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Knowledge Spillover Effects and Employment Productivity in the Innovative Startups: Evidence from Italy*

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Abstract: This paper analyzes the determinants and effects of technological catch-up and knowledge spillover effects on employment productivity in the Innovation Startup Segment in Italy using a sample of 260 Innovative Startup companies. Estimates indicate that regional specialization provides the highest potential for employment productivity gains, while higher levels of competition and higher regional diversity suppress the prospects for knowledge spillover effects to develop. Particularly, the analysis using the comprehensive sample of firms indicates the presence of forces leading to output per worker convergence at the national level, i.e., technological catch-up is present at the per-worker level; yet, the overall value of production convergence across regions is not present. We also detect the presence of Spatial Dependency in relation to the neighboring firms. That is, there is support for weak convergence across regions in favor of the Marshallian hypotheses. However, sectorial estimations for the Services, Information Technology, and Manufacturing sector indicate the presence of large differences in terms of technological catch-up effects.

Keywords: innovative startups, knowledge spillover effects, economic growth, entrepreneurship

JEL Codes: L26, M13, M21, O33, R11

1. INTRODUCTION

Regional and local pools of knowledge, labor, and output are strong determinants of new firm formation and increased labor productivity. Thus, understanding the potential benefits from

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regional/local spillover advantages is a relevant economic issue that has received significant attention in the literature. Notably, previous literature indicates that knowledge does not flow freely, but is mainly regionally bounded (Ellison et al., 2010; Kerr and Robert-Nicoud, 2020) and time conditional (Anselin et al., 1997; Fritsch and Wyrwich, 2018). Consequently, knowledge spillovers and the capacity for new firm generation appear to be determined by the local/regional pool of knowledge, timing, and geographic location. In this respect, policy-induced changes fostering the development and transfer of knowledge may serve as mechanisms to reduce geographic and regional conditionality by promoting an environment that is conducive to the proliferation of new firms.

This study's main objective is to empirically investigate the determinants of value creation of Innovative Startup (IS hereafter) companies in Italy. To describe this phenomenon, this study uses the definition by Blank (2010), who states that a startup is a company designed to search for a repeatable and scalable business model. In the literature, it is clearly exposed that startups play a key role in innovation processes (Davila et al., 2003; Colombo and Piva, 2008; Mustar et al., 2008). In the analysis of the phenomena, the link to the territory at different levels of data aggregation (local, regional, national, etc.) assumes significant importance considering that due to their smallness, startups suffer a structural lack of tangible and intangible resources (Wymer and Regan, 2005).

In Italy, this family of firms is a relatively new phenomenon promoted by developing and implementing the new legislation Decree-Law 179/12. This legislative change intends to facilitate and generate positive knowledge spillover effects and lead the economy to higher levels of economic growth by boosting labor productivity. In particular, the legislation change serves as an example in favor of the Knowledge Spillover Theory of Entrepreneurship (Audretsch and Belitski, 2013). Consequently, the promotion and development of such enterprises aim to stimulate a new kind of successful and sustainable family of businesses, capable of generating high levels of output and high levels of workers' productivity. As noted by Matricano (2022), several countries have enacted similar initiatives such as the US government (Zhao and Ziedonis, 2020); French Government Jeunes Enterprises Innovates (Depret et al., 2004; Savignac, 2007); Belgian efforts to support innovative startups (Czarnitzki and Delanote, 2013) and Germany financial and infrastructure support for innovation (Hottenrott and Richstein, 2020). Studying the innovative startup phenomenon is most relevant when one considers that the development of entrepreneurship opportunities does not follow naturally an even distribution across space (see, for instance, Sternberg et al., 2009; Ellison et al., 2010; Andersson and Koster, 2011; Fritsch and Wyrwich, 2014, among others). In this context, Pellegrino and Zingales (2017) note that labor productivity in Italy has consistently fallen behind other developed nations. In addition, several studies have documented the existence of marked regional differences in productivity and overall quality of life. Thus, understanding the potential of IS-firms in closing observed regional gaps in labor productivity might provide relevant information in the process of new firm formation, employment generation, and overall output growth.

The historical background of profound economic differences across regions in Italy becomes relevant when trying to understand whether efforts to promote the development of the IS companies might be constrained by the same regional differences that could affect other economic activity sectors. Of particular interest is to understand whether the process of technological transfer, as a means to promote business development through the generation and transfer of knowledge-related spillover effects (Marshall, 1920), creates a dynamic process of economic activity that is undifferentiated across economic sectors and across regions. In this context, and using the case of Law Decree 179/12 in Italy, IS are present in a large breadth of economic sectors generating new technological possibilities. In fact, the literature states that tacit and practical knowledge might be industry-specific or diverse enough to create positive effects across sectors in the same region or even across regions within the same country. This new knowledge could potentially increase productivity in the originating sector or sprawl the development of new applications and adaptations of such sector across related, complementary, or competing sectors as well.

From an empirical point of view, this study explores some of the main determinants of labor productivity in the IS segment while accounting for sectorial and regional conditioning in Italy. It adds to the existing body of literature by providing empirical evidence using a database of two hundred sixty Italian IS firms, including the sector of Services, Information Technology, and Manufacturing. We use time and spatial considerations as they relate to year and region of origin, as well as levels of regional and national technological gaps, to study the development of new enterprises and their respective productivity levels. This paper also studies the role that regional clusters may have in promoting the development of locally generated knowledge-spillover effects, leading to observed differences in output level and labor productivity as well. It is also relevant to note that issues concerning knowledge spillover effects (KSE) have taken center stage in the study of new firm formation well before the current COVID-19 pandemic; however, this pandemic brings forth new challenges in understanding the importance of KSE as more technologically driven economic activities are currently taking place.

The paper's organization is as follows: in the next section, we explore the most relevant literature in the field of innovative startups and provide a clear background specification of the innovative startups set up and overall regulations in Italy. Next, we provide a parsimonious description of the empirical model which uses a sample of two hundred sixty Innovative Startups drawn from a randomized sample with the date of 31 December 2015 from the AIDA database.[1] We organize the data in four industrial sectors, namely, Services, Information Technology, and Manufacturing, to conduct the empirical analysis using alternative model specifications for the overall sample and then decomposed by aggregate sectors of economic activity, using *Value of Production by Worker*, as our dependent variable. We also perform spatial diagnostic statistics and, when relevant, conduct the corresponding spatial estimations. The estimations account for the possibility of either convergence or divergence between regional and national levels of technological catchup and what the role of regional sector-specific clusters is in this process. The paper closes with conclusions and policy recommendations.

[1]https://www.bvdinfo.com/en-us/our-products/data/national/aida

2. LITERATURE REVIEW

The literature agrees that if technological-knowledge spillover effects and technological catch-up towards the technology leader are present, then these gains should be reflected as gains in labor productivity.[2] Both the differences in productivity level and the sources of these gains and consequent differences have been studied from the perspective of location, and using lower levels of data aggregation. Here multiple contributions by Feldman (1994) and Audretsch and Feldman (1996) provide excellent additions to the process of understanding how these KSE gains may occur at lower levels of data aggregation. More recently, Ellison et al. (2010) studied the manufacturing sector in the U.S. and tested for the three Marshall hypotheses related to agglomeration.[3] In their study, they argue that "ideas and knowledge spillovers may be more important in very innovative sectors." (p.1210). Thus, investigating the extent of the relationship between knowledge spillovers and new firm creation depends on both the nature and the type of spillovers. Audretsch and Lehmann (2005), in this regard, have argued that the relationship between knowledge spillovers and new venture creation is shaped by the type and not only by the nature of knowledge, either as codified or tacitly. This potential knowledge transmission across firms is shaped by the extent of the relationship between the technological leader and the followers.

