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# Peer interactions, local markets, and wages: Evidence from Italy<sup>#</sup>

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## Abstract

This paper investigates the relationship between the spatial distribution of occupations with a high content of peer interactions and wages among Italian provinces. At this aim, we use a unique employer-employee dataset obtained by merging administrative data on wages and labor market histories of individuals, with survey data on job tasks and contents. The spatial distribution of jobs intensive in peer-interactions is further measured according to the occupational structure of Italian provinces. The econometric analysis shows that the concentration of peer interactions leads to higher wages at the province level. These results are robust to firms and workers' heterogeneity and endogeneity issues.

**Keywords:** Peer interactions, Wages, Agglomeration externalities

**JEL Classification:** J31, R12, R23

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## 1. Introduction

The relationship between peer interactions and wages has drawn increasing attention from the empirical literature (Mansky, 2000, Herbst and Mas, 2015, Mas and Moretti, 2018). Behavioral models and empirical studies have highlighted different mechanisms through which social connections and implicit norms lead to productivity externalities among co-workers and, therefore, to wage premium (Feher et al. 2009; Cornelliissen, Dustmann et al. 2017). For instance, repeated workers' interactions may favor peer pressure and knowledge spillovers within firms that, in turn, induce overall gains in productive efficiency and average wages. Moreover, peer pressure and, more in general, team incentives (Ledford et al., 1995), help to mitigate free-rider problems - where technology and production lines are organized in such a way that workers' efforts are complementary (Kandel and Lazear, 1992). This may occur even in settings in which workers carry out independent tasks (i.e., that do not directly affect each other's output) and are employed in firms specialized in different phases of a single integrated value chain - as in the case of industrial districts.

These arguments may be further reinforced when social interactions emerge within firms localized in the same local labor market. Empirical evidence supports the hypothesis that peer-pressure is effective if workers feel socially obliged to increase their effort wherever it falls behind that of their colleagues or falls short of a social implicit norm.

On the other hand, implicit norms mirror common beliefs and cultural traits which typically date back in the past and have characterized the economic development of local communities (Guiso et al. 2008). Similarly, knowledge spillovers – an economic concept dating back to the late XIX century (Marshall, 1890) - capture the idea that - by personally interacting and by directly observing each other in the workplace - employees learn from each other and accumulate skills they would not have learned otherwise. Likewise, this type of human capital externalities is mainly at work within communities or local labor markets where firms and workers are connected by stable economic, technological, and cultural links (Mas and Moretti, 2009). Finally, social interactions are expected to favor the “voice” of workers or trade union representatives in the bargaining process and thus generating a “pecuniary” externality on wages. This channel seems to be amplified in local economies, especially in countries where industrial relations have been significantly affected by local market conditions, as for Italy (Damiani et al. 2022).

Based on these arguments, this paper analyzes whether, and how, the geographical localization (localization economies) of economic activities characterized by a high level of workers (peer) interactions affects local wages in Italy. In fact, as discussed by Combes et al. (2008), spatial wage disparities can be explained by: differences in the skills composition of the workforce, differences in local non-human endowments, and finally, by local interactions between workers and firms. Labor market interactions are a source of agglomeration economies which, in turn, can lead to productivity and wage gains (Rosenthal and Strange 2004).

We take advantage of a unique employer-employee dataset obtained by merging two administrative datasets on wages and labor market individual histories (INPS and SISCO archive respectively) with sampling data on professions and tasks (ICP-Inapp) over the period 2011-2018. We adopt a two-stage approach, standard procedure in urban economics (see Combes et al. 2008, Combes et al. 2011, Belloc et al. 2022) and estimate the wage elasticity to agglomeration externalities deriving from peer interactions. The regression analysis suggests that peer interactions

lead to an increase in workers' wages within Italian provinces, a result that is robust to firms and workers' heterogeneity as well as to potential endogeneity issues.

Finally, we enrich the interpretation of our findings by performing a pooled cross-sectional analysis based on the *Rilevazione Imprese e Lavoro* (RIL-Inapp) surveys. Using relevant information on corporate governance, productive characteristics, and industrial relations on a large representative sample of Italian firms, we find a positive correlation between the local peer interactions and trade union membership. This result supports the hypothesis that a union voice mechanism could explain the positive effect of social interactions into higher bargained wages. We rationalize our main results by illustrating a relatively new mechanism behind the peer wage enhancing effect at local level: the increase of union membership and workers' bargaining power that derived from the density of social connections among workers.

The main contributions of the paper to the literature are twofold. First, we analyze a particular type of localization economies by using an occupation-based measure that allows us to observe the spatial distribution of jobs characterized by a high content of peer interactions. Then, we provide evidence that social interactions among workers may be an important driver of wage growth even in settings (i.e geographical areas) where employees carry out tasks and occupations that are not necessarily complementary in the production processes and/or that do not affect the labour productivity within firms by themselves. Second, in estimating the effect of peer interactions on local wages in a country characterized by important territorial unbalances like Italy, we account for the potential role of workers' and firms' heterogeneity. This provides further evidence on the importance of social norms, knowledge spillovers, and institutions in affecting wages and productivity inequalities across geographical areas.

The structure of the paper is organized as follows. Section 2 reviews the literature on agglomeration externalities and social interactions. Section 3 describes the data; section 4 presents the empirical framework and main results. Section 5 shows evidence on the possible mechanisms at work. Finally, section 6 draws some conclusions.

