37
assets_tot	19852	2173104.11	1440536.25	485386918.11	13187883.34
liabilities_current	19852	609855.50	384360.97	184420672.18	4085172.55
creditors_trade	19459	176718.68	110655.93	46854681.11	1202840.46
liabilities_other	19852	314870.91	159181.73	99020071.45	2243086.86
debt_short_term_other	18785	35655.12	6812.76	34236247.49	416005.52
liabilities_current_other	19640	187110.06	83994.31	54231000	1398132.80
liabilities_non_current	19838	704631.59	314841.02	203026702.30	4828030.62
debt_interest_long_term	17944	519180.75	271769.31	102142069.66	3159108.34
liabilities_non_current_other	19785	238255.55	83638.02	144147161.72	2195785.14
liabilities_debt_total	19852	1313678.14	746957.25	365763296.88	8452190.35
shareholders_equity_tot	19107	899493.78	671735.36	205808202.60	5541464.89
shareholders_equity_net	17520	845757.51	632871.25	191196900.78	5268409.70
EV	16484	2468753.78	1921643.8	854929969.13	15487301.80

Table A.2 – Descriptive statistics for the balance sheet (USD), year 2020.

Variable	N	Mean	Pctl. 85	Max	Std. Dev.
assets_current	19848	1005710.342	738982.642	291501619.46	6701250.699
inventory	16827	195942.095	143142.91	162809457.25	1742525.34
accounts_receivable_net	19157	200029.071	158885.279	81540914.01	1176973.731
accounts_receivable	17147	209296.03	176311.484	81826243.73	1221999.848
assets_other	19846	650652.493	397522.97	284406637.38	5257199.8
assets_current_other	18940	280444.98	82905.309	231083405.54	3535012.452
cash_short_term_investment	19829	343666.558	250668.615	136694000	2480218.224
cash	19827	272960.703	213448.556	49443907.12	1531612.476
property_plant_equipment_net	19659	693134.804	361083.87	233631000	5285344.583
property_plant_equipment_oth_tot	17192	408371.353	106156.111	402427107.91	6208700.484
property_plant_equipment_oth_net	17023	187068.683	48338.675	160724871.55	2325285.654
intangibles	16205	552493.286	166391.028	162498000	4224432.001
intangibles_other	16156	242106.515	65770.461	120558824.87	2234783.319
assets_fixed_other	19082	559624.165	244903.473	240112100.56	4835906.506
assets_long_term_other	18274	297844.594	132798.487	202525803.51	2894917.001
assets_tot	19852	2680904.584	1823887.974	610008241.14	16107664.753
liabilities_current	19852	759549.754	468204.778	230646673.55	5379639.779
creditors_trade	19207	204921.461	120864.236	95137642.22	1595024.091
liabilities_other	19850	419187.703	211749.117	158435012.56	3150677.028
debt_short_term_other	17905	56326.889	11401.597	52838895.83	611292.605
liabilities_current_other	19281	210391.342	99667.37	72800212.69	1698315.906
liabilities_non_current	19833	909471.914	417481.696	249004216.9	6231045.774
debt_interest_long_term	16801	729272.954	412627.131	148827511.43	4346929.789
liabilities_non_current_other	19782	292090.962	102372.505	176931766.69	2691093.881
liabilities_debt_total	19852	1667799.426	955710.389	451978712.06	10836165.681
shareholders_equity_tot	18864	1080680.103	841071.705	222544001	6355806.941
shareholders_equity_net	17249	1034871.104	811176.517	222543324.78	6123186.775
EV	16459	3542317.243	2513585.8	2029991303	29594205.604

Table A.3 - Descriptive stats for income statement (USD), averages 2015-2019.

Variable	N	Mean	Pctl. 85	Max	Std. Dev.
revenues_tot	19848	1334329.164	1013771.835	307507800	8019940.901
sales_gross	19848	1329769.011	1012482.864	307397200	7981159.423
goods_sold_cost	18871	-849331.691	-2321.911	0	5561572.022
rd_expenses	19815	-35165.552	0	0	394565.936
items_operating_other	19795	-285266.955	-1412.935	0	1703017.783
depreciation_amortization	19790	-91246.637	-162.587	0	684322.83
depreciation	19783	-71408.441	-110.57	0	600337.618
amortization	19436	-20549.491	0	0	187819.617
financial_expenses	19374	-23711.743	-23.811	0	146641.961
earnings_tax	17170	-34717.898	-39.421	0	236845.594
dividends	18811	-165960.836	0	0	15704188.341
sales_net	19852	1323875.884	1004422.969	307397200	7965886.197
EBITDA	19851	213567.195	131946.684	76115200	1458440.817
operating_income	19852	122658.18	80521.279	65485200	920918.679
EBIT	19852	116624.674	77420.167	65485200	904809.707
financial_revenue	18813	6754.058	2978.944	6205923.582	81825.786
financial_result	19750	-16946.048	54.305	5654067.692	127294.892
financial_flow_other	19041	12365.438	4311.439	8863200	170651.019
earnings_before_tax	19852	111642.622	71778.515	67323200	925810.656
earnings_after_tax	19852	82793.432	53444.417	52743800	729604.601
interest_minority	18519	-5092.249	1.211	1615461.448	64888.642
profit_net	19852	78893.377	51899.466	52443800	706729.281
cash_flow	19712	171391.883	102536.679	63073800	1236795.444
earnings_retained	19701	469587.681	261127.74	415561800	5300063.53
share_reserves	18873	110452.067	50650.84	103486200	1660376.479
assets_net	19852	866189.242	633816.699	205808202.596	5466856.635
debt_net	19852	373766.284	178746.635	148583920.194	3296138.193

Table A.4 - Descriptive statistics for income statement (USD), year 2020.

