# Local human capital externalities and wages at the firm level: The case of Italian Manufacturing

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**Abstract**

Recent studies show that local human capital externalities in production are important in the U.S. but the U.S. evidence may not be easily generalizable to countries such as Italy with much lower levels of education or low-skill industries. In this paper, we provide evidence of local human capital exernalities in Italy using a unique firm-level dataset merging national social security, Population Census and survey data on manufacturing firms. Our estimates show that: (i) firms located in provinces with a larger fraction of manufacturing workers holding a university degree pay on average higher wages to their skilled workers (white collars) and this result is robust against several variants of the econometric specification that control for many potential confounding factors; (ii) when potential endogeneity of local human capital is addressed using a quasi-natural experiment induced by a reform of Italian Higher Education introduced in the early 1990s, we estimate that for white collar workers the wage rise caused by a one percentage point increase in the local college share is in the range of 1.4-1.7% ; (iii) in Italian Manufacturing, local human capital externalities exist over and above spillovers taking place within the firm, and seem to be mainly of a non-pecuniary nature.

*Keywords:* firm, local human capital externalities, Italy, Manufacturing, wages
JEL. J24 J31

## 1. Introduction and motivation

A considerable amount of evidence on the positive association between individual education and wages has been collected over time since the seminal work of Mincer (1974). Recent studies have also clarified that the positive correlation cannot be completely attributed to *ability bias* (Griliches 1977) – the fact that more able individuals simultaneously receive higher education and earn higher wages – but reflects a genuine causal effect (see Card 1999, for a review).

In some countries, estimates of substantial private returns on education and the need to keep public budgets under control have motivated a progressive shift of the burden of financing Higher Education (HE, hereafter) from the general public towards students and their families. In the UK, for instance, since the 1960s there has been a substatial reduction in public funding to HE (Greenaway and Haynes 2003), to which HE universities have responded by increasing student fees (Dearden et al. 2008). In Italy, which represents the object of the present study, state funding of public universities has been subject to heavy cuts only very recently (see below) without any possibility of universities raising student fees.[1]

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[1]In Italy the '20% rule' states that the revenue coming from student fees cannot account for more than 20% of the total public transfer (*Fondo di Finanziamento Ordinario*) received by universities.

*May 20, 2010*

This progressive disengagement from financing HE by some governments appears to be in stark contrast with one of the most widely accepted ideas in economics, that education is a public good and has substantial positive externalities. Despite the idea that the presence of educated workers could make other workers more productive being very old,[2] and having inspired many important theoretical contributions,[3] until very recently the empirical evidence on the external effects of education was very scant, mainly focused on the U.S. and in some cases even mixed. Most empirical studies focused on *local* human capital externalities, finding different results depending on the level of education considered (average years of schooling vs. college share), the level of geographical aggregation of human capital, and, sometimes, the specific identification strategy used. In particular, evidence of human capital spillovers is more likely to be found in studies considering tertiary education and geographically more disaggregated measures of human capital.[4] Moretti (2004a) offers an explanation for the first finding, mantaining that in developed countries production externalities are likely to emerge especially from university-educated workers, while Rosenthal and Strange (2008b) provide a rationale for the second finding, showing that the geographical spread of knowledge spillovers could be rather limited.

When it comes to studying local human capital externalities, Italy represents an interesting case study for a number of reasons. First, findings for the U.S. may not be easily generalizable to countries like Italy with much lower levels of tertiary education among the population[5] and whose production structure is mainly specialized in low-skill products (Faini et al. 1999).[6] In such countries, human capital externalities may be very limited in scope or even non-existent, and a reduction of public expenditure on HE could be justified. Second, Italy is one of the OECD countries spending the least on HE. According to the most recent OECD figures available (OECD 2009), in Italy annual expenditures of educational institutions per student in tertiary education were 70.7% of the OECD average, 34.7% of the U.S. and 56.5% of UK expenditures. In spite of this, Law No. 133 of 6th August 2008, reduced public transfers to HE institutions by about 1,441 million Euros (about 20%) by 2013. In response to this, HE institutions have started a process of restructuring leading to the closure of some university degrees and a plan to close some university facilities, especially those that are smaller and considered to be inefficient. Since geographic mobility of both university students and graduate workers is very low in Italy, if local human capital externalities do exist, the closing of university premises will have negative consequences especially on local production systems.[7] This is not necessarily the case in countries where there is a lot of geographic mobility of university graduates, such as the U.S. (Bound et al. 2004).

In this paper, we focus on local production spillovers originating from tertiary education using Italian Manufacturing firm-level average wage data. The idea is that if externalities do exist in production, we should see firms located in geographic areas with higher levels of human capital having a higher productivity and paying higher average wages than otherwise similar firms located in areas with lower levels of human capital. For each firm, the local level of human capital is defined as the *share of college-educated workers among all workers in Manufacturing in the province* in which the firm is located. During the period we study in Italy, there were 103 provinces.[8]

In addition to considering a country very different from the U.S., our article contributes to the existing literature in a number of ways. First, to the best of our knowledge, we are the first to match administrative data on wages from the Italian National Social Security Institute (*Istituto Nazionale della Previdenza Sociale*, INPS hereafter) with

[2]See, for instance, Marshall (1890).

[3]See, among others, Lucas (1988), Jovanovic and Rob (1989) and Acemoglu (1998).

[4]Just to take a few recent examples of studies using either instrumental variables or difference-in-differences estimation strategies, Acemoglu and Angrist (2000) and Ciccone and Peri (2006) consider average years of schooling at the state and city level, respectively, and do not find local human capital externalities in the U.S. Moretti (2004a) and Rosenthal and Strange (2008b) focus only on tertiary education at the city and Census block levels (only for the Boston area), respectively, and find evidence of human capital spillovers in the same country.

[5]According to OECD (2009), in 2007, in Italy 14% of the population of 25-65 year olds had tertiary education while the corresponding figure was 40% in the U.S.

[6]Goux and Maurin (2000) show, for instance, that in spite of the evidence on skilled bias technological change (SBTC) being pervasive in the U.S., SBTC is not the main explanation for the increasing inequality in the labor market in France, and in general may have much less importance in continental Europe which is characterized by very different institutions.

[7]Recent studies show that policies of geographic decentralization of universities may be beneficial to regional productivity and innovation (Andersson et al. 2004; 2009).

[8]In Italy, a province is an administrative division of intermediate level between municipality and region, it corresponds to NUTS-3 according to the EU Nomenclature of Territorial Units for Statistics. In 2001 – the period we study – the populations of Italian provinces ranged from 90,076 (Isernia) to 3,705,018 (Milan) inhabitants. Just to make a comparison, in 2000 the size of the population of the (366) Metropolitan Statistical Areas – that are often used in the U.S. literature – ranged between 52,457 (Enid) to 18,323,002 (New York). Therefore, the level of geographical disaggregation used in our study is very similar to that commonly adopted in previous literature.

a widely used firm-level survey on Italian Manufacturing (the Unicredit's Survey on Italian Manufacturing Firms, SIMF hereafter).[9] This offers two main advantages: (i) administrative wage data are less likely to be subject to measurement errors compared to survey data;[10] and (ii) INPS earnings data are available by level of qualification (white collars and blue collars) while SIMF only provides average labour costs by firm. This enables us to address the potential issue of 'standard neoclassical supply effects' recently emphasized by Moretti (2004a) and Ciccone and Peri (2006) by estimating separate wage equations by skill level.[11]

Second, the focus on firm-level data allows us to address the potential issue of omitted variables bias generated by firm-level unobservables, such as firm physical capital stock or R&D investment (Rauch 1993) that have been generally omitted from previous studies using worker data.

Third, since we have data on the educational composition of the workforce within the firm, we can test whether local human capital externalities emerge over and above spillovers potentially arising within a firm (see, among others, Battu et al. 2003, Martins and Jin 2008). This is important because if firm human capital is not properly controlled for in the wage equations, local human capital may simply act as a proxy for it, a fact that has been overlooked in the empirical literature using worker data.[12]

Fourth, the focus on Italy gives us a potentially good identification strategy for estimating the causal effect of local human capital on wages using a presumably exogenous source of variation in local human capital driven by the supply side of HE, much in the spirit of the studies reviewed in Card (2001). Indeed, Italy was subject to a dramatic increase in HE supply following a major HE reform introduced in the early 1990s. We argue that both the features of the reform and the empirical evidence suggest that the supply expansion can be considered exogenous with respect to wages in Manufacturing and use an instrumental variables (IVs) strategy.

Last but not least, following the suggestion in Acemoglu and Angrist (2000), we try to address also the issue of the potential endogeneity of firm human capital using IVs, which are also useful in case the firm stock of human capital is measured with error.[13]

A central finding of our paper is that the local college share is positively related to average wages paid by Italian manufacturing firms. This evidence is robust against the addition of several covariates, which might account for a spurious correlation between local human capital and wages, in the wage equations. Even though we use ordinary least squares (OLS, henceforth) and the causal interpretation of our estimates may be questioned, our findings suggest that the estimated effects are likely to capture knowledge spillovers. First, the college share has a stronger association with white collar wages. Secondly, externalities are smaller and statistically insignificant when considering the share of college educated workers in the overall population or in the workforce rather than only in Manufacturing. In both cases, it is what one would expect if the source of the externality were mainly spillovers of production-related knowledge, as virtually no university graduate works as a blue collar worker, production and non-production tasks are very different, and knowledge spillovers are likely to be higher among those performing similar tasks. When IVs are used, our estimates of local human capital spillovers remain statistically significant and are largely found to be insensitive to the specific choice of control variables. Last but not least, we show that the coefficient of firm human capital (the college share within the firm) increases when this variable is also considered endogenous and instrumented, while the coefficient of local human capital does not change, which suggests that in survey data firm human capital may be affected by a non-negligible measurement error.

