Entrepreneurship, City Size, and Heterogeneous Human Capital

Comments Welcome*

Curtis J. Simon [1]

[1]John E. Walker Department of Economics
Clemson University

June 23, 2022

Abstract

Recent microfoundations for the relationship between city size and human capital emphasize talent externalities that arise from variety in the production of intermediates, and other theoretical work has emphasized the importance of human capital variety for entrepreneurial success. However, empirical work has yet to examine the implications of human capital variety for city size and entrepreneurship. This paper is a first attempt. I distinguish between college graduates employed in the left and right portions of the occupational skill distribution. I find that it makes sense to net out college graduates employed in education occupations when characterizing the human capital composition of cities. City size is strongly positively correlated with human capital intensity of occupations throughout the occupational skill distribution. College graduates employed in the left half of the occupational skill distribution (1) account for a substantial fraction of college graduates overall; (2) are more productive and more likely to be self-employed than their non-college counterparts; (3) add to the explanatory power of regressions of log city size on human capital composition; and (4) contribute positively to entrepreneurial activity as measured by incorporated self employment per worker. College graduates in the right portion of the occupational skill distribution dominate the city size-human capital relationship, but contribute positively to entrepreneurship only among college graduates.

*I am particularly indebted to Ed Glaeser for his insights and suggestions. I am also grateful to Gilles Duranton, Raul Ramos, Will Strange, and John Winters for their feedback on earlier drafts. Scott Baier, Aspen Gorry, Bill Dougan, and Andy Hanssen provided useful discussions.

"As impressive as the role of cities in generating new innovations may be, the primary informational role of cities may not be in creating cutting edge technologies, but rather in creating learning opportunities for everyday people" (Glaeser, 1999)

1 Introduction

This paper examines the role played by human capital heterogeneity in entrepreneurship and the size of cities. Glaeser et al. (1995) Simon (1998), Simon and Nardinelli (2002), Glaeser and Saiz (2004), Shapiro (2006), and Broxterman and Yezer (2020) found that more highly educated cities tended to grow faster. Empirically speaking, most researchers have measured human capital as the fraction of the workforce with a college degree. Consider, though, that many college graduates are employed in so called non-college occupations in the left half of the distribution (Freeman, 1976; Gottschalk and Hansen, 2003; Abel and Deitz, 2017; Clark et al., 2017). Indeed, college graduates are found in virtually *all* occupations in *all* cities. The question naturally arises whether such "underemployed" college graduates contribute to citywide economies of agglomeration or entrepreneurship.

Recently, Behrens et al. (2014) and Davis and Dingel (2020) provided microfoundations for a positive relationship between city size and the average skill level in the form of agglomeration economies arising from variety in intermediate goods production. The model in Behrens et al. (2014) is distinguished by its explicit modeling of the decision to become an entrepreneur, and derives a particularly elegant equation that relates city size to human capital, and is therefore especially useful for my purposes. Their model makes three key predictions. First, entrepreneurs are always drawn from the top of a city's skill distribution. Second, the fraction of entrepreneurs in the population is independent both of the skill composition and size of the city. Third, it generates a remarkable, yet simple log-linear relationship between size and average talent in the city that makes clear the roles of worker heterogeneity, agglomeration economies, and congestion costs.

That variety of local intermediates are central to the models of both Behrens et al. (2014) and Davis and Dingel (2020) raises the question of what to make of the heterogeneity among college graduates. Like Strange (2004), I take my inspiration from Jacobs (2016), who propounded on the importance of diversity of skill in the life of the city. The availability of a wide variety of skilled workers could be particularly valuable when the optimal production process is unknown and experimentation is necessary (Duranton and Puga, 2000; Helsley and Strange, 2002; Strange et al., 2006). In these models, a denser, more varied network of local input suppliers improves the quality of the match between the needs of entrepreneurs and the inputs employed in production. However, as pointed out by Strange (2004), the quality of labor embodied in those inputs is important.

The interaction between quality and variety is central to Kremer's (1993) O-ring theory of development, which conceives as production as requiring the successful production of a variety of tasks. Because more highly skilled workers are less prone to error, there is complementarity in skill levels across tasks. When matching is costly, there is a complementarity between skill and market size, and when information about one's own skill level is imperfect, it is more valuable to be a high-skill worker if one has high-skill coworkers. The model therefore predicts that *all* occupations should be more highly skilled in cities with higher average levels of skill.

I examine the relationship between city size, entrepreneurship, and human capital composition using data between 1960 and 2020. My innovation is to distinguish college graduates according to where they lie along the occupational skill spectrum. I refer to those who are employed in occupations with relatively low levels of occupational skill as "left-tail" college graduates, and to those who are employed in occupations with relatively high levels of skill as "right tail" college graduates. I then examine how city size and entrepreneurship are related to left and right-tail college graduates.

Chinitz (1961) contended that Pittsburgh suffered a dearth of entrepreneurs relative to New York because the former's historical concentration in steel resulted in high concentrations of "company men" but few entrepreneurs. However, the dearth of entrepreneurs could also reflect a dearth of complementary human capital with which to staff their enterprises. Some researchers found that higher levels of human capital in a city promote entrepreneurship (Acs and Armington, 2006; Qin and Kong, 2021), although Glaeser and Kerr's (2009) study of manufacturing is one notable exception. However, while Doms et al. (2010) found a positive relationship between city-level human capital and individual-level self-employment, this relationship disappeared once they controlled for individual-level education.

The findings could be due to the failure to recognize the multidimensional nature of human capital, which is central to Lazear's (2005)'s theory of entrepreneurship. In his model, entrepreneurs have a comparative disadvantage in a single skill but a comparative advantage in acquiring a balance of skills. His theory implies that college-educated workers who are employed in technically sophisticated occupations may have a comparative disadvantage in entrepreneurship. Nor do the complementary inputs necessary to succeed all lie in the right half of the occupational skill spectrum.

