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# Communication externalities in cities

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**Abstract**

To identify communication externalities in French cities, we exploit a unique survey recording workplace communication of individual workers. Our hypothesis is that in larger and/or more educated cities, workers should communicate more. In turn, more communication should have a positive effect on wages. By estimating both an earnings and a communication equation, we find evidence of communication externalities. In larger and more educated cities, workers communicate more and in turn this has a positive effect on their wages. Depending on the estimates, we find that 13 to 22% of the effects of a more educated and larger city on wages percolate through this channel.


*JEL classification:* J31; R19; R29

*Keywords:* Human capital; Cities; Communication; Identification of externalities

## 1. Introduction

The strength of human capital externalities is a key determinant of the optimal subsidy to education. Furthermore, human capital externalities could constitute a crucial engine of growth and development (Lucas [29]). Because of their local dimension, human capi-

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tal externalities may also be a key source of agglomeration behind the existence of cities (Marshall [32]). Hence, obtaining reliable estimates for the strength of human capital externalities is widely acknowledged to be of fundamental importance.

It is also *essential to know how these externalities percolate*. There are three main reasons for this. First, the literature typically infers the existence of human capital externalities indirectly by estimating a wedge between private and social returns to education.[1] It speaks of human capital externality when an aggregate measure of human capital has a positive effect on individual earnings over and above that of individual characteristics. Such findings, however, might be driven by some missing variables and not by human capital externalities. Second, getting the optimal subsidy to education right is one thing but there could be other corrective policies. If, for instance, human capital externalities permeate mostly between workers in the same city and industry through face-to-face interactions, fostering regular meetings within local professional associations may be a good way to improve economic efficiency. Third, without knowing how these externalities percolate, nothing prevents the theorists from assuming whatever they like. Theoretical progress is thus hampered by our lack of knowledge about the precise nature of human capital effects. In short, knowing how human capital externalities percolate is of considerable importance for both theory and policy.

When elaborating on 'human capital externalities', the literature almost inevitably alludes to some form of technological externalities and mentions face-to-face meetings, word-of-mouth communication, direct interactions between skilled workers, and the like. This quasi-exclusive focus on a particular subset of human capital externalities, which we call *communication externalities*, may not be warranted. Human capital could have some external effects through a variety of other channels. More human capital in a city could foster the supply of specialised intermediate goods and, in turn, improve the productivity of final producers—a pecuniary externality unrelated to communication externalities. More human capital could also lead to better matches between employers and employees. One could also invoke a more efficient division of labour within a more educated workforce, etc.

In this paper, we propose a novel attempt to identify communication externalities and distinguish them from the other external effects of human capital. To do this, we exploit a unique survey recording workplace communication practices for around 6000 French workers in 1997. Because of its careful design and implementation, we believe this survey contains very valuable information about workplace communication. Our identifying assumption is that larger and/or more educated cities should favour communication, as postulated for instance by Beckmann [4], Borukhov and Hochman [7], Fujita and Ogawa [16], Black and Henderson [6], Glaeser [19], Berliant et al. [5], or Lucas [30], among others. Then more communication should have a positive impact on individual earnings (Jovanovic and Rob [28] and the references above). The intensity of communication externalities can then be computed as the effects of city size and average urban schooling on communication times that of communication on earnings.

[1] See for instance Rauch [36], Acemoglu and Angrist [1], Adserà [2], Moretti [33], or Simon and Nardinelli [40]. This literature is discussed more in depth below.

Our paper is related to the literature on human capital externalities in cities. Using Roback's [37] equilibrium location approach, Rauch [36] estimates hedonic earnings equations by regressing individual earnings on a set of individual controls together with city level variables. Despite numerous controls for individual and city characteristics, he finds a strong effect of average schooling on individual earnings within US cities. This finding has been replicated many times (e.g., Adserà [2], Simon and Nardinelli [40], etc.). According to this type of estimation, external returns to education in cities could be very large, between 50 and 100% of the private returns.

Rauch's seminal approach has been criticised on several grounds. Cross-section estimations make it difficult to distinguish human capital externalities from the effects of unobserved city heterogeneity, whereby 'high-wage' cities might attract high-education workers. A second concern regards individual unobserved heterogeneity. If workers with good unobserved characteristics tend to locate in high-education cities, the estimates for external returns to human capital obtained in a Rauch-style regression will be biased upwards.[2] The more fundamental problem, however, is whether this approach really identifies an externality of type described above or only a more mundane pecuniary effect like the complementarity in production of high- and low-skill workers (Ciccone and Peri [11]).[3]

We differ from this literature (see Moretti [34] for a survey) in our use of workplace communication data to directly identify communication externalities, a subset of human capital externalities. Unlike the aforementioned papers, our primary interest is not to provide a better measure of total external returns to education (although we attempt to follow the literature's best practice for this). The novelty in this paper is that we focus on workplace communication. That is, we concentrate on one particular channel for human capital externalities that figures prominently in our thinking about cities: communication externalities. In this regard, our approach is also related to the small literature attempting to identify the sources of urban increasing returns.

Only a few papers attempt to disentangle empirically the different micro-foundations of urban increasing returns.[4] Exemplary in this literature, Holmes [26] uses the differences in the location patterns of sales offices of small vs. large firms. This allows him to separate

[2] To deal with these issues, instrumental variables have been considered. A good instrument for average schooling would affect the schooling of the majority of workers in a given location without being otherwise correlated with local wages. Acemoglu and Angrist [1] argue that differences in school compulsory attendance laws and child labour laws in US states over the 20th century provide such variation, at least for secondary education. In their preferred estimation, they obtain only small external returns to education. In the same spirit but using instruments for participation in higher education, Moretti [33] shows that the share of higher-education graduates in a city has a strong effect on individual earnings. These results are confirmed when exploiting the longitudinal dimension of a panel of workers.

[3] Ciccone and Peri's [11] critique builds on a well-known fact: workers are imperfect substitutes in production (see Topel [42] for a recent overview) so that unskilled wages are typically expected to be higher in cities where the relative supply of skilled workers is larger. In other words, without accounting for imperfect substitutability between different types of workers, human capital externalities may be mistaken for complementarities in production. Ciccone and Peri [11] develop a novel approach to assess the effects of an increase in human capital in a city, keeping the skill composition of the workforce constant. Applying this 'constant composition' methodology to US cities, they find small and insignificant human capital externalities.

[4] See Rosenthal and Strange [38] for a more complete survey of this literature. For a more general discussion of the identification problems raised by non-market interactions, see Manski [31] and Brock and Durlauf [8].

the effects of local market size from those of cost-reducing externalities and comparative advantage. Building on Jaffe et al. [27], Almeida and Kogut [3] show that the citation trail for patents coincides with the movement of key scientific personnel. This suggests that 'spillovers' may be channelled through the labour market rather than word-of-mouth communication between scientists. In a different vein, Dumais et al. [13] use carefully constructed proxies to distinguish between the three Marshallian motives for agglomeration. They also find support for thick local labour market effects. However, we know of no previous work focusing on the identification of externalities using communication data.

Finally, although the terminology may differ, communication externalities enjoy widespread popularity and attention among other social scientists. Saxenian [39] is a good example of this type of work. She forcefully makes the case that the root of Silicon Valley's success are to be found in a unique culture. This culture is argued to favour frequent and open face-to-face contacts, which in turn lead ideas to flow freely across workers and firms. This literature is discussed at length by Storper [41] who reviews a large body of work offering suggestive evidence about communication externalities. Unfortunately, this literature relies mostly on qualitative evidence and the importance of communication externalities is never quantitatively assessed.[5]

Consistent with our two hypotheses, we find that workplace communication is positively associated with earnings and that city size and average urban schooling are positively associated with workplace communication. OLS estimates may be biased upwards because workplace communication could be suspected of being determined simultaneously with earnings. For instance, when a worker is promoted to a higher position, this is likely to involve both a higher wage and more workplace communication. To tackle this problem, one needs variables that determine workplace communication but remain uncorrelated with the residual in our earnings equation. Fortunately our survey data also contains a wealth of variables about the workplace and the working conditions of the surveyed workers. Some of these provide good instruments for workplace communication. We do find some evidence of endogeneity, but correcting for it increases rather than decreases our estimates for communication externalities. Our IV estimates indicates that *up to* 22% *of agglomeration effects percolate through communication externalities* (against 13% for OLS).

In our analysis we also successfully check the robustness of our results with respect to a variety of other estimation issues such as the spatial selection of workers, the correct identification of human capital effects on wages, and the endogeneity of other explanatory variables, etc. Nonetheless, two important limitations must be acknowledged. First, the data measures communication at the workplace only. We thus ignore potentially important effects of communication happening in social networks, outside of the workplace. These may help workers find jobs, learn about business opportunities, etc. Second, we only measure static communication externalities and not the kind of long-run learning benefits provided by the cities that are highlighted by Glaeser and Maré [20]. Bearing these caveats

[5] Of particular interest in this body of work, Goddard [21] and Goddard and Morris [22] compile very detailed communication data about a large group of workers in London. They show a strong link between the intensity of communication and central locations. They also document a wealth of interesting features about workplace communication. Unfortunately, they do not explore the links between communication and productive efficiency.

in mind, our general conclusion is that communication externalities are present in cities and serve as a conduit for a sizeable fraction of agglomeration effects.

The strategy of the rest of the paper is the following. Section 2 presents our data. Section 3 discusses the main estimation issues. Section 4 provides our main results. Section 5 performs a series of robustness tests. Section 6 draws some conclusions.

## 2. Data issues and construction of a communication index

In what follows, we exploit data from a detailed survey, "Changements organisationnels et informatisation" (COI—Organisational change and information technologies), conducted in 1997 in France. 8812 workers were randomly drawn from the labour force employed in manufacturing, retail (Do-It-Yourself chains only), and business services (accounting only). Selected workers were individually interviewed and we know their responses to around 80 questions covering a wide range of topics: working conditions, organisation of work, workplace communication and information technologies. This data was then matched with the French labour force survey, firm level data, and location data to obtain further information such as earnings, industry, establishment size and workplace location (rural, suburban, or urban with the city population).

This data, further described in Appendix A, is critically analysed by Greenan and Hamon-Cholet [23,24] and Greenan and Mairesse [25] who offer various checks regarding its quality. A key part of the questionnaire consists of around 20 questions related to the workplace communication of the surveyed workers. A first subset of questions is about communication within the firm. It contains questions such as "Except for your subordinates (if any), do you give instructions to colleagues about their work? (Yes/No)" or "Do you work in a team with colleagues?", making a distinction between colleagues with whom workers are usually working and others in the same firm.[6] A second subset of questions regards communication external to the firm. Typical questions in this subset are "Do you receive instructions from suppliers or customers about your work?" and "Are you in contact (face-to-face or telephone) with customers? (All the time/Regularly/At times/ Never)". Finally a last subset of question is concerned with the media being used to receive instructions (face-to-face, telephone, paper or computer) and the use of IT (e.g., internet or intranet access, etc.).

