SOCIAL RETURNS TO EDUCATION: EVIDENCE FROM ITALIAN LOCAL LABOUR MARKET AREAS

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1. Introduction

The idea that individuals do not entirely capture the benefits from their education is used to argue that governments should subsidize schooling. There are several explanations why social returns to education may exceed private returns. For example, a high level of average human capital may favour the diffusion of knowledge among workers, as in Lucas (1988), or make it profitable to invest in new technologies, as in Acemoglu (1996, 1997), or even generate effects that go beyond the domain of economics.[1] Even though there are good theoretical reasons to believe in education externalities, empirical evidence is surprisingly mixed. By using cross-country data, Barro (1991), Mankiw *et al.* (1992) and others find schooling to be positively correlated with the per capita GDP growth rate. But Bils and Klenow (2000) argue that the impact of schooling on growth is likely to be modest and that growth is expected to cause school enrolment. A recent and fast-developing body of literature adopts a Mincerian wage-equation approach to detect human capital spillovers in US local labour markets. But again, while Rauch (1993) and Moretti (2002) find evidence for substantial social returns to education, Acemoglu and Angrist (2000) and Ciccone and Peri (2002) claim that such returns are negligible.

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[1] According to Weisbrod (1962, p. 106): "[Education] benefits the student's future children, who will receive informal education at home; it benefits neighbours who may be affected favourably by the social values developed in children by schools and even by the quietness of the neighbourhood while the schools are in session. Schooling benefits employers seeking a trained labour force; and it benefits society at large by developing the basis of an informed electorate".

Our paper follows the Mincerian approach to quantify social returns to education in Italian local labour markets.[2] We also ask whether social returns change between the Centre-North and the South of Italy, since these areas are characterized by different levels of development.

Rauch (1993) used 1980 US Census data, treating average schooling as pre-determined. He found that a one-year increase in Metropolitan Area (MA) average education raised wages by 3 to 5 per cent. The existence of social returns to education has been confirmed by Moretti (2002), who exploits both 1979-94 NLSY and 1980-1990 Census data and elects the share of college graduates in an MA as the measure for average education. He also accounts for endogeneity in average education (while treating individual schooling as exogenous) by using the lagged city demographic structure as an instrument, and finds social returns ranging from 8 to 13 per cent. The findings in Rauch (1993) and Moretti (2002) are questioned by Acemoglu and Angrist (2000), who find no evidence for social returns in US states. Their instrumental variable strategy for both average and individual schooling in 1960-1990 Census data exploits differences in compulsory schooling and child-labour laws across states. Acemoglu and Angrist's results have been confirmed by Rudd (2000), who controls for a variety of state-level variables that may affect wages. Ciccone and Peri (2000) develop an approach that separates pure human capital spillovers from wage effects due to changes in the labour-force composition. They also find no evidence for social returns to average education in US MAs.

The conclusions on education externalities may rely on the definition of territorial unit adopted. Our analysis on Italian data exploits a definition of local labour market that is consistent with the notion of 'functional region'. A functional region is defined as "a territorial unit resulting from the organization of social and economic relations in that its boundaries do not reflect geographical particularities or historical events" (OECD, 2002, p. 11). In particular, a functional region is related to its local labour market,

2 The Mincerian approach evaluates social returns to education by simply looking at wage differences across areas. This strategy has two main limits, which tend to bias the size of actual spillovers downwards. First, average human capital may have effects that go largely beyond the boundaries of the local labour market. For example, research at the MIT can have nation-wide, or even world-wide effects, while affecting differential productivity in the Boston area only marginally. Second, Haveman and Wolfe (1984, 2002) have argued that wage differences capture only a portion (and possibly a small portion) of the full 'social' effects of education. For example, reductions in criminal activity due to schooling may generate both higher average productivity and non-market effects such as higher social cohesion. The Mincerian approach will only capture the productivity-effect on wages of less criminality.

defined in terms of commuting conditions.[3] As Lucas (1988) pointed out, the effects of average skill on the productivity of each worker have to do with "the ways various groups of people interact, which may be affected by political boundaries but are certainly an entirely different matter conceptually" (p. 37). The studies on US data we mentioned use two types of territorial units: (i) states, as in Acemoglu and Angrist (2000), and Rudd (2000) and, (ii) MAs, as in Rauch (1993), Moretti (2002) and Ciccone and Peri (2002). US states hardly fit the notion of local labour market.[4] MAs are not defined by mere administrative boundaries, but their categorization is based on their urban character rather than their labour market features (OECD, 2002, pp. 122-126). Here we adopt the OECD definition of Local Labour Market Area (LLMA). LLMAs are built through the aggregation of two or more neighbouring municipalities, characterized on the basis of daily travel flows from place of residence to place of work. The 784 Italian LLMAs (140 in the North-West, 143 in the North-East, 136 in the Centre, and 365 in the South, respectively) span the whole of the territory.[5]

Another significant difference between the Italian and the US case is variance in school quality. The Italian education system is more centralized and egalitarian, with low variability of education quality across areas. By contrast, the US exhibits high heterogeneity in school quality, since the education system is mostly financed at the local level, or is private.[6] Card and Krueger (1992a, 1992b, 1996) show that the effects of school quality on private returns to education are substantial. Therefore, the omission of measures for school quality heterogeneity across US areas may also bias the estimate of the social returns to human capital. The problem caused by this omitted variable, however, is likely to be much less serious for Italian data.

Our results show that LLMA average human capital is positively correlated with wages. In particular, we find that social returns range from 2 to 3 per cent. These results are robust to an instrumental variable approach designed to deal with the bias that may arise from the correlation between average schooling and omitted LLMA characteristics. Moreover,

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[3] For the relevance of commuting in the definition of local labour markets, see also Manning (2003).

[4] As noted by Bils (2000, p. 60), "particularly for models based on externalities in production, it is not clear if the state of residence is the relevant economy".

[5] A detailed description of territorial units (MA and LLMA, respectively) is given in the Appendix.

[6] See OECD (2001) and Checchi *et al.* (1999) for a thorough comparison. On the role of school quality see also Borjas (1995) and Bénabou (1996).

by analyzing the sub-sample of those who have not moved away from their area of birth, we also conclude that our results are not likely to be driven by selective migration.