To foreshadow my results, I show that college-educated workers earn more and are more likely to be incorporated self-employed than their non-college counterparts throughout the occupational distribution. However, those employed in education occupations display low rates of entrepreneurship, suggesting that they contribute relatively little to agglomeration economies and leading me to net them out in the calculation of the skill composition of cities. I find that bigger cities are better educated throughout the occupational skill distribution; regression analysis suggests that the right tail dominates, but left tail human capital has some independent explanatory power. Finally, I find that entrepreneurship as measured by incorporated self-employment is positively related to the presence of left-tail college graduates, while right-tail college graduates contribute positively only to entrepreneurship among college graduates.

I am not the first to examine the effects of heterogeneous human capital in an urban setting.

For example, Moretti (2004b) found that college graduates employed in high-tech plants generated larger productivity spillovers for other high-tech workers than did college graduates employed in low-tech plants. Winters (2014) estimated that college graduates with STEM degrees had greater positive external effects on earnings than non-STEM graduates. Liu (2017) found that workers in information-oriented and technical fields generated large spillovers for workers in other fields, while workers in less information-oriented and technical fields did not.

However, I am aware of only one study that distinguishes between college graduates, broadly speaking, in different portions of the occupational skill distribution. Ramos et al. (2012) estimated that European regions with greater concentrations of college workers in less-skilled occupations experienced faster GDP per capita growth between the early 1990s and 2000s. The role of human capital heterogeneity for the size distribution of U.S. cities has yet to be explored.

The remainder of the paper is organized as follows. Section 2 reviews the model of Behrens et al. (2014). Section 3 examines the case for the importance of human capital heterogeneity. Section 4 examines the occupational skill distribution of college graduates and entrepreneurship. Section 5 presents an overview of the geographic distribution of human capital, and a regression analysis is contained in Section 6. Section 7 presents a regression analysis of entrepreneurship and human capital. Section 8 concludes the paper.

2 Human Capital, Entrepreneurship and City Size

2.1 Behrens et al. (2014)

Behrens et al. (2014) assume that there is single final output good that is freely traded across cities, produced using intermediate inputs that are non-traded. Total output is equal to

$$Y_c = \{ \int_\Omega \left\{ x_c(i)^{\frac{1}{1+\epsilon}} \mathrm{d}i \right\}^{1+\epsilon}, \tag{1}$$

where $x_c(i)$ denotes the quantity of intermediate i used in final production, Ω denotes the endogenous mass of intermediates available, all in city c, and $-(1+\epsilon)/\epsilon$ is the own-price elasticity of demand for intermediates. Intermediate inputs are symmetric, and are produced using human capital according to

$$x_c(i) = \varphi(i) l_c(i) \tag{2}$$

where l_c is labor demanded in efficiency units and $\varphi(i) \equiv t(i) \times s$ is entrepreneur i's productivity, which depends positively on her talent, $t(i)$, and serendipity, s. Serendipity is a random shock that impacts workers only once they have chosen their location, and has the effect of generating heterogeneity in labor outcomes in a city even when talent is the same.

The heterogeneity in talent $t(i)$, combined with the economies of agglomeration inherent in the imperfect substitution across varieties of intermediates, will generate a positive relationship between average city talent and city population in equilibrium. There are two key results.

Result 1: Selection into Entrepreneurship The probability that a worker decides to become an entrepreneur is independent of city size (their Proposition 1). An individual i of productivity $\varphi(i)$ will choose to become an entrepreneur if the profit $\pi(i)$ exceeds the labor income they would earn otherwise:

$$\pi(i) = \kappa_1 \left[\frac{\varphi(i)}{\Phi}\right]^{1/\epsilon} \geq w \times \varphi(i)^a, \tag{3}$$

where $a > 0$ is the elasticity of worker salary with respect to worker ability, κ_1 is a function of the economic size of the city and other parameters, and w is the wage per efficiency unit of labor. The key parameter Φ, aggregate productivity in the city, is equal to

$$\Phi \equiv \left[\int_{\Omega} \varphi(j)^{1/\epsilon} d\mathrm{j}\right]^{\epsilon}, \tag{4}$$

where Ω is the endogenous measure of entrepreneurs in the city. Notice that Φ will be higher, the higher the average level of talent, both because the integrand is larger and because it increases the measure of Ω.

Behrens et al. (2014) show there exists a lower bound $\underline{\varphi}$ such that all individuals with $\varphi(i) \geq \underline{\varphi}$ become entrepreneurs and all others become workers. Greater city size leads to greater aggregate productivity Φ via increased variety Ω, which raises productivity in the city but toughens competition among entrepreneurs. Larger cities have higher demands, thus lowering the cutoff, but have more entrepreneurs, which raises the cutoff. In addition to the usual agglomeration economies due to variety, there are talent externalities as well.[1]

Result 2: Complementarity Between Skill and City Size More talented individuals benefit more by being in a large city (their Proposition 3). The equilibrium population in a city of talent level t is given by

$$L(t) = \left(\frac{1+\gamma}{1+\epsilon}\xi t^{(1+a)}\right)^{\frac{1}{\gamma-\epsilon}}, \tag{5}$$

where $L(t)$ is city size, γ measures urban costs and ϵ is a measure of agglomeration economies, and where ξ can be taken as constant. Key here is that equilibrium city size is a positive function of city talent t, rises in economies of agglomeration as measured by ϵ, and decreases in urban costs γ.[2]

[1] Glaeser et al. (2010) show that industries with greater reliance on product variety will tend to sort into cities with higher amenities, that is, lower wages (their Proposition 2). Accounting for the possibility that entrepreneurship uses human capital more intensively than other types of productive activity does not have implications for the distribution of entrepreneurship across cities (their Proposition 3 addresses only within-city variation).