The paper is organized as follows. Section 2 describes the econometric model. Section 3 summarizes the main characteristics of the dataset. Section 4 reports the empirical results and section 5 concludes.

[9] Some recent papers using the same survey are, for instance, Parisi et al. (2006), Boeri and Garibaldi (2007), Benfratello et al. (2008) and Angelini and Generale (2008).

[10] If measurement error is classical, having a more precise measure of wages will only increase efficiency, while if measurement error is nonclassical and depends on some or all the covariates included in our econometric models, the advantages are more substantial.

[11] In what follows, we will use the words skilled workers (unskilled workers), white collars (blue collars) and non-production (production) workers interchangeably.

[12] This represents an improvement over Moretti (2004c) who studies local human capital spillovers estimating firm production functions, but not having data on firm skill level has to impute them using 3-digit industry-city cells from the U.S. Census of Population (p. 684).

[13] The ones listed above are also the main differences with two studies that have investigated local human capital externalities for Italy of which we are aware, Dalmazzo and de Blasio (2007b) and Dalmazzo and de Blasio (2007a). These papers focus on household survey data, the Bank of Italy Survey on Household Income and Wealth (SHIW) and average years of schooling, and are unable to control for firm-level variables such as R&D expenditure or human capital within the firm. Both papers use an IVs strategy and instruments based on the lagged age structure of the population and find evidence of local human capital spillovers in Italy.

## 2. Econometric model

We adopt the Mincer approach by estimating a firm-level (log) wage regression by skill level augmented with an indicator of local human capital. In particular, we follow Moretti (2004a) and estimate the following wage equations for white collars (W) and blue collars (B), respectively:

$$w_{ipW} = \alpha_0 + \alpha_1 K_i + \mathbf{T_i'}\boldsymbol{\alpha_2} + \alpha_3 FCS_i + \alpha_4 LCS_p + \mathbf{X_i'}\boldsymbol{\alpha_5} + u_{iW} + u_{pW} + \epsilon_{iW} \quad (1)$$

$$w_{ipB} = \beta_0 + \beta_1 K_i + \mathbf{T_i'}\boldsymbol{\beta_2} + \beta_3 FCS_i + \beta_4 LCS_p + \mathbf{X_i'}\boldsymbol{\beta_5} + u_{iB} + u_{pB} + \epsilon_{iB} \quad (2)$$

where $i$ is the firm subscript, $p$ is the spatial subscript and $W$, $B$ are the skill-level subscripts, respectively.[14] We use as the relevant spatial unit Italian provinces.[15] We distinguish two levels of skills, blue collars and white collars. This distinction is due to the fact that earnings data come from INPS archives (see section 3), which do not collect information on workers' educational levels but only on their level of qualification. $w_{ips}$ is the natural logarithm of the firm-level nominal annual average wage for firm $i$, in province $p$ and for skill-level $s = W, B$ (see Appendix B). We follow Acemoglu and Angrist (2000) and Moretti (2004a) and use nominal wages as our dependent variable. Indeed, as we are considering Manufacturing, a sector producing tradable goods, average productivity has to be higher in provinces where nominal wages are higher. $K_i$ is the natural logarithm of physical capital intensity, which is the ratio between the real capital stock and the total number of workers. $\mathbf{T_i}$ is a vector of technological indicators, $FCS_i$ is firm human capital proxied by the firm college share (the proportion of university graduate workers of the total firm's employment) and $\mathbf{X_i}$ a vector of other firm-level controls. $LCS_p$ is the measure of local human capital, i.e. the proportion of local college graduates among manufacturing workers and $\alpha_4$ is the main parameter of interest. We will interpret a statistically significant $\alpha_4 > 0$ as evidence for positive local human capital spillovers. In particular, given that we are controlling for firms' investments in physical capital, R&D and ICT, $\alpha_4$ is likely to mainly capture non-pecuniary externalities, i.e. knowledge spillovers, rather than pecuniary ones. In contrast, a positive $\beta_4$ is not necessarily an indication of positive spillovers, since it might be generated by supply substitution effects in case of imperfect substitution of workers by skill level.[16] A positive $\alpha_3$ in the white-collar wage equation is largely expected given that university graduates are likely to be in white-collar occupations and that there are positive private returns from tertiary education in Italy. However, since we are estimating a wage equation at the firm-level, $\alpha_3$ is likely to capture not only private returns but also within-firm spillovers to higher education. A positive and significant $\beta_3$ in the wage equation for blue collars could instead be interpreted as evidence for within-firm human capital spillovers, as blue collars are unlikely to have a university degree. $u_{is}$ and $u_{ps}$ are firm-level and province-level skill-specific unobservables, respectively, which may be correlated with the regressors included in each equation, and $\epsilon_{is}$ is assumed to be white noise. A more detailed description of the variables used is available in Appendix A.

Moretti (2004a) discusses the problem of endogeneity of local human capital. The problem is likely to be produced by the correlation between firm-level or province-level unobservable characteristics and local human capital.[17] Examples of unobservables that might generate such a correlation are, for instance, demand shocks to specific sectors or firms that may attract skilled workers to a given area and also raise workers' productivity (endogenous migration). Moretti (2004a) takes the example of San Jose in California following the internet boom which drove up demand for qualified workers, increased their wages and attracted highly educated workers to the area. This could also be seen as a problem of reverse causality in case of endogenous mobility, that is, one is likely to find a higher supply of human capital in areas where firms pay higher wages to highly educated workers. In this case, OLS estimates will be biased upward. However, the bias need not be necessarily positive. Indeed, since workers in Italian Manufacturing are often

[14] Although the underlying theory has been developed for the case of a perfectly competitive labor market (see Moretti 2004a), in which the wage equals the worker's marginal productivity, the same specification can also be used in the case of imperfectly competitive markets. In this case, it must be noted that with the augmented Mincer equations usually estimated in the literature, researchers are testing the joint hypothesis that there are localized human capital externalities in production (i.e. workers are more productive) and that workers receive part of the productivity rise.

[15] Since our measure of local human capital is computed using the 2001 Population Census public use micro-file, which for privacy reasons does not include a municipality identifier for municipalities with less than 100,000 inhabitants, it is not possible to consider finer geographical disaggregations, such as municipalities or local labour market systems.

[16] When local human capital increases, unskilled workers become relatively more scarce and their wages rise.

[17] Taking the difference between white collar and blue collar wages within the firm solves the endogeneity problem only in very specific situations, such as $u_{iW} = u_{iB}$ and $u_{pW} = u_{pB}$.

low skilled, high wages offered by local manufacturing firms raise the opportunity cost of university education and may create a disincentive to invest in human capital. A classical example is the Veneto region (North-Eastern Italy), which is characterized by an industrial structure based on Manufacturing, and by low unemployment rates and high university drop-out rates (Di Pietro 2006). In this case, unobservable factors positively affecting local manufacturing firm productivity might be negatively correlated with the accumulation of local human capital and OLS estimates could be biased downward. As noted by Moretti (2004a), in general finding proxies for all possible unobservables is not a viable solution to the endogeneity problem and an alternative is to resort to IVs techniques. This poses, of course, the uncomfortable task of finding variables correlated with the local college share but not with average wages paid by manufacturing firms. In section 4, we will make an attempt to address the issue of endogeneity of local human capital using IVs.

As stated, our empirical specification offers some advantages with respect to both Moretti (2004a) and Dalmazzo and de Blasio (2007b), among others. Using firm-level data, we are able to control for many firm-level characteristics that might simultaneously affect firm productivity and attract human capital from neighbouring provinces (such as capital intensity or investments in R&D and ICT). Moreover, our specification enables us to assess whether local human capital externalities emerge over and above firm-level spillovers.[18]

## 3. Data

We measure the local stock of human capital with the *share of manufacturing workers with a tertiary degree at province level*.[19] Our choice deserves some comments. As we will include in the wage equations controls for firm physical capital stock and technological inputs, our local human capital variable is aimed mainly at capturing knowledge rather then pecuniary spillovers, that is those emerging from the exchange of work-related knowledge between workers. For this reason, we use as a proxy of local human capital the tertiary educational achievement only of workers in the Manufacturing sector. The idea is that work-related knowledge is more likely to be exchanged between workers, and to induce an increase in firm productivity the more similar are workers' job tasks.[20] For this reason, we prefer to compute a sector-specific measure of local human capital.[21] We employ the public-use microdata file of the 2001 Italian Population Census released by the Italian National Statistical Institute (ISTAT) gathering information on a representative sample of 1,117,928 individuals, 2% of the total Italian population in 2001. The share of university educated workers in Manufacturing by province is computed using sample weights that expand the sample to the whole Italian population (see Appendix A).[22] The college share in Manufacturing varies across Italian provinces. The average share in our sample is 0.05, with a maximum of 0.13 for the province of Rome (Italy's capital) and a minimum of 0.02 for the province of Lecce (Southern Italy). The average share of college educated workers employed by Manufacturing firms in the estimation sample is equally low, and amounts to only 0.04. The average share of white collars in the total employment across firms in the sample is instead 0.26. Hence, *college educated workers only account for a small minority of white-collar employees in Manufacturing firms*.

'Wage' data are gathered by INPS. In particular, the data refer to *firms' average annual wages by skill-level for full-time workers* (blue collars and white collars). These data have both advantages and disadvantages. The main advantage is that they come from an administrative source and are less likely to be affected by measurement errors compared to the self-declared survey data normally used in worker-level studies. The main disadvantage is that, unlike those studies, we are unable to compute a measure of hourly wage since INPS does not collect information on working hours.[23] Hence, despite our measure of average annual earnings being adjusted for part-time work in terms of days (see

[18]This is also done in Moretti (2004c) who investigates local human capital spillovers by estimating establishment-level production functions in U.S. Manufacturing.