We extend the basic analysis in three main respects. First, we test the robustness of our result by restricting our sample to manufacturing workers. This also allows us to introduce additional controls into our basic specification. Second, we investigate whether aggregate human capital has asymmetric effects on the wage of workers of different education. Third, we show that social returns tend to be higher for LLMAs located in the backward areas of the South of Italy, which display lower levels of average human capital. Finally, we analyze the role of social returns for the industrial districts, which represent spatially concentrated clusters of small and medium sized firms, specialized in manufacturing productions. We find that in these areas social returns tend to vanish.

The paper is structured as follows: Section 2 describes the dataset; Section 3 contains the empirical evidence; and Section 4 concludes.

2. Data

The analysis is mainly based on two datasets: micro-data from the Bank of Italy's Survey of Household Income and Wealth (SHIW) are merged with the Cannari-Signorini dataset (CS), reporting several socio-economic characteristics of Italian LLMAs.

The SHIW is a bi-annual survey on the microeconomic behaviour of Italian families. We use observations from four of the surveys (1993, 1995, 1998, 2000). The SHIW provides detailed information[7] on several characteristics of workers, such as wage, educational attainment, job experience, sex, marital status, sector of employment, and size of the employer. Hourly wage is calculated as total annual earnings divided by the number of hours worked in a year. Thus, *Hourly Wage = Total Annual Earnings /(Average Hours Worked per Week × Months Worked × 4.3333)*, where the constant 4.3333 represents the average number of weeks in a month. Total annual earnings are net of taxes and social security contributions and include overtime, additional monthly salary, bonuses or

[7] Full details are provided in: Italian Household Budgets; Supplements to the Statistical Bulletin, Banca d'Italia, various years.

special emoluments, and fringe benefits as evaluated by the interviewee. We restrict our sample to employees with non-zero total annual income and non-zero weekly hours, or months, worked. We also exclude those who did not provide information on their family background, used here as an instrument for individual education. Our measure of work experience is calculated as the difference between the worker's age at the survey date and age when the first job was taken.[8]

The SHIW also provides information on industry and size of the current employer. The branches of activity of the company for which the individual works are recorded as follows: agriculture; manufacturing; building; trade; transportation; credit and insurance; real estate; IT and research; private services; government; extraterritorial organizations; others. Information on the employer size is divided into the following classes: up to 4 employees; from 5 to 19 employees; from 20 to 49; from 50 to 99; from 100 to 499; 500 or more employees; 'not applicable' or public sector employee. Because of the sampling design of the SHIW, only a sub-sample of families is interviewed in more than one survey: for example, among the 8,001 households that constituted the sample in year 2000, 399 had participated since 1993, 245 since 1995, and 1,993 since 1998. Our sample therefore has an unbalanced panel structure and includes 17,251 workers, 12,224 of which are truly independent. In particular, there are respectively 649 workers who were observed in all the four surveys; 607 in three surveys; 1,866 in two; and 9,102 in only one survey. We use a confidential version of the SHIW, which includes information on both place of birth and place of residence. The place of residence is used as a matching variable with the CS data-set.

The CS dataset contains an array of demographic and socio-economic variables for each of the LLMAs, and is derived from a variety of sources (Census; Company Accounts Data Service; Istat's Surveys on Exports, Value Added, Labour Force, Capital Stock: see Cannari and Signorini, 2000, for details). All the data refer to the beginning of the 1990s. Our analysis mainly builds on the following measures for each

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8 Workers who did not report their age when taking their first job are therefore dropped from the sample. Our measure of experience is more accurate than the most widely used measure of seniority (*Experience=Age–Years of Schooling–6*), which classifies "waiting unemployment" after school as work experience.

Table 1(a)

Descriptive statistics for workers. SHIW dataset

	1993	1995	1998	2000
Log of HOURLY WAGE RATE	2.49	2.53	2.62	2.66
	(0.46)	(0.43)	(0.44)	(0.42)
INDIVIDUAL EDUCATION	10.36	10.75	11.28	11.29
	(4.34)	(4.26)	(4.11)	(4.09)
EXPERIENCE	22.72	23.42	23.31	23.57
	(10.31)	(10.36)	(9.93)	(10.06)
D_FEMALE	0.37	0.39	0.41	0.41
D_MARRIED	0.89	0.88	0.88	0.85
Branch of activity:				
Agriculture	151	126	129	149
Manufacturing	1,124	1,163	1,086	1,112
Building and construction	248	214	167	201
Wholesale and retail trade	347	363	339	356
Transport and communication	160	142	163	178
Credit and insurance	152	163	157	158
Real estate	103	88	135	125
Domestic services	200	200	139	171
Government	1,969	1,888	1,721	1,569
Extra-territorial organizations	5	7	14	9
Others	83	118	96	63
Firm size:				
Up to 4 employees	321	365	324	330
From 5 to 19	596	672	653	651
From 20 to 49	395	338	479	425
From 50 to 99	267	192	293	344
From 100 to 499	425	389	417	456
500 or more	687	600	542	544
Not applicable, public sector employee	1,851	1,916	1,438	1,341

(contd.)

(Table 1(a) contd.)

	1993	1995	1998	2000
GEO controls:				
North West	1,111	1,102	1,047	1,047
North East	864	974	791	958
Centre	1,047	931	926	914
South	1,121	1,049	974	789
Islands	399	416	408	383
HOUSE PRICES	2.62	1.87	2.14	2.31
	(26.17)	(25.68)	(24.72))	(24.51)
FATHER'S BACKGROUND	2.16	2,19	2.31	2.37
	(0.98)	(0.97)	(0.98)	(1.13)
MOTHER'S BACKGROUND	1.98	2.02	2.13	2.16
	(0.85)	(0.84)	(0.86)	(1.00)
DREFORM62	0.30	0.30	0.32	0.31
	(0.46)	(0.46)	(0.47)	(0.46)
No. Obs.	4,542	4,472	4,146	4,091

Note: Standard deviations of continuous variables in brackets.

