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CONTENTS:

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ABSTRACT

Technological externalities and wages: new evidence from Italian provinces

In this paper, we investigate the relationship between local wages and the internal structure of the regional knowledge base. The purpose is to assess if the workers' compensations are related to the peculiarities of the technological space where they supply their labor services. To test this hypothesis, we apply the concepts of related and unrelated variety to the firms' patenting activity as to assess if wages grow more in a framework of 'knowledge deepening' (generated by firms innovating in related technological domains) or in one of 'knowledge widening' (generated by firms innovating in unrelated technological domains). The empirical analysis is carried out using a unique employer-employee dataset containing administrative data. First, using OECD-PATREG data on patent filing, we build two information entropy indexes that capture the degree of technological relatedness in the regions' innovative activities. Second, we assess the impact of these indexes on individual wages. Our results suggest that workers employed in regions with a diversified knowledge structure earn positive wages premia, while technological specialization has a negative effect on compensation levels.

KEYWORDS: technological change, firm-level innovation, provinces, wage, agglomeration externalities

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1. Introduction

Economists have long investigated the nexus between labor market dynamics and agglomeration economies. These latter, following the well-established Marshallian tenet, are engendered by three main forces, i.e. thick labor markets, thick markets for intermediate goods, and knowledge spillovers. Indeed, these dynamics are actually an important driver of productivity differentials across local labor markets, and consequently they are deemed to have a significant impact on cross-regional differences in workers' earnings.

Accordingly, a large stream of empirical literature has investigated the relationship between firms' location choices and agglomeration (Ellison and Glaeser 1997; Rosenthal and Strange 2003). Yet, while this approach can be informative on the existence of some sort of agglomeration incentive, it does not imply the actual existence of agglomeration economies (Moretti 2011).

Some literature has instead dealt with the empirical appreciation of agglomeration externalities by taking individual wages as a proxy of marginal product of labour, to verify the existence of a premium to agglomeration (Glaeser and Maré 2001). Extant literature has mainly focused on externalities linked to urban or industrial agglomeration, as proxied respectively by the density of inhabitants and of production plants (Moretti 2011; De Blasio and Di Addario 2005; Di Addario and Patacchini 2008).

However, as recalled above, one of the key arguments put forth by Marshall (1890) points to the role of knowledge spillovers. Technological externalities emerge out of the concentration of technological activities in local contexts and affect the capacity of firms to generate and adopt innovation, which in turn leads to productivity gains. Despite the importance of these dynamics, empirical studies so far have overlooked the direct investigation of the impact of technological externalities on workers' earnings differentials.

This paper aims at filling this gap, by articulating an empirical framework to investigate the effect of knowledge spillovers on individual wages. In doing so, we extend the scope of the analysis by appreciating the differential impact of Marshall vis-à-vis Jacobs' externalities. As is well known, the former are associated to technological specialization while the latter is associated to technological diversification in local economies. If knowledge spillovers affect wages because of their impact on innovation and hence on productivity, distinguishing between different kinds of technological externalities is important, as Jacobs' externalities have proved to be systematically associated to the introduction of more impactful innovation (Castaldi *et al.* 2015).

In this direction, we graft the recombinant knowledge approach onto the debate on the nexus between agglomeration and wages. More impactful innovation emerges out the recombination of knowledge across a variety of seemingly unrelated fields. We accordingly posit that in areas featured by higher levels of unrelated technological variety wages are higher than in areas feature by higher level of specialization (or related variety), in view of the capacity to foster high-impact innovation yielding higher productivity gains. From the labor market perspective, the wage premium is expected to be positive in areas characterized by high levels of Jacobs' externalities, where the productivity effect dominates. On the contrary, in areas characterized by a high degree of specialization (related variety) one can expect to observe the counterbalancing supply effect to prevail, pushing wages downwards.

To analyze empirically the effect of patenting concentration on regional wages, we use a unique employer-employee dataset built using administrative data. To allow for different patterns of regional innovativeness, we then distinguish between related and unrelated diversification, that is, between situations where local innovators issue their patents in closely related technological domains (related variety) and situation where they conversely diversify their patenting activity by innovating in a variety of unrelated domains (unrelated variety)[1]. To do so, we first build two different indexes of regional innovativeness, capturing, respectively, the degrees of related and unrelated variety of a regions' knowledge base. Then, we regress these indexes against individual wage levels, adding a number of relevant controls that account for a variety of individual and firm characteristics that are likely to have an important role in determining individual salaries. In doing so, we should be able to capture the wage effect of being employed in regions with well-defined innovative characteristics. To rationalize our results, we draw from the literatures of economic geography and urban economics. While these streams of research have extensively analyzed the effect of both sectoral and urban concentration, a key novelty of our approach, as anticipated, is that of considering the agglomeration of innovative activities. We find that workers employed in diversified regions earns positive premia, while the effect of related variety seems to be non-significant, or even negative.
The remainder of the paper is organized as follows. Section 2 reviews the literature on agglomeration externalities and put forward our working hypotheses. Section 3 presents the empirical framework and our main results. Section 4 concludes.

