Measuring Human Capital Divergence in a Growing Economy

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Abstract

The stylized fact that the fraction of workers who are college graduates appears to increase more in US cities where the initial share is larger has attracted significant attention. Furthermore, more educated cities appear to grow faster. These two trends could portend the divergence of cities by skill, with low-skill workers segregated in slow-growing or declining cities. This paper compares measures of skill divergence and finds that relative measures, which have the property of scale invariance, show no divergence for the period from 1970 to 2010. In addition, the relation between skill intensity and city growth appears to be concave, so that growth rate differences may diminish over time as the average college share of the country rises.

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1. Introduction

A variety of works, including Moretti (2004, 2012, 2013), Berry and Glaeser (2005), Glaeser (2012), and Diamond (2016), have noted a divergence in the human capital levels of US cities. The two most commonly reported measures of an area's skill level are the share of adults who are college graduates, and the ratio of college graduates to those who lack a college degree, known as the skill intensity ratio, or SIR. Studies have considered the period since 1940, but research has concentrated on 1970 to 2010. Over this period, measures of absolute dispersion in these human capital metrics across cities have increased.

The literature has regarded such divergence as a consequence of two particular results on the dynamics of local economies (Glaeser et al., 1995; Simon, 1998, 2004; Simon and Nardinelli, 2002; Glaeser and Shapiro, 2003; Glaeser and Saiz, 2003; Shapiro, 2006; Wheeler, 2006). First, absolute change in the SIR of cities has been found to vary positively with lagged SIR. Thus it appears that differences in the skill intensity of cities propagate, in that they are caused by prior differences. Second, urban growth rates have been an increasing function of lagged SIR. These results together suggest that more-educated workers are increasingly concentrated spatially and that concentration is found in fast growing cities. Conversely, it appears that low-skilled workers are concentrating in locations where population is either slow growing or declining. This implies that the evolution of the skill intensity of cities is contributing to inequality of income or opportunity.

These patterns of changing skill intensity appear difficult to explain by simple application of economic theory. Absolute divergence in the SIR of cities implies that areas where human capital is relatively abundant have larger increases in human capital than places where it is scarce. This is puzzling given incentives to relocate and the relatively low cost of mobility. The idea of regional income convergence seems similarly inconsistent with findings of diverging local human capital. Diverging SIR, especially if SIR is positively related to urban growth rates, appears to require special explanation because of implications for the possible failure of labor allocation across cities to conform to requirements for economic efficiency.

In this paper, we examine different measures of the average human capital per worker of a city and alternative ways to measure changes in the distribution of these metrics. Just as income inequality can be measured in absolute terms using variance, or relative terms using the coefficient of variation or Gini coefficient, different indexes of skill divergence are possible. Because income and skill ratios are growing nationally, absolute and relative measures of inequality provide dramatically different results on divergence. In particular, we show that relative measures of divergence, which are scale invariant, indicate that the spatial distribution of SIR was mostly constant over period from 1970 to 2010. During the same time period, absolute measures, which lack the property of scale invariance, indicate SIR diverged rapidly.

The finding that relative and absolute measures of divergence produce different results is common in economics. In growing societies, many characteristics of cities are subject to aggregate change over time. Total population, human capital, output, income, etc., are all growing systematically and therefore create scale independence challenges for measures of divergence. The specific case of human capital per worker is a useful illustration because its potential divergence has been the object of significant attention due to concerns over changing inequality in society.

The remainder of this paper is divided into six sections. Section 2 discusses the difference between absolute and relative measures of divergence and their use in a growing economy. Section 3 discusses the relation between divergence, relative or absolute, and urban growth. Next are two parallel empirical sections. Section 4 reports results from testing whether absolute and relative changes in the human capital intensity of cities are positively related to initial level. Then, in Section 5 a non-linear parametric growth equation is estimated relating rates of growth in city population to initial city size and human capital intensity. Section 6 concludes.

2. Absolute versus relative divergence

Measures of absolute divergence are used when comparisons are made against a fixed standard. For example, poverty can be measured as an absolute count of the number of individuals with income below a fixed standard. Relative divergence is used when there is no such fixed standard and the base of measurement is changing. Thus, the Gini coefficient measures dispersion normalized against a mean that is changing across time, space, or units in which income is measured.

Differences in human capital per worker are commonly measured by observing variation across locations in SIR, represented as S/U, where S is the number of college graduates, or "skilled workers", and U is the number of adults who did not graduate from college, or "unskilled workers". At the national level, S/U has been rising which results in a difference between absolute and relative measures of divergence. Formally, if λ is the growth rate of U workers, then the growth rate of S workers is $\phi\lambda$, where $\phi > 1$. Consider two cities whose skill intensity at the beginning of a period differs such that $S_{1t}/U_{1t} = \theta(S_{2t}/U_{2t})$, where $\theta > 1$. Assume that the growth rates of S and U are identical across the two cities. Then, the relative change in the skill intensity ratio in the two areas, normalized for the change in the base over time due to growth at rate λ will be identical. That is, the ratio of skill intensities will not vary over time, i.e., $S_{t+1}/U_{t+1} = \phi\lambda/\lambda(S_t/U_t)$ in each area.

