Capital, Wages, and Growth: Theory and Evidence

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Abstract: Returns to scale to capital and the strength of capital externalities play a key role for the empirical predictions and policy implications of different growth theories. We show that both can be identified with individual wage data and implement our approach at the city-level using US Census data on individuals in 173 cities for 1970, 1980, and 1990. Estimation takes into account fixed effects, endogeneity of capital accumulation, and measurement error. We find no evidence for human or physical capital externalities and decreasing aggregate returns to capital. Returns to scale to physical and human capital are around 80 percent. We also find strong complementarities between human capital and labor and substantial total employment externalities.

Key Words: Returns to Scale to Capital, Human Capital, Capital Externalities, Complementarities, Scale Effects, Cities.
JEL Codes: O0, O4, R0, J3.

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1. Introduction

Aggregate returns to scale to human and physical capital and the strength of human or physical capital externalities play a central role for the empirical predictions and policy implications of different (modern) growth theories. For example, endogenous growth models by Rebelo (1991) and Lucas (1993) are based on the idea of constant aggregate returns to scale to capital; Romer (1986) and Lucas (1988) argue that constant or increasing aggregate returns to scale to capital may be due to physical or human capital externalities; and physical or human capital externalities are often used to justify investment subsidies. Aggregate returns to scale to capital also play a key role in the Solow (Mankiw, Romer, and Weil (1992)) growth model. For example, they determine the rate of convergence of income per capita to the steady-state and the effect of an increase in the savings-rate on steady-state income per capita.

In this paper we show how aggregate returns to scale to capital and capital externalities can be identified with individual wage data for a class of growth models that includes Romer (1986), Lucas (1988), Romer (1990), and Mankiw, Romer, and Weil (1992) among others. We implement our approach at the city-level with US Census data on individual wages across 173 cities in 1970, 1980 and 1990. The main advantages of our approach compared to the previous literature are that we show how to identify capital externalities; that we estimate aggregate returns to scale directly from the effect of capital accumulation on wages (not indirectly from the rate of convergence of income or wages); and that we take into account fixed effects, endogeneity of rates of capital accumulation, and measurement error in the estimation. We find no physical or human capital externalities in cities and decreasing aggregate returns to physical and human capital. Our estimates imply aggregate returns to scale to physical and human capital of around 80 percent. There are significant total employment (aggregate scale) externalities in cities however. The estimates suggest that a 10 percent increase in total employment increases labor productivity in cities by 1.1 percent. We also find strong complementarities between workers with low levels of human capital and workers with high levels of human capital. For example, our estimates yield that a one year increase in the average level of schooling in a city increases the wage of workers with no schooling and average experience by 26 percent. Complementarities between workers with low levels of human capital and workers with high levels of human capital also explain why we find that an increase in the average level of human capital decreases wage-inequality in cities.

The paper is organized in the following way. The next section discusses the related literature. Section 3 shows how human capital externalities can be identified under the assumption that the average level of human capital affects wages only through human capital externalities, and Section 4 estimates human capital externalities under this assumption. Section 5 allows for standard relative supply effects of the average level of human capital on wages, and Section 6 shows how aggregate returns to scale to capital and capital externalities can be identified in a framework that includes endogenous growth models and growth models with decreasing aggregate returns to scale to physical and human capital. Section 7 explains how our approach to identification can be implemented empirically, and Section 8 presents and discusses the empirical results. Section 9 looks at the dispersion of average levels of schooling and average wages across cities over time. Section 10 summarizes.

2. Related Literature

The key role of aggregate returns to scale to capital and capital externalities in modern growth theory explains why estimating aggregate returns to scale and capital externalities has become one of the main issues in the growth literature. Most approaches follow Barro and Sala-i-Martin (1992) and Mankiw, Romer, and Weil (1992) and infer aggregate returns to scale to capital from the rate of convergence of income per capita to steady-state income per capita. This inference is possible under certain assumptions, which include that countries can be seen as converging to a steady-state, that countries are close to their steady-state, and that the econometrician observes the variables that determine countries' steady-states. The estimates in Barro and Sala-i-Martin (1992) and Mankiw, Romer, and Weil (1992) suggest a value of aggregate returns to scale to capital of 80 percent. Their cross-country approach may however overestimate aggregate returns to scale to capital because it does not control for permanent differences in total factor productivity across countries. Panel-data approaches, like Islam (1995) for example, take such differences into account and generally find significantly lower estimates of aggregate returns to scale to capital. Shioji (1997) and de la Fuente (1998) show however that panel-data approaches suffer from the problem that high rates of convergence of income (which correspond to low values of aggregate returns to scale to capital) may be driven by medium-term income dynamics related to the business-cycle. We do not infer aggregate returns to scale to capital from income (or wage) convergence but estimate them directly from the effect of capital accumulation on wages. Our data allows us to control for permanent differences in total factor productivity across cities in a way that avoids the problems of the panel data approach.

There is less work on estimating the strength of capital externalities emphasized by Romer (1986) and Lucas (1988) than on estimating aggregate returns to scale to capital. Ciccone (1997) shows how human capital externalities can be identified with regional data and finds that human capital externalities play no role at the US county-level. Vayá et al (1998) use a similar approach with European data and find significant human capital externalities. Most of the empirical work on externalities has concentrated on cities however. This is for two main reasons. First, city-level data allows for an empirical approach that takes into account problems like endogeneity of regressors, omitted variables, and measurement error that cannot be addressed with country-level data. Second, the concept of externalities is based on group interactions and the diffusion and exchange of ideas that are one of the reasons for the existence of cities, see Marshall (1890), Jacobs (1969, 1984), Lucas (1988), and Glaeser et al (1992) for details and examples. City-level data can also be used to test for "pecuniary externalities" based on increasing returns to specialization as in Krugman (1979) and Romer (1990) or search in the labor market as in Pissarides (1990) and Acemoglu (1996). Empirical work at the city-level will however be unable to capture externalities that only work through social conventions and institutions at the national level, see Hall and Jones (1999). Most of the empirical literature on externalities in cities concentrates on effects of city-size (measured by total employment or population) on wages or productivity, see Henderson (1988). A more recent literature looks at the effects of intra-industry and inter-industry externalities on employment growth, see Glaeser et al (1992). Human capital externalities in cities are estimated in Rauch (1993). He identifies the human capital externalities in the Lucas (1988) model at the city-level with individual wage data and finds significant human capital externalities. His approach is limited to the Lucas (1988) endogenous growth model and therefore cannot be used to estimate aggregate returns to scale to capital and capital externalities for the wide class of growth models (including models with decreasing aggregate returns to capital) in modern growth theory. Rauch's approach serves as a good starting point for our analysis however. We will therefore discuss it, and some related literature, in more detail in the next section.

3. Introduction to the Identification Problem

Rauch's (1993) approach to the identification of human capital externalities at the city-level relies on decomposing the wage of individuals in different cities into the part that is due to their characteristics, like their level of schooling and experience, and the part that is due to city-specific factors, like the average level of schooling in the city. His starting point is the following equilibrium wage-schedule at the city-level,

$$w_{ct}(z_i, x_i, a_i) = p_{ct}\left(h_t(z_i), x_i\right)a_i \tag{1}$$

where a_i denotes individual ability (which is unobserved by the econometrician), z_i denotes individual characteristics that affect the individual level of human capital h, and x_i denotes other individual control variables; $p_{ct}(h, x)$ will be referred to as the wage per unit of ability. Rauch assumes that the wage per unit of ability depends on the mentioned individual characteristics and an index A_{ct} of labor productivity in city c at time t,

$$p_{ct}\left(h_t(z_i), x_i\right) = A_{ct}h_t(z_i)d_t(x_i)\ . \tag{2}$$

The expressions for individual wages in (1) and (2) are combined with three equations that capture the effect of city-specific variables on the index of labor productivity A and the effect of individual characteristics on individual wages. Rauch captures the effect of individual characteristics on wages in the way that has become standard in labor economics,

(3) $$\ln h_t(z_i) = b_t S_i + c_t E_i - e_t E_i^2 \text{ and } \ln d_t(x_i) = r_t R_i + f_t F_i$$

where S_i, E_i denote the individual level of schooling and experience and R_i, F_i are dummies for individual race and gender. The effect of city-specific variables on the index of labor productivity is captured by

(4) $$\ln A_{ct} = a + bS_{ct} + gE_{ct} + dL_{ct} + u_{ct},$$

where S_{ct}, E_{ct} denote the average level of schooling and experience in the city, and L_{ct} denotes total employment in the city; u_{ct} summarizes factors affecting labor productivity across cities that are unobserved by the econometrician. Rauch interprets (4) as capturing human capital externalities and scale externalities at the city-level.

The approach to the identification of human capital externalities in (2)-(4) is consistent with the Lucas (1988) endogenous growth model implemented at the city-level. Lucas assumes that production takes place according to

(5) $$Y = K^a \left(A\int_0^\infty hL(h)dh\right)^{1-a},$$

where Y is output, K is the amount of physical capital used, $L(h)$ is the number of individuals with human capital h employed, and A is an index of aggregate labor productivity (which in Lucas' formulation may depend on the average level of human capital in the economy through externalities). This production function assumes constant returns to physical and human capital (for a given value of the index of labor productivity A) and perfect substitutability among workers with different levels of human capital. Lucas' production function and perfectly competitive labor markets at the city-level, combined with perfectly competitive capital markets at the country-level, imply that individual wages in city c are

$w_c(h) = fA_c h$ where f does not vary across cities (Section 6 contains a more detailed derivation of the implications of different growth theories, including Lucas' model, for wages). All effects of the average level of human capital in the city on wages must therefore work through the index of labor productivity A and can be interpreted as externalities.

Rauch combines (1)-(4) with the assumption that unobservable ability $\ln a_i$ is normally distributed across individuals. This results in a simple Mincerian wage-regression where *only* the intercept depends on city-specific variables. He estimates this wage-regression with data on individuals in 237 cities in 1980 and finds that the (external) effect of average schooling on individual wages is statistically significant and falls between 2.8 and 3.9 percent (he finds only small external effects of average experience and total employment). Almond (1997) replicates Rauch's approach for 1990 and finds a statistically significant (external) effect of the average level of schooling of 7.7 percent. Interpreting these estimates from the point of view of the Lucas model indicates human capital externalities and (combined with constant returns to scale to capital for a given value of the index of labor productivity A in (5)) aggregate increasing returns to scale to physical and human capital within US cities.

