INAPP
PUBLIC POLICY INNOVATION

WORKING PAPER

INAPP WP n. 41

Skill Gap, Mismatch, and the Dynamics of Italian Companies' Productivity

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OTTOBRE 2019

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ABSTRACT

Skill Gap, Mismatch, and the Dynamics of Italian Companies' Productivity

Relying on a unique integrated database, this work explores the relationship between labour productivity, on one side; intensity and characteristics of companies' skills need and degree of skill mismatch, on the other. The analysis focuses on a representative sample of Italian limited liability companies observed during the years 2012, 2014 and 2017. First, companies acknowledging the need to update their knowledge base display a higher productivity *vis-à-vis* other firms. Second, when it comes to the skill need distinguished by competence/knowledge domains (management, STEM, social and soft skills, technical operatives and humanities) it emerges that companies looking for technical operative and social skills show lower labour productivity as compared to other firms. On the contrary, companies characterized by a need in managerial, STEM or humanities-related skills show higher productivity. Third, the ability to match the skill need via new hiring is always positively correlated with firms' productivity. This result is confirmed across all the adopted specifications.

KEYWORDS: labour productivity, skill mismatch, firm-level heterogeneity, knowledge-base, organizational capabilities

JEL CODES: D22, D80, J24

1. Introduction

Introducing new products, changing existing ones, organizing production in a more efficient way are all key elements to market success. From Schumpeter onwards, technological and organizational innovation mirror the capacity of a firm to gain and consolidate market shares at the expenses of competitors. For a firm to be characterized by such an economic and technological dynamism, however, there is an essential condition that needs to be verified: being equipped with a solid, rich and up-to-date knowledge base. A company's knowledge base might be defined as the combination of workers' individual skills that by interacting with the organizational environment evolve into firm-specific (collective) knowledge. Once consolidated such knowledge assumes the form of the 'lifeblood' by means of which companies adapt to changing contexts becoming capable to transform the latter according to their needs. With the unfolding of the ICTs' technological trajectory (Dosi 1982), (continuously) enriching and updating their own knowledge base became, for firms, an even more urgent matter. Increasing competitive pressure, swarming innovations and raising production fragmentation make past (formal and informal) skills obsolete or, at best, suitable to achieve a poor innovative and economic performance.

In this context, the ability of firms to strategically reflect on their knowledge base – i.e. a reflection intended as consciousness about the current shape of their own knowledge base and the potential needs in terms of change and upgrading – turns out to be a crucial pre-condition to undertake medium and long-run initiatives aimed at increasing competitiveness and market shares. Indeed, firms displaying an intense propensity towards periodically reviewing the adequateness of their knowledge base and eventually enriching it (i.e. injecting new skills via new hiring or training those who are already employed) might be considered relatively more dynamic and oriented towards long-term competitive strategies (mostly based on technological and organizational competitive advantages) as compared to other firms. In other words, a 'skills need', i.e. the need to add or increase their knowledge-base with respect to one or more specific skills, might constitute a sign of dynamism heralding a phase of transformation and strengthening in knowledge-related, organizational and technological terms. On the other hand, companies acknowledging to have such a need may be facing difficulties, insofar a persistent skills need can be the result of a lack of adequate (skill) supply in the labour market.

When a skills need is recognized and/or an enrichment/upgrading of the internal knowledge base is planned, there are two major roads that a firm is likely to follow: transferring new skills to the employed workforce via specific training programs; relying on the labour market to hire workers endowed with the needed skills. These solutions are not necessarily alternative and their attractiveness (or suitability) might vary according to the type of skill 'in-need': if the skills to be added are completely new and peculiar, for example because they are complementary to a radically new technology, training the 'old' workforce can be inefficient and costly *vis-à-vis* hiring new workers already endowed with the required skills. Moreover, the opportunity-cost of internal training as opposed to hire (appropriately) skilled workers might vary according to the type of firm facing such need. Large firms are more likely to have the internal resources (both monetary and organizational) required to set an *ad hoc* training program capable to fill in a reasonable amount of time the skills need. Small and medium sized firms, in turn, are more likely to lack such resources and to prefer hiring new professional figures expected to bring new competences, knowledge, abilities and eventually to spread them into the organization. Both the skills need and the strategy adopted to fill it are also expected to have a significantly heterogeneous shape according to the sector that is taken into account. Industries characterized by high-tech productions are likely to demand sophisticated skills that are normally acquired through specialized higher-education programs. In this case, is less probable that companies opt for internal training given the effort (and in most cases the length) required to transfer such skills. The same holds in the case of relatively low-tech services (as, for example, in the case of health care and social-assistance related services) whereby skills as empathy, ability to interact with others and, more in general, experiential (tacit) knowledge are crucial to successfully perform tasks. In these sectors, training has scarce probability to be the preferred option to fill a specific skills need while it is more likely that companies decide to explore the labour market looking for 'someone with a long and specific experience which fits for purpose'.

A large amount of literature in this field has displayed how the presence (lack) of adequate (inadequate) skills might be one of the key drivers (constraints) of companies' productivity and growth performance (see, among the others, Meschi *et al.* 2011; Crinò 2012). Their relative importance as elements favouring (hampering) companies performance, however, varies given the shape of other relevant supply (companies' technological capabilities and absorptive capacity, labour market and education institutions quality and characteristics, degree of competitiveness, managerial profile), demand (intensity and composition of demand flows) and structural (industrial structure and degree of production internationalization) factors (Cetrulo *et al*. 2019).

Relying on a unique integrated database, this work explores the relationship between labour productivity, on one side; intensity and characteristics of companies' skills need and degree of skill mismatch, on the other. The analysis focuses on a representative sample of Italian limited liability companies observed during the years 2012, 2014 and 2017. In this respect, this work adds to the growing empirical literature attempting to provide an explanation to the persistently sluggish dynamics of Italian firms' productivity (Codogno 2009; Dosi *et al.* 2012; Calligaris *et al.* 2016; Dosi *et al*. 2018). Among the potential drivers of such a poor productivity dynamics, a number of structural factors have been identified: stagnant internal demand, geographical dualism, prevalence of small and micro firms mostly operating in low-tech low-value added sectors, weak innovation propensity and insufficient degree of internationalization. Besides these undeniably relevant factors, however, the availability of a sound skill endowment might represent an additional element capable to explain heterogeneities in terms of firm-level productivity performance. This might be particularly true if one considers the documented complementarity (Black and Lynch 2001, 2005; Cetrulo *et al.* 2019) between firms' skill endowment and propensity towards the introduction of innovations.

The relationship between labour productivity, skills need and mismatch is explored adopting an evolutionary perspective whereby workers skills (both those already present within the company's perimeter as well as those identified as 'in-need') are not considered as individual independent attributes, but as components of the firm's internal (and complex) knowledge-base. Contrarily, most of the existing studies (see the next section) tend to analyse the role of skills and the presence of a potential mismatch in explaining firm performance focusing on workers' individual productivity, conceived as independent 'bricks' constituting the overall company's productivity edifice. According to this framework, skills are expected to be, on the one hand, directly related to education; on the other, capable to magnify their productive potential only when perfectly matched with firms' techno-organizational needs (i.e. with the latter reflected in the tasks that workers are asked to perform). Finally, we explicitly account for the role of demand (Piva and Vivarelli 2007) as a driver of both firms' performance as well as of their propensity towards change in terms of knowledge base renewal and upgrading.

The empirical analysis carried out here overcomes most of the limitations faced by previous studies focusing on skill mismatch and firm performance. Firstly, thanks to the availability of extremely detailed information on skills at both the firm and the occupation-level, we do not need to rely on education-related proxies circumventing the theoretical and empirical problems that such choice might entail. Secondly, we exploit unique information on the characteristics of the company's knowledge base distinguishing the latter in terms of: occupations (at the maximum level of disaggregation of the Italian occupational classification) populating the firm workforce; and skills that these occupations need to add to their endowment (see the Data Section for a detailed description of the adopted sources). In addition, we include a comprehensive set of technology-related variables capturing both product, process as well as organizational innovation. In this way, we take into consideration the heterogeneity characterizing different type of innovation and, not less relevantly, the differentiated relationship that each of those types might have with skills and firms' performance. Taking advantage of such a rich set of information, we analyse, first, Italian companies' productivity dynamics against the skill gap they recognize and discriminating such gap by clustering skills in: managerial, STEM, humanities, technical and, social and soft skills. Given the presence of a skill gap we than study companies' productivity in relation to their capacity to fill such gap via new hiring (i.e. productivity vs degree of skill match) controlling for a large set of supply and demand side factors. The empirical investigation relies on an innovative measure of skill match combining firm-level information on the share of competence/knowledge to be updated with occupation-worker level one regarding the skill characteristics of new hiring flows (see the description in the Data Section). The relationships under analysis are explored relying on a variety of econometric techniques exploiting both the repeated cross-sectional as well as the panel component of the sample of Italian companies included in the analysis. The effect of skill demand and mismatch on labour productivity is estimated via Least Squared Dummy Variable (LSDV) with clustered standard errors and maximum likelihood (ML) random intercept model, controlling for company-level idiosyncratic characteristics. In order to reduce the risk of a selection bias, potentially stemming from the presence of unobservable factors determining whether a firm acknowledges or not the existence of a skills need, we rely on a two-steps *Heckman* procedure using, as exclusion restriction, the regional share of graduates observed some decades before the acknowledgement of the skill demand.

The key results are the following. First, companies acknowledging the need to update their knowledge base display a higher productivity *vis-à-vis* other firms. Second, when it comes to the skill gap distinguished by competence/knowledge domain (management, STEM, social and soft skills, technical operatives and humanities) it emerges that companies displaying a skill need related to technical operative and social skills show lower labour productivity as compared to other firms. On the contrary, companies characterized by a need in managerial, STEM or humanities-related skills show higher productivity *vis-à-vis* other firms. Third, the ability to fill the skill gap via new hiring is always positively correlated with firms' productivity. This result is confirmed across all the adopted specifications.

The article is structured in the following way. The next section provides a brief review of the literature analysing, both theoretically and empirically, the relation between companies' knowledge base characteristics, degree of skill mismatch and productivity. Section 3 illustrates the database used for the analysis and describes the indicators capturing skill demand and mismatch at the firm-level. Section 4 introduces the key hypotheses and the specification adopted to test the latter. Section 5 describes the econometric strategy and reports the results of the analysis while the last section discusses the results providing some policy considerations.

2. Firms' Productivity, Knowledge Base and Mismatch

Since the classics (Smith 1776; Ricardo 1817; Schumpeter 1942), knowledge and technology are identified as key drivers shaping the evolution of economic processes, markets and organizations. In this context, firms assume the form of *loci* attracting knowledge flows incorporated in workers (heterogeneously distributed)' skills to achieve their internal (technological and organizational) and external (gaining market shares) objectives. At the same time, firms are *loci* where knowledge is created and transformed via idiosyncratic learning processes and specific organizational practices (Penrose 1952; Nelson and Winter 1982; Dosi and Marengo 2015). Thus, the interplay between technological and organizational transformations, on one side, and workers skills and capabilities, on the other, represents a crucial element driving the evolutionary dynamics of capitalistic economies. The acquisition and the development of knowledge and technologies are thus directly related to companies' productivity and market success. Concerning the role of knowledge, the economic literature has emphasized its paramount importance in explaining individual (worker) and, indirectly, firm-level productivity (Becker 1962; Mincer 1981). In his seminal contribution, Becker (1962, 1) argues that the acquisition of knowledge (and/or the development of skills) means 'imbedding resources in people' via the investment in what the author defines 'human capital'. The key hypothesis is that a larger amount of human capital (measurable, according to Becker, by the year of schooling or training that an individual can get) increases individual productivity with the prospect of 'influencing real income in the future'.