## 2. Literature Review

There is a large consensus on the positive effects deriving from agglomeration externalities (Rosenthal and Strange 2004; Melo et al. 2009). Most of the empirical evidence focuses on agglomeration within the field of regional and urban economics, but there are other strands of research estimating productivity benefits from agglomeration economies, for instance estimates of the “urban wage premium” from Mincerian wage models augmented with measures of agglomeration economies (Melo and Graham, 2009).

Agglomeration economies are generally measured with total population/employment or density. However, these measures are not able to capture the spatial distribution of the effects from agglomeration externalities. To solve this drawback, some studies adopt “market potential” type measures capturing, amongst other indicators, the spatial proximity to economic activity (Mion and Naticchioni 2009, Graham and Kim 2008, Combes et al. 2008).

Closely related to the benefits of spatial proximity between interacting parties is the concept of localized learning referring to the knowledge creation that takes place when several co-located firms undertake similar and related activities (Malmberg and Maskell 2006). These benefits stem from the ease of interaction across firms and workers located in proximity of one another.

Therefore, localized learning helps in explaining why there is geographical economic specialization and why similar and related firms tend to co-locate to form clusters. In clusters, knowledge spillovers are caused by social interactions between individuals, which function as channels for informal knowledge exchange (Breschi and Lissoni, 2009), and since the density of social interactions is higher within than between clusters, co-location is expected to be advantageous for firm's performance and higher wages (Sorenson 2003).

Besides several laboratory experiments and single-firm/single-occupation analysis such as Mas and Moretti (2009), Falk and Ichino (2006), Waldinger (2012), Azoulay et al. (2010), Jackson and Bruegmann (2009) (see the meta-analysis by Herbst and Mas, 2015), only a recent and limited body of the empirical literature, has investigated the link between social interactions and workers' productivity/wages.

A notable contribution in this field is made by Cornelissen et al. (2017). The authors estimate the importance of social interactions through the effect of peer ability on co-workers' wage and find a small though significant effect – which is larger in low-skilled occupations where “co-workers can easily observe each other's output”. Differently, Borghans et al. (2006) estimate wage returns to a whole range of soft skills, approximated by the importance of “people tasks” for job performance. Results show that individuals working in jobs where people tasks are more relevant face lower wages. A standard deviation increase in the importance of people tasks is estimated to have a wage penalty of about 5% in the U.S. and 4.9% in the UK. However, in a subsequent study Borghans et al. (2008) show that one standard deviation increases in “directness” relative to “caring” (proxy for interpersonal interaction) raises wages by 9.6% in 1997 and 10.8% in 2001 in the UK, and by 3.8% in 1979 and 10.2% in 1998 in Germany. Further, the premium for directness is higher in occupations where this is more important.<sup>1</sup> By using Dictionary of Occupations Titles (DOT) data and the CPS survey 1968-1990, Bacolod and Blum (2010) reveal that wage returns to “people-skills” nearly doubled in the period from 1968 to 1990, while returns to cognitive skills increased by 60% and returns to “motor” skills decreased by 50%.

Using similar occupational indicators and by relying on metropolitan statistical area (MSA) level data, Bacolod et al. (2009) find that the urban wage premium is larger for workers with stronger cognitive and “people skills”. In contrast, motor skills and physical strength are not rewarded to a greater degree in large cities. In a similar vein, Choi (2020) explores the advantage of regional concentrations of workers specialized in different types of skills. He estimates the agglomeration effects of skill-based labor pooling on wage levels and wage growth. The author finds that the urban wage premium of skill-based local labor pooling varies between types of skills. According to Choi (2020), the greatest magnitude of benefit is incurred by workers employed in cognitive-skill-oriented occupations, while an urban wage premium is non-existent in social-skill-oriented occupations.

### 3. Data and descriptive statistics

#### 3.1 Data

The relationship between the spatial concentration of social interactions and wages is analyzed for a representative sample of Italian employees over the period 2011-2018. To measure the level

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<sup>1</sup> For a general review of the empirical literature on wage returns to “soft-skills” see Balcar, (2014).

of social interaction within firms located in the same geographical area (in our case the Italian provinces), we use a synthetic index that provides a snapshot of the occupational structure. The dataset is built linking three archives: the administrative archive of employees collected by the Italian National Social Security Institute (INPS); the archive of Compulsory Communications System (*Sistema delle Comunicazioni Obbligatorie*; COB hereafter) provided by the Ministry of Labor and Social Policies; and the sample survey *Indagine Campionaria delle Professioni* (ICP 2013) provided by Inapp<sup>2</sup>.

The INPS archive includes the population of employees, and it records a wide range of variables: annual gross wages, age, gender, occupation, annual weeks worked, information on the type of contract (part-time versus full-time, temporary versus permanent), on the sector of activity, and on the geographical localization (the province) of the work arrangement. From the INPS archive, we extract a dataset based on a random sample of all employees born on four different days of each month of any year. The COB archive records from year 2009, each job relationship that started, changed or ended for firing, dismissal, retirement, or transformation (e.g. from a fixed-term to an open-ended arrangement) of the contractual arrangement within the same firm for all individuals working in Italy as employee or apprenticeship, temporary agency work arrangements, and para-subordinate workers. Moreover, it includes detailed educational and occupational information (5-digit). This data source makes it possible to observe flows in and out of the labor market.