Before going any further in the analysis, it is worth pausing to assess what can be learnt from the data. Our assessment is that such data, despite obvious drawbacks, contain valuable information about workplace communication. Note that the questions about whom the workers communicate with speak about "instructions", which are defined as "important information given or received on a regular basis and are necessary for the conduct of your work". Gossiping around the coffee machine does not constitute giving or receiving instructions. Instead meeting with a consultant with a view to solving a problem or asking a colleague how to operate a machine does. Hence part of the communication detected

[6] See Appendix A for a complete list of questions.

in the survey should reflect the circulation of knowledge at the heart of communication externalities.

However, the survey is limited in how far we can describe and characterise workplace communication. First, we know nothing about the geographic destination of the communication. We know where workers are and with whom they communicate with but not where these other workers are. Then, there is only one question about the intensity of communication. This is limiting because this question is framed in a particular context (communication with customers using face-to-face or telephone). The last limitation results from the absence of a question about the diversity of workers with whom communication takes place even though this issue plays a crucial role in our thinking about the communication advantages of large cities.

A complete exploration of the determinants and the implications of each and every communication-related question would not be practical for our purpose.[7] Instead, we can aggregate the answers to these questions into synthetic communication indices for each worker. Which questions to consider and how to aggregate them are potentially fundamental issues for our estimations since communication is used both as a dependent variable in a communication equation and as an explanatory variable in an earnings equation. The results might be very sensitive to the choices made at this stage.

For simplicity, we decided to use as baseline communication index the total score on all the communication questions, bar those on communication internal to the firm.[8] This series of question is excluded on the ground that internal communication may not have much to do with agglomeration economies. This index was then normalised to be between 0 and 100. The mean score for the sample is 39.1 and the standard error is 20.7. We experimented with a wide array of possible indices. They are usually strongly correlated with each other. For instance the correlation between our baseline index and a similar index considering all the questions without restriction is 0.93 (see Appendix A for details). The correlation between the baseline and an alternative index, constructed using the first eigenvector of a principle component analysis (PCA), is 0.91. The reason behind these high correlations is that workers who communicate a lot tend to communicate within their firm as well as outside and use a wide array of media. As a consequence our results are not sensitive to the exact details of the index we choose.

Table 1 reports some summary statistics with a spatial breakdown for the main variables we use in the analysis. As can be seen clearly from the table, wages are higher in larger cities. Communication also increases with city size. Workers in larger cities also tend to be more educated.

## 3. Estimation

Our estimation strategy relies on two ideas. The first one is that individual labour market earnings, which reflect the productivity of workers, are determined by a set of individual

[7] In a companion paper (Charlot and Duranton [9]), we explore the details of the data.

[8] The answers to all binary questions were coded 1 for yes and 0 for no. Answers to the question about the intensity of communication were coded: 3 for the highest level of communication; 2; 1; and 0 for the lowest.

Table 1
Summary statistics

| | Rural | Suburb | Urban1 | Urban2 | Urban3 | Paris | All |
|---|---|---|---|---|---|---|---|
| *Outcomes* | | | | | | | |
| Communication | 31.9 | 36.0 | 38.8 | 41.4 | 42.5 | 50.3 | 39.1 |
| | (19.2) | (20.5) | (19.8) | (20.0) | (21.6) | (20.0) | (20.7) |
| Communication (PCA) | 26.5 | 30.9 | 31.4 | 34.5 | 35.3 | 42.0 | 32.4 |
| | (20.0) | (21.5) | (20.4) | (20.6) | (22.7) | (21.5) | (20.0) |
| log Wages | 3.91 | 4.01 | 3.99 | 4.05 | 4.08 | 4.32 | 4.03 |
| | (0.42) | (0.43) | (0.43) | (0.44) | (0.45) | (0.52) | (0.46) |
| *Characteristics* | | | | | | | |
| % female | 36.3 | 29.0 | 39.4 | 38.2 | 39.6 | 42.1 | 37.8 |
| % h.-e. graduates | 13.7 | 18.1 | 19.8 | 24.3 | 31.3 | 44.2 | 23.0 |
| Age | 40.3 | 40.4 | 40.4 | 40.7 | 40.6 | 40.6 | 40.5 |
| *No. of obs.* | 1294 | 535 | 1421 | 982 | 375 | 702 | 5309 |

*Notes*. Urban1: population $< 100{,}000$; Urban2: $100{,}000 \leqslant$ population $< 500{,}000$; Urban3: $500{,}000 \leqslant$ population $<$ 2m; Paris is the only city with a population above 2 million. Communication (PCA) is constructed using the first eigenvector of a principle component analysis (see Appendix A for details) and h.-e. graduates refers to the share of higher-education graduates in the sample. Standard errors are in parentheses.

characteristics and by a set of environmental characteristics. The second idea is that workplace communication itself is in turn determined by individual and local characteristics.

With respect to earnings, the individual characteristics should proxy for the human capital of workers. Standard specifications in the literature typically include some measure of education, labour market experience or some proxy for it and its square, as well as gender. We can think of education and experience as variables reflecting mostly the formal (or codified) skills of workers. However, this type of specification misses all the informal (or tacit) knowledge that can make workers more productive.[9] Being efficient at work is not only about having a degree reflecting some formal knowledge but also about knowing how to apply this formal knowledge, knowing who to call in case of a problem, being aware of the latest market and technological evolutions, etc. We think of our communication index as reflecting this tacit and informal knowledge.

Regarding the environmental characteristics that influence earnings, note that previous research has shown that workers tend to be more productive in larger and more educated cities (see Rosenthal and Strange [38] for a survey). These considerations suggest that the earnings, $W_j$, of worker $j$ living in city $i$ are given by:

$$\log W_j = X_j a + \mathrm{Com}_j b + Z_{i(j)} c + \epsilon_j, \tag{1}$$

where $X_j$ is a vector of standard observable individual characteristics, $\mathrm{Com}_j$ is the communication of worker $j$, $Z_i$ is a vector of characteristics for area $i$ where $j$ lives, and $\epsilon_j$ is an error term, best thought of as some unmeasured productive ability.

[9] The distinction between formal (or codified) knowledge and informal (or tacit) knowledge has not received much attention in economics but it is the subject of a voluminous literature in other social science disciplines—see Gertler [18] for a recent discussion.

Turning to workplace communication, it depends obviously on the characteristics of the worker. Some workers may be better at communicating because of better formal skills (viz, reading, writing, etc.). Furthermore, social skills may foster one's abilities to extract information during face-to-face communication, to put forward ideas in small-group meetings or to generate trust from colleagues, subordinates, employers, etc. Existing models of communication externalities also suggest that larger cities offer more opportunities for face-to-face meeting (Glaeser [19] and Berliant et al. [5]) and that during these meetings, skilled workers learn more from other skilled workers than from unskilled workers (Jovanovic and Rob [28]). Combining the two effects, larger and more educated cities are assumed to increase workplace communication and, in turn, to raise wages. These considerations suggest that the workplace communication of worker $j$ in city $i$ is given by:

$$\mathrm{Com}_j = V_j d + Y_{i(j)} e + \mu_j, \tag{2}$$

where $V_j$ is a vector of individual characteristics, $Y_i$ a vector of local characteristics, and $\mu_j$ an error term encompassing unobserved social abilities. This error term is discussed further.

Following the estimation of (1) and (2), it is possible to compute $b \times e$, the indirect effect of the economic environment on earnings that percolate through communication externalities, and compare it to $c + b \times e$, the total effect of the environment on earnings (which sums the direct and indirect effects). This is the key novelty of the paper. Previous literature (e.g., Rauch [36], Moretti [33], etc.) typically estimates a specification like: $\log W_j = X_j a + Z_i c + \epsilon_j$. This only yields estimates for the total effect of the local environment on earnings but it does not say anything about how these effects percolate. By estimating (1) and (2), we are able to trace the effect of the local environment on workplace communication and in turn estimate the effect of workplace communication on earnings.

Equations (1) and (2) raise a series of estimation issues that need to be answered before presenting our results. The first one regards which explanatory variables to use for $V$, $X$, $Y$, and $Z$. The exact form of the baseline specification follows the model given in Appendix B, which derives a detailed specification for Eq. (1) from first principles. For individual characteristics in the earnings equation, $X$, we use gender, educational attainment, age, and age-squared. For city level characteristics in the earnings equation, $Z$, we use log city population, the proportion of higher-education graduates in the city workforce, and average city communication. Average city communication is required for consistency in the specification because if we assume that communication increases a worker's output, it must also have aggregate implications (again, see Appendix B for a justification). In the communication equation and following the predictions of the literature (Jovanovic and Rob [28], Glaeser [19], Berliant et al. [5]), we use the same individual characteristics as in the earnings equation (i.e., $V = X$). For city level characteristics, $Y$, we use log city population and the proportion of higher-education graduates.

The second estimation issue is about a possible correlation between the two error terms, $\epsilon_j$ and $\mu_j$. For instance workers with higher unobserved productive abilities ($\epsilon_j$) are likely to occupy positions implying both a higher wage and more communication.[10] More formally, the error terms may be related in the following way: $\mu_j = f\epsilon_j + \eta_j$, where $f$ is a scalar and the $\eta_j$ are i.i.d. and uncorrelated with the $\epsilon_j$. A positive correlation between $\epsilon_j$ and $\mu_j$ would imply an upward bias for the OLS estimate of the coefficient $b$ in Eq. (1). Instead, a negative correlation would imply a downward bias.

When estimating (1) and (2) using the specifications described above, all the identification of the effects of communication in the earnings equation comes from the residual $\mu_j$. This is because all the explanatory variables of the communication equation are also in the earnings equation ($V = X$). Hence, the system composed of Eqs. (1) and (2) can only be identified if the errors are assumed to be orthogonal. This may be fairly restrictive in light of the arguments above. To investigate the possible simultaneous determination of wages and communication, instrumental variables are needed in a 2SLS estimation. For good instruments, we need exogenous variables, which determine workplace communication, but remain uncorrelated with the residuals in our earnings equation. Put differently, we need to estimate:

$$\mathrm{Com}_j = X_j d + Y_{i(j)} e + S_j g + \mu_j, \tag{3}$$

where $S_j$ is a vector of instruments whose content is discussed below.

To summarise, the estimation of Eqs. (1) and (2) must be done through separate OLS whereas the estimation of (1) and (3) can be done with a single two-step estimation. A smaller worry with respect to the error structure in these equations is that we mix individual and city-level characteristics. This may lead to clustered standard errors. To avoid this problem, we estimate our regressions with robust standard errors.