LLMA: average human capital, unemployment rate, an index of infrastructures, as calculated by the ratio between kilometers of roads and LLMA surface area. As for the manufacturing sector, we employ a value-added based index of physical capital; manufacturing share, determined as the ratio between manufacturing employees and population or total employees; and average firm size. For a few additional variables, we use data from other sources.[9]

The 17,251 workers of our sample are randomly distributed over 235 LLMAs. The variables used in the present analysis, together with their sample statistics, are reported in Table 1a, describing the employee SHIW sample, and in Table 1b, which overviews CS data.

9 We use the 1981 Census to derive our demographic instruments; information from the 1993 Company Accounts Data Service for a measure of LLMA capital per worker.

Table 1(b)

Descriptive statistics for LLMAs. CS dataset and 1981 Census

CS dataset			
HC	7.01	UNEMPLOYMENT	10.35
	(0.64)		*(6.03)*
PHYSICAL CAPITAL	44.70	SHAREMANUF	9.26
	(17.43)		*(6.19)*
INFRASTRUCTURE	43.86	COMPETITION	8.08
	(22.48)		*(3.14)*
1981 Census: shares of the population in the cohort indicated			
AGE<5	5.93	40<AGE<44	6.60
	(1.52)		*(0.68)*
5<AGE<9	7.34	45<AGE<49	6.26
	(1.38)		*(0.57)*
10<AGE<14	7.92	50<AGE<54	6.38
	(1.27)		*(0.73)*
15<AGE<19	8.17	55<AGE<59	6.21
	(1.11)		*(0.91)*
20<AGE<24	7.26	60<AGE<64	4.29
	(0.72)		*(0.73)*
25<AGE<29	6.68	65<AGE<69	4.78
	(0.50)		*(0.95)*
30<AGE<34	6.98	70<AGE<74	4.07
	(0.48)		*(0.95)*
35<AGE<39	6.09	AGE<75	5.04
	(0.62)		*(1.44)*
No. Obs. = 235			

Note: Standard deviations in brackets.

3. Empirical results

We estimate the effect of average human capital at the LLMA level on individual log earnings (hourly wage rate) denoted by (ln w_{ijt}). Estimation is based on the following Mincerian equation for individual i residing in LLMA j in period t:

$$\ln w_{ijt} = X_{it}\beta + \eta HC_j + z_j\delta + \varepsilon_{ijt} \quad (1)$$

where X is a vector of individual observable characteristics, which include individual education and experience; HC denotes LLMA average human capital, as measured by average years of schooling of the population in the area; and z is a vector of LLMA characteristics, which may be correlated with average human capital. The variables referring to LLMAs do not vary over time, since the CS dataset only contains cross-LLMA observations for the beginning of the 1990s. Finally ε denotes the regression error.

The goal of the paper is to estimate η, the impact of human capital on the average wage. As emphasized in Acemoglu and Angrist (2000), Moretti (2002), and Ciccone and Peri (2002), the parameter η captures all the external effects arising from higher human capital that are reflected in the wage rate. Whenever workers of different education are imperfect substitutes in production, external effects originate both from 'composition effects', due to a higher proportion of educated workers in the labour supply, and 'spillover effects', due to pure human capital externalities as in Lucas (1988). Competitive theory also predicts that, even when spillovers are absent, η must be positive.[10] Intuitively, an increase in the proportion of skilled labour tends to drive up average productivity. Although the Mincerian approach followed by Rauch (1993), Acemoglu and Angrist (2000), Moretti (2002) and here does not allow us to disentangle pure human capital spillovers from composition effects, we will try to assess the relevance of the bias deriving from labour-force composition changes by using a simple test derived from Ciccone and Peri (2002).

3.1 *Baseline regressions*

We start by estimating a baseline specification, which includes the Mincerian set of individual characteristics and controls for observable heterogeneity among individuals. Mincerian characteristics include labour market experience (EXPERIENCE), its squared value (EXPERIENCE2),

[10] Acemoglu and Angrist (2000) and Ciccone and Peri (2002) point out that, unless the elasticity of substitution is infinite, the effect of the average level of local education on the average local wage-level is positive for any CES technology even in the absence of spillovers. Ciccone and Peri (2002) tackle this issue by adopting a 'constant-composition approach' which is designed to measure pure human capital externalities.

the number of years of schooling (INDIVIDUAL EDUCATION) and two dummies for sex (D_FEMALE) and marital status (D_MARRIED). Finally, we add a set of geographic controls for macro-areas (North West, North East, Centre, South, Islands) and a set of dummies that control for time effects in the years of the survey. Table 2 provides the results. Column (2.1) reports GLS estimates treating both average and private education as exogenous, for our sample of 17,251 observations. The R^2 is above 0.30 and all the Mincerian variables enter significantly with point estimates close to previous studies based on the SHIW: see Cannari and D'Alessio (1995) and Colussi (1997). We find that each individual year of

Table 2

Estimates of social and private returns to education. Full sample

	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)	(2.6)
SOCIAL RETURNS to Schooling	0.036***	0.029***	0.033***	0.032***	0.021***	0.021***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
PRIVATE RETURNS to Schooling	0.055***	0.043***	0.055***	0.043***	0.072***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
EXPERIENCE	0.017***	0.014***	0.017***	0.014***	0.018***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EXPERIENCE2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_FEMALE	-0.102***	-0.095***	-0.102***	-0.095***	-0.109***	-0.097***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
D_MARRIED	0.057***	0.055***	0.057***	0.055***	0.060***	0.057***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
No. Obs.	17,251	17,251	17,251	17,251	17,251	17,251
No. Groups	12,224	12,224	12,224	12,224	12,224	12,224
Controls for branch of activity and firm-size?	NO	YES	NO	YES	NO	YES
Average education instrumented?	NO	NO	YES	YES	YES	YES
Individual education instrumented?	NO	NO	NO	NO	YES	YES

Notes: Random-effect regressions. Dependent variable: Log of hourly wage rate. Standard errors in brackets. (**) [***] denotes statistical significance at 10 (5) [1] per cent level. The controls for firm size and branch of economic activity include 10 branch-of-activity dummies and 6 firm-size dummies. All regressions also include 4 geographic-dummies and 3 year-dummies.

schooling increases hourly wages by 5.5 per cent.[11] Experience increases wages over the entire working life. Wages of women are 10 per cent lower than men's wages. Married workers enjoy a 5.7 per cent premium due to family allowances, a specific feature of the Italian wage system. Local human capital enters the earning equation with a positive and statistically significant coefficient. A percentage point increase in LLMA average education is associated with a 3.6 percent increase in wages.