Variable	N	Mean	Pctl. 85	Max	Std. Dev.
revenues_tot	19845	1421365.873	1081463.077	386064000	8347597.528
sales_gross	19842	1411830.724	1077775.089	386064000	8275956.021
goods_sold_cost	18551	-890829.702	-2165.184	0	5494320.822
rd_expenses	19818	-44653.888	0	0	566226.442
items_operating_other	19770	-319305.92	-1453.395	0	2018319.61
depreciation_amortization	19811	-123695.264	-182.866	0	965889.892
depreciation	19804	-93625.579	-128.909	0	793351.366
amortization	19378	-30779	0	0	346556.588
financial_expenses	18911	-28435.023	-25.287	0	166547.733
earnings_tax	15579	-39149.031	-23.209	0	270425.844
dividends	18148	-402207.423	0	0	48269842.221
sales_net	19852	1405923.154	1073072.984	386064000	8260824.688
EBITDA	19851	229113.556	142224.345	81154057.632	1768300.941
operating_income	19852	105690.553	75750.273	73272612.127	1274271.815
EBIT	19852	98731.04	71784.871	66288000	1216161.062
financial_revenue	17047	7355.74	2963.627	10172248.278	108899.182
financial_result	19525	-21117.261	40.339	9489962.403	164363.286
financial_flow_other	18440	10438.733	5190.285	18954082.654	309063.862
earnings_before_tax	19852	87657.884	66089.781	67091000	1279450.309
earnings_after_tax	19852	61694.767	49939.58	57411000	1073979.571
interest_minority	18452	-5279.648	249	2043000	83385.96
profit_net	19852	58599.934	47867.115	57411000	1072749.431
cash_flow	19508	185316.346	113164.415	68467000	1535836.518
earnings_retained	19496	531075.3	327700.906	383943000	5629810.37
share_reserves	18452	125803.899	52707.319	99205000	2276457.06
assets_net	19852	1020787.46	767824.153	222544001	6232143.518
debt_net	19848	466958.901	218135.351	199390437.597	4322852.209

Table A.5 – Production coefficient estimates.

	OP	LP	ACF
β_l	0.521	0.328	0.57
ϕ_t	0.509	0.559	-
β_k	0.334	0.384	0.443

Figure A.1 (a-b) – Number of clusters selection, pre-Covid period.

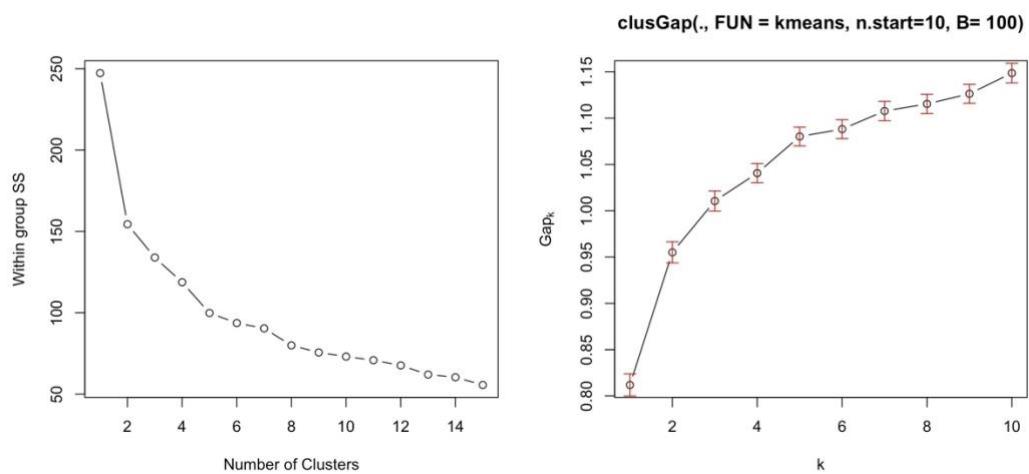


Figure A.2 (a-b) – Number of clusters selection, pre-Covid period.

