THE COMPLEMENTARITY BETWEEN CITIES AND SKILLS

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Abstract

There is a strong connection between per worker productivity and metropolitan area population, which is commonly interpreted as evidence for the existence of agglomeration economies. Yet this correlation is particularly strong in cities with higher levels of skill and virtually non-existent in less skilled metropolitan areas. This fact is particularly compatible with the view that urban density is important because proximity spreads knowledge, either making workers more skilled or entrepreneurs more productive. Bigger cities certainly attract more skilled workers, and there is some evidence suggesting that human capital accumulates more quickly in urban areas.

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I. Introduction

The connection between area size and per worker productivity or income is a core fact at the center of urban economics. The fact that workers in cities earn more is understood to be one of the primary reasons that cities exist. Understanding the connection between city size and productivity is a core task for students of agglomeration. Yet the connection between city size and productivity does not hold for less skilled metropolitan areas. In the least well-educated third of metropolitan areas, there is virtually no connection between city size and productivity or income. In the most well educated third of metropolitan areas, area population can explain 45 percent of the variation in per worker productivity.

Why does productivity increase with area population for skilled places, but not for unskilled places? One hypothesis is that the connection between productivity and area size reflects a tendency of more skilled people to locate in big cities. However, even in the more skilled places, controlling for area level skills can only explain a quarter of the measured agglomeration effect. Real wages do rise with city size for this class of cities, which suggests that unobserved human capital may also be higher in these places, but that effect can, perhaps, explain 25 percent of the connection between city size and income or productivity, leaving the bulk of the relationship unexplained.

We divide the theories of agglomeration into two broad categories—those that emphasize the spread of knowledge in cities and those that do not. Among the latter group is the view that cities are more productive because of advantages, unrelated to agglomeration, such as access to ports or harbors or good government. Non-knowledge based theories also include standard agglomeration models, such as the ability to reduce transport costs for goods, and higher levels of capital per worker. In Section III, we address these theories. While there is little evidence that directly supports these hypotheses, there is little evidence with which to reject them either.

In Section IV, we turn to two core knowledge-based theories of urban agglomeration, which can both readily explain why the productivity-city size connection is so much stronger in higher human capital metropolitan areas. The first hypothesis, which comes from Marshall's statement that in agglomeration the "mysteries of the trade" are in the air, is that density makes it easier for workers to learn from each other. The second hypothesis is that high levels of human capital and city size interact to push out the frontier of knowledge and the level of productivity. In some versions, the two hypotheses give opposite predictions about the age earnings profile in cities. The learning interpretation suggests that age-earnings profiles should be steeper in big, skilled areas, because workers are learning more rapidly. The innovation interpretation can mean that age-earnings profiles in such places are flatter, because technological change is proceeding rapidly and making the skills of older people obsolete.

As in Glaeser and Mare (2001), we find some evidence supporting the view that workers learn more quickly in metropolitan areas. We also find that this learning effect is stronger in more skilled areas. However, we do not find that age-earnings profiles are steeper in bigger metropolitan areas, and the interaction between area size, area skills and experience is insignificant. While these findings are quite compatible with the view that cities and skills are complements, they do not clearly indicate whether this complementarity works through learning, innovation, both or neither.

The natural implication of the view that cities and human capital are complements is that cities will become more, not less, important if humanity continues acquiring knowledge. The importance of connecting in dense urban areas will only increase with skills, at least as long as technological shifts don't eliminate the urban edge in transferring information.

II. The Interaction between Skills and City Population

Figure 1 illustrates the well-known connection between city size and productivity per worker. In this figure, productivity per worker is calculated as the ratio of Gross Metropolitan Product in 2001 (as calculated by the Bureau of Economic Analysis) to the total labor force. The raw elasticity is .13.

Of course, one part of this connection is that bigger metropolitan areas do seem to have more skilled workers, as shown in Figure 2. The tendency of more skilled people to live in metropolitan areas could reflect a greater demand of more skilled people for urban amenities, or perhaps that cities disproportionately increase the productivity of more skilled workers. A naïve attempt to control for the share of adults with college degrees at the metropolitan area level yields the following regression:

$$\text{(1)} \quad \text{Log (Output per Worker)} = \underset{(.11)}{9.49} + \underset{(.010)}{.098}\text{*Log(Population)} + \underset{(.14)}{1.18}\text{*Share with BAs}$$

Output per worker continues to be gross metropolitan product divided by the size of the labor force. Standard errors are in parentheses. The r-squared is .47 and there are 335 observations. The coefficient on log of population declines slightly, from .13 to .098, a roughly 25 percent decline. Just controlling for human capital eliminates about one-quarter of the connection between area population and output per worker.

But it appears that the effects of human capital and city size are not independent. When we interact the two variables, we estimate:

$$\text{(2)} \text{Log (Output per Worker)} = \underset{(.01)}{.08}\text{*Log(Population)} + \underset{(.14)}{1.26}\text{*Share with BAs} + \underset{(.13)}{.51}\text{*BA*Pop}$$

The term BA*Pop refers to the product of log of area population (demeaned) and share with college degrees (also demeaned). An intercept was included in the estimation but is not reported for space reasons. The r-squared is now .49. The demeaning of the variables means that both raw coefficients can be interpreted as the impact of the variable, when the other variable has taken on its mean level. The interaction means that when the share with college degrees is at its minimum observed value of .09 (which would be -.13 relative to the mean), the estimated coefficient on population is just .01, whereas for the maximum value of .52, the estimated effect is .23.

If we instead run this regression with the logarithm of per capita income, we estimate coefficients of .026, 1.43 and .42 on population, share with college degrees and the interaction respectively. In that case, the t-statistic on the interaction is 4.5. If we use log of median family income as the dependent variable, the estimated coefficients are .019, 1.55 and .36 on the three variables. The t-statistic on the interaction remains over 4.

Our independent variables are themselves quite endogenous, and we have no perfect fix for this problem. However, similar results appear if we use variables from 1940 (population, share with college degrees and the interaction) instead of contemporaneous variables to explain current gross metropolitan product. In that case, we estimate:

$$\text{(2')} \text{Log (Output per Worker)} = \underset{(.01)}{.07}\text{*Log(Population)} + \underset{(.68)}{5.04}\text{*Share with BAs} + \underset{(.60)}{2.47}\text{*BA*Pop}$$

In this case, there are 334 observations and the r-squared is .34. The high coefficient on the lagged share of the population with college degrees reflects, in part, the tendency of skilled places to become more skilled over time, as discussed in Berry and Glaeser (2005).