The main problem we see with Rauch's approach to the identification of human capital externalities is that all effects of the average level of schooling in cities on individual wages (controlling for individual characteristics) are interpreted as externalities. It seems reasonable to expect however that the average level of schooling in cities may affect wages even in the absence of any externalities. For example, suppose there are no human capital externalities and production takes place under constant returns to scale. Suppose also that the only two inputs in production are workers with one of two schooling levels, low and high, and that low-schooling workers and high-schooling workers are *imperfect substitutes* in production. Then we would expect wages of low-schooling workers to be higher in cities with relatively more high-schooling workers (cities with higher average levels of schooling) simply because of the (assumed) imperfect substitutability (complementarity) between the two "types" of labor. We would also expect wages of high-schooling workers to be lower in these cities. But higher wages of low-schooling workers in cities with relatively more high-schooling workers might more than offset lower wages of high-schooling workers in the following sense: Average wages adjusted for the schooling composition of the labor force may be higher the higher the average level of schooling in the city. Rauch's approach would in this case mistakenly attribute the effect of higher average levels of schooling on average wages adjusted for schooling composition to schooling externalities (the example is worked out in more detail in the appendix). To put it differently, the main problem we see with Rauch's approach is that he assumes implicitly that average levels of schooling affect wages only through externality-driven shifts of labor demand curves. But average levels of schooling may affect wages also through relative-supply-driven movements along labor demand curves (which we will call relative supply effects). This may explain why Ciccone (1997)—who estimates human capital externalities with an approach that does not suffer from this problem—finds no evidence for human capital externalities in US counties.

The main reason for our interest in relative (human capital) supply effects is that they arise naturally in growth theories without human capital externalities and with decreasing aggregate returns to physical and human capital. An increase in the average level of human capital will, in these models, increase the wage of low-human-capital workers and decrease the wage of high-human-capital workers. To use individual wage data to estimate human capital externalities (and aggregate returns to scale to capital) in a class of models that includes endogenous growth models as well as the Mankiw, Romer, and Weil (1992) version of the Solow growth model, it is therefore necessary to understand how wages are affected by the average level of human capital in cities when both human capital externalities and relative (human capital) supply effects are at work.

Three additional problems with Rauch's approach stem from the fact that (1) is estimated without controls for city-specific fixed effects; without using instruments for the average level of schooling, the average level of experience, and employment; and without taking into account measurement error. Most of these problems are resolved in Moretti (1998) who estimates schooling externalities using an approach that controls for city-specific fixed effects and accounts for endogeneity of average levels of schooling as well as measurement error. His empirical approach can be shown to yield consistent estimates of schooling externalities exactly if workers with different levels of human capital are perfect substitutes.[1] Moretti finds significant schooling externalities between 18 and 25 percent for the 10-year period 1980-1990. He uses the same approach to estimate schooling externalities for four different educational groups.

4. Human Capital Externalities Without Relative Supply Effects

Before turning to the identification of human capital externalities in the presence of relative supply effects, it is useful to reconsider Rauch's analysis while addressing three of the problems that may have biased his results: city-specific fixed effects; endogeneity of the average level of schooling, the average level of experience, and

[1] Moretti's empirical framework differs from Rauch (1993) as he takes into account downward sloping labor demand curves. The main differences with our empirical

the level of employment across cities; and measurement error. In this section we use our data to do so.

Our data contains the same information as Rauch’s at the individual level. We have only 173 cities compared to his 237 but have individual wage data for these cities for 1970 and 1990 in addition to 1980 (the data are described in the appendix). This enables us to use (1)-(3) to estimate the index of labor productivity A_{ct} in each of the 173 cities in our sample for 1970, 1980, and 1990. We can therefore relate changes in a city’s labor-productivity index between two years t and $t < t$, $\Delta \ln A_{ct} = \ln A_{ct} - \ln A_{ct}$, to changes in the average level of schooling and experience as well as changes in total employment,

$$(6) \qquad \Delta \ln A_{ct} = a_t + b\Delta S_{ct} + g\Delta E_{ct} + d\Delta L_{ct} + \Delta u_{ct} .$$

The advantage of (6) over (4) is that city-specific fixed effects are eliminated by differencing. There still is the problem of measurement error and endogeneity of right-hand side variables however. To address these problems, we use three sets of instrumental variables for the right-hand side variables in (6). The first set of instruments are variables that are related to the quality of life (but not to the change in unobservable productivity Δu_{ct}) of cities, such as climate; whether cities are at the coast or not; an index of the availability of recreational opportunities like good restaurants, sports teams, theme parks and so on in 1970; and an index based on the presence of symphony orchestras, opera companies, theaters, public libraries and so on in 1970. The second set of instruments are variables that are related to the ethnic composition of the population in 1970. Finally, following Moretti (1998), we also use the demographic composition of the

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framework is that we also take into account complementarities between different “types” of labor.

population in 1970 as instruments (the instruments are described in more detail in the appendix). The identifying hypothesis is that these instruments are unrelated to the exogenous change in (ln-) productivity over the period 1970-1990. Our 20 instruments predict 38 percent of the variation of employment and more than 40 percent of the variation of the average level of schooling and experience across cities for the 20-year period 1970-1990. Tests of the exogeneity of our instruments yield that exogeneity cannot be rejected at the 95-percent significance level.[2] Using these instruments we estimate (6) with generalized two-stage least squares (G2SLS). Results for the 20-year period 1970-1990 are summarized in Table 1.[3]

Table 1: G2SLS Estimates of Externalities in Mincerian Framework

For the 20-Year Period 1970-1990		
ΔS	ΔE	ΔL
0.15 (0.04)	0.021 (0.012)	0.11 (0.06)

Notes: The equation estimated is (6) by G2SLS. Weighting takes into account the fact that the left-hand side of (6) (estimated using (1)-(3)) is estimated more precisely in larger cities than in smaller cities. Numbers in brackets denote standard errors.

The externality from a one year increase in the average level of schooling in a city is estimated to be 15 percent for the 20-year period 1970-1990 (significant at the 1-percent level). Pooling the two 10-year periods (allowing for different intercepts in (6)) yields G2SLS estimates of the external effect of average schooling of 19

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[2] The Sargan (1988) test statistic (distributed $c^2(20)$) is 29.79 with all 20 instruments.

[3] One may be concerned about our quality of life instruments being correlated with the increase in average ability of the labor force in cities between 1970 and 1990 (and the increase in ability being correlated with the increase in average schooling). We therefore re-estimated (6) with G2SLS without our quality of life instruments. The estimates are 19 percent (standard error 5 percent) for the change in average schooling; 0.2 percent (s.e. 1 percent) for the change in average experience; and 25 percent (s.e. 9 percent) for the change in total employment.

percent (significant at the 5-percent level). This last estimate is consistent with the 18 to 25 percent estimates of Moretti (1998) for the 10-year period 1980-1990.

5. Identifying Human Capital Externalities with Relative Supply Effects

The Mincerian approach in the previous section yields substantial schooling externalities in cities. It is unclear however whether this finding may be (partly) driven by relative supply effects absent in the Mincerian approach. To address this issue we need to develop an empirically implementable approach where the average level of human capital in cities may affect wages through externality-driven shifts of labor demand curves as well as relative-supply-driven movements along labor demand curves (relative supply effects). The main difficulty in developing such an approach lies in dealing with the fact that our data contains approximately 360 different "types" of labor if we differentiate labor by level of schooling and experience alone.

To deal with relative supply effects in a way that is as closely as possible related to the Mincerian approach in the previous section, we allow wages per unit of ability $p_{ct}(h_{it}, x_i)$ in (1) to be a linear function of the individual level of human capital,

$$p_{ct}(h_{it}) = p_{ct}^{l} + p_{ct}^{h} h_{it}, \tag{7}$$

where we refer to p^l as the price of labor and p^h as the price of human capital. The role of other individual characteristics x_i is ignored for now to keep the exposition simple; x_i will be re-introduced when we implement our approach empirically. We assume that prices of labor and human capital are determined by exogenous factors, human capital externalities, and relative supply effects. Formally, the price of labor is given by

(8) $$p_{ct}^{l} = B_{ct} A(h_{ct}) q^{l}(h_{ct}),$$

where h_{ct} denotes the supply of human capital relative to labor in the city,

(9) $$h_{ct} = \frac{H_{ct}}{L_{ct}} = \frac{1}{L_{ct}} \int_{0}^{\infty} h L_{ct}(h) dh,$$

with $L_{ct}(h) / L_{ct}$ the fraction of workers with human capital in city c t. Notice that the supply of human capital relative to labor is equal to the average

$B_{ct} A(h_{ct})$, captures that the price of labor may depend on exogenous factors B_{ct} as well as the average level of human capital through externalities. The second term on the right-hand side of (8), $q^{l}(h_{ct})$, captures that the supply of human capital relative to labor in the city may affect the price of labor for a *given* value of the index A of labor productivity. Standard relative supply considerations suggest that an increase in the supply of human capital relative to labor increases the price of labor (for a given value of the index of labor productivity) because labor becomes relatively scarcer. The price of human capital can be written in a way that is analogous to (8),

(10) $$p_{ct}^{h} = C_{ct} A(h_{ct}) q^{h}(h_{ct}),$$

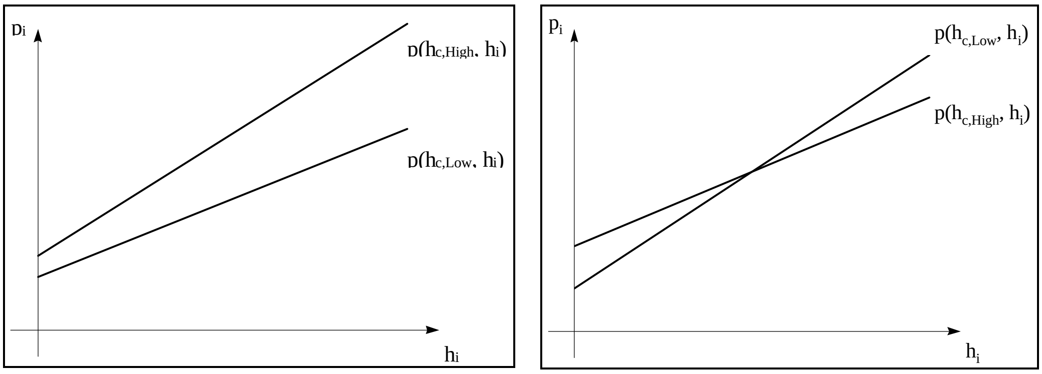
where $C_{ct} A(h_{ct})$ captures that the price of human capital may be affected by exogenous factors C_{ct} as well as the average level of human capital through externalities and $q^{h}(h_{ct})$ captures that the supply of human capital relative to labor may affect the price of human capital for a given value of the index A of labor productivity. Standard relative supply considerations suggest that an increase in the supply of human capital relative to labor decreases the price of human capital (for a given value of the index of labor productivity) because human capital becomes relatively more abundant. Finally, the average wage in cities adjusted by ability

(11) $$p_{ct}(h_{ct}) = p_{ct}^{l} + p_{ct}^{h} h_{ct}$$

depends on the price of labor, the price of human capital, and the average level of human capital.

Figure 1 illustrates what happens to the wage per unit of ability in a city when the average level of human capital increases and there are no relative supply effects but human capital externalities (left-hand side). The same figure also illustrates the case with standard relative supply effects and no human capital externalities (right-hand side).

