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# Labor Market Pooling

*Guido de Blasio and Sabrina Di Addario*

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Prepared by Guido de Blasio and Sabrina Di Addario[1]

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## Abstract



The paper provides an empirical investigation of labor market pooling. The analysis concentrates on Italian industrial districts and shows that there is scattered evidence of a widespread wage premium. In particular, there is no evidence of district differentials for the returns to seniority while there is evidence of negative differentials for the returns to education. Moreover, dwelling in a district has no impact on the probability of being self-employed and only a minor impact on the likelihood of transiting from wage-and-salary to self-employment. Finally, there is no evidence of higher district worker mobility across jobs.

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Authors' E-Mail Address: deblasio.guido@insedia.interbusiness.it
diaddario.sabrina@insedia.interbusiness.it

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[1] Both the authors are economists at the Research Department of the Bank of Italy.
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## I. Introduction

The classic argument for agglomeration is based on Marshall's three-pillar doctrine. According to Marshall (1890), three different reasons explain the geographical concentration of a number of firms in the same industry. First, agglomeration creates a pooled market for workers with specialized skills. Second, it saves on transport costs owing to producers' proximity to input suppliers or final consumers. Third, it generates technological spillovers.

Following the contributions of Abdel-Rahman and Fujita (1990) and Krugman (1991), the new wave of theoretical and applied research on agglomeration developed Marshall's intuition in a number of directions. With reference to the second pillar, the impact of geographical concentration of industries on the availability of intermediate and final goods has been widely modeled (see Ottaviano and Puga (1998) for a survey). The intuition, however, remains straightforward. On the one hand, a localized industry can support more specialized local suppliers. On the other hand, a localized industry implies a localized demand for final goods, which, in turn, makes localization more attractive to firms willing to save on shipping costs.

Regarding the third pillar, the importance for agglomeration of knowledge spillovers between nearby firms was well described by Marshall himself (1890): "The mysteries of the trade become no mystery; but are as it were in the air… . Good work is rightly appreciated, inventions and improvements in machinery, in processes and the general organization of the business have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the sources of further new ideas". Notwithstanding Krugman's warning on the difficulties with measuring the third pillar ("knowledge flows (…) are invisible; they leave no paper trail"), the papers by Jaffe, Trajtenberg, and Henderson (1993) and by Guiso and Schivardi (2000) provide some evidence on the relevance of the information-spillover motive.

The labor-market motive, the first pillar, has received a great deal of attention, but this has been focused on the theoretical side. Marshall's idea is that a pooled labor market benefits both firms and workers: "A localized industry gains a great advantage from the fact that it offers a constant market for skill. Employers are apt to resort to any place where they are likely to find a good choice of workers with the special skill which they require; while men seeking employment naturally go to places where there are many employers who need such skill as theirs and where therefore it is likely to find a good market. The owner of an isolated factory, even if he has good access to plentiful supply of general labor, is often put to great shifts for want of some special skilled labor; and a skilled workman, when thrown out of employment in it, has no easy refuge" (Marshall, 1890).

In his seminal work, Krugman (1991) shows that the efficiency gains from creating a localized industry with a pooled labor market are due to imperfectly correlated labor demand schedules for firms that may experience either "good times" or "bad times." Being in the same place would allow firms to take advantage of additional workers available during peak periods. At the same time, it would benefit workers, since the average rate of unemployment will correspondingly be lower. In particular, Krugman (1991) shows that agglomeration would drive wages up. Because of efficiency gains, clustering would emerge as the outcome of a tug-of-war between firms, who prefer a less competitive labor market and hence dispersed production locations, and workers, who prefer a more competitive market and hence concentration.

In a vein similar to Krugman's tug-of-war, Rotemberg and Saloner (1990) suggest that workers – suppliers of industry-specific human capital, which is costly to acquire – might find it advantageous to locate where there are several potential firms that need such an input. In a pooled labor market, competition among firms would ensure a fair return to workers. In the absence of such competition, workers would be subject to the monopsony power of the firms. Anticipating such an outcome, workers would not choose to invest in industry-specific human capital. This model explains why the location decision of firms and workers are interdependent and provides the prediction that wages within a cluster should be higher. In contrast, Diamond and Simon (1990) show the importance of an insurance motive: workers could be willing to accept lower wages in locations where other firms stand by ready to hire them. In a recent paper, Combes and Duranton (2001) propose a duopoly game in which firms face a trade-off between the benefits of labor pooling (availability of workers whose knowledge helps reducing costs) and the costs of labor poaching (loss of some key workers to competition and the indirect effects of a higher wage bill to retain workers). The model combines the first and the second of Marshall's pillars, since workers have access to firm-specific knowledge and the pooled labor market acts a conduit for spillovers, generating a set of predictions for wages and mobility. In particular, clusters should show higher wages and greater flows of workers between firms than isolated firms. Moreover, wages should be increasing over time, because experienced workers accumulate the kind of firm-specific knowledge that triggers poaching.

While a number of empirical analyses have been carried out for such well-known clusters as Silicon Valley in California and Route 128 in Massachusetts (or Prato in Tuscany and Biella in Piedmont, in the Italian case), the lack of data has severely constrained the investigation of pooled labor markets *taken as a whole*. Poor data are the outcome of two shortcomings. First, macro data are not fine enough to capture clusters (even when desegregated by regions or smaller areas), since the geographical extension of a cluster does not usually coincide with the administrative area level for which the data are available (e.g. municipality, province, etc.). Second, in order to empirically investigate clusters taken as a whole, a definition providing a sensible singling-out criterion is needed.

Following Signorini (2000), this paper proposes an empirical investigation of the labor market in Italian industrial districts (IIDs) that tries to overcome the above shortcomings by compounding the Bank of Italy's Survey of Household Income and Wealth micro data with the official Istat-Sforzi Algorithm that singles out IIDs. Our empirical strategy is composed of three blocks. First, we measure whether wages in IIDs are significantly different from those in isolated firms, controlling for workers', firms' and geographic areas' observable characteristics. In this context, we also analyze the role of the Mincerian determinants of wages. Second, we estimate the extent to which the probability of being self-employed, the likelihood of transiting from wage-and-salary work to self-employment, and the worker's mobility across jobs are higher within IIDs. Finally, we provide a robustness check for the results based on sample restrictions and a finer definition of industrial districts. To this end, we undertake the same analysis on both Superdistricts and a continuous district variable, as defined by Cannari and Signorini (2000). Superdistricts are an IID's subsample in which the Istat-Sforzi district characteristics are highly emphasized. The continuous district variable is a variable that assigns each area (whether it is a district or not) a value representing the degree of district features shown.

Our empirical investigation is linked to the recent applied literature on the returns to seniority and schooling. Neal (1995) and Parent (2000) show that the share of returns to seniority that could be attributed to firm-specific skills (which could represent a wage loss in case of displacement) is modest compared with the one that could be related to sector-specific skills (which are not lost as long as the worker remains in the same industry). Acemoglu and Angrist (2000) and Ciccone and Peri (2000) observe that the returns to schooling might be higher in agglomerations, since clustering facilitates the exchange of ideas and triggers externalities that, in turn, raise private returns. Thus, the role of returns to seniority and schooling for cluster workers could shed light on these issues. Moreover, our work is related to a number of studies that concentrate on the peculiar functioning of the labor market within Italian industrial districts. This literature is mostly based on the analysis of specific case studies. Based on the evidence available for Prato and Biella, Signorini (1994) suggests that average wages are higher in districts than elsewhere. In studies on Carpi, Solinas (1982, 1991) argues that districts are characterized by a wider role for firms in providing training to junior workers and by higher returns for skilled senior workers. This implies the existence of a peculiar IID wage curve, as workers are willing to accept reduced entry wages in exchange for on-the-job training, with the expectation that they will move upward on the wage scale when they become senior workers, and/or will be able to start up their own firms.[2] However, in a study on the provinces of Treviso and Vicenza, Cingano (2000) does not find any evidence of a difference in the returns to seniority between IIDs and non-IIDs. In an analysis of the IID labor market using data from the Italian National Security Service, Casavola, Pellegrini, and Romagnano (2000) do not find any clear evidence of a district wage premium and argue in favor of higher returns to seniority, greater district worker mobility across jobs and higher district propensity to self-employment.[3] To our

[2] According to this literature, IID entrepreneurs encourage the most active employees to start up firms of their own as subcontractors, which would help the parent firm to gain an advantageous relationship with the subcontracting firms, thereby increasing the flexibility (Dei Ottati (1992); Pyke, Becattini, and Sengenberger (1990)).

[3] In order to analyze these issues, the authors reconstruct work experience and tenure for an average district worker and compare them with analogous measures for a non-district employee. Yet, the difference between district and non-district workers is very small and could depend on some ad-hoc assumptions adopted to reconstruct the past work-experience

knowledge, no prior empirical analysis on the returns to education in IIDs was ever undertaken.