Now consider what happens if an absolute measure of divergence in SIR is used in the same siutation. The skill intensity ratio at time $t+1$ in one area can be written in terms of

SIR at time t for the other.

$$\frac{S_{1,t+1}}{U_{1,t+1}} = \left(\frac{\phi\lambda}{\lambda}\right)\left(\frac{S_{1t}}{U_{1t}}\right) = \theta\phi\left(\frac{S_{2t}}{U_{2t}}\right)$$

This means that the absolute difference in differences in skill intensity between the two areas over the discrete interval from t to $t+1$ can be written as

$$\begin{aligned}\left(\frac{S_{1,t+1}}{U_{1,t+1}} - \frac{S_{2,t+1}}{U_{2,t+1}}\right) - \left(\frac{S_{1t}}{U_{1t}} - \frac{S_{2t}}{U_{2t}}\right) &= \left((\theta\phi - \phi) - (\theta - 1)\right)\left(\frac{S_{2t}}{U_{2t}}\right) \\ &= (\phi - 1)(\theta - 1)\left(\frac{S_{2t}}{U_{2t}}\right). \qquad (1)\end{aligned}$$

Eq. (1) has an easy interpretation. If skill intensity is unequally distributed initially ($\theta \neq 1$) and growing nationally ($\phi > 1$), then absolute divergence, measured as the absolute differences in differences of skill intensity ratios, will be non-zero even if there is no relative divergence. In particular, absolute divergence will exist provided $\phi > 1$ and $\theta > 1$. This does not imply that relative divergence is positive because, in this example, the skill intensity ratio would is increasing at the same rate in each city. Accordingly, there is no relation between initial skill intensity and the rate of growth in skill intensity in each city.

This establishes the logical point that, because skill intensity is rising nationally, current findings of absolute divergence do not imply that there has been relative divergence. Furthermore, note that the absolute divergence measure in (1) increases with the skill intensity ratio in city 2 which means that measures of absolute divergence will appear to be increasing over time even if there is no relative divergence.[3] The specific issue of measuring human capital divergence covered in this paper is an illustration of the more general case of the

[3]A simple numerical example illustrates the points made above. Suppose the skill intensity ratios of two cities are 1/2 and 2/2, respectively. If the population of skilled workers in both locations increases by a factor of 3 and the unskilled worker population increases by a factor of 2, then the new ratio values are 3/4 and 3/2. Thus, the absolute difference in SIR between the cities increases from 1/2 in the first time period to 3/4 in the second, even though growth rates of the two worker types were identical across locations.

relation between relative and absolute measures of divergence discussed in the context of income inequality measurement by Foster and Sen (1997).

3. Divergence and urban growth

In addition to the finding that there is absolute divergence in SIR across cities, the second stylized fact about SIR noted in the introduction is that city population growth rates vary directly with lagged values of city SIR. This possible direct association between SIR and rates of city growth is perhaps more important as policy issue. If SIR causes future city growth, such a trend could result in differential segregation of low-skill workers in cities that are declining or growing slowly compared to large, fast-growing cities. This section considers whether absolute divergence alone, i.e., with no change in relative divergence, is sufficient to produce an association between urban growth rates and SIR in an economy with rising SIR.

Population growth in city i can be decomposed into a sum of products of the growth rates of skilled and unskilled workers and their respective concentrations, or

$$\frac{\Delta N_i}{N_i} = \frac{\Delta S_i}{S_i}\frac{S_i}{N_i} + \frac{\Delta U_i}{U_i}\frac{U_i}{N_i}. \tag{2}$$

Consider the case discussed in Section 2 where there is absolute divergence in the SIR of cities but no relative divergence. Assume again that two cities differ in initial skill intensity so that $S_1/N_1 = \theta(S_2/N_2)$, where $\theta > 1$, and unskilled workers are growing nationally at rate λ, while skilled workers are increasing at rate $\phi\lambda$, where $\phi > 1$. It follows from (2) that

$$\frac{\Delta N_i}{N_i} = \phi\lambda\left(\frac{S_i}{N_i}\right) + \lambda\left(\frac{U_i}{N_i}\right) = \phi\lambda\left(\frac{S_i}{N_i}\right) + \lambda\left(1 - \frac{S_i}{N_i}\right) = \lambda + \lambda(\phi - 1)\left(\frac{S_i}{N_i}\right). \tag{3}$$

Using (3), the difference in population growth rates between the two locations can be written as a function of initial skill level, or

$$\frac{\Delta N_1}{N_1} - \frac{\Delta N_2}{N_2} = \lambda(\theta - 1)(\phi - 1)\left(\frac{S_2}{U_2}\right).$$

As was the case when there was no relative divergence in the SIR of cities, equality of growth rates requires that either there is no change in national skill intensity ratio ($\phi = 1$) or that skill intensity ratios be identical everywhere ($\theta = 1$). If neither condition holds, as appears to be the case for US cities, there will be a systematic difference in the population growth rates of cities based on their initial skill intensity ratios. Thus, even if there is no relative divergence, absolute divergence is sufficient to eventually produce an association between the population of cities and their population growth rates. Relative divergence would make the association between SIR and city growth even stronger because, even if the overall SIR were not growing, the variance in SIR would still rise over time as SIR growth would be negative (positive) in low (high) SIR cities.