2. Theoretical framework

2.1 On agglomeration externalities

Economic geographers have long insisted on the importance of technological diversification for regional development, debating if the latter benefit more from the local agglomeration of related or unrelated activities (Content and Frenken 2016; Glaeser *et al.* 1992). The issue is tightly intertwined with the well-known controversy known as "MAR versus Jacobs". Indeed, while the Marshall's, Arrow's and Romer's theory (MAR) of industrial clustering suggests that regional economic performance benefits more from the specialization externalities occurring within sectors (Arrow 1962; Marshall 1890; Romer 1986) – and thus, that the concentration of similar activities in a given area should be encouraged – Jacob (1969) postulates that knowledge spillovers boosting productivity, innovation and growth accrue mainly across industries of different kind.
The controversy is further complicated by the fact that the two types of externalities are not mutually exclusive, neither in space, nor in time. Most of the existing literature has indeed found that they often

[1] The concepts of related and unrelated variety originally introduced by Content and Frenken (2016, 2097-2098) have been mostly employed in studies that analyze the effect of industrial specialization or diversification on economic performance. These concepts, in turn, are closely related to the controversy commonly known as 'MAR versus Jacobs'. The Marshall, Arrow, Romer's theory (MAR) suggests that increasing specialization is the key to regional success, and thus, that patterns of industrial agglomeration should be encouraged. Conversely, Jacobs (1969) maintains that regional success mainly depends on economic diversity.

co-occur within the same region. The theoretical explanation is simple: while MAR economies are both industry and region-specific, Jacob's are only geographically bounded, since "a diversified region may also accommodate the larger part of a particular industry. Hence, regions can be both diversified and specialized towards particular industries simultaneously" (van der Panne 2004, 599). In addition, the knowledge spillovers that generate most of the external effects of diversification may occur across sectors of different kind, generating externalities that, although probably less significant that those engendered by MAR economies (industry-specific), may still have a significant impact on regional performance.

As to the time dynamics affecting the evolution of these two patterns, product life cycle theory (PLC) suggests that phases of unrelated and related diversification may follow one another by accommodating the pace of industrial evolution. Indeed, entrepreneurs in younger industries that going through their exploration phase normally seize new commercial opportunities by innovating products, while firms in more mature sectors that have already entered the standardization stage tend to experience a transition from product to process innovation (Capasso *et al.* 2016; Duranton and Puga 2001; van Oort *et al.* 2015). This is where MAR and Jacobs' external effects are likely to alternate over time. Indeed, while diversified industrial structures allow the exchange of different pieces of knowledge and thus favor the recombinant creation of novelty (Henderson *et al.* 1995), specialized economies boost the intra-sector transmission of industry-specific knowledge, which is a key input for innovating processes and/or refining the existing products. More broadly, as recalled by Frenken *et al.* (2007, 687): "[MAR] economies are expected to spur incremental innovation and process innovation, as the knowledge that spills over originates from similar firms producing similar products […] Jacob's externalities are expected to facilitate particularly radical innovation and product innovation, as knowledge and technologies from different sectors are recombined leading to complete new products or technologies". In this framework, there exist complementarities between the entrepreneurs' innovation strategies and the economic environment where they operate. In young industries, entrepreneurs will find it rational to invest in radical and/or product innovation, progressively diversifying the industrial structure, that, in turn, will generate Jacob's externalities favouring radical and/or product innovation. Conversely, more mature sectors will provide incentives for firms to invest in incremental and/or process innovation, thus generating MAR externalities that will promote more specialization. Demidova *et al.* (2020) find evidence of this type of time dynamics for the case of Russia, showing that Marshallian effects were predominant over the period 2013-2016, while Jacob's externalities were relatively more significant over the period 2010-2013.

Despite the dispute over which of the two diversification paths is the most beneficial is far from being settled[2], there seems to be converging evidence that related diversification (hereafter, RTV) is the most recurring pattern of regional branching, although growing concerns have been raised regarding the long-run risks deriving from excessive specialization[3]. Indeed, unrelated diversification (hereafter, UTV) seems to be crucial for long-term development, thanks to portfolio effects protecting workers

[2] For a broad review of the effects of RTV and UTV on economic performance (i.e., productivity, employment and unemployment, innovation, and growth), see Beaudry and Schiffauerova (2009).

[3] For empirical evidence on the predominance or RTV, see van den Berge and Weterings 2014; Boschma *et al.* 2015; 2014; 2013; Colombelli *et al.* 2014; Essletzbichler 2015; Feldman *et al.* 2015; Heimeriks and Balland 2015; Kogler *et al.* 2013; Neffke *et al.* 2011; Rigby 2015; Tanner 2014.

from unemployment and firms from economic stagnation (Saviotti and Frenken 2008). The proposed rationalization as to why firms tend to enter in related activities expands on the product space approach proposed by Hidalgo *et al.* (2007) and highlights the path-dependency character of technological diversification. In this framework, firms tend conform to the prevailing diversification pattern as to seize the short-term benefits of the agglomeration externalities in place, neglecting the potential lock-in effects that may eventually occur in the longer-run (Boschma and Frenken 2007; 2011)[4]. To what extent these effects actually exist, however, is still an open issue.