Our results, based on IIDs taken as a whole, are striking. We find a very limited role for geographical proximity. As for wages, we find only scattered evidence of a widespread wage premium within districts. Moreover, we find no evidence of district differentials for the returns to seniority, while district differentials for the returns to education might be negative. As for self-employment and labor mobility, we find that dwelling in a district has no impact on the probability of being self-employed and only a minor impact on the likelihood of transiting from wage-and-salary work to self-employment. Finally, there is no evidence of higher district worker mobility across jobs.

The paper is structured as follows. Section II provides some background information on the Italian industrial districts. Section III describes the data set. Section IV provides the results. Section V concludes.

## II. Italian Industrial Districts

IIDs are geographically defined productive systems, characterized by a large number of firms that are involved, at various stages and in various ways, in the production of a homogeneous product (Pyke, Becattini, and Sengenberger (1990)). Most of IIDs are located in the Center and in the North of Italy (in particular in the North-East). District firms are mostly small and medium sized enterprises (SMEs) specialized mainly in traditional sectors. Different IIDs specialize in different products of varying complexity and intended end-use. The role of IIDs can hardly be overstated: while SMEs provide over 70 percent of the Italian manufacturing output (Eurostat (1996)), the IID share of the national output is over 42 percent (Istat (1996)). This latter share is even higher for sectors like apparel, textile, furniture, and leather. The most famous examples of IIDs are Prato, Carpi and Biella (specialized in textile), Sassuolo (ceramic tiles), S. Croce sull'Arno and Solofra (leather), Martina Franca (furniture), Barletta and Civitanova Marche (shoes).

A number of definitions have been proposed for IIDs (Becattini (1991) and Brusco (1991)). These definitions refer to a set of elements of various nature: economic, institutional, sociological, and demographic. They extend Marshall's rationale to include also the role played by the community and by the local institutions in favoring the diffusion of information and co-operative behavior among agents. For example, Becattini (1991) defines IIDs as "a socio-territorial entity which is characterized by the active presence of both a community of people and a population of firms in one naturally and historically bounded area" where "community and firms tend to merge". These definitions are certainly intriguing. They are however difficult to bring back to a quantitative benchmark, which is necessary to

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and tenure for the cohort of workers who were already in the sample at the beginning of the observation period.

undertake empirical work. In the last decade, the shortcomings of the descriptive definitions led to the search for statistical criteria based on the productive system's structural characteristics, like the specialization pattern and the presence of SMEs. These methodologies are necessarily partial with respect to the descriptive concept of industrial district. They are also discretionary, since minor changes in the key algorithm parameters would deliver different results. In this study (see next section), in order to minimize the extent of discretion involved, we use three different measures of agglomeration.

## III. Data

We use data from the 1998 Bank of Italy Household Survey (SHIW). This is a biannual survey that collects information on the economic behavior of Italian families at the microeconomic level (detailed information on the SHIW can be found in Brandolini (1999)).[4] In 1998 the SHIW surveyed 7,147 families, amounting to 20,901 individuals. In order to analyze the IID labor market, we focused on persons working in the non-farm private sector (excluding services to households) for a total of 4,665 observations.[5] Our sample hence includes 3,161 employees and 1,504 self-employed workers, distributed in 63 different IIDs out of 217 LLMAs.

Individuals have been assigned to industrial districts by matching the 1998 SHIW with the 1991 Istat-Sforzi Algorithm (ISA). According to ISA, an area is defined as industrial district if: a) it is a 'local labor market area' and b) the structure of its productive system is characterized by a dominant specialization and by the prevalence of SMEs.[6] A local labor market area (LLMA) is a self-contained geographical area, capable to offer work opportunities to the majority of the residing population. The degree of self-containment is measured by the daily flows between production and residential sites. A geographical area is

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[4] The SHIW considers households as the basic survey unit, and the sampling design is carried out in two stages: municipalities first, and then households. Data are collected in personal interviews by professional trained interviewers, and are heavily processed to preserve data quality.

[5] In particular, we exclude from the SHIW all the not employed individuals and those employed as school teachers. We also excluded the following sectors: agriculture, hunting, forestry, and fishing; general government, defense, education, health and other public services; extraterritorial organizations and entities; domestic services provided to households and other private services.

[6] According to the ISA definition, SMEs are firms with less than 250 employees. This ceiling has been deemed as controversial (see for example Brusco and Paba (1997) and Cannari and Signorini (2000)) on the grounds that it could be a too high threshold for IID firms. In Section IV, we consider SMEs only firms with less than 100 employees.

classified as LLMA if the ratio between the number of persons who work and dwell in the area, and the number of persons who work but do not dwell in the area is above 70/75.

IIDs are singled out from LLMAs by the following four criteria:

(1) The share of manufacturing employment in total non-farm employment must be higher than the corresponding share at the national level.
(2) The share of SME manufacturing employment in total non-farm employment must be higher than the corresponding share at the national level.
(3) For at least one sector, the specialization index must be greater than one. The specialization index is the ratio between the share of sector employment in total manufacturing employment and the corresponding share at the national level.
(4) In at least one sector for which the specialization index is greater than one, the share of SME employment in total employment must be higher than the corresponding share at the national level.

In 1991, there were 784 LLMAs and 199 IIDs (as defined by the ISA). In our 1998 sample, 908 employees and 411 self-employed belong to IIDs.

Section IV.A and IV.B provide evidence based on the ISA definition of IIDs. Section IV.C provides a robustness check for these results, by using the Cannari and Signorini (2000) Superdistricts and District Continuous Variable. Superdistricts represent the sub-sample of the Istat-Sforzi clusters where the ISA characteristics are highly emphasized. They are identified by a cluster analysis based on the four above ISA criteria. In particular, Superdistricts typically display a very high incidence of manufacturing employment and SME manufacturing employment in total non-farm employment. 99 IIDs are classified as Superdistricts. The District Continuous Variable associates to each LLMAs a value representing the degree of district features shown by the area. It is calculated with a Logit estimating the probability for each LLMA to be classified as an IID according to the ISA four criteria. Thus, it represents an extension of the ISA methodology to the continuum.

## IV. Evidence

Our empirical strategy includes three building blocks. First, in Section IV.A we measure whether wages within IIDs are significantly different from wages elsewhere, controlling for worker's, firm's and geographic area's observable characteristics. In this section, we also analyze the role of the Mincerian determinants of wages. Then, in Section IV.B we estimate the extent to which the probability of being self-employed, the likelihood of transiting from wage-and-salary to self-employment, and the worker mobility across jobs are higher in IIDs than elsewhere. Section IV.A and IV.B rely on the ISA definition. Section IV.C provides a robustness check based on two alternative measures of agglomeration.

### A. Wages

To test whether wages are higher in IIDs, we estimate the following Mincerian[7] wage function:

$$\log w_i = \alpha_0 + \alpha_1 SCHOOL_i + \alpha_2 EXP_i + \alpha_3 EXP_i^2 + \alpha_4 DISTRICT + Z_i \beta + u_i \quad (1)$$

where the dependent variable is the log of the hourly wage rate,[8] SCHOOL indicates the number of years of schooling, EXP denotes labor market experience, DISTRICT is a dummy variable for IIDs as defined by the ISA, Z represents a vector of control variables for observable characteristics of firms and workers, and u is the error term.

A few features of our specification should be noted (see also the APPENDIX for the list of variables and APPENDIX TABLES for descriptive statistics).[9] (i) The variable EXP is calculated as total number of years spent working (current age less the age at the time of the first job). To control for the potential endogeneity bias, we also use AGE instead than EXP. (ii) The vector of control variables includes some observable worker's and firm's characteristics available in the SHIW dataset (dummy variables for FEMALE, SMEs, MANUFACTURING). Moreover, it includes two additional set of controls: the LLMA's unemployment rate from the 1996 Istat Survey on the Labor Force, and the LLMA's PAVITT specialization indexes, computed by the authors. This last set of controls allows us to provide some correction for the fact that the SHIW makes available only a breakdown between manufacturing and services, and does not provide more detailed information about

[7] See Mincer (1958) and Becker (1964). For a survey see Willis (1986) and Card (1999).

[8] Earnings are measured after tax. We do not expect the use of net rather than gross earnings to significantly underestimate wage differentials, since the tax structure is very similar across LLMAs. An additional problem is underreported income: if the gray economy is more prominent in IIDs then the omission of this income source leads to underestimation of district differentials. We use hourly earnings in order to take into account irregular and overtime hours, which could be of some relevance in IIDs.

[9] We also tested different specifications not shown here for the sake of conciseness. In particular, we estimated a version of Eq. (1) by decomposing EXP in two components: TENURE with the current employer, and PRIOR EXP, computed as EXP – TENURE (see below). Moreover we replicated the estimation with both EXP and AGE augmented with TENURE. Finally, we also run all the regressions on the log of annual wages rather than the log of hourly wages. Since these last set of specifications did not give particularly interesting results, we will not comment them any further.

the branch of activity of the employee's firm.[10] (iii) The SHIW dataset provides information about the employee's work status (blue-collar, office worker, junior manager, and manager). However, whether to control for work status is an open issue, since wages are likely to be correlated with status. Controlling for work status could hence bias downwards the education coefficient. We tackle this issue on the empirical ground and we provide estimates for both controlling and non-controlling for the employee's work status.