Figure 1: Wages Per Unit of Ability With/Without Relative Supply Effects and Externalities



Notes: The figure on the left-hand side illustrates the case without relative (human capital) supply effects but with (human capital) externalities. The figure on the right-hand side illustrates the case with relative (human capital) supply effects but without (human capital) externalities.

The combination of human capital externalities and standard relative supply considerations captured in (8) and (10) suggests that an increase in the average level of human capital in a city should increase the price of labor. This is because we expect externalities and the relative supply effect to work in the same direction.

An increase in the average level of human capital may have an ambiguous effect on the price of human capital however as the price of human capital should decrease because of the relative supply effect but increase because of externalities. The presence of relative supply effects in (8) and (10) complicates the identification of human capital externalities considerably. To identify the strength of human capital externalities it is now necessary to disentangle externalities from relative supply effects. The approach developed so far does not allow us to do so. It is possible however to find sufficient conditions for the existence of human capital externalities. For example, if the effect of the average level of human capital on the price of human capital is strictly positive, then we would suspect that human capital externalities could play a role because relative supply effects predict a (weakly) negative sign. We would however be unable to identify the strength of externalities because the positive effect of the average level of human capital on the price of human capital may be the result of a strong (positive) externality combined with a strong (negative) relative supply effect or the result of a weak externality combined with a weak relative supply effect. The strength of human capital externalities could be identified however (with the Mincerian approach in the previous section) in the special case where the price of labor is zero and the price of human capital is independent of its supply relative to labor for a given value of the index A of labor productivity.

6. Externalities, Wages, and Growth Theory

The approach in the previous section can be used to identify aggregate returns to scale to capital and capital externalities once it is embedded in the framework of modern growth theory. To show how the approach can be embedded in the framework of modern growth theory we assume that value added Y_{ct} in city c at time t is produced according to

(12) $$Y_{ct} = F\left(K_{ct}, \Omega_{ct} G\left(L_{ct}, \Lambda_{ct} H_{ct}\right)\right),$$

where K_{ct} denotes the amount of physical capital employed, Ω_{ct} denotes an index of labor productivity, L_{ct} denotes total employment, Λ_{ct} captures human capital augmenting technological change, and H_{ct} denotes the total level of human capital,

(13) $$H_{ct} = \int_0^{\infty} h L_{ct}(h) dh,$$

with $L_{ct}(h)$ the number of workers with human capital h in the city. The only assumption imposed on the "labor composite" $G(L, \Lambda H)$ and the production function $F(K, \Omega G)$ is constant returns to L, H and K, G respectively. This amounts to assuming constant returns to scale of the aggregate production function in capital and labor of different "types" $L_{ct}(h)$. Returns to scale to physical and human capital of the aggregate production function will be unrestricted. One of the attractive features of the specification in (12) and (13) is that workers are better substitutes the closer their levels of human capital.

We assume also, following the idea of Romer (1986) and Lucas (1988), that the index of labor productivity in a city Ω_{ct} may depend on the average level of human capital and the physical capital intensity in the city through externalities (effects that are not taken into account by firms when they decide on capital purchases or labor hiring). This can be captured by

(14) $$\Omega_{ct} = \Phi_{ct} h_{ct}^{s} k_{ct}^{g}, \quad s, g \geq 0$$

where k_{ct} is the capital intensity in city c at time t; Φ_{ct} denotes other factors that affect labor productivity. To simplify the exposition we are assuming that there are no effects of total employment on the index of labor productivity (no aggregate scale effects). We will however allow for such effects when implementing our approach empirically.

The formulation in (12)-(14) admits Romer (1986), Lucas (1988) and Mankiw, Romer, and Weil (1992) among others as special cases. For example, Lucas (1988) can be obtained by assuming constant returns to scale to physical and human capital for a given value of the index of labor productivity Ω and no physical capital externalities. Mankiw, Romer, and Weil (1992) can be obtained by assuming that there are no physical and human capital externalities and that the elasticity of substitution between labor and human capital is unity. The appendix shows that models based on increasing returns to scale, imperfect competition, and non-tradability of some goods, like Romer (1990) for example, can also be fitted into our approach.

Aggregate returns to scale to physical and human capital (ARTSC) implied by (12) and (14) can be calculated as

$$\text{ARTSC} = a + (1 - a)(b + s + g)\,, \tag{15}$$

where a denotes the elasticity of production with respect to physical capital and $(1 - a)b$ denotes the elasticity of production with respect to human capital; b is the elasticity of the labor composite $G(L, \Lambda H)$ with respect to human capital; and s , g denote the strength of externalities to human capital and physical capital respectively.

The framework in (12) and (13) combined with competitive labor markets at the city-level and with profit-maximization implies a linear equilibrium wage-schedule at the city-level

$$\hat{p}_{ct}(h_i) = \hat{p}^{l}_{ct} + \hat{p}^{h}_{ct} h_i\,, \tag{16}$$

where $\hat{p}_{ct}(h)$ is the wage of a worker with human capital h. The linearity of the wage-schedule implied by (12) and (13) allows us to think of the modern growth framework as a foundation of $p_{ct}(h)$ in (7). This is why we drop the hats in (16) and in what follows.

Assuming that capital markets are competitive at the country-level enables us to determine the price of labor and human capital as a function of the average level of human capital in the city. This is because profit-maximization, competitive capital markets at the country-level, and competitive labor markets at the city-level imply that $F_1(K/\Omega G,1) = r$, $F_2(K/\Omega G,1)\Omega G_1(L,\Lambda H) = p^l$, and $F_2(K/\Omega G,1)\Omega G_2(L,\Lambda H)\Lambda = p^h$, where r denotes the rental cost of capital in the country (subscripts 1,2 denote partial derivatives with respect to the first and second argument of the function). The first of these conditions implies that $K/\Omega G = v(r)$ and therefore that $F_2(K/\Omega G,1) = f(r)$. Combined with the other two profit-maximization conditions, this yields

$$p_{ct}^l = f\Omega_{ct}G_1(1,\Lambda_{ct}h_{ct}) \tag{17}$$

and

$$p_{ct}^h = f\Omega_{ct}G_2(1,\Lambda_{ct}h_{ct})\Lambda_{ct}\,. \tag{18}$$

The average wage adjusted by ability in (11) as a function of the average level of human capital can be obtained by making use of (17), (18), and constant returns to scale of the labor composite

$$p_{ct} = f\Omega_{ct}G(1,\Lambda_{ct}h_{ct})\,. \tag{19}$$

The index of labor productivity Ω_{ct} in cities can also be written as a function of the average level of human capital only. Combining (14) with the fact that profit-maximization and perfect capital markets at the country-level imply $K/\Omega G = v(r)$, yields

(20) $$\Omega_{ct} = \Theta_{ct}(h_{ct})^{\frac{s}{1-g}} G(1, \Lambda_{ct} h_{ct})^{\frac{g}{1-g}}$$

where Θ_{ct} denotes other factors that affect the index of labor productivity. Thus, there will be a positive effect of the average level of human capital in the city on the index of labor productivity if there is a strictly positive human capital externality $s > 0$ or a strictly positive physical capital externality $g > 0$ (assuming that the marginal product of human capital is strictly positive). This is because an increase in the average level of human capital in a city, combined with competitive capital markets at the country-level, implies an increase in the physical capital intensity.

Constant returns to scale of the labor composite in labor and human capital yields decreasing returns to human capital, $G_{22} \leq 0$, and hence that an increase in the supply of human capital relative to labor will (weakly) decrease the price of human capital for a given value of the index of labor productivity Ω. The effect of an increase in the relative supply of human capital on the price of labor for a given Ω depends on whether there are complementarities between human capital and labor. If human capital and labor are complements, $G_{12} > 0$, then an increase in the supply of human capital relative to labor will increase the price of labor holding the index of labor productivity Ω constant. These relative supply effects, discussed more generally in the previous section, complicate identification of capital externalities in growth models with decreasing aggregate returns to capital. If there are constant returns to capital for a given value of the index of labor productivity (formally $G(L, \Lambda H) = \Lambda H$ and hence $G_{22} = G_{12} = 0$) it becomes possible to identify capital externalities with the Mincerian approach in the previous section.

This is because all effects of the average level of human capital on the price of human capital can be interpreted as externalities in this case.

6.1 Identification of Human Capital Externalities

To identify aggregate returns to scale to capital and capital externalities it is necessary to first identify the effect of human capital on the index of labor productivity

$$q_{ct} = \frac{\P \ln \Omega_{ct}}{\P \ln h} = \frac{s + g b_{ct}}{1 - g} \tag{21}$$

where we made use of (20). This can be done with data on the price of human capital, the price of labor, and the average level of human capital across cities and over time. To see how, it is useful to start by analyzing the elasticity of the prices of labor and human capital with respect to the average level of human capital. Partially differentiating (17) yields

$$e_{ct}^{l} = \frac{\P \ln p_{ct}^{l}}{\P \ln h} = \frac{G_{12}(1, \Lambda_{ct} h_{ct}) \Lambda_{ct} h_{ct}}{G_1(1, h_{ct})} + q_{ct} . \tag{22}$$

There are two effects of an increase in the average level of human capital on the price of labor: First, the effect conditional on the index of labor productivity $G_{12} \Lambda h_{ct} / G_1$ which captures the relative supply effect; this effect is positive if and only if human capital and labor are complements. Second, the effect of an increase in the index of labor productivity as captured by q . We expect the externality and relative supply effect to be (weakly) positive, so that an increase in the average level of human capital should (weakly) increase the price of labor. Differentiating (18) partially with respect to human capital yields the elasticity of the price of human capital with respect to human capital,

(23) $$e_{ct}^{h} = \frac{\P \ln p_{ct}^{h}}{\P \ln h} = \frac{G_{22}\left(1, \Lambda_{ct} h_{ct}\right) \Lambda_{ct} h_{ct}}{G_{2}(1, h_{ct})} + q_{ct} .$$

The effect of an increase in the average level of human capital on the price of human capital conditional on the index of labor productivity can never be strictly positive because $G_{22} \leq 0$ implies that the relative supply effect is always (weakly) negative. Taking into account capital externalities captured by q , the total effect of an increase in the average level of human capital on the price of human capital may either be positive or negative however, depending on the strength of the relative supply effect and externalities.