By definition, incidentally, the technological leader must be located in a particular geographic region, with region-specific characteristics not necessarily present in all regions. For the purpose of this paper, it is enough to state that the literature agrees that innovative firms are typically located near centers of innovation where larger pools of higher human capital may be available (Kerr and Robert-Nicoud, 2020). In this regard, Fritsch and Wyrwich (2018) argue that historical and geographical elements are significant drivers of firm location. In a similar context, Colombelli and Quatraro (2018) argue that, regionally, lower levels of asymmetries and less heterogeneity of firms should lead to a faster rate of development of new firms within the same region. This, of course, would be the case if technological spillovers are not constrained by adaptation filters or potential tight spillover length in clusters (Kerr and Robert-Nicoud, 2020). Consequently, if true, then an observed convergence in labor productivity levels across sectors and regions should follow. The fundamental piece of the logic is that if technological catch-up occurs, then firms will gain from the initiatives and developments occurring in firms in the same sector and the same region, same sector across regions, or even differentiated sectors either in the same region or across the nation. Furthermore, these gains can result from third-party efforts, such as research institutions, universities, or deriving from a more efficient administration and public and regulatory body of institutions. The transmission of knowledge can vary according to the specific regional

[2]An alternative expression of the catch-up effects could be observed in a growing number of new firms according to Audretsch and Fritsch (1994). Other studies such as (Ghio et al., 2016; Bloom et al., 2017) use the number of firms as the dependent variable to capture positive effects from knowledge spillover.

[3]Agglomeration in the Marshall context indicates that firms will locate close to each other as a response to gains in lowering costs. These gains could be derived from inputs, labor, and technology. Respectively, lower input costs gain are the result of gaining access to suppliers located close to the source of production; gains in labor costs are the result of facilitation of the transfer of workers from companies in the same economic sector that are located nearby; and gains from technological knowledge spillover effects are the result of access to innovation generated within the sector by firms located near to each other.

considerations of each industry and economic sector. In addition, the existence of explicit or implicit barriers to the transmission of knowledge across firms in different sectors in the same economic region or for similar firms across regions may be conditioned to the role that extra-firm actors such as institutions, government incentives, or regulations may bring to these processes. In some cases, industries characterized by higher levels of specialization may lead to higher gains and possible catch-up effects within the region (see Barboza and Capocchi, 2020, for instance); while in other regions, higher levels of economic diversity may serve best for technological catch-up and diffusion of ideas (Jacobs, 1969 seminal work). By the same token, elements such as the firm's adaptability capacity to adopt new technologies and the entrepreneurial adaptability capacity (Ghio et al., 2016) may speed or retard the adaptation and/or convergence across firms. Regarding these ideas, early work by Nelson and Phelps (1966) indicates that the rate of adoption of a new technology depends on the ability of regions to implement new ideas as well as on the gap between the theoretical level of technology and the level of technology in practice.

This paper pays particular attention to Innovative Startups (IS) in Italy. It is relevant to provide a brief description of what constitutes an IS under the current legislation.

As stated earlier in the introduction and according to the recent developments in the literature, of particular interest for our study are those elements dealing with a firm's spatial distribution across regions – that is, region-specific effects. Under these conditions, one could study the potential effects on technological catch-up processes, production levels, and, consequently, overall labor productivity. As a recent development in the literature indicates and follows the theory, one can state that at lower levels of spatial aggregation, sub-national regions are highly likely to be conditioned by higher mobility patterns as it relates to labor, capital, and knowledge flows. This is particularly true in the context of the Marshallian (1920) transaction costs (Ellison et al., 2010). These gains in transaction costs (goods, people, and ideas) may or may not be in line with what can be observed at the national level though. In turn, if there were potential barriers at the national level for knowledge spillover effects to develop, then one may observe a lack of convergence across firms and regions as noted above, or just evidence in favor of conditional convergence. To this extent, Pede et al. (2021) note that in the presence of technological catch-up and, therefore, the convergence of technologies, firms located farther away from the technological frontier is more likely to experience larger gains in productivity; however, Kerr and Robert-Nicoud (2020) argue that in the presence of tight length spillover effect, these gains may be limited to smaller interaction areas in the form of Clusters. If convergence is not present, then the existence of local, regional, or national barriers preclude firms from enjoying positive knowledge-spillover effects. In other words, under specific conditions, one may only observe a conditional level of convergence (predominantly across firms and possible sectors within a limited geographical region), but not absolute convergence at the national level. The observed lack of convergence should be manifested as large and persistent gaps in terms of labor productivity. Thus, *this paper proposes to provide empirical evidence that tests the direct implications of the technological leader-follower relationship (at the regional and national levels) on possible differences in labor productivity, even for innovative startup companies.* The argument is that the level-of-industry agglomeration may be present as region-specific effects driven by location and not as a rule across the nation. Because of historical production patterns observed in Italy, this

Table 1

The Decree Law 179/12 defines IS according to the following criteria:	**Furthermore, the startups shall satisfy at least one of the following requirements:**
The society shall be constituted and operating for no more than 60 months.	It shall sustain R&D expenses to an extent equal to or greater than 20 percent of total costs or the total value of production, depending on which one is bigger.
It shall be resident either in Italy according to art.73 DPR 22^{nd} December 1986, n° 917, or in one of the member states of the European Union or in adherent states to the Accord on the European Economic Space, provided that it has a productive center or a branch in Italy.	It shall employ highly skilled human capital for at least one-third of the total number of employees;
The total value of annual production shall not exceed €5,000,000;	It shall be the owner of at least one patent related to an industrial, biotechnological, invention, topography of semiconductor product, vegetal variety, or an original elaborator, registered to the Public Register.
It shall not distribute or have distributed profits.	
It shall have the development, production, or commercialization of products or innovative high-technological-value services as the exclusive or prevalent scope of activity.	
It shall not have been constituted with a fusion, division, or following the transfer of a firm.	

study proposes that testing these hypotheses using data for the innovative startup sector may be of relevance.

To illustrate some of the points just addressed above, in a recent study, Pellegrino and Zingales (2017) identify a significant component in the labor-productivity slowdown observed in Italy during the 1990s because of cronyism and familyism. The authors argue that contrary to the typical argumentation, lower or slower-growing labor productivity in Italy is traditionally the result of poor institutional support and excessive government inefficiencies, while other internal elements of the firm are also relevant to consider. Thus, the authors indicate that poor selection of managers by families owing to the companies is a significant player in the slowdown of labor productivity. In line with the work by Ghio et al. (2016), firms holding lower entrepreneurial adaptability capacities are more likely to fall behind.