A third estimation worry regards some possible omitted variables in one or both estimated equations. To deal with this problem, we can add in the two equations further individual characteristics (i.e., marital status, number of children, etc.). We can also add a set of firm level characteristics (such as sectoral dummies and firm size) or work level characteristics (such as the occupation). These variables do not appear in our theoretical specification of the earnings equation but they are expected to have some explanatory power. The main problem with some of these extra explanatory variables, like the occupation, is that they may be simultaneously determined with location. To understand the problems associated with such 'controls', an illustrative example is useful. Assume the existence of 'blue' jobs subject to no communication externality and 'white' jobs subject to strong communication externalities. With communication fostered by city size and the cost of workers also increasing with city size, we expect white jobs to be located in large cities and blue jobs to be located in small cities or rural areas in equilibrium. Controlling for the 'colour' of jobs would not be very helpful in this model since the 'white job' dummy would also control for communication externalities. Leaving this issue aside,

[10] Related to this is the possibility for communication to be a 'secondary' input in production (like stationeries or office space), rather than a primary input as we assume (i.e., a proxy for informal knowledge to be put on a par with formal knowledge). If communication was a secondary input, we would expect more productive workers to use more communication, just like they would use more stationeries or more office space, even in absence of communication externalities. This objection also implies a positive correlation between the error terms in the two equations.

we nonetheless decided to run augmented regressions as a check on the robustness of our results.[11]

There are several further estimation issues regarding the spatial sorting of workers, the possible simultaneous determination of city size, average education, and wages, and whether the coefficient on average education in cities really identifies some human capital externalities or only some complementarities across skills. Given that these concerns have already been discussed at length in the literature (Moretti [34]), we leave them aside temporarily and return to them in Section 5.

## 4. Results

### 4.1. Specification

Our detailed econometric specification for the earnings equations (1) is the following:

$$\begin{aligned}\log W_j = {} & a_0 + a_1 \cdot \text{Gender}_j + a_2 \cdot \text{Educ}_j + a_3 \cdot \text{Age}_j + a_4 \cdot \text{Age}_j^2 + b \cdot \text{Com}_j \\ & + c_1 \cdot \text{Urban}_j \times \log \text{Pop}_{i(j)} + c_{1'} \cdot \text{Suburb}_j + c_{1''} \cdot \text{Rural}_j \\ & + c_2 \cdot \text{shareGraduates}_{i(j)} + c_3 \cdot \text{meanCom}_{i(j)} + \epsilon_j. \end{aligned} \tag{4}$$

In Eq. (4), the (natural) log of the earnings of each worker is regressed on a set of personal and city level characteristics. Education (Educ) is measured by 6 dummies for educational attainment.[12] Age and its square proxy for labour market experience, which is unknown.[13] Com is our main index of individual workplace communication described above. It ranges from 0 to 100. We also use a set of location characteristics. Because population is unknown for rural and (remote) suburban location, we introduce three dummy variables Urban, Suburb, and Rural for workers located in urban, suburban, and rural areas respectively. For urban areas, we proxy the city workforce by total city population, $\text{Pop}_i$, which is interacted with the Urban dummy. Note that the two location dummies represent the total effect of working in suburban and rural areas whereas the coefficient on city size represents the marginal effect of city size.[14] The average skill level in an area is measured by the share of higher-education graduates (i.e., college and university graduates, the two

[11] Another problem with these extra explanatory variables is that, in some cases, their interpretation is unclear. For instance, the coefficient on firm size is typically positive and highly significant in earnings equations. However, it is unclear whether it reflects some selection of workers across firms or the fact that larger firms are more efficient and share their rents with their workers.

[12] Educ1 corresponds to university graduates (with at least three years of higher education), Educ2 denotes college graduates (two years of higher education), Educ3 is for high-school graduates, Educ4 is for graduates from vocational schools, Educ5 is for junior high-school graduates, and Educ6 (our reference) corresponds to the absence of degree. See Appendix A for more details.

[13] Since we know only the educational attainment and not the number of years of education, we cannot proxy labour market experience in the usual way (i.e., age − number years of education − 5). Note that this variable will capture not only the effects of experience but also cohort effects. This need not worry us because the structural interpretation of the coefficient on this variable is not of fundamental importance here.

[14] To compute the total effect of working in a given city this latter coefficient must be multiplied by the log population of this city.

highest educational attainments). Finally we construct an index of average communication for each area, meanCom, from our individual communication data. It also ranges from 0 to 100. See Appendix A for more details on this area communication index.

Turning to the communication equation (2), our detailed econometric specification is:

$$\begin{aligned}\mathrm{Com}_j = {} & d_0 + d_1 \cdot \mathrm{Gender}_j + d_2 \cdot \mathrm{Educ}_j + d_3 \cdot \mathrm{Age}_j + d_4 \cdot \mathrm{Age}_j^2 \\ & + e_1 \cdot \mathrm{Urban}_j \times \log \mathrm{Pop}_{i(j)} + e_{1'} \cdot \mathrm{Suburb}_j + e_{1''} \cdot \mathrm{Rural}_j \\ & + e_2 \cdot \mathrm{shareGraduates}_{i(j)} + \mu_j. \end{aligned} \tag{5}$$

To estimate (3), we use the same specification with more explanatory variables (the instruments)—see below.

### *4.2. Results for the communication equation*

In Table 2 we first report some results about the determinants of individual workplace communication. Given the paucity of data on this topic, these results are of independent interest.[15] Column (1) is our baseline specification, which corresponds to Eq. (5). The coefficients on educational attainments show that education is a strong determinant of workplace communication. The difference between university and high-school graduates (i.e., Educ1 and Educ3) is 12 points whereas that between high-school graduates and dropouts with no degree is even larger at 26 points (i.e., more than one standard deviation). The effects of the other individual characteristics are much smaller. Among them, the effect of age is non-monotonic. Communication peaks at around 50. It increases by around 0.7 point per year when aged 20. At age 40, the increase for each extra year is smaller: 0.2 points. There is also a small gender gap. The communication score of women is about 0.8 point below that of men. Given that the mean communication score is 39.1, the relative communication gap between men and women is only of around 2%.

Turning to city level variables, we find first a significant effect of city population. Moving from the smallest city (with a population about 10, 000) to the largest (with population about 10 million) corresponds to an increase in the individual communication score of about 4 points. Regarding the share of higher-education graduates, we again find a significant effect. Moving from the least educated city (with 8% of graduates) to the most educated (with 28% of graduates) corresponds to an increase in the individual communication score of slightly less than 4 points.

In column (2) of Table 2, we use an alternative communication index computed from the first eigenvector of a principal component analysis on all the communication questions. The results are very similar. Adding industry dummies and more demographic variables in column (3) also leaves our initial results mostly unchanged. Finally in column (4), firm employment and a control for the function of the worker are also added. As could be expected, the functional dummy that distinguishes occupations with routine tasks from those with non-routine tasks has a very large and significant coefficient. But even in the pres-

[15] We are not aware of any similar analysis in the literature. The only exception is Gaspar and Glaeser [17] who regress a few city level telecommunication variables on city characteristics.

Table 2
Communication equations

| Regressors: | (1) OLS | (2) OLS | (3) OLS | (4) OLS |
|---|---|---|---|---|
| | Com | ComPCA | Com | Com |
| Intercept | −11.083 | −21.394 | −9.811[b] | −7.992[ns] |
| | (4.292) | (4.846) | (5.841) | (5.221) |
| Gender | −0.848[b] | −4.804 | −11.521[ns] | −2.832[ns] |
| | (0.468) | (0.502) | (8.764) | (7.806) |
| Educ1 | 37.573 | 38.238 | 35.149 | 21.483 |
| | (0.864) | (1.054) | (0.994) | (0.959) |
| Educ2 | 33.061 | 31.943 | 31.339 | 18.095 |
| | (0.793) | (0.977) | (0.914) | (0.889) |
| Educ3 | 25.883 | 24.596 | 23.617 | 13.330 |
| | (0.833) | (0.963) | (0.902) | (0.850) |
| Educ4 | 13.967 | 13.485 | 12.713 | 7.673 |
| | (0.608) | (0.762) | (0.704) | (0.641) |
| Educ5 | 5.323 | 4.988 | 4.742 | 3.723 |
| | (0.838) | (1.000) | (0.919) | (0.819) |
| Age | 1.130 | 1.431 | 1.329 | 1.178 |
| | (0.194) | (0.221) | (0.279) | (0.248) |
| Age$^2$ | −0.0115 | −0.0151 | −0.0132 | −0.0135 |
| | (0.0023) | (0.0026) | (0.0033) | (0.0030) |
| Non-routine occup. | | | | 20.229 |
| | | | | (0.549) |
| Accounting | | | −9.189 | −2.484 |
| | | | (0.666) | (0.744) |
| Retail | | | 4.466 | 2.845 |
| | | | (1.110) | (0.991) |
| log FirmEmp | | | | 0.613 |
| | | | | (0.179) |
| Rural | 1.334[ns] | 2.939[ns] | 5.743 | 3.098[b] |
| | (1.984) | (2.176) | (2.010) | (1.792) |
| Suburb | 2.930[ns] | 4.623[b] | 6.857 | 4.039 |
| | (2.194) | (2.399) | (2.214) | (1.974) |
| **log Pop** | **0.443**[a] | **0.428**[a] | **0.637** | **0.361**[a] |
| | (0.172) | (0.189) | (0.173) | (0.155) |
| **shareGraduates** | **17.782** | **12.628**[a] | **16.064** | **8.400**[b] |
| | (5.327) | (5.711) | (5.244) | (4.673) |
| Other demographics | No | No | Yes | Yes |
| Adj. $R^2$ | 0.359 | 0.327 | 0.400 | 0.526 |
| No. of obs. | 5309 | 5309 | 5309 | 5309 |

*Notes*. OLS estimations with robust standard errors. Standard errors are shown in parentheses. Other demographic variables include the number of children, the number of children interacted with gender, and age interacted with gender. ComPCA is a communication index build using the first eigenvector of a principle component analysis on all communication questions and normalised to be between 0 and 100. All coefficients significant at the 1% level, except:

[a] significantly different from zero at the 5% level,
[b] significantly different from zero at the 10% level,
[ns] non-significant.

ence of these extra controls, the coefficients on city size and on the city share of graduates remain significant.[16]

The main conclusions we draw from Table 2 are the following. We first find that individual workplace communication is fairly well explained by individual characteristics (especially education). The local environment also matters to determine individual communication. How big are the effects of the local environment? To explain individual communication, they are relatively small: moving an 'average worker' from the worst to the best local environment increases her communication by about 20% (or 8 points), that is much less than a standard deviation. However, the effects of the local environment are much larger when it comes to explaining differences across areas (rather than across individual workers). The communication gap between Paris (the largest and most educated French city) and the smallest (and least educated) cities is around 15 points (and nearly 20 points with rural areas). Up to half of this gap can be accounted for by location characteristics.