When we run individual level regressions, controlling for individual level human capital and experience the results are somewhat weaker. The first regression of Table 1 shows the .041 coefficient when individual yearly log earnings are regressed on metropolitan area size (also found in Glaeser and Gottlieb, 2008). This coefficient is less than one-half of the baseline coefficient in the gross metropolitan product regression. Controlling for the share of the population with college degrees pushes the coefficient down further to .028. In the third regression, we show that the interaction between population and the share with college degrees is positive, although significant only at the 10 percent level. The results are qualitatively similar to those above although weaker in magnitude, reflecting largely the fact that our results are generally weaker for the largest metropolitan areas, which are weighted heavily in these individual level regressions. Regression (4) repeats regression (3) weighting by the inverse of MSA population (so smaller metropolitan areas get more weight). In this case, the results look closer to the aggregate results.

Figures 3 and 4 show this interaction graphically. Figure 3 shows the relationship between metropolitan area population and output per worker in the 100 least well educated metropolitan areas with populations over 100,000. Figure 4 shows the relationship between metropolitan area population and output per worker in the 100 most well educated areas with populations over 100,000. Among less well educated places, there is essentially no agglomeration elasticity. In the most well educated places, population can explain 45 percent of the variation in productivity. In these well educated places, there is virtually no effect of including further controls for education on the city effect so the measured coefficient of .13 is the same with or without controlling for human capital. The same basic pattern appears with different measures of earnings, such as per capita income or median family income. In high human capital cities, the agglomeration effect is strong. In low human capital cities, it is weak or non-existent.[2]

One hypothesis is that the connection between cities and productivity represents omitted skills that are either obtained before working or learned on the job. It would certainly be possible, that the connection between city size and productivity is higher in skilled cities because the correlation between skills and population is particularly strong in such places.[3] We will address the theory that cities enhance skill acquisition later, and here just discuss the possibility that the urban wage premium reflects pre-existing skills. Glaeser and Mare (2001) do a fair amount of work showing that the urban wage premium (as opposed to the more continuous correlation between city size and productivity or earnings), survives a large number of measures of individual human capital, such as test scores and instrumental variables approaches that use parental state of birth characteristics.

One of their pieces of evidence supporting the view that omitted pre-market human capital variables are not higher in cities is that real wages, i.e. wages controlling for local price levels do not rise significantly in urban areas. If people in cities had more innate human capital, then they should be earning higher real wages as well as higher nominal wages. Of course, this measure is troubled by the fact that amenities may be either higher or lower in large urban areas. Glaeser and Mare find little connection between city size and real wages in their sample of cities. In our considerably larger sample, we also find little connection between the log of median family income, divided by the American Chamber of Commerce Research Association local price index, and city population, at least once we control for the share of the population with college degrees.

However, this result is not true in the more skilled cities where agglomeration elasticities are strongest. For example, if we look only at those areas where the share of population with college degrees is greater than 25.025 percent (the same cutoff used to establish the top 100 skilled cities above), we find that:

$$\text{(3)} \quad \text{Log (Real Family Income)} = \underset{(.10)}{9.07} + \underset{(.006)}{0.025}*\text{Log(Population)} + \underset{(.15)}{1.00}*\text{Share with BAs}$$

There are 262 observations and the r-squared is .27. All data comes from the Census except for the price indices used to turn nominal into real income, which comes from the American Chamber of Commerce Research Association.[4]

[2] Interestingly, there is significant cross effect between city human capital and city size in the population growth context. While highly skilled cities grow more swiftly than less skilled areas (Glaeser and Saiz, 2005, Shapiro, 2006), that effect is not larger in bigger areas.

[3] If skills were learned in big cities, then more human capital in big cities would lead to more learning in the model of Glaeser (1999). If skills were pre-existing, then it would be possible that omitted aspects of human capital were more important at the high end of the skill distribution which is over-represented in skilled places.

[4] A better procedure would be to use individual level data and individual level price controls as in Moretti (2008).

Real incomes rise significantly with skills, which is compatible with the view that more skilled people are more productive. While real incomes do not rise with city size, across the entire population, in these skilled areas, there is a positive connection. This connection can be interpreted as either reflecting the greater level of unobserved human capital in these area or that these bigger cities are less pleasant and higher wages are compensation for negative amenities. However, controlling for amenities does little to change this result, and we have trouble believing that there are more negative amenities in big skilled cities than in big unskilled cities.

If the coefficient on city size is treated as a measure of the extent to which unobserved skills rise with city size in this skilled city subsample, this would mean that about 30 percent of the urban productivity coefficient can be explained by human capital (.025/.08). Since observed human capital is uncorrelated with city size in this subsample, this is a plausible measure of the extent to which human capital explains the city size effect in these cities. In contrast, in the overall sample, bigger cities do have higher observed levels of human capital, and controlling for skills can explain about one-quarter of the connection between city size and productivity, but there is little sign that unobserved human capital is higher in bigger metropolitan areas. In either case, human capital appears to explain at most 30 percent of the city size effect, leaving at least seventy percent to be explained.[5] Understanding why the city size effect is larger in skilled places seems particularly pressing.

III. Urban Productivity Framework

In a standard production function, output per worker can be written as PAF(K, hL)/L, where P is price of the good, A is the level of productivity, K is the level of capital and hL reflects the amount of effective labor, with h as human capital and L as the number of workers. If the production function is homogenous of degree one, which is necessary for a zero-profit equilibrium, then output per worker can be rewritten as PAF(k, h), where k reflects physical capital per worker and h reflects human capital. If the production function is Cobb-Douglas, with parameter β on labor, then differentiating this quantity with respect to any exogenous variable "Z", such as city population, yields the following decomposition:

$$\text{(4)} \quad \frac{\partial Log(Output\ Per\ Worker)}{\partial Log(Z)} = \frac{\partial Log(P)}{\partial Log(Z)} + \frac{\partial Log(A)}{\partial Log(Z)} + (1-\beta)\frac{\partial Log(k)}{\partial Log(Z)} + \beta\frac{\partial Log(h)}{\partial Log(Z)}$$

Wages per worker equal the wage per effective unit of human capital times the amount of human capital per worker. In a standard Cobb-Douglas formulation, wages per worker equal β times output per worker.

To close the model, capital and labor should presumably also be endogenized. If workers are to be indifferent across locations, spatial equilibrium being the hallmark of urban models, then high costs of living must offset high wages. But that does not change the fact that high wages must also be offset by something making firms more productive, and our focus is on this latter relationship.