2.2 Agglomeration externalities and labor market dynamics

A key aspect discussed in the literature on agglomeration externalities is the relationship between variety and labor market dynamics, since most of these external economies that affect productivity, innovation and growth are driven by labor market conditions. Indeed, both the MAR and the Jacob's model predict that knowledge spillovers will arise either directly – through imitation and business interactions – or indirectly, through the inter-firm circulation of skilled workers. When well-educated or experienced workers move across occupations, in fact, they take with them valuable pieces of tacit knowledge, thus providing firms with learning opportunities that can be crucial for their economic success. Interestingly, these knowledge spillovers may increase the marginal productivity of both skilled and unskilled workers, generating productivity and wage effects that occur across the entire skill distribution. A recent study by Kuusk (2021) find support to this hypothesis by showing that labor mobility is a required channel to convert the potential benefits of RTV in actual growth, while the evidence provided in Grinza and Quatraro (2019) shows that workers' replacements have a negative effect on innovation, suggesting that a key part of a firm's innovative ability is actually embodied in its personnel and thus, that it may be transferred to others when labor is mobile across firms.

Moreover, the role of workers in actualizing the potential benefits of related and unrelated diversification is not limited to the knowledge spillovers accruing from labor mobility. Labor market pooling is indeed another relevant channel. When industries grow in size in well-defined geographical areas, they attract workers with suitable skills. This sorting mechanism, in turn, improves the match-quality between workers and firms, with positive repercussion on labor productivity both at the firm and at the industry level. As put forward by (Combes and Duranton 2006), however, the gains from labor pooling are mitigated by the costs of labor poaching, since firm must offer their strategic worker a higher wage to prevent the latter from leaving the firm taking away their valuable expertise.

While all the elements listed above may have different and potentially diverging effects on the workers' wage, the following working hypotheses can be advanced as concerns the relationship wages and the structure of the regional knowledge base. In regions where clear technological trajectories have been identified, innovation is likely to be more incremental, producing less impactful effects on firm performance. Conversely, it has been shown that more impactful innovation is systematically associated to knowledge diversification (Castaldi *et al.* 2015). The intuition is straightforward: when the firms' activities are dispersed across different technological domains, competition is less severe in

[4] The few existing studies stress the role of market institutions, foreign firms, specialization in cross-cutting technologies and the role of academic inventors in mitigating the constraining impact of relatedness (Boschma and Capone 2015; D'Ambrosio *et al.* 2019; Montresor and Quatraro 2017; Neffke *et al.* 2018).

each of the latter, and potential innovative breakthroughs are more likely to be introduced. In this framework, assuming that workers acquire (or build up) part of the internal knowledge of the firm – as modelled by Combes and Duranton (2006) – they can subsequently leverage on the acquired expertise to either obtain a wage raise or leave the firm for better employment opportunities. Hence, the more significant is the knowledge generated by a given firm, the greater are the strategic benefits that its workers can seize in the labor market[5].

There are at least two complementary mechanisms that may reinforce this explanation. The first can be referred to as a composition effect: if regional labor markets coevolve with local technological structures, related variety may increase the supply of technology-specific skills, generating labor pooling benefits for employers using those technologies, while simultaneously reducing the wage premium required to attract workers. In this framework, workers with similar skills are attracted towards the specialized regions, and this may create a supply effect pushing wages downwards. The second effect is more structural in nature and refers to the already anticipated fact that technological diversification creates portfolio effects that protect regions from sector-specific shocks, while excessive specialization creates lock-in effects that are detrimental in the long-run (Boschma and Frenken 2007; 2011). If firms' productivity is somehow reflected in the workers' wage, these two mechanisms may affect compensation levels. All in all, it seems plausible that wage premia will be higher in more diversified regions.

3. Empirical analysis

3.1 Data

The analyses concerning the relationship between regional innovation performances and individual wages are developed integrating two different sources of information at the individual and province level. Individual information on wage levels and workers' characteristics are retrieved from the administrative archive containing information on the employees' financial conditions provided by the Italian National Institute of Social Security (Inps). The second type of information concerning Data on the firms' patenting activity is taken from the OECD REGPAT archive.

Data from Inps comes from the statement of account of the f individual contributions paid by each worker to the *Fondo pensioni lavoratori dipendenti* of the sample of 48 dates. The dataset makes it possible to retrieve a wide range of information on the demographic profile and contractual conditions, age, sex, occupation, duration of contract (fixed-term or open-ended), working hours (part-time or full-time), gross salary, number of weeks worked, industrial sector of employment, firm size, geographical location etc.