Table 1 provides results.[11] The fit of the regression is quite good and all the variables are significant with point estimates close to what was found in previous studies using the SHIW (Cannari and D'Alessio (1995) and Colussi (1997)),[12] even though returns to education turn out lower and returns to labor market experience higher than other authors' estimates. This is true irrespectively of the proxy used for labor market experience, and it is due to the fact that we exclude from our sample public sector workers, who have relatively high education levels and a compressed wage structure (Alesina, Danninger and Rostagno (2001)). Crucially, DISTRICT is positive and significant at the usual levels only in the regressions with EXP,[13] with an earning premium for cluster workers amounting to 3 percent.[14]

To analyze the role of the Mincerian determinants of wages within clusters, we estimate a version of Eq. (1) that allows for interaction terms between RHS variables and DISTRICT.[15] Results are shown in Table 2. Our results are noticeable. As for the district

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[10] In particular, wages differ in low and high-intensity sectors. Thus, controlling for the extent to which the LLMA contains traditional versus high technology industries (PAVITT1-4), should help to offset the SHIW's lack of information on the firms' branches of activity.

[11] While the results presented in this paper are based on the 1998 SHIW, our conclusions are overwhelming confirmed by pooling 1995-1998 SHIW data.

[12] The aim of these papers is the analysis of the nationwide returns to education and to labor experience, with no reference to IIDs.

[13] In the specification in which we decompose EXP into TENURE and PRIOR EXP, we find that the nationwide effect of TENURE is quite strong and comparable in size with the effect of PRIOR EXP. However, we do not find any effect specific to the district.

[14] While in principle the presence of a centralized wage bargaining system could reduce earning differentials between areas, there is still considerable margin for wage differentials in Italy (according to Mauro, Prasad, and Spilinbergo (1999) wage differentials across regions, sectors and gender, vary between 10 and 30 percent; see also Alesina, Danninger, Rostagno (2001)).

[15] Since the error disturbance is not significantly different across IIDs and non-IID LLMAs, the here adopted specification where data are pooled is more efficient than running two

differential effects, no significant contribution of labor market experience is found (the interaction terms of EXP and AGE with DISTRICT are never significant). Moreover, there is evidence of negative cluster differentials for the returns to education (in column (2.1) the reduction in the SCHOOL coefficient associated with cluster workers is about a half of the national average). The dummy DISTRICT, which is now meant to capture district wage differentials due to factors beyond education and labor market experience, continues to be positive and significant only in the specifications with EXP. Summarizing, these results would suggest that IID wages might display a small positive premium, which however does not reflect labor market experience. Moreover, this premium is eroded by a negative district differential for education, which penalizes relatively more the workers with higher human capital (for example, results of column (2.1) would indicate that district wages are higher for workers with less than 13 years of schooling, which is the threshold for a high school diploma).[16]

There are a number of issues related to the choice of what to include within IIDs. ISA provides a criterion to identify IIDs. However, once a LLMA is classified as IID, ISA leaves the question of which firms to include in the district quite open. In particular: (i) while ISA is based on the prevalence of manufacturing, it is a matter of debate whether firms located within IIDs but belonging to sectors other than the industrial ones should be considered as part of the district; (ii) while ISA is based on the prevalence of SMEs, it is a matter of debate whether large firms located within IIDs should be considered as part of the district; (iii) it is also matter of debate whether our nationwide sample should rather be replaced by the sub-sample of IIDs located in Center-North of Italy, which represent a more homogeneous geographic area. In order to provide some robustness checks for the above issues, in Table 3 and Table 4 we show the results respectively for the specifications of column (1.1) and (2.1) estimated in different sub-samples. In the first column we exclude non manufacturing firms from the sample. In the second column, we keep only SMEs, lifting the restriction on the manufacturing sector. In the third column, we apply the two restrictions simultaneously so that our sample comprises only manufacturing SMEs. Finally, we add a new restriction: we keep only the manufacturing SMEs located in Center-North of Italy. The main consequence of our check is that DISTRICT loses its significance (Table 3). This is also due to the fact that restricting the sample towards narrower characterizations of IIDs makes the negative district differential in SCHOOL even more pronounced: it represents 72 percent of the returns to education in (4.1) and above 80 percent in (4.3) and (4.4).

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separate regressions for the two sub-groups and then comparing the results (Greene W.H., 2000).

[16] This result is consistent with our findings (not reported here) according to which within IIDs: (1) the average level of education is lower; (2) workers enter the labor market earlier. It is also consistent with the evidence presented by Casavola, Pellegrini and Romagnano (2000) on entrance in the IID labor market.

We turn then to econometric issues. Since Griliches (1977), it is well-known that there are a number of problems with the estimation of Eq. (1) by least squares using measured data. In particular, there are three issues. First, there could be an omitted variable problem since ability, which is not observed, is presumably correlated with both Mincerian variables and wages. Second, there could be an endogeneity bias since human capital accumulation is the result of optimizing choices, taken by both individuals and their families in contexts where financial possibilities matter. Third, there could be a measurement error problem with both the education data, which are available as years of schooling, and proxies for labor market experience, which are measured as number of years spent working.

It is worth mentioning that the huge literature on the subject has not provided a clear-cut answer regarding the sign and the size of the bias. Moreover, since we focus on wage differentials between IIDs and isolated firms, the role of these biases for our results could be secondary: if there are biases, they may be similar across district and non-district areas and thus our estimates still give useful cross-location information. Nevertheless, to provide some correction with the three econometric problems mentioned above we use instrumental variable estimates as suggested for example by Rosen (1977). This is also the preferred estimation strategy employed by Cannari and D'Alessio (1995) and Colussi (1997), so that their results could be easily compared with ours. In line with this work, we use family background variables as instruments: mother's and father's years of schooling and age. Table 5 and Table 6 show IV and OLS estimates for the sample of workers who provided information on age and education attainment of the parents (the regressions correspond respectively to the specifications (1.1) and (1.2); and (2.1) and (2.2)).

The endogeneity of education does not seem to be a problem in our data: the Hausman test does not enable us to reject the null hypothesis of esogeneity. This is somewhat contrary to what expected. Indeed, the Hausman test indicated that there was an endogeneity issue with SCHOOL in both the papers by Cannari and D'Alessio (1995) and Colussi (1997). Our results are due to the fact that we use the 1998 survey of the SHIW, while the two papers refer to previous year surveys.[17] It is also worth mentioning that the Sargan test never enables us to reject the null hypothesis of orthogonality between the earning function residuals and the instruments. This implies that the variables of family background can be considered good instruments.

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[17] To understand the reasons of this discrepancy, we replicated the specification used by Colussi (1997), which excludes the LLMA's unemployment rate and PAVITT specialization index and all DISTRICT variables, both for 1993 (the year he analyzes) and 1998. Since Colussi's sample differs from ours (it includes, for instance, only heads of the household, males, working full-time and all year), we also replicated his sample. We find that for the 1998 data, the null hypothesis of no systematic difference between the IV and OLS coefficients cannot be rejected, even with the model specification and the sample used by Colussi.

By and large, our findings remain confirmed.[18] In Table 5, while the point estimate of SCHOOL increases as expected, DISTRICT remains of a little size and barely significant. In Table 6, the IV correction brings about a reduction in the statistical significance of both DISTRICT and SCHOOL*DISTRICT. Overall signs and sizes of the corrections resulting from IV estimates are minor, as expected given the results of the Hausman test.

Finally, it should be mentioned that our findings could in principle be affected by self-selection. If the hypothesis that within IIDs the transition from wage-and-salary to self-employment is easier turns out to be true, then our IID sample of observed wages could be biased downwards. Experienced and/or more talented workers would disappear from our sample, so lowering average wages. To correct for such a problem we estimate an Heckman selection model. In order to determine whether the dependent variable is observed, the Heckman selection model calculates the likelihood of being an employee among a sample of employees and self-employed persons, using parents' educational attainment (MSCHOOL and FSCHOOL) and parents' work status (MWSTATUS and FWSTATUS) as selection variables. This set of selection variables are proven to be key for the Italian case due to the offspring propensity to follow the father's profession (Barca and Cannari (1997)). The likelihood-ratio test for correlation between the regression and the selection equations always allows us to reject the null hypothesis of no correlation (at 1% statistical significance), which justifies the Heckman selection model with our data.

Table 7 and Table 8 show the results (again, the specifications shown correspond to (1.1), (1.2) and (2.1), (2.1)). The Heckman selection model does not provide any significant correction (for example, in columns (7.1) and (7.2) the average predicted dependent variable is equal respectively to 2.60 and 2.64). As it will be clear in the next section, this comes to no surprise, since the hypothesis of quicker district move to self-employment does not receive empirical support.