However, both the decision about investing in human capital as well as the linkage between skills and productivity are influenced by uncertainties concerning the prospect of taking economic benefits out of such investment. A similar degree of uncertainty is expected to affect firms' ability to exploit the productivity gains potentially associated to workers' skills; as well as to appropriately evaluate the latter (in terms of quantity and quality) during the recruitment phase. Growing extensively after Becker (1962)'s contribution, this strand of literature frames the relationship between knowledge, skills, organizations' dynamics and performance as an 'individual matter' reflected in the productivity differential characterizing high-skilled (labour) as opposed to less qualified productive inputs. Subsequent refinements of this literature have introduced novel elements of complexity by considering the role of knowledge and skills in presence of market failures (i.e. imperfect competition in labour markets, asymmetric information ecc.) as well as by exploring more in depth the 'signalling mechanisms' by means of which firms attempt to discriminate between high and low skill workers (Spence 1973; Weiss 1995). A further and related stream of literature, in turn, investigates both determinants and effects of company-level training (Acemoglu and Pischke 1999) keeping the major analytical and theoretical pillars of the human capital theory untouched.

These approaches conceptualize productivity as a matter of workers' marginal contribution to the production process, accounting for individual skills and knowledge as 'production function-augmenting' analytical *addenda*. In this framework, education is the proxy chosen to identify the potential gap or mismatch between workers' individual characteristics and companies' job requirements.

Other theoretical interpretations have been proposed to identify determinants and effects of educational mismatch on wages or productivity performances. Adopting a job competition approach, Thurow (1975, 1979) builds a theoretical framework according to which heterogeneities in terms of labour productivity are explained by jobs rather than by workers' individual characteristics. Therefore, wages are determined by job requirements with workers ranked according to their trainability, which, in turn, depends on their educational level. Focusing on over-education (i.e. a case of mismatch according to which high-skilled workers are assigned to low-skill tasks), Sicherman and Galor (1990) analyse skill mismatch with a specific emphasis on the role of career mobility. By estimating the effect of education on both wages and on the likelihood of career mobility for 24 different occupations, they find that those characterized by relatively higher wages (for a given educational level) display, on average, a weaker upward career mobility.

Other contributions investigate the roots of educational mismatch by analysing the process leading workers towards differentiated (sub-optimal) choices concerning their investments in human capital (Lazear 1977; Oosterbeek and Van Ophem 2000). Building on the human capital theory, these contributions provide an explanation of educational mismatch associating the latter to the preference between labour and leisure as well as to job satisfaction. Along similar lines, the search-and-matching models (Albrecht and Vroman 2002; Gautier 2002; Dolado *et al.* 2009) interpret over-education as the result of frictions affecting labour markets dynamics.

Within this theoretical framework, skill gap and mismatch are the result of labour market frictions affecting the search-and-matching process with negative impacts on both workers and firms' productivity.

Indeed, different measures of skill mismatch have been proposed. Some contributions rely on education as a proxy of workers' skill concentrating their attention on the so-called 'vertical mismatch' (Freeman 1976; Heijke *et al.* 2003). The focus is on the effect that (under) over-education (i.e. the difference between workers' attained educational levels and those required for a certain job) might have on individual productivity.

Other contributions relate educational mismatch to the difference that might emerge between the educational field workers have attended and the characteristics of the job they are asked to perform – the so-called 'horizontal mismatch' (Robst 2007). This differentiation allows distinguishing between 'subjective' (mostly related to job satisfaction) and 'objective' measures of mismatch. From an empirical standpoint, this group of contributions aims at estimating the impact of over, required or under-education (ORU) on workers' productivity and wages. Others, as Büchel (2002), focus on the effect of (under) over-education on job satisfaction or related factors such as absenteeism or turnover. Skill mismatch is found to have a significant impact on individual productivity, with positive effects for over-educated and negative for under-educated workers as compared to those displaying a perfect match (Rumberger 1987; Groot 1996; Sloane *et al.* 1999; Dolton and Vignoles 2000; Groot and Van

Den Brink 2000; Van der Meer 2006). However, firm-level analyses focusing on the indirect productivity effects attributable to (under) over-education (via the job satisfaction channel) report different results. In this case, over-educated workers show a lower individual productivity as opposed to their properly matched peers. The main explanation relates to the fact that over-educated workers use a lower level of skills with respect to their endowment inducing a dissatisfaction capable to negatively affect their productivity (Vroom 1964). However, this strand of literature does not provide conclusive results. By using cross-sectional data for the Oregon area (US), Hersch (1991) highlights the presence of a negative and significant relationship between job satisfaction and over-education. Analysing the Belgian case, Verhaest and Omey (2006) show that over-educated workers face a higher turnover rate, identifying the latter as a proxy of job dissatisfaction. Relatedly, the theory of career mobility (Sicherman and Galor 1990) assumes that wage penalties for over-educated workers might be compensated by better promotion prospects. Even in this case, the empirical evidence is not univocal. Sicherman (1991) confirms its main predictions using panel data, but Robst (1995) reports statistically fragile or non-significant results.

With the aim of testing the career mobility theory and relying on the German Socio-Economic Panel, Büchel and Mertens (2004) found that overeducated workers in Germany have markedly lower relative wage growth rates than adequately educated workers, casting doubts on the soundness of the career mobility theory's hypotheses. This result is partly corroborated by the evidence provided by Pischke (2001) finding that overeducated workers have less access to formal and informal on-the-job training, being potentially penalized in terms of productivity and, ultimately, wages.

One of the main weaknesses of the empirical investigations focusing on the effect exerted by over-education on productivity is that these studies point to indirect effects operating via wages or via the job satisfaction channel (Hartog 2000).

More recently, Kampelmann and Rycx (2012) and Grunau (2016) have provided evidence regarding the direct impact of over-education on labour productivity claiming for, respectively, a significant and positive and a non-significant effect. Using employer-employee data on Belgium, Mahy *et al.* (2015) report a significant and positive (negative) effect of over (under)-education on firm productivity showing that this effect might vary across firms depending on the share of high-skilled jobs, the technological/knowledge intensity of their activities, and the degree of uncertainty characterizing their economic environment.

Overall, the studies exploring the impact of a lack (or a mismatch) of skills on productivity face a major limitation that is, at the same time, both theoretical and empirical. On the theoretical side, the main drawback consists in overlapping the educational qualification with the skills that a worker actually holds. Skills are, in fact, a radically complex object assuming and changing shape according to the characteristics of the organizational context triggering their activation. Moreover, skills combine, as constitutive elements, both formal and informal education as well as experience. The latter is in fact completely neglected when education is relied upon as the only proxy for skills, in spite of a fundamental role played by tacit and experience-related factors in explaining workers performance (Pfeiffer 2016). Furthermore, workers and firms' performance are increasingly explained by soft (Heckman and Kautz 2012) and social (Deming 2017) skills complementing and sometimes overcoming formal ones in determining individual and organizational productivity. The raising importance of soft and social skills is mostly due to the transition, generalized but uneven among sectors and countries, from a 'Tayloristic' organizational set-up, where tasks are clear, codified and assigned for a long time span to the same worker; to the more flexible and uncertain organizational arrangements characterizing nowadays firms (for a detailed description of this shift and of its organizational implications see, among the others, Vidal 2011). Within such arrangements, the skills most in demand are those referring to adaptability, capacity to solve unexpected problems, propensity towards teamwork and cooperation.

The studies reviewed so far refer to a (neoclassical) theoretical framework simplifying firms' technological and organizational complexity by means of a production function representation. As a result the knowledge which flows, settles and moults within organizations is represented by individual bricks (or by their simple summation) having as a quantitative counterpart (i.e. proxy) the number of workers holding a certain educational degree or the years of schooling they have attained.

In line with a different theorization of the firm (see the foundational works of Penrose 1952 and Nelson and Winter 1982) we attempt here to put the company's knowledge base at the centre of the stage emphasizing the technological and organizational heterogeneities making each firm radically different from one another[1].

This theoretical approach delves deep into the complex interplay between technological innovation, organizational transformations and the evolution of firms' internal knowledge base. Following this line of reasoning, enriching and updating the knowledge base via the development of firm-specific skills, routines and procedures turns out to be the pivotal driver to foster performance and to gain market power (Winter 1997; Kleinknecht *et al.* 2014, Cetrulo *et al.* 2019).

In this work, we look at workers' skills as (dynamic) modules constituting the firm internal knowledge base, that is a complex set of capabilities (made of formal and informal knowledge and abilities) interacting with the (firm-specific) organizational environment. This conceptualization moves away from the simplistic representations of the firm's knowledge base as those previously illustrated. On the other hand, we frame the evolution of the internal knowledge base as the result of companies' strategic reflections and actions. In this way, we explicitly link the dynamics of skills (inside and outside the firm) to the complex array of determinants (economic, technological and organizational) explaining firms' market behaviour.

Not less relevantly, we measure skills in a significantly more precise way as compared to the existing literature (thanks to the richness of the PEC-Inapp firm-level survey), without any need to resort on education-based indicators. In addition, we provide an innovative measure of skill match computed as the difference between skills that need to be updated or added to the firm's internal knowledge base *vis-à-vis* those entering that firm through new hiring flows.

Finally, we consider the role of demand and structural factors as additional drivers of both firm-level decisions in terms of technology and skills change and upgrading; as well as of their economic performance.

[1] According to such a holistic evolutionary perspective, the development of companies' knowledge became a complex and composite firm-specific process. Firms are framed as the loci where different pieces of knowledge, shaped by idiosyncratic learning processes, can be aggregated and catalysed through specific organizational procedures and power structures (Dosi and Marengo 2015).

3. Research questions

As argued in the Introduction, this work lies between the labour economics approach to skill (mis)match, which emphasises the characteristics of workers' individual skill endowment, and the evolutionary approach to innovation and knowledge, underlining the importance of firm-level heterogeneities. Adopting a firm-level perspective, we focus on the interaction between companies' strategic behaviour (i.e. the reflection on skills needs and strategies to enrich/upgrade the knowledge base by introducing new competences), workers' skills captured at a very high level of detail and productivity performance (measured at the company-level). The analysis is articulated in the following research questions.

First, we investigate the relationship between skills need and firms' productivity controlling for a large set of company-level characteristics as well as accounting for sector, geographical area and time. The first research question can be thus be spelled out as follows:

RQ1. *Does having a skill gap in their knowledge base affect companies' performance in terms of labour productivity?*

There is no clear-cut expectations on RQ1, given the heterogeneous meaning that a skills need may assume according to firm-specific idiosyncratic characteristics; as well as to the economic and technological characteristics of the environment where firms operate. As pointed out in the Introduction, the acknowledgement of a skill gap might be part of an overall process of (technological and organizational) expected to have positive effects on productivity. On the other hand, a skill gap might be the signal of an inadequate supply of competences hampering companies' projects of upgrading and growth. A typical example: a firm intending to introduce a process or a product innovation to increase her market shares being frustrated by the lack of the skills required to exploit the productive potential of such innovation. Therefore, the shape of the relationship between productivity and skill gap might assume different shapes and intensity according to the prevalent effect (i.e. dynamism vs lack of resources).