The connection between output per worker and city size could represent an increase in prices, productivity, capital per worker or human capital per worker, in big cities. The relative importance of the different forces will surely differ across industries. Barbers will have a higher output per worker in bigger cities, but much of that difference will reflect higher prices, not capital per worker, or even human capital. In contrast, the prices of traded manufactured goods are more or less constant over space, and any variation in output per worker must reflect productivity or capital, either physical or human.

We will divide up these theories into two sets of hypotheses. One set of theories emphasizes greater knowledge in cities, which could mean higher levels of "h" or a higher level of "A" brought on by the urban exchange of ideas. We will address that set of theories in the next section. The other set of

[5] These effects are much smaller than the very large effects estimated by Combes, Duranton and Gobillon (2008). We suspect that this reflects a greater connection between human capital and city size in France.

theories focuses on other causes of urban productivity, which include innate urban advantages, such as access to waterways or good government, higher levels of capital per worker, and non-knowledge based agglomeration economies.

Conceptually, it would certainly be quite possible for the strong connection between city size and productivity to reflect omitted characteristics of a location that both enhance productivity and attract workers. In the 19th century, it seems undebatable that the waterways of New York and Chicago made these places economically successful and attracted people to them (Glaeser, 2005). Yet few urbanists today believe that locational advantages have much direct impact.[6] Cities long ago gave up on those industries that were tied to their local geography. Today, cities are more likely to specialize in business services (Kolko and Neumark, 2008) and it is hard to see how those services get an edge from a harbor or a coal mine. Natural advantages seem to explain only twenty five percent of the concentration of manufacturing industries (Ellison and Glaeser, 2009).

We are less sure that natural advantage is irrelevant in explaining the connection between city size and productivity, but it seems unlikely that any natural advantages can explain why that connection is stronger in more skilled cities. After all, many of these natural advantages would seem to have their largest impact on less skilled industries. Indeed, that is exactly what a cursory examination of the data reveals. Variables like proximity to the great lakes or harbors positively impact productivity in less skilled places, but have no impact in more skilled areas. For example, the correlation between per capita income and miles from the nearest body of water is -.33 for less educated cities and -.03 for more educated cities. If this result holds more generally, and innate advantage matters more for less skilled workers, then the fact that city size increases productivity more for places with more skills is evidence against the importance of such natural advantages.

One way in which natural advantage might matter today is that past historical natural advantages might have led to more investment in physical capital. Typically, physical capital is treated as endogenous and for that reason, not really a plausible determinant of agglomeration economies. For example, in the model sketched above, if purchased by producers at a cost "r", which might differ across space, then a Cobb-Douglas relationship would imply that:

$$\text{(4')} \quad \frac{\partial Log(Output\ Per\ Worker)}{\partial Log(Z)} = \frac{1}{\beta}\left(\frac{\partial Log(P)}{\partial Log(Z)} + \frac{\partial Log(A)}{\partial Log(Z)}\right) - \frac{1-\beta}{\beta}\frac{\partial Log(r)}{\partial Log(Z)} + \frac{\partial Log(h)}{\partial Log(Z)}$$

If physical capital is endogenously determined, then it can only increase the connection between city size and output per worker if capital is cheaper in big, dense cities. Typically, evidence on real estate costs would suggest that capital is, if anything more expensive in big cities, which reflects the greater scarcity of land.

However, if big cities have long invested in durable physical capital, then that capital might remain and might increase productivity today. Certainly, casual observation of cities such as New York, London and Paris suggest that they have advantages which come from centuries of public and private investment in physical capital. Is there any evidence to support this view?

Unfortunately, there is little good measurement of physical capital at the metropolitan area level. A few heroic social scientists, such as Munnell (1990) and Garofalo and Yankin (1996) have created state level estimates of the capital stock, but these estimates have been based on apportioning the national capital stock to states on the basis of the types of industries in those states.[7] At the state level, for manufacturing industries, the Census of Manufacturers provides an estimate of expenditures on capital.

[6] Combes, Duranton, Gobillon and Roux (2008) go so far as to use historical sources of innate advantage as instruments for current population density, which requires that these variables be orthogonal to current productivity.

[7] A similar procedure could be used at the metropolitan area level, but we doubt that it would be seen as particularly compelling to suggest that the New York City's capital stock is the same as the nation, except for its mix of major industries.

These numbers are problematic in two ways: they represent an estimate of the flow of investment not the stock of capital and they address only manufacturing.

While there is certainly a robust relationship between capital expenditures and value added per worker, shown in Figure 5, controlling for capital expenditures only increases the relationship between state level density and value added per worker or income. Table 2 shows the relationship between the Ciccone and Hall (1996) index of state level density and two measures of output: value added per worker and hourly wage for production workers for states with more than 50,000 manufacturing workers. Columns (2) and (4) show the increased connection between output and density when a control for capital expenditures is added. The raw correlation between the capital expenditures and density is negative. These results should not lead us to think that the capital stock explanation for urban productivity is disproved, but rather that this sliver of available evidence does not support that hypothesis.

In columns (3) and (6), we include controls for years of schooling taken, for comparability reasons, also from Ciccone and Hall (1996). Schooling has a tiny and insignificant, impact on valued added per worker, and a larger but still insignificant effect on the hourly wage. Controlling for schooling reduces the coefficient on density in the wage regression, but not the value added regression, because education seems to influence wages more than value added.

Still, this evidence only informs us about current expenditures, not the stock of accumulated urban capital. We know of no good measures of such historical investment, but we can at least ask whether historical development eliminates either the current link between population and productivity or the interaction between that variable and the share of the population with college degrees. Including the logarithm of population in 1900 as a control in regression (2) yields:

(2") Log (Output per Worker)=

$$\underset{(.01)}{.072 \cdot \text{Log(Pop. in 2000)}} + \underset{(.14)}{1.23 \cdot \text{Share with BAs}} + \underset{(.13)}{.53 \cdot \text{BA} \cdot \text{Pop}} + \underset{(.008)}{.015 \cdot \text{Log(Pop. in 1900)}}$$

There are many issues with this regression, including the fact that population growth between 1900 and today is hardly random, but it does give little hope to the view that historical investment in capital stock explains either the basic agglomeration effect or the interaction between education and population. Neither coefficient is substantially changed from equation (2). We have also experimented using geographic instruments, like proximity to the Great Lakes or rivers navigable in 1900, which do predict population in that year, but instrumental variables regressions show little change relative to the ordinary least squares regressions. As such, we find little evidence to support the view that greater capital in cities explains much.

Equations (4) and (4') leave us with two alternative views about the connection between productivity and area size. In principle, the equations suggest that either higher prices, or standard agglomeration effects, coming from reductions in transport costs, could explain the productivity-area size link. We believe that these two views can be taken together, since in many cases, higher prices are directly reflecting agglomeration economies. For example in Krugman (1991), concentrated firms are able to get more for their goods because other firms are located in the same area.