[19]In particular, we consider as tertiary degrees university diplomas, university undergraduate and postgraduate degrees and non-university tertiary education. For brevity, we refer to individuals holding these degrees as 'college educated' or 'university educated' workers.

[20]This idea is not new in economics and dates back to Marshall (1890). Also, Moretti (2004c) recently showed that human capital spillovers are stronger between 'economically close' sectors.

[21]Previous studies have considered a variety of definitions of local human capital. Dalmazzo and de Blasio (2007b;a) and Muravyev (2008) focus on the whole population, Acemoglu and Angrist (2000), Moretti (2004a) and Ciccone and Peri (2006) focus on all workers and Moretti (2004c) on workers in Manufacturing only.

[22]Like most of the empirical literature on this topic, we focus in this paper on spillovers that arise from the share of college graduates, although spillovers may also arise from the number and density of graduates.

[23]This often happens with administrative data from other countries as well (cf. Dustmann et al. 2009, for Germany).

Appendix B), our dependent variable mixes information on hourly wages with data on hours worked. For instance, a higher local stock of human capital might induce higher competition for promotions among college educated workers and a higher effort among white collars, e.g. longer working hours (cf. Rosenthal and Strange 2008a). This would cause some problems in the interpretation of our estimates since in this case an increase in annual labor earnings that is produced by an increase in working hours could be wrongly ascribed to a rise in hourly productivity (i.e. hourly wage). We will address this and other issues in Section 4.1.1.[24]

Firm data come from SIMF, currently managed by the Unicredit banking group (formerly by Mediocredito and later by Capitalia). The survey collects information on a sample of manufacturing firms with 11-500 employees and on all firms with more than 500 employees. The SIMF has been repeated over time at three-year intervals since 1991 and in each wave a part of the sample is fixed while the other part is completely renewed each time (see Capitalia 2002, p. 39). This helps to analyse both variations over time of the firms observed in different waves (panel section) and structural changes of the Italian economy, for the part of the sample varying in each wave. Like many other surveys used in the empirical literature, SIMF is not representative of micro-firms. The dataset gathers a wealth of information on: balance sheet data integrated with information on the structure of the workforce and governance aspects; R&D expenditures and ICT; international activities (e.g. export, FDI flows); information on financial structure and strategies. Information about the educational level of the firm's workforce, that is the firm's college share that we include as a control in equations (1) and (2), is reported only for the final year in each wave. Given that we have a measure of local human capital only for 2001, the year of the Census, while we do not have good measures of local human capital for other years, we limit our analysis to 2001. In particular, we merge the 8th wave of SIMF with the 2001 Census and INPS data for 2001.[25] In the empirical analysis, we analyze wages in 2001 (INPS) by relating them to local human capital in 2001 (Population Census) and to lagged firm-level variables referring to 1998-2000 coming from the 8th SIMF wave.

## 4. Results

In this section we report the main results of the empirical analysis by distinguishing between the econometric specifications using OLS and those using IV.

### *4.1. OLS estimates*

The aim of this section is to provide some preliminary descriptive evidence on the association between local human capital and average firm wages. In particular, we assess whether this association is robust against the inclusion in wage equations of several potential confounding factors.

Tables 2 and 3 report the OLS estimates using as dependent variable firms' (log) average wages for white collars and blue collars, respectively. Each column shows estimates from specifications progressively adding controls.

Column (1) reports estimates with a specification that only includes the local college share. Both for white collars and for blue collars, the coefficient of college share is statistically significant at the 1% level. A one percentage point (p.p., hereafter) rise in LCS is associated with a 1.4 percent increase in white collar wage and a one percent increase in blue collar wage.

Column (2) adds controls for firm human capital, namely the firm college share and the firm upper secondary school share (i.e. the proportion of workers who completed upper secondary schooling). The coefficient of local college share falls only marginally and remains highly stastically significant for both white collars and blue collars. This evidence is consistent with large local human capital external effects existing over and above those potentially emerging within the firm. The coefficient of firm college share is higher for white collars while the opposite is true for the coefficient of firm upper secondary school share. Both results are intuitive. As we explained in section 3, the coefficient of firm college share in the white collar equation captures both private returns to college education and firm-level spillovers among skilled workers, as only a minority of production workers has tertiary education. The higher

[24] However, this problem is likely to be more relevant for blue collars than for white collars, since for the latter overtime work is usually unpaid but compensated in terms of work permits. Moreover, Rosenthal and Strange (2008a) finds evidence of rat-race effects only for professionals.

[25] The merging procedure between SIMF and INPS wage data was made under a confidentiality agreement at the INPS Head Office (Rome). See Appendix B for more detailed information.

positive coefficient of firm upper secondary school share in the blue collar equation is due to the fact that secondary education, conditional on qualification, is likely to produce positive returns only for non-production workers, while it can be considered as the entry level of education for non-production workers. The coefficient of FCS in the blue collar equation is positive but stastically significant only at the 10% level and is consistent with firm-level human capital spillovers.

In order to clean out the effect of local human capital from that of other local characteristics, which might simultaneously affect firm productivity and the education of the local workforce, column (3) includes administrative region fixed effects (NUTS-2), province-level male unemployment rates in the population aged 15-24 and a dummy for the presence of university facilities in the province in 2000. Unemployment is likely to impact negatively on wages and positively on local human capital accumulation (due to the lower opportunity costs of education), while the presence of university campuses within the province might produce positive spin-offs with firms and have a positive effect on both local human capital and wages. Regional fixed effects capture other region-level unobservables, and after including them, the effect of local human capital is now identified by between-province variation within regions. The main consequence of including such controls is to reduce the size of the coefficient of local human capital in both wage equations. The effects of a one p.p. increase in local human capital are reduced to about one percent for white collars and to 0.8 percent for blue collars, and are both statistically significant at the 1% level.

Given the potential complementarity between human capital and other forms of capital, a possible source of correlation between local college share and wages is that more physical capital-intensive firms or those using advanced technologies may pay higher wages and attract highly educated workers in the region where they are located (*endogenous migration*). In order to control for these potential confounding factors, column (4) includes firm (log) physical capital intensity as an additional regressor. The effects of local human capital rise to 1.2 and 0.9 percent for white collars and blue collars, respectively. Column (5) adds some proxies of technological inputs, namely R&D intensity (i.e. the ratio between R&D workers and total employment), a dummy for having invested in ICT and a dummy for R&D cooperation with universities. Including these variables has no appreciable effect neither on the coefficient of LCS nor on the coefficient of FCS. From column (5), the elasticities of white collar and blue collar wages with physical capital stock are 0.032 and 0.02, respectively. Technological inputs are statistially insignificant in both equations. This is likely to be due to the extremely low investment in R&D and new technologies by Italian firms. Our results suggest that there is no strong positive correlation between the LCS and firm's investments in physical capital or technology.[26]

The stock of physical capital and the proxies of technological level included by us probably do not fully capture all the heterogeneity existing across different industries. On the one hand, we know from the rich literature on inter-industry wage differentials that firms in some industries systematically pay higher wages and hire more educated workers (see Katz and Summers 1989). On the other hand, firms operating in those industries may be more likely to locate in areas where human capital is abundant. In both cases, the coefficient of local college share may capture industry effects. To test these hypotheses we include in column (6) dummies for 2-digit ATECO industries (see Appendix A). The coefficient of local human capital is almost halved both for white collars and for blue collars. One p.p. increase in LCS is associated with a 0.7 percent increase in wages of white collars and to a 0.4 percent increase in wages of blue collars. The coefficient of local human capital remains statistically significant at the 5% level in the white collar equation only.[27]

As already stated, the inter-industry wage differentials literature has emphasized that firms' market power might allow them to pay rents to their workers and that this might attract high ability or better educated workers to the provinces where they are located. Along with firm industry (which may be more or less exposed to competition), another proxy of a firm's market power may be its size, which is then added to column (7). The results are very similar

[26]This is in sharp contrast to Iranzo and Peri (2009) who find that for the U.S. higher firm investments in physical capital and technology are among the main channels through which local human capital spillovers take place, at least in Manufacturing. As investiments in physical capital and technology could represent either a confounding factor or a mediating factor for the effect of LCS (i.e. pecuniary externalities), we also estimated regressions using them as dependent variables. However, consistent with the results we found in the wage equations, we did not find any significant positive association of LCS either with physical capital intensity or with proxies of firm technological inputs.

[27]We were somewhat surprised by the relatively low $R^2$ of the regressions controlling for industry fixed effects, given that in Italy the most substantial part of wages is set by bargaining and the national industry level. For this reason, we run wage regressions both with WHIP data and with data from the *Osservatorio* (see Appendices I and II) including 2-digit ATECO fixed effects and found very similar $R^2$'s. We also tried to use a finer classification of industries in our data, using 3-digit ATECO. The estimates of the LCS were not statistically different and we preferred the more parsimonious specification reported in tables 2 and 3.

to those in the previous column. The coefficient of firm size is positive and significant in both wage equations.[28]

Summarizing, we find a very robust positive association between local human capital and both white collar and blue collar wages. However, while the former remains statistically significant also after controlling for a wide range of covariates that might account for such an association, the latter looses statistical significance (at 5%) in our most general specification. As stressed in section 2, these results could be interpreted as evidence for positive province-level human capital spillovers. The order of magnitude of the spillovers that we estimate with OLS is similar to that found by Moretti (2004a;c) for the U.S.