There is no shared agreement on the control variables that are to be included in equation (1). Some argue that only the traditional Mincerian variables should be considered, since they represent the only sources of individual productivity: see, for example, Duranton and Monastiriotis (2002). Others suggest that controlling for the branch of economic activity and firm size improves the precision of estimates. This argument may be particularly relevant in the case of Italy, since inter-industry wage differentials appear to be quite substantial: see Mauro *et al.*, (1999). Moreover, industry dummies can partly capture endogenous matching of better workers with high-wage firms: see Bartel and Sicherman (1999). To this end, we add ten dummies to pin down the branch of activity of the company for which each individual works (with manufacturing being the left-out dummy). We also control for firm-size wage differentials by including dummies that divide employment per firm into six classes (with the size class from 20 to 49 employees being the left-out dummy). Inter-industry wage differentials turn out to be considerable. Compared with manufacturing, we find that the wage premium is around 7 per cent in transport, communications and the public sector; the premium is above 23 per cent in banking and insurance companies. Furthermore, wages increase with the size of the firm. Compared with wages in firms with 20 to 49 employees, we find that wages in very small firms (up to 4 employees) are 14 per cent lower, while wages in firms with more than 500 employees are 12 per cent higher. The estimates of the private and social returns to schooling after controlling for industry and firm size turn out to be slightly lower. As reported in column (2.2), private returns are equal to 4.3 per cent, while social returns amount to 2.9 per cent.

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[11] We also estimate a model in which private returns to education are non-linear in the years of schooling. For this purpose, we replace the categorical variable INDIVIDUAL EDUCATION with dummies for each year of schooling as suggested by Heckman *et al.* (1996). This has negligible effects on the estimates of average human capital returns.

GLS estimates, however, may be biased for several reasons. In the following pages we tackle two possible main sources of bias: (i) local shocks and (ii) selective migration.

Finally, we also check for 'composition effects' in the workforce's human capital.

Local shocks. As noted by Acemoglu and Angrist (2000) and Moretti (2002), the hypothesis that average schooling is exogenous is unlikely to hold true. For instance, productivity shocks on the local labour market may raise the wage of skilled workers and attract more skilled workers at the same time. Thus, shocks might drive our result by stimulating migration of skilled workers, or by making higher education more attractive to residents. Thus, we need an instrument that is related to average local human capital but uncorrelated with contemporary LLMA-specific productivity shocks. Like Moretti (2002),[12] we take the lagged age-structure of the population in each LLMA as the instrument and estimate earnings by G2SLS. We use the 1981 share of individuals in each 5-year cohort between the ages of 5 and 75, which generates 16 cohorts: see Table 1(b). The first-stage regression on the instrument, together with the exogenous right-hand-side variables as from equation (1), predicts over 70 per cent of variation of average years of schooling across LLMAs in 1991.[13] We test for the validity of the instrument using the Sargan (1988) test and find that exogeneity cannot be rejected at the 95 per cent significance level. The minimal specification, reported in column (2.3), shows that instrumenting average education by the lagged age structure of the population produces an estimate of social returns equal to 3.3 per cent. When controlling for industry and firm size, the instrumental variable approach leads to estimated social returns equal to 3.2 per cent: see column (2.4).[14] Thus, the bias generated by shock-driven migration on GLS estimates appears to be fairly unimportant.

The treatment of average education in the labour market as an endogenous variable while keeping the assumption of exogeneity for

[12] Acemoglu and Angrist (2002, p. 20) address the same problem by distinguishing between state-of-birth and state-of-residence across individuals.

[13] The F-test on the instruments displays a P-value equal to 0.000.

[14] Instrumenting with the 1971 demographic structure delivers similar results. This instrumental variable strategy, however, can deal only with 'temporary' shocks. In fact, if our results were driven by historical, permanent local characteristics, our 1981 (or 1971) demographic instrument would be endogenous as well.

individual education has been criticized by Acemoglu and Angrist (2000).[15] Therefore, only an instrumental strategy that treats both individual and average education as endogenous can generate unbiased estimates of social returns. To address this issue we proceed by instrumenting individual education by both family background[16] and compulsory schooling laws. Instrumentation of individual education by family background variables has a long tradition in labour economics, and it has been applied by Cannari and D'Alessio (1995) and Colussi (1997) to SHIW data. However, family-background based instruments (in our case, mother's and father's years of schooling) may be criticized as a bias can still arise unless all unobserved ability components are captured by family background: see Card (1999). To make our estimates more robust to this criticism, we complement family background with an instrument that captures the exogenous variation in school achievement that was induced by the 1962 Mandatory Middle-School Reform. The 1962 reform raised mandatory school attendance from 5 to 8 years of schooling. As explained by Brandolini and Cipollone (2002), the individuals exposed to the effects of the 1962 reform were those who were born between 1949 and 1956. In the first-stage regression of individual years of schooling on the set of instruments, we find that an increase in educational qualification of the father (mother), – recorded as none; elementary school; middle school; high school; university degree – leads to an increase of 0.46 (0.34) in years of schooling. Moreover, exposure to the 1962 reform leads to a further increase of 0.23 (all the instruments enter with 1 per cent significance). Roughly 40 per cent of variation in individual education is explained by the set of instruments, together with the remaining exogenous and instrumented variables. The F-test for the set of instruments displays a P-value of 0.0000 and the Sargan test cannot reject instrument exogeneity at the 95 per cent significance level.[17] The results are reported in column (2.5) for the minimal specification, and in column (2.6) for the specification

[15] Acemoglu and Angrist (2000, pp. 21-22) justify instrumentation of individual education on two grounds: (1) private returns to education may vary across individuals, and (2) the fact that one regressor, here HC, is the average of another regressor (individual schooling) may distort OLS estimates.