There is a long and distinguished literature on agglomeration economies, and there is little doubt that many forms of such economies exist. Such traditional agglomeration effects are compatible with the absence of agglomeration economies in low human capital cities only if there is some reason why the industries in those cities don't benefit from proximity, while industries in high human capital cities do. Yet controlling for the industrial characteristics of the metropolitan area, and for interactions between these variables and area population, has little impact on the robust interaction between population and skill levels. It isn't clear if all of these theories can explain the interaction between city size and human capital but at least some of them can. For example, if agglomeration economies came from the reduction of transaction costs in business services, and if those costs took the form of lost time, then the value of reducing these time costs would be higher in place with higher levels of human capital. If these standard agglomeration economies explain the city size-productivity link, then hopefully future work will help us to understand why these effects are stronger in more educated places.

IV. The Link Between Human Capital and Agglomeration Economies

While standard agglomeration theories do not automatically predict the interaction between urban size and area education, theories that emphasize the spread of knowledge in urban areas do. If cities facilitate the spread of information, then this advantage will be more important when the people living in those cities have higher levels of human capital. This suggests that there are two, in some senses quite similar, hypotheses that can explain the agglomeration results and why the agglomeration effects are so much stronger in skilled places. One view is that workers acquire more skills in big, skilled areas. The second view is that the Solow residual is higher in such places because of the speedy spread of ideas. According to the first of these theories, the workers on Wall Street benefit from the ability to learn more quickly from each other. According to the other view, their firms' leaders are better able to acquire ideas in these areas.

While this latter hypothesis has been taken seriously since Lucas (1988), we know of little direct evidence testing this view. There has been more work on the connection between worker human capital accumulation and urban density. The two views differ in their predictions about the age-earnings profile in cities. The worker learning hypothesis suggests that age-earnings profiles should be steeper in skilled, dense areas where workers learn from each other. The innovation hypothesis can mean that skills depreciate more quickly in such places, which would make the age-earnings profile flatter. We test between these two hypotheses here.

Evidence on Worker Learning in Cities

Glaeser and Mare (2001) examined the urban wage premium in models with worker fixed effects. They find that only a modest fraction of the urban wage premium is earned by workers when they came to urban areas. Similarly, the urban wage premium is not lost by workers when they leave big cities. Instead, workers who came to cities experience somewhat faster wage growth. This evidence seems to point against a generalized urban productivity effect towards a wage growth effect, which could be interpreted as faster learning in cities.

Since human capital accumulation is typically inferred by looking at age-earnings profiles, it is particularly natural to test the hypothesis that cities increase the rate of human capital accumulation by looking at whether wage growth is faster over the life cycle in metropolitan areas. Table 3 shows the basic pattern of wage growth in urban areas. The dependent variable is the log of hourly wage and data comes from the 2000 Census. The first column shows the basic pattern of wage growth over the life-cycle for males between the ages of 25 and 65 (to avoid retirement issues and working part time). Experience is defined as age minus years of education minus six.

The first column shows that the majority of earnings growth occurs over the first 15 years. Relative to workers with between zero and five years of experience, workers with between six and ten years of experience earn .194 log points higher wages and workers with between eleven and fifteen years of experience gain .335 log points in wages. Wage growth continues, albeit at a slower clip, throughout one's life.

In the second column, we show the interactions of years of the independent variables with residing in a metropolitan area. We do not report the overall experience coefficients to save space, though they remain similar to those shown in the first column. The coefficients in the second column reflect the extra gains in wages that seem to accrue to metropolitan workers at each experience level. Metropolitan area workers earn a level effect of .036 log points more than non-metro workers at the start of their careers. This gap rises an additional .028 log points for workers with between six and ten years of experience. Workers with between eleven and fifteen years of experience earn .06 log points on top of the level effect, meaning a total premium of .096 log points. The coefficient then levels off.

These results, which repeat those found in Glaeser and Mare (2001) for a more recent census, suggest that human capital accumulation is faster in metropolitan areas. The metropolitan area wage effect for inexperienced workers is about one-third its value for more experienced workers. This finding hints at the possibility that much of the effect of cities comes over time, as workers either acquire skills more quickly, or perhaps match more efficiently in large places.

While there is a significant interaction between metropolitan area status and experience, there isn't a clear link between metropolitan area population and log of experience. In regression (5) of table 1, we report the absence of such a connection. Being in a metropolitan area seems to steepen the age-earnings profile, but being in a bigger metropolitan area does not. In regression (6) of Table 1, we show that being in a skilled area does steepen the age-earnings profile, which is compatible with the view that people are learning more in skilled areas. Regression (7) shows that there is no interaction between metropolitan area population and share with college degrees, which perhaps is unsurprising because there was no experience effect of metropolitan area population.

Returning to Table 3, where there is a basic metropolitan area effect, we now look to see whether there is an interaction between that effect and the skill level of the metropolitan area. Column 3 shows the comparison between those in the 100 most skilled MSAs and those living outside metropolitan areas. Working in these areas provides a large level effect of .069 log points to workers immediately upon starting employment. More importantly for our hypothesis, the experience profile is also steeper in these cities than in the full sample in column 2. Workers with 6 to 10 years of experience earn an additional .035 log point premium, and this rises to .075 for those with 11 to 15 years and .093 log points for those with 16 to 20 years, meaning that experience is garnering these workers a .162 log point premium on non-metropolitan workers.

Column 4 shows that the same does not hold in the 100 least skilled MSAs. Here the level effect is small and insignificant, and the experience trajectory substantially flatter, showing no significant difference with the non-metropolitan workers until the 16 to 20 year group. The wage growth associated with living in a metro area is coming primarily from highly-skilled cities. F-tests on the coefficients in columns 3 and 4 show that these differences are significant at the 1% level.

Similarly to the results in Table 1, the fifth and sixth columns find less support for an interaction between city size and experience. Column 5 compares those living in the 25 most populated metropolitan areas to those living in all other metro areas and finds a significant level effect of .081 log points, but no effect on the experience profile. The presence of an interaction between city size and city skill would imply that we might see a stronger effect if we limit the sample to only those in highly skilled cities, but this turns out not to be the case, as Column 6 shows a similar level effect, and no effect on the experience-earnings path.

Other direct evidence on knowledge fails to provide much support to the learning in cities hypothesis. In Table 4, we look at the connection between tests of reasoning and vocabulary and both being raised in and currently residing in a city. This evidence is from the General Social Survey which subjects adults to tests and has a question about the place in which the adult was brought up. Using place of childhood residence is presumably slightly more exogenous than using place of current residence, but we use both.