As far as innovation indexes are concerned, the measures calculated from the OECD REGPAT archive are basically three. The first accounts for the overall technological variety in each of our geographical units ($TV =$ total variety). The second quantifies how many are of this mass of patents belong to the

[5] Incidentally, this is consistent with the theory and calibration provided in Cahuc *et al.* (2006), that shows that between employer competition for valuable workers has a significant impact on the wage level.

same technological variety ($RTV =$ related variety). The third captures the degree of technological diversification ($UTV =$ unrelated variety). To calculate these measures, we used the information entropy index[6]. Such index was introduced to economic analysis by Theil (1967). Its earlier applications aimed at measuring the diversity degree of industrial activity (or of a sample of firms within an industry) against a uniform distribution of economic activities in all sectors, or among firms (Attaran 1986; Frenken *et al.* 2007; Boschma and Iammarino 2009). Differently from common measures of variety and concentration, the information entropy has some interesting properties (Frenken 2004). An important feature of the entropy measure is its multidimensional extension. Consider a pair of events (X_j, Y_m), and the probability of co-occurrence of both of them p_{jm}. A two-dimensional (total) entropy measure can be expressed as follows (region and time subscripts are omitted for the sake of clarity):

$$H(X_j, Y_m) = \sum_{j=1}^{q} \sum_{m=1}^{w} p_{jm} \log_2 \frac{1}{p_{jm}} \tag{1}$$

If one considers p_{jm} to be the probability that two technological classes *j* and *m* co-occur within the same patent, then the measure of multidimensional entropy focuses on the variety of co-occurrences of technological classes within regional patents applications. Moreover, the total index can be decomposed in a 'within' and a 'between' part anytime the events to be investigated can be aggregated in a smaller number of subsets. Within-entropy measures the average degree of disorder or variety within the subsets, while between-entropy focuses on the subsets measuring the variety across them. It can be easily shown that the decomposition theorem holds also for the multidimensional case. Hence if one allows $j \in S_g$ and $m \in S_z$ ($g = 1, \dots, G$; $z = 1, \dots, Z$), we can rewrite $H(X_j, Y_m)$ as follows:

$$H(X_j, Y_m) = H_Q + \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} H_{gz} \tag{2}$$

Where the first term of the right-hand-side is the between-group entropy, and the second term is the (weighted) within-group entropy. In particular:

$$H_Q = \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} \log_2 \frac{1}{P_{gz}} \tag{2a}$$

$$P_{gz} = \sum_{j \in S_g} \sum_{m \in S_z} p_{jm} \tag{2b}$$

$$H_{gz} = \sum_{j \in S_g} \sum_{m \in S_z} \frac{p_{ij}}{P_{gz}} \log_2 \frac{1}{p_{ij}/P_{gz}} \tag{2c}$$

[6] Entropy measures the degree of disorder or randomness of the system, so that systems characterized by high entropy will also be characterized by a high degree of uncertainty (Saviotti 1988).

Following Frenken *et al.* (2007), we can refer to between-group and within-group entropy respectively as *unrelated technological variety* (*UTV*) and *related technological variety* (*RTV*), while total information entropy is referred to as *general technological variety (TV)*. The distinction between related and unrelated variety is based on the assumption that any pair of entities included in the former generally are more closely related, or more similar to any pair of entities included in the latter. This assumption is reasonable when a given type of entity (patent, industrial sector, trade categories etc.) is organized according to a hierarchical classification. In this case each class at a given level of aggregation contains 'smaller' classes, which, in turn contain yet 'smaller' classes. Here, small refers to a low level of aggregation.

Finally, to relate the information on individual workers and the measures of regional innovativeness we have just discussed, we have used the NUTS geographic identification codes.

3.2 Estimation strategy

Our empirical strategy follows a very well established two-stage approach first introduced by Combes *et al.* (2008) and widely used in urban economics (see for instance De la Roca and Puga 2017; Belloc *et al.* 2022; Loschiavo 2021). With this setting by including in the first stage, time-varying area effects (province) we are able to separately identify the effects of worker's characteristics from the effects of area's characteristics and, hence, to properly estimate the wage elasticity to innovation externalities, while accounting for observed and unobserved individual and firm specific heterogeneity. Besides, the two-stage setting seems to be the most suitable method since yields standard errors that account for the grouped structure of the data (individual and province)[7]. For an accurate discussion on the advantages of the two- stage compared with a one-stage estimation strategy see Combes *et al.* (2011), Combes and Gobillon (2015).

In the first stage, following the notation proposed by Combes *et al.* (2011) we regress wages on individual and firm-specific factors appealing to the standard Mincer's (1974) wage equation, which has a long-established literature describing the positive impact of human capital on wages (Heckman *et al.* 2003). The period of analysis is 2005-2018.

$$\log(W_{it}) = \alpha_{a(it)t} + \eta_1 X_{it} + \eta_2 Z_{j(it)t} + \gamma_i + \varepsilon_{it} \tag{3}$$

$\log(W_{it})$ is the logarithm of the real wage (adjusted for part time) of individual i at time t; X_{it} is the vector of individual controls, which includes, for worker i at time t: gender, having a part-time contract, having a fixed-term contract, occupation dummies (blue collar, white collar, executives, other), and dummies for age groups. Z_{jit} is the vector of firm-level controls: firm size (in classes), 2-digit sector of activities and a dummy variable indicating how many times a person changes firm, thus capturing skill transferability.

In order to account for unobservable workers' heterogeneity in some specifications of the first stage we also include individual fixed effects, γ_i (see for instance Glaeser and Maré 2001; Combes *et al.* 2008). The importance of firm fixed effects in explaining wage differentials is more controversial (see

[7] By contrast, a one-step procedure would generate large biases in the standard error for the coefficients on aggregate explanatory variables (see Loschiavo 2021).