Constant returns to scale of the aggregate production function for a given value of the index of labor productivity implies that the effect of an increase in the level of human capital on the price of human capital is linked to its effect on the price of labor. To see this, notice that constant returns to scale and continuous differentiability of the labor composite yields

(24) $$G_{12}(1, \Lambda h) + G_{22}(1, \Lambda h) \Lambda h = 0 .$$

Intuitively, (24) states that an increase in the supply of human capital relative to labor cannot strictly increase both the price of labor and the price of human capital (for a given value of the index of labor productivity Ω). It also states the relationship between the increase in the price of labor and the decrease in the price of human capital (for a given value of the index of labor productivity). Making use of the restriction between (22) and (23) implied by (24), and defining l_{ct} as the share of human capital in wages adjusted by ability

(25) $$l_{ct} = \frac{p_{ct}^{h} h_{ct}}{p_{ct}} ,$$

we can determine the strength of capital externalities q as

$$q_{ct} = e_{ct}^{h} l_{ct} + e_{ct}^{l} (1 - l_{ct}) . \tag{26}$$

The strength of capital externalities can therefore be identified as a weighted average of the percentage change in the price of labor and the price of human capital due to an increase in the average level of human capital in the city. The weights are simply the share of wages adjusted by ability going to labor and human capital respectively.

Equation (26) is not quite sufficient to obtain an estimate of capital externalities with our data however. This is because it requires estimates of the effect of an increase in the average level of human capital on the prices of labor and human capital for each city. The best we can hope for with our data is an estimate of the average effect of an increase in the average level of human capital on the prices of labor and human capital across cities, $e_t^l = E_t e_{ct}^l$ and $e_t^h = E_t e_{ct}^h$. These estimates are sufficient to identify the strength of capital externalities if the share of human capital in wages adjusted by ability l_{ct} and the difference between the percentage change in the price of labor and the percentage change in price of human capital induced by a one percent increase in the average level of human capital $e_{ct}^l - e_{ct}^h$ are independently distributed across cities. In this case, (26) implies

$$q_t = e_t^h l_t + e_t^l (1 - l_t) , \tag{27}$$

where $q_t = E_t q_{ct}$ and $l_t = E_t l_{ct}$. It is straightforward to show that the condition for (27) to be valid is satisfied for a class of aggregate production functions that includes the (Cobb-Douglas) aggregate production function used in growth theory. In particular, if $G(L, \Lambda H)$ is of the constant-elasticity-of-substitution type,

(28) $$G(L, \Lambda H) = \left(g\,(L)^{1-h} + (1-g\,)(\Lambda H)^{1-h}\right)^{\frac{1}{1-h}}, \qquad h \geq 0,$$

with $1/h$ the elasticity of substitution between human capital and labor, then $e_{ct}^{l} - e_{ct}^{h} = h$. This has two useful implications: First, $e_{ct}^{l} - e_{ct}^{h}$ and l_{ct} are obviously independently distributed across cities. Second, $1/(e_{ct}^{l} - e_{ct}^{h})$ gives us an estimate of the elasticity of substitution between human capital and labor.

There is an alternative way to identify capital externalities q. The partial elasticity of the average wage adjusted by ability in (9) with respect to the average level of human capital is

(29) $$e_{ct} = \frac{\P \ln p_{ct}}{\P \ln h} = b_{ct} + q_{ct},$$

where b_{ct} is the elasticity of the labor composite with respect to human capital. Competitive labor markets imply that b is equal to the share of human capital in wages adjusted by ability,

(30) $$b_{ct} = l_{ct}.$$

Combining (29) and (30) yields that $q_{ct} = e_{ct} - b_{ct} = e_{ct} - l_{ct}$, which suggests that capital externalities can also be identified as

(31) $$q_{t} = e_{t} - l_{t},$$

where $e_{t} = E_{t}e_{ct}$.

7. Empirical Implementation

We implement our approach to the identification of aggregate returns to scale to capital and capital externalities empirically by first using individual-level data to estimate the price of labor, the price of human capital, the average wage adjusted by ability, and the average level of human capital for the 173 cities in our sample in 1970, 1980, and 1990. This allows us to calculate the change in the price of labor $\Delta \ln p_{ct}^{l}$, the change in the price of human capital $\Delta \ln p_{ct}^{h}$, the change in the average wage adjusted by ability $\Delta \ln p_{ct}$, and the change in the level of human capital $\Delta \ln h_{ct}$ between any two of the three years considered. We then estimate the effect of an increase in the average level of human capital on the price of labor, the price of human capital, and the average wage adjusted by ability. Finally, we combine these estimates with the share of human capital in wages adjusted by ability to assess the strength of capital externalities q_t.

The prices of labor and human capital and the average level of human capital by city and year are obtained by estimating the wage-regression implied by our approach. There is however an issue that we have to address before implementing these wage-regressions. It is well known in labor economics that gender and race are significant determinants of wages. These variables could be included as determinants of the individual level of human capital (in addition to schooling and experience) in our approach. We think of gender and race as driving a wedge between marginal productivity and wage however. This is why we modify (7) to

(32) $$p_{ct}\left(h_t(z_i), x_i\right) = d_t(x_i)\left(p_{ct}^{l} + p_{ct}^{h} h_t(z_i)\right)$$

where $d_t(x)$, which captures the fraction of their marginal product that individuals with characteristics x can appropriate, and $h_t(z)$ are specified in (3). Combining (32) with (1) and (3) yields the following wage-regression

$$\text{(33)} \qquad \ln w_{ct}(S,E,R,F,u) = \ln\left(p^l_{ct} + p^h_{ct}\exp\left(b_t S + c_t E - e_t E^2\right)\right) + r_t R + f_t F + u$$

where we assume that the unobservable u is normally distributed across individuals.[4,5] Implementing (33) with individual-level data for each of our 173 cities in 1970, 1980, and 1990 using non-linear least-squares estimation yields estimates of the prices of labor and human capital as well as estimates of the average level of human capital by city and year. The average level of human capital can be obtained by first estimating the individual level of human capital and then using (9) to aggregate across individuals in the same city. The wage-regression in (33) reduces to the Mincerian wage-regression when $p^l = 0$.[6]

Partial elasticities of the prices of labor and human capital with respect to the average level of human capital can be estimated by relating (ln-) changes in the prices of labor and human capital between any two of the three years considered to (ln-) changes in human capital. This is done by estimating

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[4] The formulation in (33) assumes implicitly that a worker with no schooling and experience has one unit of human capital. This could be changed so that a worker with no schooling and experience has v units of human capital. In this case, p^h in (33) would become vp^h. The empirical analysis would be unchanged because we use the cross-city variation of the time-change of $\ln(vp^h)$ to estimate capital externalities.

[5] We also added dummies for the industry where individuals are employed. This did not make much of a difference for the empirical results however.

[6] We also ran standard Mincerian wage-regressions on our data. The results from these regressions (discussed in the appendix) are in line with the findings in labor economics.

(34) $$\Delta \ln p_{ct}^{l} = T_t^{l} + \text{Controls}_c + e^{l} \Delta \ln h_{ct} + u_{ct}$$

and

(35) $$\Delta \ln p_{ct}^{h} = T_t^{h} + \text{Controls}_c + e^{h} \Delta \ln h_{ct} + v_{ct} ,$$

where T_l, T_h denote constants. Differencing takes care of all city-specific fixed effects on the index of labor productivity, like the presence of a harbor, climate, and so on. “Controls” always include the change in employment in the city over the time-period considered and also includes 4 geographic dummies (Midwest, West, Mountain, and South) that capture regional differences in the exogenous growth rate of labor productivity. There are two important issues that must be addressed in the estimation of (34) and (35). First, both u and v contain the change in the (unobservable) exogenous level of technology across cities between any two of the three years considered. This leads us to suspect that least-squares estimates of the elasticities in (34) and (35) would be biased upwards as changes in the average level of human capital across cities and changes in total employment (which is part of the controls) are probably positively correlated with the (unobservable) rate of exogenous technological change of cities (as workers move to cities with higher levels of labor productivity and wages). Consistent estimation of (34) and (35) will therefore require instrumental variables for the change in the average level of human capital and the change in employment. The instruments we use are the same ones used to estimate (6). The second important problem with the estimation of (34) and (35) is that the change in human capital is itself estimated from previous wage-regressions and will therefore contain an estimation error. Least-squares estimation would therefore lead to attenuation bias. Instrumental variables estimation of (34) and (35) will however address this problem as the instruments are unrelated to the estimation error. Finally, efficient estimation of (34) and (35) requires taking into account that the precision of the estimates of $\Delta \ln p_{ct}^{l}$ and $\Delta \ln p_{ct}^{h}$ differs across cities, giving rise to heteroskedasticity, and that the errors across the two equations may be correlated due to (common) effects of exogenous changes in labor productivity. Our preferred method of estimation of (34) and (35) is therefore generalized three-stage least squares (G3SLS).

To implement the alternative way to identify capital externalities in (31) we need to estimate the partial elasticity of the average wage adjusted by ability with respect to the average level of human capital between any two of the three years considered. To do so we estimate

$$(36) \qquad \Delta \ln p_{ct} = T_t + \text{GeoControls}_{\text{c}} + e\Delta \ln h_{ct} + m\Delta \ln L_{ct} + u_{ct} ,$$

where T denotes a constant and $p_{ct} = p_{ct}^{l} + p_{ct}^{h} h_{ct}$. "GeoControls" refers to 4 geographic dummies that capture regional differences in the exogenous growth rate of labor productivity. Consistent estimation of (36) poses similar problems as estimation of (34) and (35). This is why (36) will be estimated with the same set of instruments used to estimate (34) and (35). Comparing the estimate of e obtained from (36) with the estimate of l obtained from (33) allows us to get an alternative estimate of the strength of capital externalities using (31).

Estimation of (36) also serves to estimate the strength of externalities associated with total employment in the city (aggregate scale effects). From (19) it can be seen that m in (36) gives an estimate of effects of total employment in cities on the index of labor productivity.

8. Results

It is useful to start by estimating e^{l} and e^{h} in (34) and (35) with generalized least squares (GLS). This gives a sense for the partial correlations in the data as well as a benchmark against which the instrumental variables estimates can be evaluated.

Table 2 summarizes the results of GLS estimation for the 20-year period 1970-1990. There is a positive effect of an increase in the average level of human capital on the price of labor and a weak negative effect on the price of human capital when we do not use geographic controls (in the first column). When we allow for different rates of exogenous labor productivity growth by region (in the second column) we find a weak positive effect of an increase in the average level of human capital on the price of human capital: the price of human capital increases in cities that experienced an increase in the supply of human capital relative to labor.

Table 2: GLS Estimation of e^l and e^h in (34) and (35)

	GLS 70-90	GLS 70-90 with 4 Geo Controls
	$\Delta\ln(h)$	$\Delta\ln(h)$
$\Delta\ln(p^l)$	1.99*** (0.71)	0.89 (0.79)
$\Delta\ln(p^h)$	-0.57* (0.31)	0.17 (0.34)

Notes: Weighting takes into account that the left-hand sides of (34) and (35) are estimated more precisely in larger cities than in smaller cities. "4 Geo Controls" refers to geographic dummies (Midwest, West, Mountain, and South). Numbers in brackets are standard errors. Three (two, one) asterisks denote estimates that are different from zero at the 1-percent (5-percent, 10-percent) significance level.