Finally, the ICP survey was last run in 2013 by the National Institute for Public Policies Analysis (Inapp) and involves 16,000 workers recording detailed information on all the 5-digit occupations (i.e., 811 occupational codes) of the Italian labour market, from those operating in private firms, public institutions and structures, up to independent companies. The ICP-Inapp is the Italian equivalent of the American O\*NET, that is the most comprehensive repertoire reporting qualitative and quantitative information on tasks, work context, organizational features of workplaces at detailed level. A relevant aspect of ICP-Inapp is that tasks and skills variables are specific to the Italian economy allowing for the definition of the structure of the labor market and the industrial relations characterizing the Italian economy. Thus, the use of ICP variables avoid potential methodologic problems which may arise when information related to the American occupational structure (i.e., contained in the US O\*Net repertoire) are matched with labor market data referring to European countries.

The INPS and COB datasets have been merged via workers' tax codes. This dataset is then matched with the peer interaction index (PII hereafter) derived from ICP-Inapp survey. Following the approach proposed by Barbieri et al. (2020), the PII index is computed by considering workers' responses to the following ICP question: i) *how much important is in your job to personally interact with work colleagues or to be part of teams or working groups?* The answers are then overall standardized in an index with a 0–100 range, according to the following formula:

$$X = \left( \frac{Y - \min}{\max - \min} \right) * 100$$

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<sup>2</sup> The *Indagine Campionaria delle Professioni* (ICP) was jointly created by the National Institute for Public Policies Analysis (INAPP) and the National Institute of Statistics (ISTAT), in 2004. It is currently carried out by INAPP in the context of the initiatives launched for the construction and constant updating of a permanent national system for the observation of professional needs.

where  $Y$  is the original answer (from 1 to 5) to the question and  $max$  and  $min$  are the maximum and the minimum value reported for each occupation. The ICP index has been firstly aggregated from 5-digit to 3-digit CP2011 occupations, and then at the province level (107 Italian provinces) by means of the ISTAT *Rilevazione Continua delle Forze di Lavoro* (RCFL).

As dependent variable we employ the weekly real gross wage at the individual level (full-time equivalent wage for part-timers)<sup>3</sup>. In the case of multiple contracts associated with the same individual in the same year, we consider the longer contract only. We end up with an INPS-COB sample reaching around 11.000.000 individuals aged 16-67 over the 2011-2018 period. The spatial unit of observation is the province where the individual work.

### 3.2 Descriptive statistics

In this section, we summarize relevant variables in the INPS-COB sample, illustrate the occupational and geographical distribution of our measure of within-occupation peer interactions, and broadly explore its relationship with wages, education, and urbanization. As shown in Table 1, our sample is made by more than 11 million observations, with an average gross weekly wage of about 470 euros. Moreover, 43 per cent of the sample is characterized by female workers, with an average age of 39. Also, on average, workers changed 3 firms over the reference period (indicator of labour flexibility). Differently, fixed-term and part-time contract workers amount to, respectively, 31 and 32 per cent of our sample. As for the occupational variable's dummies, Table 1 shows that almost 60 per cent of the sample is made by "blue-collar" workers, while "white-collar" workers amount to almost 1/3 of the sample. Conversely, shares are far smaller in the case of "apprentice" workers (6 per cent) and "managers" (2 per cent), while the share of "executives" is below 1 per cent. Finally, our sample is characterized by small or medium firms, and a distribution of educational attainments which is in line with the empirical evidence in Italy.

Table 1. INPS-COB sample descriptive statistics.

	Obs.	Mean	Std. dev.	Min	Max
Weekly wage	11,630,253	472.68	352.48	0.025	103,032.8
Female	11,637,841	0.433	0.49	0	1
Age	11,637,841	38.88	11.66	16	67
Number of firms	11,637,841	2.96	1.8073	1	14
Fixed term	11,637,841	0.31	0.46	0	1
Part time	11,637,841	0.32	0.46	0	1
Blue collar	11,637,841	0.59	0.49	0	1
White collar	11,637,841	0.33	0.47	0	1
Manager	11,637,841	0.02	0.12	0	1
Executive	11,637,841	0.006	0.082	0	1
Apprentice	11,637,841	0.06	0.23	0	1
<i>Firms size</i>					
0-9 employees	11,632,116	0.33	0.47	0	1
10-49 employees	11,632,116	0.26	0.44	0	1

<sup>3</sup> INPS archive provides information concerning the individual percentage of part time with respect of full-time workers. The nominal wages are deflated by the national CPI (base year=2018).

50-249 employees	11,632,116	0.16	0.36	0	1
>250 employees	11,632,116	0.25	0.43	0	1
Lower secondary ed.	10,935,006	0.33	0.47	0	1
Upper secondary ed.	10,935,006	0.49	0.50	0	1
Tertiary education	10,935,006	0.18	0.39	0	1

Notes: Authors' elaborations on INPS-COB data.

To consistently describe the individual distribution of our occupational indicator before the province-level aggregation of our empirical analysis, we first report statistics by using the INPS-SISCO database in Table 2 and Table 3, and then use the ISTAT-RCFL survey to graphically display the 2011 geographical distribution of peer interactions, wages, and population density in Figure 1.