### *4.3. Results for the earnings equation*

In Table 3 we report the results for a variety of specifications for the earnings equation. Column (1) is our baseline specification, which corresponds to Eq. (4). The effects on wages of the standard individual variables (gender, education, age and its square) are in line with what is usually obtained in this type of exercise. There is no need to comment on them further here. The first novel feature in this estimation regards the magnitude of the coefficient on individual communication. A one-point increase in the communication index, on a scale from 0 to 100, corresponds to a wage increase of 0.49%. More tellingly perhaps, a one-standard-deviation increase in the communication index (20.7 points) corresponds to a wage increase of more than 10%. This effect is rather large and highly significant.

The effect of city size is in line with previous results in the literature (albeit in the lower tier of existing estimates): an increase of 1% in city size corresponds to a wage increase of 0.019%. This corresponds to scale economies of around 2%. The coefficient on mean city communication is also significant and its magnitude is around one third of that on individual communication. Finally, the coefficient on the share of higher-education graduates is large, like in all previous estimates using this variable (Rauch [36], Adserà [2], Moretti [33,35], etc.). A percentage point increase in the share of graduates in a city corresponds to a 0.46% increase in wages for all workers in this city. Stated differently, the measured

[16] As highlighted above, some caution is however needed with respect to how the results in column (4) can be interpreted. Managerial occupations, in which workers communicate a lot, are overwhelmingly located in large and highly educated cities. However, occupation and location are likely to be jointly determined, making the interpretation of column (4) problematic (and good instruments for the occupations are missing). Even when accepting the results in this column at face value, one would need to explain why high-communication positions tend to be disproportionately located in larger and more educated cities. More generally, it is worth noting that a 'full ceteris paribus' is not desirable here. We expect communication intensive jobs to be predominantly located in larger cities. Controlling for all the features that explain communication and determine location at the same time is not likely to be very enlightening to the extent that they are likely to be the two sides of the same coin.

Table 3
Earnings equations

| Regressors: | (1) OLS | (2) OLS | (3) OLS | (4) OLS | (5) OLS |
|---|---|---|---|---|---|
| Intercept | 1.624 | 1.672 | 1.609 | 1.683 | 1.618 |
| | (0.114) | (0.096) | (0.093) | (0.120) | (0.120) |
| Gender | −0.223 | −0.199 | −0.225 | −0.252[ns] | −0.221[ns] |
| | (0.0091) | (0.0094) | (0.0096) | (0.175) | (0.173) |
| Educ1 | 0.560 | 0.546 | 0.742 | 0.532 | 0.494 |
| | (0.026) | (0.021) | (0.020) | (0.022) | (0.022) |
| Educ2 | 0.309 | 0.306 | 0.469 | 0.283 | 0.245 |
| | (0.020) | (0.020) | (0.019) | (0.020) | (0.020) |
| Educ3 | 0.190 | 0.193 | 0.319 | 0.185 | 0.154 |
| | (0.020) | (0.019) | (0.019) | (0.019) | (0.019) |
| Educ4 | 0.097 | 0.095 | 0.164 | 0.096 | 0.082 |
| | (0.015) | (0.015) | (0.015) | (0.014) | (0.014) |
| Educ5 | 0.019[ns] | 0.019[ns] | 0.044[a] | 0.020[ns] | 0.020[ns] |
| | (0.021) | (0.019) | (0.019) | (0.017) | (0.018) |
| Age | 0.069 | 0.069 | 0.076 | 0.062 | 0.062 |
| | (0.0050) | (0.0041) | (0.0042) | (0.0056) | (0.0055) |
| $Age^2$ | −0.00060 | −0.00060 | −0.00068 | −0.00051 | −0.00052 |
| | (0.000061) | (0.000050) | (0.000051) | (0.000066) | (0.000066) |
| **Com** | **0.0049** | **0.0051** | | **0.0057** | **0.0044** |
| | (0.00028) | (0.00026) | | (0.00028) | (0.00031) |
| Non-routine occup. | | | | | 0.114 |
| | | | | | (0.014) |
| Accounting | | | | 0.073 | 0.048 |
| | | | | (0.013) | (0.016) |
| Retail | | | | −0.158 | −0.169 |
| | | | | (0.022) | (0.022) |
| log FirmEmp | | | | | 0.027 |
| | | | | | (0.0040) |
| Rural | 0.206 | 0.208 | 0.226 | 0.159 | 0.160 |
| | (0.043) | (0.040) | (0.042) | (0.040) | (0.040) |
| Suburb | 0.227 | 0.230 | 0.258 | 0.185 | 0.187 |
| | (0.047) | (0.044) | (0.046) | (0.044) | (0.044) |
| **log Pop** | **0.019** | **0.020** | **0.022** | **0.016** | **0.016** |
| | (0.0037) | (0.0035) | (0.0036) | (0.0035) | (0.0034) |
| **meanCom** | **0.0017**[a] | **0.0011**[ns] | | **0.0019**[a] | **0.0020** |
| | (0.00084) | (0.00077) | | (0.00076) | (0.00075) |
| **shareGraduates** | **0.464** | **0.482** | **0.525** | **0.508** | **0.487** |
| | (0.112) | (0.107) | (0.110) | (0.106) | (0.105) |
| Other demographics | No | No | No | Yes | Yes |
| Adj. $R^2$ | 0.490 | 0.496 | 0.456 | 0.507 | 0.517 |
| No. of obs. | 5309 | 5309 | 5309 | 5309 | 5309 |

*Notes*. Dependent variable: log W in all columns. OLS estimations with robust standard errors. Standard errors are shown in parentheses. Other demographic variables include the number of children, the number of children interacted with gender, and age interacted with gender. Column (2) is estimated using ComPCA, a communication index build using the first eigenvector of a principle component analysis on all communication questions and normalised to be between 0 and 100. All coefficients significant at the 1% level, except:

[a] significantly different from zero at the 5% level,

[ns] non-significant.

external returns on college and university education are roughly of the same magnitude as the measured private returns.[17]

Columns (2)–(5) of Table 3 report estimation results for a few variations around our baseline, adding or leaving aside explanatory variables. They confirm the basic findings in column (1) regarding the importance of individual communication and those of city level variables (city size, the share of graduates, and average communication). More specifically, in column (2) we take an alternative communication index. This yields identical results except for the coefficient on average communication, which becomes marginally insignificant at 10%. In column (3), we drop the communication variables. The only difference is that the coefficients on education are higher. This suggests that the returns to education as they are typically measured (i.e., omitting workplace communication as control) can also include some unmeasured social abilities captured by the communication variable. Adding further demographic and sectoral controls in column (4) changes close to nothing. Finally introducing a complete set of controls in column (5) leaves the coefficients on communication and city variables mostly unchanged.[18]

### *4.4. Endogeneity of communication*

As highlighted above, the use of communication as an explanatory variable in the earnings equation could be problematic given that communication and wages may be jointly determined. We deal with this problem by instrumenting for communication with factors that are unlikely to be directly related to wages but should affect communication.

In the data, two types of variables can a priori be used as instruments. First, the survey contains some information about the organisation of the firm and the characteristics of the tasks conducted by the worker. These characteristics (such as the number of hours spent daily in front of a computer) may be good predictors of communication without being correlated with the residual in the earnings equation. Similarly some management practices in a firm may determine workplace communication without being otherwise correlated with wages. Second, the survey also contains some information about the birthplace of workers and the occupation of their parents at birth. These may proxy for social abilities and social networks and thus determine communication. In this last group of possible instruments, the variables relating to the birthplace (like employment density of the birthplace in 1990 or a foreigner dummy) are typically rejected as instruments because of their direct correlation with wages. The variables relating to the occupation of the parents at birth are in most cases not rejected as instruments but their predictive power for communication is low.

[17] We do not know in which proportions innate abilities and educational inputs determine educational attainment. This issue is of secondary importance in our analysis because our model takes educational attainments as given and tries to estimate their external effects going through communication. However, any fully thought-through policy attempting to make individuals internalise human capital externalities will require a precise answer to this question.

[18] In regressions not reported here, we also used city population instead of its log as is common in the literature (e.g., Rauch [36]). We also ran our regressions using different classes of city size, instead of log population, with no significant change. To test the robustness of our communication index, we also ran the regressions reported in Tables 2 and 3 using a variety of alternative communication indices. Again the differences were minimal.

Table 4
Communication equations with instruments

| Regressors: | (1) OLS | (2) OLS |
| --- | --- | --- |
| | Com | ComPCA |
| 12 exogenous variables[c] | Yes | Yes |
| Computer use | −0.202 | −0.208 |
| | (0.0048) | (0.0052) |
| Repetitive movements | −5.547 | −3.545 |
| | (0.640) | (0.693) |
| Mother's occupation | Yes[d] | Yes[f] |
| Father's occupation | Yes[e] | Yes[g] |
| Adj. $R^2$ | 0.550 | 0.502 |
| No. of obs. | 5309 | 5309 |

*Notes*. OLS estimations with robust standard errors. Standard errors are shown in parentheses. All reported coefficients are significant at the 1% level. See the Appendix A for the exact definition of the instruments.
[c] The same 12 explanatory variables used in the baseline communication equations (i.e., columns (1) and (2) of Table 1), which also appear in the earnings equation.
[d] 9 entries (inactive/student, unskilled blue-collar, skilled blue-collar, white-collar employee, self-employed, intermediate profession, professional, no known mother) with intermediate profession being the reference. Three dummies significant at 10%.
[e] 9 entries (inactive/student, unskilled blue-collar, skilled blue-collar, white-collar employee, self-employed, intermediate profession, professional, apprentice, no known father) with intermediate profession being the reference. Only 2 dummies significant at 10%.
[f] Same as [d] except that only 2 dummies are significant at 10%.
[g] Same as [e] with 2 dummies significant at 10%.

After extensive search, our set of instruments comprises the time spent weekly in front of a computer, whether the worker performs repetitive movements, and the dummies for parental occupations at birth.[19] These instruments (particularly the first two) have a lot of independent explanatory power. When they are added to the baseline communication equation in the instrumental regression, the $R^2$ increases from 36 to 55%. As expected spending more time in front of a computer and performing repetitive tasks are both negatively correlated with communication since a higher value for these two variables makes it less likely to be in direct contact with customers or suppliers, etc. The results for this instrumental regression are reported in column (1) of Table 4. In column (2) we report the results for a similar regression using ComPCA, our alternative communication index for robustness purpose.