As a second step, we explore the heterogeneity of the skill gap. Not only demand *per se* may appear as a different attribute according to intrinsic firms' differences, but also the nature of the required skills might differently correlate with performance. We select six relevant skill groups: STEM, managerial, technical and operatives, soft, social and humanities related skills. Once again, we are agnostic about the sign of the relationship with labour productivity. Nevertheless, different skill domains are supposed to associate to different technological-organizational needs and competitive strategies. Technical operative skills, mostly characterising the endowment of workers in the middle of the skill distribution, are largely connected to manufacturing activities. Soft skills are in turn cross-cutting and are significantly related to firm-level upgrading strategies aiming (in many cases) at a more flexible, technologically enhanced and internationalized organizational set-up. A similar argument might hold for social skill and humanities (Deming 2017). The latter, however, can also be linked to adoption of high-level managerial practices (i.e. among the others, HR practices and marketing) which are increasingly related to the use of high-profile resources with strong competences in humanities related skills (i.e. these skills are considered increasingly important to perform tasks, as HR and project management, requiring particular abilities in interacting, understanding and persuading others). As a result, the relationship between skill gap, differentiated by skill domain, and productivity is expected to be significantly heterogeneous according to the domain taken into account. This extension of the first research question can be spelled out as follows:

RQ1a. *Does the relationship between skill gap and labour productivity change in shape and intensity when different skill domains (i.e. STEM, managerial, technical and operatives, soft, social and humanities) are separately accounted for?*

RQ2 regards the ability of a firm to fill the skill gap by acquiring the needed competences on the labour market. That is, we test to what extent the ability to fill promptly the skill gap by injecting (via new hires) the needed skills into the firm organizational perimeter has a statistically significant effect in terms of productivity performance.

The expectation here is more clear-cut as compared to the previous discussion on the skill gap-productivity relationship. In this case, companies capable to fill rapidly their skill gap are expected to be also more successful in achieving upgrading and competitive strategies. RQ2, thus, can be phrased in the following way:

RQ2. *Is there a relationship between firms' productivity performance and their ability to match their skills needs in the labour market via new hires?*

4. Data, descriptive evidence and the 'skill match' indicator

In what follows, we illustrate the integrated database adopted for the analysis reporting, for each component, descriptive evidence concerning the key variables under investigation. We merge four major sources of statistical and administrative information. The *Indagine sulle Professioni e le Competenze* (PEC, Inapp) provides survey-based information on a representative sample of Italian firms' with respect to their skills needs, innovative activities, internationalization strategies besides a number of standard variables on size and characteristics of the employed workforce. The *Analisi Informatizzata delle Aziende Italiane* (AIDA, Bureau Van Dijk) reports certified balance-sheet information (used to retrieve labour productivity for all the companies included in the analysis) for the universe of Italian limited liability companies (i.e. the information are restricted to limited liability companies which are the ones that have to publish their balance-sheet). The *Comunicazioni Obbligatorie* (COB, Italian Labour Ministry) provides information on all 'contractual events' (i.e. new labour contracts, terminations, transformations of contract-type) allowing to trace, for all Italian companies, labour (inward and outward) flows distinguishing the latter by occupation. Finally, the *Indagine Campionaria sulle Professioni* (ICP, Inapp) – the Italian O*NET (see Gualtieri *et al.* 2018 for a thorough description) – comprises more than 300 variables on task, skills, work attitude for the whole spectrum of Italian occupation (at the 5th digit of the Italian occupation classification).

Table 1 reports the full list of variables adopted for the analysis indicating name, scale and characteristics and source.

Table 1. Variables – description and sources

Variable	Description	Source
Skill-related variables		PEC
Skill Demand (intensity)	Number of skills declared as in-need by firms among the five perceived as the most important for their production activity.	
Skill Demand (categorical)	Categorical variable with four levels: 0 for no demand, 1, 2 and 3 for increasing number of skills needed.	
Skill Demand by groups (intensity)	Demand for skills by 6 groups (one variable for each group): managerial, STEM, soft, social, humanities, technical operatives. The variable reports the share of skills needed over the total amount of skills in that group.	
Skill match	Share of skills needed (PEC) entering *via* new hires (COB) and qualified in terms of skills using the 4-digit O*NET-type information (ICP).	PEC; COB; ICP
Firms characteristics		PEC
Innovation variables (dummy)	Process, product and organizational innovations introduced (or not) during the last 3 years.	
Internationalization (dummy)	Internationalization depending on whether the firm sells her products abroad.	
Market-related variables (categorical)	Type of customers in terms of sales (other firms, Retailers/wholesales, Public bodies, families).	
Size	Number of employees. Rescaled through Inverse Hyperbolic Sine (HIS) transformation.	
Economic variables		
Labour productivity	Firm's value added (in euros, AIDA) over the number of employees (PEC) plus one (in order to count the role of the entrepreneur micro firms). Rescaled through IHS transformation.	AIDA and PEC
Demand - deviation from VA	Deviation of a firm's VA (in euros) from the average macro-sectoral VA. Rescaled through IHS transformation.	AIDA
Tangible fixed assets	Tangible fixed assets (in euros) from firms' balance-sheet. Rescaled through IHS transformation.	AIDA
Age	Years from firm foundation. Rescaled through IHS transformation.	ASIA
Turnover (compensation)	New hiring (of any duration and type of contract) over separations. Rescaled through IHS transformation.	COB
Turnover (overall)	New hiring plus separations over mean total workforce. Rescaled through IHS transformation.	COB

The first component of our integrated database is represented by the AIDA archive. This is the source adopted to measure Italian firms' labour productivity[2]. AIDA provides certified information on the balance-sheet of the universe of Italian limited liability companies. Balance-sheet information allows overcoming the potential limitations of survey-based self-reported variables that, particularly in the

[2] For each company included in the AIDA archive, a detailed financial statement is available in accordance with the related European Commission Directive. Among the variables included in AIDA there are: sector of activity and commodity codes, number of employees, shareholders and participations, governance characteristics, default probability, rating and credit score, sector reports, news and extraordinary finance operations.

case of variables as the value added, may suffer of a 'respondent-bias'. In fact, when responding to surveys about the economic performance of their firm entrepreneurs might, in some cases, be incline to inflate (i.e. to provide a better impression of their company as compared to the reality) or to underestimate (i.e. in this case fearing to provide information implying consequences in terms of tax assessment) such performance. For the sake of this study, therefore, we rely on the subsample of limited liability companies surveyed in the PEC (see below for details on this survey). For these companies, we compute labour productivity as the ratio between the value added reported in AIDA and the number of employees as reported in the PEC[3]. An additional set of variables are drawn from the AIDA archive (see table 1 for details), namely the deviation of the firm-level value added from the sectoral median (a proxy of the demand flows faced by the individual firm); and tangible fixed capital (proxy of the assets amount of that firm).

4.1 The demand side: PEC

The second component of our integrated database – the component reporting information on the 'demand for skills' on the firm side – is the PEC. The PEC survey provides information on a representative sample of 35.000 Italian firms stratified by sector, size and geographical area. Three editions are available up to date: 2012, 2014 and 2017. The main aim of the survey is to collect company-level information regarding the contingent skills needs of the employed workforce (information are reported by entrepreneurs and HR responsible). Within-firm skill needs are mapped relying on the O*NET repertoire: respondents are asked to identify abilities, skills and knowledge in need using the taxonomy comprised in the relevant O*NET sections. Firms are asked to declare up to five occupations recognized as 'in need to enrich and/or upgrade their skills'. For each occupation identified as in need of skill upgrading/enrichment, respondents are than asked to identify the specific O*NET abilities and knowledge to be added. In addition to these skill related variables, the PEC survey provides a set of variables concerning the characteristics of the relevant market to which the surveyed company refers; the type of innovative activity (product, process and organizational innovation), if any, that respondent firms declare to carry out; degree of internationalization. The PEC's large size (i.e. 35.000 firms) and the accurate sample design ensures a strong representativeness, even though the match with AIDA reduces the sample considerably. It is worth noticing that the PEC is a rather unique source of information since, to the best of our knowledge, there are no other sources providing such a detailed and systematized set of variables on companies' skills needs and knowledge base characteristics.

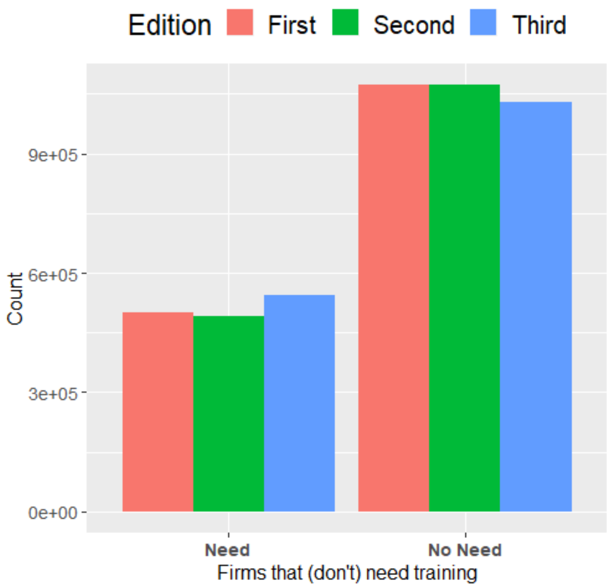
In figure 1, we count firms according to their need to add new skills or to, more broadly, enrich their knowledge base. We define a firm-level indicator of Skill Demand (SD*,* hereafter) taking value 1 when *at least* one skill needs to be added to the firm knowledge base (i.e. therefore *at least* one profession is in need of enriching/upgrading her skills), 0 otherwise.

The share of firms declaring to have a skills need is constantly around 30% of the total Italian population, irrespective the PEC wave (2012, 2014 and 2017) we take into consideration. The capacity

[3] A validity check of the PEC variable on the number of employee has been carried out using the Archivio Statistico delle Imprese Attive (ASIA) provided by ISTAT. The test has confirmed the reliability of the PEC information on employees, details are available upon request.

to recognize a skills need, however, is not homogeneously distributed across firms. In particular, size may positively correlate with propensity to recognize and declare such a need. Moreover, the same skills need is expected to be unevenly distributed across firms even in terms of intensity (i.e. number of skill to be updated/added to the company's knowledge base).