On related issues, Colombelli and Quatraro (2018) argue that firms in sectors where technology transfers more easily – such as when fewer asymmetries among firms exist and lower levels of heterogeneity characterize the production processes – are also more likely to serve as incubators for new firm formation. In addition, one finds relatively similar characteristics in regions where local knowledge plays a predominant role (see Fritsch and Wyrwich (2018) and Ghio et al. (2016), for instance). In Bloom et al. (2017), this local proximity may also result in the ability of nearby firms to have better learning-by-doing capabilities than firms located further away. In other words, it is more likely that spillover effects, in the form of new applications of new ideas beyond the gains deriving from economies of scale, are at play here.

More recently, studies by Fritsch and Wyrwich (2018) and Del Giudice et al. (2019) examine startup companies under the regional knowledge framework and cleantech startups, respectively. First, Fritsch and Wyrwich (2018), using data for Germany for the period 1907–2004, indicate the presence of persistent regional knowledge pools that, combined with a positive relationship between historical developments of entrepreneurial activities, leads to a higher rate of innovative startups driven by region-specific effects. On the other hand, Del Giudice et al. (2019) focus on the formation of cleantech innovative firms and the role that geographical proximity to "green" markets may have in the development of such enterprises. Their study focuses on Italian innovative startups (promoted under Law Decree 221/2012 in Italy)[4] using NUTS3 level of data aggregation. Of particular interest are the results indicating that the creation of startups (number of firms) relates positively to the local stock of technological knowledge, which is geographically conditioned. In this context, Del Giudice et al. (2019) argue in favor of "local factors in shaping environmentally-friendly behaviors of firms in a geographical area." To this extent, Ghio et al. (2016) test the role that university-driven knowledge plays in fostering innovative startups. Their results indicate, also using a sample of innovative startups from Italy, that university-driven knowledge spillover effects tend to dominate locally. They also argue that regional openness may be a way to mitigate strictly local spillover effects by the capacity that Entrepreneurial Absorptive Capacity (EAC) levels observed in each region.

Finaldi Russo et al. (2016) provide a detailed study comparing regular startups with

[4]For further analysis on this issue, see Ghio et al. (2016). In addition, Finaldi Russo et al. (2016) provide an excellent review of the 2012 law Decree N°179.

those innovative startups as defined by the 2012 law. First, they note that 2012 law-derived startups have a large innovation potential, which according to the authors, should lead to improved productivity and higher overall growth levels. In addition, this type of firm holds a higher ratio of intangible assets, which serves as a proxy for higher levels of innovation. Another unique characteristic of innovative startups is their late arrival to the market in terms of product commercialization. Incidentally, the authors indicate that equity is the primary source of funding associated with higher rates of investment.

Based on the review of the literature, this study also stresses that the direct implications of the technological leader-follower relationship for production activities remain somewhat unclear. Particularly, the evidence for Innovative Startups is limited, and the study of the Italian case may serve as an excellent opportunity to further explore these issues. As stated in the next section, this research places a larger emphasis on the implications derived from the firms' and industries' spatial distribution across regions and their distance to the technological leader. Hence, it proposes to provide empirical evidence of the impacts of technological distances and their relationship to regional clusters. Evidence of the technological gap is measured in relation to the technology leader and its overall level of economic activity, as reflected by the level of production and per-worker productivity. To accomplish this, the next sections address both the model specification and the data.

3. MODEL-TECHNIQUE AND ESTIMATION PROCEDURE

This study uses a dataset comprised of a randomized sample of two hundred sixty Innovative Startup companies from twenty regions in Italy. The data was collected from the AIDA database as of December 31st, 2015.[5] The original dataset includes variables such as total production value, total cost of operation, non-monetary costs, years of operation, number of employees, region of origin, and sectorial classification. With this information, this work creates several derived variables, useful to test the hypotheses of technological catch-up, spatial distribution, and geographic elements. The conceptual framework outlines a model where the value of production per worker is the dependent variable. In general, the parsimonious model specification form is:

$$y_i = \beta_0 + \beta_i x_i + \gamma_i z_i + e_i \tag{1}$$

where y_i is the per worker value of production (a proxy measure for productivity) for firm i, x_j is a vector of explanatory variables including but not limited to firm's level of employment, non-monetary costs of operation per worker (a proxy variable for the fixed cost of operation)[6], and regional employment level. In addition, z_j is a vector of additional variables, including but not limited to a sectorial dummy (there are three economic sectors: S = Services, IT =

[5]https://www.bvdinfo.com/en-us/our-products/data/national/aida

[6]Non-Monetary Cost could be considered as an approximation for fixed cost as they do not depend by the volume of activities. This is because the amortization in Italy is calculated using a specific % stated by the Ministry of Finance every year and not considering the real use of the asset as it should be following the business economics principles. The key point of Non-monetary cost is the role they play as self-financing. Self-financing because they absorb economic value as cost (less revenue) but the absorbed economic value remains inside the company as they do not represent a monetary expense.

Information Technology, and M = Manufacturing); a measure of regional sectorial cluster size; a regional and national technological gap measures; cluster production value minus the value of the firm - as a measure of the potential spillover effects from other firms in the same sector in the same region - and a geographical dummy variable between North, Center, and South.[7] Finally, $e_i \sim N(\bar{x}, \sigma^2)$ are the errors that are assumed to be normally distributed and independent. Before we are able to perform all the above-mentioned estimations, a few transformations need to be performed on the data, as described below.

3.1. Estimation Procedure

The estimation procedure follows the convention as estimations start with a simple Ordinary Least Square (OLS) estimation of the model in (1) above for all three NAICS sectors pooled. Subsequently, estimations take place for the homogeneous sectors (aggregated sectors of Services, Information Technology, and Manufacturing, respectively), and all models are re-estimated. The alternative sets of estimations allow the possibility of a full decomposition of results by pooled sectors and aggregated sectors, while accounting for the added spatial dimensions. Because of the potential relevant spatial effects, this study conducts diagnosis tests, and when relevant it proceeds to estimate the corresponding spatial estimation model.

Determination of the appropriate specification for the spatial process is based on the spatial diagnostic tests of the model estimated by OLS, following the procedure outlined in Anselin et al. (1996): using the Lagrange Multiplier (LM) tests and their robust forms to decide whether a spatial lag, a spatial error process or their combination is appropriate (Florax et al., 2003). As noted in Pede et al. (2021), it is worth pointing out that the specification of the spatial autoregressive error model is relevant when the dependence works through the error process (see Anselin, 1988). The spatial error model is rewritten as:

$$y = X\beta + \epsilon, \epsilon = \lambda W\epsilon + u \tag{2}$$

where y is an $N \times 1$ vector of observations on the dependent variable, X is an $N \times K$ matrix of explanatory variables as defined in (1) earlier, β is a vector of unknown parameters, W is an $N \times N$ weight matrix which defines the spatial structure of regions, λ is a scalar parameter, u is an $N \times 1$ vector of random error terms with mean 0 and variance σ^2, and ϵ is an $N \times 1$ vector of random error terms with mean 0 and variance-covariance matrix $\Omega = \sigma^2(I - \lambda W)^{-1}(I - \lambda W')^{-1}$. The most relevant element of the spatial lag model is when the variable under investigation (y) depends on its spatial lag (Anselin, 1988). It can be written as:

$$y = \rho Wy + X\beta + u \tag{3}$$

where ρ is a scalar parameter, and all other variables are defined as before. The choice of the appropriate spatial process model for each growth model is based on the Lagrange Multiplier tests associated with the error and lag models. In order to estimate the spatial regression models, a spatial weight matrix is defined, which represents the topology of the innovative startups in Italy. The matrix is exogenously defined based on the distances

[7] A list of the regional dummy classification is available in Table 2 (see below)

between the geographical positions of each firm. The longitude and latitude coordinates are used to compute the distance between firms. As a result, a Boolean proximity matrix, where elements are coded as unity, is constructed to indicate if the distance between firms is less than the threshold distance of 0.0133 miles[8]. This threshold distance is selected to ensure that all firms have at least one neighbor, thereby ensuring the correctness of the spatial estimations.