In Table 5, we report the results for the earnings equation when communication is instrumented as just described. In column (1), we report IV results for our baseline specification. The coefficient on communication is about 50% higher than under OLS.[20] The

[19] We also experimented with another set of instruments comprising whether the workers received some job-specific training and the tightness of the deadlines faced by workers. The results (available on request) are very similar to those obtained with our main set of instruments but the coefficients are less precisely estimated because these two instruments explain only 19% of the variance of the communication index.

[20] Note that the results here cannot be directly compared to those in Table 3 because we dropped average city communication from the estimation. This is because this variable may also be jointly determined with earnings. However, we have no good instrument for city communication.

Table 5
Earnings equations—IV estimations

| Regressors: | (1) 2SLS | (2) 2SLS | (3) 2SLS | (4) 2SLS | (5) 2SLS | (6) 2SLS |
|---|---|---|---|---|---|---|
| Intercept | 1.695 | 1.781 | 1.599 | 1.503 | 1.577 | 1.533 |
| | (0.089) | (0.089) | (0.122) | (0.103) | (0.101) | (0.103) |
| Gender | −0.216 | −0.185 | −0.218 | −0.216 | −0.213 | −0.213 |
| | (0.0093) | (0.0095) | (0.0094) | (0.0093) | (0.0094) | (0.0094) |
| Educ1 | 0.466 | 0.460 | 0.566 | 0.566 | 0.464 | 0.462 |
| | (0.027) | (0.024) | (0.021) | (0.022) | (0.027) | (0.027) |
| Educ2 | 0.216 | 0.225 | 0.306 | 0.310 | 0.218 | 0.218 |
| | (0.025) | (0.024) | (0.020) | (0.020) | (0.025) | (0.025) |
| Educ3 | 0.117 | 0.128 | 0.190 | 0.196 | 0.123 | 0.123 |
| | (0.022) | (0.022) | (0.019) | (0.019) | (0.023) | (0.023) |
| Educ4 | 0.059 | 0.062 | 0.099 | 0.105 | 0.066 | 0.066 |
| | (0.016) | (0.016) | (0.015) | (0.015) | (0.016) | (0.016) |
| Educ5 | 0.0049[ns] | 0.0042[ns] | 0.021[ns] | 0.0026[ns] | 0.0010[ns] | 0.0010[ns] |
| | (0.019) | (0.019) | (0.018) | (0.019) | (0.019) | (0.019) |
| Age | 0.066 | 0.063 | 0.070 | 0.070 | 0.066 | 0.066 |
| | (0.0041) | (0.0041) | (0.0040) | (0.0041) | (0.0041) | (0.0041) |
| $Age^2$ | −0.00057 | −0.00053 | −0.00060 | −0.00060 | −0.00057 | −0.00057 |
| | (0.000049) | (0.000049) | (0.000049) | (0.000049) | (0.000050) | (0.000050) |
| **Com** | **0.0079** | **0.0079** | **0.0050** | **0.0050** | **0.0078** | **0.0078** |
| | (0.00050) | (0.00050) | (0.00027) | (0.00027) | (0.00052) | (0.00052) |
| Rural | 0.232 | 0.220 | 0.285[a] | 0.397 | 0.354 | 0.395 |
| | (0.039) | (0.038) | (0.118) | (0.070) | (0.068) | (0.070) |
| Suburb | 0.253 | 0.239 | 0.305 | 0.422 | 0.377 | 0.417 |
| | (0.042) | (0.042) | (0.131) | (0.077) | (0.075) | (0.077) |
| **log Pop** | **0.021** | **0.021** | **0.025**[a] | **0.036** | **0.031** | **0.034** |
| | (0.0033) | (0.0033) | (0.011) | (0.0061) | (0.0062) | (0.0060) |
| **shareGraduates** | **0.318** | **0.368** | **0.488**[b] | **0.221**[b] | **0.146**[ns] | **0.162**[ns] |
| | (0.103) | (0.103) | (0.300) | (0.131) | (0.143) | (0.143) |
| Adj. $R^2$ | 0.491 | 0.493 | 0.499 | 0.508 | 0.499 | 0.498 |
| No. of obs. | 5309 | 5309 | 5309 | 5309 | 5309 | 5309 |
| Sargan test $p$-value | 0.274 | 0.131 | 0.424 | 0.389 | 0.156 | 0.463 |

*Notes*. Dependent variable: log W in all columns. Standard errors are shown in parentheses. In column (1), Com is instrumented by Computer use, Repetitive movements and the parental dummies (column (1) of Table 4). When regressing the instruments on the residual, they are all rejected at 10% except one mother dummy, which is marginally significant at 5%. Exogeneity is also strongly rejected. Column (2) is estimated using ComPCA, which is also instrumented as in column (1). When regressing the instruments on the residual, they are all rejected at 10%. Exogeneity is also strongly rejected. In column (3), log Pop and shareGraduates are instrumented by the population in 1936, the population in 1954, and the birth rate in 1990. When regressing the instruments on the residual, they are all rejected at 10%. Exogeneity is also strongly rejected. In column (4), we add the share of high-school graduates in 1968 to the instruments used in column (3). When regressing the instruments on the residual, they are all rejected at 10%. Exogeneity is NOT rejected for the share of university graduates. In column (5), log Pop and Com are instrumented by the population in 1936, the population in 1954, the birth rate in 1990, the share of high-school graduates in 1968, Computer use, and Repetitive movements. When regressing the instruments on the residual, they are all rejected at 10%. Exogeneity is also rejected (weakly for log Pop). In column (6), log Pop, Com and shareGraduates are instrumented by the population in 1936, the population in 1954, the birth rate in 1990, the share of high-school graduates in 1968, Computer use, and Repetitive movements. When regressing the instruments on the residual, they are all rejected at 10%. Exogeneity is NOT rejected for the share of university graduates. All coefficients significant at the 1% level, except:

[a] significantly different from zero at the 5% level,
[b] significantly different from zero at the 10% level,
[ns] non-significant.

same result holds for the alternative communication index in column (2) under the same instrumentation strategy. Note that these two IV estimations pass Sargan specification tests on over-identifying restrictions. Consistent with this, when regressing the residuals on the instruments, they were all rejected (except for one parental occupation dummy) confirming the orthogonality of our instruments. Finally, a Hausman specification test led to us to strongly reject the exogeneity of communication. Columns (3)–(6) report further IV estimations results which are commented on below.

These results show that in our separate OLS estimations, the residuals of the communication and earnings equations are negatively correlated. This finding suggests that the bias is not about communication being positively determined by earnings but that instead there is a negative correlation between unobserved social abilities and unobserved productive abilities. Our interpretation is that there are some workers who both communicate a lot at the workplace and are poorly productive.

To conclude on the earnings equation, it is worth noting that, despite the presence of communication variables, our results for the other coefficients are not very different from those obtained in the literature. Because he is also using the share of higher-education graduates to capture the external effects of human capital, we can directly compare our results with those of Moretti [33] who uses US wage data and Moretti [35] who is doing a similar exercise with production functions. We find that a one point increase in higher-education graduates increases wages between 0.3 and 0.7% whereas Moretti [33] obtains estimates ranging between 0.4 and 1.9% and Moretti [35] is between 0.4 and 0.9% for output per worker. Because they are using slightly different explanatory variables for urban schooling, a direct comparison with Rauch [36], Adserà [2], or Simon and Nardinelli [40] is more difficult. Nonetheless, they also find external returns to education being between 30 and 100% of the private returns.

### 4.5. Communication externalities

What about the effects of communication externalities on earnings? From the OLS estimates and using column (1) of Table 2 and column (1) of Table 3, a log point increase in city population increases individual communication by 0.443. In turn, this implies an increase of $0.443 \times 0.0049 = 0.0022$ log point for the wage. This corresponds to a wage increase of about 0.2%. At the same time, the coefficient on city size in the earnings equation, which measures the direct effect, is at 1.9%. Put differently, about 10% of the benefits of city size (i.e., $0.2/(1.9 + 0.2)$) percolate through communication. Turning to the share of higher-education graduates, a percentage point increase in the local fraction of graduates increases communication by 0.178, which implies a wage increase of 0.09%.[21] In the earnings equation, the total effect of a point increase in the share of graduates is 0.46%. This implies that about 17% of the external returns to education permeate through communication.[22] We can average these two figures for communication externalities on the ground that the effects of city size and those of average education on earnings are quantitatively

[21] The standard error on this coefficient can be calculated. It is significant at 5% just like that on city size.

[22] There is also an indirect effect of these communication externalities. A greater share of graduates and/or a larger population increase the human capital of all workers through communication externalities. In turn, more

roughly similar.[23] Under OLS, we thus find that about 13% of agglomeration effects can be traced through communication.

If we perform the same computation on our IV results (using columns (1) of Tables 2 and 5), we find that 16% of the effect of a larger city size and 28% of the effect of a more educated city permeate through communication. The effects are larger because of the larger estimates for the effect of communication on wages. Averaging these two numbers, we find that around 22% of agglomeration effects percolate through communication.

## 5. Further robustness tests

Several estimation issues were left aside above. They regard the imperfect substitutability across workers, the spatial sorting of workers, and the possible endogeneity of city characteristics. Let us discuss them in turn.

### 5.1. Imperfect substitutability across workers

As highlighted by Ciccone and Peri [11] and Moretti [33,34], the wage of unskilled workers can increase with the relative supply of skilled workers for reasons unrelated to human capital externalities. Instead of assuming perfect substitutability across workers (as we implicitly do above), we can assume only imperfectly substitutability across workers in the local production function. Then, it is easy to show that wages can on average increase with the relative supply of skilled workers (Moretti [34]). Put differently, a positive coefficient on the share of graduates in the earnings equation could reflect imperfect substitutability across workers rather than some external effects of human capital.

To help us distinguish between these two explanations, note that imperfect substitutability across workers also predicts that the wage of skilled workers should decrease with their relative local supply. Like Moretti [33], it is possible to estimate earnings equations for the most and least educated workers separately. If the coefficient on the local share of graduates is still positive for the most educated workers, this implies that the positive effect of human capital externalities more than offsets the negative effect of the increase in their relative supply.

The results are reported in Table 6 for the OLS and the IV estimates. As expected, the results show that the coefficient on the share of higher-education graduates is higher than in the baseline for the bottom three educational attainments and lower for the top three. This coefficient on the share of graduates, when estimated with only the most educated workers, is still large at 0.33 for the OLS although it captures the negative effect of the higher relative supply of skilled labour.[24] Interestingly the other coefficients such as those

human capital has a positive effect on output through the other externalities. This indirect (or combined) effect is, however, very small because the effects of average communication are only about a third of those of individual communication.