To summarize the occupational distribution of our peer-interactions index, Table 2 reports average weighted values of the original 5-digit occupational score by 1-digit occupational groups. Further, for each broad occupational group we include statistics for both education and wages. As numbers in Table 2 clearly show, our occupational measure of peer-interactions displays a clear relationship with workers' education. From Table 2 we can clearly see that peer-interactions are higher among high-education/high-wage occupations and lower among low-education/low-wage occupations (e.g., 84.4 among managers and 57.5 among elementary jobs). Furthermore, it is also worth noticing) that - except for craft and agricultural jobs - our peer interaction measure monotonically increases with the Italian ICP rank, even more than average weekly wages do (please compare with the last column in Table 3

Tab 2. Average ICP 5-digit Occupational Indicators, ISCED educational attainment groups share and average weekly wage by CP2011 1-digit occupations.

Cp2011 code	Cp2011 nomenclature	Peer Inter.	Lower second.	Upper second	Tertiary	Weekly wage
1	Managers	84.4	0.07	0.37	0.56	1460
2	Professionals	78.5	0.03	0.25	0.72	623
3	Technicians	74.1	0.09	0.52	0.39	618
4	Clerks	70.6	0.14	0.63	0.22	514
5	Sales and Services	64.3	0.33	0.57	0.10	394
6	Craft and Agricultural	65.0	0.60	0.37	0.02	423
7	Plant and Machine Op. and Assemblers	58.4	0.58	0.40	0.03	463
8	Elementary	57.5	0.58	0.39	0.04	377

Notes: Authors' elaborations on INPS-COB data.

To illustrate the relationship between wages, population density and our peer-interactions occupational index, in Table 3 we report a simple correlation matrix obtained by using INPS-COB individual data. Unsurprisingly, both peer-interactions and population density show similar positive correlations with wages, with a  $\rho$  of, respectively, .44 and .40 (slightly higher for peer interactions). The correlation between population density and peer interactions is also positive and relatively high (.30) - indicating that urbanization patterns and the spatial distribution of peer interactions are plausibly linked. For instance, it is very likely that more densely populated areas



favor the presence of jobs with higher content of peer interactions (sorting effects: best workers and firms tend to have higher probabilities of locating in urban areas see Combes et al., 2008; Mion and Naticchioni, 2009; De La Roca and Puga, 2017). Nevertheless, productivity of workers in these jobs may benefit from higher proximity in urban areas (urbanization externalities, see Marshall, 1890; Glaeser, 1998; Kim, 1987; Ciccone and Hall, 1996). Of course, the correlation between population density and peer interactions may be spurious when estimating the impact of peer interactions on wages. This issue will be addressed in section 4.

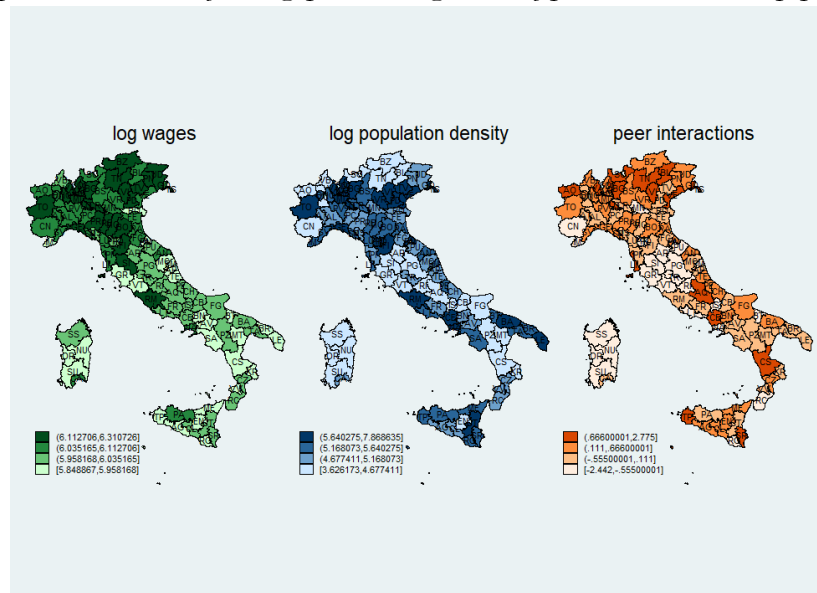
Table 3. Correlation matrix.

	Weekly Wage	Pop. Density	PII
Weekly Wage	1		
Pop density	0.4008*	1	
Peer interactions (PII)	0.4407*	0.2985*	1

Notes: 1,1630,253 observations. Authors' elaborations on individual-level INPS-COB data. All statistics are significant at the 1 per cent level.

Finally, Figure 1 plots the 2011 geographical distribution of variables considered in Table 3 (please note that, in the case of wages and the peer interaction measure, we compute weighted average values of individual-level data).

Figure 1. *Spatial distribution of average province wages, level of peer-interactions and population density*



Note: 107 Italian provinces. Source: Authors' elaborations on INPS-COB and ICP data.

As clearly illustrated in Figure 1, all three variables considered have generally higher scores in northern provinces, although - for what concerns the average (log) wages - the north-south divide of the Italian economy is visibly more pronounced. Recalling what observed in Table 3, however, it is easy to see that - in the case of population density and the peer-interactions occupational measure (resulting from differences in the occupational structure of different provinces) the spatial

distribution looks somehow similar. However, there are some clear differences, for instance, in the north-east or in the southern side of the peninsula (excluding the islands, where the spatial distribution is substantially similar).

What just described raises reasonable concerns about the presence of unobservable characteristics that might be correlated with both population density and the degree of peer interactions, hence reinforcing the need to adopt an instrumental variable approach in our empirical strategy.