### B. Self-Employment and Labor Mobility

Is self-employment made easier within IIDs? This is a crucial issue for Italy, since its economy relies more than other OECD countries on SMEs. It is therefore important to understand the relative role of agglomerations, which are deemed to be areas prone to entreprenuership. We single out two categories of self-employment: entrepreneur (business owner, owner or assistant in family business, active shareholder or partner) and free-lance (who runs his own activity with no employees). Table A.2 displays some descriptive evidence, which highlights that the share of entrepreneurs in total sample (and to a lesser extent, that of free-lance workers) is higher in IIDs than in non-IIDs. Table 9 reports the empirical results from Logit estimation where the dependent variable is a binary indicator,

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[18] IV estimates (not shown here) were also run for all the models of Tables 1 and 2. Again, our results were broadly supported.

equal to 1 if a respondent pursues: an entrepreneurial activity (column (9.1)); a free-lance activity (9.2); either of the two (9.3). The sample includes 4322 persons, 989 of whom are self-employed. We add the dummy DISTRICT to the specification adopted by Barca and Cannari (1997). In the first column, the coefficients for AGE and AGESQR display the expected sign and high significance. The coefficient for SCHOOL is not significant, highlighting the negligible role that education has for the chance of becoming entrepreneur. The dummies FMANEX and FENTFL (equal to 1 respectively for those with a father manager or executive and those with a father entrepreneur or free-lance) are large in size and significant, stressing the role of intergenerational links in Italy. Surprisingly, the IID dummy variable shows no impact on the probability of becoming entrepreneur. In the second column, the likelihood of working free-lance does not vary much with age, decreases with education, and is less affected by intergenerational persistence. The district dummy shows again no effect. The results of the third column confirm these findings.

These results have been double-checked in a number of experiments. First, in analogy with Table 2, we Logit estimated equations that allow for interactions between RHS variables and DISTRICT. Moreover, we run regressions without FMANEX and FENTFL. No differential district effects were ever found. Second, we provide sensitivity analysis for these results, in analogy with Table 3 and 4. Again, the irrelevance of agglomeration for self-employment were awesomely confirmed.

To test more directly the hypothesis that within IIDs the transition from wage-and-salary to self-employment is easier, we run two additional set of Logit estimates. First, the SHIW provides the binary variable BOTH, which is equal to 1 for those who have worked both as employees and as self-employed (757 in our sample). We estimate the probability of being BOTH=1 in column (9.4). We find again no role for DISTRICT, while this probability is affected by SCHOOL and does not depend on the family work status. Second, we estimate the probability of being self-employed only for the sub-sample of those who had at least one work experience as employees (the descriptive evidence of Table A.2 shows that the share of entrepreneurs having had previous work experience as employees is substantially higher in IIDs). This reduced our original sample to 3,545 observations, 397 of which self-employed. Results are displayed in Table 10, which corresponds to the first three columns of Table 9. The likelihood of transiting from employee to entrepreneur is highly correlated with AGE and it is not driven by intergenerational links. Instead, the transition from employee to free-lance is not affected by AGE, while SCHOOL gives some (small) contribution. In both estimates, the dummy for agglomeration is never significantly different from zero; in the third column, however, we find a positive (and barely significant) contribution of DISTRICT.

Once more, these findings have been verified both by estimating equations that allow for interactions and by moving to narrower definitions of IIDs. The only relevant upshot is that DISTRICT affects positively the likelihood of transiting from employee to free-lance (but not to entrepreneur) when the sample is comprised of only manufacturing SMEs.

Is worker mobility across jobs higher within agglomerations? To check this claim we estimate an OLS for the number of activities, including temporary ones, performed up to 31st December 1998. Results are shown in Table 11. Column (11.1) provides the results for the sub-sample of employees. Surprisingly, DISTRICT has a highly significant negative sign. We then check this result on several grounds. First, to accommodate the fact that within IIDs the distinction between types of activities could be deceitful, since employees could move to self-employment for peculiar circumstances,[19] the dependent variable was estimated for the wider sample of employees and self-employed (11.2). In this case, DISTRICT is not significant. Second, as before, we estimate for both specifications (11.1) and (11.2) equations that allow for interaction terms between RHS variables and DISTRICT, and we increasingly restrict our sample according to the sensitivity analysis proposed in Tables 3 and 4.[20] In these experiments, we never find any DISTRCT effect. Finally, we estimate these equations by Instrumental Variables (as in Table 5 and 6) to take into account the potential endogeneity, omitted variable, and measurement error issues. Again, we find no effect.

### C. Beyond the ISA Definition of Clusters

The results of Section IV.A and IV.B are based on the identification of agglomerations provided by the official ISA criterion. The extent to which the crucial features of IIDs are accurately captured by this criterion has raised a number of controversies (Brusco and Paba (1997) and Cannari and Signorini (2000)). In particular, the ISA splits up the LLMAs in two groups: districts and non-districts. The underlying idea is that non-linearities play a role: district effects materialize only above the ISA thresholds.

In this section we test whether our results could be due to the specific characteristics of the ISA. First, we verify whether the ISA thresholds are set at a too low level. In other words, the fact that in a number of respects cluster labor markets do not differ from non-cluster ones, could be due to ISA classifying too many LLMAs as IIDs. To this aim, we replicate the analysis of the above two sections for Superdistricts (DISTRICT_S) rather than for the ISA IIDs. Second, we test whether our results could be due to the ISA being too tight. That is, IIDs and non-IIDs might indeed display similar characteristics to some extent and their being split up in two groups by ISA may be too an artificial devise. To this purpose, we extend the ISA methodology to the continuum by substituting DISTRICT with a continuos variable (DISTRICT_C) that associates each LLMA a value for the degree of district features shown.[21]

[19] For example during business cycle peaks.

[20] Moreover, we run regressions on the sub-samples of blue-collar workers and of employed people younger than 50.

[21] As in Cannari and Signorini (2000).

Both DISTRICT_S and DISTRICT_C take the ISA as starting point. This is a nice feature of these indicators. As a mater of fact, different algorithms to single out districts could be proposed. However, abandoning the ISA criterion would not be without costs: to facilitate cross-country comparisons, ISA-type criteria are now being established by a number of OECD countries (OECD (2001)). Moreover, the ISA criterion is now employed as cornerstone for regional policy in Italy.

Table 12 gives a flavor of our analysis. In this table we replicate models (1.1) and (2.1), replacing DISTRICT with the two alternative indicators of agglomeration. The results of the previous sections are awesomely supported: since DISTRICT_S and DISTRICT_C are never significant in our earning functions, with the notable exception of negative Superdistrict differential returns to education (which appear only when we restrict our sample to manufacturing). Analogously, there are no different results for self-employment and labor mobility determinants. The only exception to the lack of a specific agglomeration effect lies is the likelihood of transiting from wage-and-salary worker to free-lance, as the dummy DISTRICT_C in this equation is positive and significant.

## V. Concluding Remarks

The theoretical literature on agglomeration puts a lot of emphasis on the labor market motive. Empirically, this literature suggests that labor market pooling affects wages, entry into self-employment, and worker mobility across jobs. The evidence presented in this paper amounts to a call for caution. We find little evidence of cluster differential effects for both wages and worker mobility. We also find no evidence of agglomeration differential returns to seniority, while the only cluster specific effect that our data reveals is a negative differential for the returns to education. Finally, as for self-employment, the only role that agglomeration seems to play is limited to the transition from wage-and-salary work to free-lance employment.

At a first glance, our results indicate that the first pillar of Marshall's story does not contribute much to the explanation of agglomeration in Italy. A different story could however be proposed. Indeed, our results do not deny that the gains from labor market pooling could be relevant. Rather, they challenge the view that those gains benefit both firms and workers, since the advantages from participating in a pooled labor market seem to be quite limited for employees.

It should be reiterated that, in contrast to case-studies, our conclusions rely on a general empirical investigation. That is, our analysis focuses on pooled labor markets taken as a whole, as they are singled out by the ISA cluster classification criterion (and by the two alternative criteria of Section IV.C). Consequently, our analysis does not preclude the possibility that in specific cases the theoretical predictions are true.

Finally, from our results a number of suggestions for future research could be derived. First, the relative bargaining strength of firms and workers within clusters seems to be an interesting topic, since the benefits of labor market pooling do not appear to be reaped by workers. In particular, workers who accumulated sector-specific human capital seem to have done so at the expense of education. Accordingly, it would be interesting to analyze whether this under-accumulation of generalist human capital might have weakened the worker's bargaining power (perhaps, lowering the worker's chances of finding a different job). Second, the fact that worker mobility across jobs does not appear to be higher in agglomerations than in the rest of the country, casts doubts on the idea that district firms' labor demand schedules are imperfectly correlated. Indeed, a closer look at the characteristics of demand shocks for cluster firms would add an important piece of evidence. Finally, our results suggest that within IIDs there could be a relation between the modest role for education (for both workers and entrepreneurs) and the specialization in traditional sectors. It would be extremely important to understand the features and the consequences of such a relation, also with reference to the recent findings of Bils and Klenow (2000), who take a critical view on the traditionally reiterated growth-enhancing role of schooling.