The problem with the GLS estimates of e^l and e^h in Table 2 is that they are biased towards zero by attenuation bias (as the change in the average level of human capital is itself estimated) and biased upwards due to the endogeneity of the regressors. This is why we turn to instrumental variables estimation next. Table 3 summarizes the results of estimating e^l and e^h in (34) and (35) with generalized two-stage least squares (G2SLS) using the instruments discussed in the previous section.[7]

[7] Results are similar whether or not we use the quality of life instruments (Footnote 3).

Table 3: G2SLS Estimation of e^l and e^h in (34) and (35)

	G2SLS 70-90	G2SLS 70-90 with 4 Geo Controls
	$\Delta\ln(h)$	$\Delta\ln(h)$
$\Delta\ln(p^l)$	4.24*** (1.27)	3.53*** (1.52)
$\Delta\ln(p^h)$	-2.16*** (0.59)	-1.31** (0.66)

Notes: See Table 2. The instruments used are quality of life variables and demographic and ethnic composition in 1970.

G2SLS estimation yields that the effect of the change in the average level of human capital on the price of labor and human capital is significantly different from zero at the 5-percent level. The effect of the change in human capital on the price of labor stays positive and increases relative to GLS estimation and the effect on the price of human capital is negative and has become smaller. The test of exogeneity of our instruments (using the Sargan test of Section 4) yields that exogeneity cannot be rejected at the 90-percent significance level.[8]

The G2SLS results in Table 3 show that an increase in the average level of human capital decreases the price of human capital. This implies that capital externalities (if any) are not sufficiently strong to offset the (negative) relative supply effect of an increase in the average level of human capital on its price: the "aggregate" demand curve for human capital is downward sloping. This suggests that the (positive) effect of the average level of human capital on the price of human capital obtained with GLS (in the second column of Table 2) is driven by reverse causality: it is not the increase in the average level of human capital that leads to an increase in the price of human capital but exogenous increases in labor productivity that lead to an increase of both the price of human capital and the

[8] Our instruments predict 38 percent of the change in employment and 36 percent of the change in human capital.

average level of human capital in the city. To put it differently, GLS estimation of the elasticities in (34) and (35) confounds movements along the "aggregate" human capital demand curve with shifts of the demand curve. Once we consider movements along the demand curve only (by using G2SLS estimation) we find a negative effect of the average level of human capital on its price.

The errors in the estimating equations (34) and (35) are potentially correlated and efficient estimation would therefore require using generalized three-stage least-squares (G3SLS) estimation. The G3SLS results in Table 4 are very similar to the results in Table 3 when we do not control for different growth rates of exogenous labor productivity by region. When we allow for different growth rates of exogenous labor productivity by region, the results in Table 4 become stronger than in Table 3: the positive (negative) effect of human capital on the price of labor (human capital) becomes larger (smaller) and more significant.

Table 4: G3SLS Estimation of e^l and e^h in (34) and (35)

	G3SLS 70-90	G3SLS 70-90 with 4 Geo Controls
	$\Delta\ln(h)$	$\Delta\ln(h)$
$\Delta\ln(p^l)$	4.24*** (1.27)	3.9*** (1.4)
$\Delta\ln(p^h)$	-2.26*** (0.60)	-2.5*** (0.9)

Notes: See Table 3.

Table 5 estimates the elasticities in (34) and (35) for the 10-year periods 1970-1980 and 1980-1990 pooled (allowing for different intercepts for the two 10-year periods). The results are very similar to those obtained for the 20-year period 1970-1990.[9]

[9] Re-estimating the model separately for the period 1970-1980 and 1980-1990 yields very similar point estimates. Standard errors increase however.

Table 5: G2SLS and G3SLS Estimation of e^l and e^h in (34) and (35)

	G2SLS 70-80 and 80-90 pooled	G3SLS 70-80 and 80-90 pooled
	$\Delta\ln(h)$	$\Delta\ln(h)$
$\Delta\ln(p^l)$	4.1** (2.6)	4.4** (2.3)
$\Delta\ln(p^h)$	-2.1*** (0.77)	-2.16*** (0.77)

Notes: See Table 3.

Summarizing, the evidence indicates that an increase in the average level of human capital in a city has a significant positive effect on the price of labor and a significant negative effect on the price of human capital. The positive effect on the price of labor may be due to relative (human capital) supply effects (the price of labor increases as its relative supply falls) or to human capital externalities. The negative effect of the average level of human capital on the price of human capital suggests that (negative) relative (human capital) supply effects (the price of human capital decreases as its relative supply increases) play a role: without such (negative) relative supply effects the price of human capital should (weakly) increase with the average level of human capital because of externalities.

Capital Externalities

The results so far indicate that capital externalities (if any) are not sufficiently strong to offset the (negative) relative supply effect of an increase in the average level of human capital on the price of human capital. To see whether there are capital externalities at all, it is necessary to go beyond estimation of the elasticities in (34) and (35) and estimate the strength of capital externalities q. This can be done in the framework of modern growth theory by combining the effect of an increase in the average level of human capital on the prices of human capital and labor with the share of human capital in wages l as described in (27). The average share of human capital in wages across cities and time (1970, 1980, and 1990) estimated using (25) is 70 percent. This estimate together with the estimators of e_L and e_H in (34) and (35) for 1970-1990 can be used to obtain the point estimate and standard error of q for the 20-year period 1970-1990 from (27).[10] The results are an estimate of q for 1970-1990 of 13 percent with a standard error of 46 percent in the case of G2SLS estimation without geography controls. The estimate using G3SLS without geography controls is 3 percent with a standard error of 25 percent. Both point estimates are insignificantly different from zero. The results with geography controls and the results for the periods 1970-1980 and 1980-1990 pooled are very similar.

The point estimates of q are of course not directly comparable to the point estimate of externalities of average schooling estimated with the Mincerian approach without relative supply effects in Section 4 (Table 1). To compare estimates without and with relative supply effects, it is necessary to relate the (ln-) change in the average level of human capital across cities to the change in average years of schooling and average years of experience. To do so, we regress the (ln-) change in the average level of human capital across cities for 1970-1990 on the change in average years of schooling and the change in average years of experience. This yields

$$(39) \qquad \Delta \ln h_c = C + 0.14\Delta S_c + 0.009\Delta E_c - 0.0002(\Delta E_c)^2 .$$

The R^2 of this regression is 96 percent (94 percent with schooling only).

We can now obtain point estimates of the externalities from average schooling in cities in the presence of relative (human capital) supply effects.

[10] The estimate and standard error are obtained by simulating the distribution of q in (27) using the estimated joint asymptotic distribution of the e s in (34) and (35) (which given asymptotic normality is fully characterized by the estimated means and the estimated variance-covariance matrix) and the distribution of the l s across cities.

Multiplying the coefficient on the change in average years of schooling (0.14) in (39) with the estimates of q, we obtain that point estimates of externalities from average years of schooling are between 0.4 percent (G3SLS) and 1.8 percent (G2SLS). Accounting for relative (human capital) supply effects has therefore reduced externalities from average years of schooling in cities from the highly significant 15 percent in Table 1 to a statistically insignificant 0.4-1.8 percent.

The implications of these results for the human capital externality s and the physical capital externality g in (14) can be derived from (21) and (30). The former equation states that $q = (s + bg)/(1-g)$ and the latter that $l = b$. The fact that our average value for l is 70 percent and that we find q to be insignificantly different from zero indicates that neither human capital externalities nor physical capital externalities play a role in cities.[11]

Capital Externalities: An Alternative Approach

The alternative approach to estimating capital externalities in (31) relies on comparing the partial elasticity of the average wage adjusted by ability with respect to the average level of human capital e to the share of human capital in wages. The next table contains the G2SLS estimates of e and m in (36) for the 20-year period 1970-1990.

Table 6: G2SLS Estimation of e and m in (36)

	G2SLS 70-90	
	$\Delta\ln(h)$	$\Delta\ln(L)$
$\Delta\ln p$	0.69** (0.28)	0.11** (0.03)

Notes: See Table 3. Weighting takes into account that the left-hand side of (36) is estimated more precisely in larger cities than in smaller cities; $p = p^l + p^h h$.

[11] Another interpretation is that positive (negative) human capital externalities offset negative (positive) physical capital externalities. This seems unlikely however.

The elasticity with respect to the average level of human capital is somewhat below 70 percent. Averaging our estimates of l_{ct} across cities and across years yields a value of 70 percent. Our alternative approach in (31) therefore also suggest that capital externalities play no role in cities.

Aggregate Returns to Scale to Capital

Our findings indicate no physical or human capital externalities in cities. This implies that the elasticity of output with respect to physical and human capital at the city-level can be calculated from the physical and human capital income shares. The physical capital income share in the US is approximately 30 percent. The human capital income share can be calculated by multiplying the share of income going to workers by the share of human capital in wages. The share of income going to workers in the US is 70 percent and we estimate the share of human capital in wages to be 70 percent. This yields a human capital income share of 50 percent. Combining the physical capital income share and the human capital income share yields a (total) capital income share, and hence a value of aggregate returns to scale to capital, of approximately 80 percent. This estimate is very similar to the estimates from the cross-country income convergence approach in Barro and Sala-i-Martin (1992) and Mankiw, Romer, and Weil (1992). The break-up of the estimate into human capital and physical capital is however somewhat different from the break-up in Mankiw, Romer, and Weil. They estimate a human capital income share of around 25 percent while human capital plays a more important role in our result.

Employment Externalities

The results in Table 6 suggest strong employment externalities. The point estimate of m indicates that an increase in total employment of 10 percent increased labor productivity by 1.1 percent in the 20-year period 1970-1990. Existing estimates of the elasticity of productivity with respect to employment in cities are between 4 and 8 percent, see Henderson (1988) and Ciccone and Hall (1996) for estimates and a review of the literature. These estimates are obtained without controlling for fixed effects, without taking into account the endogeneity of the level of human capital, and without taking into account measurement error however. They are therefore difficult to compare to our estimates (measurement error in employment is especially serious because the available employment data gives the number of people employed in the city without distinguishing between full-time and part-time employment).

Complementarities between Human Capital and Labor

Our results also suggest strong complementarities between human capital and labor. For example, a one percent increase in the average level of human capital in a city increases the price of labor by 4.24 percent according to the G3SLS estimate in Table 4. This estimate, combined with the result in (39) that an increase in the average level of schooling by one year increases the average level of human capital by 14 percent, implies that a one year increase in the average level of schooling in a city increases the price of labor by 60 percent. It is straightforward to translate complementarities between human capital and labor into complementarities between workers with different levels of human capital by using our estimates of (33), (34), and (35). Calculations yield that a one year increase in the average level of schooling in a city increases the wage of a worker with 8 years of schooling and average experience by approximately 8 percent and the wage of a worker with no schooling and average experience by 26 percent.