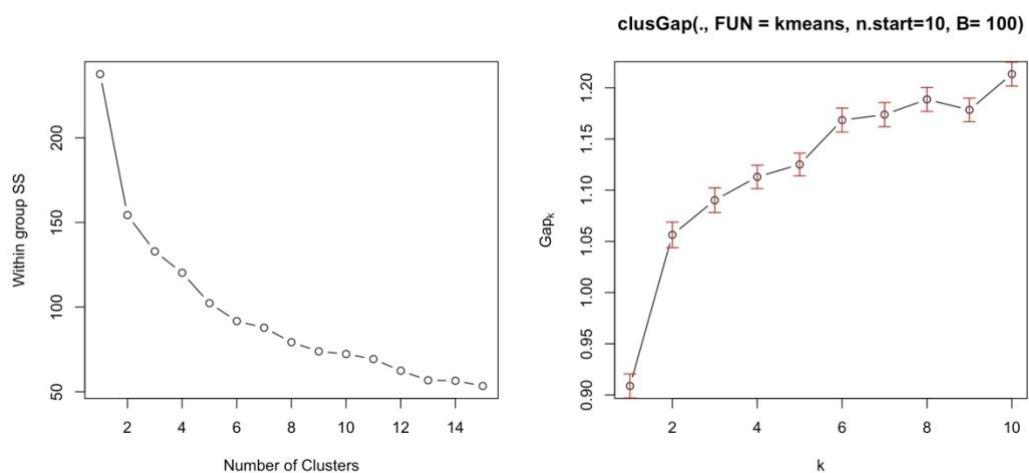


Table A.6 – Descriptive statistics for main variables (USD), pre-Covid.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5
goods_final	103373.62	91528.70	172069.41	103476.71	96608.57
workers	4534.92	3137.90	2856.25	4385.91	4818.37
assets_fixed	1425784.63	1425784.63	1967017.79	1180294.73	1901181.73
investment_short_term	102993.56	363050.86	330019.72	187340.23	123304.33
investments	68405.87	46060.40	86284.07	92655.66	196576.68
goods_interm	46985.44	17766.88	17766.88	68384.26	80437.02

Table A.7 – Descriptive statistics for main variables (USD), post-Covid.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
goods_final	122595.83	81091.72	33089.83	299324.96	110919.11	251339.53
workers	5075.83	3369.17	3501.23	4924.61	4625.79	5550.30
assets_fixed	1888225.83	1614913.02	790161.11	496146.23	1925600.51	874602.83
investment_short_term	355331.48	51054.71	43870.25	57061.75	160978.54	36687.93
investments	173185.88	64565.37	17357.24	9623.34	110224.77	18910.38
goods_interm	151376.51	46891.70	24636.83	19333.18	64002.01	9006.5

Table A.8 – Descriptive statistics for the balance sheet (USD), pre-Covid.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5
assets_current	805843.03	932488.407	757406.9074	862922.058	935217.10
inventory	176305.00	162739.110	212359.0338	173118.891	212876.79
accounts_receivable_net	193623.17	335370.110	340801.7560	170172.329	211001.16
accounts_receivable	209885.64	363852.968	395095.0598	180729.878	209035.08
assets_other	471232.39	476181.867	270449.1749	562285.794	552175.76
assets_current_other	184040.84	168179.747	135665.1499	252840.482	224763.60

cash_short_term_invest.	254688.62	287459.667	128234.1559	272028.066	292981.94
cash	209151.64	171733.150	56200.2694	192352.858	237803.15
property_plant_equip_net	651688.07	1356481.476	389480.3407	657801.079	831673.05
property_plant_oth_tot	479572.51	461705.954	249886.9369	266812.896	604148.34
property_plant_oth_net	224775.74	341263.505	148723.8327	162238.597	157927.70
intangibles	450364.01	208745.042	739564.4886	409177.116	619807.06
intangibles_other	201935.62	127586.357	381532.0175	171500.418	263704.95
assets_fixed_other	397642.58	457297.345	185095.5809	374123.553	562372.97
assets_long_term_other	207963.42	329781.826	128356.3599	186374.383	239628.97
assets_tot	2231627.66	2899506.190	1937701.6445	2233134.948	2836398.83
liabilities_current	598420.61	688393.035	886965.9259	662574.415	774967.53
creditors_trade	196663.33	252438.487	159762.8600	185160.018	251480.72
liabilities_other	295984.39	360479.472	562131.9696	354369.466	400669.80
debt_short_term_other	33925.94	63984.457	25496.3413	39679.262	50604.32
liabilities_cur-rent_other	170865.45	164055.272	124021.8055	207657.902	245774.51
liabilities_non_current	754739.58	1063847.607	417294.4821	744245.011	931501.52
debt_interest_long_term	565636.94	639332.784	298931.8114	534434.064	681068.72
liabilities_non_curr_other	250397.55	522933.238	139420.2105	268123.311	320892.25
liabilities_debt_total	1353159.77	1752240.642	1304260.4080	1405737.808	1703605.51
shareholders_equity_tot	930298.58	1180656.849	670939.7429	866227.491	1178512.58
shareholders_equity_net	867988.27	1177713.890	549077.4773	819065.912	1073669.87