There is an abundance of empirical evidence, discussed in Glaeser et al. (2014), that since 1970 lagged SIR has been positively related to population growth rates. Of course, a temporary association between SIR and the rate of city growth lasting a few decades is possible. It could be part of the pattern of idiosyncratic growth documented in the literature. Desmet and Rappaport (2017), for example, examine two centuries of change and report extended periods in which population growth was either directly or inversely related to city size.

Indeed, Glaeser et al. (2014) identify a number of variables which have been associated with faster rates of city growth for temporary periods. For example, variation in the industrial mix of cities has been shown to produce periods of unequal city growth. But again, these effects should be temporary and periods of unusual industrial expansion should generally be followed by periods of sluggish growth, thus reversing the sign of the relation between industrial composition and growth.

Estimates in Section 4 below test the hypotheses that changes in the skill intensity ratios of cities, both absolute and relative changes, are positively related to lagged skill intensity. These tests allow for the possibility that there has been an absolute but not a relative divergence of the SIR among cities over time. Regardless of the outcome of these tests, either form of divergence raises issues for the long run segregation of low skill workers in slow growth cities. Accordingly, Section 5 includes a further test for the second derivative of population growth with respect to SIR. The test is based on the possibility that the long-run segregation result will fail to hold, even in the presence of relative divergence, if the relation between lagged SIR and population growth is concave. That is, if μ is the population growth rate of cities, there is a test for the possibility that $\mathrm{d}\mu/\mathrm{d}(S_{it}/U_{it}) > 0$, but $\mathrm{d}^2\mu/\mathrm{d}(S_{it}/U_{it})^2 < 0$. A review of the literature indicates that this test, although straightforward, has not been reported. If the relation between SIR and population growth is concave, then concern that absolute divergence will result in segregation of less educated workers in slow-growing cities is substantially reduced.

4. Testing for divergence in skill intensity

The next two sections of the paper present the results of two tests regarding skill intensity. First, the nature of skill intensity divergence is tested, specifically whether there has been absolute or relative divergence in SIR. Then, the nature of the relation between diverging SIR and city growth rates is examined, recalling that the previous section established that segregation of low skill workers in slow growth cities only requires absolute and not relative divergence of SIR.

The testing performed in this paper follows approaches common in the literature. The education and population measures used are tabulations of decennial census microdata covering 1970 to 2000 performed by the U.S. Department of Housing and Urban Development's *State of the Cities Data Systems* and are the same as those used in Berry and Glaeser (2005). The panel is extended to 2010 by using tabulations by the authors from the 2008 to 2012 multi-year *American Community Survey*. Metro areas are defined in a consistent manner using the 1990 Office of Management and Budget standard for metropolitan statistical areas to avoid biases that could otherwise be introduced into the analyses due to changing definitions, that is, faster growing areas have less stable definitions.

Descriptive statistics for two measures of the human capital intensity of metros are displayed in Table 1 for the five census years between 1970 and 2010. College share is the fraction of adults (age 25 years or older) with at least a bachelor's degree, and skill intensity ratio is the ratio of adults with at least a bachelor's to those with less education. Because college share cannot be scaled without distorting its meaning, SIR, which lacks an upper bound, is the preferred measure of human capital in this paper.[4] There was substantial heterogeneity in human capital levels across time and the 316 metro areas located in the contiguous United States. SIR values in 1970 ranged from 0.05 in Johnstown, PA to 0.45 in Iowa City, IA, where 31% of adults held at least a bachelor's degree. In 2010, the range was 0.14 in Merced, CA to 1.38 in Boulder, CO, where the college share was 58%.

Both the variance and standard deviation of a measure vary with the mean level in the economy. Accordingly, these two measures of the spread of SIR across cities indicate substantial divergence over time. For example, the standard deviation of SIR reported in Table 1 nearly triples, from 0.06 to 0.17 over the 40-year period. This increase is expected for a measure of absolute divergence, because the average SIR across all MSAs also rose by a factor of three, from 0.13 in 1970 to 0.39 in 2010.

The coefficient of variation and the variance of logarithms are scale-invariant measures

[4] As well, SIR may well be superior to college share as a theoretical operationalization. In the production context with two levels of skill, SIR is simply the factor intensity ratio.

of dispersion. In contrast to the standard deviation of SIR, both statistics are remarkably stable over the study period in Table 1. Between 1970 and 2010, the coefficient of variation in SIR decreases slightly from 0.46 to 0.45, and the standard deviation of log SIR increases slightly from 0.38 to 0.41. These results indicate that there has been absolute divergence in SIR across cities but no relative divergence. Consistent with the theoretical discussion in the previous section, given that there has been no change in relative divergence, the change in absolute divergence between 1970 and 2010 appears to have been driven entirely by the 200% growth in the average level of SIR.