We can also estimate the elasticity of substitution between human capital and labor by using the fact that the elasticity of substitution $1/h$ in (28) is equal to

$1/(e^{l}-e^{h})$. Our G3SLS estimates in Table 4 yield an elasticity of substitution between human capital and labor of 15 percent.

9. Biased (Technology) Shocks, Human Capital, and Wages

The average real wage in the 20-year period 1970-1990 decreased by 8 percent in our sample of 173 cities. This decrease in average wages was accompanied by an increased dispersion of average wages across cities: the standard deviation of average wages across cities was approximately 5 percent larger in 1990 than in 1970. The increased dispersion of average wages cannot be explained by an increased dispersion of average levels of human capital across cities as the standard deviation of average levels of schooling across cities decreased by 23 percent. Looking at the dispersion of the prices of labor and human capital across cities, we find that the standard deviation of the price of labor across cities decreased by 15 percent from 1970 to 1990. The standard deviation of the price of human capital more than doubled over the same time-period. This increase in the dispersion of the price of human capital combined with the decrease in the dispersion of the average level of schooling suggests that (technology) shocks that were biased towards human capital must play a key role in explaining the increased dispersion of the price of human capital (and average wages) across cities.

The estimated residual from equation (35) allows us to explore whether cities with positive human capital biased (technology) shocks between 1970 and 1990 experienced above average growth of average levels of schooling. This is because the residual is a weighted average of the true human capital biased (technology) shock and measurement error (in the measurement of the ln-change of the average level of human capital). If the change in the average level of schooling is measured without (with little) error, then we can estimate the correlation between the human capital biased (technology) shock and the change in average levels of schooling by calculating the correlation between the estimated residual and changes in the average level of schooling. This correlation is significantly positive, suggesting that workers with higher levels of schooling moved to cities that experienced positive human capital biased (technology) shocks. We used the same method to estimate the correlation between human capital biased (technology) shocks between 1970 and 1990 and the initial average level of schooling. There we found an insignificant, very small, positive correlation, suggesting that there was no clear relationship between the level of schooling in 1970 and subsequent human capital biased (technology) shocks.

It is interesting to note that our estimates suggest that workers with low levels of human capital in cities with positive human capital biased (technology) shocks benefited indirectly from these shocks. This is because higher prices of human capital attracted workers with high levels of human capital, increasing the average level of human capital in the city. The increase in the average level of human capital increased the price of labor (and hence wages of workers with low levels of human capital) because of the complementarity between human capital and labor.

10. Summary and Conclusions

We have estimated the price of labor and the price of human capital for 173 cities for 1970, 1980, and 1990 using data on individual wages and characteristics from the US Census. This was done assuming that the level of human capital of individuals was an exponential function of their schooling and experience and that individual wages, conditional on ability as well as race and gender, depended linearly on the individual level of human capital. The resulting approach had the standard Mincerian wage-regression as a special case. We then related changes in the prices of labor and human capital across cities between 1970 and 1990 to changes in the supply of human capital relative to labor. This yielded a positive partial correlation between changes in the relative supply of human capital and changes in the price of human capital. The problem with interpreting this finding was that it could indicate a positive effect of the relative supply of human capital on the price of human capital (an upward sloping "aggregate" demand curve for human capital) or a response of the supply of human capital to exogenous changes in productivity (an exogenously shifting, downward sloping demand curve for human capital combined with labor mobility). We therefore used an instrumental variables approach to estimate the effect of the relative supply of human capital on the price of human capital. This yielded that an increase in the relative supply of human capital always decreased the price of human capital. We interpreted this finding as evidence against upward sloping "aggregate" demand curves for human capital (aggregate increasing returns to scale to human capital). Our instrumental variables estimates of the effect of an increase in the relative supply of human capital on the price of labor were significantly positive and indicated strong complementarities between labor and human capital. For example, the estimates implied that a one year increase in the average level of schooling in a city would have increased wages of workers with no schooling and average experience by 26 percent between 1970 and 1990. These complementarities explain why we found that an increase in the average level of human capital in cities decreased wage-inequality between 1970 and 1990.

We then used the framework of modern growth theory to see whether our findings about the effect of an increase in the relative supply of human capital on the price of labor (positive) and the price of human capital (negative) indicated externalities to human or physical capital in cities. To do so we noted that growth theories without human and physical capital externalities make a simple prediction linking the effect of an increase in the relative supply of human capital on the price of labor to its effect on the price of human capital. We could not reject this prediction and therefore concluded that there were no human or physical capital externalities in cities. A related restriction implied by (modern) growth theories with human or physical capital externalities could be used to obtain a point estimate (and standard error) for capital externalities. Our point estimate was basically zero. These conclusions about capital externalities in cities—obtained with a model that allowed for relative (human capital) supply effects as well as externalities—contrasted with the high and significant estimates of human capital externalities in a model that did not allow for relative supply effects.

Our estimates of the effect of changes in total employment across cities on average wages indicated significant externalities from total employment however. A 10 percent increase in total employment between 1970 and 1990 increased labor productivity by 1.1 percent. The fact that we did not find any capital externalities in cities allowed us to calculate aggregate returns to scale to capital at the city-level from data on capital income shares. Our estimate of the human capital income share of 50 percent, combined with the US physical capital income share of 30 percent, yielded a value of aggregate returns to scale to capital of 80 percent. This estimate is consistent with the findings from the cross-country regressions in Barro and Sala-i-Martin (1992) and Mankiw, Romer, and Weil (1992). Our estimates indicate a more important role for human capital than the estimates in Mankiw, Romer, and Weil however.

References

Acemoglu, Daron (1996) "A Microfoundation for Social Increasing Returns in Human Capital Accumulation," *Quarterly Journal of Economics* 111, pp. 78-93.

Almond, Douglas (1997) "Human Capital as a Local Public Good: Evidence from the 1990 Census," Mimeo, University of California, Berkeley.

Barro, Robert and Xavier Sala-i-Martin (1992) "Convergence," *Journal of Political Economy* 100, pp. 233-251.

Boyer, Robert and David Savageau (1990) "*Places Rated Almanac*," Prentice Hall, New York.

Card, David (1999) "Education in the Labor Market," in Orley Ashenfelter and David Card *Handbook of Labor Economics*, North Holland, Amsterdam.

Ciccone, Antonio and Robert Hall (1996) "Productivity and the Density of Economic Activity," *American Economic Review*, pp. 52-71.

Ciccone, Antonio (1997) "Dynamic Externalities and the Spatial Distribution of Wages in the US," Mimeo, University of California, Berkeley.

de la Fuente, Angel (1998) "What Kind of Convergence?" Mimeo, Instituto de Análisis Económico (CSIC), Barcelona.

Glaeser, Edward, Heidi Kallal, José Scheinkman, and Andrei Shleifer (1992) "Growth in Cities," *Journal of Political Economy* 100, pp. 1126-1151.

Hall, Robert E. and Charles Jones (1999) "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics* 113, pp. 89-123.

Henderson, Vernon (1988) *Urban Development: Theory, Fact, and Illusion*, Oxford University Press, Oxford, UK.

Islam, Nazrul (1995) "Growth Empirics: A Panel Data Approach," *Quarterly Journal of Economics* 82, pp. 34-56.

Jacobs, Jane (1969) *The Economy of Cities*, Random House, New York

Jacobs, Jane (1984) *Cities and the Wealth of Nations*, Random House, New York

Krugman, Paul (1979) "Increasing Returns, Monopolistic Competition, and International Trade," *Journal of International Economics* 9, pp. 469-479.

Lucas, Robert E. (1988) "On the Mechanics of Economic Development," *Journal of Monetary Economics* 22, pp. 3-41.

Lucas Robert E. (1990) “Why Doesn’t Capital Flow from Rich to Poor Countries?” *American Economic Review* 80, pp. 92-96.

Lucas, Robert E. (1993) “Making a Miracle,” *Econometrica* 34, pp. 256-271.

Mankiw, N. Gregory, David Romer, and David Weil (1992) “A Contribution to the Empirics of Economic Growth,” *Quarterly Journal of Economics* 107, pp. 407-437.

Marshall, Alfred (1890) *Principles of Economics*, Macmillan, London.

Moretti, Enrico (1998) “Social Returns to Education and Human Capital Externalities: Evidence from Cities,” Center for Labor Economics Working Paper No.9, University of California, Berkeley.

Pissarides, Christopher (1990) *Equilibrium Unemployment Theory*, Basil Blackwell, Oxford.

Rauch, James (1993) “Productivity Gains from Geographic Concentration in Cities,” *Journal of Urban Economics* 34, pp. 380-400.

Rebelo, Sergio (1991) “Long-Run Policy Analysis and Long-Run Growth,” *Journal of Political Economy* 99, pp. 500-521.

Romer, Paul (1986) “Increasing Returns and Long-Run Growth,” *Journal of Political Economy* 98, pp. 1002-1037.

Romer, Paul (1990) “Endogenous Technological Change,” *Journal of Political Economy* 94, pp. S71-S102.

Sargan, Dennis (1988) *Lectures on Advanced Econometric Theory*, Basil Blackwell, Oxford.

Shioji, Etsuro (1997) “Convergence in Panel Data: Evidence from the Skipping Estimation,” Mimeo, Universitat Pompeu Fabra, Barcelona.

U.S. Bureau of Census (1970), *Census of Population and Housing, United States*.

U.S. Bureau of Census (1980), *Census of Population and Housing, United States*.

U.S. Bureau of Census (1990), *Census of Population and Housing, United States*.

US Department of Commerce (1992), Economics and Statistics Administration, Bureau of Economic Analysis, Regional Economic Measurement Division, *REIS CD-ROM*.

Vayá, Esther, Enrique López-Bazo, and Manuel Artis (1998) “Growth, Convergence, and (Why Not?) Externalities Across Regions,” Mimeo, University of Barcelona.

A. Appendix

A1. Data

We use data on more than 4 million individuals in 1970, 1980, and 1990. The individual-level data for 1980 and 1990 comes from the public use micro samples (PUMS) of the 1980 and 1990 US Census (US Bureau of Census (1980) and (1990)). For 1970, the data comes from the PUMS of the 1970 US Census (US Bureau of Census (1970)). The definition of cities that we use corresponds, with some exceptions, to the US Bureau of Census definition of standard metropolitan statistical areas (SMSAs) in 1990. The PUMS of the 1980 and 1990 US Census have (FIPS) codes identifying the SMSA where individuals live. With this information we can assign individuals in 1980 and 1990 to one of 236 cities. The 1970 US Census does not identify the SMSAs where individuals live. Individuals are instead assigned to so-called county groups. County groups can be related to SMSAs by using the so-called county group map (attached to the PUMS in 1970). We match individuals to SMSAs in the following way. When one or more county groups were contained in one SMSA then we assign individuals located in one of the county groups to the SMSA that contains them. When a county group contained more than one SMSA then we merged the different SMSAs into one (23 of our 173 cities are obtained this way) applying the same criterion to SMSAs in 1980 and 1990 (to ensure that cities are defined in the same way in 1979, 1980, and 1990). Finally, when a county group was contained partly in an SMSA, partly in a non-SMSA area, then we assigned all individuals located in the county group that identified themselves in the census as located in a SMSA as located in the SMSA that contained part of the county group. This procedure resulted in 173 cities in 1970, 1980, and 1990. A list of these cities is contained at the end of the appendix. The code to perform the identification and merge of cities is available from us upon request.