#### 4. Estimation strategy

To estimate the wage effects associated to the local concentration of occupations characterized by a high level of peer interactions, we adopt a two-stage approach *a la* Combes et al. (2008). This method has been employed in several other analyses on agglomeration economies and allows us to account for local level unobserved heterogeneity (see Combes and Gobillon 2015; De la Roca and Puga 2017; Belloc et al. 2022).

A two-stage setting is plausibly the most suitable estimation method for local-level analysis, yielding standard errors that account for the grouped structure of the data, at the individual and province level<sup>4</sup>. Formally, in the first stage we regress workers' wages on individual and firm-specific factors in the following Mincer-type wage equation (Heckman et al. 2003):

$$[1] \quad \log(W_{ijt}) = \alpha_{p(it)t} + \rho_1 X_{it} + \rho_2 F_{j(it)t} + \gamma_i + \gamma_{j(it)} + \varepsilon_{it}$$

where  $\log(W_{ijt})$  is the logarithm of the (part-time adjusted) real wage of individual  $i$ , employed in firm  $j$  at time  $t$ , over the period 2011-2018.  $X_{it}$  is a vector of workers' characteristics: gender, part-time dummy, fixed-term dummy, age and age squared, and occupational dummies (blue collar, white collar, managers, and executives), while the vector  $F_{j(it)t}$  includes several firm-level controls for firm  $j$  where the worker  $i$  works at time  $t$ : firm-size classes, 2-digit sectors and a dummy variable indicating how many times a worker changes firm (an indicator of the degree of flexibility of the worker's career).  $\alpha_{p(it)t}$  are province-year effects, where  $p(it)$  stands for the province where individual  $i$  works at time  $t$ . To account for unobservable workers' and firms' time-invariant heterogeneity, in some specification we also include individual ( $\gamma_i$ ) and firm ( $\gamma_{j(it)}$ ) fixed effects (see for instance Glaeser and Maré 2001; Combes et al. 2008). Finally,  $\varepsilon_{ijt}$  is an idiosyncratic error term with zero mean and finite variance.

In the second stage, we estimate the relationship between local wages and our measure of localization economies, by regressing the province-year effects  $\alpha_{p(it)t}$ , estimated in the first stage, on our key explanatory variable – the peer-interactions index ( $PII_{pt}$ ) as described in section 3.1. After including a set of province-level control variables we estimate the following equation:

$$\hat{\alpha}_{pt} = \beta PII_{pt} + \sigma \zeta_{pt} + \tau_t + \mu_{pt} \quad [2]$$

where  $PII_{pt}$  is the peer interactions index in province ( $p$ ) and year ( $t$ ), and  $\zeta_{pt}$  is a vector of province-level controls such as the log of population density (measured as the total number of

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<sup>4</sup> For an accurate discussion on the advantages of the two-stage strategy, see Combes and Gobillon (2015).

inhabitants per squared kilometer), the employment share of high-skilled occupations (i.e. C.P. 1, 2 and 3), the population share of graduated individuals, forests share of total area and total land area - both in Km<sup>2</sup><sup>5</sup>. The log of population density accounts for urbanization effects, the share of high-skilled jobs is a proxy for the local average education and aims to capture the external effects of human capital in the geographical area (Moretti, 2004), while accounting for the province' occupational structure. We also directly control for average education by including in the model the graduates' share of total province population (see Di Pietro and Urwin 2006; Quintano et al. 2008, for the literature on educational and skills mismatch in Italy). As for the forest share of land area and total land area in km<sup>2</sup> - they respectively measure productive endowments and the pure scale effect (see Combes et al. 2008). Finally, we include year dummies  $\tau_t$  to control for business cycle and  $\mu_{at}$  is an idiosyncratic error. Models (1) and (2) are estimated using in turn, pooled OLS, one-way fixed effects as well as AKM models with residuals clustered at the local (province-year) level (see Abowd et al. 1999; Card et al. 2013; Belloc et al. 2022).

#### 4.1 Main estimates

We begin by presenting second stage results of our baseline specification in [2] estimated with OLS, FE and AKM models, respectively shown in columns 1, 2 and 3 of Table 4 (estimations for [1] are reported in appendix A).

The coefficient estimates of our peer interaction index points to a positive (and highly significant) correlation with wages, but it decreases in magnitude once individual and also firm fixed are accounted for: moving from .012 (OLS) to .009 (FE) and finally .003 with AKM-models. Moreover, by comparing R<sup>2</sup> across each specification we see that FE and AKM models explain almost all variation in wages (0.94 and 0.96 respectively).

Since the standard deviation of our main explanatory variable,  $PII_{pt}$ , is 1.25 an estimate of .003 (AKM) predicts a 0.4 percent increase in wages at the province level for a standard deviation increase in  $PII_{pt}$ .

Tab 4: Dep var: predicted wage with Province-Year FE: OLS, FE and AKM models.

	(1) $\hat{\alpha}_{pt}$ OLS	(2) $\hat{\alpha}_{pt}$ OLS FE	(3) $\hat{\alpha}_{pt}$ AKM
PII	0.012*** (0.002)	0.009*** (0.002)	0.003*** (0.001)
Log (population/km <sup>2</sup> )	0.002 (0.003)	-0.001 (0.003)	0.001 (0.001)
Share of high-skilled jobs	0.199** (0.078)	0.053 (0.067)	0.046 (0.036)
Share of graduates	-0.044 (0.089)	0.023 (0.073)	0.137*** (0.045)
Forest area/total area	0.068*** (0.008)	0.066*** (0.007)	0.028*** (0.004)
Total area km <sup>2</sup>	0.000**	0.000**	-0.000

<sup>5</sup> High-skilled occupations are CP2011 major groups 1, 2 and 3 – corresponding to ISCO-08 major groups 1, 2 and 3.