Differences between relative and absolute measures of dispersion in Table 1 appear especially dramatic when examining kernel density plots such as Figures 1a and 1b. Similar to results presented in Hammond and Thompson (2010) for labor market areas, Figure 1a shows the distribution of human capital across metros shifting substantially to the right and flattening. Moretti (2012) calls this development in cities – where along with the increase in educational attainment nationally, the distribution of human capital across areas has become increasingly unequal – "the Great Divergence" (p. 4). In contrast, the density plots for relative human capital intensity in Figure 1b are nearly indistinguishable across census years. Following Rattsø and Stokke (2014), the relative formula takes the absolute version and divides by the mean value for all 316 metros for that year. The density plots of relative human capital intensity, like changes in the coefficient of variation or variance of logarithms, indicate that the distribution is remarkably stable over the study period.

Beyond descriptive statistics and density plots, a more formal test for relative divergence involves estimating whether there is any relation between lagged SIR and its subsequent rate of growth. Relative divergence implies that the rate of growth in SIR in cities is independent of its prior value. However, to replicate stylized facts reported in the literature, the first tests we perform are for absolute divergence in human capital intensity, measured either as the skill intensity ratio or college share. The common finding that differences in either or both of these measures are positively related to their initial values is tested directly by estimating the following equation:

$$\Delta y_{it} = \alpha_0 + \alpha_1 y_{i,t-10} + \epsilon_{it}, \tag{4}$$

where $y_{it} = \{S_{it}/U_{it}, S_{it}/N_{it}\}$.

Panel A of Table 2 displays results from estimating Eq. 4 for absolute changes in SIR ($\Delta(S_{it}/U_{it}) = S_{it}/U_{it} - S_{i,t-10}/U_{i,t-10}$). Whether for cross-sectional estimates using individual time periods or panel estimates using data pooled across the four decades, these results confirm the standard finding that $\hat{\alpha}_1 > 0$. The estimates are uniformly positive and highly statistically significant across time periods and indicate absolute divergence of human capital among cities. Table 2 also reports results obtained when absolute changes in college share ($\Delta(S_{it}/N_{it}) = S_{it}/N_{it} - S_{i,t-10}/N_{i,t-10}$) are substituted for changes in SIR as the dependent variable in Eq. 4. Consistent with the literature, the results in Panel B also demonstrate $\hat{\alpha}_1 > 0$. Thus, measured in terms of the difference in absolute differences, human capital appears to have concentrated in cities with the highest initial rates of human capital, i.e., from 1970 to 2010 there was human capital divergence in absolute terms. As shown in Section 2, this is to be expected given that average SIR was increasing over time in this growing economy.

Tests for relative divergence in human capital intensity can take several forms. The primary test adopted here involves the relation between initial skill intensity ratio and differences in the subsequent *rate of growth* of skilled and unskilled adults indicated in the following equation

$$\frac{\Delta S_{it}}{S_{i,t-10}} - \frac{\Delta U_{it}}{U_{i,t-10}} = \beta_0 + \beta_1 \left(\frac{S_{i,t-10}}{U_{i,t-10}} \right) + \epsilon_{it}. \tag{5}$$

Panel A of Table 3 contains estimates of Eq 5 for the difference in growth *rates* between skilled and unskilled workers. The results demonstrate that $\hat{\beta}_1 < 0$, large, and significant at the 1% level for the 1970-1980 interval in Model (1). The estimate is positive and significant in Model (3) and not statistically significant in Models (2), (4), and (5). Taken together, these results indicate relative convergence during 1970s that did not continue over the next two decades.

Panels B and C of Table 3 report results from estimating Eq. 5 separately for the two components that comprise the dependent variable, i.e., the growth rates of skilled and unskilled workers, respectively. In the 1980–1990 and the 1990–2000 decades, Models (2) and (3), the growth rate of skilled workers is positively and significantly related to initial skill intensity. The unskilled worker growth rate is also positively and significantly related to skill intensity in two of the four decades. Neither of the growth rates is significantly related to initial skill intensity in Model (5) that pools the four change periods. Overall these results indicate that there is no evidence of divergence based on the relative difference in differences.[5]

The results in Tables 2 and 3 that $\hat{\alpha}_1 > 0$ and $\hat{\beta}_1 \leq 0$ show that, as suggested by the theory in Section 2 of this paper, it is perfectly reasonable to find absolute divergence when there is no relative divergence, because skill intensity ratios are increasing. As anticipated, in an economy with rising SIR, measures of the absolute difference in differences are positive and statistically significant over the same time intervals that measures of relative divergence are negative or not statistically different than zero. Furthermore, the finding from our formal testing of no relative divergence is consistent with the stable coefficient of variation and variance of logs of SIR reported in Table 1 and kernel density estimates for relative SIR illustrated in Figure 1b.

[5] The findings are qualitatively similar if we weight using initial population or exclude the 2010 ACS data in estimates (results not reported but available upon request).