Experience of individuals is measured as potential experience (age less years of schooling less six). We have nine levels of schooling for individuals. The variation of average years of schooling by city in our sample of 173 cities is the following. For the 1970-1990 period average years of schooling across cities rose on average by 1.19 years. The standard deviation across cities was 0.38 and the maximal increase of average years of schooling 2.08 years. The same figures for 1970-1980 are 0.96, 0.26, and 1.6. For 1980-1990, the figures are 0.22, 0.29, and 0.87.

Employment Data: The data on aggregate employment in cities in 1970, 1980, and 1990 comes from the 1992 *REIS CD-ROM* from the U.S. Department of Commerce. This CD-ROM contains data on non-agricultural private employment in US counties from 1969 to 1992. We constructed employment in each city in 1970, 1980, and 1990 by adding 1970, 1980, and 1990 employment in all counties that were contained in the city in 1990. These data are available from us upon request (see also the list of cities at the end of the appendix).

Instruments: Data on demographic and ethnic structure in 1970 comes from the 1970 US Census. For the demographic structure we use the share of individuals in each 5-year cohort between 15 and 70 years (11 variables). For the ethnic structure we use the share of individuals that identified themselves as: White; Black; Hispanic; Indian or Eskimo; Japanese, Chinese, or Filipino; and Pacific Islander or Hawaiian (5 variables). Quality of life data is based on 4 indices which are themselves based on 22 variables (ranging from climate to the presence of sports teams and opera companies) from Robert Boyer and David Savageau (1990) and are available from us upon request. We have 20 instruments in total.

Mincerian Wage-Regression with Our Data: We only use data on individuals in SMSAs. The results of Mincerian wage-regressions with our SMSA-sample are however virtually identical to the results using US Census data on all individuals discussed in Card (1999). For example, when we regress $\ln(Wage)$ on individual schooling, individual experience and individual experience squared, dummies for sex and race, and SMSA dummies, we find a return to schooling of 8.8 percent in 1990 and 6.7 percent in 1980. Details are available from us upon request.

A2. Why Cities with High Average Schooling May Have High Composition-Adjusted Average Wages Even in the Absence of Schooling Externalities (Details on the Example in Section 3)

Suppose that output Y_c in city c is produced with the following (twice continuously differentiable) constant-returns-to-scale production function

(A1) $$Y_c = F(L_c, H_c)$$

where L_c denotes the number of low-schooling workers and H_c the number of high-schooling workers in city c. Suppose that labor markets are competitive at the city-level. This implies that the wage of low-schooling workers is

(A2) $$w_c^l = F_1(1, h_c)$$

where subscripts 1,2 of the function $F(\bullet)$ will denote partial derivatives with respect to the first, second argument, and h_c denotes the ratio of high-schooling workers to low-schooling workers in city c. The wage of high-schooling workers is

(A3) $$w_c^h = AF_2(1, h_c).$$

Wages of low-schooling workers and wages of high-schooling workers are therefore determined by the relative supply of high-schooling workers to low-schooling workers in the city. The average wage of a group of $\overline{H}$ high-schooling workers and a group of $\overline{L}$ low-schooling workers in city c is

(A4) $$w_c^a(h_c, \overline{h}) = \frac{w_c^l(h_c)\overline{L} + w_c^h(h_c)\overline{H}}{\overline{L} + \overline{H}} = \frac{w_c^l(h_c) + w_c^h(h_c)\overline{h}}{1 + \overline{h}}.$$

Now suppose that we are looking at average wages of two groups with equal composition $\overline{h}$ in two cities with different ratios of high-schooling workers to low schooling workers $h_1 < h_2$. Which city has higher average wages adjusted for composition? To answer this question, notice that constant returns to scale implies that $w_c^a(h_c, \overline{h})$ is a hump-shaped function of h_c which reaches its unique maximum at $h_c = \overline{h}$ if low-schooling workers and high-schooling workers are imperfect substitutes, $F_{12} > 0$ (to see this notice that constant returns to scale and continuous differentiability of $F(\bullet)$ imply that $F_{12}(1,h) + F_{22}(1,h)h = 0$). Hence, it is as easy to find cases where $w_1^a(h_1, \overline{h}) < w_2^a(h_2, \overline{h})$ as it is to find cases where $w_1^a(h_1, \overline{h}) > w_2^a(h_2, \overline{h})$ when workers with different schooling levels are imperfect substitutes. This implies that the city with a high average level of schooling may have a higher average wage adjusted for composition than the city with a low average level of schooling even if there are no human capital externalities: Higher composition-adjusted average wages in cities with higher average levels of schooling is no evidence for human capital externalities. There is one exception. If workers with different schooling levels are perfect substitutes, then wages of low-schooling workers and wages of high-schooling workers in (A2) and (A3) are independent of the average level of schooling in the city. In this case, cities with high average levels of schooling will have the same average wage adjusted for composition than cities with low average levels of schooling if there are no human capital externalities.

A3. A Model with Non-Tradable Producer Services Produced with Increasing Returns to Scale

Suppose that perfectly competitive final good firms produce tradable goods according to

$$Y_f = F(S_f, G(L_f, H_f)) \tag{A5}$$

where the subscript f stands for final good firms and S is the usual constant-elasticity-of-substitution service composite

$$S_f = \left(\int_0^{\infty} (s_{if})^{\frac{s-1}{s}} di \right)^{\frac{s}{s-1}}, \tag{A6}$$

with s_{if} the amount of the non-tradable service i used in the production of final goods. Adding physical capital is straightforward and therefore omitted. Non-tradable services of type i are produced in a monopolistically competitive service sector according to

$$s_i = \mathrm{Max}\left[F(S_i, G(L_i, H_i)) - f, 0\right], \tag{A7}$$

with f the overhead resource requirement of production. Every service is produced by a different firm and there is free entry of firms into the service sector. Then, it can be shown that the equilibrium wage-schedule is

$$w = p_c^l + p_c^h h \tag{A8}$$

where

(A9) $$p_c^l = k(L_c, h_c) G_1(1, h_c) ,$$

(A10) $$p_c^h = k(L_c, h_c) G_2(1, h_c) ,$$

where L_c is the level of employment in the city, h_c is the average level of human capital in the city, and $k(L,h)$ increasing in both arguments (subscripts 1,2 denote partial derivatives). This model can be seen as an adaptation of Romer (1990) to the city-level. Detailed derivations can be obtained from us upon request.

A4. List of Cities with Key Aggregate Variables

City Name	**Average Years of Schooling**		**Average Years of Experience**		**Total Private, Non-Agricultural Employment**	
	'70	'90	'70	'90	'70	'90
Abilene, TX	11.6	13.2	24.1	18.4	54707	91746
Akron, OH	12.1	13.1	22.7	18.8	237978	285068
Albany-Schenectady-Troy, NY	12.3	13.4	23.6	19.5	262619	384949
Albuquerque, NM	12.7	13.3	21.0	18.7	100206	244273
Allentown-Bethlehem-Easton, PA-NJ	11.3	12.9	25.3	20.0	238793	303955
Altoona, PA	11.4	12.6	24.1	19.5	49094	55627
Amarillo, TX	12.0	12.9	21.2	19.3	53301	82711
Anaheim-Santa Ana, CA	12.6	13.1	20.0	18.4	429256	1405209
Appleton-Oshkosh-Neenah, WI	11.7	12.9	22.3	18.3	99351	163027
Atlanta, GA	11.9	13.5	20.6	17.9	703363	1580647
Atlantic City, NJ	10.8	12.6	25.7	20.4	131011	236189
Augusta, GA-SC	11.1	12.9	22.5	19.1	88932	177811
Austin, TX	12.4	13.5	20.5	17.1	108915	351303
Bakersfield, CA	11.6	12.9	23.6	19.8	84895	187927
Baltimore, MD	11.2	13.2	23.4	18.7	748907	1136605
Baton Rouge, LA	12.2	12.9	21.7	17.4	108653	217277
Beaumont-Port Arthur, TX	11.2	12.7	23.3	20.0	116527	143500
Billings, MT	12.2	13.5	22.6	17.7	54915	91819
Biloxi-Gulfport, MS	11.5	12.8	22.6	19.9	39027	68701
Binghamton, NY	12.3	13.4	22.7	18.8	92062	117649
Birmingham, AL	11.4	13.0	23.0	19.6	283762	418355

City Name	**Average Years of Schooling**		**Average Years of Experience**		**Total Private, Non-Agricultural Employment**	
	‘70	‘90	‘70	‘90	‘70	‘90
Bloomington-Normal, IL	12.3	13.5	22.3	17.9	36163	66448
Boise City, ID	12.8	13.3	20.6	17.6	41377	112395
Boston, MA	12.3	13.8	23.8	18.1	1716968	2314349
Bridgeport, CT	11.6	12.9	25.2	21.1	340672	447286
Brownsville-Harlingen, TX	9.2	10.7	24.9	20.3	70841	179994
Buffalo, NY	11.7	13.2	24.4	19.8	385600	450640
Canton, OY	11.6	12.6	22.9	19.1	144914	176241
Cedar Rapids, IA	12.3	13.2	20.7	19.8	68057	98237
Champaign-Urbana-Rantoul, IL	13.3	13.9	18.5	17.9	38843	72901
Charleston, SC	10.9	12.9	22.3	18.2	85389	195445
Charlotte-Gastonia-Rock Hill, NC-SC	11.8	12.7	21.4	18.5	380775	669127
Chattanooga, TN-GA	11.1	12.4	23.5	21.0	141885	202487
Chicago, IL	11.9	13.2	23.3	19.3	2620409	3262950
Cincinnati, OH-KY-IN	11.7	13.1	22.8	18.8	519052	768186
Cleveland, OH	11.9	13.1	23.6	19.5	848369	962555
Colorado Springs, CO	12.3	13.4	22.3	19.7	87520	207905
Columbia, MO	12.8	13.9	19.2	13.2	22604	50780
Columbia, SC	11.7	13.2	20.5	18.6	106882	224986
Columbus, OH	12.3	13.3	21.2	18.0	408761	712922
Corpus Christi, TX	10.8	12.6	23.5	18.4	86664	132307
Dallas, TX	11.8	13.1	21.4	17.9	987312	2082026
Davenport-Rock Island-Moline, IA-IL	11.8	13.1	23.6	18.4	128309	164751
Dayton-Springfield, OH	11.8	13.2	22.4	19.5	350730	442932
Decatur, IL	11.8	13.2	24.6	21.0	116410	154621
Denver, CO	12.6	13.4	20.9	18.8	437946	912957
Des Moines, IA	12.5	13.2	22.3	18.3	142745	242171
Detroit, MI	11.9	13.1	22.5	19.2	1578307	1993757
Duluth, MN-WI	12.1	12.8	24.5	18.8	81523	94318
El Paso, TX	11.1	11.9	22.2	19.0	99848	199834
Erie, PA	12.0	13.0	24.2	20.0	100555	126113
Eugene-Springfield, OR	12.6	13.2	21.5	19.3	65898	123967
Fayetteville, NC	11.1	13.0	20.5	16.3	42539	77154
Flint, MI	11.6	12.8	21.1	19.6	144957	171398
Fort Lauderdale-Hollywood-P.Beach, FL	11.7	13.0	24.4	20.3	206800	583406