	(0.000)	(0.000)	(0.000)
Constant	-0.891***	-0.618***	-0.273***
	(0.118)	(0.099)	(0.051)
N	856	856	856
R <sup>2</sup>	0.255	0.937	0.963

Note: N = (107provinces×8years) = 856. Robust standard errors in parentheses clustered by province and year. The share of high-skilled jobs is computed as the share of 1-digit CP2011 occupations 1, 2 and 3 of total province employment. Share of graduates is the ratio between province graduates and province total population. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

#### 4.2 Instrumental variable estimates

In this section, we address possible endogeneity drawbacks related to our peer-interaction measure (PII). Formally, the endogeneity bias could still occur if there are omitted variables causing the error term to be correlated with *PII*. In our setting, a major concern is the fact that our occupation-based peer interaction index – once aggregated at the province level - is likely to be correlated with unobservable omitted variables related to urbanization economies. Typically, this may be an outcome of sorting into geographical areas where hiring firms compete on value added, innovation and social inclusion rather than labor cost minimization (Venables 2011). For instance, economic activities that are intensive in peer-interactions may reasonably benefit from higher workers’ proximity in urban areas and, therefore, are likely to be placed in urban areas. This concern is reinforced by the descriptive evidence provided in Section 3 - showing a non-negligible positive correlation between population density and occupations intensive in peer-interactions both at the individual (Table 3) and at the spatial/geographical level (Figure 1).

Therefore, we implement an IV-2SLS approach based on the assumption that peer-interactions may be endogenous due to urbanization economies. We instrument  $PII_{at}$  with the provinces’ manufacturing employment share in 1971 ( $MJS_i$ ) interacted with a time-trend. The manufacturing data stem from the ISTAT’s *Atlante Statistico dei Comuni*<sup>6</sup>.

This instrument is assumed to be relevant - since nowadays’ peer-interactions intensive activities might plausibly benefit from the local presence of a working-class political culture developed in a relatively recent past (we choose to take 1971 as reference year because it is immediately after the end of the Italian economic boom and the raise of the historical workers’ mass protest known as “autunno caldo”). At the same time, we assume the exogeneity of the instrument rejecting the hypothesis that it might be correlated with possible unobservable drivers of urbanization. More specifically, there is a large consensus on the fact that - in the last decades - the relationship between urbanization economies and city-size growth (i.e., population-density growth) is fundamentally linked to workers’ education, skills and human-capital accumulation (Glaeser, 1998, Glaeser and Marè, 2001, Glaeser and Saiz, 2004, Glaeser and Resseger, 2010). According to this literature, the role of the manufacturing industry with reference to urbanization has been considerably important up to the first half of the XX century. Conversely, from the end of WWII onward, it is the role of skills and education - as well as of other important factors, such as consumption patterns and supply of amenities in cities (Glaeser and Saiz, 2004, Glaeser et al., 2001) that becomes fundamental in order to explain the link between productivity, wages, and city-size growth. Based

<sup>6</sup> <https://www.istat.it/it/archivio/113712>

these arguments, we feel rather confident in assuming that the relative size of manufacturing in the recent past is orthogonal to nowadays' drivers of urbanization economies.

In Table 5 we report 2SLS results by using  $MJS_i$  as instrumental variable for all three different specifications displayed in Table 4.

As we can see from Table 5, the Kleibergen-Paap Wald F statistic scores to 46.4 indicating that our instrument is indeed a good predictor of  $PII$ , hence, it seems to confirm our assumption that provinces' manufacturing share in 1971 is a relevant IV for the degree peer interactions today - at least, according to our data. However, 2SLS estimates displayed in Table 5 are considerably larger than their OLS counterparts in Table 4. Nonetheless, the positive effect of  $PII$  is still significant and robust to all the three different estimations of  $\hat{\alpha}_{pt}$ . Our results show that when accounting for both sorting of workers and firms (Table 5, Column 3) a standard deviation increase in  $PII_{pt}$  predicts between 7 and 8 percent increase in wages.

Tab 6: IV estimates: dep var predicted wage with Province-Year FE

Variables	(1) $\hat{\alpha}_{pt}$ OLS	(2) $\hat{\alpha}_{pt}$ OLS FE	(3) $\hat{\alpha}_{pt}$ AKM
PII	0.096*** (0.014)	0.055*** (0.009)	0.064*** (0.010)
Log (population/km <sup>2</sup> )	0.013* (0.007)	0.005 (0.004)	0.009* (0.005)
Share of high-skilled jobs	-1.424*** (0.314)	-0.842*** (0.199)	-1.126*** (0.210)
Share of graduates	0.483*** (0.185)	0.314*** (0.120)	0.518*** (0.130)
Total area km <sup>2</sup>	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Forest area/total area	0.051*** (0.018)	0.056*** (0.011)	0.016 (0.012)
N. Obs	856	856	856
first-stage statistics			
Manufacturing share 1971	0.335*** (0.050)	0.335*** (0.050)	0.335*** (0.050)
Kleibergen-Paap Wald F	46.378	46.378	46.378
Prob >F	0.000	0.000	0.000

Note: N = (107provinces×8years) = 856. Robust standard errors in parentheses clustered by province and year. The share of high-skilled jobs is computed as the share of 1-digit CP2011 occupations 1, 2 and 3 of total province employment. Share of graduates is the ratio between province graduates and province total population. Average province-level peer-interactions (PII) is instrumented by the interaction between provinces' 1971 manufacturing employment share and a time trend. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 5. Possible channels: peers and trade unions

We now try to understand how the geographical concentration of social interactions between peers might translate into a wage-enhancing effect.