4. DATA AND DESCRIPTION OF VARIABLES

Transformation of the original data considers the following modifications. First, as noted, we constructed a set of dummy variables for the regional classification. We also proceeded to compute the revenue and cost on a per-worker basis to construct a variable that measures levels of productivity, and levels of operation cost per worker, with a particular interest in valuing production per worker and non-monetary costs of production. The latter is used as a proxy for the relative fixed cost of operation and, hence, for the plant size related to the possible presence of economies of scale. The **Non-Monetary costs per worker** are the provisions to risk funds, severance packages, and amortizations. In addition, since the sample of companies covers several years of operation, ranging from one to several years, we proceed to compute a time variable to identify if years of operation act as an operator of the experience and knowledge-development effects, regardless of company size and sector they belong to. In addition, the year variable could serve the purpose of controlling for time-specific effects related to the overall state of the economy.

As part of the data transformation process, and in line with the previous literature, we computed alternative measures of technology leadership and consequent technological gaps, both at the regional and national levels as follows. In the technological gap measures, we follow the description presented in Pede et al. (2021) and determine the overall technological leadership in terms of employment levels[9]. More specifically, we express technological leadership as TD_{it}, where the technological distance to the technology leader is:

$$TD_{it} = \left(\frac{l_{it}^s}{L_{it}}\right)_{\max} - \left(\frac{l_{it}^s}{L_{it}}\right) \tag{4}$$

where l_{it}^s represents employment in region i, in sector s, at the initial time period t, and L_{it} is total employment in region i at time t. It is relevant to note that the location quotient is only valid under relatively strong assumptions (in line with assumptions that are required to use a revealed comparative advantage measure in international trade as a measure for comparative advantage).[10] According to Pede et al. (2021), we proceed to compute the

[8]The threshold distance is selected to ensure that all regions (counties) have at least one neighbor.

[9]The number of employees is a fundamental piece of information to compute the level of technological distance, at the regional and national level, as we will see later. It is relevant to indicate here that the number of employees refers to workers hired above and beyond the founding members of the company. In this regard, there is a selection of 15 firms (across all regions, and for several sectors) that report having zero employees. These firms report having an active economic operation, yet because of the zero-employee reporting, are consequently removed from the sample.

[10]We clearly recognize that this measure does not address in strict terms technological leadership, but rather more of specialization. The choice of this simplistic measurement is due to the non-availability of data.

technological distance at the national level as well as modify the total level of employment, L_{it}, from a regional level to the overall national level. It is relevant to notice that we are only measuring technological distance for startup firms and not for the entire economic apparatus. Thus, we create two new variables that we label respectively, the regional technological gap and the national technological gap. Intuitively, if the technological gap has a value of zero, it indicates that the firm is the technological leader or that there are no other firms in the sector in that particular region. That is, either the firm operates in a monopolistic setting or it is the driving force in the sector in the region. Conversely, higher values indicate that the gap between the leader and the rest of the firms is larger. If technological catch-up is present in the innovative startup segment of the market, then one would expect a positive coefficient of the estimated parameter; otherwise, technological catch-up is not present, and output per worker will tend to diverge. Given the likely endogeneity related to the consideration of specialization-like measures to define the technological distance, estimated coefficients in relation to both National or Regional Technological Gaps are interpreted in terms of association with labor productivity rather than causal effects.[11] Overall descriptive statistics are presented in Table 2 below.

In addition, because of the importance of knowledge-spillover effects in the innovation sector, we determine two cluster formation measures. First, we compute the total cluster size in terms of the number of firms in the specific sector in each geographical region. This variable is a direct count measure of the number of firms in the regional sector, regardless of their economic size.[12] Because of issues related to the economic (value of production) size of the cluster, we compute an alternative cluster measure. This second measure provides a cluster value, where we compute the total production value of the cluster by sector by region, minus the production value of each firm. That is, we compute the summation of all firms in the same sector in the same region to have an account of the possible external effect that other firms might have on each other in the same sector in the same region. Here, we are assuming that clusters are both region-specific and industry-specific. Our depiction is similar to that conceptualization presented by Kerr and Robert-Nicoud (2020). That is, in line with Ellison et al. (2010) and Kerr and Robert-Nicoud (2020), we argue that *knowledge spillovers are more likely to be present according to the boundaries mentioned in the cluster formation.* These clusters may be large or small depending on the potentially tight length of knowledge spillovers. In addition, and to further test the effects deriving from cluster formation, we implement the Relative Cluster Effect (RCE) variable. This variable measures the ratio of the Value of Production for the regional cluster for each economic sector, minus the value of production of each firm in that region and sector, over the value of production of the firm at hand. The RCE variable allows us to measure the impact each firm has in relation to the economic size of the cluster. In this context, we hypothesize that a positive sign in the estimated parameter would provide evidence in favor of local KSE, leading to higher labor productivity along with Porter's argumentation. If the estimated coefficient is negative, then we would argue that the evidence favors more the MAR's approach and not so much

[11] We discussed the estimates for the models that are determined to be the most appropriate estimations, based on the Moran I results. Estimates in columns b and d in Table 2 are shown to indicate the appropriate spatial process.

[12] This count measure is very similar to that suggest by Audretsch and Fritsch (1994) and recently used by Colombelli and Quatraro (2018).

Table 2: Descriptive Statistics. Italian Innovative Startups at 2-Dig NAICS Classification, Dec 2015

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**
2-Dig NAICS Classification					
Inf Technology	0.314	0	1	0	0.47
Manufacturing	0.233	0	1	0	0.42
Services	0.445	0	1	0	0.50
Regional Dummy Variables					
Center	0.392	0	1	0	0.49
North	0.408	0	1	0	0.49
South	0.200	0	1	0	0.40
2-Dig NAICS Cluster Size	10.661	8	32	1	9.00
National Technological Gap	0.025	0.029	0.033	0	0.01
Regional Technological Gap	0.086	0.048	0.750	0	0.12
Number of Employees	6.718	4	56	1	7.57
Employment per Region	176.069	111	462	2	158.97
Regional Number of Firms	25.571	20	57	1	18.14
Value of Production	839,772	515,598	6,096,820	12,154	987,274.20
Non Monetary Cost	63,341	28,870	1,675,205	86	130,324.70
Years of Operation	3.201	3	5	1	1.15

Notes: **Value of production** is the total value at the 31 of Dec 2015 date. The **Non-Monetary costs** are the Provisions to risk funds, Severance packages, and amortizations. Years of Operation is in absolute numbers and represents the total years since the Innovative Startup was first created. The Regional dummies are defined as follows: **North** includes Fiuli Venezia Giulia, Lombardia, Piemonte, Trentino Alto Adige, Val d'Osta and Veneto; **Center** includes Abruzzo, Emilia Romagna, Lazio, Liguria, Marche, Molise, Toscana and Umbria; and **South** includes Basilicata, Calabria, Campania, Puglia, Sardegna and Sicilia. The sectorial variables **Services, Information Technology** and **Manufacturing** take a value of one when the company belongs to each specific sector and zero otherwise. **Regional Tech Gap**, measures the distance between employment for a firm in a given sector for each region, as a difference to the highest ratio of employment to the firm in the same sector with the highest ratio. **Cluster Size**, is a sectorial and region-specific value that measures the number of firms in each sector for each region.

competition. This is to say that KSE would derive more heavily from industry specialization within a region.