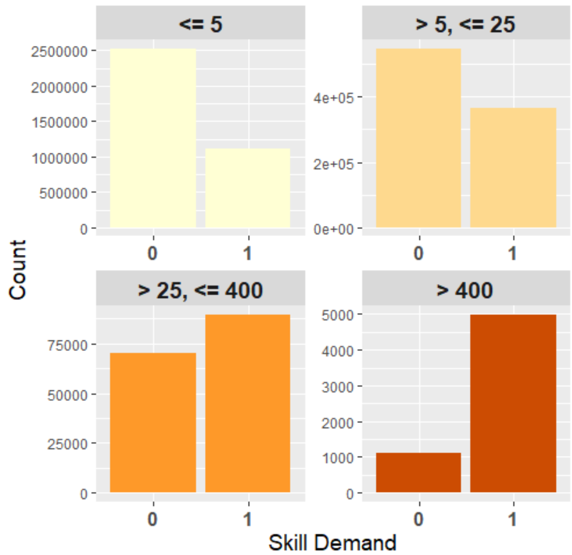
Figure 1. Firms' training needs



Source: Authors' elaboration on PEC-Inapp data

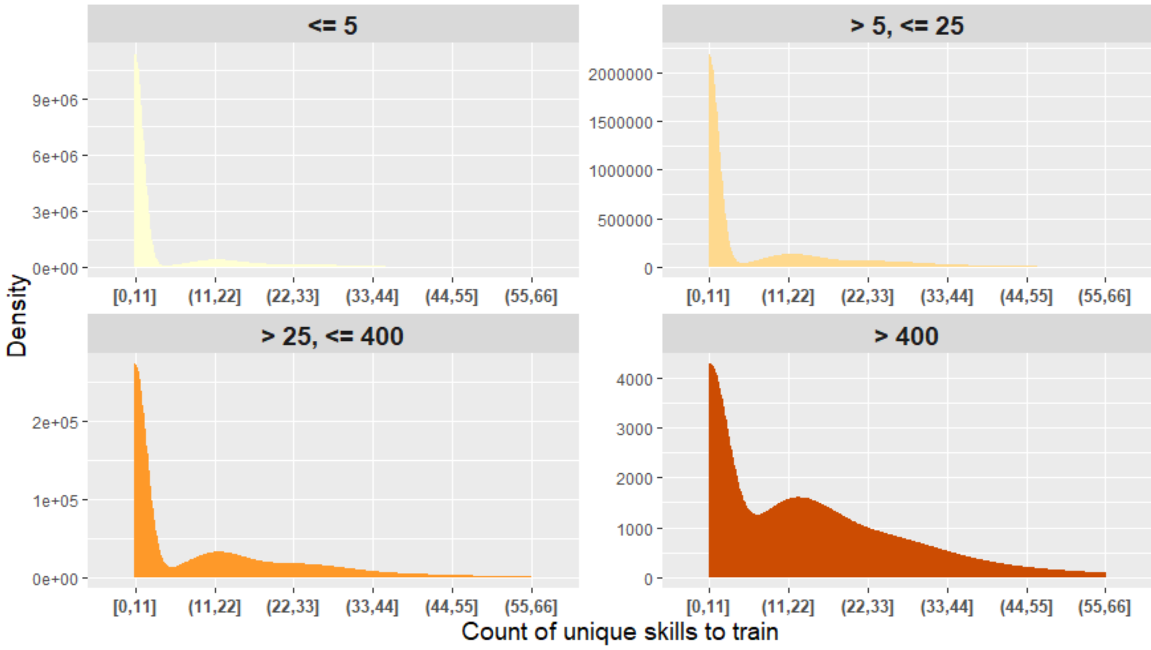
To verify the extent of such correlation (skills need vs firm size), we report a set of descriptive statistics showing the by-size distribution of the SD indicator (figures 2 and 3). As expected, large firms have a relatively higher probability of acknowledging and identifying their skills need.

Figure 2. Skill Demand and firm's size



Source: Authors' elaboration on PEC-Inapp data

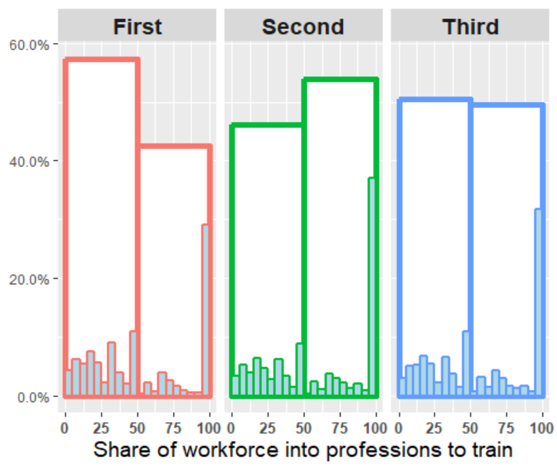
Figure 3. Count of unique skill to train and firm's size (workers)



Source: Authors' elaboration on PEC-Inapp data

Indeed, even if SMEs are expected to acknowledge and manifest skills needs with a relatively lower probability than big firms (if anything, due to their smaller and possibly less diversified workforce) their smaller size (and scope of activities) can, in turn, make them quite accurate in understanding their needs. On the other hand, big firms are more likely to be endowed with financial, managerial and training resources allowing them to adjust their knowledge base relying on internal resources and routines rather than resorting on the labour market. To evaluate descriptively the relevance of the skills need identified by PEC firms, we order the latter according to the relative weight of workers in need of skill upgrading over their total workforce. Looking at the large bars in figure 4, it emerges that for a share comprised between the 30% (2012 wave) and the 50% (2017 wave) the workers in need of skill enrichment/upgrading are more than half of the employed workforce.

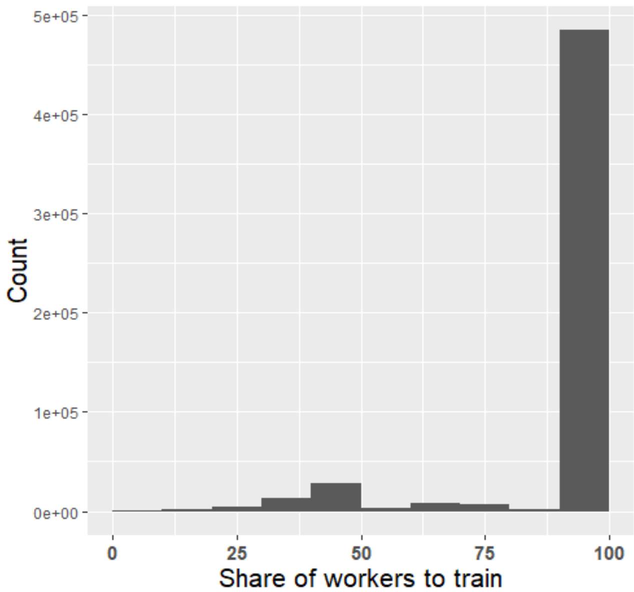
Figure 4. Share of workers in need of skill enrichment/upgrading



Source: Authors' elaboration on PEC-Inapp data

Interestingly, for a remarkable number of firms the need of skill upgrading regards almost all their workers. The numbers in figure 4, however, risk providing an inflated representation of the within-firm skills need. By reporting the ratio between the absolute number of workers belonging to occupations identified as in need and the total workforce employed by the PEC firm, in fact, we face the risk of inflating the numerator. Such an overrepresentation of the skills need might occur if workers belonging to an occupation recognized (by the PEC respondent) as in need of upgrading are not 'individually in need of skill upgrading'. Figure 5 partially solve the problem, providing precious information on the matter for the year 2017 only. In the 2017 PEC wave, in fact, firms are asked to estimate the precise number of individuals in need of skill upgrading. Therefore, it is possible to compute more precise shares and to exactly evaluate the 'quantitative' relevance of the skills need. As the figure shows, for the vast majority of firms declaring to face a skills need, the number of workers in need of skill upgrading is equal to the total volume of workers belonging to that occupation. Such evidence reinforces that of figure 4, hence the assumption that the SD indicator is substantially related to the knowledge base of the firm.

Figure 5. Share of workers in need of skill enrichment/upgrading (year 2017)



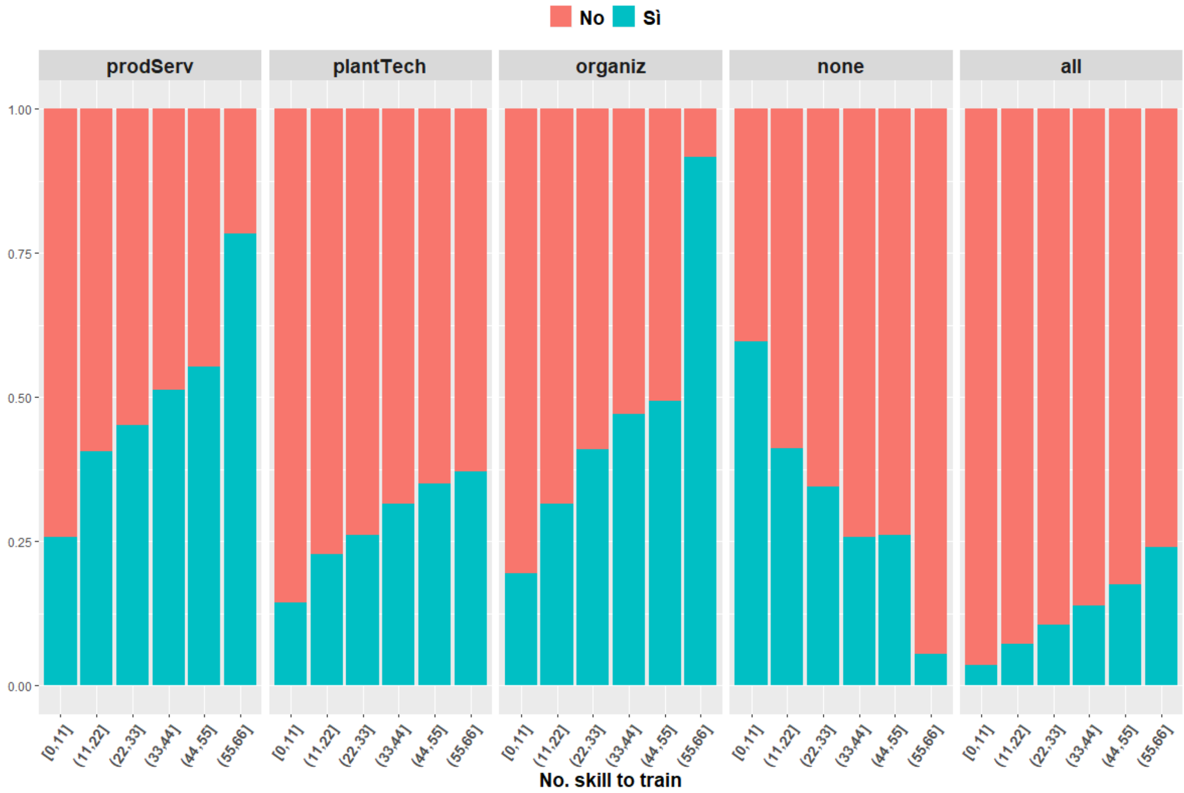
Source: Authors' elaboration on PEC-Inapp data

Figure 6 reports the count of unique skills that need to be added to the firm knowledge base (*Nskill*) against the innovative strategy adopted by such firm during the previous three years. The SD indicator is inspected against three innovation variables, namely product/service (*prodServ*), process (*plantTech*) and organizational (*organiz*) innovation.

The economics of innovation and knowledge literature brought evidence of a strong complementarity between the knowledge base of a firm and its propensity and ability to innovate (see for example Griliches 1998; Pakes and Griliches 1998; or more recent contributions such as Antonelli and Scellato 2013; Colombelli *et al.* 2013).

As data in figure 6 clearly display, the SD is unambiguously correlated with intensity of the innovative activity, irrespective the considered dimension (i.e. product, process or organizational innovation).

Figure 6. Number of skills to be added and firms' innovative activity



Source: Authors' elaboration on PEC-Inapp data

4.2 The supply side: the COB-ICP match

The third and final chunk of data comprised in our integrated dataset, apt to approximate the supply of skills, includes the match between the COB and ICP archives. The COB-ICP match is the result of a novel approach we designed to retrieve 'skill supply' data at the firm level.

The COB is an administrative archive owned by the Italian Labour Ministry and tracing all contractual events (i.e. new contracts, terminations, transformation, see above) allowing to capture, for each Italian firm, workers inflow and outflows. For each contract, the COB provides, besides the firm and the workers fiscal identifier, a large amount of worker-level information as gender, age, occupational category, educational status and contractual type.

Relying on the 4-digit occupational code, we merged the information on contracts stemming from the COB with those on skill included in the ICP.