There might be several explanations for the lower correlation found between LCS and blue collar wages. First, although Moretti (2004a) mantains that in the presence of imperfect substitution the effect on low educated workers should be higher than that on highly educated ones, his theoretical model posits equal spillovers on skilled (highly educated) and unskilled (lowly educated) workers. This is not necessarily the case in our empirical analysis, where skilled and unskilled workers are white collars and blue collars, respectively. The kind of job tasks performed by production and non-production workers are very different and almost all graduates are in non-production occupations. For this reason, we do not expect substantial interactions and knowledge spillovers from university graduates to blue collar workers. Moreover, another possible explanation could be the wage-setting mechanism prevailing in Italy. In Italy there are three potential levels of wage bargaining: 1) industry (national) level; 2) firm level; 3) individual level. However, industry level bargaining is responsible for the largest part of workers' wages. This is particularly true for unskilled workers, for whom individual wage bargaining is extremely rare. Casadio (2008) reports that for blue collars the percentage of wage above the minimum level collectively bargained by unions at industry level amounts on average to 5.3% for firms between 20 and 49 employees, and to 11.6% for those with more than 500 employees. The corresponding figures for white collars are 7.8% and 20.3%, respectively. As a consequence, blue collar wages could be less responsive to local or firm-level conditions.[29]

#### *4.1.1. Sensitivity analysis*

The aim of this section is twofold. First, we check the sensitivity of the positive association between local college share and firm wages to some potential weaknesses of our data and other confounding factors not considered in the previous section. Second, we aim to qualify this association as consistent with knowledge spillovers.

We use as a starting point the specification estimated in column (7) of Tables 2 and 3, which we will refer to as our "baseline specification". All these robustness checks are reported in Table 4.

*Working hours*. We already anticipated in section 3 that since we do not have data on working hours, our estimates of externalities could capture the combined effect of local human capital on both working hours and hourly wage. For this reason, we used the 2001 Italian labor force survey data to create province-sector-skill cells and computed the average number of weekly working hours.[30] We used 12 2-digit ATECO sectors for Manufacturing.[31] Weekly

[28]Some researchers have estimated wage equations by also including measures of housing rents or a proxy for city amenities among the covariates. As for the former, models of spatial equilibrium predict rents to increase in cities with higher stocks of human capital in the presence of production externalities (see Roback 1982, Rauch 1993), that is rents are endogenous. The relative increase of wages with respect to housing costs depends on the relative elasticity of labor and housing supply (Moretti 2010). For Italy, Dalmazzo and de Blasio (2007a) find a high and significant effect of local human capital on rents, which is higher than the effect on wages. As for the amenities, their omission would cause a problem only if they were correlated with LCS. This could happen because highly educated individuals value certain types of amenities more, for instance good schools. However, if this is the case, the presence of such amenities will be clearly endogenous, as highly educated parents will induce local goverments to invest more in school quality in those areas where they live. In any case, omission of these amenities causes a downward bias in the estimation of human capital production externalities as individuals will accept lower wages in exchange for higher 'quality of life' (Roback 1982). Other kinds of amenities, such as low crime rates, are equally endogenous and clearly correlated with the LCS. For these reasons, we excluded from the wage equations both housing rents and amenities.

[29]Blanchflower et al. (1996) and Hildreth and Oswarld (1997) show that in countries characterized by a high degree of decentralization of the wage bargaining system, there is a strong link between wages and firm or industry profitability. As already stated, we estimated the wage equations also including 3-digit ATECO industry fixed effects and the coefficients of LCS and FCS were very similar. The latter specification is equivalent to running a first-stage regression of firm average wages on 3-digit industry fixed effects, taking the residual (which is approximately the 'wage drift' since bargaining is mainly at industry level) and regressing it on the other covariates.

[30]The 2001 Italian labor force survey does not release information on firm size.

[31]The complete list of ATECO industries for Manufacturing are: DA (food products, beverages and tobacco), DB (textiles and textile products), DC (leather and leather products), DD (wood and wood products), DE (pulp, paper and paper products; publishing and printing), DF (coke, refined petroleum products and nuclear fuel), DG (chemicals, chemical products and man-made fibres), DH (rubber and plastic products), DI (non-metallic mineral products), DJ (basic metals and fabricated metal products), DK (machinery and equipment), DL (electrical and optical equipment), DM

working hours were added to the baseline specification and the estimates are reported in model (1) in Table 4. Including the number of working hours has the effect of increasing both the magnitude and precision of the coefficient of LCS, which now turns out to be statistically significant at the 1% level also for blue collars.

*Worker characteristics*. Using firm-level average data does not allow us to control for some characteristics of workers that are likely to be correlated with wages, and potentially also with local human capital. We used the 2001 Work Histories Italian Panel (WHIP) data to compute statistics for average worker experience and seniority (in months) and the percentage of female workers by province-sector-skill cells and province-size-skill cells in manufacturing firms.[32] Due to empty or small size cells in WHIP, it was not possible to compute such statistics for province-sector-size-skill combinations. Because of the same issue, we had to consider only three broad categories of firm size (11-100, 101-500, more than 500) while we considered all 14 two-digit ATECO sectors for Manufacturing. Model (2) shows no noticeable change when experience, seniority and percentage of female workers, matched by firm sector, are included in the regressions. By contrast, model (3) shows that when the same variables are matched by firm size, the coefficient of LCS looses statistical significance in the blue-collar equation while the estimate for the white-collar equation is robust. Models (4) and (5) control for working hours, experience, seniority and percentage of female workers matched in the two different ways. The results for the white-collar equation are very robust while model (5) shows, as before, a reduction in the significance and magnitude of the coefficient of local human capital in the blue-collar equation.

*Human capital externalities vs. other 'local effects'*. In general, it is difficult to separately identify human capital externalities from agglomeration effects. This is due to the fact that human capital externalities may account for a substantial part of agglomeration economies (see Glaeser and Mare 2001, Rosenthal and Strange 2008b, Moretti 2010). For this reason, we did not include the province populations in our regressions, since this would cause 'over-control'. Indeed, when we take some proxies of agglomeration effects commonly used in the literature, such as the population in the province for *urbanization* effects (urban agglomerations) or the number of manufacturing workers in the province for *localization* effects (cf. Rosenthal and Strange 2004), the correlation coefficients with local human capital are very high. The high correlation is likely to create multicollinearity problems. This is indeed confirmed by the fact that when both population (or number of manufacturing workers) and local human capital are simultaneously included in the white-collar equation, they are statistically insignificant, while both population (or number of manufacturing workers) and local human capital are significant when they are included separately. The same happens for the blue-collar wage equation. Hence, one might believe that the coefficient of local human capital in our baseline specification may be capturing the effect of other forms of urbanization economies that have nothing to do with the transfer of knowledge among workers. If this were the case, we should find that other proxies of local human capital, such as the share of workers with a university degree in all sectors or the share of university educated population, should have similar effects on the wage of white collars and blue collars to the share of graduate workers in Manufacturing. In model (6), we use as a proxy of local human capital the share of all workers with a university degree, while in model (7) we use the share of the university educated population. These two alternative measures of local human capital turn out to be statistically insignificant and their coefficients are remarkably lower in magnitude than the coefficient of LCS. We interpret this evidence as consistent with the fact that the coefficient of local human capital is likely to be capturing knowledge spillovers rather than other forms of urbanization economies, since knowledge transfer is likely to be larger among employees working in the same industry and therefore performing similar tasks.[33]

*Multi-unit firms*. We use firm-level data but we do not have data on single establishments. This means that local human capital is attributed according to the firm's headquarters' province and may be measured with error in multi-unit firms. This may cause an attenuation bias on the coefficient of LCS. For this reason, in model (8), we run our estimations in two separate samples including small firms (<25 employees), which are unlikely to be multi-unit, and large firms (≥25 employees). Our estimates show that the magnitude of the local spillover is higher and more precisely

(transport equipment), DN (other manufacturing). Due to the small cell size, DF, DG and DH industries were aggregated. Given the very large number of cells (12 industries × 103 provinces), some turn out to be empty, especially for white collar workers, and the sample size drops.

[32]For a description of the WHIP dataset, see Contini et al. (2009). We used WHIP since the information on firm size was not publicly released in the 2001 Italian labor force survey data.

[33]This evidence is not necessarily in contrast with Dalmazzo and de Blasio (2007a) who using the years of education in the whole population find a positive effect on individual wages. Firstly, they consider the whole economy, and not only the Manufacturing sector. Secondly, since their specification does not include firm-level covariates, which are not available in SHIW, their estimates of human capital externalities also capture pecuniary externalities.

estimated in smaller firms, which is consistent with either LCS being more likely to be measured with error for larger firms, or with the effect of LCS being higher in smaller firms, or both.

*Quality of university graduates*. Although, as will be argued in Section 4.2, the geographical mobility of Italian university graduates is quite limited and on average we have no reason to expect graduates to be of better quality where the college share is higher, endogenous mobility cannot be completely ruled out, especially for South to North migrations.[34] In case of endogenous migration, a positive coefficient of local human capital may capture a better average quality of graduates employed by firms located in areas where the college share is higher. A way to address this issue is by allowing the coefficients of firm level college and secondary school share to vary across provinces (see, Moretti 2004c). The estimates in model (10) show that allowing heterogeneity in the effect of firm human capital does not change our previous conclusions.