[16] See, for example, Card (1999). For a discussion of the role of family background in schooling in Italy and the US, see Checchi *et al.*,(1999).

[17] The first-stage F-test on the 1962 Mandatory Middle School Reform has a low predictive power in our sample when used as the only instrument. Similarly, Brunello *et al.* (2001) use compulsory schooling laws to augment family background variables when estimating private returns to schooling for the 1995 SHIW sample.

including industry and size controls. The use of parental education and the 1962 compulsory school reform as instruments leads to an increase in the estimates of private returns to education in both specifications which reach, respectively, 7.2 per cent and 6.0 per cent. This is in line with both international evidence surveyed by Card (1999) and the results obtained by Cannari and D'Alessio (1995), Colussi (1997) and Brunello *et. al.* (2001) for Italy. The estimates of social returns decrease roughly by one third in both specifications: estimated social returns are approximately equal to 2 per cent and remain highly significant.

Selective migration. Even abstracting from temporary productivity shocks, there remains the possibility that our results are generated by 'selective migration' of talented workers across local markets.[18] In particular, workers with high (unobserved) ability may tend to move to areas that are characterized by high average levels of schooling. In this case, the correlation between wages and local human capital may partially reflect unobserved ability rather than true schooling externalities. In other words, omitted ability could affect G2SLS estimates as long as average unobserved ability is correlated with average schooling as predicted by the instruments: see Acemoglu and Angrist (2000). Our data allow us to provide an evaluation for endogenous sorting. Because our data include information on both the LLMA of birth and the LLMA of residence of each worker, we can identify as *stayers* those who never moved from their LLMA of birth.[19,20]

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18 Migration flows in Italy have limited size compared with the US. Internal migration from the South of Italy to the northern regions, a salient feature of the Italian development process during the 1950s and the 1960s, died out in the first half of the 1970s: see Faini *et al.* (1997).

19 In order to control for endogenous sorting, Moretti (2002) includes a set of Individual×City dummies in the 1979-1994 NLSY panel, so that variation coming from migrants is lost and identification is based on stayers only. He concludes that unobserved ability is not a major source of bias. By contrast, Ciccone and Peri (2002) find some evidence that cities with higher average schooling do attract better workers. However, Ciccone and Peri (2002) restrict the definition of stayers to (i) those who lived in the same house over a 20-year period, and (ii) those who had been living in the same city five years before their wages were observed and who were born in the state where they reside. Our criteria for defining 'stayers' is based on the worker's entire lifetime, and it is possibly more accurate than the alternative definitions reported above.

20 Since we can match the LLMA of residence with the LLMA of birth for each individual during the 1990s, our identifying assumption fails to capture 'comebacks', such as individuals who migrated in youth and returned to the place of birth later on. However, 'comebacks' are a small percentage of the internal migration rates and are mostly confined to retired workers, who are not included in our sample: see Bonifazi (1999).

Out of the 17,251 workers of our sample, 12,467 were resident in their original LLMA of birth at the time of the survey. The estimates of equation (1) based on the *stayers* sub-sample are reported in Table 3.

Table 3

Estimates of social and private returns to education: *stayers* sub-sample

	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)	(3.6)
SOCIAL RETURNS to Schooling	0.037***	0.031***	0.039***	0.037***	0.028***	0.029***
	(0.007)	(0.007)	(0.010)	(0.009)	(0.010)	(0.010)
PRIVATE RETURNS to Schooling	0.055***	0.042***	0.055***	0.042***	0.070***	0.057***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
EXPERIENCE	0.017***	0.014***	0.017***	0.014***	0.018***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EXPERIENCE2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_FEMALE	-0.091***	-0.086***	-0.091***	-0.086***	-0.099***	-0.089***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
D_MARRIED	0.045***	0.047***	0.045***	0.047***	0.050***	0.050***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
No. Obs.	12,467	12,467	12,467	12,467	12,467	12,467
No. Groups	8,796	8,796	8,796	8,796	8,796	8,796
Controls for branch of activity and firm-size?	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
Average education instrumented?	*NO*	*NO*	*YES*	*YES*	*YES*	*YES*
Individual education instrumented?	*NO*	*NO*	*NO*	*NO*	*YES*	*YES*

Notes: Random-effect regressions. Dependent variable: Log of hourly wage rate. Standard errors in brackets. (**) [***] denotes statistical significance at 10 (5) [1] per cent level. The controls for firm size and branch of economic activity include 10 branch-of- activity dummies and 6 firm-size dummies. All regressions also include 4 geographic- dummies and 3 year-dummies.

Estimated social returns are larger in all specifications.[21] Our results thus mitigate the concern that sorting may strongly bias our estimates.

Glaeser and Maré (2001) propose a different approach to evaluate whether 'selective migration' is substantial. Their analysis is based on the comparison between real and nominal wages, according to the following argument. Since competitive firms remain in areas where they pay higher average wages, they must do so because they enjoy higher productivity. However, high local productivity may depend on two reasons. First, as we argue here, high local productivity may be generated by positive spillovers, such as human capital externalities. Alternatively, high local productivity may simply be generated by the presence of better workers (in this case, education and experience would only capture a part of workers' true ability). Both alternatives are consistent with high average wages. However, we expect that better workers obtain higher *real* wages, as happens when a worker is more educated or experienced. Dalmazzo and de Blasio (2003) show that when 'local cost of living' – as measured by house prices and rents – is included in the estimated wage equation, average human capital no longer has any significant effect on local wages. Summarizing, when we observe nominal wage differentials across LLMAs, we find that: (1) firms that locate in high-wage areas must enjoy high productivity and (2) higher nominal wages do not correspond to higher real wages, as one would expect if local workers are intrinsically better and firms reward their skills. Like Glaeser and Maré (2001), we conclude that the high wage level characterizing certain areas is generated by local externalities, and not by the presence of exceptionally able workers. This result has an additional implication. The productivity gains created by human capital externalities are mostly captured by the owners of inelastic factors such as 'land'.