[2] A similar complementarity features in the model of comparative advantage of Davis and Dingel (2020). Behrens et al. (2014) focus their attention on an equilibrium with a single level of talent in each city. They consider the possibility of a symmetric equilibrium in which all levels of talent are represented in all cities, and they show that such an equilibrium is stable only at low population sizes.

3 Why Human Capital Heterogeneity Matters

Taking logs of Equation 5 yields an elegant, log-linear relationship between city size and city talent. Notice that although more talented cities have a wider variety of intermediate goods production, there is only one level of talent in each city, and serendipity aside, all workers of given talent are equally productive in every industry and equally productive as entrepreneurs. The question I am addressing is whether this lack of human capital heterogeneity matters, empirically speaking.

3.1 Jane Jacobs

Jacobs (2016) emphasized that the prosperity of cities may emanate as much from proletarian innovations such as cleaning fluid, professional home and office organization, playground equipment, furniture, and fashion boutiques as from the sophisticated research and development activities of scientists and engineers (the full passage is reproduced in Appendix B.1). There are two key insights. First is that innovation does not always involve cutting edge technologies, but can come from anywhere along the occupational spectrum. Second is that learning-by-doing is critical. A highly skilled computer programmer or data scientist is unlikely to come up with an innovative process to clean fabric, for example, without actually doing the job.

As for the importance of human capital as measured by college graduates in empirical work on city growth and size, Jacobs (2016) observed that not everyone is equally likely to discover "new solutions to the problems that arise in their work," nor able to "glimpse new possibilities in the materials or skills that they use. The creator of the new work must have an insight and, combining the idea or observation with the suggestion from the work itself make a new departure" (60). College graduates do not have a monopoly on entrepreneurial activity, but they are more likely to engage in it.

3.2 The Quimby-Madison Effect

For example, San Francisco Art Institute graduate Roxanne Quimby went to Maine to help her partner raise bees (see Appendix B.1 for sources and additional examples.) She began selling candles made with the left-over beeswax in local fairs and eventually came upon the idea of producing a lip balm. The company, Burt's Bees, was acquired by Clorox for $295 million. Quimby lived and worked in a decidedly non-urban setting (Maine). However, Stacy Madison, who earned an MA in Social Work, opened a food cart with her husband in Boston, MA in 1996. They began giving away pita chips for free to keep waiting customers happy. In 1998 they closed the food cart business and began producing Stacy's Pita Chips, eventually acquired by Pepsi for $250 million. Of course, neither Quimby nor Madison are the norm, but the Quimby-Madison effect illustrates the hazard of dismissing college graduates in less technical occupations as "underemployed."

3.3 Balanced Skills and Entrepreneurship

Glaeser et al. (2015) hinted at the multi-dimensional nature of human capital in their study of Chinitz's (1961) hypothesis, observing that large companies "create executives, not entrepreneurs." This multidimensionality is central to Lazear's (2005) theory of entrepreneurship. "Because the entrepreneur must bring together many different resources, he or she must have knowledge, at least at a basic level, of a large number of business areas."[3] Lazear (2005) hypothesized that entrepreneurs have a comparative *disadvantage* in a single skill but have balanced talents that span a number of different skills. Consider a simple model with two skills $\varphi_1 \geq 0$ and $\varphi_2 \geq 0$. An individual can be a specialist and earn income $\max\left[\phi_1, \phi_2\right]$, or an entrepreneur and earn income $\min \lambda \left[\phi_1, \phi_2\right]$, where λ is the market value of entrepreneurial talent. An individual chooses to become an entrepreneur if

$$\min \lambda \left[\varphi_1, \varphi_2\right] > \max \left[\varphi_1, \varphi_2\right]. \tag{6}$$

Equation 6 implies that entrepreneurs will tend to have more balanced skill sets. This appears to be borne out in data. For example, Lazear (2005) found that most entrepreneurs were not in technical fields, but in industries such as construction, real estate, and retail trade (662).

Unlike Behrens et al. (2014), there is a difference between ability in a single skill φ_i and and ability in entrepreneurship. "The man who opens up a small dry-cleaning shop with two employees might be termed an entrepreneur, whereas the half-million-dollar-per-year executive whose suit he cleans is someone else's employee. It is unlikely that the shop owner is more able than the typical executive (Lazear, 2005)." Similarly, college graduates employed in technically sophisticated occupations likely have a comparative *disadvantage* in entrepreneurship.[4]

3.4 O-Ring Production, Entrepreneurship, and City Size

Jacobs (2016) had little to say about the importance of skill among those who do not choose to become entrepreneurs. However, the availability of a wide variety of high-quality inputs is particularly crucial when the optimal production process is unknown and experimentation is necessary (Duranton and Puga, 2000; Helsley and Strange, 2002). A key insight of the urban economics literature is that the supply of such factors may vary spatially, as in Helsley and Strange (2011). While city size is often taken as a proxy for variety, cities are not all alike; they produce different goods with different intensities of different types of human capital and different bodies of knowledge

[3] Culture may also play a role (Glaeser and Kerr, 2009).

[4] This could help explain the lack of relationship between city growth and patenting activity (Glaeser and Saiz, 2004). Patenting is geographically concentrated, exhibits evidence of strong economies of agglomeration (Buzard et al., 2020; Goldman et al., 2019; Chattergoon and Kerr, 2021), and generates localized knowledge spillovers (Jaffe et al., 1993; Moretti, 2021). Furthermore, college graduates have a higher propensity to innovate (Biasi et al., 2021) and industries that employ more STEM workers produce more patents (Jay Shambaugh and Portman, 2017). Put differently, college-educated workers employed in entrepreneurial *firms* are not necessarily more entrepreneurial *individuals*.

(Black and Henderson, 1999).