Card *et al.* 2013; Dauth *et al.* 2018). Nonetheless, we also adopt for our first-stage regressions a two-way fixed effects AKM specification (see Abowd *et al.* 1999; Belloc *et al.* 2022).

As described in section 3.1 we build two different indexes of regional innovativeness, capturing, respectively, the degrees of related (RTV) and unrelated variety (UTV) as well as total variety (TV=RTV+UTV) of a province' knowledge base. We then regress these indexes against province-year effects estimated in the first stage in which individual wage levels are explained with a number of relevant controls that account for a variety of individual and firm characteristics that are likely to have an important role in determining individual payments (equation 3). In doing so, we should be able to capture the wage effect of being employed in provinces with well-defined innovative characteristic (see Aarstad *et al.* 2016).

More in detail, in the second stage, the province-year effects estimated in the first stage, $\alpha_{a(it)t}$, are regressed on a vector V_{at-1} of (lagged) provincial indicators of technological varieties. The vector includes in turn, each of the indicators, TV, UTV or RTV, and in a last specification, the separate contribution of UTV and RTV.

$$\hat{\alpha}_{at} = \beta \log(V_{at-1}) + \varsigma_{at-1} + \tau_t \tag{4}$$

The model also includes τ_t year fixed effects to control for business cycle – as in Combes *et al.* (2008) – and ς_{at} province level controls: $Kcap\_ratio_{at}$, knowledge capital divided by the total labour force and it's square, and the logarithm of population density (per squared km) of province a at time t to account for agglomeration effects (Frenken *et al.* 2007). β captures the wage elasticity to innovation externalities, thus doubling V_{at-1} increases wages by β. Notice that a modified versions of model (4) allow us to estimate different sets of elasticities with respect to technology, depending on the measure employed.

The inclusion of population density along with related and unrelated varieties will be able to capture their potential effects on wages and innovation (see Frenken *et al.* 2007). In this way unrelated and related varieties will be constant for individuals residing within a particular province and will vary between provinces.

Models (3)-(4) are estimated using OLS, FE, or AKM models, with residuals clustered at the local (province-year) level. However, we reckon that endogeneity bias could still occur if there are omitted variables causing the error term to be correlated with our indicators of variety. Typically, this may be an outcome of sorting into highly innovative areas (Venables 2011).

We therefore also perform IV regression by relying on synthetic variables, typically used when working with spatial data series. The point of departure is the use of eigenvector analysis of the usual spatial weight matrix used in spatial statistics. Eigenvectors obtained from a transformed weights matrix are known to represent latent map patterns. Our proposal is to use these patterns to obtain synthetic variables for use as instruments in IV estimation. By their very nature, instruments based on synthetic variables are exogenous. Furthermore, they can provide relatively high levels of correlation with the endogenous variable (Le Gallo and Pàez 2013). Following Doran and Fingleton (2015) we produce a synthetic instrument for each endogenous variable, TV, UTV and RTV. We first define a contiguity matrix and obtain the eigenvectors of this matrix. Then each eigenvector is regressed on the endogenous variable and the significant eigenvectors are retained and summed to create an exogenous instrument (each significant eigenvector is weighted according to the regression coefficient obtained by regressing the eigenvector on the endogenous variable). For a full explanation of the approach, see Gallo and Páez (2013).

3.3 Results

Tables 1 and 2 report respectively the spearman rank correlations and some descriptive statistics for our provincial level variables. Table 3 shows instead descriptive statistics for our individual and firm level variables of the Inps database.

Table 1. Correlation matrix, provincial variables

Variables	(1)	(2)	(3)	(4)	(5)
(1) TV	1				
(2) RTV	0.973*	1			
(3) UTV	0.752*	0.605*	1		
(4) kcap_flav	0.641*	0.605*	0.537*	1	
(5) logpop	-0.026	-0.022	-0.012	-0.244*	1

Note: spearman rho $= -0.244$.
Source: Authors' calculations on Inps 48 date sample 2005-2018

Table 2. Descriptive statistics, provincial variables

	TV	RTV	UTV	logpop	kcap_flav
2004					
Mean	1.76868	1.39914	1.03621	5.14155	1.07928
Sd	0.45636	0.47562	0.2871	0.76629	1.85781
Min	0	0	0	3.44265	0.00169
Max	2.34009	2.04955	1.31116	7.86704	9.58936
Skewness	-1.9115	-1.4506	-2.3164	0.57884	2.71845
Kurtosis	7.15633	5.01824	8.4992	4.28264	10.5219
2017					
Mean	1.90295	1.56381	1.07227	5.17749	1.35112
Sd	0.41923	0.42384	0.28684	0.77025	2.88382
Min	0	0	0	3.39557	0.00229
Max	2.42957	2.17364	1.31547	7.86157	16.6314
Skewness	-2.4232	-1.4773	-2.6231	0.49544	3.70515
Kurtosis	10.9822	5.84397	9.70351	4.12221	16.9264
Count	91	91	91	91	91
Total					
Mean	1.8429	1.48582	1.06423	5.16547	1.2825
Sd	0.42707	0.43554	0.28836	0.76415	2.43562
Min	0	0	0	3.39557	0.00035
Max	2.42957	2.17364	1.37387	7.86864	18.3904
Skewness	-2.0665	-1.4273	-2.2967	0.51956	3.42041
Kurtosis	8.68595	5.45091	8.47654	4.14119	16.5626
Count	1273	1273	1273	1273	1273