*Nonlinearities*. There are several reasons for expecting nonlinearities in the effect of local human capital. The first is that uneducated workers might learn more than proportionally with the increase of college share, for instance because it becomes easier to meet (and interact with) college graduates (Jovanovic and Rob 1989). That is, the relation between local human capital and wages might be increasing and convex. Alternatively, it might be the case that above a given threshold, a further increase in college share does not produce any further increase in productivity, since there are already many university graduates from whom non-graduates can learn, that is the relation may be increasing and concave. Another potential source of nonlinear effects might be a quantity-quality trade-off for university graduates. As HE expands and the college share increases, one might expect graduates to be increasingly drawn from the bottom part of the ability distribution, that is they may be of lower average quality (see Carneiro and Lee 2009). In this case, the spillovers of local human capital may fall after the college share reaches a given threshold. However, this is not necessarily true if the HE expansion mainly benefits able but credit-constrained individuals. We investigate potential nonlinearities in the effect of local human capital by allowing different slopes for provinces with college shares above and below the sample median (0.0488).[35] Model (11) reports the corresponding estimates. The slope of the average firm wage-local human capital relationship is decreasing in the local college share: the effect below the median is about one percent higher than that above the median. Although, due to the limited variation in college share, we are not able to further explore potential nonlinearities in the effect of local human capital, we simply observe that the results obtained from a specification that is linear in college share may understate the real magnitude of local human capital spillovers.[36]

### 4.2. *Instrumental variables estimates*

Before discussing our identification strategy, we would like to make a point. The problem of reverse causality of local human capital with productivity and wages, that is the fact that graduates could migrate towards provinces where firms pay higher wages (*worker endogenous migration*), is likely to be less severe for Italy than for other countries where graduates are very mobile, such as the U.S. (Bound et al. 2004). Indeed, individual geographical mobility is relatively low in Italy compared to other developed countries (Cannari et al. 2000). Di Addario and Patacchini (2008), for instance, maintain that non-pecuniary benefits from residence (e.g. social networks) and substantial mobility costs related to travel and housing are likely to be responsible for low worker geographical mobility in Italy. This means that the ability of firms to attract human capital from other provinces is generally limited and that human capital must be often produced locally. A possible endogeneity problem might also be caused by individuals in provinces with a higher expected future demand for skilled workers in Manufacturing being more likely to enroll in HE. However, a minority of Italian university graduates finds employment in Manufacturing, most of them working in the Service sector. Therefore it is unlikely that individuals base their HE decisions primarily on their expectations about wages in Manufacturing.[37]

[34] Actually, the correlation may be of the opposite sign, the average quality of graduates may fall in provinces where the expansion of HE is higher if one focuses only on the local production (and not import) of graduates, see the following point.

[35] We used the median of the white-collar sample for both white-collar and blue-collar samples. In the blue-collar sample the median is slightly lower (0.0481).

[36] We also estimated a specification including a quadratic term in LCS but due to the high correlation between the linear and the quadratic terms, both terms turned out to be insignificant.

[37] According to the 2001 ISTAT Survey of University graduates, about 23% and 75% of the 1998 graduate cohort were working in Industry and Services, respectively, the remaining working in Agriculture (our computation on microdata).

It must also be noted that the issue that more productive firms may tend to move where there is more local human capital (*firm endogenous migration*) is not particularly relevant for the Italian case. Michelacci and Silva (2007) using SHIW data for 1991-1995 demonstrate the low geographical mobility of firms: about 79% of entrepreneurs established firms in the same province where they were born. This is likely to be explained by the small size and family nature of many Italian businesses.

Despite these facts, we cannot exclude of course that local human capital is endogenous, and for this reason we make use of IVs.

To identify the causal effect of local college share, we draw from previous work exploiting the geographic variation in the location of university facilities, such as Card (1993) and Currie and Moretti (2003), among others. The idea is that individuals living close to colleges have lower costs of enrolling in HE, and firms close to colleges will dispose accordingly of a more educated workforce, especially if worker mobility is low.

As will become clearer later, our instrument is related to the size of the supply of HE degree courses (*corsi di laurea*) by local colleges. In order to be a valid instrument, the local HE supply must in turn be exogenous with respect to the wages paid in Manufacturing. We seek to meet this requirement mainly in three ways. First, we do not use the level of HE supply but we exploit a shock, i.e. a change, in the supply. In this way, we try to get rid of time-invariant (long-term) province effects correlated with the level of HE supply which might also determine the long-term level of wages in Manufacturing. This is important since, as we said, the local college share is measured at the provincial level, and using a cross-section we cannot control for province fixed effects in the wage equations. Secondly, we consider a lagged shock. In particular, we employ the change in HE supply that took place during 1990-95, between 11 and 6 years before the wages were observed. Third, and most important, we consider a period in which the change of HE supply was mainly due to an institutional source of potential quasi-experimental variation. The early 1990s were a period of intense HE reform in Italy. With Law No. 341 of 19th December 1990, the requirement of parliamentary approval for the creation of new university initiatives (i.e. creation of new Universities, Faculties and degrees in newly created university facilities) was abandoned. The new initiatives autonomously advanced by the HE institutions had to be included in a 3 year university development plan subject to the Ministry of University and Research's (*Ministero dell'Università e della Ricerca Scientifica e Tecnologica*, MURST) approval. The other major innovation of Law n. 341 was the allocation of substantial public resources for the development plan. This is likely to be important to ensure the instrument's exogeneity with respect to the characteristics of local economies, as it means that local resources were not needed to finance the new initiatives. The main objectives of the 1991-93 plan were: 1) the development of university supply and its geographical rebalancing through the creation of new Universities, Faculties or satellite campuses, which ought to take place on a *regional* (NUTS-2) basis; 2) the decongestion of overcrowded universities; 3) the activation and development of university diplomas.[38] The further objectives of the development of research activities and rebalancing of supply across fields of study were instead postponed to later development plans (MURST 1997). The 1994-96 development plan was mainly conceived as an instrument targeted at the consolidation of the initiatives already started in the previous plans, with the additional objectives of increasing tutorial and orientation activities for students, staff reasearch activities and of organising the evaluation procedure for the Italian HE system (MIUR 2002).

On the basis of the stated objectives of the development plans, the new initiatives were mainly oriented towards the primary beneficiaries of university education, that is prospective students, rather than towards potential secondary beneficiaries such as local communities and firms, which makes the assumption of 'quasi-randomness' of the policy with respect to the phenomenon we are studying credible (cf. Besley and Case 2000). This is further acknowledged in MURST (1997) (pp. 25-26) according to which the inspiring principle of the plan was that the State, following article 34 paragraph 2 of Italian Constitutional Law – the equality of educational opportunity – should have granted to all individuals the right to engage in HE within an acceptable distance of their residences, avoiding migrations that were made difficult or even impossible by a series of economic or family impediments. The equality of educational opportunities was therefore interpreted not from the side of the demand of HE, through the promotion of financial help for students, but as their right to have access to a university facility sufficiently close to their home.

According to the Ministry of University and Research's evaluation (MURST 1997, pp. 3-4) the (too) numerous new initiatives that were contained in the 1991-93 plan did not take into account the local demand for university

[38] University diplomas are short (two or three year) degrees introduced in 1990.

education by students, the potential employment outcomes for university graduates (or the country's needs) or existing infrastructures. The main criterion appeared to be a geographic rebalancing of university premises, with the objective of getting the supply of university education closer to individuals, neglecting not only the real entity of student demand, which was often less than the minimum required to ensure the efficacy and efficiency of the new initiatives, but also the important role played by the transportation system, the receptive capacity of the student population and the financial help available to students to access the new facilities.

We now describe how the instruments were built. First, we selected graduates who are more likely to be employed in manufacturing firms. They are typically graduates in technical and science degrees (engineering, chemistry, mathematics, physics and natural sciences) or hard social science degrees (economics, business, banking, statistics). These are defined as "manufacturing-related fields". Using the Italian Ministry of Education University and Research's (MIUR) data on university supply, we computed the number of manufacturing-related degrees in 1990 and 1995 and their density per 10 square km in each province. Then, we computed the change in course density by province between 1990 and 1995, which we label $\Delta DEGDENS$ and this represents our first instrument.

In order to control for other possible forms of university spillovers, and to satisfy the exclusion restriction assumption, we included among the covariates in the wage equations a dummy for the presence of a manufacturing-related Faculty (as defined above) in the province in 2000, in addition to a dummy for R&D cooperation with universities and a college province dummy that were already in the baseline OLS specification.

As stated, the HE reform encouraged a large number of new university initiatives. For instance, the number of degree courses increased from 898 to 988 and the number of Faculties from 365 to 412, between 1990 and 1995 (MIUR 2001). There were large differences in the change of university supply across provinces. In our estimation sample of white collar workers, the change in density (per 10 square kms) of manufacturing-related degree courses ranges from -0.02 (Pesaro province, located in Central Italy) to 2.88 (Trieste province, located in North-Eastern Italy).

Since the increase of local HE supply of manufacturing-related degrees does not necessarily predict *per se* an increase in college share in Manufacturing, we use as a second instrument its interaction with the fraction of the population aged 5-14 in 1982, which is a proxy of the *local potential demand* for HE associated only with demographic factors. Individuals aged 5-14 in 1982 are those who were the most likely to enter university during 1990-1995, the period which our variable of supply expansion refers to.[39] An advantage offered by this second instrument is that by interacting the change in local university supply with the lagged demographic structure in the province, it mainly captures the *local production of graduates* and helps address potential issues of endogenous migration of college educated workers towards high-productivity (i.e. high wage) provinces.[40]

Despite the existing evidence and MIUR evaluation that the expansion of the university system spurred by the HE reform was very likely to be exogenous, we made some robustness checks. One potential threat to our identification strategy is that manufacturing-related degrees might have been created in locations where there was a higher expected demand for manufacturing workers. In this case, openinigs of these courses would also be correlated with future manufacturing wages, and the instrument would be invalid. For this reason in Table 5, we regress the share of manufacturing workers in the province on the change in course density and its interaction with lagged demographic structure. Columns (1) and (3) show that neither instrument predicts the employment share in manufacturing.

Another potential threat to identification comes from the fact that HEIs may have opened courses where there was a higher potential demand for HE, perhaps due to the higher ability of local students. In this case we will observe a positive correlation between the expansion of HE supply and province-level unobservables of wages that will make the instruments invalid. However, if this were the case, we would observe that both instruments also predict the local share of secondary school educated manufacturing workers (cf. Moretti 2004b). Columns (2) and (4) of Table 5 show that this is not the case, both instruments are uncorrelated with the share of manufacturing workers with upper secondary schooling.