The first two columns show that while rural children do worse, the highest test scores were earned by people who were brought up in suburbs. People brought up in big cities do slightly worse on these tests than people brought up in small towns. In the second two columns, we look at place of current residence and find little evidence of a connection between city residence and these skills. While these tests will not capture the most important skills learned working in a big metropolitan area, the fact that we don't find any significant link is not supportive of the learning in cities hypothesis.

These results are meant primarily to illustrate the type of evidence that could definitively show that people in cities learn more quickly. So far, no such evidence exists. It is true that people in cities enjoy faster wage growth, but that wage growth is concentrated in more skilled areas. There is no direct evidence linking measurable skill accumulation to urban residence.

V. Conclusion

In this paper, we document that agglomeration effects are much stronger for cities with more skills. This finding points to agglomeration theories that emphasize knowledge accumulation in big cities, rather than theories that emphasize natural advantage or gains from speedy movement of basic commodities. Yet, there is little direct evidence on the knowledge based agglomeration economies. Empirical researchers have not managed as of yet, to sort out how these agglomeration economies work.

Glaeser and Mare (2001) put forward some evidence suggesting the skill accumulation works faster in metropolitan areas. We duplicate that evidence here, and find that these learning effects are strongest in more skilled metropolitan areas. While these results suggest a complementarity between skills, city size and learning, other direct tests of that complementarity find little evidence. At present we are left with tantalizing hints, but little that is conclusive.

One speculative interpretation of the results is that two things are simultaneously happening in skilled, big cities. First, workers are indeed learning from one another more quickly. Second, the rate of technological change is faster. Together, both effects create the strong interaction between city size and population in the metropolitan area data and the weaker interaction in the individual level data. The results on age-earnings profiles would be ambiguous, according to this hypothesis, because sometimes the learning effect (which steepens the profile) dominates and sometimes the technological change effect (which flattens the profile) dominates. We hope that further research will sort out these interpretations.

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Table 1: Log Annual Income on City Population and Skill Levels interacted with Experience

	1	2	3	4	5	6	7
Log Population	0.041	0.028	0.022	0.038	0.034	0.044	0.021
	[0.011]***	[0.011]**	[0.012]*	[0.006]***	[0.016]**	[0.019]**	[0.018]
Pct with BA		0.639	0.411	0.208	0.415	-0.11	-0.895
		[0.144]***	[0.122]***	[0.086]**	[0.123]***	[0.318]	[0.287]***
LogPop*PctBA			0.196	0.413	0.193	0.193	0.885
Interaction			[0.113]*	[0.087]***	[0.113]*	[0.113]*	[0.229]***
Log Pop * Log Exp					-0.004	-0.007	0
					[0.004]	[0.005]	[0.004]
Pct BA * Log Exp						0.18	0.448
						[0.095]*	[0.086]***
LogPop*PctBA*LogExp							-0.236
							[0.057]***
Log Experience	0.25	0.252	0.252	0.251	0.258	0.256	0.254
	[0.004]***	[0.004]***	[0.004]***	[0.005]***	[0.006]***	[0.005]***	[0.005]***
Education Dummies:							
0-9 years	-0.59	-0.587	-0.586	-0.584	-0.586	-0.585	-0.585
	[0.010]***	[0.009]***	[0.009]***	[0.011]***	[0.009]***	[0.009]***	[0.009]***
10-11 years	-0.33	-0.327	-0.327	-0.319	-0.327	-0.327	-0.326
	[0.005]***	[0.005]***	[0.006]***	[0.006]***	[0.006]***	[0.006]***	[0.006]***
13-15 years	0.207	0.204	0.204	0.179	0.204	0.204	0.204
	[0.004]***	[0.004]***	[0.004]***	[0.004]***	[0.004]***	[0.004]***	[0.004]***
16 years	0.575	0.565	0.566	0.516	0.566	0.566	0.566
	[0.008]***	[0.008]***	[0.008]***	[0.006]***	[0.008]***	[0.008]***	[0.008]***
17+ years	0.788	0.774	0.774	0.717	0.774	0.774	0.775
	[0.011]***	[0.010]***	[0.010]***	[0.008]***	[0.010]***	[0.010]***	[0.010]***
Constant	9.409	9.406	9.406	9.41	9.388	9.394	9.401
	[0.015]***	[0.015]***	[0.015]***	[0.018]***	[0.019]***	[0.018]***	[0.017]***
Observations	2102175	2102175	2102175	2102175	2102175	2102175	2102175
R-Squared	0.16	0.17	0.17	0.15	0.17	0.17	0.17

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: State Level Density and Output

	Log Value Added			Log Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
State Level Density	0.585*	0.787**	0.559	0.458**	0.551***	0.342*
	[0.304]	[0.314]	[0.337]	[0.178]	[0.188]	[0.192]
Log Capital per Worker		0.244*			0.112	
		[0.132]			[0.0789]	
Years of Schooling			0.0177			0.0775
			[0.0911]			[0.0518]
Constant	4.339***	3.516***	4.137***	2.297***	1.919***	1.416**
	[0.397]	[0.588]	[1.111]	[0.233]	[0.351]	[0.632]
Observations	37	37	37	37	37	37
R-squared	0.096	0.178	0.097	0.158	0.205	0.21

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes:
(1) State level density and years of schooling from Ciconne and Hall (1996)
(2) Log value added, log wage, and log capital per worker from 2006 Annual Survey of Manufactures at factfinder.census.gov

Table 3: Log Hourly Wage on the Interactions of Metropolitan Residence and Human Capital Variables