Table 1. Earning Functions: OLS Estimates

| Dependent variable: Log of hourly wage rate | (1.1) | (1.2) | (1.3) | (1.4) |
|---|---|---|---|---|
| DISTRICT | 0.0285* | 0.0339** | 0.0235 | 0.0281 |
| | (0.0167) | (0.0172) | (0.0167) | (0.0172) |
| EXP | 0.0317*** | 0.0338*** | - | - |
| | (0.0021) | (0.0022) | - | - |
| EXPSQR | -0.0005*** | -0.0005*** | - | - |
| | (0.0000) | (0.0000) | - | - |
| AGE | - | - | 0.0499*** | 0.0506*** |
| | - | - | (0.0046) | (0.0048) |
| AGESQR | - | - | -0.0005*** | -0.0005*** |
| | - | - | (0.0001) | (0.0001) |
| SCHOOL | 0.0281*** | 0.0407*** | 0.0207*** | 0.0325*** |
| | (0.0032) | (0.0028) | (0.0029) | (0.0026) |
| CONSTANT | 1.7073*** | 1.7057*** | 0.9883*** | 0.9750*** |
| | (0.0873) | (0.0913) | (0.1186) | (0.1227) |
| $R^2$ | 0.39 | 0.36 | 0.39 | 0.36 |
| No. of observations | 3,129 | 3,129 | 3,129 | 3,129 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's PAVITT specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. Equations (1.2) and (1.4) do not include controls for employee's work status.

Table 2. Earning Functions: OLS Estimates with Interaction Terms

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (2.1) | (2.2) | (2.3) | (2.4) |
| DISTRICT | 0.1865** | 0.2243** | 0.2929 | 0.2972 |
| | (0.0931) | (0.1038) | (0.1933) | (0.1996) |
| EXP | 0.0324*** | 0.0343*** | - | - |
| | (0.0027) | (0.0027) | - | - |
| EXPSQR | -0.0005*** | -0.0005*** | - | - |
| | (0.0001) | (0.0001) | - | - |
| AGE | - | - | 0.0533*** | 0.0538*** |
| | - | - | (0.0058) | (0.0060) |
| AGESQR | - | - | -0.0005*** | -0.0005*** |
| | - | - | (0.0001) | (0.0001) |
| SCHOOL | 0.0317*** | 0.0432*** | 0.0232*** | 0.0340*** |
| | (0.0035) | (0.0031) | (0.0033) | (0.0029) |
| EXP*DISTRICT | -0.0014 | -0.0004 | - | - |
| | (0.0044) | (0.0044) | - | - |
| EXPSQR*DISTRICT | -0.0001 | -0.0001 | - | - |
| | (0.0001) | (0.0001) | - | - |
| AGE*DISTRICT | - | - | -0.0040 | -0.0029 |
| | - | - | (0.0096) | (0.0099) |
| AGESQR*DISTRICT | - | - | -0.0000 | -0.0000 |
| | - | - | (0.0001) | (0.0001) |
| SCHOOL*DISTRICT | -0.0150** | -0.0111* | -0.0124* | -0.0082 |
| | (0.0073) | (0.0065) | (0.0067) | (0.0058) |
| CONSTANT | 1.6727*** | 1.6642*** | 0.8878*** | 0.8748*** |
| | (0.0912) | (0.0945) | (0.1371) | (0.1411) |
| $R^2$ | 0.40 | 0.36 | 0.40 | 0.36 |
| No. of observations | 3,129 | 3,129 | 3,129 | 3,129 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's PAVITT specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The additional controls have been interacted with DISTRICT. Equations (2.2) and (2.4) do not include controls for employee's work status.

Table 3. Earning Functions: Robustness

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (3.1) | (3.2) | (3.3) | (3.4) |
| | Manufacturing | SMEs | Manufacturing and SMEs | Manufacturing and SMEs in the Centre-North |
| DISTRICT | 0.0142 | 0.0159 | 0.0078 | -0.0059 |
| | (0.0196) | (0.0197) | (0.2464) | (0.0245) |
| EXP | 0.0305*** | 0.0318*** | 0.0310*** | 0.0291*** |
| | (0.0027) | (0.0024) | (0.0034) | (0.0038) |
| EXPSQR | -0.0005*** | -0.0005*** | -0.0005*** | -0.0005*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| SCHOOL | 0.0279*** | 0.0244*** | 0.0264*** | 0.0198*** |
| | (0.0044) | (0.0039) | (0.0050) | (0.0068) |
| CONSTANT | 1.6620*** | 1.5341*** | 1.5000*** | 1.7471*** |
| | (0.1455) | (0.1163) | (0.1977) | (0.2058) |
| $R^2$ | 0.38 | 0.30 | 0.32 | 0.29 |
| No. of observations | 1,660 | 2,098 | 1,026 | 825 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
(**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's PAVITT specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING.

Table 4. Earning Functions: Robustness with Interaction Terms

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (4.1) | (4.2) | (4.3) | (4.4) |
| | Manufacturing | SMEs | Manufacturing and SMEs | Manufacturing and SMEs in the Centre-North |
| DISTRICT | 0.2025** | 0.2023** | 0.1459 | 0.1153 |
| | (0.0930) | (0.0982) | (0.1080) | (0.1308) |
| EXP | 0.0312*** | 0.0336*** | 0.0326*** | 0.0307*** |
| | (0.0034) | (0.0030) | (0.0045) | (0.0056) |
| EXPSQR | -0.0004*** | -0.0005*** | -0.0005*** | -0.0005*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| SCHOOL | 0.0338*** | 0.0282*** | 0.0323*** | 0.0289*** |
| | (0.0049) | (0.0044) | (0.0061) | (0.0104) |
| EXP*DISTRICT | -0.0016 | -0.0041 | -0.0025 | -0.0014 |
| | (0.0052) | (0.0049) | (0.0061) | (0.0068) |
| EXPSQR*DISTRICT | -0.0001 | -0.0000 | -0.0001 | -0.0001 |
| | (-0.0001) | (0.0001) | (0.0001) | (0.0002) |
| SCHOOL*DISTRICT | -0.0244*** | -0.0140* | -0.0275*** | -0.0244** |
| | (0.0072) | (0.0086) | (0.0082) | (0.0118) |
| CONSTANT | 1.5994*** | 1.4856*** | 1.4382*** | 1.6748*** |
| | (0.1533) | (0.1209) | (0.2111) | (0.2320) |
| $R^2$ | 0.39 | 0.31 | 0.34 | 0.30 |
| No. of observations | 1,660 | 2,089 | 1,026 | 825 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
(**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's PAVITT specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The additional controls have been interacted with DISTRICT.

Table 5. Earning Functions: OLS and IV Estimates

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (5.1) | (5.2) | (5.3) | (5.4) |
| | OLS | IV | OLS | IV |
| DISTRICT | 0.0259 | 0.0252 | 0.0312* | 0.0288 |
| | (0.0175) | (0.0176) | (0.0180) | (0.0182) |
| EXP | 0.0322*** | 0.0327*** | 0.0342*** | 0.0348*** |
| | (0.0022) | (0.0023) | (0.0022) | (0.0023) |
| EXPSQR | -00005*** | -00005*** | -00005*** | -00005*** |
| | (0.0000) | (0.0000) | (0.0001) | (0.0001) |
| SCHOOL | 0.0303*** | 0.0370*** | 0.0425*** | 0.0530*** |
| | (0.0022) | (0.0087) | (0.0030) | (0.0067) |
| CONSTANT | 1.6526*** | 1.5728*** | 1.6486*** | 1.4927*** |
| | (0.0941) | (0.1297) | (0.0990) | (0.1275) |
| $R^2$ | 0.40 | 0.40 | 0.36 | 0.36 |
| No. of observations | 2,777 | 2,777 | 2,777 | 2,777 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
(**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's PAVITT specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. Equations (5.3) and (5.4) do not include controls for employee's work status. Instruments: age and educational qualifications of the parents. The Hausman test never allows us to reject the null hypothesis of esogeneity (at 1% statistical significance). The Sargan test never allows us to reject the hypothesis of orthogonality of the IV regression residuals and the instruments (at 1% statistical significance). The sample includes only workers who provided information on parents' age and educational qualification.

Table 6. Earning Functions: OLS and IV Estimates with Interaction Terms

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (6.1) | (6.2) | (6.3) | (6.4) |
| | OLS | IV | OLS | IV |
| DISTRICT | 0.1896* | 0.1566 | 0.2354** | 0.2501 |
| | (0.0998) | (0.2326) | (0.1123) | (0.2405) |
| EXP | 0.0326*** | 0.0331*** | 0.0345*** | 0.0352*** |
| | (0.0027) | (0.0029) | (0.0027) | (0.0028) |
| EXPSQR | -00005*** | -00005*** | -00005*** | -00005*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| SCHOOL | 0.0343*** | 0.0408*** | 0.0452*** | 0.0563*** |
| | (0.0037) | (0.0101) | (0.0033) | (0.0075) |
| EXP*DISTRICT | -0.0001 | -0.0002 | 0.0006 | 0.0002 |
| | (0.0047) | (0.0050) | (0.0047) | (0.0048) |
| EXPSQR*DISTRICT | -0.0001 | -0.0001 | -0.0001 | -0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| SCHOOL*DISTRICT | -0.0159** | -0.0134 | -0.0120* | -0.0136 |
| | (0.0078) | (0.0198) | (0.0071) | (0.0161) |
| CONSTANT | 1.6161*** | 1.5362*** | 1.6044*** | 1.4411*** |
| | (0.0977) | (0.1367) | (0.1016) | (0.1328) |
| $R^2$ | 0.40 | 0.37 | 0.37 | 0.30 |
| No. of observations | 2,777 | 2,777 | 2,777 | 2,777 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
(**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's PAVITT specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The additional controls have been interacted with DISTRICT. Equations (6.3) and (6.4) do not include controls for employee's work status. Instruments: age and educational qualifications of the parents. The Hausman test never allows us to reject the null hypothesis of esogeneity (at 1% statistical significance). The Sargan test never allows us to reject the hypothesis of orthogonality of the IV regression residuals and the instruments (at 1% statistical significance). The sample includes only workers who provided information on parents' age and educational qualification.