Workforce 'composition effects'. Once we conclude that the effects of average schooling are unlikely to be spurious, there remains a central

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21 Census variables (such as human capital in 1991 and population structure in 1981and 1971) may reflect the changes in the labour-composition structure induced by migration from southern to northern Italy, a phenomenon which largely died out after 1975. However, it must be noted that movers and stayers were broadly characterized by similar skills in Italy: see Cannari *et al.*(2000). Moreover, we also consider local human capital effects limited to young cohorts, i.e. those born after 1959 (3,607 individuals, aged under 15 in 1975), and after 1964 (1,592 individuals, who were under 10 in 1975). Our Census variable tends to measure more accurately the human capital level to which the younger cohorts were actually exposed. The estimated social returns, obtained for a specification and methodology analogous to the ones followed in column (2.6), are respectively equal to 0.033 for post-1959 cohorts and 0.036 for post-1964 cohorts.

issue to be investigated. As emphasized by Acemoglu and Angrist (2000), Moretti (2002) and Ciccone and Peri (2002), the parameter η captures *all* the external effects on average wages that arise from a higher level of human capital. Whenever workers who have different levels of education are imperfect substitutes in production, these external effects can be driven both by 'composition effects', due to a larger proportion of educated workers on average productivity, and by genuine spillovers, due to human capital externalities. As a consequence, competitive theory implies that – even if spillovers are zero – the estimated value of η must still be positive. Even if the Mincerian approach followed here, and in Rauch (1993), Moretti (2002) and Acemoglu and Angrist (2000), does not allow us to separate spillovers from mere composition effects, it is possible to evaluate the bias due to workforce composition by a simple test based on Ciccone and Peri (2002). Indeed, Ciccone and Peri (2002) show that the magnitude of the composition effect bias in the Mincerian wage equation largely depends on the interaction between individual return to schooling and the average level of human capital. To estimate the composition effect, we thus included the interaction term (*individual education* $\times$ *average education*) in specifications (2.1)-(2.6).[22] The coefficient associated with this term is statistically insignificant in all of the specifications, suggesting that our estimates of η mainly capture the effects of human capital spillovers.

3.2 *Manufacturing sample*

In this section we restrict our attention to the sub-sample of manufacturing workers. This exercise is motivated by three considerations. First, wages paid in the public sector may reflect an inter-regional redistributive motive, as suggested by Alesina *et al.* (2001), which may bias cross-LLMA differentials. Second, wages in the service sector might reflect imperfections in the local markets for non-tradable goods and services. By contrast, for industries that produce tradable goods in national or international competitive markets, nominal wage differentials should reflect differences in the marginal productivity of labour. As noted by Rauch (1993) and Glaeser and Maré (2001), if nominal wage differentials did not reflect true productivity differences, firms would move to less expensive locations. Third, there are some LLMA characteristics, such as unemployment, endowment of public infrastructures, or intensity of industrial activity, that might be correlated with average human capital.

[22] We thank Antonio Ciccone for suggesting this procedure.

Focusing on the manufacturing sub-sample enables us to control for these potential sources of spurious correlation, since we can use the specific information on manufacturing contained in the CS database.[23,24]

Benchmark estimations based on the manufacturing sample, which includes only 4,485 workers (3,390 of which are truly independent) are reported in the first line of Table 4. We find that social returns in manufacturing range from 3.1 per cent to 4.6 per cent, about 50 per cent higher than those based on the full sample.

Table 4 shows the impact of each additional control on the estimates. We start by considering physical capital in the private sector. Due to capital-skill complementarities[25], local human capital might pick up the contribution of physical capital. The variable PHYSICAL CAPITAL denotes local capital intensity in manufacturing, calculated as the ratio between stock of capital (valued at the replacement price) and value added in each LLMA[26]. We also control for the local level of infrastructures (INFRASTRUCTURE). This variable is measured as the ratio between kilometers of roads and LLMA surface area in square kilometers (see Ciccone and Hall (1996) among many others). Our results show that PHYSICAL CAPITAL enters significantly but with a very low point estimate, while INFRASTRUCTURE does not enter significantly. More important, the coefficient for aggregate human capital is only very marginally affected.

The correlation between education and earnings might also be affected by the distribution of unemployment across LLMAs. If better-educated individuals are less likely to be unemployed, then average human capital might pick up the effect of the unemployment rate. When the LLMA-specific unemployment rate is considered, however, the average human capital coefficient remains essentially unchanged. As found by many others (see for example Casavola *et al.,* 2000), local unemployment is not an important determinant of wages in local labour markets.

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23 Local unemployment and public infrastructure do not specifically refer to manufacturing. The inclusion of such controls in the specifications considered in Tables 2 and 3 does not lead to any change in our results.

24 As mentioned, a limit of this extension, common to Rudd (2000) and Moretti (2002), is that additional controls are treated as exogenous.

25 See, for example, Goldin and Katz (1998).

26 We have also used the 1993 Company Accounts Data Service index of capital per worker, which was calculated at the LLMA level by Fabiano Schivardi. The results do not differ from those reported above.

Table 4

Manufacturing sample. estimated social returns

BENCHMARK	0.045***	0.046***	0.031***
	(0.009)	(0.011)	(0.011)
1) PHYSICAL CAPITAL	0.045***	0.048***	0.033***
	(0.009)	(0.011)	(0.011)
2) INFRASTRUCTURE	0.045***	0.046***	0.031***
	(0.009)	(0.011)	(0.011)
3) UNEMPLOYMENT	0.045***	0.045***	0.029***
	(0.009)	(0.011)	(0.011)
4) SHARE MANUF	0.050***	0.047***	0.034***
	(0.010)	(0.011)	(0.011)
5) COMPETITION	0.045***	0.046***	0.030***
	(0.009)	(0.011)	(0.011)
1) + 2)	0.044***	0.049***	0.034***
	(0.009)	(0.011)	(0.011)
4) + 5)	0.051***	0.047***	0.033***
	(0.010)	(0.012)	(0.011)
1) + 2) + 3) + 4) + 5)	0.054***	0.052***	0.038***
	(0.010)	(0.012)	(0.012)
Controls for firm-size?	YES	YES	YES
Average education instrumented?	NO	YES	YES
Individual education instrumented?	NO	NO	YES
No. Obs.	4,485	4,485	4,485
No. Groups	3,390	3,390	3,390

Notes: Random-effect regressions. Dependent variable: Log of hourly wage rate. Standard errors in brackets. (**) [***] denotes statistical significance at 10 (5) [1] per cent level. Controls for firm size include 6 firm -size dummies. All regressions also include INDIVIDUAL EDUCATION, EXPERIENCE, EXPPERIENCE2, D_FEMALE, D_MARRIED, 4 geographic controls and 3 year-dummies.