City Name	Average Years of Schooling		Average Years of Experience		Total Private, Non-Agricultural Employment	
	‘70	‘90	‘70	‘90	‘70	‘90
Fort Wayne, IN	12.2	12.8	21.4	19.7	141088	212278
Fresno, CA	11.9	12.7	21.8	19.2	122350	257420
Gainesville, FL	12.9	13.9	19.8	16.2	29092	78446
Gary-Hammond, IN	11.4	12.8	23.6	20.5	227318	247774
Grand Rapids, MI	11.8	13.1	22.9	17.7	199974	396412
Green Bay, WI	11.9	12.8	21.3	18.2	55787	108272
Greensboro-Winston-Salem-High Point, NC	11.1	12.7	22.8	19.9	330504	537601
Greenville-Spartanburg, SC	10.9	12.7	22.2	19.9	202077	352503
Hamilton-Middletown, OH	11.3	12.8	22.7	18.2	68885	96991
Harrisburg-Lebanon-Carlisle, PA	11.6	12.8	23.7	19.2	191536	289589
Hartford, CT	11.9	13.5	24.0	19.6	97244	153015
Honolulu, HI	12.2	13.3	21.3	19.6	218323	388070
Houston, TX	11.8	12.8	20.8	18.2	829788	1728781
Huntington-Ashland, WV-KY-OH	11.7	12.8	24.4	20.6	93553	112138
Indianapolis, IN	11.9	12.9	22.3	18.6	428858	686737
Jackson, MI	11.8	12.6	23.6	19.7	48035	54326
Jackson, MS	12.1	13.8	21.4	18.5	106672	175415
Jacksonville, FL	11.6	12.7	22.7	19.3	211580	429792
Jersey City, NJ	10.4	12.2	26.3	20.8	252752	234772
Johnstown, PA	11.3	12.6	24.8	21.5	76736	85583
Kalamazoo, MI	12.4	13.4	20.9	18.3	70735	114059
Kansas City, MO-KS	12.1	13.2	22.8	19.1	525933	808325
Kenosha, WI	11.6	12.9	23.5	19.5	90329	121051
Knoxville, TN	11.6	12.6	23.4	21.0	149498	280887
Lafayette, LA	11.4	12.8	22.1	17.7	42068	103342
Lafayette, IN	12.6	13.5	22.7	14.7	36562	59149
Lancaster, PA	11.0	12.4	24.4	20.5	130428	215469
Lansing-East Lansing, MI	12.5	13.5	20.2	18.0	107632	177065
Las Vegas, NY	12.1	12.4	21.2	20.0	105346	390749
Lawton, OK	11.7	12.2	23.6	20.8	53294	86708
Lexington-Fayette, KY	12.4	13.5	19.5	17.7	96774	189803
Lima, OH	11.7	12.3	23.4	21.9	59761	76125
Lincoln, NE	12.8	13.5	21.0	16.9	62273	111918
Little Rock-North Little Rock, AR	11.9	13.1	21.9	19.4	137982	248532
Lorain-Elyria, OH	11.2	12.5	23.7	20.6	79172	93067

City Name	Average Years of Schooling		Average Years of Experience		Total Private, Non-Agricultural Employment	
	'70	'90	'70	'90	'70	'90
Los Angeles-Long Beach, CA	12.3	12.4	22.1	19.1	2867092	4617235
Louisville, KY-IN	11.4	13.2	23.2	20.2	356409	499585
Lubbock, TX	11.5	13.0	21.4	17.1	58604	97582
Macon-Warner Robins, GA	11.1	12.8	23.7	17.1	71820	115158
Madison, WI	13.0	14.1	20.0	16.9	94819	192086
Mansfield, OH	11.4	12.6	22.7	19.6	52239	62090
Memphis, TN-AR-MS	11.5	13.2	22.5	18.2	288933	490942
Miami-Hialeah, FL	11.5	12.5	24.2	21.4	552362	961182
Milwaukee, WI	12.0	13.2	22.7	19.0	569223	786156
Minneapolis-St. Paul, MN-WI	12.4	13.5	21.2	18.0	798927	1410586
Modesto, CA	12.0	12.4	22.0	18.5	57558	133340
Monroe, LA	11.5	12.9	23.6	17.8	35308	56537
Montgomery, AL	11.3	13.1	23.7	19.3	72900	121578
Muncie, IN	11.6	12.6	22.4	19.7	94302	103926
Nashville, TN	11.7	13.0	22.2	18.8	270000	537601
New Orleans, LA	11.4	13.3	23.2	19.4	400789	545158
New York, NY	11.8	13.1	24.3	20.5	4008941	4057008
Newark, NJ	11.7	13.3	24.5	21.3	814079	948960
Norfolk-Virginia Beach-Newport News, VA	11.3	13.0	22.7	18.8	277854	552493
Odessa, TX	11.8	12.0	21.9	18.7	59032	101496
Oklahoma City, OK	12.3	13.2	21.5	18.4	245768	423628
Omaha, NE-IA	12.2	13.3	21.7	18.8	214619	340565
Orlando, FL	11.7	13.1	22.5	18.7	154095	598302
Oxnard-Ventura, CA	12.1	13.3	21.6	18.5	83511	259407
Pensacola, FL	11.5	12.8	22.9	20.1	175921	307537
Peoria, IL	11.8	13.0	23.3	19.3	131764	159114
Philadelphia, PA-NJ	11.7	13.3	24.0	19.9	1782621	2268610
Phoenix, AZ	12.3	13.2	21.3	18.5	339996	1048770
Pittsburgh, PA	11.8	13.3	24.6	19.9	835990	956984
Portland, OR	12.5	13.4	22.2	18.5	359393	683078
Providence, RI	11.2	13.1	24.8	18.4	14104	17932
Raleigh-Durham, NC	11.9	14.0	20.8	17.5	166559	410551
Reading, PA	11.0	12.6	24.7	20.0	125883	162847
Reno, NY	12.5	13.1	21.9	19.5	56132	151804
Richmond-Petersburg, VA	11.4	13.2	22.9	18.7	265752	461658

City Name	Average Years of Schooling		Average Years of Experience		Total Private, Non-Agricultural Employment	
	‘70	‘90	‘70	‘90	‘70	‘90
Riverside-San Bernardino, CA	12.0	12.5	22.7	18.4	282666	774484
Roanoke, VA	11.6	12.6	23.0	21.0	86656	135770
Rochester, NY	12.1	13.5	22.7	18.8	355418	500441
Rockford, IL	11.4	12.7	23.3	19.9	111209	150339
Sacramento, CA	12.6	13.4	22.2	18.5	211398	594227
Saginaw-Bay City-Midland, MI	11.6	13.0	22.4	20.5	127609	167441
St. Louis, MO-IL	11.6	13.1	23.8	19.3	903707	1249521
Salem, OR	12.4	12.8	22.8	19.1	48702	101563
Salinas-Seaside-Monterey, CA	12.0	12.7	22.1	20.2	61677	139790
Salt Lake City-Ogden, UT	12.8	13.4	21.3	17.5	253032	575744
San Antonio, TX	11.1	12.8	22.6	18.6	244385	498204
San Diego, CA	12.7	13.3	21.7	17.2	363752	1061203
San Francisco, CA	12.7	13.8	22.2	19.0	1191491	2030555
San Jose, CA	12.9	13.6	19.7	17.7	373632	910406
Santa Barbara-Santa Maria-Lompoc, CA	12.8	13.1	21.5	19.0	78815	172008
Santa Rosa-Petaluma, CA	12.5	13.4	22.4	19.1	51310	169499
Seattle, WA	12.7	13.6	21.2	18.5	509810	1169623
Shreveport, LA	11.5	13.0	23.9	20.1	96858	135989
South Bend-Mishawaka, IN	11.6	12.9	24.5	18.5	91007	123928
Spokane, WA	12.6	13.4	22.7	17.1	91290	159042
Springfield, MO	12.0	12.9	21.0	17.0	67234	135646
Springfield, MA	11.4	12.6	24.8	18.8	39372	73488
Stockton, CA	11.7	12.4	24.3	19.7	83178	165017
Syracuse, NY	12.2	13.4	23.3	17.9	212629	316047
Tacoma, WA	12.1	13.1	23.5	18.6	98195	196004
Tampa-St. Petersburg-Clearwater, FL	11.8	13.0	23.9	20.3	353339	964453
Terre Haute, IN	11.8	12.9	24.2	19.1	47586	56424
Toledo, OH	11.8	13.0	23.0	18.5	232895	291353
Trenton, NJ	11.7	13.6	24.0	20.2	120430	165416
Tucson, AZ	12.3	13.2	22.9	17.6	102945	256183
Tulsa, OK	12.0	13.2	21.8	18.7	199945	354355
Tuscaloosa, AL	12.0	13.0	21.1	16.3	31720	55412
Tyler, TX	11.5	12.9	25.1	20.6	38249	71843
Utica-Rome, NY	11.7	13.1	24.9	19.8	102463	118367
Vallejo-Fairfield-Napa, CA	12.2	13.1	23.8	19.8	49785	137181

City Name	Average Years of Schooling		Average Years of Experience		Total Private, Non-Agricultural Employment	
	‘70	‘90	‘70	‘90	‘70	‘90
Waco, TX	11.3	12.5	25.2	20.6	52641	80474
Washington, DC-MD-VA	12.8	14.0	20.5	18.0	930498	2046568
Waterloo-Cedar Falls, IA	12.2	13.2	22.4	18.2	56209	68731
West Palm Beach-Boca Raton-D. Beach, FL	11.6	12.9	24.7	21.1	129228	422008
Wichita, KS	12.3	13.1	22.6	19.7	156370	261496
Wilmington, DE-NJ-MD	12.0	13.4	22.2	19.7	190549	303117
Wilmington, NC	11.4	13.0	22.1	18.6	35038	64160
Worcester, MA	11.5	13.2	26.3	18.7	49470	84359
York, PA	11.0	12.5	24.8	19.2	137163	194569
Youngstown-Warren, OH	11.8	12.7	23.9	20.9	198600	207001