[23] Ceteris paribus, the earnings effect of moving from the least educated city to the most educated is about the same as moving from the smallest to the largest.

[24] The coefficient on the share of graduates is 0.13 when communication is instrumented but the exogeneity of communication is not rejected in this regression.

Table 6
Separate earnings equations for most and least educated workers

| log W: Regressors: | Educ1–3 (1) OLS | Educ1–3 (2) 2SLS | Educ4–6 (3) OLS | Educ4–6 (4) 2SLS |
|---|---|---|---|---|
| Intercept | 1.132 | 1.322 | 2.337 | 2.381 |
| | (0.163) | (0.144) | (0.117) | (0.111) |
| Gender | −0.211 | −0.199 | −0.212 | −0.208 |
| | (0.017) | (0.016) | (0.011) | (0.011) |
| Educ1 | 0.380 | 0.372 | | |
| | (0.021) | (0.024) | | |
| Educ2 | 0.144 | 0.130 | | |
| | (0.019) | (0.020) | | |
| Educ4 | | | 0.074 | 0.031[a] |
| | | | (0.014) | (0.016) |
| Educ5 | | | 0.040[a] | 0.027[ns] |
| | | | (0.018) | (0.018) |
| Age | 0.093 | 0.088 | 0.041 | 0.037 |
| | (0.0072) | (0.0072) | (0.0050) | (0.0050) |
| $Age^2$ | −0.00079 | −0.00073 | −0.00033 | −0.00029 |
| | (0.000089) | (0.000090) | (0.000059) | (0.000059) |
| **Com** | **0.0035** | **0.0056** | **0.0057** | **0.0088** |
| | (0.0005) | (0.0011) | (0.00032) | (0.00054) |
| Rural | 0.241 | 0.272 | 0.189 | 0.204 |
| | (0.065) | (0.061) | (0.051) | (0.050) |
| Suburb | 0.236 | 0.274 | 0.216 | 0.227 |
| | (0.072) | (0.067) | (0.056) | (0.055) |
| **log Pop** | **0.020** | **0.023** | **0.018** | **0.019** |
| | (0.0053) | (0.0048) | (0.0046) | (0.0045) |
| **meanCom** | **0.0049** | | **0.00043**[ns] | |
| | (0.0015) | | (0.00086) | |
| **shareGraduates** | **0.323**[a] | **0.133**[ns] | **0.564** | **0.443** |
| | (0.165) | (0.158) | (0.136) | (0.134) |
| Adj. $R^2$ | 0.589 | 0.587 | 0.332 | 0.320 |
| No. of obs. | 1826 | 1826 | 3483 | 3483 |
| Sargan test $p$-value | – | 0.538 | – | 0.293 |

*Notes*. Robust standard errors are shown in parentheses. Com is instrumented by Computer use, Repetitive movements and the parental dummies (see column (1) of Table 4). When regressing the instruments on the residual, they are all rejected at 10% except one mother dummy that is significant at 5% in both cases. Exogeneity is not rejected from column (2). It is rejected from column (4). All coefficients significant at the 1% level, except:
[a] significantly different from zero at the 5% level,
[ns] non-significant.

on gender, age, or city size are very close to their baseline values for the whole sample. Furthermore, the coefficient on individual communication is higher for the less educated workers than for more educated workers whereas the coefficient on average communication is only significant for the more educated workers.

### 5.2. Spatial sorting

As noted long ago by Alfred Marshall [32]: "the large towns and especially London absorb the very best blood of all the rest of England; the most enterprising, the most highly gifted, those with the highest physique and strongest character go there to find scope for their abilities" (p. 199). Of course, what applies to London could certainly apply to Paris and the largest French cities. Such spatial sorting implies a positive correlation between the unobserved idiosyncratic component in the communication or earnings equation and city characteristics. Such correlation, if present, would bias our estimations.

To deal with this issue, note that our data contains some information about the birthplace of workers. This information is at the level of the 95 French 'départements', which cover the country. This is certainly not ideal but we should be able to detect spatial sorting (if any) through differences in outcomes between those who work where they were born (the 'stayers') and the others (the 'movers'). The results for these separate regressions are reported in Table 7.[25]

Columns (1) and (2) in Table 7 report the results for the communication equation for movers and stayers, respectively. Turning to earnings, columns (3) and (4) report OLS results for the two education groups, and columns (5) and (6) report IV results. The main conclusion we draw from this table is that despite some differences between movers and stayers, the above results on communication externalities are not driven by the sorting of workers with good unobserved communication and production abilities in the largest cities.

The differences between movers and stayers are nonetheless interesting. First movers tend to communicate more than stayers. Their average communication index is equal to 42.2 against 36.0 for stayers. These differences are explained to a large extent by the higher average educational attainments of movers (17% of movers are higher-education graduates as opposed to 6% of stayers) and their location in larger and more educated cities. From the communication equations, it also appears that the communication of stayers is more strongly influenced by the characteristics of their location. The coefficient on the share of graduates is nearly 50% higher for stayers whereas that on city size is nearly 100% higher. This stronger effect of the local environment on stayers suggests that the characteristics of the local environment are more important for workers who have been embedded in it for longer.

By contrast, the effects of city size and the local share of graduates on earnings are stronger for movers than for stayers. Hence movers appear to benefit more than stayers from more educated cities although their communication is less sensitive to the local environment. For movers and using OLS estimates, communication externalities represent only 16% of the effect of city education and 8% of the effect of city size, as opposed to 32% of the effect of city education and 12% of the effect of city size for the stayers. When using IV estimates, we find that communication externalities represent 28% of the effect of city education and 14% of the effect of city size for movers, as opposed to 48% of the effect of city education and 17% of the effect of city size for the stayers.

In conclusion we seem to have, on the one hand, good communicators who go to educated cities and benefit strongly from them. These good communicators, however, do not gain much from communication externalities. On the other hand, we have stayers with less

[25] We also tried to instrument the population and the share of graduates of the city of residence using the information about the birthplace and the occupation of the parents at birth. However, either the predictive power of these variables is very weak (parental occupation) or they are clearly rejected as instruments (characteristics of the place of birth).

Table 7
Separate earnings and communication equations for movers and stayers

| Regressors: | Com<br>Movers<br>(1) OLS | Com<br>Stayers<br>(2) OLS | log W<br>Movers<br>(3) OLS | log W<br>Stayers<br>(4) OLS | log W<br>Movers<br>(5) 2SLS | log W<br>Stayers<br>(6) 2SLS |
|---|---|---|---|---|---|---|
| Intercept | $-8.124^{ns}$ | $-12.839^{a}$ | 1.325 | 1.859 | 1.502 | 1.824 |
| | (7.248) | (6.115) | (0.163) | (0.122) | (0.149) | (0.115) |
| Gender | $-1.232^{b}$ | $-0.600^{ns}$ | −0.238 | −0.210 | −0.224 | −0.205 |
| | (0.751) | (0.604) | (0.015) | (0.011) | (0.015) | (0.011) |
| Educ1 | 38.199 | 37.847 | 0.571 | 0.507 | 0.427 | 0.457 |
| | (1.379) | (1.547) | (0.033) | (0.032) | (0.042) | (0.037) |
| Educ2 | 34.398 | 31.642 | 0.319 | 0.293 | 0.181 | 0.229 |
| | (1.400) | (1.218) | (0.032) | (0.026) | (0.040) | (0.030) |
| Educ3 | 28.429 | 24.014 | 0.201 | 0.173 | $0.086^{a}$ | 0.126 |
| | (1.423) | (1.169) | (0.032) | (0.024) | (0.037) | (0.027) |
| Educ4 | 17.566 | 11.512 | 0.091 | 0.098 | $0.024^{ns}$ | 0.075 |
| | (1.160) | (0.906) | (0.025) | (0.018) | (0.028) | (0.018) |
| Educ5 | 8.341 | $2.425^{a}$ | $0.012^{ns}$ | $0.032^{ns}$ | $-0.020^{ns}$ | $0.027^{ns}$ |
| | (1.533) | (1.191) | (0.032) | (0.023) | (0.032) | (0.023) |
| Age | 1.057 | 1.119 | 0.075 | 0.069 | 0.071 | 0.066 |
| | (0.331) | (0.269) | (0.0068) | (0.0051) | (0.0068) | (0.0059) |
| $\text{Age}^2$ | −0.011 | −0.011 | −0.00064 | −0.00063 | −0.00060 | −0.00059 |
| | (0.0039) | (0.0033) | (0.000081) | (0.000062) | (0.000080) | (0.000063) |
| **Com** | | | **0.0055** | **0.0045** | **0.0097** | **0.0066** |
| | | | (0.00044) | (0.00035) | (0.00080) | (0.00063) |
| Rural | $0.957^{ns}$ | $2.711^{ns}$ | 0.251 | $0.091^{ns}$ | 0.247 | 0.182 |
| | (2.962) | (3.124) | (0.061) | (0.059) | (0.061) | (0.049) |
| Suburb | $3.236^{ns}$ | $3.643^{ns}$ | 0.241 | $0.135^{a}$ | 0.235 | 0.227 |
| | (3.303) | (3.340) | (0.068) | (0.063) | (0.065) | (0.060) |
| **log Pop** | $\mathbf{0.337}^{b}$ | $\mathbf{0.583}^{a}$ | **0.020** | $\mathbf{0.011}^{a}$ | **0.019** | **0.018** |
| | (0.201) | (0.275) | (0.0051) | (0.0050) | (0.0048) | (0.0049) |
| **meanCom** | | | **0.0040** | $\mathbf{0.00038}^{ns}$ | | |
| | | | (0.0013) | (0.00090) | | |
| **shareGraduates** | $\mathbf{14.692}^{b}$ | **21.913** | **0.521** | $\mathbf{0.310}^{a}$ | **0.380** | $\mathbf{0.257}^{b}$ |
| | (8.030) | (7.342) | (0.167) | (0.141) | (0.159) | (0.139) |
| Adj. $R^2$ | 0.365 | 0.334 | 0.515 | 0.423 | 0.509 | 0.427 |
| No. of obs. | 2260 | 3049 | 2260 | 3049 | 2260 | 3049 |
| Sargan test $p$-value | – | – | – | – | 0.451 | 0.613 |

*Notes*. Standard errors are shown in parentheses. Com is instrumented by Computer use, Repetitive movements and the parental dummies (see column (1) of Table 4). Exogeneity is strongly rejected in both cases. One parental dummy is marginally significant at 10% in the estimation column (5). All coefficients significant at the 1% level, except:

[a] significantly different from zero at the 5% level,
[b] significantly different from zero at the 10% level,
[ns] non-significant.

favourable characteristics who are able to benefit more from communication externalities. This interesting feature does not, however, modify greatly our previous conclusions.[26]

[26] Even if sorting accounted for all our results, one would still need to explain why ‘good communicators’ cluster in large cities. If this were because they want to communicate more and these places offer opportunities

### 5.3. City level characteristics

That city characteristics could be simultaneously determined with earnings is a frequent worry in the literature (Moretti [33,34], Ciccone and Peri [11]). For instance, it could be the case that the provision of education is biased with high-wage cities offering more and better education. This channel could explain a positive correlation between earnings and the local share of graduates. This is a serious worry in countries with decentralised education systems. In France however, primary and secondary education are both managed by the central government. The curriculum is the same everywhere and class size and resources spent per pupil are equalised. Hence strong biases at the level of primary or secondary education are unlikely.