Table 7. Earning Functions: OLS and Heckman Selection Model Estimates

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (7.1) | (7.2) | (7.3) | (7.4) |
| | OLS | Heckman Selection Model | OLS | Heckman Selection Model |
| DISTRICT | 0.0277 | 0.0275 | 0.0330* | 0.0345* |
| | (0.0173) | (0.0173) | (0.0179) | (0.0179) |
| EXP | 0.0323*** | 0.0319*** | 0.0344*** | 0.0347*** |
| | (0.0022) | (0.0022) | (0.0022) | (0.0022) |
| EXPSQR | -0.0005** | -0.0005*** | -0.0005*** | -0.0005*** |
| | (0.0001) | (0.0000) | (0.0000) | (0.0001) |
| SCHOOL | 0.0298*** | 0.0279*** | 0.0419*** | 0.0433*** |
| | (0.0034) | (0.0033) | (0.0029) | (0.0029) |
| CONSTANT | 1.6611*** | 1.6506*** | 1.6555*** | 1.6420** |
| | (0.0923) | (0.0922) | (0.0968) | (0.0977) |
| $R^2$ | 0.40 | - | 0.36 | - |
| No. of observations | 2,809 | 4,045 | 2,809 | 4,045 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's ATECO specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. Equations (7.3) and (7.4) do not include controls for employee's work status. Selection variables: educational qualification and work status of the parents. The likelihood-ratio test for correlation between the regression and the selection equations always allows us to reject the null hypothesis of no correlation (at 1% statistical significance). The sample includes all the employees and self-employed persons who provided information on education qualification and work status of the parents. The Heckman Selection Model estimates the likelihood of earning a wage (that is, of observing the dependent variable) by using 4,045 observations (2,809 employees and 1,236 self-employed).

Table 8. Earning Functions: OLS and Heckman Selection Model Estimates with Interaction Terms

| Dependent variable: Log of hourly wage rate | | | | |
|---|---|---|---|---|
| | (8.1) | (8.2) | (8.3) | (8.4) |
| | OLS | Heckman Selection Model | OLS | Heckman Selection Model |
| DISTRICT | 0.1792* | 0.1755* | 0.2259** | 0.2223** |
| | (0.0991) | (0.0983) | (0.1115) | (0.1120) |
| EXP | 0.0327*** | 0.0324*** | 0.0346*** | 0.0349*** |
| | (0.0026) | (0.0026) | (0.0027) | (0.0026) |
| EXPSQR | -0.0005*** | -0.0005*** | -0.0005*** | -0.0005*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| SCHOOL | 0.0337*** | 0.0317*** | 0.0445*** | 0.0456*** |
| | (0.0037) | (0.0036) | (0.0033) | (0.0032) |
| EXP*DISTRICT | -0.0002 | -0.0003 | 0.0006 | 0.0005 |
| | (0.0047) | (0.0046) | (0.0047) | (0.0047) |
| EXPSQR*DISTRICT | -0.0001 | -0.0001 | -0.0001 | -0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| SCHOOL*DISTRICT | -0.0154** | -0.0146** | -0.0114 | -0.0109 |
| | (0.0077) | (0.0076) | (0.0070) | (0.0070) |
| CONSTANT | 1.6282*** | 1.6189*** | 1.6149*** | 1.6046*** |
| | (0.0959) | (0.0956) | (0.0996) | (0.1003) |
| $R^2$ | 0.40 | - | 0.37 | - |
| No. of observations | 2,809 | 4,045 | 2,809 | 4,045 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's ATECO specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The additional controls have been interacted with DISTRICT. Equations (8.3) and (8.4) do not include controls for employee's work status. Selection variables: educational qualification and work status of the parents. The likelihood-ratio test for correlation between the regression and the selection equations always allows us to reject the null hypothesis of no correlation (at 1% statistical significance). The sample includes all the employees and self-employed who provided information on education qualification and work status of the parents. The Heckman Selection Model estimates the likelihood of earning a wage (that is, of observing the dependent variable) by using 4,045 observations (2,809 employees and 1,236 self-employed).

Table 9: Self-Employment

| Dependent variable: Probability of being Entrepreneur or Free Lance | | | | |
|---|---|---|---|---|
| | (9.1) | (9.2) | (9.3) | (9.4) |
| | Dependent Variable: ENT | Dependent Variable: FL | Dependent Variable: ENT and FL | Dependent Variable: BOTH |
| DISTRICT | 0.0917 | 0.0987 | 0.1325 | 0.1155 |
| | (0.1922) | (0.1790) | (0.1487) | (0.1440) |
| AGE | 0.1602*** | 0.0567* | 0.1057*** | 0.2002*** |
| | (0.0437) | (0.0327) | (0.0298) | (0.0373) |
| AGESQR | -0.0013*** | -0.0002 | -0.0006* | -0.0019*** |
| | (0.0005) | (0.0004) | (0.0004) | (0.0004) |
| SCHOOL | 0.0035 | -0.0474** | -0.0331* | 0.1052*** |
| | (0.0225) | (0.0214) | (0.0182) | (0.0233) |
| FMANEX | 0.5636* | -0.2276 | 0.1983 | 0.2959 |
| | (0.3122) | (0.2959) | (0.2484) | (0.2602) |
| FENTFL | 0.6556*** | 0.3415** | 0.6317*** | -0.0014 |
| | (0.1522) | (0.1358) | (0.1183) | (0.1212) |
| CONSTANT | -9.7052*** | -8.5283*** | -8.5072*** | -5.0649 |
| | (1.4160) | (1.1954) | (1.0212) | (1.0286) |
| No. of observations | 4,322 | 4,322 | 4,322 | 4,322 |
| Wald $\chi^2$ | 125.96 | 167.87 | 277.51 | 270.12 |
| Prob > $\chi^2$ | 0.000 | 0.0000 | 0.0000 | 0.0000 |
| *Pseudo* $R^2$ | 0.15 | 0.16 | 0.22 | 0.13 |
| Log likelihood | -1196.3807 | -1415.1103 | -1820.5003 | -1726.6561 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's ATECO specialization indexes, employee's work status, age at the time of the first job, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The sample includes 4,322 persons, (3,333 employees and 989 self-employed) who provided information on parents' work status. Persons who worked BOTH as employee and self-employed are 757.

Table 10. The Transition from Wage-and-Salary Work to Self-Employment

| Dependent variable: Probability of being Entrepreneur or Free Lance | (10.1) | (10.2) | (10.3) |
|---|---|---|---|
| | Dependent Variable: ENTWITH | Dependent Variable: FLWITH | Dependent Variable: ENTWITH and FLWITH |
| DISTRICT | 0.2053 | 0.3422 | 0.3369* |
| | (0.2797) | (0.2471) | (0.2008) |
| AGE | 0.2758*** | 0.0534 | 0.1435*** |
| | (0.0651) | (0.0552) | (0.0424) |
| AGESQR | -0.0024*** | -0.0001 | -0.0009* |
| | (0.0008) | (0.0007) | (0.0005) |
| SCHOOL | 0.0470 | 0.0575* | 0.0572* |
| | (0.0373) | (0.0338) | (0.0308) |
| FMANEX | 0.6824 | 0.2814 | 0.5714 |
| | (0.5489) | (0.5054) | (0.4248) |
| FENTFL | 0.3417 | 0.3186 | 0.3852** |
| | (0.2190) | (0.2005) | (0.1604) |
| CONSTANT | -14.9048*** | -8.7028*** | -10.8878*** |
| | (2.0006) | (1.7956) | (1.4685) |
| No. of observations | 3,545 | 3,545 | 3,545 |
| Wald $\chi^2$ | 150.54 | 140.80 | 240.34 |
| Prob > $\chi^2$ | 0.0000 | 0.0000 | 0.0000 |
| *Pseudo* $R^2$ | 0.22 | 0.19 | 0.24 |
| Log likelihood | -558.0304 | -687.4855 | -960.8347 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's ATECO specialization indexes, employee's work status, age at the time of the first job, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The sample includes 3,545 persons (of which 397 entrepreneurs and free lance with previous experience as employees) who provided information on parents' work status.