Table A.9 – Descriptive statistics for the balance sheet (USD), post-Covid.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
assets_current	1245465.35	642079.703	741482.814	1042313.52	1128602.03	659634.32
inventory	296257.779	138745.060	191983.372	282983.030	197835.856	281300.17
accounts_receivable_net	216616.617	149840.213	115946.370	210226.799	202224.937	74895.27
accounts_receivable	219215.944	149509.469	126429.199	239151.153	217280.905	80572.46
assets_other	800379.117	384473.518	507392.830	596267.497	775866.117	334694.46
assets_current_other	342346.270	77457.4633	329177.304	330462.810	379859.821	65047.01
cash_short_term_invest.	430301.895	278256.808	162584.450	227774.796	359918.779	234509.62
cash	319524.995	262412.24	149085.912	202414.018	306741.630	216845.06
property_plant_equip._net	813378.799	669636.582	201982.544	165187.768	826625.095	296963.70
property_plant_oth_tot	426833.135	302041.531	97557.349	39741.605	492641.080	47883.79
property_plant_oth_net	165939.568	229678.902	71222.690	22653.820	210813.983	18197.70
intangibles	602863.818	656485.994	188960.232	198736.716	650327.517	244636.16
intangibles_other	280073.025	231772.111	72079.671	71889.466	286045.994	117779.16
assets_fixed_other	608600.206	428775.079	457359.940	154303.575	597034.779	378305.98
assets_long_term_other	337962.293	172424.758	41852.132	139279.870	332890.646	338268.86
assets_tot	3133691.18	2256992.72	1531643.88	1538459.72	3053952.74	1534237.15
liabilities_current	903631.803	470390.635	707180.072	726583.469	886569.310	419156.73
creditors_trade	272951.099	117422.565	253786.557	246712.347	240546.019	88937.98
liabilities_other	501096.228	251524.746	216294.989	399700.532	500980.396	209640.75
debt_short_term_other	66996.720	51121.0900	59188.090	95659.714	70817.072	4800.15
liabilities_current_other	250664.241	133649.889	48117.591	70537.255	222256.401	136180.08
liabilities_non_current	1043592.46	850987.826	382076.947	332891.731	1115170.57	394648.83
debt_interest_long_term	827000.506	841052.292	546435.667	330232.040	877995.783	385904.03

liabilities_non_curr_other	335325.288	168874.58	45808.844	57698.337	378101.112	51623.03
liabilities_debt_total	1946883.38	1321378.47	1089257.02	1059475.20	1998962.87	813805.58
shareholders_equity_tot	1260396.32	999495.835	479425.793	478984.519	1125347.07	748584.71
shareholders_equity_net	1213093.37	745592.377	472926.783	467579.226	1057777.54	773460.93

Table A.10 - Descriptive statistics for the income statement (USD), pre-Covid.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5
revenues_tot	1386321.68	1639997.338	1742448.4952	1377170.474	1654809.12
sales_gross	1385020.32	1589403.964	1743662.6149	1373719.737	1665759.65
goods_sold_cost	-876893.06	-1061455.692	-1464904.074	-876259.862	-1026193.29
rd_expenses	-35004.85	-9688.007	-17186.0534	-38620.339	-42848.74
items_operating_other	-317727.69	-293674.207	-346824.9495	-305861.278	-331283.04
depreciation_amortization	-93269.32	-183518.686	-60423.9217	-88964.676	-127692.91
depreciation	-73735.89	-170997.798	-54372.3158	-69475.842	-105461.42
amortization	-21611.34	-12521.382	-6407.5827	-20173.926	-23848.63
financial_expenses	-27623.38	-68282.448	-4757.9768	-25479.963	-31590.44
earnings_tax	-33453.11	-79577.177	-35829.3382	-36267.142	-48717.51
dividends	-55576.22	-19269.880	-21591.4357	-40043.764	-163687.96
sales_net	1379336.89	1604003.226	1741689.4298	1366699.114	1641016.51
EBITDA	215690.80	319555.666	158512.7400	212724.431	312311.75
operating_income	122947.53	138627.694	98088.8183	124116.002	184736.14
EBIT	120401.81	121771.118	91585.6608	118278.020	178429.40
financial_revenue	5873.41	40320.632	2400.2204	8270.697	10289.32
financial_result	-21671.54	-28302.280	-1966.3055	-17478.068	-21362.34
financial_flow_other	3715.26	6123.058	6691.2887	12343.034	18776.17

earnings_before_tax	102583.89	99256.421	95944.6603	112805.588	175007.68
earnings_after_tax	75823.78	25390.511	64150.3096	82874.492	134439.64
interest_minority	-6516.94	-5220.858	749.8761	-5506.503	-8966.36
profit_net	72495.45	14067.623	64738.1136	76948.006	126477.24
cash_flow	167260.88	198110.560	125162.0353	167139.122	257114.20
earnings_retained	470383.57	633926.840	349755.4575	476749.273	662713.92
share_reserves	122711.87	355474.661	-7468.8824	113826.969	92427.33
assets_net	897733.31	1147267.911	633441.2365	836001.570	1141897.77
debt_net	392812.50	420003.110	331914.9415	370207.448	491663.98