The interaction between human capital quality and variety is central to the O-ring model of Kremer (1993). He considers a production process involving n tasks (occupations), each performed by a single worker, in which the quantity of labor cannot substitute for quality of labor. Let q be the expected percentage of maximum value the product retains if the worker performs the task; assume that the probability of mistakes is independent across workers; and let B equal output per worker if all tasks are carried out perfectly. Ignoring capital, expected production equals

$$E(y) = \{\prod_{i=1}^{n} q_i\} nB. \tag{7}$$

There is complementarity in worker quality q because

$$\frac{d^2 y}{dq_i d\{\prod_{j \neq i} q_j\}} = nB > 0. \tag{8}$$

An entrepreneur who employs high-q workers in the first $n-1$ tasks places the highest value on having high-skill workers in the nth task, and so will bid the most for those workers.

Implication 1: Sorting Workers will sort geographically according to skill level *throughout the occupational skill distribution*. Some of the tasks in Equation 7 may be complex (computer programming) and others less so (administration). The O-ring model implies that cities with relatively high overall ability on average will tend to have higher-ability individuals in all occupations.[5]

Put informally, the problem is one of finding the right supplier, which extends to such mundane activities as the staging of a wedding.[6] Skilled individuals in ostensibly unskilled jobs could be an important resource for – that is, complement the skills of – innovative entrepreneurs.[7] This is consistent with Berry and Glaeser (2005), who argued that more highly skilled managers will tend to manage other highly skilled workers.[8]

Implication 2: Complementarity between Skill and City Size Kremer (1993) shows that if skill acquisition is endogenous and matching is imperfect, the marginal product of skill rises in population: the larger the population, the smaller the magnitude of the difference between

[5] Evidence of human capital complementarity across US industries is found by Voigtländer (2013), while (Demir et al., 2021) finds evidence of human capital complementarity in interfirm manufacturing production chains within Turkey. Simon (2022) finds evidence consistent with complementarity in a study of human capital composition in U.S. industries and occupations across cities.

[6] The example is from HGTV's *Escape to the Chateau*. On encountering difficulties in securing satisfactory wedding flower arrangements, owner Angel Adoree emphasized the importance of assembling the right team. The quality of a final good, here, a wedding, is a function of the quality of all of the intermediate services, including the florist.

[7] Helsley and Strange (2011) show (their Proposition 5) that when entrepreneurs have balanced skills as in (Lazear, 2005), cities with balanced skills minimize completion time of projects, in the spirit of Jacobs (2016).

[8] A different sort of heterogeneity is implemented by Davis and Dingel (2020), who distinguish between simple and complex intermediate production. Larger cities are more skill-abundant and specialize in skill-intensive activities. However, I am interested in the level of skill in a given occupation, which seems to be distinct from their concerns.

co-workers' skills, thus increasing expected productivity.

Implication 3: The (Over-) Education Decision When workers are imperfectly informed about their ability, it is more valuable to be a high-skill worker, the higher the average skill in the local population, even for those not destined to be employed in technically sophisticated occupations. This in turn implies that workers throughout the occupational distribution will tend to be more highly educated in cities that are more educated on average.

4 Disaggregating the College Educated

4.1 Data and Units of Observation

I rely primarily on five-percent samples from the decennial Censuses and American Community Surveys (ACS) (Flood et al., 2020). Only a two-percent sample is available for 1970, which year as a result contains fewer cities and is of limited value. For years beyond 2000, I use five-year samples of the American Community Surveys: 2007-2011 for the year 2010 (to avoid a change in metro definition in 2012) and 2015-2019 for the year 2020. The **occupational** unit of observation is the three-digit 1990 IPUMS occupation, which is used for virtually all of the statistical analysis, but for the purposes of description I also use an aggregation into 45 broad groups. The **geographic** unit of observation is the Consolidated Statistical Area or Core-Based Statistical Area, whichever is larger, called "cities" for the purposes of exposition (see Appendix A.2 for details).

4.2 Education as a Measure of Occupational Skill

I measure occupational skill as the fraction of employees who have a college degree, also used by Gottschalk and Hansen (2003). Appendix Table B1 shows the occupational distribution of skill across 45 broad occupations, ranked by 1980 percent college graduates. Health, higher-education, legal, and scientific occupations are the highest-skilled, in the right tail of the skill distribution. Management executives, technicians, and sales workers are in the middle, and household service workers and operatives are in the left tail. Percent college graduates is highly positively correlated with measures of cognitive and verbal skill derived following the procedure in Bacolod et al. (2009) from the 1991 Dictionary of Occupational Titles, described in Appendix A.3. Across three-digit occupations, the correlations between year 2000 percent college graduates on the one hand and cognitive and people skills on the other are 0.80 and 0.69. Like Bacolod et al. (2009), I also constructed a measure of motor skills, which is not highly correlated with percent college graduates (-0.149), and is negatively correlated with the cognitive and verbal skill measures (-0.28 and -0.45); the correlations across the 353 3-digit occupations are all statistically significant at the 0.005 level or better.

4.3 Left and Right-Tail College Graduates

I divide college graduates into left and right "tails" (a misnomer, but convenient for the purposes of exposition).[9] Denote C_{it} the number of college graduates employed nationally and denote $CG_{it} = C_{it}/E_{it}$ the fraction of employment that is college educated in year t in occupation $\mathcal{O}i,\ i = 1, ...N$.[10] Order the occupations from low skill to high: $CG_{1t} < CG_{2t} < ... < CG_{Nt}$. The set of left-tail occupations $\mathcal{L}_t(\theta_t)$ contains the L occupations that employ the first θ_t percent of college graduates,

$$\mathcal{L}_t(\theta_t) \equiv \{\mathcal{O}_i \mid \sum_{i=1}^{L} C_{it}/C_t = \theta_t/100\}. \tag{9}$$

The set of right-tail occupations $\mathcal{R}_t(\theta_t) \equiv \{\mathcal{O}_i \mid \sum_{i=L+1}^{N} C_{it}/C_t = 1 - \theta_t/100\}$ consists of the $N - L$ occupations that employ the remaining $100 - \theta_t$ percent. The t subscript indicates these sets are permitted to evolve over time along with the distribution of occupational skill. The numbers of left and right-tail college graduates are denoted

$$C_t^{\mathcal{L}} = \sum_{i \in \mathcal{L}_t(\theta_t)} C_{it} \quad \text{and} \quad C_t^{\mathcal{R}} = \sum_{i \in \mathcal{R}_t(\theta_t)} C_{it}. \tag{10}$$

Thus, letting $C_t = C_t^{\mathcal{L}} + C_t^{\mathcal{R}}$, we have $C_t^{\mathcal{L}}/C_t = C_t^{\mathcal{R}}/C_t = 50\%$ when $\theta_t = 50$; and we have $C_t^{\mathcal{L}}/C_t = 40\%$ and $C_t^{\mathcal{R}}/C_t = 60\%$ when $\theta_t = 40$.