The relation between LLMA human capital and earnings could also reflect agglomeration effects, as suggested by Ciccone and Hall (1996).[27] If

[27] In a search model of skill acquisitions, Jovanovic and Robb (1989) suggest that productivity depends on both the overall level and spatial concentration of human capital in a local market.

the density of economic activities attracts human capital by driving returns to education up, one should expect that controlling for agglomeration would reduce the impact of average human capital on earnings. We consider here the LLMA-level share of manufacturing workers over the population (SHAREMANUF).[28] Again, the average human capital coefficient is unaffected.

Finally, as in Glaeser *et al.* (1992) we control for competition. The index COMPETITION, measured as the ratio between manufacturing average firm-size in the LLMA and the average size at national level, is not significant.

The last specification in Table 4 includes all the controls jointly. In conclusion, our findings from the manufacturing sub-sample support the existence of social returns to education.

In the following pages we consider two additional tests which gather additional evidence on external effects from schooling. First, we estimate the impact of social returns when the sample is split according to educational attainments of workers, those who have high education and those who have low education. Second, we estimate the impact of social returns when the sample is split according to geographical areas, workers in the Centre-North and workers in the South.

3.3 *High-education workers versuss. low-education workers*

As emphasized above, when workers of different skills are imperfect substitutes in production, the average external effect of human capital on wages will depend both on the composition of labour supply and on human capital spillovers. In Section 3.1 we argued that composition effects seem to have a negligible impact on our results. However, as noted by Ciccone and Peri (2002), there is also the possibility that human capital externalities at the aggregate level are not Hicks-neutral. Aggregate human capital may have a different impact on the productivity of workers of different education.

[28] Cingano and Schivardi (in this volume) find that this measure of agglomeration affects total factor productivity in Italian manufacturing. To account for differences in labour market participation rates, we also replaced this measure with the LLMA share of manufacturing workers over total employment. Results did not change.

In order to investigate the presence of differential effects of aggregate human capital, we estimate separately social returns to education for two skill groups. The first group, the unskilled, are those with 8 years of schooling, corresponding to an Italian middle-school diploma or less. The second group, the skilled, are those with more than 8 years of schooling (high school, college and post-graduate).[29] Results are reported in Table 5. We find some evidence that average education has a larger effect on the wage of the less educated, both for the full sample and the manufacturing sub-sample.

Table 5

Low-education versus high-education workers. Estimated social returns

	LOW-EDUCATION			HIGH-EDUCATION		
Full sample	0.032***	0.035***	0.030***	0.022***	0.021**	0.005
	(0.009)	(0.011)	(0.010)	(0.008)	(0.011)	(0.011)
No. obs.	7,856	7,856	7,856	9,395	9,395	9,395
Manufacturing sample	0.044***	0.032**	0.034***	0.040**	0.054**	0.023
	(0.010)	(0.013)	(0.013)	(0.017)	(0.021)	(0.023)
No. obs.	2,731	2,731	2,731	1,754	1,754	1,754
Controls for branch of activity and firm-size?	YES	YES	YES	YES	YES	YES
Average education instrumented?	NO	YES	YES	NO	YES	YES
Individual education instrumented?	NO	NO	YES	NO	NO	YES

Notes: Random-effect regressions. Dependent variable: Log of hourly wage rate. Standard errors in brackets. * (**) [***] denotes statistical significance at 10 (5) [1] per cent level. Controls for branch of activity and firm size include 10 dummies for branch of economic activity (only for full-sample regressions) and 6 dummies for firm size. All regressions include INDIVIDUAL EDUCATION, EXPERIENCE, EXPERIENCE2, D_FEMALE, D_MARRIED, 4 geographic controls and 3 year -dummies.

[29] This two-group separation is quite natural in Italy, given that mandatory school covers up to 8 years of schooling.

3.4 *Centre-North versus South*

In this section we concentrate on regional asymmetries to assess whether human capital effects depend on the level of local economic development. As is well known, Italy exhibits a pronounced gap between the Centre-North and the South. In 1991 per capita income in the South amounted only to 57 per cent of the corresponding figure for the Centre-North and this gap has persisted over the last 11 years. Census data also indicate that in 1991 average education in the South was 6.5 years of schooling, against 7.5 years of schooling in the Centre-North.[30]

A key question is to evaluate whether social returns are similar between the Centre-North and the South of Italy. In Table 6 we estimate social returns separately for the two areas. Although we find no substantial

Table 6

Centre-North versus. South. Estimated social returns

	SOUTH			CENTRE-NORTH		
Full sample	0.038***	0.026**	0.021*	0.026***	0.029***	0.019***
	(0.013)	(0.013)	(0.012)	(0.007)	(0.008)	(0.007)
N. obs.	5,539	5,539	5,539	11,712	11,712	11,712
Manufacturing sample	0.080***	0.090***	0.089**	0.035***	0.037***	0.018
	(0.028)	(0.035)	(0.033)	(0.009)	(0.011)	(0.011)
No. obs.	793	793	793	3,692	3,692	3,692
Controls for branch of activity and firm-size?	YES	YES	YES	YES	YES	YES
Average education instrumented?	NO	YES	YES	NO	YES	YES
Individual education instrumented?	NO	NO	YES	NO	NO	YES

Notes: Random-effect regressions. Dependent variable: Log of hourly wage rate. Standard errors in brackets. * (**) [***] denotes statistical significance at 10 (5) [1] per cent level. Controls for branch of activity and firm size include 10 dummies for branch of economic activity (only for full-sample regressions) and 6 dummies for firm size. All regressions include INDIVIDUAL EDUCATION, EXPERIENCE, EXPERIENCE2, D_FEMALE, D_MARRIED, 4 geographic controls and 3 year-dummies.