The ICP[4] involves a representative sample of 16.000 workers covering the whole spectrum of the Italian 5-digit occupations. Relying on about 1-hour long face-to-face interviews, the ICP is capable to provide more than 400 variables on skill, work contents, attitudes, tasks and many other subjective and objective information on occupations.

[4] For this analysis we rely on the latest available information referring to the year 2012.

Our goal is to qualify the firm inflow of workers (net of outflows within three months of the starting date of the contract) in terms of the skills they bring in.
In order to be consistent with the information on skill demand available in the PEC, we restricted the section of the ICP variables by relying on competence and knowledge items[5]. The build-up of the indicator is made of two steps. The first regards the qualification of workers' inflow in terms of prevalent skills.

As in the American O*NET (see Autor *et al.* 2003 for a thorough description of the O*NET repertoire), each ICP competence/knowledge item comes with two values, one related to its importance (*vis-à-vis* the other skills characterizing a specific occupation), the other regarding the relative complexity of the former. The two dimensions are rather correlated and for the sake of our analysis, in line with previous studies using the ICP database (see Gualtieri *et al.* 2018) we rely on the *importance* scale to characterize workers inflows. Thus, we end up with a matrix M, with all the Italian 4-digit occupations[6] as rows $i \in [1, 507]$ and competence and knowledge items as columns $j \in [1, 68]$. Each occupation-competence cell, thus, comprises the mean importance $m_{i,j}$ of the item it_j for the respondents (surveyed by the ICP 2012 wave) within that occupation i.

We qualify each profession in terms of 'prevalent skills' exploiting the joint rows (M_i)-column (M_j) distribution of matrix M. In this way, we are capable to qualify each 4-digit Italian occupation in terms of both within (verifying if a specific skill j is among the more important among those characterizing a certain occupation i or not) and between-occupation skill prevalence. More specifically, we define a skill j as prevalent for an occupation i when $m_{i,j}$ belongs to the upper 30% of *both* the M_i and the M_j distributions.

Finally, we assign to each firm k a vector of skill inflow s at each point in time. Thus, each firm is characterized by the type of prevalent skills inflowing through workers hired by these firms and belonging to specific occupations as reported by the COB[7].

4.3 The skill match indicator

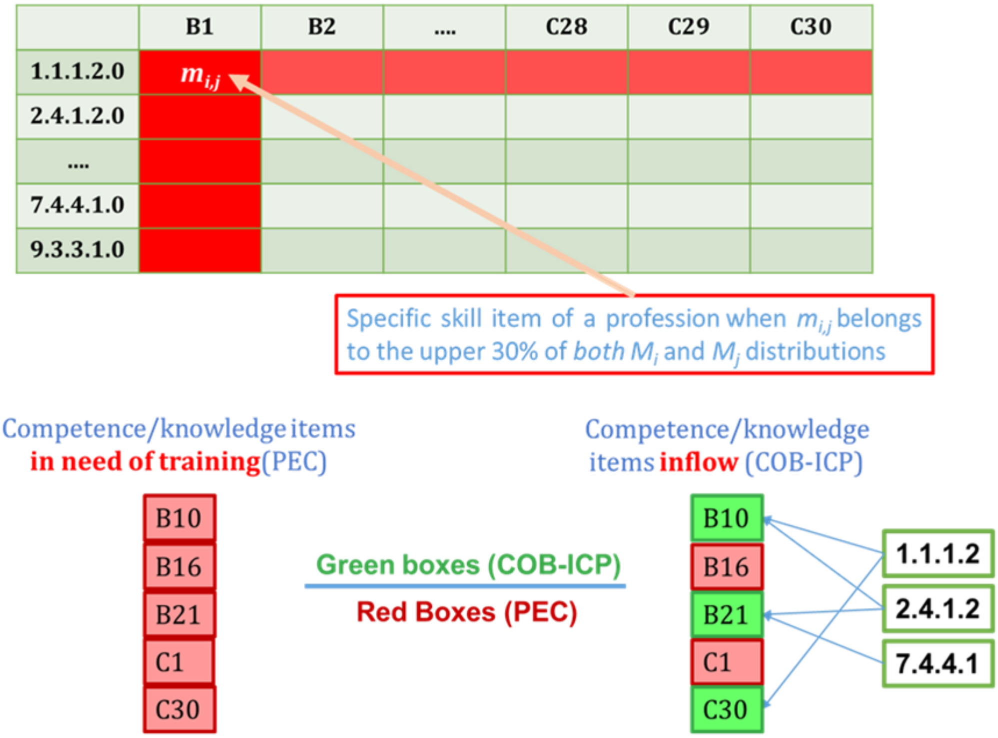
The characterization of firm-level skill inflows obtained by exploiting the ICP-COB integrated information is the base upon which we built our skill match (SM) indicator. The steps followed to compute the SM indicator are:

First, we merge PEC firms fiscal IDs with the same identifier present in the COB-ICP so to match information on SD with those on the inflow of competences and knowledge. The SM indicator is

[5] The questions on the skills need included in the PEC survey are based on the O*NET repertoire as in the case of the ICP. However, the PEC questions are a subsample of those in the ICP, listing only items related to competences and knowledge.
[6] Excluding the armed forces, which are not considered in the ICP-Inapp survey.
[7] Notice that skill inflows are not weighted by the number of new employees entering the firm. At this stage of the analysis, we limited the investigation to the observation of the type of (prevalent) skill entering into the company organizational perimeter at a certain point in time.

than computed as the share of skills entering via new hires (information drawn from the ICP-COB match, see above) over those that the entrepreneur identify as in need to be added to the company's knowledge base (information drawn from the PEC, see above). Figure 7 provides a graphical illustration of the procedure.

Figure 7. The methodology adopted to compute the Skill Match indicator

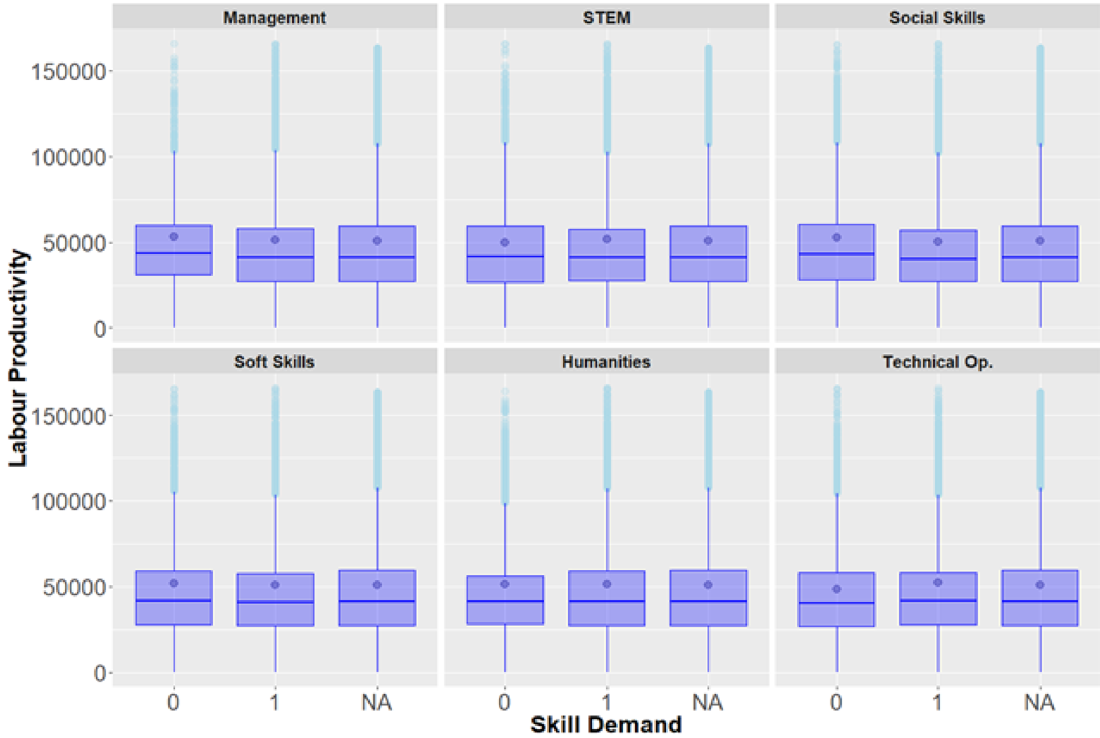


As spelled out in the theoretical section of the paper, the aim of this work is to investigate the relationship between SD and SM, on the one hand, and labour productivity, on the other. In this respect, figure 8 and figure 9 provide a first descriptive exploration of this relationship, supporting a positive correlation between SM and productivity, whereas spotting no evidence on the demand side only.

Notice that figure 8 breaks down SD into six sub-categories, namely managerial, STEM, humanities, technical, social and soft skills[8]. All indicators assume value 1 when a firm identify one (or more) skills belonging to a specific one out of the six groups, 0 when the skill in need belongs to another skill group, and NA when there is no skills need.

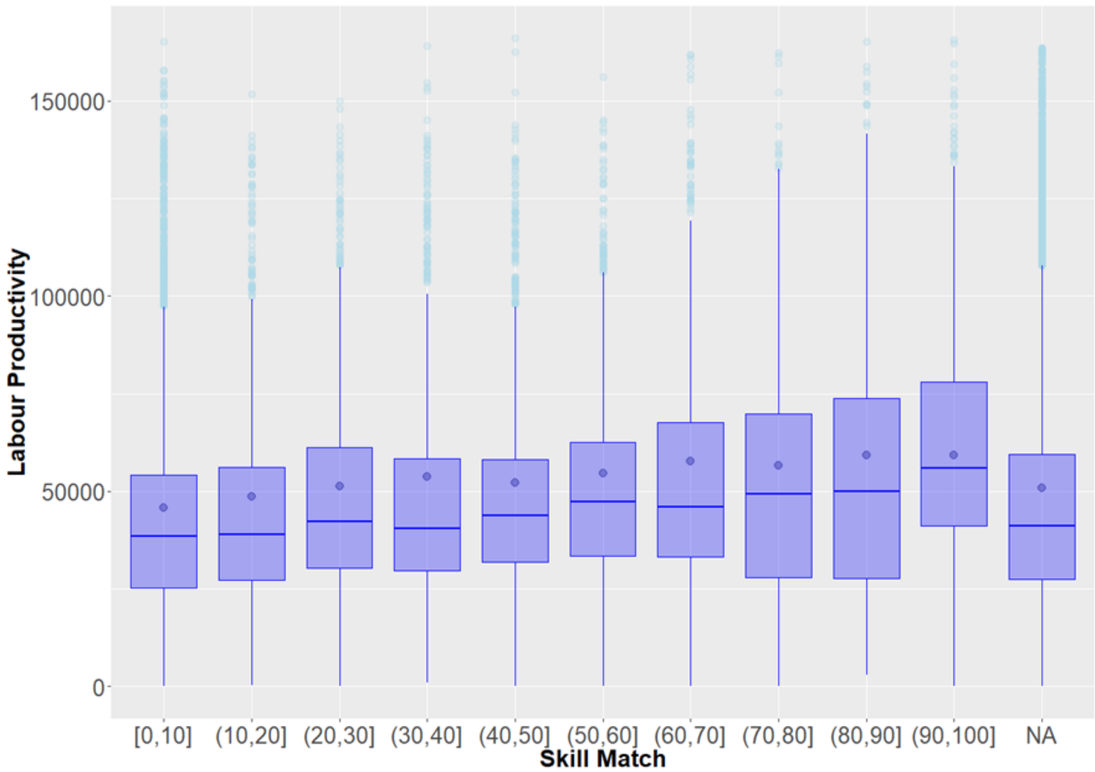
[8] Management: B1-B6, B29-B30; C10, C23, C32-C35. STEM: B9-B11, B14-B17, B31; C5-C6, C18-C22, C29-C30. Social Skills: C11-C15. Soft skills: C7-C9, C16-C17, C27, C31. Humanities: B18-B28, B32; C1-C4. Technical Operative: B7-B8, B12-B13, B33; C24-C26, C28. Find the Italian 2012-2014 questionnaire at: https://inapp.org/it/dati/Audit. Once again, each group indicator takes non-zero value when at least one item belonging to the respective group is in demanded.