Figure 1 shows the cumulative distributions of college-educated and non-college workers for 1980, 2000, and 2020 across 45 occupational groups as a function of occupational skill (CG_i); graphs across 359 three-digit occupations look similar. In 1980, about 60% of college graduates were employed in occupations of skill level 0.5 or lower (seen as the vertical dotted line), a conventional threshold to distinguish occupations "requiring" a degree (Abel and Deitz, 2017).[11] This fraction falls to 40% in 2000 and to around 30% in 2020, reflecting a general rise in occupational skill intensity.

[9] There are other ways to characterize the distribution of college graduates. For example, Strange (2004) proposed using a Herfindahl-Hirschman index, an approach used by Zhang (2020) and Backman and Kohlhase (2022). My approach has the advantage of characterizing the intensity of skill in the city. In addition, because more diverse cities have been found to grow faster (Glaeser et al., 1992; Duranton and Puga, 2000, 2001), it could be necessary to distinguish between diversity of skill and overall diversity, which I leave for future research.

[10] I take the occupational distribution as given. See Goldman et al. (2019) on occupational concentration in the U.S.; Hendricks (2011) and Davis and Dingel (2020) on the variation in skill across U.S. cities; and Ehrl and Monasterio (2019) on the variation of skill across Brazilian cities.

[11] Taken across 3-digit occupations, not shown to reduce clutter, the figure is 50% rather than 60%. The larger figure is due to the aggregation from 359 3-dgit occupations to just 45 occupational groups.

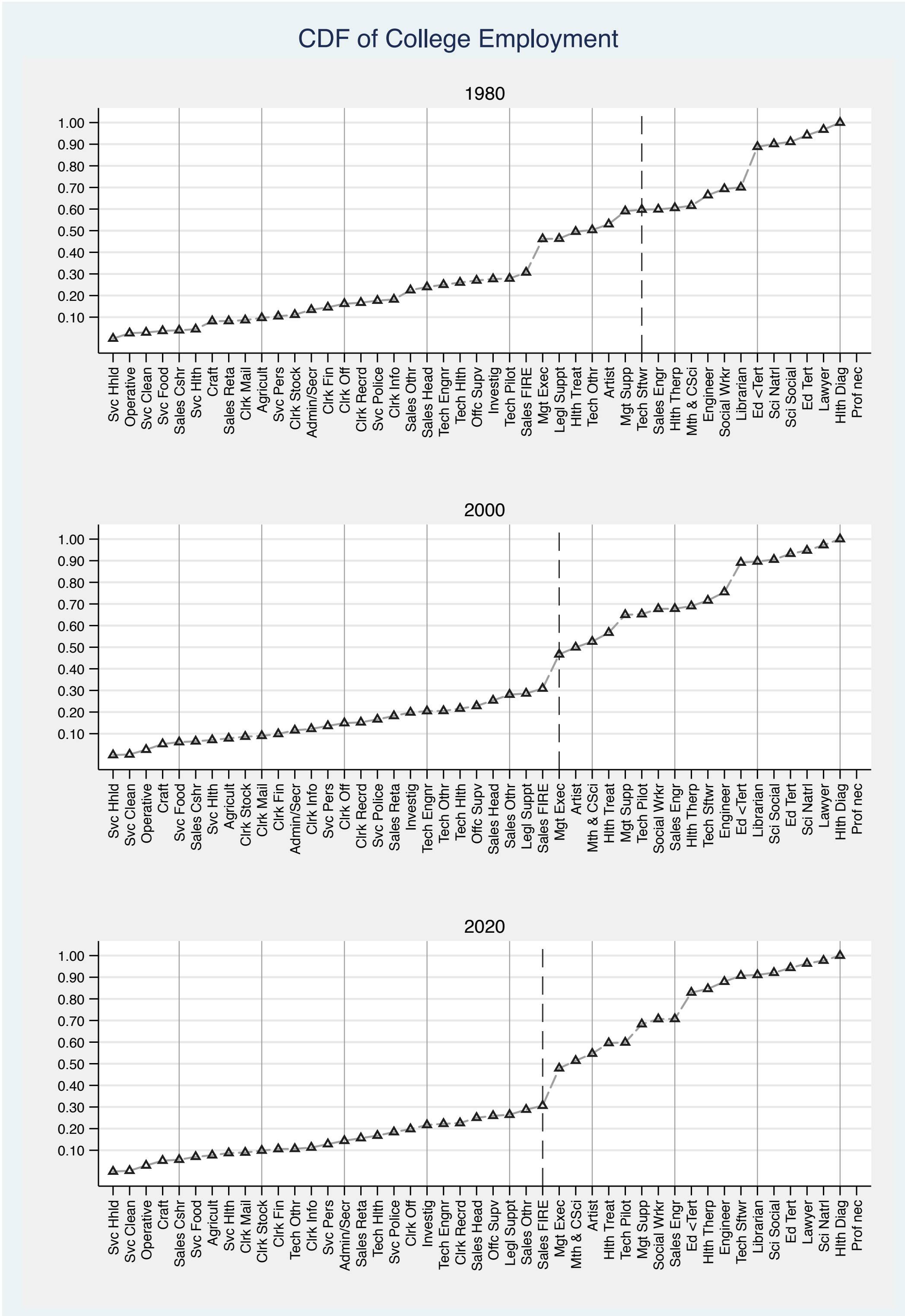

Figure 1: Cumulative Distributions of College Employment

Cumulative distributions of college and non-college employment across 45 broad occupation groups.