5. Testing the relation between skill intensity and city growth rate

The previous section demonstrated that growth rates of skilled and unskilled workers were not strongly or systematically related to the lagged SIR of cities for the years between 1970 and 2010. In this section, the nature of the relation between skill intensity and the subsequent rate of growth in city size, which has been reported in the previous literature to be positive, is examined by inserting a quadratic term in the expression. Specifically, this involves estimating the following general relation:

$$\frac{\Delta N_{it}}{N_{i,t-10}} = \gamma_0 + \gamma_1 N_{i,t-10} + \gamma_2 \left(\frac{S_{i,t-10}}{U_{i,t-10}}\right) + \gamma_3 \left(\frac{S_{i,t-10}}{U_{i,t-10}}\right)^2 + \epsilon_{it}. \quad (6)$$

In this formulation, a typical stochastic growth model implies $\hat{\gamma}_1 = 0$, and the possibility that SIR has an independent relation to urban growth is reflected in estimates of γ_2 and γ_3. Based on the previous literature, the expectation is that $\hat{\gamma}_2 > 0$. What is different here is that the possibility of a concave or convex relation between SIR and population growth, rather than linear as assumed implicitly in previous tests, is based on the sign and significance of estimates of γ_3. A review of the literature indicates that while the stability of estimates of γ_2 has been examined, the possibility of a convex or concave relation has not been considered.

Estimates of Eq. (6) are reported in Table 4 separately for individual time periods in Panels A to D and pooled across the four decades in Panel E. In estimates of Model (1), which omits skill intensity, the value of $\hat{\gamma}_1$ is not significantly different than zero in three of the four change intervals and also in the pooled estimate. This is consistent with a stochastic growth model in which rates of city growth are independent of size. When skill intensity is included in estimates of Model (2), the values of $\hat{\gamma}_2$, consistent with the literature, are greater than zero. Finally, when the quadratic term in SIR is included in the regression in

Model (3), $\hat{\gamma}_2 > 0$, and $\hat{\gamma}_3 < 0$, indicating that the relation between SIR and the rate of population growth is indeed concave.[6]

Furthermore, the concavity of the relation between SIR and population growth is sufficiently pronounced so that the slope becomes negative in the range of SIR values that characterizes several cities in the US today. Table 4 contains point estimates of the 'break-even' value of SIR at which $\mathrm{d}\left(\frac{\Delta N_{it}}{N_{i,t-10}}\right)/\mathrm{d}SIR = 0$. Based on Model (3), these values fall around 0.5, which is above the national mean of 0.39 in 2010, but well below the national maximum of 1.38. Depending on the year, between 4 and 16 cities have SIR values that exceed the break-even threshold.

The results in Table 4 indicate that, given high and rising national SIR, a number of cities are already past the region in which the relation between SIR and city growth becomes negative. This suggests that a future in which high SIR cities grow significantly faster than other cities is unlikely. However, the relation has shifted over time, and the results indicate that the break even SIR is shifting up. Accordingly, future monitoring of this relation will be needed to determine if the relation between SIR and city growth rates remains concave and hence attenuated as SIR rises.

It could be that the estimates of Eq. 6 in Table 4 suffer from omitted variable bias because variables previously found to be significant in growth equations have been excluded from the estimating equation. For example, a substantial literature shows that selective technology shocks to individual industries can result in growth or decline of cities where those industries are concentrated. In addition, the literature has noted the mass migration of households to coastal locations and locations with temperate climates, suggesting these consumption amenities are dominating the costs of congestion. Black and Henderson (2003), for example, find amenity variables such as coastal location, heating and cooling days, and

[6] The finding of concavity does not appear to be driven by outliers as the results are qualitatively similar if we estimate the equations using robust regression (results not reported but available upon request).

precipitation all have significant coefficients in their estimate of a long term (1900 to 1990) parametric growth equation.[7]

Consistent with previous research, amenity variables and variables reflecting the concentration of local employment in professional services, manufacturing, and retail trade are included next in Eq. (6) to reflect industrial groups where national growth trends have differed. In estimates of Model (4) in Table 4, industry mix and amenity measures (not reported) are statistically significant over the 1970 to 2010 period. As is the case in Model (3), when a quadratic term in SIR is included, the result that $\hat{\gamma}_2 > 0$ and $\hat{\gamma}_3 < 0$ is retained. The results from the fully-specified model reinforce the finding that the relation between SIR and the rate of population growth may be concave rather than linear as previously reported.

Furthermore, the value of SIR at which the relation between the rate of population growth and SIR becomes negative remains within the range of SIR for cities in 2010. Given that the SIR is diverging in absolute value naturally due to the rise in average SIR in the economy, the potential for SIR effects to cause segregation of low skill workers in slow growing cities is evident. The finding that the relation between SIR and population growth has been concave provides some assurance that the divergence in absolute SIR, which is likely to continue as average SIR rises, does not have permanent implications for this potential segregation problem.

6. Conclusions

This paper began with two stylized facts from the literature. The variance of SIR across cities has been rising and lagged SIR is positively related to future city population growth. Taken

[7]A parallel literature has analyzed Zipf's law by first estimating the Zipf coefficient for cities in individual countries and then attempting to determine the source of departures from unity by regressing the divergence from unity on country characteristics. See Rossi-Hansberg and Wright (2007) for an example indicating that industrial composition and geography are important factors.

together, these facts appear to imply a future in which the largest, fastest growing cities are dominated by high-skill workers, while lower-skill workers are concentrated in slowly growing or even declining cities.