In the IVs specifications, we only included presumably exogenous covariates (2-digit ATECO industry, NUTS-2 regions), variables that are useful to ensure the exclusion restriction assumption (dummies for the presence in the province of colleges and manufacturing-related colleges, the unemployment rate in the province, and worker

[39] The typical age at entry into HE in Italy was in the period under study, and still is, 18-19.

[40] Unless such forward-looking migration took place 20 years earlier. In any case, due to the age group we consider (5-14), residence is likely to have been decided not directly by the individuals but by their parents.

characteristics) and firm and province college shares.[41] Table 6 shows the results of our IVs estimation when worker covariates are matched to firm size. In columns (1)-(3) and (6)-(8), we first report estimates obtained for the two skill levels using the two instruments separately (just identified models), and then those obtained from the overidentified models using both instruments, which also allow us to perform an overidentification test (Hansen J statistic). For white collars, IVs diagnostics show the relevance of the instruments, and their validity in the overidentified models. The spillover estimates for white collars are statistically highly significant, very stable across specifications using different instruments, and range from 1.6 to 1.7 percent. In contrast, as we already observed in the OLS estimates, there is no effect of LCS on blue collar wage. In columns (4) and (9), we report estimates using as instrument only the interaction between $\Delta DEGDENS$ and lagged demographic structure, which turns out to be the strongest instrument, but including the richest specification used for OLS, which can be compared to model (5) in Table 4. A comparison of columns (2) and (4) of Table 6 for white collars and (7) and (9) for blue collars clearly shows that IVs estimates are largely insensitive to the choice of controls, which is what one would have expected if the instrument were truly exogenous and uncorrelated with the characteristics of local firms.

A potential pitfall of these estimates is that firm college share may be endogenous, in which case all coefficients, not only the coefficient of firm college share, would be biased. To address this issue, we also instrumented the firm college share.[42] We used as an instrument the average college share by 3-digit industry from the 2000 US Population Census.[43] The idea is that there are technical constraints to producing certain goods, which depend on their nature, and that these constraints are reflected in the average education of the workforce in the industry producing them. For this reason, the average college share in the U.S. by industry should be a good predictor of the college share of firms *in the same industry* in other countries, but at the same time should be uncorrelated with firm or province-specific wage 'shocks' in Italy. Columns (4) and (9) report the results when both firm and local college share are instrumented. The main difference compared to earlier estimates is a large increase in the coefficient of firm college share, which is consistent with the latter being affected by a substantial (classical) measurement error. Indeed, as far as the firm's college share is concerned, errors in self-reported education made by individual workers are added to those potentially made by who responds to the SIMF questionnaire. When IVs are used, the coefficients of local and firm college share are not statistically different.[44]

We also estimated specifications with worker controls matched by firm sector and the main difference is that the coefficient of LCS was also statistically significant in the blue-collar wage equation (see Table W1 in the Web Appendix). Models excluding firms located in the three largest Italian metropolises (Naples, Milan and Rome) were also estimated. Excluding these cities may be important as they are also cities with over-crowded universities according to the definition of Law No. 341, in which the increase in HE supply may have been simply due to the fact that pre-existing HE institutions were split to create new universities. The results are reported in the Web Appendix (Table W2) and are very similar.

## 5. Concluding remarks

The idea that local human capital could produce positive production externalities is both old and appealing, but the empirical evidence on local human capital spillovers is still 'mixed'.

The emergence and magnitude of human capital externalities may be country- and sector-specific and the findings of the U.S. literature may not be easily generalizable to other countries. In particular, positive externalities could be

[41] We have already discussed the reasons for including college and manufacturing-related college dummies and the unemployment rate, while inclusion of worker characteristics – especially experience and seniority – is useful as they are likely to be correlated with the share of the population in the 5-14 age group, which is used to build our second instrument.

[42] This also helps solve potential problems of measurement error in firm college share. Indeed, Acemoglu and Angrist (2000) show that if an individual's – or firm's in our case – level of education is measured with some error, the coefficient of local human capital may turn out significant and positive in a wage regression even in the absence of local production externalities, simply because the latter partly captures the effect of the variable measured with an error.

[43] The mapping procedure between the 3-digit North American Industry Classification System (NAICS) 1997 adopted in the U.S. Population Census and the 3-digit ATECO 1991 adopted by SIMF was performed by the author. The table of correspondences is available in the Web Appendix (Table W3). Average college shares by industry were computed using the 5-percent Public Use Microdata Sample (PUMS) of the 2000 U.S. Census of Population and Housing and individual weights. One hundred industry cells were used.

[44] Although the exclusion of firm physical capital stock did not seem to affect the LCS coefficient estimates (see columns (4) and (9)), we also estimated a specification including physical capital stock and instrumenting it with the 2-year lagged stock, and the estimates were very similar.

more likely to emerge in countries and sectors specializing in complex technologies and high-tech products ('knowledge economies' or high-tech sectors) compared to countries and industries specialized in traditional sectors and unskilled labor-intensive products like Italy.

In this paper, we use a unique cross-sectional dataset combining firms' balance sheets and survey data, Population Census data on local human capital and administrative data on earnings to investigate the existence of human capital spillovers in Italian Manufacturing. In particular, we focus on spillovers originating from the share of graduate workers in Manufacturing at province level, and we investigate whether firms located in provinces with a larger college share paid higher wages in 2001 (the year of the Italian Census) than otherwise similar firms located in provinces with a smaller stock of human capital.

Using OLS we find that, even after controlling for a variety of firm and local characteristics, there is a robust positive correlation between average wages paid by firms, especially to white collar workers, and local human capital. Although the possibility that unobserved province heterogeneity may partly explain these effects cannot be completely ruled out, we provide several pieces of evidence suggesting that the effects we estimated are likely to reflect local knowledge spillovers. Indeed, the positive association between firm-level average wages and the local share of college educated workers in Manufacturing, who are unlikely to be production workers, is lower for production workers (blue-collars) than for non-production workers (white collars). Moreover, unlike the college share in Manufacturing, the college share in the population and in the workforce have much smaller positive associations with average wages in Manufacturing and are never statistically significant. This is what one would predict if our estimates were capturing knowledge spillovers, since the transmission of productivity-enhancing knowledge is more likely to take place among employees working in the same sector, and performing similar tasks.

In order to address the issue of potential endogeneity of local human capital with respect to productivity and wages, we use an IVs strategy. We propose instruments based on the lagged change (1990-1995) in the university supply of manufacturing-related degree courses, i.e. degree courses whose graduates are more likely to find employment in Manufacturing, and on its interaction with a 20-year lagged demographic structure. We argue that the expansion of HE supply that took place in Italy during 1990-1995 was both sizeable, thanks to a reform that eased both the opening of new university facilities and of new degree courses by HE institutions, and presumably exogenous with respect to wages in Manufacturing. Our IVs estimates are qualitatively consistent with the OLS estimates and very robust against the choice of instruments and of control variables. We also tackle the potential endogeneity of the firm college share by using IVs and find a large increase in its coefficient, suggesting that the latter may be affected by substantial measurement error.

Our analysis shows overall that sizeable positive human capital spillovers also exist in relatively less technologically advanced industries, such as Italian Manufacturing.

What are the policy implications of our analysis? Firstly, the existence of substantial positive production externalities suggests that the burden of HE should not be completely moved towards university students and their families, since this may produce a sub-optimal investment in higher education, and that tertiary education expenditures should be partly financed by general taxation. Secondly, our analysis does not show an equity-efficiency trade-off as the effect of local human capital appears to be higher in provinces where the college share is lower. Although this evidence of non-linearities is only preliminary, it is not clear from an efficiency point of view whether it would be optimal for a country to concentrate the supply of HE in a limited number of facilities and close smaller campuses, which Italian universities will probably have to do in response to the current reduction of public funding. However, from an equity point of view, our findings suggest that policies of spatial concentration of HE supply will be likely to exacerbate geographical differences in productivity and wages, unless sufficient measures are taken to substantially raise the very low geographical mobility of Italian workers.

**Acknowledgements**

This project was partly developed while Massimiliano Bratti was visiting the Center for Labor Economics (CLE) at the University of California, Berkeley, whose kind hospitality is gratefully acknowledged. We would like to thank participants of all seminars at which this paper was presented and of the ITSG 2008, ESPE 2009 and EALE 2009 conferences. We also acknowledge Paolo Buonanno, David Card, Alberto Dalmazzo, Patrick Kline, Enrico Moretti, Konstantinos Tatsiramos and Jan van Ours for very useful discussions. The usual disclaimers apply.

**Appendices**

*Appendix A. Description of variables*

*Wages*. Firm annual average wages data by skill level, our dependent variable, come from the Italian National Social Security Institute's administrative archives. They are full-time adjusted average earnings by skill-level (white collars and blue collars) of *all* workers employed by a firm in Euros. For more details, see Appendix II. Data refer to 2001. The variable is included as a natural logarithm.

*Local college share*. This is the proportion of manufacturing workers with tertiary education who are *resident* in the province (NUTS 3) in which the firm is located, computed using the public-use microdata file of the 2001 Italian Census (ISTAT). In the Census, *residents* are those individuals who usually live in the province even if at the date of the Census they were temporarily absent.

*Population share with college education*. This is the proportion of the population with tertiary education in the province computed using the public-use microdata file of the 2001 Italian Census.

*Worker share with college education*. This is the proportion of all workers with tertiary education in the province computed using the public-use microdata file of the 2001 Italian Census.

*Firm college share*. This is the proportion of workers within the firm with tertiary education. Data refer to 2000 and come from the 8th wave of SIMF.