5. RESULTS AND DISCUSSION

Our exploratory estimations provide some very interesting results. We first report results about the value of production per worker in Table 3. We then present in Table 4 sectorial estimations with output per worker as a dependent variable, for Services, Information Technology, and Manufacturing, respectively. To test the validity of the proposed model specification, we conduct two OLS estimations of the models (for the overall sample) for all three aggregated sectors first, and then report the estimations for each of the sectors second.

In the estimations, if the spatial estimation shows a positive and significant Moran's I, this is indicative of the presence of spatial autocorrelation. To select the most appropriate spatial dependency, we use the highest value between the LM-error and the LM-lag. If the LM-error is higher in magnitude than the LM-lag, then the model with a spatial autoregressive error process is deemed appropriate; and if the LM-lag is higher than the LM-error, then the spatial dependency on the lagged dependent variable from neighbors is the appropriate model specification.[13]

5.1. Per worker value of production

To explore the dynamics of IS and the role of KSE in terms of labor productivity, we conduct our estimations with output per worker as the dependent variable. It is relevant to note that the overall per-worker data uses the number of employees as the dividing factor of total production and not the actual number of people working in each firm. This is a possibly significant shortcoming of the data, yet the available data in AIDA (Bureau Van Dijk) does not report the number of stockholders. Because of this limitation, per-worker data clearly overestimates the level of productivity per worker; however, we do not have any mechanism to control for the possible upward bias in the data. With these considerations, we proceed to analyze the results. Notice that we provide two sets of alternative model estimations in Table 3. First, we estimate the model (1A) including the Regional Technological Gap (RTG) and, second, the model (2A) including the National Technological Gap. In addition, notice that we conduct the Spatial Diagnostic Test for both models. Consequently, in Table 3 we only analyze the results of the Spatial Estimated models (columns a and c) given that in both cases the Moran's I is statistically significant. Based on the comparison between the Lagrange Multiplier for Lag and Error, we select the statistic with the highest value and thus estimate the model Spatial Lag specification. This is to say, we include the Spatially Lag Dependent Variable (Wy where $y{=}VPPW$), and report results in Columns c and d. We hypothesize that this empirical evidence provides support to the idea of knowledge-spillover effects across firms in the same region, leading to gains in productivity. That is, *the gains of one firm are not limited to itself, but extend to other firms in the same region. More importantly, as we will see later, these gains are associated with the positive performance of neighboring firms.* The results that we observe for the entire sample indicate that these positive effects are present across economic sectors. In general, all these results are as expected.[14]

We observe that higher employment levels (Employ) lead to lower levels of per-worker value of production, also as expected. This evidence supports a positive knowledge-spillover effect that is region-specific, where higher levels of employment in the region, in relation to the rest of the nation, promote workers from the same region to be more productive. In terms of Non-Monetary Costs, the estimated coefficient is positive, in support of the economies-of-scale effect, yet not statistically significant. Finally, years of operation do not seem to have an impact on productivity levels as estimations across models are not statistically significant; we interpret this result in favor of the hypothesis that most employment decisions in the

[13]Given that the LM-error and LM-lag are significant together with their robust form, one could argue the appropriate spatial process is the ARAR model which incorporates an error process and an autoregressive lag progress. We have also estimated the ARAR model for all six aggregate industries, but the estimated spatial lag parameter was either negative or insignificant. Therefore, the spatial error process stands.

[14]Elsewhere Barboza and Capocchi (2020) find that level of employment for Innovative Startups benefits the most in the presence of higher levels of local/regional industry specialization.

innovative startup sector take place in the year of the original operation. This result may need to be further analyzed, yet we are limited given the data available at the time of the analysis.

In relation to the existence of catch-up effects in technology, our results indicate that there are strong effects from the Regional Technological Gap, although not statistically significant effects at the national level. First, Regional Technological Gap has a positive coefficient, and it is statistically significant at the ten percent conventional level. Second, and perhaps most importantly, the proxy for National Technological Gap provides a positive and larger coefficient but it is not statistically significant. This positive coefficient would support the hypothesis that *those companies further away from the regional technological leader, while initially having lower levels of output per worker, are more likely to benefit the most from this catch-up process.*

Furthermore, when we use the National Technological Gap, our empirical estimates (Model d – Spatial Lag) point out to the presence of national divergence in terms of a technological catch-up effect. That is, on average and across economic sectors, *firms across regions do not benefit from the technology developed in other regions in terms of labor productivity*, and thus the evidence indicates a lack of strong enough KSE to support convergence to the national leader. In other words, IS companies are markedly different from one region to another region, and there is a lack of evidence supporting otherwise. Thus, there exists a large gap in terms of the overall level of technology available to them across regions. Conversely, the level of technological catch-up and convergence could be sector and region-specific. If this were to be the case, then we could safely argue that a lower level of data aggregation does provide a significantly different result than larger levels of data aggregation.

We argue that the evidence from the first estimation indicates *the presence of "conditional convergence" at the regional level in terms of labor productivity, but not "absolute convergence" at the national level* given the lack of statistical significance of the NTG variable. This result is in line with the evidence presented by Matricano (2020); however, this result requires further research to untangle the apparent dilemma of convergence at the per-worker level of output at the regional level but not at the national level. A preview note in this regard is that we further argue and confirm later that the convergence is sector-specific with the strongest effect present in the Service and Information Technology sectors.

Analysis of the Spatial Lag (models b and c, Table 3) indicates the strong presence of dependent variable spatial dependency. Intuitively, we argue that labor productivity (measured as output per worker) is dependent on the level of output per worker in the nearby firms. We observe that this dependency is present when we use either the RTG or the NTG, and hold a stable value. Our estimations, with the overall sample of firms from all three sectors of economic activity, do support our hypothesis, that *labor productivity is affected by the observed levels of productivity in nearby locations.* Furthermore, we argue that this spatial dependency supports the argumentation that KSE is conditional to the proximity of firms, and given the positive effects of the RTG variable, much stronger at the regional level than at the national level. In other words, *labor productivity is much more conditional to the economic conditions where firms operate.*

In this line of thought, we argue that the evidence in favor of the positive association of technology, as depicted by the positive regional technological coefficient, is possibly the result of two possible forces. First, it is highly likely that firms in the same region already have highly similar levels of technology as geographical regions in Italy are relatively small and production activities within the same region are highly interrelated. Ghio et al. (2016) and Del Giudice et al. (2019) found similar evidence supported by the presence of localized spillover effects. Second, it is also possible that firms already draw from workers in the same region with relatively similar skills, supporting the Marshallian transportation cost hypothesis in terms of labor and knowledge. It is possible, though, that the dependent variable of choice may have some influence on the estimated coefficient signs supporting argumentation per Audretsch and Fritsch (1994).