The first contribution of this paper is to note that changes in the variance and standard deviation of the SIR of cities are measures of absolute divergence and are not scale invariant. Given that the SIR is growing nationally, divergence in absolute SIR of cities is a natural consequence even if the rate of growth in the SIR is equal everywhere. Next, using a scale invariant measure, the coefficient of variation, it appears that relative divergence of city SIR has been remarkably constant and that the rise in absolute divergence is due to the general rise in national SIR. Statistical testing demonstrates that there is no significant relation between SIR and either the growth rate of skilled or unskilled workers and that there has been no statistically significant divergence in relative SIR across cities. If anything, our results indicate possible convergence in human capital levels across cities consistent with recent studies on cities in Germany (Suedekum, 2008) and Norway (Rattsø and Stokke, 2014). Of course, labor markets in these countries differ from the U.S. and the importance of natural resource production in remote regions of Norway may make it a special case. However, as suggested by Rattsø and Stokke, the contradictory findings using European versus U.S. samples may also stem from "methodological differences," whereby the U.S. papers estimate absolute changes in college share while the European papers analyze relative changes (p. 1678). This paper extends this observation on method. We show that because absolute differences in differences lack the property of scale invariance, in a growing economy, they may indicate divergence when relative growth rates are actually promoting convergence.

The finding that relative and absolute measures of divergence produce different results is common in economics. Income inequality measures are generally required to have the property of scale invariance, so that an equi-proportionate change in income does not change measured inequality. This is particularly important if nominal rather than real income measures are used or if comparisons are to be made across countries where the average level of income differs substantially. Thus, the difference in absolute and relative divergence measures is particularly consequential in a growing economy. This suggests reliance on relative measures, such as the Gini coefficient, rather than absolute indicators, like income variance, to measure inequality.[8] In general, scale invariance is an important property to consider when selecting measures of divergence in a growing economy

Additionally the paper demonstrates that, even with no relative divergence, absolute divergence is sufficient to produce substantial segregation of skilled workers in faster growing cities if SIR is related to growth. However, statistical tests demonstrate that the actual relation between city SIR and rates of population growth is concave. Furthermore, a number of cities with the highest SIR levels are on the portion of the growth function where the relation between SIR and growth is negative. Given that rising national SIR will inevitably push an even larger fraction of cities into this region, the prospect that the relation between SIR and city growth rate will result in outcomes where low-skill workers are segregated into the slowest-growing cities appears less likely. Previous research has shown that these relations may change over time and the patterns of absolute and relative divergence in SIR as well as the relation between SIR and city growth should be monitored. In performing future analysis, it will be important to distinguish scale invariant measures and to allow for non-linearity in functional forms.

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Tables and Figures

Figure 1a: Distribution of human capital across cities

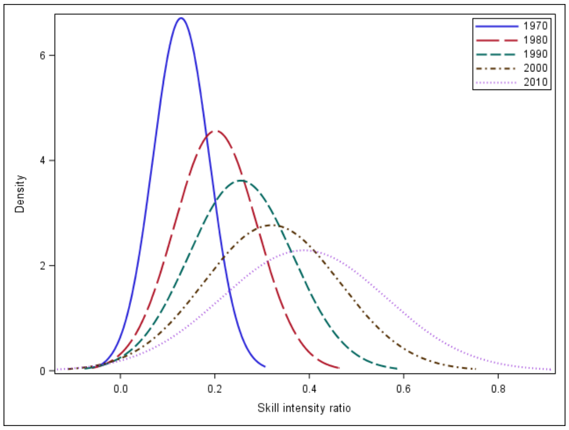
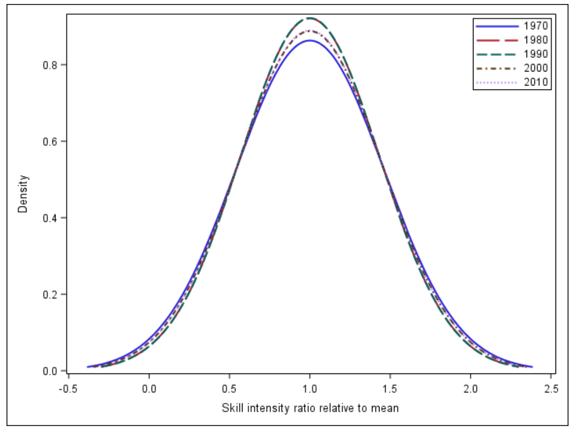


Figure 1b: Distribution of relative human capital across cities



NOTES: Kernel density estimates by decade for 316 metropolitan areas. Skill intensity ratio is the ratio of adults (age 25 years or older) with at least a bachelor's degree to those with less education. The relative formula takes the absolute version and divides by the mean value for that decade.

Table 1: Descriptive statistics for the human capital level of metros by decade.