*Firm (upper) secondary school share*. This is the proportion of workers within the firm with an upper secondary education. Data refer to 2000 and come from the 8th wave of SIMF.

*Male unemployment rate 15-24*. This is the unemployment rate in the province among men aged 15-24 in 2001 (source: ISTAT). We consider the youth unemployment rate since it is less likely to be affected by the local college share and men because they are more likely to work in Manufacturing and more likely to participate in the labor force.

*College province 2000*. This is a dummy variable that takes the value one if a college was present in the province in 2000 (source: MIUR).

*R&D cooperation with university*. This is a dummy variable that takes the value one if the firm did cooperate with a university in R&D in 2000, information available from the 8th wave of SIMF.

*Capital intensity*. This is the real physical capital stock per worker in thousands of Euros. The nominal capital stock is derived from balance sheet data and is evaluated at the net 'historical cost', that is the cost originally borne by the firm when buying the good, reduced by the depreciation measured according to the relevant fiscal law (*Fondo di ammortamento*), which accounts for obsolescence and use of the good. The real capital stock is obtained using capital stock deflators provided by the ISTAT (cf. Moretti 2004c). All variables are deflated with the appropriate three-digit production price index (ISTAT). Data refer to 2000 and come from the 8th wave of SIMF. The variable is included as a natural logarithm.

*R&D intensity*. This is the ratio between R&D workers and total number of workers within the firm. Data refer to 2000 and come from the 9th wave of SIMF.

*ICT investment*. This is a dummy variable that takes the value one if the firm performed ICT investments in 1998-2000 and zero otherwise (see section 3). Data come from the 8th wave of SIMF.

*Change in university course density (1990-1995)*. This is the change density of manufacturing-related university degrees (both university degrees and university diplomas) at the province level between 1990 and 1995. See Section 4.2 for further details on how the variable was built (source: MIUR).

*Population 5-14 ratio in 1982*. This is the proportion of 5-14 year olds in the whole population in 1982 at province level (source: ISTAT).

*Manufacturing-related college*. This is a dummy variable that takes the value one if a technical (engineering, chemistry, mathematics, physics or natural sciences) or hard social sciences (economics, business and economics, banking, statistics) Faculty was present in the province in 2000 (source: MIUR).

*Average workers' weekly working hours*. This is computed from the Italian 2001 labor force survey data (ISTAT) and is matched with SIMF by province-sector-skill cells. For more details see Section 4.1.1.

*Average workers' experience (months).* This is computed from WHIP (INPS) and is matched with SIMF either by province-sector-skill or by province-size-skill cells. For more details see Section 4.1.1.

*Average workers' seniority (months).* This is computed from WHIP (INPS) and is matched with SIMF either by province-sector-skill or by province-size-skill cells. For more details see Section 4.1.1.

*Percentage of female workers*. This is computed from WHIP (INPS) and is matched with SIMF either by province-sector-skill or by province-size-skill cells. For more details see Section 4.1.1.

*Sector dummies*. 2-digit ATECO sector dummies. ATECO stands for *Classificazione delle attività economiche*, which is an Italian classification of economic activities (i.e. industries) similar to the NACE European classification. Data come from the 8th wave of SIMF.

*Region dummies*. Region (NUTS 2) dummies. In Italy there are 20 regions. Data come from the 8th wave of SIMF.

*Appendix B. Earnings data and INPS-SIMF matching*

*i. Matching procedure*

To perform the analyses in this paper, we linked together two different firm-level data archives: the *Osservatorio sulle Imprese, occupati dipendenti del settore privato non agricolo e retribuzioni medie annue di operai ed impiegati* (Observatory on firms, non-agricultural private sector employees and yearly average earnings of blue collar and white collar workers), built from INPS administrative archives, with SIMF.

The *Osservatorio* is based on the compulsory contributions forms collected by INPS from all private Italian firms with at least one employee on a monthly basis. It includes high quality data on employment size and earnings broken down by skill level (manual and non-manual workers, cadre and managers, apprentices), plus information on the sector of activity, firm's foundation and closure dates.

We linked the INPS data (covering the years from 1997 to 2002), to the 8th wave of SIMF (covering the years from 1998 to 2000) using the fiscal ID number as a key linkage. Probably due to clerical errors in the maintenance of both archives, the match was not perfect, but link failures remained below 2% of SIMF data.

Since firm province is used to impute local human capital to firms, in case of disagreement between SIMF and INPS data, we used the province in SIMF that was built using the municipality in which the firm was located.

*ii. Average annual wage data*

Since the 1990-1994 edition of the *Osservatorio*, the computation of employees' average earnings has been performed by adjusting the firms' total monthly wage bill to the maximum number of working days in a month (26), according to the following formula:

$$Mrm_i = \frac{Mr_i}{Gr_i} \times 26 \times d_i$$

where:
$Mrm_i$: total share of wage bill of month $i$ for a full month;
$Mr_i$: actual share of monthly wage bill for month $i$;
$Gr_i$: actual number of working days in month $i$;
$d_i$: average number of employees in month $i$.

For part-time white collar and blue collar workers, the total number of working days is obtained by dividing by 6.66 the total number of hours indicated on INPS form DM10 (40 hours per week divided by 6 days). Wages also include employer's social contributions, withholding income tax, sick pay, paid overtime work, Christmas bonus, back payments.

Further details are available (in Italian) at:
http://servizi.inps.it/banchedatistatistiche/menu/imprese/main.html

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Table 1: Descriptive statistics

| | white collars | | | blue collars | | |
|---|---|---|---|---|---|---|
| Variable | N. obs. | Mean | S.D. | N. obs. | Mean | S.D. |
| Average gross annual wage (ln) | 3,512 | 10.10 | 0.25 | 3,527 | 9.85 | 0.17 |
| Local college share | 3,512 | 0.05 | 0.02 | 3,527 | 0.05 | 0.02 |
| Population share with college education | 3,512 | 12.32 | 2.70 | 3,527 | 12.29 | 2.69 |
| Workers share with college education | 3,512 | 10.75 | 2.35 | 3,527 | 10.73 | 2.34 |
| Firm college share | 3,512 | 0.04 | 0.07 | 3,527 | 0.03 | 0.06 |
| Firm secondary school share | 3,512 | 0.30 | 0.23 | 3,527 | 0.30 | 0.23 |
| Male unemployment rate 15-24 | 3,512 | 15.97 | 13.36 | 3,527 | 15.99 | 13.42 |
| College province 2000 (D) | 3,512 | 0.99 | 0.10 | 3,527 | 0.99 | 0.10 |
| R&D cooperation with university (D) | 3,512 | 0.04 | 0.20 | 3,527 | 0.04 | 0.20 |
| Capital intensity (ln) | 3,512 | -3.87 | 1.16 | 3,527 | -3.85 | 1.15 |
| R&D intensity | 3,512 | 0.03 | 0.07 | 3,527 | 0.03 | 0.06 |
| ICT investments (D) | 3,512 | 0.79 | 0.41 | 3,527 | 0.78 | 0.41 |
| Firm size (,00) | 3,512 | 6.79 | 22.62 | 3,527 | 6.66 | 22.48 |
| Export (D) | 3,512 | 0.68 | 0.47 | 3,527 | 0.68 | 0.47 |
| FDI (D) | 3,512 | 0.02 | 0.14 | 3,527 | 0.02 | 0.13 |
| Change in university course density (90-95) | 3,512 | 0.18 | 0.27 | 3,527 | 0.18 | 0.27 |
| Population 5-14 ratio in 1982 | 3,512 | 0.15 | 0.01 | 3,527 | 0.15 | 0.01 |
| Manufacturing college (D) | 3,512 | 0.18 | 0.38 | 3,527 | 0.18 | 0.38 |
| Average weekly working hours | 2,981 | 38.51 | 5.09 | 3,227 | 37.31 | 4.59 |
| *Worker controls merged by firm sector* | | | | | | |
| Average experience (months) | 3,446 | 176.19 | 49.52 | 3,525 | 178.45 | 35.09 |
| Average seniority (months) | 3,446 | 82.56 | 27.49 | 3,525 | 72.93 | 18.52 |
| Percentage of female workers (months) | 3,446 | 0.48 | 0.21 | 3,525 | 0.27 | 0.21 |
| *Worker controls merged by firm size* | | | | | | |
| Average experience (months) | 3,510 | 162.63 | 28.07 | 3,527 | 178.25 | 22.62 |
| Average seniority (months) | 3,510 | 73.12 | 14.46 | 3,527 | 70.60 | 12.48 |
| Percentage of female workers | 3,510 | 0.47 | 0.10 | 3,527 | 0.29 | 0.08 |

Note. Descriptive statistics refer to the main white-collar and blue-collar estimation samples in Tables 2 and 3 and the main variables used. Averages and standard deviations (S.D.) of weekly working hours and workers' controls are computed only for the non-missing observations in the main estimation samples. For a detailed description of the variables see Appendix A. Dummy variables are indicated with D in parentheses.