In this regard one can possibly distinguish at least two channels: a direct mechanism based on the bargaining power of the workers and an indirect one that leverages on productivity spillovers.

Undoubtedly, in local markets characterized by intense economic and social interactions between colleagues (and firms) in the production processes, we expect that workers are more likely to be associated to trade union representations. The presence of union strengthens the bargaining power of workers and, therefore, leads to wage increases at the local level. Moreover, peer interactions are a potential source of productivity spillovers by means of social pressure and knowledge externalities (Cornellissen et al, 2021). Social pressure occurs if there are cultural and/or implicit social norms that induce workers to participate in a fair way to the productive process, i.e. that induce workers to feel socially obliged to increase their own effort/productivity in comparison with other individuals. Knowledge externalities reflects the idea that by communicating and observing each other within the same geographical area, workers (and firms) learn from each other and build up skills and competitive strategies they would not otherwise have<sup>7</sup>. In both cases, we expect that productivity externalities enhanced by the importance of peer interactions, translate into higher wages if the presence of trade union representatives is stronger and rooted in the territories. These arguments suggest to rationalise the following hypothesis:

*H1: the local concentration of peer interactions favours the incidence of trade union membership and thus the bargaining power of workers. The higher the bargaining power of workers, the higher the share of the productivity that will be shared with employees.*

*H2: the local concentration of peer interactions mainly increases the incidence of trade union bodies that are elected at the firm level rather than those appointed through national collective bargaining. Then the union enhancing wage effect is positively affected by the positive relationship between the geographical concentration of peers and the presence of decentralised union representative bodies with respect to nationwide one,*

To verify hypotheses H1 and H2 we run a set of ancillary regressions on microdata drawn from *Rilevazione Imprese e Lavoro* (RIL) surveys, conducted by INAPP in 2010, 2015 and 2018 on a nationally representative sample of limited liability and partnership firms. The INAPP-RIL survey collects a rich set of information about employment composition, personnel organization, industrial relations, and other workplace characteristics. For what concerns our purposes, the RIL questionnaire provides useful information about the firm-level presence of trade union representative bodies, allowing us to distinguish between the *Rappresentanza Sindacale Aziendale* (RSA) and *Rappresentanza Sindacale Unitaria* (RSU)<sup>8</sup>. The RIL surveys also offer information on firm strategies (innovation and export), sales per employee, family ownership and management structure.

Finally, we collapse RIL cross-sectional data at province and sample period levels (107 provinces and three years 2010, 2014, 2018) to investigate the relationship between the incidence of union representative bodies and peer interactions at the province level.

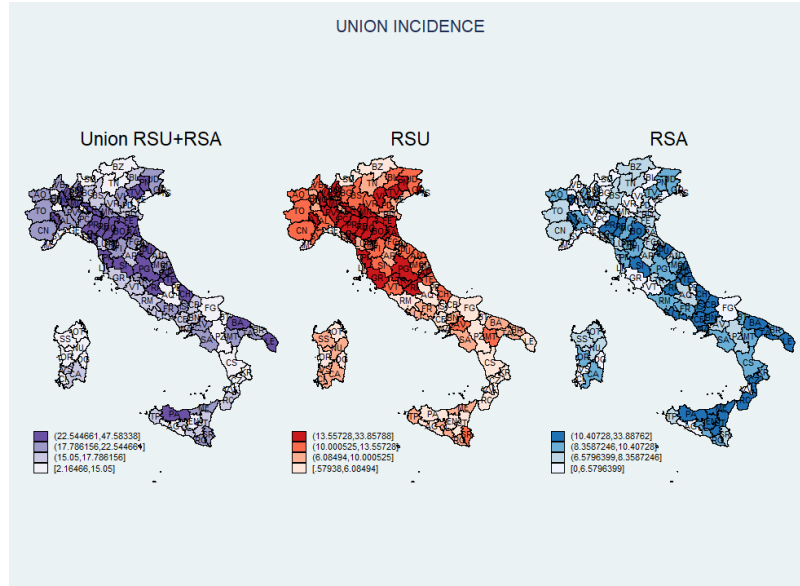
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<sup>7</sup> Of course, the productivity-enhancing peer effects are reinforced in geographical areas where the production processes are organised in an integrated economic environment (i.e. industrial districts). However, these effects may be relevant even in local environments where workers and firms carry out "independent" tasks, product and services that do not directly affect each other's economic outcomes.

<sup>8</sup> According to the "The Workers Statute" adopted in 1970, workers have the right to organize, at the plant-level, union representations (*Rappresentanza Sindacale Aziendale*, RSA). In addition, the tripartite agreement of July 1993 introduced the possibility of a so-called unitary workplace union structure (*Rappresentanza Sindacale Unitaria*, RSU). This body is elected by all employees, but representatives are usually elected through trade union lists.