Source: Authors' calculations on Inps 48 date sample 2005-2018

Table 3. Descriptive statistics, Inps variables 2005-2018

	Whole sample		**Male**		**Female**	
	Mean	Std dev	Mean	Std dev	Mean	Std dev
Log (weekly wage)	6.151	0.543	6.221	0.549	6.051	0.518
Female	0.413	0.492				
Age (in years)	40.306	10.878	40.818	11.094	39.579	10.521
Fixed term contract	0.172	0.377	0.143	0.350	0.213	0.409
Part time contract	0.224	0.417	0.110	0.313	0.385	0.487
Other professions	0.047	0.212	0.052	0.222	0.040	0.196
Blue collar	0.539	0.499	0.632	0.482	0.405	0.491
White collar	0.382	0.486	0.275	0.447	0.534	0.499
Executives	0,032	0.176	0.040	0.196	0.021	0.143
Job mobility	2.384	1.635	2.417	1.679	2.337	1.569
Firm size						
N of employee<10	0.273	0.446	0.254	0.435	0.301	0.459
9<n of employees<50	0.244	0.430	0.262	0.440	0.220	0.414
49< n of employees<250	0.175	0.380	0.187	0.390	0.159	0.365
N of employee>249	0.307	0.461	0.297	0.457	0.321	0.467
Sector of activities						
Agriculture	0.008	0.088	0.010	0.098	0.005	0.071
Mining	0.003	0.056	0.004	0.067	0.001	0.035
Manufacturing	0.286	0.452	0.343	0.475	0.206	0.405
Public utilities	0.017	0.130	0.024	0.154	0.007	0.083
Construction	0.075	0.264	0.118	0.323	0.015	0.121
Commerce	0.147	0.355	0.129	0.335	0.174	0.379
Transportation	0.064	0.245	0.085	0.279	0.034	0.182
Tourism, hotel restaurants	0.079	0.270	0.059	0.236	0.108	0.311
Information & communication	0.032	0.177	0.032	0.175	0.033	0.179
Finance, banking, insurance	0.040	0.196	0.037	0.188	0.044	0.206
Real estate, other services	0.113	0.317	0.085	0.279	0.153	0.360
Private social services etc.	0.134	0.340	0.074	0.261	0.219	0.413
N of Obs	22320728		13368349		8952379	

Note: Sampling weights applied.
Source: Authors' calculations on Inps 48 date sample 2005-2018

The output of our first stage estimates (equation 1) for to the whole sample of Italian private sector employees aged 18-64, is thereby reported in table 4.

The Mincerian variables are always highly significant (at 1 percent level) in all the specifications. In line with the predictions of the human capital literature, female, part time fixed term and dummy for changing firm, are all negatively correlated with wages. Higher wage premia are associated with higher qualifications as well as larger firms.

Table 4. First stage regressions

	Whole sample			Male workers		
	OLS	FE	AKM	OLS	FE	AKM
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Job mobility	-0.0204***			-0.0233***		
	[0.000]			[0.000]		
Female	-0.1977***					
	[0.000]					
Fixed term contract	-0.2117***	-0.1026***	-0.0751***	-0.2107***	-0.1055***	-0.0769***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Part time	-0.0273***	0.1211***	0.1237***	-0.0728***	0.0868***	0.1029***
	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Blue collar	-0.3365***	0,0006	0.0484***	-0.3823***	0.0400***	0.0679***
	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
White collar	-0.0286***	0.1473***	0.1102***	-0.0810***	0.1596***	0.1116***
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]
Executives	0.5334***	0.2827***	0.2179***	0.4413***	0.2854***	0.2096***
	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
10<n of workers<50	0.0933***	0.0410***	0.0146***	0.1021***	0.0388***	0.0222***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
49< n of workers <250	0.1505***	0.0710***	0.0377***	0.1524***	0.0638***	0.0507***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
N of workers >249	0.2219***	0.1050***	0.0538***	0.2522***	0.1105***	0.0714***
	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-province FE	Yes	Yes	Yes	Yes	Yes	Yes
Workers FE	No	Yes	Yes	No	Yes	Yes
Firms FE	No	No	Yes	No	No	Yes
Obs	22320728	2,2E+07	2,1E+07	13368349	1,3E+07	1,3E+07
R-squared	0.367	0.739	0.816	0.389	0.779	0.857

Note: estimations results of Model (1) in text. Other controls include, age, sector of activity and province-year fixed effects. Clustered standard errors (for each year-province cell) in parentheses. *** p<0.001, **p<0.005, *p<0.010.
Source: Authors' calculations on Inps 48 date sample 2005-2018

In table 5 we show our second stage OLS results of the wage elasticity of regional innovativeness (province-year effects estimated in the first stage regressed on the logarithm of our varieties indicators and controls as displayed in equation 4).