Table A.11 - Descriptive statistics for the income statement (USD), post-Covid.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
revenues_tot	1743005.99	881254.423	751368.027	1620342.24	1525226.82	1327529.35
sales_gross	1750504.24	909494.245	736445.187	1610756.57	1508615.18	1341157.29
goods_sold_cost	-1113886.7	-412512.85	-372515.53	-1143791.6	-940694.48	-633860.18
rd_expenses	-65733.723	-27341.64	-9611.107	-10398.555	-43337.440	-9870.12
items_operating_other	-373451.06	-266220.16	-353628.83	-353244.98	-356569.29	-373206.25
depreciation_amortization	-146609.65	-99081.172	-28558.596	-50758.483	-138340.53	-129506.24
depreciation	-107036.19	-71586.67	-18124.929	-38193.867	-103568.69	-115885.41
amortization	-40825.728	-28889.187	-9631.077	-12564.616	-35650.334	-14144.72
financial_expenses	-31806.366	-28270.177	-14401.276	-14999.224	-37618.112	-10665.41
earnings_tax	-47377.371	-21994.195	-4235.445	-36459.276	-43040.897	-30815.35
dividends	-52934.705	-32709.851	-12953.655	-46845.191	-52399.387	-6522.05
sales_net	1728463.34	876032.048	735254.401	1610779.64	1503228.14	1326836.78
EBITDA	277000.865	200795.854	44267.600	176451.026	248461.234	310592.82

operating_income	130697.151	101714.69	18152.370	125692.571	110304.537	181086.56
EBIT	123993.255	97712.5642	9198.251	125508.220	105289.460	178521.48
financial_revenue	10363.383	4139.3370	3397.893	2546.809	9954.432	4228.83
financial_result	-21677.714	-24478.272	-10418.384	-12593.876	-27554.171	-5721.40
financial_flow_other	12764.321	3619.9374	13971.629	4069.772	323.739	17736.95
earnings_before_tax	114509.272	76629.5470	11676.717	116984.060	78427.563	188566.26
earnings_after_tax	85009.706	60557.6479	9322.739	86769.409	49644.956	168246.82
interest_minority	-5610.504	-3223.8369	-11.073	2936.197	-9598.274	-789.73
profit_net	81026.185	57684.9158	10315.977	89939.552	42341.395	167585.26
cash_flow	230940.552	156766.088	33565.959	148962.119	183893.987	297091.50
earnings_retained	707221.915	412813.421	214548.132	491395.929	509517.015	497673.90
share_reserves	130615.550	72774.9154	45213.089	-4453.560	166079.000	-4831.94
assets_net	1196331.93	939404.706	442386.901	479911.908	1068018.88	720438.98
debt_net	479178.753	557053.579	456311.479	217934.473	592954.390	233538.76

Table A.12 – Descriptive statistics for the balance sheet per workers (USD), pre-Covid period.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5
assets_current	528.86	470.294	409.9252	1239.854	568.26
inventory	66.53	148.329	45.1637	1294.228	96.68
accounts_receivable_net	75.21	75.583	66.9127	95.667	89.66
accounts_receivable	83.20	84.392	79.0808	99.896	83.53
assets_other	406.74	369.358	311.7454	648.837	423.49
assets_current_other	158.76	118.958	31.2088	256.436	171.52
cash_short_term_invest.	228.47	204.905	270.5978	348.903	214.45
cash	164.07	195.004	95.6418	282.569	183.18

property_plant_equip._net	372.20	160.610	157.1796	495.519	365.43
property_plant_oth_tot	209.12	46.931	47.4477	174.932	147.40
property_plant_oth_net	124.34	47.126	15.3541	118.715	61.28
intangibles	102.97	72.849	79.4992	198.349	318.78
intangibles_other	66.08	52.678	37.2646	123.978	260.06
assets_fixed_other	828.15	1267.174	33.4346	1062.317	795.84
assets_long_term_other	71.36	62.739	20.1331	244.356	168.74
assets_tot	1789.11	1809.198	664.7844	2919.777	1969.56
liabilities_current	366.06	261.206	195.5837	602.029	326.95
creditors_trade	53.11	55.449	40.2203	176.155	62.99
liabilities_other	202.58	110.840	119.1238	266.149	180.65
debt_short_term_other	20.56	30.089	4.6393	20.659	37.84
liabilities_cur-rent_other	115.34	55.679	38.3256	184.238	86.16
liabilities_non_current	598.33	741.992	136.0895	1047.257	725.73
debt_interest_long_term	503.10	830.506	40.4398	933.522	632.59
liabilities_non_curr._other	159.44	58.180	100.2468	289.355	164.12
liabilities_debt_total	964.38	1003.198	331.6732	1647.737	1052.61
shareholders_equity_tot	911.71	882.992	353.0255	1398.402	970.99
shareholders_equity_net	662.72	810.220	334.3879	1268.721	744.30

Table A.13 – Descriptive statistics for the balance sheet per workers (USD), post-Covid period.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
assets_current	2952.119	465.4132	1009.850	380.871	700.364	303.19
inventory	1991.935	72.9905	26.946	27.722	105.735	52.88
accounts_receivable_net	110.226	86.1559	72.231	27.533	104.704	93.66