	Basic Human Capital Regression	Metro Areas vs. Non-Metro	Highly Educated Metro Area vs. Non-Metro	Low Educated Metro Area vs. Non-Metro	Cols. 3 & 4 differ at 1% level	Highly Populated vs. Less Populated MSAs	High Pop vs. Less Pop: Highly Educated MSAs
In Metro Area		0.034					
		[0.007]***					
In High Educ MSA			0.069				
			[0.007]***		yes		
In Low Educ MSA				0.015			
				[0.011]			
In High Pop MSA						0.081	0.088
						[0.006]***	[0.008]***
Experience Dummies:							
0-5 years	(omitted)	(omitted)	(omitted)	(omitted)		(omitted)	(omitted)
6-10 years	0.194	0.028	0.035	0.004	yes	0.002	-0.005
	[0.003]***	[0.007]***	[0.007]***	[0.012]		[0.006]	[0.008]
11-15 years	0.335	0.06	0.075	0.017	yes	0.006	-0.009
	[0.003]***	[0.007]***	[0.007]***	[0.012]		[0.006]	[0.008]
16-20 years	0.423	0.074	0.093	0.027	yes	0.01	-0.014
	[0.003]***	[0.007]***	[0.007]***	[0.012]**		[0.006]*	[0.008]*
21-25 years	0.466	0.074	0.089	0.044	yes	0.007	-0.009
	[0.003]***	[0.007]***	[0.007]***	[0.012]***		[0.006]	[0.008]
26-30 years	0.493	0.067	0.077	0.043	yes	0	-0.014
	[0.003]***	[0.007]***	[0.007]***	[0.012]***		[0.006]	[0.008]*
31-35 years	0.523	0.075	0.084	0.053	yes	-0.001	-0.019
	[0.003]***	[0.007]***	[0.008]***	[0.012]***		[0.006]	[0.008]**
36-40 years	0.535	0.067	0.076	0.046	no	-0.001	-0.013
	[0.003]***	[0.008]***	[0.008]***	[0.013]***		[0.007]	[0.009]
41+ years	0.515	0.079	0.09	0.051	yes	0	0
Education Dummies:							
0-9 years	-0.297	-0.047	-0.055	-0.06	no	-0.036	-0.026
	[0.002]***	[0.005]***	[0.005]***	[0.007]***		[0.005]***	[0.007]***
10-11 years	-0.152	-0.007	-0.006	-0.015	no	-0.011	-0.02
	[0.002]***	[0.004]*	[0.004]	[0.006]**		[0.004]**	[0.006]***
13-15 years	0.108	0.025	0.021	0.026	no	0.015	0.01
	[0.001]***	[0.003]***	[0.003]***	[0.004]***		[0.003]***	[0.004]***
16 years	0.304	0.093	0.093	0.032	yes	0.015	0.004
	[0.002]***	[0.004]***	[0.004]***	[0.007]***		[0.003]***	[0.005]
17+ years	0.407	0.099	0.095	0.062	yes	0.016	0.008
	[0.002]***	[0.006]***	[0.006]***	[0.010]***		[0.005]***	[0.006]
Nonwhite	-0.117	-0.011	-0.03	0.018	yes	-0.038	-0.068
	[0.001]***	[0.003]***	[0.003]***	[0.005]***		[0.002]***	[0.003]***
Pct in Occup. with BA	0.508	0.095	0.103	0.007	yes	0.03	0.011
	[0.002]***	[0.005]***	[0.006]***	[0.009]		[0.005]***	[0.007]
Constant	2.161						
	[0.003]***						
Observations	2914329	3E+06	1928911	1071431		2102498	1117080
R-squared	0.19	0.19	0.21	0.13		0.2	0.21

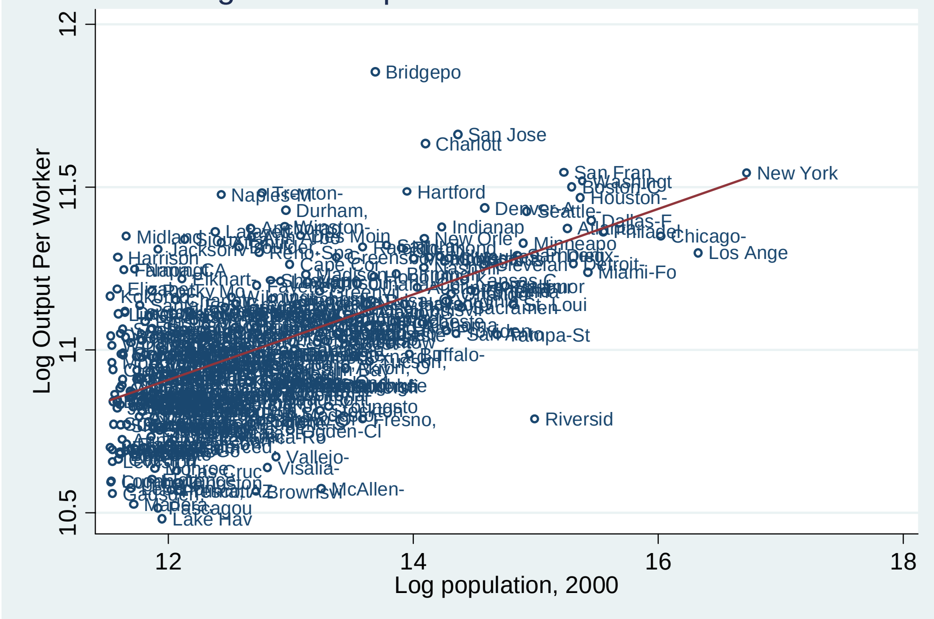
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Vocabulary and Reasoning across Places of Residence

	# Correct on Vocab Test	# Correct on Reasoning Test	# Correct on Vocab Test	# Correct on Reasoning Test
	(1)	(2)	(3)	(4)
Residence at Age 16:				
Rural, Non-Farm	-0.261	-0.323		
	[0.046]***	[0.128]**		
Rural, Farm	-0.423	-0.266		
	[0.041]***	[0.117]**		
Small Town (under 50,000)	(omitted)	(omitted)		
Small City	0.024	-0.11		
(50,000 - 250,000)	[0.042]	[0.105]		
Suburb of Large City	0.283	0.081		
	[0.046]***	[0.108]		
Large City (250,000+)	-0.075	-0.261		
	[0.043]*	[0.116]**		
Current Residence:				
Rural			-0.108	0.002
			[0.048]**	[0.152]
Small Town (under 50,000)			(omitted)	(omitted)
Suburb of Small City			0.112	0.177
			[0.046]**	[0.131]
Small City			-0.134	0.309
(50,000 - 250,000)			[0.051]***	[0.135]**
Suburb of Large City			0.196	0.011
			[0.044]***	[0.125]
Large City (250,000+)			-0.094	0.147
			[0.050]*	[0.139]
Years of Schooling	0.348	0.196	0.359	0.203
	[0.005]***	[0.013]***	[0.005]***	[0.013]***
Age	0.054	0.024	0.05	0.023
	[0.004]***	[0.013]*	[0.004]***	[0.013]*
Age Squared	0	0	0	0
	[0.000]***	[0.000]**	[0.000]***	[0.000]**
Male Dummy	-0.191	0.023	-0.206	0.017
	[0.027]***	[0.071]	[0.027]***	[0.071]
Constant	0.075	0.298	-0.016	0.017
	[0.114]	[0.344]	[0.115]	[0.362]
Observations	22929	2182	22970	2185
R-Squared	0.27	0.15	0.27	0.14