Table 11. Worker Mobility Across Jobs: OLS Estimates

| Dependent Variable: Number of activities held up to 12-31-1998 | | |
|---|---|---|
| | (11.1) | (11.2) |
| | Employees | Employees and Self-employed |
| DISTRICT | -0.1768** | -0.0963 |
| | (0.0757) | (0.0622) |
| AGE | 0.0956*** | 0.0874*** |
| | (0.0166) | (0.0125) |
| AGESQR | -0.0010*** | -0.0009*** |
| | (0.0002) | (0.0002) |
| SCHOOL | 0.0407*** | 0.0373*** |
| | (0.0119) | (0.0083) |
| CONSTANT | 2.1688*** | 2.1507*** |
| | (0.4431) | (0.3743) |
| $R^2$ | 0.14 | 0.12 |
| No. of observations | 3,015 | 4,343 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's ATECO specialization indexes, work status, age at the time of the first job, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. The sample includes all the people (4,343, of which 3,015 employees) who provided information on both the number activities held up in work-life and the age at the first job held.

Table 12. Sensitivity Checks with Superdistricts and District Continuous Variable

| Dependent Variable: Hourly Wage Rate | | | | |
|---|---|---|---|---|
| | (12.1) | (12.2) | (12.3) | (12.4) |
| DISTRICT_S | -0.0023 | - | 0.0234 | - |
| | (0.0202) | - | (0.1177) | - |
| DISTICT_C | - | 0.0365 | - | 0.0757 |
| | - | (0.0256) | - | (0.1178) |
| EXP | 0.0316** | 0.0317*** | 0.0315*** | 0.0324*** |
| | (0.0021) | (0.0021) | (0.0023) | (0.0030) |
| EXPSQR | -0.0005*** | -0.0005*** | -0.0005*** | -0.0005*** |
| | (0.0000) | (0.0000) | (0.0001) | (0.0001) |
| SCHOOL | 0.0281*** | 0.0283*** | 0.0273*** | 0.0299*** |
| | (0.0032) | (0.0032) | (0.0035) | (0.0039) |
| EXP*DISTRICT_S | - | - | 0.0026 | - |
| | - | - | (0.0059) | - |
| EXPSQR*DISTRICT_S | - | - | -0.0001 | - |
| | - | - | (0.0001) | - |
| EXP*DISTRICT_C | - | - | - | -0.0026 |
| | - | - | - | (0.0057) |
| EXPSQR*DISTRICT_C | - | - | - | -0.0000 |
| | - | - | - | (0.0001) |
| SCHOOL*DISTRICT_S | - | - | 0.0064 | - |
| | - | - | (0.0082) | - |
| SCHOOL*DISTRICT_C | - | - | - | -0.0072 |
| | - | - | - | (0.0082) |
| CONSTANT | 1.7077*** | 1.7141*** | 1.7062*** | 1.7036*** |
| | (0.0875) | (0.0870) | (0.0889) | (0.0941) |
| $R^2$ | 0.39 | 0.39 | 0.39 | 0.40 |
| No. of observations | 3,129 | 3,129 | 3,129 | 3,129 |

Notes: All regressions are weighted to population proportions. White-robust standard errors in parentheses.
* (**) [***] denotes statistical significance at 10 (5) [1] percent level.
The additional controls included in the regressions are LLMA's unemployment rate, LLMA's ATECO specialization indexes, employee's work status, and the following dummy variables: FEMALE, SOUTH, SMEs, MANUFACTURING. In (12.3) and (12.4) the additional controls are also interacted with DISTRICT_S (C).

## List of Variables

AGE. Age is defined as the difference between the survey year and the individual's year of birth.

AGESQR. Age squared.

AGE1JOB. Age at first job held.

BOTH. This is a dummy variable that equals one if the individual had mixed work experience, both as employee and as self-employed.

DISTRICT. This is a dummy variable that equals one if the LLMA is an IID according to the ISA classification.

DISTRICT_C. This is a continuous variable denoting the extent to which district characteristics are present in a LLMA, as in Cannari and Signorini(2000).

DISTRICT_S. This is a dummy variable that equals one if the LLMA is a Superdistrict, as in Cannari and Signorini (2000).

ENT. This is a dummy variable that equals one if the individual is an entrepreneur.

ENTWITH. This is a dummy variable that equals one if the individual is an entrepreneur who had at least one work experience as employee.

EXP. Work experience has been defined as the difference between current age and age at first job held.

EXPSQR. Work experience squared.

FAGE. Father's age.

FEMALE. This is a dummy variable that equals one if the individual is female.

FL. This is a dummy variable that equals one if the individual is a free lance worker.

FLWITH. This is a dummy variable that equals one if the individual is a free lance worker who had at least one work experience as employee.

FENTFL. This is a dummy variable that equals one if the individual's father is an entrepreneur or a free-lance worker.

FMANEX. This is a dummy variable that equals one if the individual's father is a manager or an executive.

FSCHOOL. Father's educational attainment.

FWSTATUS. Father's work status.

LWAGE. Hourly wages were calculated by dividing the annual earnings (from any activity as employee, including fringe benefits, net of taxes and social security contributions) by the total amount of hours worked in a year. In the analysis we used the natural logarithm of hourly wages:

*lwage* $\log\left(\frac{annualearnings}{no.hours * no.months * 4.3333}\right)$

MAGE. Mother's age.

MANUFACTURING. This is a dummy variable that equals one if the individual works in a manufacturing firm.

MSCHOOL. Mother's educational attainment.

MWSTATUS. Mother's work status.

NUMJOBS. Number of jobs held.

PAVITT1-4. These four variables denote the LLMA's PAVITT specialization index for the following categories: high technology, specialization, scale intensive, and traditional sectors. For each PAVITT category j, the specialization index is the ratio between the share relative to the LLMA and the share relative to the country of category j's employees in total manufacturing industry's employees:

$$I_{SP} = \frac{(\frac{Nj}{Nm})_{LLMa}}{(\frac{Nj}{Nm})_{ITA}}$$

where N is the number of employees, j refers to Pavitt's four categories, m to manufacturing, LLMA to local labor market area, and ITA to Italy. PAVITT1-4 are computed by adapting PAVITT's classification, originally made for the 1981 ATECO system, to the 1991 ATECO system.

SCHOOL. The information on education available in the survey refers to the highest qualification earned by the individual. We derived the length of education by assigning: 0 years to no qualification; 5 years to elementary school; 8 years to middle school; 11 years to professional secondary school diploma; 13 years to high school; 16 years to an associate degree or other short course university degree; 18 years to a bachelor's degree; and 20 years to a postgraduate qualification.

SMEs. This is a dummy that equals 1 if firms have less than 100 employees.

SOUTH. This is a dummy that equals 1 if the individual resides in the South of Italy.

UNEMPLOYMENT RATE. The LLMA unemployment rate is calculated as the ratio of job seekers in total labor force, using 1996 Istat's Survey on the Labor Force.

WSTATUS. This is variable that assumes the following values: 1 – Blue-collar workers 2 – Office worker; 3 – Junior manager; 4 – Manager; 5 – Member of the professions; 6 – Business owner; 7 – Free-lance; 8 – Owner or assistant of a family business; 9 – Active shareholder or partner.

■

Table A.1. Summary Statistics

| | Total sample | | | IIDs | | |
|---|---|---|---|---|---|---|
| | No. of obs. | Average | Std. Dev. | No. of obs. | Average | Std. Dev. |
| AGE | 4665 | 39.012 | 11.628 | 1319 | 38.553 | 11.715 |
| AGE1JOB | 4663 | 19.118 | 4.774 | 1319 | 18.509 | 4.406 |
| AGESQR | 4665 | 1657.144 | 952.701 | 1319 | 1623.453 | 948.541 |
| BOTH | 4665 | 0.177 | 0.382 | 1319 | 0.208 | 0.406 |
| DISTRICT | 4665 | 0.283 | 0.450 | 1319 | 1.000 | 0.000 |
| DISTRICT_C | 4665 | 0.296 | 0.350 | 1319 | 0.755 | 0.251 |
| DISTRICT_S | 4665 | 0.101 | 0.302 | 1319 | 0.359 | 0.480 |
| ENT | 4665 | 0.123 | 0.328 | 1319 | 0.136 | 0.343 |
| ENTWITH | 3743 | 0.120 | 0.325 | 1108 | 0.151 | 0.358 |
| EXP | 4663 | 19.896 | 12.759 | 1319 | 20.043 | 12.510 |
| EXPSQR | 4663 | 558.590 | 587.875 | 1319 | 558.111 | 561.148 |
| FAGE | 4423 | 70.742 | 13.942 | 1265 | 70.152 | 14.021 |
| FEMALE | 4665 | 0.308 | 0.462 | 1319 | 0.355 | 0.479 |
| FL | 4665 | 0.130 | 0.336 | 1319 | 0.124 | 0.329 |
| FLWITH | 3743 | 0.058 | 0.234 | 1108 | 0.080 | 0.272 |
| FENTFL | 4464 | 0.393 | 0.488 | 1273 | 0.414 | 0.493 |
| FMANEX | 4464 | 0.066 | 0.248 | 1273 | 0.049 | 0.217 |
| FSCHOOL | 4502 | 6.139 | 4.093 | 1283 | 6.089 | 3.639 |
| FWSTATUS | 4464 | 4.256 | 3.416 | 1273 | 4.313 | 3.479 |
| LWAGE | 3129 | 2.446 | 0.425 | 909 | 2.458 | 0.381 |
| MAGE | 4209 | 67.745 | 13.385 | 1194 | 67.098 | 13.287 |
| MANUFACTURING | 4665 | 0.419 | 0.493 | 1319 | 0.516 | 0.500 |
| MSCHOOL | 4294 | 5.475 | 3.600 | 1215 | 5.570 | 3.361 |
| MWSTATUS | 4257 | 7.288 | 3.052 | 1205 | 6.683 | 3.386 |
| NUMJOBS | 4665 | 2.058 | 1.650 | 1319 | 2.071 | 1.438 |
| PAVITT1 | 4665 | 0.620 | 0.893 | 1319 | 0.290 | 0.530 |
| PAVITT2 | 4665 | 0.984 | 0.578 | 1319 | 1.139 | 0.627 |
| PAVITT3 | 4665 | 0.890 | 0.582 | 1319 | 0.847 | 0.647 |
| PAVITT4 | 4665 | 1.277 | 0.530 | 1319 | 1.408 | 0.541 |
| SCHOOL | 4665 | 10.373 | 3.650 | 1319 | 10.299 | 3.505 |
| SMEs | 4519 | 0.769 | 0.422 | 1282 | 0.782 | 0.413 |
| SOUTH | 4665 | 0.257 | 0.437 | 1319 | 0.022 | 0.147 |
| UNEMPLOYMENT RATE | 4665 | 10.890 | 7.307 | 1319 | 6.182 | 2.579 |
| WSTATUS | 4665 | 3.635 | 3.143 | 1319 | 3.604 | 3.219 |