	Min	Max	Mean	SD	CV
1970					
College Share	0.05	0.31	0.11	0.04	0.38
Skill Intensity Ratio	0.05	0.45	0.13	0.06	0.46
Log (College Share)	-2.98	-1.18	-2.25	0.33	-0.15
Log (Skill Intensity Ratio)	-2.93	-0.81	-2.13	0.38	-0.18
1980					
College Share	0.08	0.39	0.16	0.05	0.33
Skill Intensity Ratio	0.08	0.63	0.20	0.09	0.43
Log (College Share)	-2.56	-0.95	-1.86	0.31	-0.16
Log (Skill Intensity Ratio)	-2.48	-0.47	-1.68	0.37	-0.22
1990					
College Share	0.09	0.44	0.20	0.06	0.32
Skill Intensity Ratio	0.10	0.79	0.25	0.11	0.43
Log (College Share)	-2.35	-0.82	-1.67	0.30	-0.18
Log (Skill Intensity Ratio)	-2.26	-0.24	-1.45	0.39	-0.27
2000					
College Share	0.11	0.53	0.23	0.07	0.31
Skill Intensity Ratio	0.12	1.14	0.32	0.14	0.45
Log (College Share)	-2.20	-0.63	-1.50	0.30	-0.20
Log (Skill Intensity Ratio)	-2.09	0.13	-1.22	0.40	-0.33
2010					
College Share	0.13	0.58	0.27	0.08	0.30
Skill Intensity Ratio	0.14	1.38	0.39	0.17	0.45
Log (College Share)	-2.08	-0.54	-1.35	0.29	-0.22
Log (Skill Intensity Ratio)	-1.95	0.32	-1.03	0.41	-0.39

Cross section observations = 316 MSAs
[1]Divided by 1,000

NOTES: College share is the fraction of adults (age 25 years or older) with at least a bachelor's degree, and skill intensity ratio is the ratio of adults with at least a bachelor's degree to those with less education.

Table 2: Models of absolute change in human capital level.

	1980 (1)	1990 (2)	2000 (3)	2010 (4)	All (5)
A. Δ*(Skill Intensity Ratio$_t$)*					
Skill Intensity Ratio$_{t-10}$	0.43***	0.23***	0.28***	0.19***	0.24***
	(11.27)	(11.10)	(8.77)	(11.53)	(16.41)
Adj R^2	0.59	0.41	0.56	0.51	0.51
B. Δ*(College Share$_t$)*					
College Share$_{t-10}$	0.24***	0.13***	0.14***	0.08***	0.13***
	(8.82)	(7.83)	(8.73)	(7.35)	(13.21)
Adj R^2	0.36	0.20	0.29	0.16	0.36

$^{***}p < 0.01$. Absolute value of t-statistics in parentheses based on heteroskedasticity consistent standard errors. All period model (5) includes year fixed effects and standard errors clustered at the MSA level. Cross section observations = 316 MSAs

NOTES: Ordinary least squares estimates of Eq. (4). The dependent variable in Panel A is absolute change in the ratio of adults (age 25 years or older) with at least a bachelor's degree (S) to those with less education (U) in city i: $\Delta(S_{it}/U_{it}) = S_{it}/U_{it} - S_{i,t-10}/U_{i,t-10}$. For Panel B, the dependent variable is the absolute change in the share of adults with at least a bachelor's degree: $\Delta(S_{it}/n_{it}) = S_{it}/n_{it} - S_{i,t-10}/n_{i,t-10}$, where $n_{it} = S_{it} + U_{it}$.

Table 3: Models of proportionate change in human capital level.

	1980 (1)	1990 (2)	2000 (3)	2010 (4)	All (5)
A. *Percent* Δ*(College Graduate$_t$) - Percent* Δ*(Less than College$_t$)*					
Skill Intensity Ratio$_{t-10}$	-0.45^{**}	0.04	0.10^{*}	-0.03	-0.01
	(2.50)	(0.59)	(1.65)	(0.90)	(0.30)
Adj R^2	0.02	0.00	0.01	0.00	0.66
B. *Percent* Δ*(College Graduate$_t$)*					
Skill Intensity Ratio$_{t-10}$	-0.01	0.22^{*}	0.14^{*}	-0.02	0.06
	(0.02)	(1.90)	(1.71)	(0.44)	(0.99)
Adj R^2	0.00	0.00	0.00	0.00	0.56
C. *Percent* Δ*(Less than College$_t$)*					
Skill Intensity Ratio$_{t-10}$	0.44^{***}	0.17^{**}	0.03	0.00	0.08
	(2.80)	(2.13)	(0.59)	(0.12)	(1.49)
Adj R^2	0.01	0.01	0.00	0.00	0.14

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Absolute value of t-statistics in parentheses based on heteroskedasticity consistent standard errors. Cross section observations = 316 MSAs

NOTES: Ordinary least squares estimates of Eq. (5). The explanatory variable in all three panels is the lagged ratio of adults (age 25 years or older) with at least a bachelor's degree (S) to those with less education (U) in city i: S_{it-10}/U_{it-10}. The dependent variable in Panel A is percent change in the number of adults with at least a bachelor's degree: $\Delta S_{it}/S_{i,t-10} = (S_{it} - S_{i,t-10})/S_{i,t-10}$. For Panel B, the dependent variable is percent change in the number of adults with less than a bachelor's degree: $\Delta U_{it}/U_{i,t-10} = (U_{it} - U_{i,t-10})/U_{i,t-10}$. In Panel C, the dependent variable is difference between the two growth rates from Panels A and B. All period model (5) includes year fixed effects and standard errors clustered at the MSA level.