In terms of the cluster variables, our empirical estimates provide some interesting results. Notably, we observe that a larger cluster size has a positive effect on the per-worker value of production; yet, none of the measures are statistically significant; however, the RCE measure yields a negative and statistically significant coefficient robust in all models where it is introduced. Per our previous discussion, a negative sign of the estimated coefficient indicates that output per worker for the firm decreases as the firm becomes relatively smaller in the cluster. In other words, *larger firms in the cluster also tend to have higher per-worker output, so the cluster leader is also the firm with higher per-worker productivity.* In this regard, lower values of the Relative Cluster Effect ratio indicate that the firm may be the initial source of knowledge-spillover effects to the rest of the cluster (Fritsch and Wyrwich find similar evidence (2018)). This result is in line with the previously estimated National Technological Gap effect discussed earlier, yet this effect dominates at the regional level.

The evidence presented in Table 3 points out a combination of relevant determinants of the value of production per worker as our proxy for labor productivity. We observe a statistically significant negative effect of employment growth on overall labor productivity, indicating the possibility that economies of scale in the Innovative Startup sector are reached at lower levels of employment and production. In addition, we observe the presence of a strong and significant Regional Technological Gap, where some regions are significantly ahead of others, and, thus, being far away from the leader, drives possible catch-up effects. There is not enough evidence to indicate the expected catch-up duration effect, however. A more detailed count on Innovative Startup ownership structure and headcount of owners could produce more robust empirical estimates. Nevertheless, our study provides significant statistical evidence of several key factors at play in explaining possible sources of output-per-worker differences across firms.

Table 3: Technological Catch-up Effects on Innovative Startups with Value of Production per Worker as Dependent Variable

	a	b	c	d
	1A	**1A_Spatial Lag**	**2A**	**2A_Spatial Lag**
CONSTANT	185,091***	165,104***	195,494***	175,500***
	(0.001)	(0.001)	(0.001)	(0.001)
Non-Monetary Cost per Worker	1.005	1.042	1.133	1.168
	(0.193)	(0.159)	(0.143)	(0.115)
Years of Operation	-10,866	-11,259	-11,588	-11,975
	(0.252)	(0.215)	(0.224)	(0.190)
Cluster Size	2,144.65	2,297.96	1,554.76	1,711.56
	(0.488)	(0.439)	(0.615)	(0.564)
Cluster Value minus Firm Value	0.004**	0.004**	0.004**	0.004**
	(0.014)	(0.025)	(0.022)	(0.039)
Regional Cluster Effect	-1,507.62***	-1,422.57***	-1,148.53***	-1,066.08***
	(0.001)	(0.001)	(0.002)	(0.003)
Employment Level	-6,671.49***	-6,847.4***	-6,780.41***	-6,955.35***
	(0.001)	(0.001)	(0.001)	(0.001)
Regional Technological Gap	175,270*	174,103*		
	(0.092)	(0.080)		
National Technological Gap			360,579	357,816
			(0.811)	(0.804)
Spatial Lag		0.145***		0.144***
		(0.004)		(0.004)
Moran's I (error)	2.399**		2.457**	
	(0.016)		(0.014)	
Lagrange Multiplier (lag)	7.629***		7.523***	
	(0.006)		(0.006)	
Robust LM (lag)	3.718*		2.899*	
	(0.054)		(0.089)	
Lagrange Multiplier (error)	4.996**		5.305**	
	(0.025)		(0.021)	
Robust LM (error)	1.086		0.681	
	(0.297)		(0.409)	
Lagrange Multiplier (SARMA)	8.715**		8.204**	
	(0.013)		(0.017)	
Number of Observations	244	244	244	244
F-statistic	9.860		9.348	
Prob(F-statistic)	(0.001)		(0.001)	
Log likelihood	-3,273.27	-3,269.30	-3,274.71	-3,270.79
Akaike info criterion	6,562.54	6,556.60	6,565.43	6,559.58

Note: The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Note (continued): **Value of production per worker** is the total value at the 31st of Dec 2015 date divided by the number of reported workers, in addition to any owner/stockholder working at the firm. The **Non-Monetary costs per worker** are the provisions to risk funds, severance packages, and amortizations. **Years of Operation** is in absolute numbers and represents the total years since the Innovative Startup was first created. **Employment** is the number of current employees at the startup firm, in addition to any founding member or stockholder, who are not accounted for as employees. The dummy classification for **Services, Information Technology**, and **Manufacturing** is conducted according to the classification standards described earlier in the paper; each sector takes a value of 1 or 0 accordingly. We use the Manufacturing Dummy variable as the reference variable when the constant (C) is not included. The Regional dummies are defined as follows: **North** includes Fiuli Venezia Giulia, Lombardia, Piemonte, Trentino Alto Adige, Val d'Osta, and Veneto; **Center** includes Abruzzo, Emilia Romagna, Lazio, Liguria, Marche, Molise, Toscana, and Umbria; and **South** includes Basilicata, Calabria, Campania, Puglia, Sardegna, and Sicilia. Regional employment is the proportion of employees in each firm relative to all employees in the region, regardless of industry classification. Technological gap variables are defined at the regional and national level by sectorial classification. The **Regional Technological Gap** is the difference in the employment ratio between the highest ratio of employment in each region for each sector in relation to the total level of employment in the region, minus the ratio of employment in the region for each sector. The **National Technological Gap** resembles that of the region but uses the maximum ratio of employment for the nation instead of the regional. **Cluster Size** is defined as the number of firms in the same sector per region, and it is intended to measure the relative positive effect of belonging to a cluster. The **Cluster Production Value** – Firm is the total value of production for each cluster per region per sector, minus the value contribution for each firm in that sector in that region; thus, it measures the potential contributions of the other firms' production to each individual cluster member. Regional Cluster Effect **(RCE)** is defined as the ratio of Cluster Value per region per sector minus firm value of production, divided by the firm's value of production.

5.2. Sectorial estimations

To uncover issues of knowledge spillovers and spatial dependence, we tease the data to further explore the validity of our model, and we now apply the same estimation procedure (as reported in Table 3) to each of the aggregated sectors defined in the data section, namely Services, Information Technology, and Manufacturing. Estimation results for each of the aggregated sectors are reported in Table 4, under columns a, b, and c for Services, columns d and e for Information Technology, and columns f and g for Manufacturing, respectively. We first report the OLS estimates for the basic models (a, b, d, e, f, and g) and provide the spatial diagnostic tests as well. When the presence of spatial dependency is detected, we provide the corresponding spatial estimation, either Spatial Lag or Spatial Error. Notice that in the case of the estimations by sector, the spatial diagnostic is only significant for model 3B in column b. The corresponding estimation is reported in column c, under Spatial Error Model. For all other model estimations, the Moran's I is not statistically significant at any conventional level. It is, therefore, relevant to point out that most of the Spatial Dependency diagnostic from Table 3 is present in the Service sector but not in Information Technology and Manufacturing. Alternatively, we may argue that Spatial Dependency is observed across sectors of economic activity but not detected once focusing on single sector estimations.