Figure 8. Skill Demand by groups and labour productivity



Source: Authors' elaboration on AIDA-PEC data

Figure 9. Skill Match and labour productivity



Source: Authors' elaboration on AIDA-PEC data

5. Econometric strategy and results

The relationship between skills need, skill (mis)match and labour productivity is now explored relying on regression analysis. In what follows, we illustrate the three specifications adopted to analyse the relationships at stake. Then, we describe the econometric strategy. Finally, we report the results reflecting the adopted specifications and the order of the RQs listed in section 3.

5.1 Equations

$$Lab\ Prod_{i,s,a,t} = SD_{i,s,a,t} + X_{i,s,a,t} + \rho_t + \sigma_s + \varphi_a + \varepsilon_{i,s,a,t} \quad (1)$$

$$Lab\ Prod_{i,s,a,t} = Manag_{i,s,a,t} + STEM_{i,s,a,t} + Soft_{i,s,a,t} + Social_{i,s,a,t} + Human_{i,s,a,t} + TechOp_{i,s,a,t} + X_{i,s,a,t} + \rho_t + \sigma_s + \varphi_a + \varepsilon_{i,s,a,t} \quad (2)$$

$$Lab\ Prod_{i,s,a,t} = SM_{i,s,a,t} + SD_{i,s,a,t} + X_{i,s,a,t} + \rho_t + \sigma_s + \varphi_a + \varepsilon_{i,s,a,t} \quad (3)$$

In equation (1), labour productivity (*Lab Prod*)[9], rescaled through the Inverse Hyperbolic Sine (HIS) transformation, of firm *i* belonging to sector *s*, geographical area *a*[10] and observed at time *t* (2012, 2014 and 2017), has been regressed against skills demand. The skill need is captured relying on a categorical variable reporting the intensity of demand in terms of number of skills needed. Therefore, in equations (1) and (3), SD enters in four levels (no demand, low-medium-high demand). The matrix *X* includes a number of controls reflecting key demand and supply factors likely to affect productivity dynamics. In order to account for the relationship between capital endowment and production capabilities, we include a variable reporting, for each firm, the value of (tangible) fixed assets. Another crucial element concerns the role of demand as a productivity (and innovation) enhancing factor (Schmookler 1976; Mowery and Rosenberg 1979; Scherer 1982; Piva and Vivarelli 2007). We control for demand by plugging in the deviance of each firm's VA from the sectorial (VA) mean. The type of market the firms rely upon is captured by a categorical variable reporting information about the prevalent customers to which companies sell their goods and services: households, retailers, other firms and public administration. A dummy variable assuming value 1 if the firm is internationalized (i.e. sells abroad) and 0 otherwise is also included. Innovation is controlled for relying on a set of CIS-type (dummy) variables providing information concerning the introduction (during the previous three years) of product, process and organizational innovation. Moreover, we control for firm size and age. It is worth underlining that, despite being quite a standard variable in firm-level analysis, controlling for size is of paramount importance in our case since large companies are expected to be more capable to recognize and evaluate their skills needs (see the discussion in the Introduction) as well as to be

[9] Labour productivity is the ratio between VA and total occupation (plus one, in order to account for the role of the entrepreneur in micro firms) for i at the time t.

[10] Sectors and geographical areas correspond to the sampling strata of the survey, and are: wood and Paper; Metallurgical; Mining; Food and Textile; Chemicals, Pharmaceuticals and Plastics; Communication, Financial Services and other Services to enterprises; Energy, Water and Garbage; Non-Metalliferous Minerals; Construction; Electronics; Commerce, Transportation and Tourism; Furniture and Other; Education, Healthcare and other Services to persons. As for geographical areas: North-West, North-East, Centre, South and Islands.

endowed with stronger capabilities to address the latter. Given that our investigation deals with the propensity of a firm to enhance its workforce, it is important to account for the entrepreneurial "culture" in terms of inclination towards labour relations management. Therefore, two variables measuring turnover rates (overall and compensation) step in. Finally, each specification control for time, macro-sector and macro-region the observed firm belong to.

In equation (2), the relationship between labour productivity and SD is analysed by distinguishing the latter in terms of skill domains (see above). In terms of controls, equation (2) perfectly overlaps what has been already described for equation (1) and (3).

Equation (3) is the one allowing studying the relation between firms' productivity and degree of SM (see the previous section for a thorough description of the SM indicator). Besides the matrix of controls X, equation (3) includes also the categorical variable capturing SD. Therefore, this specification allows accounting, simultaneously, for both the presence (and the intensity) of a skills need; as well as for the ability of firms to match their need with the competences offered by the labour market.

5.2 Econometric strategy

In order to estimate the impact of skill need and the degree of skill match on Italian companies' labour productivity we rely on an articulated empirical strategy. The reference of our newly built integrated dataset is the PEC survey, which is a Repeated Cross-Section (RCS, with a small panel component). The adopted sample includes ~36.000 Italian companies. However, given the empirical strategy we follow – a random intercept model with time-demeaned variables estimated through ML, following the indications of Lebo and Weber (2015) and Barr et al. (2013) – we are in need of a large number of control variables, causing us to lose further observations. As a result, the model specifications go from a maximum of ~20.000 to a minimum of ~9.500 observations.

Given the cross-sectional nature of the data and the way the most important explanatory variable (SM) is built, two major drawbacks must be addressed. As Lebo and Weber (2015) state, RCS are a data format increasingly available in social sciences, allowing researchers to delve into questions otherwise inaccessible because of lack of longitudinal data.

The drawback to the empirical difficulty in accounting for the invariant, fixed, individual component of the variance at stake. In our case, the extremely short time span makes impossible to compute and clear out auto-regressive components from regression variables (we simply demean each variable with its yearly mean). Nevertheless, the repeated nature of RCS data provides the chance to exploit hierarchical, random intercept models (Raudenbush and Bryk 2002) taking advantage of the nested structure of the survey design (observations nested in regions, sectors and waves, in the PEC case). Moreover, the unique database we built, integrating administrative and high-quality survey data, allows us controlling for a great number of firms' characteristics. In so doing, we are able to capture almost all the salient firm's characteristics thus reducing the potential bias associated to the presence of idiosyncratic effects.

Another relevant issue concerns the risk of selection bias. The companies surveyed by the PEC and signalling a skills need might in fact be a *selected chunk* of the whole PEC sample. One might reasonably argue that those companies acknowledging a skills need are in a rather 'good shape' as compared as compared to other firms (i.e. when swimming in bad waters, companies are less likely to be prone towards strategic self-reflection); structurally more incline to acknowledge such type of needs (i.e. an argument applying, for example, to large firms – see the discussion above); and/or located in areas and sectors facing a phase of upgrading and change. Even if these elements are partly controlled for via the controls included in matrix X (see above), a relevant risk of selection remains.

To address this identification issue, we adopt the Heckman 2-step procedure (Heckman 1976). As a first step, a Probit regression is run to estimates the probability, for each firm, to manifest a skill training need (SD = 1). Out of this estimation, the Inverse Mills Ratio (IMR) for each observation is computed. The IMR will account for the selection probability related to each observation in the second step. Indeed, the idea is to treat the selection bias as an omitted variable bias (Wooldridge 2010). In the second step, an OLS regression fits the data with the preferred model augmented with the IMR variable. In theory, the set of explanatory variables for the first and the second step may coincide. However, in order for the IMR to convincingly remedy for the omitted variable bias, there should be an explanatory variable in the first step that affects the probability of manifesting a skills need, without directly influencing labour productivity. The variable we choose for this end is the share of laureates in the region where the firm resides, some decades before. Specifically, we recover from the National Institute of Statistics (Istat) the variable for 1961, 1971 and 1981, matched with, respectively, 2012, 2014 and 2017. The rationale for such variable is that the educational attainments of the workforce are reasonably correlated with its skill endowment, therefore determining the supply of skills for firms in the territory. Labour productivity, instead, is much more contingent of contextual factors other than the educational level of the labour supply. In other words, we assume that the educational level of the population, as a proxy of the educational system of the territory, explains a substantial part of the same population's skill endowment, whereas it accounts for a little portion of firm's labour productivity. Moreover, going back of some decades, in virtue of the intergenerational transmission of education levels, we posit that the direct effect on productivity becomes negligible, whereas the effect on the skill endowment is not.

Equations (1), (2) and (3) are than estimated adopting the following procedure. First of all, we implement a random intercept model (with intercepts for time, macro-sector and macro-region) on the RCS database (see the first three columns of table 2), with the variables of interest demeaned by their yearly mean (i.e. var – mean (var)) in order to reduce as much as possible the common time trend. Then, due to the potential selection bias we implement the Heckman's procedure in order to retake the estimation of equations (2) and (3) (columns two and three of table 2), with SD measured by the count of skills needed instead of the categorical variable due to the singularity issues emerging during the second step of the procedure. All the controls enter at once. From Istat-CVTS we take information on the number of firms implementing some sort of training over the time-span covered by the survey (2010 and 2015). We use this information to build a ranking of our macro-sectors in terms of propensity to train the workforce. Out of this ranking, we create a categorical variable for low, medium and high training (at the macro-sectoral level). The table (in the appendix) report the results. In the first column, there is the RCS baseline equation (3) with an interaction between SM and the training dummy. It works as a test of significance for the difference of the SM coefficients across the groups defined by the training dummy. The last three columns display the Heckman's model results (again equation (3) but by training group). In parenthesis we have the confidence intervals.