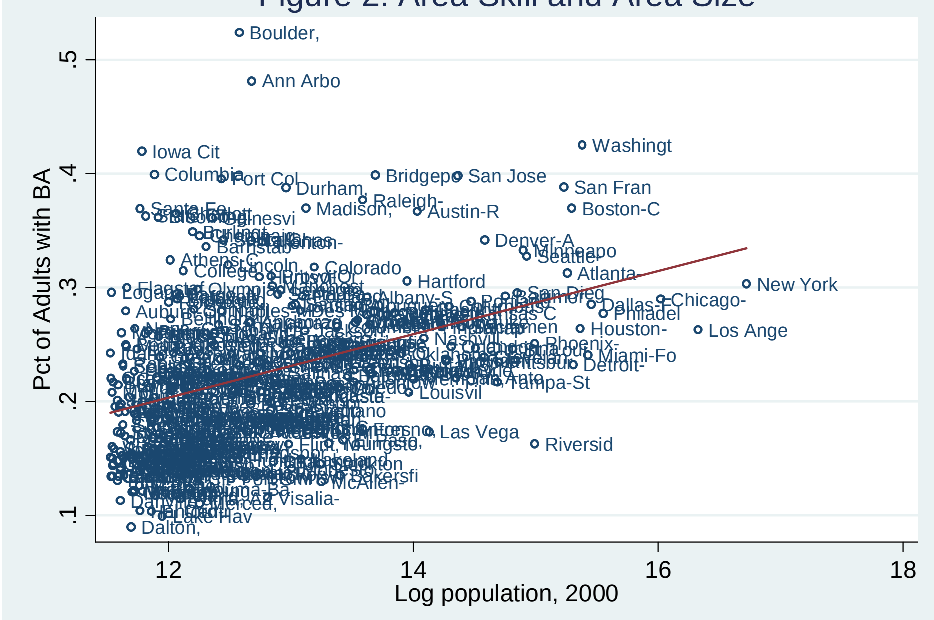
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Notes: All Data for General Social Survey as described in data appendix

Figure 1: Output Per Worker and Area Size



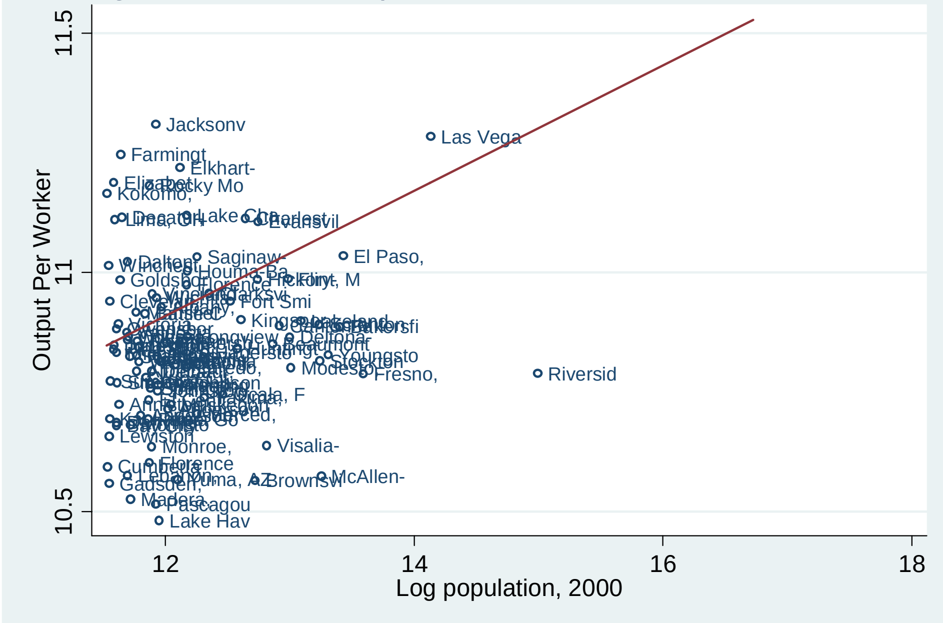
Note: Units of observation are Metropolitan Statistical Areas under the 2006 definitions with populations above 100,000. Labor force and population is from the Census, as described in the Data Appendix. Gross Metropolitan Product is from the Bureau of Economic Analysis.
The regression line is *Log GMP per capita* = 0.13 [0.01] * *Log population* + 9.3 [0.12]. R^2 = 0.36 and N = 335.

Figure 2: Area Skill and Area Size



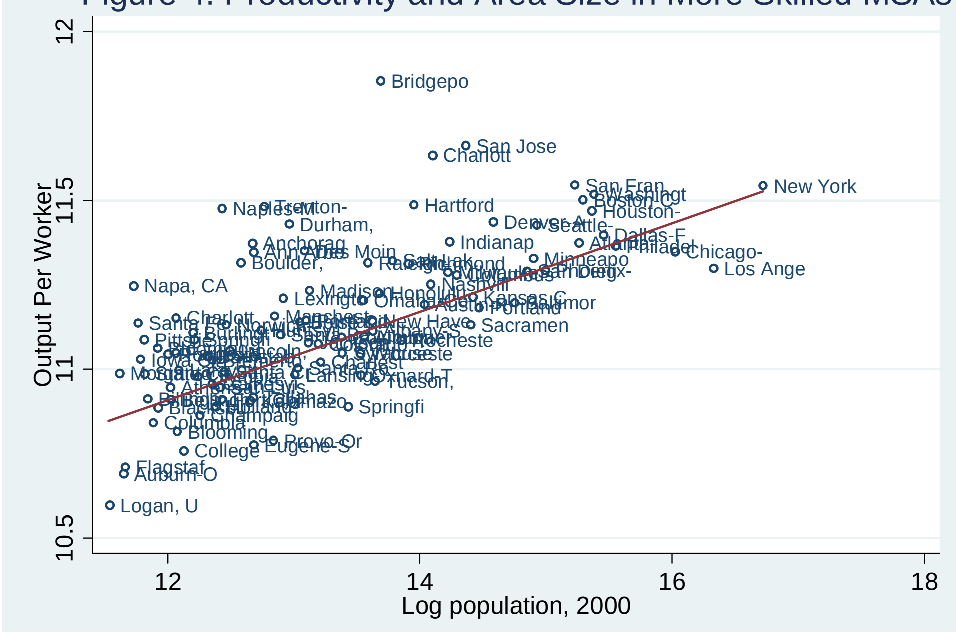
Note: Units of observation are Metropolitan Statistical Areas under the 2006 definitions with populations above 100,000. Statistics are from the Census.
The regression line is *Share with BAs* = 0.028 [0.003] * *Log population* -.13 [.044]. R^2 = 0.16 and N = 335.