In the first specification (column 1), only TV is included as variety indicator. Column 2 includes instead UTV, column 3 RTV and the last column disentangles the total variety into the separate contribution of RTV and UTV. All specifications add knowledge capital in a quadratic form and the logarithm of population density, as shown in equation (4).

Table 5. OLS estimates

	OLS			
	(1)	(2)	(3)	(4)
	TV	RTV	UTV	RTV+UTV
TV	0.0128***			
	[0.005]			
RTV		0.0107**		0.0037
		[0.005]		[0.005]
UTV			0.0197***	0.0165**
			[0.006]	[0.007]
Kcap/flav	-0.0113***	-0.0110***	-0.0109***	-0.0113***
	[0.002]	[0.002]	[0.002]	[0.002]
(kcap/flav)^2	0.0008***	0.0008***	0.0008***	0.0008***
	[0.000]	[0.000]	[0.000]	[0.000]
Log population density	0.0134***	0.0137***	0.0135***	0.0135***
	[0.002]	[0.002]	[0.002]	[0.002]
Year fe	Yes	Yes	Yes	Yes
Worker fe	No	No	No	No
Obs	1009	1009	1009	1009
R-squared	0.137	0.134	0.138	0.137

Note: estimation results of Model (2) in text. Clustered standard errors (for each year-province cell) in parentheses. *** p<0.001, **p<0.005, *p<0.010.
Source: Authors' calculations on Inps 48 date sample 2005-2018

Total variety as well as related and unrelated variates (columns 1-3) seem to have a positive and statistically significant effect on wages in provinces with same population density and knowledge capital. When we decompose this mechanism by assessing separately the effects of unrelated and related variety (column 4), we see that only UTV remains statistically significant. Part of the observed elasticity seems to be explained by individual time varying fixed effects. In fact, in table 6, we observe a drop in the magnitude of each of the varieties indicators once workers fixed effects are included. However, the sign of the correlations remains unchanged.
In table 7, we report the results of a series of OLS regressions where our dependent variable, i.e., the province-year effects estimated in the first stage has been computed using AKM estimates accounting for both individual and firm specific time invariant characteristics. Specification of column (1), (2) and (3) show that each of the indicator becomes non-significant, while in the last column (4) we observe an inversion of the sign on the elasticity of RTV to wages, although the coefficient is not statistically significant.
Of course, these estimates remain highly correlational, as we are in no position to use the latter to infer a clear causal effect linking regional innovativeness to the local wage level.

Table 6. FE estimates

	Fixed Effects			
	(1)	(2)	(3)	(4)
	TV	RTV	UTV	RTV+UTV
TV	0.0080**			
	[0.004]			
RTV		0.0063*		0,001
		[0.004]		[0.005]
UTV			0.0136***	0.0128**
			[0.005]	[0.006]
Kcap/flav	-0.0083***	-0.0080***	-0.0082***	-0.0083***
	[0.001]	[0.001]	[0.001]	[0.001]
(kcap/flav) ^2	0.0006***	0.0006***	0.0006***	0.0006***
	[0.000]	[0.000]	[0.000]	[0.000]
Log population density	0.0069***	0.0070***	0.0069***	0.0068***
	[0.002]	[0.002]	[0.002]	[0.002]
Year fe	Yes	Yes	Yes	Yes
Worker fe	Yes	Yes	Yes	Yes
Obs	986	986	986	986
R-squared	0.587	0.587	0.588	0.588

Note: estimation results of Model (2) in text. Clustered standard errors (for each year-province cell) in parentheses. *** p<0.001, **p<0.005, *p<0.010.
Source: Authors' calculations on Inps 48 date sample 2005-2018

Table 7. AKM Estimates

	AKM			
	(1)	(2)	(3)	(4)
	TV	RTV	UTV	RTV+UTV
TV	0.0031			
	[0.002]			
RTV		0.0019		-0.0022
		[0.002]		[0.003]
UTV			0.0079***	0.0097***
			[0.003]	[0.003]
Kcap/flav	-0.0034***	-0.0032***	-0.0036***	-0.0033***
	[0.001]	[0.001]	[0.001]	[0.001]
(kcap/flav) ^2	0.0002**	0.0002**	0.0003***	0.0002**
	[0.000]	[0.000]	[0.000]	[0.000]
Log population density	0.0051***	0.0051***	0.0050***	0.0050***
	[0.001]	[0.001]	[0.001]	[0.001]
Year fe	Yes	Yes	Yes	Yes
Worker fe	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes
Obs	969	969	969	969
R-squared	0.777	0.777	0.778	0.778

Note: estimation results of Model (2) in text. Clustered standard errors (for each year-province cell) in parentheses. *** p<0.001, **p<0.005, *p<0.010.
Source: Authors' calculations on Inps 48 date sample 2005-2018

Therefore, in table 8 and 9, we show a series of results based on the instrumental variable approach discussed in the previous section. More specifically, table 8 reports the outcome of our 2SLS regressions where the dependent variable has been computed using only workers' fixed effect in the first stage, while table 9 refers to AKM specifications in the first-stage. The key difference between these results and those obtained in the previous estimations is evident: while the effect of RTV is no longer significant and even negative in some specifications, UTV still exerts a positive and significant effect on the workers' wages, consistently with the ideas expressed in section 2 according to which worker in diversified regions are likely to command higher wages, for a variety of multiple and non-mutually exclusive reasons.