accounts_receivable	123.383	100.0693	83.908	31.407	115.479	100.34
assets_other	1220.720	323.2188	921.037	330.237	523.747	162.52
assets_current_other	442.704	84.8117	230.032	245.556	214.303	41.95
cash_short_term_invest.	737.085	213.2885	677.336	74.870	283.495	101.27
cash	691.480	200.0591	420.547	60.146	240.622	74.70
property_plant_eqipm.	508.487	464.2823	205.496	34.142	591.404	108.20
property_plant_oth_tot	181.994	199.8232	92.191	10.385	225.688	19.14
property_plant_oth_net	88.943	69.7694	91.681	5.584	107.721	14.53
intangibles	258.338	255.8772	57.817	17.770	176.090	43.45
intangibles_other	208.537	90.7600	30.922	6.362	106.497	13.51
assets_fixed_other	1694.792	569.3460	5077.286	78.701	1312.679	76.41
assets_long_term_other	227.521	395.0216	31.021	19.955	307.447	49.89
assets_tot	5301.851	1683.7135	6332.658	509.509	2691.113	523.20
liabilities_current	1044.835	371.3240	1572.323	314.928	435.965	204.01
creditors_trade	208.065	88.8112	99.449	47.647	86.525	28.48
liabilities_other	437.104	201.7403	488.946	216.172	203.557	65.17
debt_short_term_other	28.071	18.9672	365.079	42.081	27.331	2.64
liabilities_curr-rent_other	319.619	119.9176	106.878	19.790	97.639	35.55
liabilities_non-current	1742.456	659.8299	2269.760	48.327	975.094	55.05
debt_interest_long_term	1216.987	447.4549	3150.893	42.463	847.151	43.71
liabilities_non_curr._other	700.873	299.8298	330.749	12.941	265.166	16.20
liabilities_debt_total	2786.720	1031.1539	3842.083	363.256	1409.957	259.07
shareholders_equity_tot	2680.630	702.9196	2700.876	146.253	1467.211	276.69
shareholders_equity_net	2548.975	604.8337	3106.122	104.167	1146.941	252.82

Table A.14 – Descriptive statistics for the income statement per workers (USD), pre-Covid period.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5
revenues_tot	462.49	513.530	403.9042	800.874	582.08
sales_gross	453.71	507.942	402.8361	769.296	572.99
goods_sold_cost	-271.05	-322.177	-328.7534	-508.797	-270.16
rd_expenses	-22.16	-20.792	-70.6737	-25.011	-19.37
items_operating_other	-112.93	-150.290	-92.1283	-238.192	-161.48
depreciation_amortization	-38.92	-21.460	-13.1795	-55.030	-55.77
depreciation	-28.46	-12.581	-10.2356	-39.946	-41.49
amortization	-12.08	-8.882	-3.1171	-16.276	-14.91
financial_expenses	-28.66	-61.610	-2.1629	-50.659	-29.14
earnings_tax	-17.69	-13.638	-3.8301	-30.027	-33.02
dividends	-30.85	-11.212	-2.3422	-33.357	-37.67
sales_net	454.33	505.848	403.0136	779.438	571.59
EBITDA	75.59	33.990	-29.8786	146.011	149.86
operating_income	37.06	12.902	-43.0581	92.919	94.14
EBIT	34.90	6.600	-44.5478	89.210	90.42
financial_revenue	5.05	33.194	4.3839	5.790	4.11
financial_result	-23.06	-28.112	2.2053	-44.065	-24.21
financial_flow_other	17.75	32.239	-1.7896	34.711	14.11
earnings_before_tax	26.72	14.369	-44.0280	76.966	79.60
earnings_after_tax	14.44	2.936	-47.2850	53.762	52.62
interest_minority	-1.23	-1.054	0.1107	-5.115	-1.81
profit_net	12.91	2.190	-47.4574	46.468	50.24
cash_flow	48.52	18.484	-34.2779	99.279	97.24
earnings_retained	-34.00	-292.903	-163.1484	-9.348	13.75

share_reserves	83.47	-27.684	16.4525	215.539	99.38
assets_net	878.91	806.018	333.1112	1325.869	935.62
debt_net	342.96	609.262	-195.6186	592.884	467.75

Table A.15 – Descriptive statistics for the income statement per workers (USD), post-Covid period.

Variables	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
revenues_tot	1088.740	604.4937	523.453	254.321	618.306	310.346
sales_gross	1033.185	594.2889	490.542	252.757	607.271	325.720
goods_sold_cost	-306.516	-262.8598	-132.404	-186.437	-320.490	-193.452
rd_expenses	-37.761	-12.9977	-0.394	-1.914	-20.295	-7.534
items_operating_other	-693.591	-278.0936	-378.875	-54.215	-164.747	-46.407
depreciation_amortization	-73.935	-124.0031	-14.680	-6.942	-66.760	-13.861
depreciation	-39.207	-104.3565	-5.605	-5.159	-52.866	-10.544
amortization	-35.772	-20.6452	-8.377	-1.783	-14.254	-3.445
financial_expenses	-61.270	-38.0892	-53.866	-2.636	-46.358	-8.431
earnings_tax	-51.203	-10.1811	-41.064	-6.646	-30.830	-14.411
dividends	-26.140	-6.4001	-121.038	-8.227	-52.391	-13.199
sales_net	1030.217	592.3661	486.486	253.100	607.189	309.201
EBITDA	195.801	67.2310	21.965	22.112	139.356	62.953
operating_income	122.492	-56.7720	13.893	15.169	72.702	49.092
EBIT	121.036	-64.4116	13.308	17.209	84.242	46.847
financial_revenue	73.417	2.9711	6.996	0.766	7.939	1.872
financial_result	5.132	-35.2448	-43.804	-1.913	-37.700	-5.830
financial_flow_other	14.793	14.2805	186.418	2.675	-6.663	3.711
earnings_before_tax	139.896	-86.2621	141.582	17.971	40.862	44.315