Figure 3: Productivity and Area Size in Less Skilled MSAs



Note: Units of observation are MSAs under the 2006 definitions with populations above 100,000 and where the share of adults with college degrees is less than 17.65%. Labor force and population is from the Census, as described in the Data Appendix. Gross Metropolitan Product is from the Bureau of Economic Analysis.
The regression line is *Log GMP per capita* = 0.028 [0.028] * *Log population* + 10.50[0.34]. R^2 = 0.01 and *N* = 100.

Figure 4: Productivity and Area Size in More Skilled MSAs



Note: Units of observation are MSAs under the 2006 definitions with populations above 100,000 and where the share of adults with college degrees is greater than 25.025%. Labor force and population is from the Census, as described in the Data Appendix. Gross Metropolitan Product is from the Bureau of Economic Analysis.
The regression line is *Log GMP per capita* = 0.128 [0.015] * *Log population* + 9.46[0.19]. R^2 = 0.44 and *N* = 100.

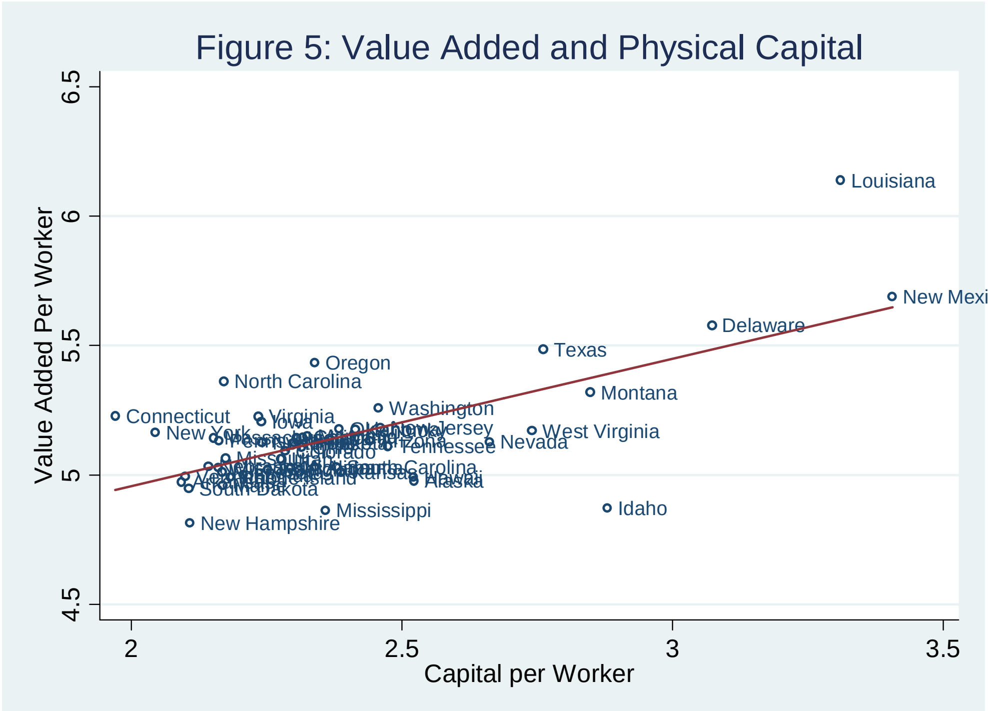


Figure 5: Value Added and Physical Capital

Note: Measures of value added and capital per worker are taken from the Census of Manufacturers as described in the data appendix.

The regression line is *Log Value Added per Worker* = 0. 4924 [0.079] * *Log Capital per Worker* + 3.97 [.191].

R^2 = 0.45 and N = 49.

Data Appendix

For figures 1, 3 and 4, and equations (1) and (2), productivity (or output per worker) is calculated by dividing the Gross Metropolitan Product for 2001 (from the Bureau of Economic Analysis at http://www.bea.gov/regional/gdpmetro/) by the total labor force for 2000 (from published 2000 Census figures). Population and share with BAs also comes from the published 2000 Census figures, and this population and BA data is also used in figure 2. For figure 3, "less skilled MSAs" refer to those MSAs which have the share of the population with BAs in 2000 less than 17.64%. For figure 3, "more skilled MSAs" refer to those MSAs which have the share of the population with BAs in 2000 more than 25.025%.

For equation (2'), population and share with BAs in 1940 comes from published 1940 Census figures. For equation (2"), population in 1900 comes from published 1900 Census figures. For equation (3), real family income is calculated using family median income from the published 2000 Census figures, divided by the cost of living index for each MSA published by the American Chamber of Commerce Research Association (ACCRA) at http://www.coli.org/. Data for Figure 5 is calculated using the 2006 *Annual Survey of Manufactures*, with details described in the paragraph about table 2 below.

The individual level data used in tables 1 and 3 comes from the IPUMS 2000 5% Census sample. Where aggregate metro area numbers such as population and the percent of workers over 25 with a college degree are used in conjunction with individual level data, these are merged on from published Census figures, since the IPUMS does not fully identify all metro areas. All individual level regressions are run for male workers aged 25 to 65. Hourly earnings are calculated by dividing yearly earned income by number of weeks worked and usual weekly hours. Experience is calculated as age minus years of schooling minus 6, where years of schooling is approximated as precisely as possible using the categorical schooling variable provided in the 2000 Census. All calculations are weighted by person weight unless otherwise noted.

In table 2, the state level log capital per worker, log value added per worker and log hourly wage were calculated using the total capital expenditures, total value added, number of employees, total production workers wages, and total production workers hours data from the 2006 *Annual Survey of Manufactures* at factfinder.census.gov. The state level density and years of schooling variables come directly from table 2 of "Productivity and the Density of Economic Activity" by Antonio Ciccone and Robert E. Hall, *American Economic Review*, March 1996.

Data for table 4 comes from the General Social Survey. In 1994, eight reasoning questions were asked that required the respondent to assess the similarities between various objects and ideas. Their responses were coded as correct, partly correct or incorrect by the GSS, and information on this coding is available in Appendix D of the GSS cumulative codebook. Our dependent variable is the number of fully correct responses out of the 8 questions. The vocabulary test, given in 17 waves of the survey spaced between 1974 and 2006, asks the respondent ten vocabulary questions and records the number of correct responses. We pool across the waves, weighting using the WTSSALL variable. For the residence variables, categories of xnorcsize (current residence) are combined so as to mirror the categories of the res16 (residence at age 16) variable as closely as possible.