4.4 Are Left-Tail Grads More Productive than Non-Grads?

While some observers contend that college graduates employed in left-tail occupations are "underemployed," the O-ring model of Kremer (1993) suggests that it could pay for some individuals to earn a college degree even if they are eventually employed in occupations that ostensibly do not "require" a college degree. In this section, I show that left-tail college graduates are in fact more productive than their non-graduate counterparts within an occupation.[12]

First, I compare the percentage of college graduates who earn more than high school graduates at various points in the percentile real weekly wage distribution, corrected for labor market experience, selected demographics (gender, race, and Hispanic origin), and differences in the cost of living across cities. My measure of real weekly wages is the empirical residual error term $\hat{\omega}_{ijec}$ from the ordinary least squares regression for log real weekly earnings given by

$$\ln w_{ijec} = \beta_X X_i + \beta_D D_i + \phi_c + \omega_{ijec}, \tag{11}$$

where w_{ijec} is the real (CPI-corrected) weekly wage of individual i who works in occupation j with education level e in city c, X_i is a vector of experience groups (0 to 4, 5-9, 20-29, 30-39, and 40 plus years), D_i is a vector of demographics, and ϕ_c is a city fixed effect.

Denote the p^{th} percentile of $\hat{\omega}_{ijec}$ for a high school graduate who works in occupation j as $\omega^p_{HS;j}$ where j represents one of the 3-digit IPUMS 1990 occupations. If the distribution of earnings for college graduates is the same as for high school graduates, then $\omega^p_{HS;j} = \omega^p_{CG;j}$, that is, the percentile values of residual earnings are the same for college and high school graduates. Denote the fraction of college graduates in occupation j who earn more than $\omega^p_{HS;j}$ as $\Phi_C(\omega^p_{HS;j}) = 1 - F_C(\omega^p_{HS;j})$, where $F_C(\omega^p_{HS;j})$ is the cumulative distribution of college earnings evaluated at $\omega^p_{HS;j}$. Finally, define the *excess fraction* of college graduates who earn more than $\omega^p_{HS;j}$ as $\Phi_C(\omega^p_{HS;j}) - (1-p)$. For example, by definition, 25% of high school graduates earn more than $\omega^{75}_{HS;j}$; if 40% of college graduates earn more than $\omega^{75}_{HS;j}$, then the excess fraction equals (40-25=) 15%.

Figure 2 graphs the excess fraction of college graduates who earn more than the 50^{th} and 75^{th} percentile high school wage by occupation as a function of (2020) occupational skill, along with a local polynomial regression. All seven years of data are combined, and each point is weighted by the number of college graduates. If the earnings distributions of college graduates and high school graduates were identical, the markers would line up along the horizontal axis at zero. In fact, the earnings of college graduates tend to exceed those of high school graduates across the occupational spectrum, even at the lowest occupational skill levels. The excess percentage is increasing and concave in occupational skill, leveling off around 0.75.

[12] It is beyond the scope of this paper to explain why individuals with a college degree would choose to work in a left-tail occupation, whether such individuals made an ex-post poor investment decision, or whether differences in earnings that are associated with differences in education reflect a causal effect of education.

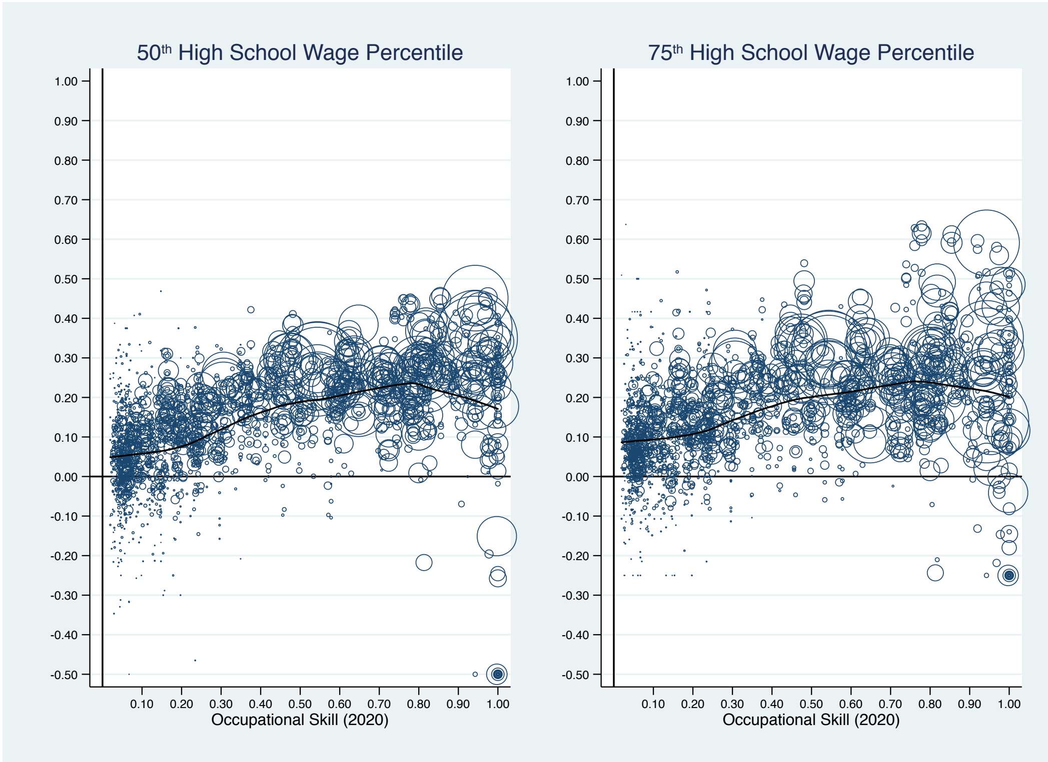

Figure 2: Excess Percent of College Grads Who Earn More Than 50^{th} and 75^{th} High School Percentile Wage