earnings_after_tax	105.267	-77.0801	110.606	13.201	23.721	38.410
interest_minority	4.805	-2.9142	0.849	2.467	-6.928	-0.256
profit_net	108.063	-79.5924	122.771	15.811	15.268	38.159
cash_flow	186.238	44.4106	94.912	23.742	87.410	52.020
earnings_retained	720.013	-465.2084	1321.179	59.619	44.349	52.260
share_reserves	369.338	280.2710	237.654	22.935	134.097	-38.817
assets_net	2523.037	652.9880	2490.577	146.451	1364.998	264.133
debt_net	739.505	251.2056	2526.433	51.369	600.164	50.396

Table A.16 - Principal component regressions with controls, full sample.

ACF	Pre-Covid period			Post-Covid period		
	Estimate	Pr(> t)		Estimate	Pr(> t)	
PC1	- 0.2148	0.002	**	- 0.18762	0.01236	*
PC2	- 0.4383	< 0.002	***	- 0.30444	< 0.002	***
PC3	0.3385	< 0.002	***	0.29996	< 0.002	***
PC4	0.1053	0.1246		- 0.45836	< 0.002	***
PC5	0.3741	< 0.002	***	0.00435	0.95438	
PC6	0.2406	0.0028	**	- 0.79532	< 0.002	***
PC7	0.0185	0.8033		- 0.24969	< 0.002	***
PC8	- 0.7642	< 0.002	***	0.36492	< 0.002	***
<i>country_d</i>	<i>yes</i>			<i>yes</i>		
<i>sector_d</i>	<i>yes</i>			<i>yes</i>		

Table A.17 – PCR with/without controls, cluster 1 (pre-Covid period).

ACF	Pre-Covid period			Pre-Covid period		
	Estimate	Pr(> t)		Estimate	Pr(> t)	
PC1	1.1634	< 0.002	***	0.2887	< 0.002	***
PC2	0.0529	0.69		0.0226	0.81672	
PC3	2.4619	< 0.002	***	0.2794	< 0.002	**
PC4	- 3.0561	< 0.002	***	0.4339	0.00273	**
PC5	0.8480	< 0.002	***	- 0.3095	< 0.002	***
PC6	1.1339	< 0.002	***	0.3667	< 0.002	**
PC7	- 1.2899	< 0.002	***	- 0.4635	< 0.002	***

PC8	0.7343	< 0.002	***	- 0.1086	0.27586
<i>country_d</i>		<i>no</i>		<i>yes</i>	
<i>sector_d</i>		<i>no</i>		<i>yes</i>	

Table A.18 – PCR with/without controls, cluster 2 (pre-Covid period).

ACF	Pre-Covid period		Pre-Covid period	
	Estimate	Pr(> t)	Estimate	Pr(> t)
PC1	0.5299	0.5105	- 0.2872	0.71
PC2	0.4462	0.3453	0.4719	0.43
PC3	- 0.1379	0.3807	0.0404	0.95
PC4	0.5383	0.2415	*	0.3249
PC5	- 0.0341	0.3221	0.0577	0.89
PC6	- 0.1778	0.7220	0.2874	0.80
PC7	0.1898	0.6103	- 0.8187	0.40
PC8	- 0.0198	0.2747	- 0.3389	0.44
<i>country_d</i>		<i>no</i>		<i>yes</i>
<i>sector_d</i>		<i>no</i>		<i>yes</i>

Table A.19 – PCR without controls, cluster 3 (pre-Covid period).

ACF	Pre-Covid period	
	Estimate	Pr(> t)
PC1	- 1.344	0.00387 **
PC2	- 0.993	0.00573 **
PC3	- 0.298	0.09279 .
PC4	- 1.017	0.03183 *
PC5	2.621	< 0.002 ***
PC6	- 0.152	0.58695
PC7	- 0.406	0.24330
PC8	- 0.305	0.11095
<i>country_d</i>		<i>no</i>
<i>sector_d</i>		<i>no</i>

(Sample observations are not enough for controls)

Table A.20 – PCR with/without controls, cluster 4 (pre-Covid period).

ACF	Pre-Covid period		Pre-Covid period	
	Estimate	Pr(> t)	Estimate	Pr(> t)
PC1	- 0.5437	< 0.002 ***	0.07069	0.2568
PC2	0.0417	0.45	0.07413	0.1785

PC3	- 0.0315	0.64	0.29549	< 0.002	***
PC4	0.0562	0.33	0.15637	0.0062	**
PC5	- 0.0300	0.48	0.04662	0.2656	
PC6	0.2476	< 0.002	***	0.09532	0.0923
PC7	- 0.0218	0.73	- 0.14175	0.0256	*
PC8	- 0.7473	< 0.002	***	- 0.46515	< 0.002
<i>country_d</i>	<i>no</i>		<i>yes</i>		
<i>sector_d</i>	<i>no</i>		<i>yes</i>		

Table A.21 – PCR with/without controls, cluster 5 (pre-Covid period).