Table 2: Wage equation for white collars (OLS)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Local college share | 1.442** | 1.302** | 1.022*** | 1.145*** | 1.151*** | .678** | .672** |
| | (0.595) | (0.592) | (.298) | (.281) | (.276) | (.290) | (.289) |
| Firm college share | | .343*** | .352*** | .337*** | .303*** | .217*** | .204*** |
| | | (.054) | (.054) | (.055) | (.056) | (.058) | (.058) |
| Firm secondary school share | | .028 | .034* | .039** | .034* | .009 | .014 |
| | | (.021) | (.019) | (.019) | (.020) | (.019) | (.020) |
| Capital intensity (ln) | | | | .032*** | .032*** | .026*** | .025*** |
| | | | | (.004) | (.004) | (.004) | (.004) |
| R&D intensity | | | | | .123 | .019 | .014 |
| | | | | | (.076) | (.086) | (.088) |
| R&D cooperation with university (D) | | | | | .040* | .028 | .015 |
| | | | | | (.021) | (.020) | (.018) |
| ICT investments (D) | | | | | -.001 | -.003 | -.006 |
| | | | | | (.013) | (.012) | (.012) |
| Firm size (,00) | | | | | | | .000** |
| | | | | | | | (.000) |
| *Other controls:* | | | | | | | |
| Region fixed effects | | | √ | √ | √ | √ | √ |
| Unemployment rate | | | √ | √ | √ | √ | √ |
| College-province dummy | | | √ | √ | √ | √ | √ |
| 2-digit ATECO sectors | | | | | | √ | √ |
| $R^2$ | .014 | .023 | .088 | .109 | .111 | .183 | .191 |
| N. obs. | 3,512 | 3,512 | 3,512 | 3,512 | 3,512 | 3,512 | 3,512 |

*** significant at 1%; ** significant at 5%; * significant at 10%
Note. The dependent variable is the (ln) full-time annual wage. Heteroskedasticity robust standard errors clustered at province-level in parentheses. Observations are weighted to population proportions. Dummy variables are indicated with D in parentheses. For the description of the variables see Appendix A.

Table 3: Wage equation for blue collars (OLS)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Local college share | .996*** | .945** | .833*** | .904*** | .914*** | .403* | .403* |
| | (.366) | (.366) | (.238) | (.230) | (.225) | (.222) | (.223) |
| Firm college share | | .089* | .106** | .071 | .052 | .004 | -.002 |
| | | (.051) | (.049) | (.049) | (.050) | (.050) | (.050) |
| Firm secondary school share | | .047*** | .051*** | .055*** | .052*** | .035*** | .036*** |
| | | (.015) | (.014) | (.014) | (.014) | (.012) | (.012) |
| Capital intensity (ln) | | | | .020*** | .020*** | .012*** | .011*** |
| | | | | (.003) | (.003) | (.002) | (.003) |
| R&D intensity | | | | | .088 | .022 | .021 |
| | | | | | (.070) | (.071) | (.072) |
| R&D cooperation with university (D) | | | | | .014 | .013 | .009 |
| | | | | | (.014) | (.013) | (.012) |
| ICT investments (D) | | | | | -.006 | -.008 | -.009 |
| | | | | | (.007) | (.006) | (.006) |
| Firm's size (,00) | | | | | | | .000*** |
| | | | | | | | (.000) |
| *Other controls:* | | | | | | | |
| Region fixed effects | | | √ | √ | √ | √ | √ |
| Unemployment rate | | | √ | √ | √ | √ | √ |
| College-province dummy | | | √ | √ | √ | √ | √ |
| 2-digit ATECO sectors | | | | | | √ | √ |
| $R^2$ | .014 | .019 | .086 | .104 | .105 | .274 | .275 |
| N. obs. | 3,527 | 3,527 | 3,527 | 3,527 | 3,527 | 3,527 | 3,527 |

*** significant at 1%; ** significant at 5%; * significant at 10%
Note. The dependent variable is the (ln) full-time annual wage. Heteroskedasticity robust standard errors clustered at province-level in parentheses. Observations are weighted to population proportions. Dummy variables are indicated with D in parentheses. For the description of the variables see Appendix A.

Table 4: Robustness checks (OLS)

| | | white collars | | blue collars | |
|---|---|---|---|---|---|
| *Controlling for:* | | | | | |
| (1) | working hours | 1.002*** | (.283) | .594*** | ( .176) |
| | *baseline* | .996*** | (.233) | .593*** | (.177) |
| | N. obs. | 2,981 | | 3,227 | |
| (2) | experience, seniority, % females (by firm sector) | .690** | (.271) | 0.496*** | (.193) |
| | *baseline* | .699** | (.288) | .397* | (.223) |
| | N. obs. | 3,446 | | 3,525 | |
| (3) | experience, seniority, % females (by firm size) | .878*** | (.297) | .066 | (.236) |
| | *baseline* | .670** | (.289) | .403* | (.223) |
| | N. obs. | 3,510 | | 3,527 | |
| (4) | (1)+(2) | .982*** | (.230) | .617*** | (.174) |
| | *baseline* | 1.002*** | (.233) | .590*** | (.177) |
| | N. obs. | 2,958 | | 3,226 | |
| (5) | (1)+(3) | 1.214*** | (.232) | .346* | ( .192) |
| | *baseline* | .996*** | (.233) | .593*** | (.177) |
| | N. obs. | 2,980 | | 3,227 | |
| (6) | quality of graduates | .866** | (.363) | .228 | (.305) |
| *Using other independent variables, subsamples or interaction terms:* | | | | | |
| (7) | (dep. var.) population share with tertiary education | .252 | (.375) | .153 | (.286) |
| (8) | (dep. var.) workers share with tertiary education | .219 | (.335) | .153 | (.257) |
| (9) | by firm size | | | | |
| | small (<25 workers) | .966** | (.444) | .267 | (.283) |
| | N. obs. | 1,669 | | 1,697 | |
| | Large (≥25 workers) | .546** | (.278) | .594 | (.211) |
| | N. obs. | 1,843 | | 1,830 | |
| (10) | nonlinearities | | | | |
| | LCS | 1.323*** | (.339) | .753*** | (.262) |
| | LCS below median | 1.052*** | (.383) | .569* | (.292) |

*** significant at 1%; ** significant at 5%; * significant at 10%
Note. The dependent variable is the average (ln) full-time annual wage at the firm level. When it is not differently specified, each row reports the coefficient on the local college share (LCS) estimated from a separate regression adding the controls specified in each row after the model number to the specification (7) in Tables 2 and 3 (baseline specification), for white collars and blue collars, respectively. Heteroskedasticity robust standard errors clustered at province level in parentheses. Since the additional controls are not available for all observations in the original sample, the row *baseline* reports the coefficient on local human capital obtained from the baseline specification estimated in the same sample. Observations are weighted to population proportions. See Appendix A for the description of the variables.

Table 5: First-stage effects of instruments on other manufacturing-related variables

| | Dependent variable | | | |
|---|---|---|---|---|
| | secondary school share (2001) | | employment share (2001) | |
| $\Delta DEGDENS$ | .042 | | -.038 | |
| | (.031) | | (.037) | |
| $\Delta DEGDENS$ $\times$ population 5-14 in 1982 | | .286 | | -.228 |
| | | (.199) | | (.269) |
| $R^2$ | .58 | .58 | .69 | .69 |
| N. obs. | 103 | 103 | 103 | 103 |

Note. The dependent variables are the upper secondary school share in manufacturing and the employment share in manufacturing, the unit of observations are provinces and the regressions are performed on the public use microdata file of the 2001 Italian Population Census data aggregated by province and using individual weights. $\Delta DEGDENS$ is the change of manufacturing-related university courses density (per 10 square km) at the province level between 1990 and 1995. Heteroskedasticity robust standard errors in parentheses. All regressions include region (NUTS-2) fixed effects and male unemployment rates in the age group 15-24. In the regressions, observations are weighted by the number of manufacturing workers by province.

Table 6: Wage equations for white collars and blue collars (instrumental variables) – worker characteristics matched by firm size

| | white collars | | | | | blue collars | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Local college share (LCS) | 1.622*** | 1.664*** | 1.636*** | 1.655*** | 1.379*** | .381 | .449 | .418 | .578 | .445 |
| | (.383) | (.408) | (.391) | (.361) | (.409) | (.367) | (.375) | (.370) | (.390) | (.393) |
| Firm college share (FCS) | .214*** | .214*** | .214*** | .193*** | 1.203*** | .038 | .037 | .037 | -.000 | 0.054 |
| | (.052) | (.052) | (.052) | (.055) | (.292) | (.049) | (.049) | (.049) | (.051) | (.278) |
| *Instruments for LCS* | | | | | | | | | | |
| $\Delta DEGDENS^{(b)}$ (1990-1995) | √ | | √ | | | √ | | √ | | |
| $\Delta DEGDENS$ × | | | | | | | | | | |
| population 5-14 in 1982 | | √ | √ | √ | √ | | √ | √ | | √ |
| F-test instruments | 15.22 | 20.56 | 9.40 | 19.46 | 10.30 | 11.83 | 17.2 | 7.86 | 16.08 | 8.62 |
| Partial R2 instruments | .45 | .44 | .45 | .44 | .45 | .35 | .35 | .35 | .34 | .35 |
| *Instruments for FCS* | | | | | | | | | | |
| US industry college share (2000 Census) | | | | | √ | | | | | √ |
| F-test instruments | | | | | 35.18 | | | | | 28.99 |
| Partial R2 instruments | | | | | .05 | | | | | .04 |
| Other controls[(c)] | | | | √ | | | | | √ | |
| N. obs. | 2,980 | 2,980 | 2,980 | 2,980 | 2,971[(d)] | 3,227 | 3,227 | 3,227 | 3,227 | 3,216[(d)] |
| Hansen J-statistic (p-value) | - | - | .88 | - | - | - | - | .22 | - | - |

*** significant at 1%; ** significant at 5%; * significant at 10%

Note. The dependent variable is the average (ln) full-time annual wage at the firm level. Heteroskedasticity robust standard errors clustered at province level in parentheses. Observations are weighted to population proportions. For the description of the variables see Appendix A. [(a)] The covariates matched are employees' average experience, seniority and percentage of female workers at the firm level by skill level; [(b)] It is the change of manufacturing-related university courses density (per 10 square km) at the province level between 1990 and 1995; [(c)] Are all controls included in specification (7) of tables 2 and 3 ; [(d)] For nine and eleven observations ATECO codes are well defined only at the 2-digit level, in the white-collar and the blue-collar sample, respectively.