At this aim, we first show the spatial distribution of trade union *tout court*, of RSA and RSU bodies. Figure 2 makes it clear that RSU bodies are relatively concentrated in northern and central regions, while RSA bodies are visibly distributed also in southern regions.

Figure 2. Average union incidence by province (2010-2014-2018)



Source: authors' calculations on pooled cross sections RIL data 2010-2014-2018.  
Note: sampling weights applied

Table 7 displays pooled OLS estimates obtained by collapsing RIL data at the province level for the three different years 2010-2014-2018. As dependent variables we alternatively model: i) the local incidence of unionized firms, ii) the local incidence of firms with RSU bodies, iii) the local incidence of firms with RSA bodies. Among the explanatory variables, we include our measure of peer interactions, the (log of) population density, provinces' share of graduate workers, a set of local productive characteristics (computed by relying on RIL data) and a full set of province and year fixed-effects.

In the first column of Table 7, the OLS estimate associated with PII supports the hypothesis H1, that is, the geographical distribution of peer interactions favours the local incidence of trade union membership (0.008). Since union representations strengthen the bargaining power of employees, we expect that the positive effect of peers on wages is somehow shaped by the “union voice” (Medoff and Freeman, 1984). Further the estimates reported in the second and third column of Table 7 support the hypothesis H2: the density of peer interactions is positively associated with the local presence of RSU bodies (0.005) while no significant effect is found for RSA bodies. As the RSU representatives are elected by all employees at firm level rather than appointed through national collective bargaining, one may argue that the union enhancing wage effect is shaped by the positive relationship between the geographical concentration of peers and the presence of decentralised union representative bodies with respect to nationwide one.

Table 7 Pooled ols estimates. Dep var: Incidence of unionized firms

	RSU/RSA	RSU	RSA
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PII	0.008*	0.005*	0.002
	(0.004)	(0.003)	(0.002)
Ln (population density)	0.019	0.011	0.008
	(0.031)	(0.022)	(0.013)
Share of tertiary education	-0.332	-0.216	-0.116
	(0.242)	(0.204)	(0.130)
Other controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Constant	-0.675*	-0.470*	-0.206
	(0.365)	(0.281)	(0.157)
N. Obs	327	327	327
R2	0.383	0.316	0.295

Source: authors' calculations on pooled cross section ICP-RIL 2010-2014-2018.

Notes: Other controls includes local composition of management and corporate governance (managers' education, firms' ownership), local productive specialization (share of multinationals, share of firms selling their product or services on international markets, share of firms in manufacture, etc). Standard errors clustered at province level in parenthesis. \*\*\* statistical significance at 1%, \*\* at 5% \* at 10%

## 6. Conclusions

In this paper, we show that the spatial concentration of peer interactions leads to an increase of average wages in the Italian provinces. This result supports the idea that social connections among workers are important drivers of wage growth also in settings/geographical areas where workers carry out tasks and occupations that are not necessarily complementary in the local production processes and/or that do not affect the labour productivity within firms.

Our data do not allow us to directly test whether this result reflects the two main channels already illustrated in the literature, namely if wage enhancing effects derive from peer pressure and/or knowledge spillovers emerging at local level. However, ancillary regressions make it clear that the density of peer interactions is positively associated with the incidence of union representative bodies – mainly those representative bodies elected by all employees at the firm level (RSUs).

This further evidence helps to rationalize our results. In particular, the peer enhancing wage effect at the province level may partly reflect the positive association between the intensity of social interactions and workers bargaining power at workplace. Moreover, the strong and rooted presence of trade union in specific areas may play an indirect role in shaping the peer enhancing wage effects by favouring social pressure and knowledge externalities.



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## Appendix A

Table A.1: First stage estimate. Dep var: (log of) weekly wage

	OLS	FE	AKM
Upper Sec. Educ.	0.0568*** (0.0006)		
Tertiary Educ.	0.0865*** (0.0009)		
Number of firms	-0.0082*** (0.0001)		
Age	0.0327*** (0.0002)		
Age2	-0.0003*** (0.0000)	-0.0007*** (0.0000)	-0.0005*** (0.0000)
Sex	-0.1813*** (0.0005)		
Fixed term	-0.1982*** (0.0005)	-0.0702*** (0.0005)	-0.0604*** (0.0005)
Part time	0.0165*** (0.0005)	0.1728*** (0.0007)	0.1724*** (0.0009)
Blue collar	-0.0028*** (0.0010)	-0.0191*** (0.0011)	0.0400*** (0.0010)
White collar	0.2531*** (0.0010)	0.1470*** (0.0012)	0.1240*** (0.0011)
Managers	0.9469*** (0.0019)	0.3590*** (0.0027)	0.2949*** (0.0025)
Executives	1.3601*** (0.0022)	0.5554*** (0.0061)	0.4606*** (0.0058)
Others controls	Yes	Yes	Yes
Province*year FE	Yes	Yes	Yes
Worker FE	No	Yes	Yes
Firm's FE	No	No	Yes
Constant	5.609*** (0.001)	5.923*** (0.001)	5.949*** (0.001)
R <sup>2</sup>	0.337	0.663	0.763
Obs.	11044747	10710300	10449147

**Source:** Authors elaborations on INPS-SISCO dataset 2011-2018.

**Notes:** Other controls includes firms' size, ATECO sector of activity. Robust clustered standard errors in parenthesis. \*\*\*\* statistical significance at 1%, \*\* at 5% \* at 10%