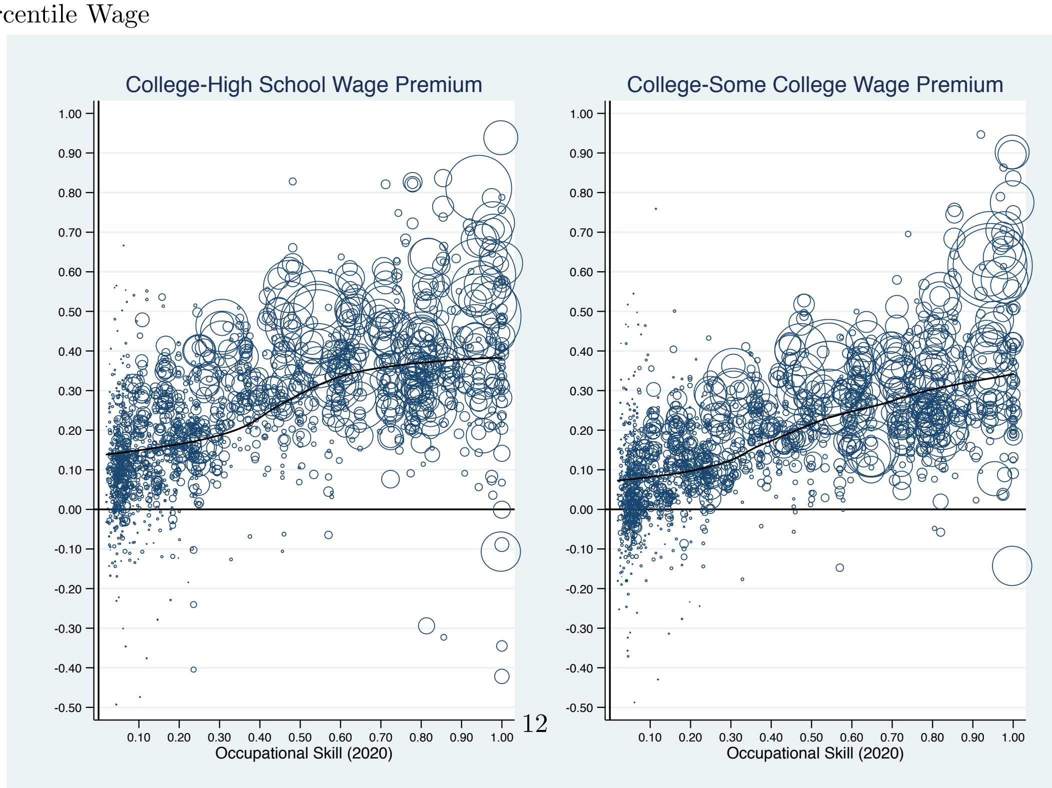

Figure 3: College Wage Premium Relative to High School and Some College

All years combined. Occupational skill measured as of 2020.

Figure 3 graphs occupation-specific college wage premiums relative to high school graduates and those with some college as a function of occupational skill. These wage premiums are calculated using the same specification as Equation 11 except that they are estimated on a year-by-year, occupation-by-occupation basis. Like the excess percentages in Figure 5, the wage premia increase at a decreasing rate in occupational skill.

Taken as a whole, the evidence on earnings suggests that college graduates are more productive than non-graduates across the occupational spectrum, including those employed in occupations in the left tail of the skill distribution. Additional suggestive evidence from the Current Population Survey reveals that college graduates are more likely to adopt computers – and hence are more productive – across the occupational spectrum than non-graduates. However, as this evidence is indirect and makes use of data beyond those in the main analysis, this analysis is relegated to Appendix D.

4.5 Occupational Distribution of Entrepreneurship

Lazear (2005) proposed that entrepreneurs have balanced skill sets relative to specialists. This suggests that that those who are self-employed in a given occupation, especially in left-tail occupations, are more highly skilled than their non-college counterparts.

I measure entrepreneurship as the rate of incorporated self-employment, incorporated because such individuals are more likely to employ others (Lazear, 2005; Glaeser, 2007), and self-employment among business non-owners is dominated by contract work and home-based, single-person pursuits (Light and Munk, 2018). The incorporated self-employed are also better-educated, earn more, have stronger analytical skills, and average ten times the starting capital of their unincorporated counterparts (Levine and Rubinstein, 2016, 2018). Data on incorporated self-employment are available in the Census and ACS microdata starting in 1970, but for just 108 cities and hence downplayed, and since 1980 for between 231 and 338 cities.

Figure 4 graphs the cumulative probabilities of self-employment conditional as a function of skill level k, conditional on education, equal to

$$P_k(SE^C) \equiv \sum_{i=1}^{k} SE_i^C / \sum_{i=1}^{k} C_i \quad \text{and} \quad P_k(SE^N) \equiv \sum_{i=1}^{k} SE_i^N / \sum_{i=1}^{k} N_i. \tag{12}$$

$P_k(SE^C)$ peaks towards the left of the occupational skill distribution in 1980, 2000 (albeit only slightly), and 2020, and dips below the mean (the horizontal solid line) at higher skill levels in all three years. Notice that $P_k(SE^C)$ lies everywhere above $P_k(SE^N)$, which is consistent with the notion that college-educated workers in the left portion of the occupational skill distribution are more productive on average than their non-college counterparts.