The main idea behind the sectorial estimations is to separate elements that could potentially be sector-specific across regions and, thus, use much lower levels of data aggregation to discover the dynamics of technological catch-up and KSE effects. We openly acknowledge that data limitations (as sectorial samples are smaller) may create some biases in the estimations, and as such, the results stand exploratory in nature. However, we can clearly indicate that the *sectorial dynamics are consistently different in the IS sector in Italy.*

There are several discoveries that we make by using lower levels of data aggregation that we believe are essential in the understanding of possible flows of ideas and KSE in the IS segment of the market. First, the coefficient for Non-Monetary cost per worker reveals statistical significance only in the Manufacturing sector while having a reverse sign for Services, albeit not statistically significant. We believe that the positive coefficient in Manufacturing reflects the capability of the sector to still increase productivity as firms' size expands. Second, the coefficient for years of operation estimates for Information Technology and Manufacturing are positive yet not statistically significant, providing evidence in support of the hypothesis that in these sectors, the beginning year of operation is the main conditional factor for employment-productivity determination. This, unfortunately, provides evidence against the presence of per-worker output gains through learning by doing or experience in the job place. In the Service sector, the results are discouraging as the estimate for years of operation indicates that as firms mature, the value of production per worker declines. This negative coefficient is observed as well in the number of employees. Notice that a negative coefficient for employment is present in all three sectors, while the largest negative value is in Information Technology. In relation to the Spatial dependency, notice that only model 3B-Spatial Error (column c) is significant. This model corresponds to the specification when the National Technology Gap is used. The spatial dependency is present in the error term, which indicates that this spatial conditionality in the Services sector is not explained by the model itself but by the error term. As noted in the estimations using the entire sample in Table 3, columns b and d, the spatial dependency in the sectorial case is not as clear in terms of the labor productivity being affected by nearby firms.

Table 4: Technological Catch-up Effects on Innovative Startups with Value of Production per Worker as Dependent Variable

	a	b	c	d	e	f	g
	Services			**Information Technology**		**Manufacturing**	
	3A	**3B**	**3B-Spatial Error**	**4A**	**4B**	**5A**	**5B**
CONSTANT	89,110.8***	-61,600.9	-74,909.3*	26,793.9	246,606.0***	39,504.9	-80,372.1**
	(0.003)	(0.131)	(0.060)	(0.288)	(0.001)	(0.157)	(0.037)
Non-Monetary Cost per Worker	-0.352	-0.377	-0.274	0.102	0.196	1.165**	1.228**
	(0.549)	(0.495)	(0.609)	(0.835)	(0.633)	(0.033)	(0.019)
Years of Operation	-16,484.7**	-16,222.0**	-16,508.2**	3,425.4	2,725.8	3,503.6	3,246.9
	(0.023)	(0.018)	(0.012)	(0.571)	(0.592)	(0.600)	(0.614)
Cluster Size	3,346.36	3,503.79	3,880.92*	3,838.39*	3,348.31**	-3,083.34	-3,341.30
	(0.156)	(0.115)	(0.086)	(0.053)	(0.043)	(0.158)	(0.111)
Cluster Value minus Firm Value	0.004***	0.003***	0.003**	-0.002*	-0.001	0.002	0.001
	(0.003)	(0.010)	(0.016)	(0.054)	(0.152)	(0.133)	(0.348)
Regional Cluster Effect	-645.483**	-595.406**	-554.614**	-254.853	-164.8	-638.151**	-358.407
	(0.047)	(0.025)	(0.031)	(0.348)	(0.403)	(0.034)	(0.152)
Employment Level	-3,924.21***	-664.347	-356.793	-854.046	-5,556.31***	-1,215.87	1,453.86
	(0.001)	(0.591)	(0.768)	(0.364)	(0.001)	(0.242)	(0.213)
Regional Technological Gap	79,252.80			-34,283.60		182,644**	
	(0.315)			(0.604)		(0.031)	
National Technological Gap		5,671,450***	5,995,640***		-7,933,460***		5,008,760***
		(0.001)	(0.001)		(0.001)		(0.001)
LAMBDA / Spatial Error			0.102*				
			(0.058)				
Moran's I (error)	1.159	1.958**		-0.358	0.446	1.073	0.771
	(0.246)	(0.050)		(0.720)	(0.656)	(0.283)	(0.441)
Lagrange Multiplier (lag)	0.114	0.822		0.277	0.210	0.991	0.556
	(0.735)	(0.365)		(0.599)	(0.647)	(0.320)	(0.456)
Robust LM (lag)	2.065	2.297		0.028	2.903*	0.244	0.261
	(0.151)	(0.130)		(0.867)	(0.088)	(0.621)	(0.609)
Lagrange Multiplier (error)	1.002	3.264*		0.260	0.091	0.839	0.391
	(0.317)	(0.071)		(0.610)	(0.763)	(0.360)	(0.532)
Robust LM (error)	2.953*	4.739**		0.011	2.784*	0.092	0.096
	(0.086)	(0.029)		(0.917)	(0.095)	(0.762)	(0.756)
Lagrange Multiplier (SARMA)	3.067	5.561*		0.288	2.994	1.082	0.652
	(0.216)	(0.062)		(0.866)	(0.224)	(0.582)	(0.722)
Number of Observations	244	244	244	244	244	244	244
F-statistic	16.150	21.770		1.211	15.640	2.956	5.685
Prob(F-statistic)	(0.001)	(0.001)		(0.297)	(0.001)	(0.005)	(0.001)
Log likelihood	-3,206.56	-3,193.53	-3,191.82	-3,163.73	-3,121.54	-3,188.19	-3,179.44
Akaike info criterion	6,429.12	6,403.06	6,399.65	6,343.45	6,259.08	6,392.30	6,374.87

Note: The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Note (continued): **Value of production per worker** is the total value at the 31st of Dec 2015 date divided by the number of reported workers, in addition to any owner/stockholder working at the firm. The **Non-Monetary costs per worker** are the provisions to risk funds, severance packages, and amortizations. **Years of Operation** is in absolute numbers and represents the total years since the Innovative Startup was first created. **Employment** is the number of current employees at the startup firm, in addition to any founding member or stockholder, who are not accounted for as employees. The Regional dummies are defined as follows: **North** includes Fiuli Venezia Giulia, Lombardia, Piemonte, Trentino Alto Adige, Val d'Osta, and Veneto; **Center** includes Abruzzo, Emilia Romagna, Lazio, Liguria, Marche, Molise, Toscana, and Umbria; and **South** includes Basilicata, Calabria, Campania, Puglia, Sardegna, and Sicilia. Regional employment is the proportion of employees in each firm relative to all employees in the region, regardless of industry classification. Technological gap variables are defined at the regional and national level by sectorial classification. The **Regional Technological Gap** is the difference in the employment ratio between the highest ratio of employment in each region for each sector in relation to the total level of employment in the region, minus the ratio of employment in the region for each sector. The **National Technological Gap** resembles that of the region but uses the maximum ratio of employment for the nation instead of the regional. **Cluster Size** is defined as the number of firms in the same sector per region, and it is intended to measure the relative positive effect of belonging to a cluster. The **Cluster Production Value** – Firm is the total value of production for each cluster per region per sector, minus the value contribution for each firm in that sector in that region; thus, it measures the potential contributions of the other firms' production to each individual cluster member. Regional Cluster Effect **(RCE)** is defined as the ratio of Cluster Value per region per sector minus the firm value of production, divided by the firm's value of production.