5.3 Results

Overall, we do not find evidence for a significant effect of low and medium intensity of skill training demand on labour productivity (table 2, column 1). However, high SD intensity appears significant and positive, possibly depicting firms' manifested demand as a signal of their strategic awareness – more conscious about their productive potential and well-managed firms are those who have better results. However, the picture changes when the skill demand is disaggregated into six sub-groups reflecting different competences/knowledge domains (table 2, column 2). This means that distinguishing for different competences/knowledge domains is insightful but it also suggests the need of investigating in a deeper way the sub-groups definitions. On the one hand, social and technical operative skills are always negatively and significantly associated to productivity. In the first case, the negative correlation might be related to the lack of an adequate supply of an increasingly important category of skills (for a discussion concerning the importance of social skills for worker and firm-level productivity, see Deming 2017). In the case of technical-operative skills, the negative correlation might mirror an overall weakness of the manufacturing sector (i.e. wherein this type of skills are prevalently demanded) resulting, among the other things, in the difficulty, on the firm side, in finding the needed competences. Managerial, STEM, and humanities are, in turn, significantly and positively correlated to productivity, all across the specifications. Behind these positive correlation there might be – in the case of Managerial and STEM skills – the complementarity between the latter and the introduction of new technologies (or the adoption of a renewed organizational set-up). In the case of Humanities, in turn, the increasing importance psychology and communication-related skills (i.e. particularly relevant for the implementation of high-level HR management tasks) can explain the positive and statistically significant relationship with productivity. The SM index, is consistently significant and positive irrespective the adopted specification. It unambiguously indicates that fulfilling skills needs provides firms with a more solid, befitting and productive internal knowledge base (table 2, column 3).
In order to estimate the three models of interest in the RCS setting, we retrieve insights from the work of Lebo and Weber (2015). The double filtering with ARFIMA they propose is not suitable in our context because we only have three time instances – not enough to control for integration. Therefore, we opt for a hierarchical model clustering data by sector, area and year. Moreover, we demean variables (subtracting the yearly mean) clearing out the structural, common component. In this way, we are capable to account for (common) temporal and structural trends likely to affect the companies included in the sample.
The positive and significant relationship between skill match (SM) and productivity is robust to potential selection effects (i.e. columns 4 and 5 report the results of the Heckman specification).
Remarkably enough, the indicator capturing the demand-pull effect (i.e. the deviation from sectoral average value added) is always significant and positive, confirming the key role of demand in explaining firm-level performance (for a thorough discussion, see Piva and Vivarelli 2007). Similarly positive and significant is the variable related to intangible assists while the picture concerning the various innovative activities is rather mixed. Organizational and product innovations are negatively correlated with productivity, whereas a positive effect emerges only looking at process innovation. Two potential explanations. In the first case, the positive impact on revenues and value added that product and/or organizational innovations are expected to generate might take some time before showing up in terms of performance (i.e. productivity).

Table 2. Repeated Cross-Section framework, all models. Continuous variables are demeaned by survey edition's averages to control out the structural component. Hierarchical model estimated through ML

	Dependent variable				
	Labour Productivity				
	linear mixed-effects			***selection***	
	SD (1)	**SD by group (2)**	**SM (3)**	**Heckit - SD by group (4)**	**Heckit - SM (5)**
Skills demand (Low)	0.063 (-0.212, 0.339)				
Skills demand (Medium)	0.005 (-0.274, 0.283)		-0.051 (-0.371, 0.270)		
Skills demand (High)	0.694*** (0.223, 1.165)		0.750*** (0.265, 1.234)		
Manag. demand (share)		1.324*** (0.513, 2.135)		1.325*** (0.506, 2.144)	
STEM demand (share)		1.115** (0.061, 2.168)		1.086** (0.062, 2.110)	
Social Skills demand (share)		-1.799*** (-2.383, -1.215)		-1.770*** (-2.366, -1.174)	
Soft Skills demand (share)		0.001 (-0.624, 0.627)		-0.040 (-0.679, 0.598)	
Humanities demand (share)		1.165** (0.035, 2.295)		1.200** (0.011, 2.389)	
Technical Operatives demand (share)		-0.924** (-1.746, -0.103)		-0.923** (-1.685, -0.162)	
Skills demand (number of skills)					-0.021 (-0.100, 0.057)
Skill Match			0.342*** (0.295, 0.390)		0.336*** (0.287, 0.386)
Deviation from mean VA (Sector)	0.172*** (0.151, 0.193)	0.168*** (0.141, 0.194)	0.152*** (0.126, 0.178)	0.204*** (0.164, 0.243)	0.186*** (0.148, 0.225)
Tangible fixed assets	1.173*** (1.120, 1.226)	1.299*** (1.222, 1.377)	1.291*** (1.214, 1.367)	1.327*** (1.207, 1.447)	1.310*** (1.192, 1.428)
Product Innovation (3 years - YES)	-0.468*** (-0.700, -0.236)	-0.216 (-0.544, 0.112)	-0.370** (-0.695, -0.045)	-2.074*** (-3.222, -0.925)	-2.126*** (-3.258, -0.994)
Process Innovation (3 years - YES)	0.196 (-0.069, 0.460)	-0.026 (-0.387, 0.336)	-0.063 (-0.421, 0.295)	-0.774** (-1.456, -0.091)	-0.768** (-1.437, -0.098)
Organizational Innovation (3 years - YES)	-1.104*** (-1.336, -0.872)	-1.059*** (-1.384, -0.733)	-0.956*** (-1.278, -0.634)	-2.884*** (-4.014, -1.754)	-2.688*** (-3.802, -1.574)
Other Controls*	yes	yes	yes	yes	yes
Observations	20,689	9,469	9,469	22,166	22,166
Log Likelihood	-79,846.450	-36,343.100	-36,269.350		
Akaike Inf. Crit.	159,734.900	72,734.210	72,580.690		
Bayesian Inf. Crit.	159,901.600	72,905.940	72,730.960		
Rho				-0.968	-0.956
Inverse Mills Ratio				-11.120*** (3.279)	-10.731*** (3.238)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Ref Market: Firms. Ref Skills demand: None
* Other controls include: Size, Market variables (Retailers/wholesales/ecc., Public bodies, Families), Internationalization, Age and Turnover rate (compensation and overall)

Table 3. LSDV regression with clustered standard errors (sectoral level)

	Dependent variable			
	Labour Productivity			
	linear mixed-effects	***selection***		
	Full sample (1)	**Heckit - Low Train (2)**	**Heckit - Medium Train (3)**	**Heckit - High Train (4)**
Skills demand (Medium)	-0.068 (-0.454, 0.319)			
Skills demand (High)	0.749** (0.168, 1.330)			
Skills demand (number of skills)		0.046 (-0.092, 0.184)	-0.089 (-0.224, 0.045)	-0.038 (-0.166, 0.089)
Skill Match	0.395*** (0.315, 0.475)	0.341*** (0.256, 0.426)	0.236*** (0.157, 0.316)	0.368*** (0.285, 0.451)
Training (Medium)	0.437 (-1.210, 2.084)			
Training (High)	1.221 (-0.422, 2.865)			
Deviation from mean VA (Sector)	0.234*** (0.203, 0.265)	0.224*** (0.119, 0.330)	0.063 (-0.052, 0.178)	0.317*** (0.164, 0.469)
Tangible fixed assets	1.413*** (1.319, 1.508)	1.370*** (1.082, 1.657)	1.492*** (1.009, 1.976)	1.468*** (1.046, 1.891)
Product Innovation (3 years - YES)	-0.396** (-0.788, -0.004)	-1.542** (-3.077, -0.008)	-1.659 (-4.142, 0.824)	-9.921*** (-14.454, -5.388)
Process Innovation (3 years - YES)	0.116 (-0.312, 0.544)	-2.602*** (-4.166, -1.037)	0.763 (-1.197, 2.722)	-2.107 (-4.624, 0.410)
Organizational Innovation (3 years - YES)	-0.971*** (-1.357, -0.585)	-5.083*** (-7.395, -2.770)	-5.493*** (-8.648, -2.337)	-3.168** (-5.663, -0.673)
Other Controls	yes	yes	yes	yes
Skill Match * Training (Medium)	-0.142** (-0.281, -0.003)			
Skill Match * Training (High)	0.055 (-0.052, 0.162)			
Observations	9,464	7,355	7,791	7,020
Log Likelihood	-37,945.560			
Akaike Inf. Crit.	75,941.120			
Bayesian Inf. Crit.	76,120.010			
Rho		-1.090	-1.147	-1.216
Inverse Mills Ratio		-16.328*** (6.185)	-20.672*** (7.086)	-30.906*** (7.843)

Note: *p<0.1; **p<0.05; ***p<0.01
Ref Market: Firms. Ref Skills demand: Low. Ref Training: Low

At the same time, the investment efforts (and the restructuring process that might meanwhile occur) characterizing the phase of introduction of product and/or organizational innovations can determine a contraction or at least a stagnation of revenues and value added. The positive effect of process innovation is, in turn, more in line with the expectations. If successful, a process innovation is likely to reduce the relative weight (or to increase its efficiency) of labour inputs within the production process. This results in a contraction of the denominator (i.e. number of employees) leading to a positive effect

of this type of innovation on productivity. As mentioned, the PEC survey comes with a chunk populated by 6620[11] firms repeating in the three waves: a firm-wave panel. However, given the small number of points in time (T much smaller than N) characterizing our dataset a standard FE within estimator is not suitable for this analysis., In order to appropriately exploit the longitudinal component of the dataset, thus, we project the first survey wave (2012) onto the third (2017). In this way we can explore the medium term skill-productivity relationship. As for the unobserved heterogeneity, we rely on the large set of firm level controls[12] accounting, in addition, for sectorial and geographical heterogeneities.
Table 3 displays the result of LSDV regression with clustered standard errors at the sectoral level for the projected cross-section (see above). Differently from the RCS results, SD is no longer significant. On the other hand, Soft Skills and Technical Operatives are significant and, respectively, positive and negative. The positive effect of soft skills on productivity confirms the findings of, among the others, Deming (2017); while for technical operatives the above considerations apply. The positive effect of SM is confirmed even when the potential selection effect is accounted for by using the Heckman's model. Finally, the evidence in table 3 show that results (in particular those concerning SD by domain and SM) are robust to the introduction of the training indicator (see above for a description).

6. Conclusions

This work aimed at exploring, at the firm-level, the relationship between labour productivity, skill need (both aggregate and distinguished by skill domains) and degree of skill match. We contribute to the existing literature in a number of ways. First, we overcome some of the major empirical limitations faced by the literature studying the role of skills in explaining firms' performance. We have the opportunity to control for variables directly referring to workers' competences without any need to resort on the theoretically and empirically fragile education-related indicators. Second, adopting an evolutionary approach (i.e. emphasize the importance of firm level-heterogeneities) to explore the interplay between the nature and the dynamics of companies' knowledge-base; organizational and technological characteristics of such companies; and their performance in terms of productivity. Third, the evidence on the nature and importance of firm-level skill is provided at a level of qualitative detailed which is completely uncommon for the literature in this field.
A novel, unique dataset tailored specifically for this analysis is used, integrating a variety of administrative and survey data regarding the Italian panorama on three years (2012, 2014 and 2017). The empirical investigation delivers at least two take away. In the first place, when dealing with skills, it is important to differentiate between groups or domains. Indeed, a firm's skill endowment is not a homogeneous production factor, rather it is a heterogeneous bundle of items each reflecting a variety

[11] 3396 with available labour productivity.
[12] We are working on a further expansion of the controls set. In particular, we think the major source of bias embodies in the firm's work-related managerial culture, affecting the propensity to invest on training and workforce re-skilling. We are working on two variables measuring turnover and the typology of contract issued to account for it. Furthermore, we acknowledge an important omitted variable: training expenses. Unfortunately, such variable is nowhere available at the firm level. We are working on the – scarce – available data at the macro-sectoral level to solve partially the issue.

of firm's characteristics: strategic choices in labour management, production deficiency, positioning within the sectorial features, and so on. How these domains should be defined if one relates them to productivity is a topic that deserves further investigation. According to our results, STEM and Management related skill (probably due to their complementarity with technological and organizational innovations) turn out to be positively and significantly correlated with productivity; and the same holds for Humanities and Soft-skills. On the other hand, Technical Operative skills display a negative and significant correlation with productivity likely to mirror a generalized fragility of manufacturing firms (those mostly demanding this type of skills).

Second, the ability to rapidly match their skill need seems to be of paramount importance to improve companies' productivity performance. This evidence has a certain relevance from both a scientific and a policy perspective. A timely adaptation of the knowledge base (via the introduction of appropriate skills), in fact, turns out to be a key driver of companies' economic, technological and organisational dynamism. From this point of view, policies improving the process of search by increasing transparency and detail about the skill supply can prove to be of some importance. In addition, firm-labour market boundaries seem to be 'blurring' for an increasing share of firms opting for a continuous search of the needed skills on the market; rather than to invest in internal training.