The case of higher education is subtler. France has a two-tier system with (non-selective) universities and (highly selective) 'grandes écoles'. Universities have a local catchment area at the bachelor level and funding per student across universities is also equalised. Nonetheless, it is true that Parisian universities tend to be more prestigious. Whether the more distinguished professors in Parisian universities are enough to create a large bias in the accumulation of human capital at the bachelor level is doubtful. Then, universities have a national recruitment at postgraduate level. The recruitment of most grandes écoles is also national in scope. However, any effect here should be part of the spatial sorting bias already explored.

One may also argue that city size is endogenous to wages. As shown by Eaton and Eckstein [15], French cities have experienced mostly parallel population growth over the last 200 years making it difficult to argue for large simultaneity bias. To corroborate this, Ciccone [10] instruments the population of French départements in his analysis of agglomeration effects in Europe and finds only weak endogeneity problems.

Nonetheless, to investigate this further in columns (3) to (6) of Table 5, we instrument the local share of graduates and city size with lagged population (1936 and 1954), the birth rate in 1990, and the share of high-school graduates in 1968. The results confirm our priors. We find some (weak) evidence of endogeneity of city size but the exogeneity of city education is far from being rejected as soon as we introduce education in 1968 in our set of instruments. Notwithstanding this issue, the results about communication are in line with what we found previously. The only difference is that after instrumenting for city population, its coefficient in the earnings equation increases by about 50% whereas that of the share of graduates declines by the same amount and becomes insignificant.

## 6. Conclusions

This paper addresses the issue of the external returns to human capital in cities. We focus on one particular channel through which human capital externalities are often alleged to

(or a lower cost) to do so, the spirit of our results would not be modified. More serious would be the case of an omitted ability bias such that (i) it makes workers more efficient, (ii) it is correlated with large city location, and (iii) it leads workers to communicate more in a world where (iv) communication plays no productive role. However, it is unclear to us which plausible model could satisfy these four conditions.

percolate: communication externalities at the workplace. To estimate such externalities, we use a unique French data set, which surveys workplace communication for around 6000 workers in 1997. This allows us to estimate both a communication equation and an earnings equation. Our main result is that up to 22% of the effects of a larger and more educated city percolate through communication.

These conclusions indicate three directions for future research. First, we are yet to explore the full richness of our data. These findings, based on an aggregate communication index, warrant further research into the details of the different media being used, the workers involved, the type of communication taking place and how location matters with respect to these issues. Charlot and Duranton [9] take some steps in this direction. The analysis of workplace communication could also be enriched by looking at firms rather than workers. Second, note that this paper makes some progress towards the identification of one channel through which human capital externalities are often argued to permeate. It also proposes a quantitative assessment of its importance, taking into account the possible endogeneity of communication. We also took small steps to deal with the possible endogeneity of workers' location. Future work should be doing more on this aspect. Furthermore, the issues surrounding the endogeneity of firm location should also be dealt with. Third, channels other than (or related to) communication should be explored in more details. In particular and with respect to city size and average urban schooling, the benefits of labour market pooling and input-output linkages should receive more attention.

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## Appendix A. Data description

### *A.1. The COI data*

The basic data is from the 1997 "Changement Organisationnel et Informatisation" (COI) survey. This data is composed of four different business surveys matched with one labour force survey. The first business survey (manufacturing) and the workforce survey for the associated workers were conducted by the French Ministry of Industry. The second (food industry) was conducted by the French Ministry of Agriculture, while the last two surveys (DIY chains and accountants) were carried out by INSEE (French National Institute for Statistics and Economics Studies). The conception of the business survey in manufacturing, that of the labour survey, and the coordination of the four surveys were directed by Nathalie Greenan at the Centre d'Etudes de l'Emploi at the French Ministry of Labour.

This firm/employee matched survey is mostly concerned with organisational change and information technologies. This data was later on matched with the Déclaration Annuelle Des Salaires (DADS) and with Enquête Annuelle d'Entreprises (EAE) also from INSEE. The DADS data is collected for fiscal purpose. It is exhaustive on all French salaried workers and contains information about employment and earnings. Furthermore, for all workers born in October of even years (those selected for COI), it also contains a wealth of personal characteristics. The EAE survey is also exhaustive for all firms with more than 20 employees. It contains firm level data.

Initially 4025 representative firms were selected from general manufacturing (2541), the Food industry (478), accounting firms (734), and DIY shops (272). Within each group (general manufacturing, food industry, accounting, DIY), firms were randomly drawn among those with 50 or more employees.

Interviewers went to interview directly 1, 2 or 3 randomly chosen employees in each selected firm. When it was impossible to meet face-to-face with an employee, the interviewers did the survey on the phone. A total of 8812 employees were initially drawn. In total, 6157 employee questionnaires were obtained from 3153 firms. The 30% of non-respondents include employees who refused to respond (about 9%), those who could not be found by the interviewers (11%) and those who had left their firm by the end of the year (9%) and could not subsequently be matched with the DADS data. Further details on the data can be found in Greenan and Mairesse [25] and Greenan and Hamon-Cholet [23,24].

After deleting observation for which a key individual characteristic (age, birthplace, etc.) was missing, we were left with 5958 observations. Finally after deleting observations for which one or more communication answer were missing, we were left with 5463 observations. Among them, the wage or some essential firm level information (industry or firm size) is unknown for 154 observations. The earnings and communication equations are thus estimated using 5309 observations.

### *A.2. Location data*

Using postcode data at the establishment level, this survey was matched to a set of spatial units. Metropolitan France contains 361 urban areas where employment is at least 5000. The rest of the country is classified into different levels of 'peri-urban' (i.e., remote suburban) and rural areas. For simplicity, outside urban areas we only distinguish suburban from rural areas.

Note that the French definition of urban areas in this typology is rather broad and matches rather closely that of (consolidated) metropolitan areas in the US except that the threshold is much below (5000 jobs instead of 100,000 inhabitants). As a consequence the definition of suburban area is rather restrictive and narrow. A 'suburban' area in this typology is usually a rather remote ring around an urban area (a.k.a. ex-urban or peri-urban). Unfortunately, because a significant fraction of these remote suburban areas are functionally linked with two or more cities, they cannot be matched easily to particular adjacent urban areas. Urban areas contain about 60% of the French population and 70% of

French employment. 65% of the observations are located in urban areas. This slight urban under-representation is due to the over-representation of the food industry whose location is often rural. Suburban areas account for around 10% of the observations. Finally, 25% of the observations are located in rural areas.

### *A.3. The communication questions*

The employee questionnaire contains around 80 questions covering a wide range of topics about working conditions, organisational change and information technologies. Regarding communication, the most relevant questions are:

- 30. Are you in contact (face-to-face or telephone) with customers? (All the time/Regularly/At times/Never).
- 31. Except for your subordinates (if any), do you give instructions to the following persons about their work?
  - a/ Colleagues with whom you are usually working: Yes/No/Not Applicable.
  - b/ Others, working for the same firm: Y/N/NA.
  - c/ Others, working for another firm (customer, supplier, etc.): Y/N/NA.
- 32. Except for your superior(s), do you receive instructions from the following persons about your work?
  - a/ Colleagues with whom you are usually working: Y/N/NA.
  - b/ Others, working for the same firm: Y/N/NA.
  - c/ Others, working for another firm (customer, supplier, etc.): Y/N/NA.
- 34. How do you receive important instructions about your work?
  - a/ Face-to-face communication: Y/N.
  - b/ Telephone: Y/N.
  - c/ Paper (including fax, telex, etc.): Y/N.
  - d/ Computer (electronic mail, etc.): Y/N.
- 40. Do you do some of your work in a team? Y/N.
- 40b. If yes, are you involved with the following?
  - i/ Colleagues from the same unit: Y/N.
  - ii/ Others, from the same firm: Y/N.
  - iii/ Others, external from your firm: Y/N.
- 40c. If yes, what type of work is concerned? Conception (or design, or research)/ Production.
- 52. Do you use ever a PC or a workstation at work? Y/N.
- 55. Do you use information technologies to search for information? Y/N.
- 68. Do you use internet at work? Y/N.
- 69. Do you use an intranet at work? Y/N.

### *A.4. The individual communication indices*

The answers to all binary questions were coded 1 for yes and 0 for no. Answers to questions 30 were coded 3 for the highest level of communication, 2, 1, and 0 for the lowest. Our main index, Com, is a sum of the score on all the above questions except those on internal communication (i.e., questions 30, 31c, 32c, 34a–d, 40b(iii), 40c, 52, 55, 68 and 69) normalised to be between 0 and 100.

We considered a variety of alternatives such as a similar index without the questions on the media (i.e., without 52, 55, 68, and 69) on the ground that they could apply mostly to internal communication. The correlation with Com is 0.96. If, on the contrary, we add to Com the questions on internal communication the correlation is 0.93. Of particular interest is an index of weighted communication Com_b. To construct it, we gave an equal weight to the following five dimensions:

- Communication internal to the firm (sum 31a, 31b, 32a, 32b, 40b(i), and 40b(ii)).
- Communication external to the firm (sum of 31c, 32c, and 40b(iii)).
- Intensity of communication (30).
- Media (sum of 34a, b, c, d, e, 52, 55, 68, and 69).
- Involvement in creative activities with others (40c).

The correlation with Com is 0.90. Finally we also constructed a communication index using the first eigenvector of a principal component analysis performed on all communication questions (ComPCA). The correlation with Com is 0.91 (see Charlot and Duranton [9] for details on this principal component analysis).