ACF	Pre-Covid period			Pre-Covid period		
	Estimate	Pr(> t)		Estimate	Pr(> t)	
PC1	- 3.8990	< 0.002	***	- 0.5818	< 0.002	***
PC2	- 1.4580	< 0.002	***	- 0.2321	0.0037	**
PC3	- 0.2214	0.074	.	0.2041	0.0196	*
PC4	2.0709	< 0.002	***	0.3426	< 0.002	***
PC5	1.6326	< 0.002	***	0.4468	< 0.002	***
PC6	0.7378	< 0.002	***	0.2498	0.0176	*
PC7	1.3446	< 0.002	***	0.0111	0.8802	
PC8	- 1.1746	< 0.002	***	- 0.0536	0.3120	
<i>country_d</i>	<i>no</i>		<i>yes</i>			
<i>sector_d</i>	<i>no</i>		<i>yes</i>			

Table A.22 – PCR with/without controls, cluster 1 (post-Covid period).

ACF	Post-Covid period			Post-Covid period		
	Estimate	Pr(> t)		Estimate	Pr(> t)	
PC1	1.8682	< 0.002	***	0.0917	0.33325	
PC2	- 0.4673	< 0.002	***	0.0964	0.30770	
PC3	0.5813	< 0.002	***	0.0985	0.22236	
PC4	- 0.3302	< 0.002	***	0.1602	0.02800	*
PC5	- 0.9517	< 0.002	***	- 0.4489	< 0.002	***
PC6	0.8085	< 0.002	***	0.0351	0.67683	
PC7	- 0.3708	0.0014	**	0.1029	0.32263	
PC8	0.5152	< 0.002	***	0.2721	0.00113	**
<i>country_d</i>	<i>no</i>		<i>yes</i>			
<i>sector_d</i>	<i>no</i>		<i>yes</i>			

Table A.23 – PCR with/without controls, cluster 2 (post-Covid period).

ACF	Post-Covid period		Post-Covid period	
	Estimate	Pr(> t)	Estimate	Pr(> t)
PC1	- 0.000258	1	0.1801	0.60
PC2	0.072159	0.78	0.1458	0.65
PC3	- 0.186444	0.30	- 0.0589	0.78
PC4	0.128134	0.42	0.0160	0.94
PC5	0.052009	0.86	0.1785	0.60
PC6	- 0.067024	0.80	- 0.1953	0.54
PC7	- 0.141538	0.59	- 0.1523	0.64
PC8	0.165931	0.49	0.0977	0.74
<i>country_d</i>	<i>no</i>		<i>yes</i>	
<i>sector_d</i>	<i>no</i>		<i>yes</i>	

Table A.24 – PCR with/without controls, cluster 3 (post-Covid period).

ACF	Post-Covid period	
	Estimate	Pr(> t)
PC1	- 0.0733	0.918
PC2	- 0.4778	0.214
PC3	0.4474	0.191
PC4	- 0.0164	0.979
PC5	0.1069	0.763
PC6	- 0.2621	0.469
PC7	- 0.2162	0.634
PC8	0.4133	0.053
<i>country_d</i>	<i>no</i>	
<i>sector_d</i>	<i>no</i>	

(Sample observations are not enough for
controls)

Table A.25 – PCR with/without controls, cluster 4 (post-Covid period).

ACF	Post-Covid period	
	Estimate	Pr(> t)
PC1	- 0.0418	0.93
PC2	0.2055	0.74
PC3	- 0.6288	0.26
PC4	- 0.0906	0.86
PC5	0.0618	0.90
PC6	- 0.5458	0.36
PC7	- 0.2133	0.68

PC8	- 0.4296	0.52	
<i>country_d</i>		<i>no</i>	(<i>Sample observations are not enough for controls</i>)
<i>sector_d</i>		<i>no</i>	

Table A.26 – PCR with/without controls, cluster 5 (post-Covid period).

ACF	Post-Covid period		Post-Covid period		
	Estimate	Pr(> t)	Estimate	Pr(> t)	
PC1	- 2.8690	< 0.002	***	- 0.02177	0.84549
PC2	- 0.5667	< 0.002	***	- 0.04716	0.54899
PC3	0.5162	< 0.002	***	0.19092	0.02763 *
PC4	- 0.5657	< 0.002	***	- 0.41581	< 0.002 ***
PC5	1.0303	< 0.002	***	- 0.05048	0.54803
PC6	- 1.3535	< 0.002	***	- 0.53766	< 0.002 ***
PC7	0.0579	0.423		- 0.28912	< 0.002 ***
PC8	- 0.1267	0.024	*	0.38573	< 0.002 ***
<i>country_d</i>		<i>no</i>		<i>yes</i>	
<i>sector_d</i>		<i>no</i>		<i>yes</i>	

Table A.27 – PCR with/without controls, cluster 6 (post-Covid period).

ACF	Post-Covid period	
	Estimate	Pr(> t)
PC1	0.585	0.76
PC2	- 0.834	0.62
PC3	0.906	0.69
PC4	0.304	0.87
PC5	- 2.154	0.46
PC6	- 0.336	0.75
PC7	0.282	0.86
PC8	0.427	0.85
<i>country_d</i>		<i>no</i>
<i>sector_d</i>		<i>no</i>

(*Sample observations are not enough for controls*)