Testing for technological catch-up effects at the regional and national level provides some interesting sectorial results. First, as we separate estimations by sectors, we now observe that the National Technological catch-up effect is statistically significant for all sectors when estimated independently, although it displays reverse signs for Information Technology where it is negative. In this context, we also observe that the speed of catching up, measured by the overall value of the estimated coefficient, is slightly faster in the Service sector than in Manufacturing. As we have argued earlier, the evidence provides support for a weak form (conditional) of convergence but no evidence of an overall convergence across all sectors. In this context, when we look at the Regional Technological Gap variable, the results diverge significantly in comparison to the overall sample results reported previously in Table 3. In addition, Regional Technological catch-up evidence is only statistically significant – with correct positive signs – in the Manufacturing sector. For the other sectors, the coefficients, positive for Services and negative for Information Technology, are not significant at any conventional level of confidence. Notice that in comparison with the overall sample, the RTG was positive and significant, clearly demonstrating that the manufacturing effect dominates for the overall sample. In this sense, we can argue that *in the Manufacturing sector, firms located further away from the regional leader have a large potential to benefit from development at the highest level of technology.* Conversely, for the other sectors, firms located further away from the leader will remain as such in terms of technological catch-up. In other words, *the lack of regional convergence in the information technology and services sectors indicates that firms may be operating in silos and promoting low levels of cooperation across firms in the same sector.* This, of course, is a topic of further exploration.

Finally, the estimation for the alternative measures of Cluster effects yields substantially differentiated results across economic sectors. Firstly, the coefficients for cluster size have reversed signs: positive and statistically significant for Services (column c – Model 3B Spatial Error) and Information technology (columns d and e, Models 4A and 4B), and negative but not statistically significant for Manufacturing. Secondly, the value of production of the cluster minus the firm's provides a positive and statistically significant coefficient for Services (columns a and c) and negative for Information Technology (column d), but not for Manufacturing. In this sense, the larger the Sectorial Cluster, the larger the possible spillover gain the firm derives for the case of Services, that is positive KSE; but negative for the case of Information Technology. Notice that this set of results confirms what we have found earlier for the overall sample: in the case of the overall sample, the positive cluster value size from Services has a dominant effect. In the Information Technology segment, the evidence actually indicates a negative coefficient, indicating that a larger cluster value reduces productivity. Lastly, the estimates for the relative cluster effect are all negative and statistically significant under the alternative model specifications. The robustness of this variable, in addition to the combined effect of Cluster Value, indicates that smaller firms in the sectorial cluster are in the position to gain the most, the larger the Cluster gets. Furthermore, the Non-Monetary cost coefficient is only statistically significant for the Manufacturing sector, providing support for the hypothesis that manufacturing is still an expanding sector, which has not yet achieved the optimal plant size.

6. LIMITATIONS AND CAVEATS

We must acknowledge several elements regarding possible limitations with our data and, consequently, empirical estimations. First, we recognize that our measures partially approximate the technological gap, and, thus, our proxy is imperfect. These limitations lead us to be cautious about the interpretation of results and the elaboration of policy recommendations. We also understand that possible mismeasurement on both the output and input sides is clearly a cause for concern in general. We, however, have no means to correct this possible shortcoming with the available data. We also lack information regarding labor composition at the internal of the firm(s) regarding the number of owners, and the overall level of human capital (flow and stock). In this context, we are forced to make the strong assumption that one unit of labor is identical across firms and across sectors. Further, exploring the data and a more comprehensive level of detail in the labor force composition is clearly interesting. At this point, all these possibilities are beyond the scope of our analysis, yet they remain relevant topics of study for future research.

An additional limitation that our paper may bear relates to the low level of data availability and the possible limitations regarding variation within regions. In this context, one has to be mindful of how the firm data is only for firms actively operating as of December 31 of the year 2015; that is, our sample is composed mainly of firms that have survived, and we do not have data on firms that have failed. In this sense, one can assume that competition itself has led us to a sample of persevering firms. We are uncertain about how to deal with a situation like this, other than explicitly stating the possible presence of biases. This is to say that at regional levels of (dis)aggregation, the data may be too similar among firms and, thus, we might find biased estimators. This would be a possible result if the standard errors were clustered at the regional level. As noted, given the current dataset availability, our results might need to be interpreted with caution.

7. CONCLUSIONS AND POLICY IMPLICATIONS

The phenomenon of startups in Italy is very contemporary and has not been studied yet at length by the scientific community. The phenomenon assumes particular importance both for what concerns the distribution of startups on a regional scale and for the effects that the new entrepreneurship initiative may have on social and economic territorial systems. The study of the phenomenon must be included in the Italian national context where, currently, there is no system for coordinating and managing startups and where the different actors (companies, universities, research centers, etc.) are disconnected from the system. This makes the investigation of the phenomenon from an economic, managerial, and social perspective even more important.

Results indicate the presence of supporting evidence in favor of knowledge spillover effects across firms in the same region. Furthermore, we also find that regional differences are stronger than local differences by sector; that is, location is an important factor in the creation and productivity of recently formed Innovative Startups. In a related issue, the lack of statistical significance of the regional technological gap variable provides evidence against regional technological convergence in the Service and Information Technology sectors.

The presence of divergence in terms of a technological catch-up effect at the national level complements this result. On average and across economic sectors, firms across regions do not benefit from technology developed in other regions; that is, there is evidence indicating that the overall level of technology available to firms is significantly different across regions and potentially limited to within-cluster firms. Our results of the spatial diagnostics indicate the presence of significant evidence of both spatial-lag and spatial-error dependency. These forces indicate that labor productivity, in general, is dependent on the neighbors' productivity, and, consequently indicates a strong presence of KSE. In addition, at the sectorial level, we find that a significant spatial dependency is present in the error term and, thus, above and beyond the current model specification.

In terms of workers' productivity, we also find evidence in support of the hypothesis of regional conditionality, where output per worker is consistently higher in the North region. This regional conditionality points out strong effects from the region, but, more importantly, at the national level. Based on the exploratory results, we conclude that a *"conditional convergence" effect is present at the regional and national levels in terms of labor productivity*, yet there is no supporting evidence for absolute convergence. Our results are in line with those presented by Matricano (2022), more specifically, when using sectorial data, we find a stronger presence of convergence in Service and Manufacturing; and divergence for Information Technology.

Two further results indicate that larger firms in a cluster tend to display larger output per worker, providing evidence in favor of economies of scale. In addition, we find that productivity gains are inversely affected by regional cluster size.

We draw a few relevant policy implications. This study shows evidence in support of fostering and exploiting the gains from KSE through further integration and incentives for firms to get closer to the center of the action and engage in more exchange of ideas. While the initial implications apply to Italy, the results are easily extended to other economies, where the stimulation of innovative entrepreneurship is or could become highly valuable as a means to increase employment and economic growth. Following Audretsch (1995), we back up the idea that new firms are an important source of job creation. A better understanding of both natural advantages (barriers) of regions plus the gains from location advantages needs to be translated into regional advantages and firm–industry-specific advantages.

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