Policy maker must be especially aware that, as we tried to frame, the outcome of the entrepreneurial skills search-and-retrieval is not exclusively dependent on market imperfections, rather it is the outcome of the continuous restructuring of the companies' knowledge base, as a consequence of the generation, diffusion and adoption of innovations (Dosi 1982; Dosi *et al.* 2003; Antonelli 2017). Dedicated policies, therefore, should not tackle directly – and exclusively – the issue of information asymmetries dampening the search-and-retrieval process (Akerlof 1970) but take into account the specificities of industrial and firms trajectories and, consequently, their skills potential.

References

Acemoglu D., Pischke J.S. (1999), The Structure of Wages and Investment in General Training, *Journal of Political Economy*, 107, n.3, pp.539-572

Akerlof G. (1970), The Market for "Lemons". Quality Uncertainty and the Market Mechanism, *The Quarterly Journal of Economics*, 84, n.3, pp.488-500

Albrecht J., Vroman S. (2002), A Matching Model with Endogenous Skill Requirements, *International Economic Review*, 43, n.1, pp.283-305

Antonelli C. (2017), *Endogenous Innovation. The Economics of an Emergent System Property*, Cheltenham UK, Edward Elgar Publishing

Antonelli C., Scellato G. (2013), Complexity and Technological Change. Knowledge Interactions and Firm Level Total Factor Productivity, *Journal of Evolutionary Economics*, 23, n.1, pp.77-96

Becker G.S. (1962), Investment in human capital. A theoretical analysis, *Journal of Political Economy*, 70, n.5, pp.9-49

Black S., Lynch L. (2005), Measuring organizational capital in the new economy, in Corrado C., Haltiwanger J., Sichel D. (eds.), *Measuring capital in the new economy*, Chicago, The University of Chicago Press, pp.205-236

Black S., Lynch L. (2001), How to compete. The impact of workplace practices and information technology on productivity, *Review of Economics and statistics*, 83, n.3, pp.434-445

Büchel F., Mertens A. (2004), Overeducation, undereducation, and the theory of career mobility, *Applied Economics*, 36, n.8, pp.803-816

Büchel F. (2002), The Effects of Overeducation on Productivity in Germany – The Firms' Viewpoint, *Economics of Education Review*, 21, n.3, pp.263-275

Cetrulo A., Cirillo V., Guarascio D. (2019), Weaker Jobs, Weaker Innovation. Exploring the Temporary Employment-Product Innovation Nexus, *Applied Economics*, Online first, pp.1-28

Colombelli A., Krafft J., Quatraro F. (2013), Properties of Knowledge Base and Firm Survival. Evidence from a Sample of French Manufacturing Firms, *Technological Forecasting and Social Change*, 80, n.8, pp.1469-1483

Deming D.J. (2017), The Growing Importance of Social Skills in the Labour Market, *The Quarterly Journal of Economics*, 132, n.4, pp.1593-1640

Dolado J.J., Jansen M., Jimeno J.F. (2009), On the Job-Search in a Matching Model with Heterogeneous Jobs and Workers, *The Economic Journal*, 119, n.534, pp.200-228

Dolton P., Vignoles A. (2000), The Incidence and Effects of Overeducation in the U.K. Graduate Labour Market, *Economics of Education Review*, 19, n.2, pp.179-198

Dosi G. (1982), Technological Paradigms and Technological Trajectories, *Research Policy*, 11, n.3, pp.147-162

Dosi G., Grazzi M., Tomasi C., Zeli A. (2012), Turbulence underneath the big calm? The micro-evidence behind Italian productivity dynamics, *Small Business Economics*, 39, n.4, pp.1043-1067

Dosi G., Guarascio D., Ricci A., Virgillito M.E. (2018), *Neodualism in the Italian business firms: training, organizational capabilities and productivity distributions*, LEM Working Paper Series n.34, Pisa, Scuola Superiore Sant'Anna

Dosi G., Marengo L. (2015), The Dynamics of Organizational Structures and Performances under Diverging Distributions of Knowledge and Different Power Structures, *Journal of Institutional Economics*, 11, n.3, pp.535-559

Dosi G., Nelson R., Winter S. (2003), *The Nature and Dynamics of Organizational Capabilities*, Oxford, Oxford University Press

Freeman R. (1976), *The Overeducated American*, New York, Academic Press

Gautier P. (2002), Unemployment and Search Externalities in a Model with Heterogeneous Jobs and Workers, *Economica*, 69, n.273, pp.21-40

Griliches Z. (1998), *R&D and Productivity. The Econometric Evidence*, Chicago, University of Chicago Press

Groot W. (1996), The Incidence of, and Return to Overeducation in the UK, *Applied Economics*, 28, n.10, pp.1345-1350

Groot W., Van Der Brink H.M. (2000), Overeducation in the Labour Market. A Meta-Data Analysis, *Economics of Education Review*, 19, n.2, pp.149-158

Grunau P. (2016), The Impact of Overeducated and Undereducated Workers on Establishment-Level Productivity. First Evidence for Germany, *International Journal of Manpower*, 37, n.2, pp.372-392

Gualtieri V., Guarascio D., Quaranta R. (2018), *Does routinization affect occupation dynamics? Evidence from the 'Italian O* Net'data*, Inapp Working Paper n.3, Roma, Inapp

Hartog J. (2000), Over-Education and Earnings. Where Are We, Where Should We Go?, *Economics of Education Review*, 19, n.2, pp.131-147

Heckman J.J. (1976), The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models, *Annals of Economic and Social Measurement*, 5, n.4, pp.475-492

Heckman J.J., Kautz T. (2012), Hard Evidence on Soft Skills, *Labour economics*, 19, n.4, pp.451-464

Heijke H., Meng C., Ris C. (2003), Fitting to the Job. The Role of Generic and Vocational Competencies in Adjustment and Performance, *Labour Economics*, 10, n.2, pp.215-229

Hersch J. (1991), Education Match and Job Match, *Review of Economics and Statistics*, 73, n.1, pp.140-144

Kampelmann S., Rycx F. (2012), The Impact of Educational Mismatch on Labour Productivity. Evidence from Linked Panel Data, *Economics of Education Review*, 31, n.6, pp.918-931

Kleinknecht A., Van Shaik N., Zhou H. (2014), Is Flexible Labour Market Good for Innovation? Evidence from Firm-Level Data, *Cambridge Journal of Economics*, 38, n.5, pp.1207-1219

Lazear E.P. (1977), Education. Consumption or Production?, *Journal of Political Economy*, 85, n.3, pp.569-598

Lebo M.J., Weber C. (2015), An Effective Approach to the Repeated Cross-Sectional Design. Repeated Cross-Sectional Design Approach, *American Journal of Political Science*, 59, n.1, pp.242-258

Mahy B., Rycx F., Vermeylen G. (2015), *Educational Mismatch and Firm Productivity. Do Skills, Technology and Uncertainty Matter?*, IZA Discussion Paper n.8885, Bonn, IZA

Mincer J. (1981), *Union Effects. Wages, Turnover and Job Training*, NBER Working Paper n.808, Cambridge MA, NBER

Mowery D.C., Rosenberg N. (1979), The Influence of Market Demand upon Innovation. A Critical Review of Some Recent Empirical Studies, *Research Policy*, 8, n.2, pp.102-153

Nelson R., Winter S. (1982), *An Evolutionary Theory of Economic Change*, Cambridge MA, Harvard University Press

Oosterbeek H., Van Ophem H. (2000), Schooling Choices. Preferences, Discount rates, and Rates of Return, *Empirical Economics*, 25, n.1, pp.15-34

Pakes A., Griliches Z. (1998), Patents and R&D at the Firm Level. A First Look, in Griliches Z. (ed.), *R&D and Productivity. The Econometric Evidence,* Chicago, University of Chicago Press, pp.55-72

Penrose E.T. (1952), Biological Analogies in the Theory of the Firm, *The American Economic Review*, 42, n.5, pp.804-819

Pfeiffer S. (2016), *Beyond Routine: Assembly Work and the Role of Experience at the Dawn of Industry 4.0. Consequences for Vocational Training*, Department of Sociology Working Paper n.1, Stuttgart, University of Hohenheim, <https://bit.ly/2OK8VZ9>

Piva M., Vivarelli M. (2007), Is demand-pulled innovation equally important in different groups of firms?, *Cambridge Journal of Economics*, 31, n.5, pp.691-710

Raudenbush S.W., Bryk A.S. (2002), *Hierarchical Linear Models. Applications and Data Analysis Methods*, Thousand Oaks, Sage Publications

Robst J. (1995), Career mobility, job match, and overeducation, *Eastern Economic Journal*, 21, n.4, pp.539-550

Robst J. (2007), Education and Job Match. The Relatedness of College Major and Work, *Economics of Education Review*, 26, n.4, pp.397-407

Rumberger R. (1987), The Impact of Surplus Schooling on Productivity and Earnings, *Journal of Human Resources*, 22, n.1, pp.24-50

Scherer F.M. (1982), Demand-Pull and Technological Invention. Schmookler Revisted, *The Journal of Industrial Economics*, 30, n.3, pp.225-237

Schmookler J. (1976), *Invention and Economic Growth*, Cambridge MA, Harvard University Press

Schumpeter J.A. (1942), *Capitalism, Socialism and Democracy*, New York, Harper & Row

Sicherman N. (1991), 'Overeducation' in the Labor Market, *Journal of Labor Economics*, 9, n.2, pp.101-122

Sicherman N., Galor O. (1990), A Theory of Career Mobility, *Journal of Political Economy*, 98, n.1, pp.169-192

Sloane P., Battu H., Seaman P. (1999), Overeducation, Undereducation and the British Labour Market, *Applied Economics*, 31, n.11, pp.1437-1453

Smith A. (1776), *An Inquiry into the Nature and Causes of the Wealth of Nations*, Edited by Edwin Cannan, Chicago, The University of Chicago Press 1976

Spence M. (1973), Job Market Signalling, *Quarterly Journal of Economics*, 87, n.3, pp.355-374

Thurow L. (1975), *Generating Inequality. Mechanisms of Distribution in the U.S. Economy*, New York, Basic Books

Thurow L. (1979), A Job-Competition Model, in Piore M. (ed.) *Unemployment and Inflation. Institutionalist and Structuralist Views*, New York, Sharpe

Van der Meer P.H. (2006), Two Validity of Two Education Requirement Measures, *Economics of Education Review*, 25, n.2, pp.211-219

Verhaest D., Omey E. (2006), The Impact of Overeducation and its Measurement, *Social Indicators Research*, 77, n.3, pp.419-448

Vidal M. (2011), Reworking Postfordism. Labour Process versus Employment Relations, *Sociology Compass*, 5, n.4, pp.273-286

Vroom V. (1964), *Work and Motivation*, New York, Wiley

Weiss A. (1995), Human Capital vs. Signalling Explanations of Wages, *Journal of Economic Perspectives*, 9, n.4, pp.133-154

Winter S.G. (1997), Knowledge and Competences as Strategic Assets, in Klein A. (ed.), *The Strategic Management of Intellectual Capital*, New York, Elsevier, pp.165-187

Wooldridge J.M. (2010), *Econometric Analysis of Cross Section and Panel Data*, Cambridge MA, MIT Press