[30] Our sample confirms this 1 percentage point difference between North and Centre-South.

difference for the sample including all sectors, there is large and significant evidence of social returns for southern workers in manufacturing, ranging from 8.0 to 9.0 per cent. Thus, our results are broadly consistent with Schultz (1994), who suggests that social returns to schooling are higher in backward areas.

3.5 *Industrial districts*

We turn now to the role of average schooling in the Italian manufacturing clusters. As it is well known, the Italian economy is characterized by a significant presence of small and medium-sized enterprises, many of which are agglomerated into specialized "industrial

Table 7

Districts versus non-district LLMAs. Estimated social returns

	DISTRICTS			NON-DISTRICTS		
Full sample	0.007	0.008	-0.006	0.033***	0.028***	0.020***
	(0.015)	(0.018)	(0.019)	(0.007)	(0.009)	(0.010)
No. obs.	4,032	4,032	4,032	13.219	13.219	13.219
Manufacturing sample	0.017	0.025	0.002	0.059***	0.051***	0.038***
	(0.020)	(0.025)	(0.026)	(0.012)	(0.015)	(0.014)
N. obs.	1,538	1,538	1,538	2,947	2,947	2,947
Controls for branch of activity and firm-size?	YES	YES	YES	YES	YES	YES
Average education instrumented?	NO	YES	YES	NO	YES	YES
Individual education instrumented?	NO	NO	YES	NO	NO	YES

Notes: Random-effects regressions. Dependent variable: log of hourly wage rate. Standard errors in parentheses. * (**) [***] denotes statistical significance at 10 (5) [1] percent level. Controls for branch of activity and firm-size include 10 dummies for branch of economic activity (only for full sample regressions) and 6 dummies for firm-size. All regressions include INDIVIDUAL EDUCATION, EXPERIENCE, EXPERIENCE2, D_FEMALE, D_MARRIED, 4 geographic controls, and 3 year dummies.

districts". Industrial districts are spatially concentrated clusters of small and medium sized firms, specialized into one or few stages of a main manufacturing production. Their importance cannot be overstated: 199 LLMAs out of the 784 total LLMAs are defined as industrial districts (see de Blasio and Di Addario, in this volume, and Iuzzolino, in this volume); in 2001, their share in total industrial employment was equal to 41.7 per cent. Previous work has suggested that, given also the district specialization towards traditional sectors, the role of formal education in industrial districts is quite limited (see Cannari and Signorini, 2000). For instance, Barca and Cannari (1997) show that higher education attainments are negatively correlated with entrepreneurship. Casavola *et al.* (2000) suggest that district workers enter in the labor market in advance compared to non-district counterparts. Finally, de Blasio and Di Addario (in this volume) report that the private returns to education in industrial districts are significantly lower than elsewhere. In Table 7, we split our sample between districts and other LLMAs. Consistent with previous work, we are never able to find a role for the social returns in the districts.

4. Concluding remarks

The role of social returns to education has been widely debated during the last decade, after Lucas (1988) showed that human capital externalities may generate sustained growth over the long run. However, cross-country evidence on the effects of human capital on aggregate productivity remains quite controversial: see Barro (1991), Mankiw *et al.*, (1992), Bils and Klenow (2000), De la Fuente and Doménech (2001).

Recent applied work has shifted towards a Mincerian wage-regression approach to investigate the role of average human capital on individual wages across local labour markets. This approach, which has focused on US data, still casts doubts on the relevance of social returns to education. This paper adds new evidence to the debate by exploiting a sample of workers in Italian local labour market areas.

Our results rely on a definition of local labour market based on the concept of 'functional region' (OECD, 2001). We find that social returns to education range between 2 and 3 per cent. In addition, our results underscore a feature of the relation between local average human capital and individual productivity that has received limited attention so far. In particular, we show that social returns are higher for local markets located in the backward areas of the South of Italy, where levels of average human capital are lower. Finally, we find no evidence of social returns in the Italian industrial districts.

Our conclusions also raise some questions about Italian schooling financing policy, which provides the same amount of per-student funding across areas. Although social benefits of education go beyond the productivity effect measured in this paper, our preliminary results suggest that funding should be primarily directed to backward southern areas.

APPENDIX

Definitions of territorial units

Local Labour Market Area (LLMA). LLMAs are functional regions that correspond to local labour markets. The concept of local labour market is strictly related to the concept of self-containment, which describes the ability of an area to concentrate the highest possible amount of human relations taking place between the places where production activities are performed (place of work) and the places related to social reproduction (place of residence). The areas so identified form a local system because inside them there is a concentration of residential activities (such as most individual and family consumption), work activities (such as expenses for production and distribution) and the social relations created between these two poles. The reference to daily travel contributes to the definition of local system in terms of space and time. LLMAs are the aggregation of two or more neighbouring municipalities defined on the basis of daily travel flows from place of residence to place of work to place of residence. The procedure is based on the 1991 Census intra-municipality daily commuting flows matrix: see Istat (1997). Self-containment is defined on both the labour demand side (number of employed persons living and working in a LLMA compared with total number of employed persons in that LLMA) and the supply side (number of employed persons living and working in an LLMA compared with the total number of residents in that LLMA), with a threshold level set at 75 per cent (which is fully stringent on the demand side, while on the supply side it does not apply in 270 LLMAs). As emphasized in OECD (2002), LLMAs provide an attractive concept of local labour markets: by construction, labour mobility within LLMAs is very high while mobility from and to other LLMAs is little.

Metropolitan Area (MA). MAs are based on county units. To be considered an MA, a county needs a city or ‘urban areas’ (residents in contiguous area with a population density of at least 1,000 residents per square mile) of at least 50,000 residents. Adjacent counties are part of the metropolitan area if at least half of their population is in the urban area surrounding the largest city, while additional outlying counties are included in the MA if they meet specified requirements of commuting to the central counties and other selected requirements of metropolitan character (such as population density and per cent urban). Approximately 20 per cent of the US population and 80 per cent of its territory are outside MAs.

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