Table 8. IV and IV-FE estimates

	IV				**IV-FE**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	TV	RTV	UTV	RTV+UTV	TV	RTV	UTV	RTV+UTV
TV	0.008 [0.008]				0.006 [0.007]			
RTV		0.0053 [0.007]		-0.0377*** [0.012]		0.0025 [0.006]		-0.0286*** [0.001]
UTV			0.0552*** [0.013]	0.1130*** [0.022]			0.0393*** [0.011]	0.0831*** [0.018]
Kcap/flav	-0.0105*** [0.002]	-0.0100*** [0.002]	-0.0143*** [0.002]	-0.0129*** [0.002]	-0.0079*** [0.002]	-0.0074*** [0.002]	-0.0106*** [0.002]	-0.0094*** [0.002]
(kcap/flav) ^2	0.0008*** [0.000]	0.0008*** [0.000]	0.0010*** [0.000]	0.0010*** [0.000]	0.0006*** [0.000]	0.0006*** [0.000]	0.0008*** [0.000]	0.0007*** [0.000]
Log population density	0.0136*** [0.002]	0.0138*** [0.002]	0.0126*** [0.002]	0.0122*** [0.003]	0.0069*** [0.002]	0.0071*** [0.002]	0.0063*** [0.002]	0.0061*** [0.002]
Year fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker fe	No	No	No	No	Yes	Yes	Yes	Yes
Obs	1009	1009	1009	1009	986	986	986	986
	First stage statistics							
S_TV	47.790*** [0.000]				46,8667 [0.000]			
S_RTV		43.860*** [0.000]		29.631*** [0.000]		43.463*** [0.000]		29.939*** [0.000]
S_UTV			31.843*** [0.000]	35.485*** [0.000]			31.276*** [0.000]	34.688*** [0.000]
K-P rk Wald F statistic	520.502	657.561	296.817	107.201	536.96	639.119	286.156	101.59

Note: estimation results of Model (2) in text. Clustered standard errors (for each year-province cell) in parentheses. *** p<0.001, **p<0.005, *p<0.010.
Source: Authors' calculations on Inps 48 date sample 2005-2018

Table 9. IV estimates

	IV			
	(1)	(2)	(3)	(4)
	TV	RTV	UTV	RTV+UTV
TV	-0.0008 [0.005]			
RTV		-0.0019 [0.004]		-0.0255*** [0.008]
UTV			0.0235*** [0.007]	0.0625*** [0.013]
Kcap/flav	-0.0027** [0.001]	-0.0025* [0.001]	-0.0050*** [0.001]	-0.0041*** [0.001]
(kcap/flav) ^2	0.0002* [0.000]	0.0002* [0.000]	0.0003*** [0.000]	0.0003*** [0.000]
Log population density	0.0052*** [0.001]	0.0052*** [0.001]	0.0047*** [0.001]	0.0044*** [0.001]
Year fe	Yes	Yes	Yes	Yes
Worker fe	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes
Obs	969	969	969	969
	First stage statistics			
S_TV	45.296*** [0.000]			
S_RTV		42.391*** [0.000]		30.334*** [0.000]
S_UTV			30.323*** [0.000]	33.619*** [0.000]
F - test excl instr	295.605	357.349	168.316	67.812

Note: estimation results of Model (2) in text. Clustered standard errors (for each year-province cell) in parentheses. *** p<0.001, **p<0.005, *p<0.010.
Source: Authors' calculations on Inps 48 date sample 2005-2018

4. Conclusions

In this paper, we have developed an empirical framework to investigate the relationship between technological agglomeration and wage premia. Using PATSTAT information on the innovative activity of Italian firms, we have built a set of entropy indexes to qualify the knowledge structure of our geographical units, as to assess if the workers' compensations are somewhat related to the peculiarities of the technological space where they supply their labor services. By distinguishing between related and unrelated technological variety, we have analyzed if wages are more affected in technologically specialized or diversified regions. To do so, we applied the empirical strategy proposed by Combes *et al.* (2008) using a rich administrative data on Italian workers and firms. Consistently with the idea that technological diversification spurs more impactful innovation (Castaldi *et al.* 2015) and thus, generates learning dynamics that are more significant for workers, we have found that workers in diversified regions earn positive premia, while the effect of related variety is less clear-cut, being either negative or non-significant, depending on the specification. Once again, this is consistent with the already established fact that an excess of specialization may generate long-term lock in effects, affecting both productivity and wages. The policy implication is straightforward: innovation incentives should be designed as to encourage firms to enter in previously unexplored domains, tying novel connections with loosely related technological fields and pursuing more radical innovation strategies. Indeed, by following already consolidated technological strategies, firms may seize immediate benefits (that may not be shared with workers because of labor supply effects) but remain trapped in inferior long-run situations.

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INAPP
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