### *A.5. The area communication index*

The variable measuring average communication is the weighted mean city communication $\text{meanCom}_i$. It is constructed from our individual data in the following way. In each city, we summed across educational attainments (denoted $g$), the product of their 1999-census shares of workers ($s_i(g)$) by their empirical mean level of communication ($\text{Com\_b}_i(g)$):

$$\text{meanCom}_i = \sum_{g=1}^{6} s_i(g)\text{Com\_b}_i(g). \tag{A.1}$$

Note that we use Com_b rather than Com to construct aggregate communication. There are two reasons for doing that. First, we think that Com_b (which includes internal communication) better reflects total communication in a city. Second, it reduces possible collinearity problems when both individual and city communication are used together in earnings equations. Note also that in small cities, we sometimes have no observation for some educational attainments. To fill the blanks and using all the observations we have for the city, we computed the following communication ratio:

$$q_i = \sum_{g=1}^{6} \left[ \frac{n_i(g)}{n_i} \frac{\text{Com\_b}_i(g)}{\text{Com\_b}(g)} \right], \tag{A.2}$$

where $n_i(g)$ is the number of workers in the sample with educational attainment $g$ in city $i$, $n_i$ is the sampled population in city $i$, and $\text{Com\_b}(g)$ is the national mean for workers of educational attainment $j$. We then proxied $\text{Com\_b}_i(g)$ by $q_i\text{Com\_b}(g)$.

Because we use the local census shares for each educational attainment, this index avoids sample selection biases for the composition of educational attainment for small urban areas for which we have no more than a handful of observations. Note finally that the correlation between meanCom and Com is low at 0.15.

### A.6. Working conditions variables

To instrument for the possible endogeneity of workplace communication, we use data regarding working conditions:

- *Computer use*: number of hours spent daily in front of a computer.
  (The information is coming from Question 79: How many hours do you spend in front of your computer if at all? Hours per week on average.)
- *Repetitive movements*: whether the position occupied by the worker involves the repetition of the same movement(s).
  (Question 43. Does your work involve the continuous repetition of the same series of movements and/or operations? Y/N.)

### A.7. Other variables

The COI data contains 14 possible levels of educational attainment. Given the small population in some cells and the lack of discernible wage differences between some cells, we aggregated these 14 categories into the six, which are used by the French census.

- Educ1: university graduates (a degree involving at least three years of higher education).
- Educ2: college graduates (two years of higher education).
- Educ3: high-school graduates.
- Educ4: vocational school graduates.
- Educ5: junior high-school graduates.
- Educ6 (our reference): no degree (early school dropout).

The variable shareGraduates was constructed from the 1999 census. It reports the share of the population in each area with our two highest levels of educational attainments (Educ1 or Educ2).

To distinguish retail (DIY) and accounting firms from manufacturing, we created two dummy variables:

- *Accounting* for workers employed in accounting firms.
- *Retail* for workers employed in DIY firms.

Workers in manufacturing are used as the reference.

The earnings variable, $W$, refers to the net annualised earnings received by the employee. It comes from the DADS data. This data is collected from all employers (and self-employed) in France for pension, benefits and tax purposes. A report must be filled by every establishment for each of its employees so that there is a unique record for each employee-establishment-year combination. The mandatory aspect of this data and its importance for the workers is a guarantee of its quality.

The occupational dummy *Non-routine* was created from the detailed information in the COI data about the occupation. We classified as 'non-routine' all jobs that *a priori* involve some autonomy for the employee. All other occupations were classified as 'routine'. Among non-routine jobs, we have functions such as: sales, management, accounting, research, teaching, etc whereas we classified as routines functions like cleaning, production, domestic work, handling of goods, etc. This distinction attempts to generalise the usual white collar/blue collar opposition in manufacturing.

We exploited the information about the place of birth (at the level of the 95 French départements—these units are comparable to counties in the UK or the US) and the place of work. If someone works in the département he or she was born, this person is classified as a stayer. Otherwise, this person is a mover. In our sample, we have 44% of movers and 56% of stayers. We also used data from the 1990 census to compute population density in the place of birth in 1990 and the local share of higher education graduates. We also used the 1968 census to compute the lagged values of the local shares of higher-education graduates. The 1936 and 1954 population by areas were computed from the 1988 'inventaire comunal' (census of local authorities).

The occupational status of the father and mother at birth is also coming from the COI data. Occupations are classified according to the one-digit French classification of occupations, which contains eight entries (inactive/student, unskilled blue-collar, skilled blue-collar, white-collar employee, self-employed, intermediate profession, professional, apprentice).

## Appendix B. Communication externalities vs. other human capital effects in cities

The model below shows that *not all human capital externalities can be interpreted as communication externalities.* Instead, more human capital in a city can generate both stronger communication externalities and stronger other human capital externalities unrelated to communication, which we model here as an input sharing mechanism.[27]

### *B.1. Urban scale effects unrelated to communication externalities*

We use a standard Dixit and Stiglitz's [12] model of monopolistic competition that we embed in an urban framework. Final good producers use intermediate goods produced by differentiated suppliers to produce a homogeneous consumption good under constant

[27] We build on a specific model wherein input sharing between final producers implies increasing returns at the city level. Similar results can be obtained with any alternative source of local increasing returns that does *not* rely on communication externalities. See Duranton and Puga [14] for a survey of the different microeconomic foundations of urban increasing returns. Our preference for input-sharing as opposed to, say, matching is that the former mechanism naturally benefits all workers symmetrically whereas it is more difficult to conceive how a larger fraction of skilled workers in a city could help the matching of unskilled workers to jobs.

returns to scale. This final good, which also serves as numéraire, can be traded across cities at no cost. By contrast, intermediates cannot be traded across cities so that final good producers can only buy from intermediate producers located in the same city. Final producer $k$ in city $i$ produces according to:

$$y_k = \left[ \int\limits_{z \in i} q_k(z)^{(\sigma-1)/\sigma} \, \mathrm{d}z \right]^{\sigma/(\sigma-1)}, \quad \sigma > 1, \tag{B.1}$$

where $q_k(z)$ is the quantity of intermediate $z$ bought by $k$, $\sigma (> 1)$ is the elasticity of substitution across intermediates, and the notation $z \in i$ denotes any (intermediate producer) $z$ located in city $i$. After denoting by $p(z)$ the price of intermediate $z$, final producer $k$'s profit is given by:

$$\pi_k = y_k - \int\limits_{z \in i} p(z) q_k(z) \, \mathrm{d}z. \tag{B.2}$$

Intermediate goods are produced by monopolistically competitive firms. To produce any variety of intermediates, there is a fixed labour overhead to start production and a constant quantity of labour is needed for each marginal unit. Employment in firm $z$, expressed in *effective* units of labour, is thus:

$$l(z) = \beta q(z) + \alpha. \tag{B.3}$$

Denoting by $w_i$ the wage rate in city $i$, the profit of intermediate producer $z$ in city $i$ is:

$$\pi(z) = p(z) q(z) - w_i \big[ \beta q(z) + \alpha \big]. \tag{B.4}$$

To solve the model, note first that profit maximisation by final producer $k$ implies:

$$p(z) = \frac{q_k(z)^{-1/\sigma} y_k}{\int_{z \in i} q_k(z) \, \mathrm{d}z}. \tag{B.5}$$

Since intermediates cannot be traded across cities, summing over all final producers in the city yields the inverse-demand faced by intermediate producer $z$. This can be inserted into the profit of $z$ given by Eq. (B.4). Profit maximisation by intermediate producers then implies that the price of intermediates, $p(z) = \sigma \beta w_i (\sigma - 1)$, is a mark-up over marginal cost and is independent of total market size. Then under free entry in the production of intermediates, the output of any intermediate producer is independent of market size: $q(z) = \alpha(\sigma - 1)/\beta$. After denoting by $L_i$ total *effective* labour supply in city $i$, total output is then given by:

$$Y_i = \frac{(\sigma - 1)}{\alpha^{1/(\sigma-1)} \beta \sigma^{\sigma/(\sigma-1)}} L_i^{\sigma/(\sigma-1)} \equiv \Phi L_i^{\sigma/(\sigma-1)}. \tag{B.6}$$

Finally, clearing on the labour market and free entry for final producers imply that final output is fully dissipated in the wage bill. This yields the following wage rate:

$$w_i = \Phi L_i^{1/(\sigma-1)}. \tag{B.7}$$

This wage increases with city size. A larger workforce in a city leads to a wider range of local intermediates being produced for final good production. Since these intermediates enter the production function of final good producers with the same constant elasticity of substitution a wider range of intermediates results in final output rising more than proportionately. Hence, despite constant returns to scale at the firm level in final production, there are aggregate increasing returns working through this pecuniary externality. The strength of these aggregate increasing returns decreases with the elasticity of substitution between intermediates.

### *B.2. Human capital in cities*

The effective labour supply of worker $j$, denoted $l_j$, is a function of her human capital, $h_j$. Then, aggregate effective labour supply in city $i$, $L_i$ is the sum of the effective labour supply of all workers living in the city. Specifically:

$$L_i = \sum_{j \in i} l_j, \tag{B.8}$$

where $l_j = \mathrm{e}^{h_j}$. In turn, the human capital of worker $j$ living in city $i$, $h_j$, is a linear function of her formal/codified knowledge measured by education and labour market experience, $s_j$, her informal/tacit knowledge measured by her volume of communication, $x_j$, and some unobserved productivity shock, $\epsilon_j$:

$$h_j = \delta s_j + \gamma x_j + \epsilon_j. \tag{B.9}$$

The idiosyncratic shocks, $\epsilon$, are assumed to be normal and i.i.d.

The labour market earnings of worker $j$ living in city $i$, $W_j$ are equal to $w_i l_j$. After inserting (B.8) and (B.9) into (B.7), we obtain:

$$W_j = \Phi \left( \sum_{g \in i} \mathrm{e}^{\delta s_g + \gamma x_g + \epsilon_g} \right)^{1/(\sigma - 1)} \mathrm{e}^{\delta s_j + \gamma x_j + \epsilon_j}. \tag{B.10}$$

When $\delta s$ and $\gamma x$ are small, a Taylor expansion implies

$$\log W_j \approx \log \Phi + \frac{1}{\sigma - 1} (\log N_i + \delta \bar{s}_i + \gamma \bar{x}_i + \bar{\epsilon}_i) + \delta s_j + \gamma x_j + \epsilon_j, \tag{B.11}$$

where $N_i$ is the population in city $i$. By the law of large numbers $\bar{\epsilon}_i = 0$ so that $\delta \bar{s}_i + \gamma \bar{x}_i$ is the average human capital in city $i$. According to (B.11), individual earnings increase with the individual effective labour supply. In turn, the latter is determined by individual characteristics (i.e., skills, $s_j$, communication, $x_j$, and the unobserved random component, $\epsilon_j$). At the same time, earnings are also influenced by city aggregates. Because of input sharing, earnings are higher in cities where aggregate effective labour supply is higher, that is where workers are more numerous, more skilled, and communicate more (i.e., higher $N_i$, $\bar{s}_i$, and $\bar{x}_i$, respectively).

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