Table 4: Models of urban growth.

	Percent Δ(Population$_t$)			
	(1)	(2)	(3)	(4)
A. *1980*				
Population$_{t-10}$	-0.45^{***}	-0.46^{***}	-0.54^{***}	-0.47^{***}
	(5.94)	(5.98)	(6.02)	(6.01)
Skill Intensity Ratio$_{t-10}$		0.60^{***}	2.84^{***}	1.14^{**}
		(3.38)	(5.09)	(2.20)
(Skill Intensity Ratio$_{t-10}$)^2			-5.74^{***}	-1.40
			(4.68)	(1.45)
Break-Even Value			0.25	0.41
Adj R^2	0.05	0.08	0.11	0.48
B. *1990*				
Population$_{t-10}$	-0.01	-0.04	-0.08	-0.13^{***}
	(0.11)	(0.64)	(1.31)	(2.70)
Skill Intensity Ratio$_{t-10}$		0.32^{***}	1.07^{***}	0.59^{*}
		(3.95)	(3.32)	(1.94)
(Skill Intensity Ratio$_{t-10}$)^2			-1.31^{***}	-0.37
			(2.68)	(0.88)
Break-Even Value			0.41	0.79
Adj R^2	0.00	0.03	0.04	0.44
C. *2000*				
Population$_{t-10}$	0.01	-0.04	-0.06	-0.16^{***}
	(0.25)	(0.81)	(1.29)	(2.89)
Skill Intensity Ratio$_{t-10}$		0.20^{***}	0.56^{**}	0.67^{***}
		(3.60)	(2.39)	(3.01)
(Skill Intensity Ratio$_{t-10}$)^2			-0.47	-0.16
			(1.60)	(0.58)
Break-Even Value			0.60	2.07
Adj R^2	0.00	0.04	0.04	0.39

Continues...

Table 4 (continued): Models of urban growth.

	Percent Δ(Population$_t$)			
	(1)	(2)	(3)	(4)
D. *2010*				
Population$_{t-10}$	0.00	-0.03	-0.05	-0.09^{**}
	(0.04)	(0.60)	(1.22)	(2.40)
Skill Intensity Ratio$_{t-10}$		0.10^{***}	0.41^{***}	0.65^{***}
		(2.47)	(3.29)	(5.19)
(Skill Intensity Ratio$_{t-10}$)^2			-0.34^{***}	-0.44^{***}
			(3.00)	(3.35)
Break-Even Value			0.60	0.74
Adj R^2	0.00	0.02	0.03	0.38
E. *All Periods*				
Population$_{t-10}$	0.00	-0.06	-0.08^{*}	-0.19^{***}
	(0.04)	(1.34)	(1.91)	(4.66)
Skill Intensity Ratio$_{t-10}$		0.22^{***}	0.71^{***}	0.75^{***}
		(4.09)	(4.44)	(5.32)
(Skill Intensity Ratio$_{t-10}$)^2			-0.66^{***}	-0.56^{***}
			(3.97)	(4.05)
y1980 $\times$ Population$_{t-10}$	-0.45^{***}	-0.40^{***}	-0.39^{***}	-0.25^{***}
	(4.93)	(4.68)	(4.52)	(4.61)
y1990 $\times$ Population$_{t-10}$	-0.01	0.03	0.02	0.10^{**}
	(0.17)	(0.58)	(0.40)	(2.48)
y2000 $\times$ Population$_{t-10}$	0.01	0.02	0.01	0.02
	(0.49)	(1.03)	(0.39)	(0.69)
Break-Even Value			0.54	0.67
Adj R^2	0.07	0.09	0.11	0.44

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Absolute value of t-statistics in parentheses based on heteroskedasticity consistent standard errors. Cross section observations = 316 MSAs

NOTES: Ordinary least squares estimates of Eq. (6). The dependent variable is percent change in total population of city i: $\Delta N_{it}/N_{i,t-10} = (N_{it} - N_{i,t-10})/N_{i,t-10}$. Population is in tens of millions. Skill intensity ratio is the ratio of adults (age 25 years or older) with at least a bachelor's degree to those with less education. Model (4) includes controls for natural amenities and industry mix: precipitation, heating and cooling degree days, coastal indicator, and employment shares in manufacturing, trade (retail and wholesale), and professional services. Break-Even Value is the level of Skill Intensity Ratio (SIR) at which $\mathrm{d}\left(\frac{\Delta N_{it}}{N_{i,t-10}}\right)/\mathrm{d}SIR = 0$. Models in Panel D include year fixed effects and standard errors clustered at the MSA level.