Table A.2. Frequency of Entrepreneurs and Free-Lance Workers in the Sample

| | IIDs | | NON-IIDs | | TOTAL | |
|---|---|---|---|---|---|---|
| | No. | % | No. | % | No. | % |
| | | | Overall sample | | | |
| ENT | 138 | 11.2 | 269 | 8.7 | 407 | 9.4 |
| FL | 159 | 12.9 | 423 | 13.7 | 582 | 13.5 |
| ENT-FL | 297 | 24.1 | 692 | 22.4 | 989 | 22.9 |
| Total | 1232 | 100.0 | 3086 | 100.0 | 4322 | 100.0 |
| | | | Sample of those with previous experience as employee | | | |
| ENTWITH | 75 | 29.4 | 101 | 20.1 | 176 | 23.2 |
| FLWITH | 76 | 29.8 | 145 | 28.9 | 221 | 29.2 |
| ENTWITH- FLWITH | 151 | 59.2 | 246 | 49.0 | 397 | 52.4 |
| Total | 1057 | 100.0 | 2488 | 100.0 | 3545 | 100.0 |

## References

Acemoglu, D., and J. Angrist, 2000, "How Large Are Human Capital Externalities? Evidence from Compulsory Schooling Laws," *National Bureau of Economic Research Macroannual 2000* (Cambridge MA).

Abdel-Rahman, H., and M. Fujita, 1990, "Product Variety, Marshallian Externalities, and City Sizes," *Journal of Regional Science*, Vol. 30, pp. 165-183.

Alesina, A., S. Danninger, and M. Rostagno, 2001, "Redistribution Through Public Employment: The Case of Italy," International Monetary Fund, Staff Papers, Vol. 48-3, pp. 447-73.

Barca, F., and L. Cannari, 1997, "Imprenditori e investitori: il ruolo dell'istruzione," in *L'istruzione in Italia: solo un pezzo di carta?*, ed. by N. Rossi (Bologna: Il Mulino).

Becattini, G., 1990, "The Marshallian Industrial District as Socio-Economic Notion," in Pyke, Becattini, and Sengenberger (1990).

Becker, G. S., 1964, *Human Capital* (New York: National Bureau Economic Research).

Bils, M., and P. Klenow, 2000, "Does Schooling Cause Growth?" *American Economic Review*, Vol. 90-5, pp. 1160-83.

Brandolini, A., 1999, "The Distribution of Personal Income in Post-War Italy: Source Description, Data Quality, and the Time Pattern of Income Inequality," Bank of Italy, Temi di discussione 350 (Rome).

Brusco, S., 1991, "The Idea of the Industrial Districts: Its Genesis," in Pyke, Becattini, and Sengenberger (1990).

____, and S. Paba, 1997, "Per una storia dei distretti industriali italiani dal secondo dopoguerra agli anni novanta," in *Storia del capitalismo italiano dal dopoguerra ad oggi*, ed. by F. Barca (Rome: Donzelli).

Cannari, L. and G. D'Alessio, 1995, "Il rendimento dell'istruzione: alcuni problemi di stima," Bank of Italy, Temi di discussione 253 (Rome).

Cannari, L. and L.F. Signorini, 2000, "Nuovi strumenti per la classificazione del sistemi industriali," in Signorini (2000).

Card, D., 1999, "The Causal Effect of Education on Earnings," in *Handbook of Labor Economics*, ed. by O. Ashenfelter and D. Card (Amsterdam: Elsevier).

Casavola, P., G. Pellegrini, and E. Romagnano, 2000, "Imprese e mercato del lavoro nei distretti industriali," in Signorini (2000).

Ciccone, A. and G. Peri, 2000, "Human Capital and Externalities in Cities," Centre Economic Policy Research, Discussion Paper 2599.

Cingano, F., 1999, "Returns to Specific Skills in Industrial Districts," mimeo.

Colussi, A., 1997, "Il tasso di rendimento dell'isrtuzione in Italia," in *L'istruzione in Italia: solo un pezzo di carta?*, ed. by N. Rossi (Bologna: Il Mulino).

Combes, P., and G. Duranton, 2001, "Labor Pooling, Labor Pooling and Spatial Clustering," CERAS Working Paper, Vol. 01-03.

Dei Ottati G., 1992, "Fiducia, transazioni intrecciate e credito nel distretto industriale," *Note Economiche*, Vol. 22-1/2.

Diamond, C.A., and C.J. Simon, 1990, "Industrial Specialization and the Returns to Labor," *Journal of Labor Economics*, Vol. 8-2, pp. 175-201.

Eurostat, 1996, *Enterprises in Europe*, Fourth Report (Bruxelles).

Greene, W.H., 2000, *Econometric Analysis* (New York: Prentice Hall International).

Griliches, Z., 1977, "Estimating the Returns to Schooling: Some Econometric Problems," *Econometrica*, Vol. 45-1, pp. 1-22.

Istat, 1996, *Rapporto Annuale. La situazione del Paese nel 1995*, Istituto poligrafico dello Stato, Roma.

Jaffe, A., M. Trajtenberg, and R. Henderson, 1993, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics*, Vol. 108, pp. 577-598.

Krugman, P., 1991, *Geography and Trade* (Cambridge, Mass.: MIT Press).

Marshall, A.,1890, *The Principles of Economics* (London: Macmillan, 1920).

Mauro, P., E. Prasad, and A. Spilimbergo, 1999, "Perspectives on Regional Unemployment in Europe," International Monetary Fund, Occasional Paper 177.

Mincer, J., 1958, "Investment in Human Capital and Personal Income Distribution," *Journal of Political Economy*, Vol. 66-4, pp. 281-302.

Neal, D., 1995, "Industry-specific Human Capital: Evidence from Displaced Workers," *Journal of labor Economics*, Vol. 13-4, pp. 653-77.

OECD, 2001, *Territorial Reviews: Italy* (Paris).

Ottaviano, G. and D. Puga, 1998, "Agglomeration in the Global Economy: A Survey of the 'New Economic Geography'," *World Economy*, Vol. 21-6.

Parent, D., 2000, "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics," *Journal of labor Economics*, 18-2, pp. 306-23.

Putnam, R.D., 1993, *Making Democracy Work: Civic Tradition in Modern Italy* (Princeton: Princeton University Press).

Pyke, F., G. Becattini, and W. Sengenberger, 1990, *Industrial Districts and Inter-firm Co-operation in Italy* (Geneva: International Institute for Labour Studies).

Rosen, S., 1977, "Human Capital: A Survey of Empirical Research," in *Research in Labor Economics*, ed. by H. Ehrenberg (Greenwich, Conn.: JAI Press).

Rotemberg, J.J., and Saloner, G., 1990, "Competition and Human Capital Accumulation: A Theory of Interregional Specialization and Trade," National Bureau Economic Research Working Paper 3228.

Signorini, L.F., 1994, "Una verifica quantitativa dell'effetto distretto," *Sviluppo Locale*, 1.

___, 2000, *Lo sviluppo locale* (Roma: Donzelli).

Solinas, G., 1982, "Labour Market Segmentation and Workers' Careers: The Case of the Italian Knitwear Industry," *Cambridge Journal of Economics*, 4.

___, 1991, "L'anzianità aziendale: alcune considerazioni sul caso emiliano," *Politica economica*, 3.

Willis, R. J., 1986, "Wage Determinants: a Survey and Reinterpretation of Human Capital Earnings Functions," in *Handbook of Labour Economics*, ed. by O. Ashenfelter and R. Layard, Vol. 1 (Amsterdam and New York: North Holland).