Figure 5 graphs the "excess cumulative distribution" (cdf) of college incorporated self-employment, equal to the difference between the cumulative distributions of self- and total employment.[13] The excess cdfs turn positive for management executives, and sharply negative for education (tertiary and "other"). Both the positive and negative inflections are particularly pronounced in 1980, but are visible in the other years.[14]

4.6 Implications for Treatment of Education Occupations

The fact that the excess cumulative distribution of self-employment turns sharply negative when educators are included suggests strongly that educators should be netted out from other college graduates. Such individuals are apparently unlikely to contribute much to the economies of agglomeration deriving from human capital in Equation 4. It will be seen in the Section 5 that college "towns" are over-represented, and large cities under-represented in the 20 most human-capital intensive cities when ranked by the broader measure of human capital. It will also be seen in Section 6 that the narrower measure of college graduates is a stronger predictor of city size than the broader measure.

[13] The cdf of overall college employment is seen in Figure 1. The cdf of college incorporated self-employment looks very similar. The cdfs of overall and self-employment of non-college graduates are also very close. I therefore suppress the cdfs of self-employment to save space.

[14] Figures (not shown to reduce clutter) that show the cumulative fraction at occupation of skill rank k of college employment relative to total employment, and of college incorporated self-employment relative to total incorporated self-employment, equal to

$$F_k(C) = \sum_{i=1}^{k} C_i/E \quad \text{and} \quad F_k(SE^C) = \sum_{i=1}^{k} SE_i^C/SE, \tag{13}$$

where C_i and SE_i^C are college overall and incorporated self employment in occupation i, and E and SE are total overall and incorporated self employment. These Figures reveal that college graduates are over-represented in incorporated self-employment ($F_k(SE^C) > F_k(C)$) across the entire occupational spectrum.

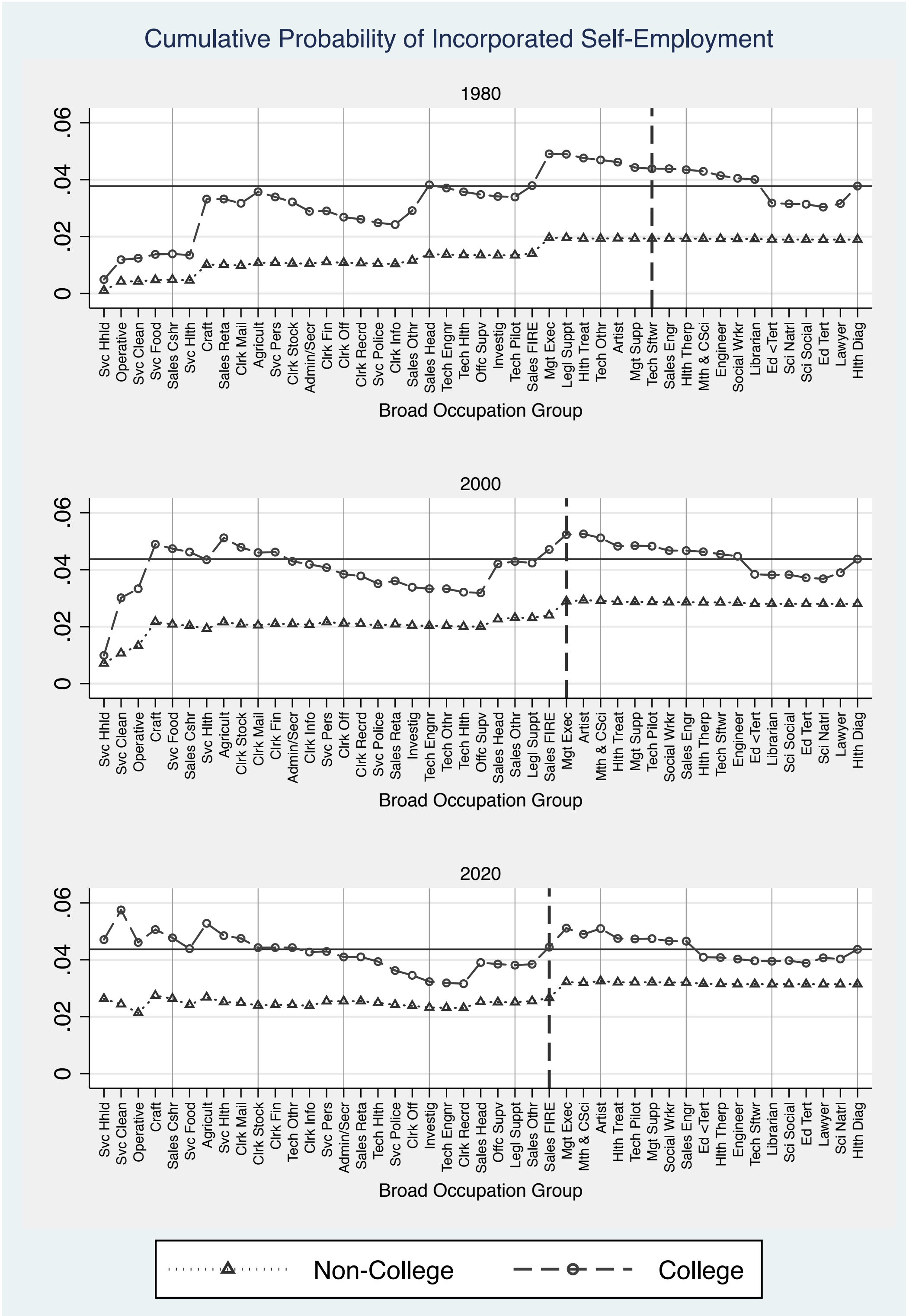

Figure 4: Cumulative Probabilities of Incorporated Self-Employment

Horizontal solid line denotes mean college self-employment in the sample as a whole and vertical dotted line separates occupations with less than and more than 50% college graduates. By construction, the graph for college graduate self employment meets the horizontal solid line at the far right of the graph.

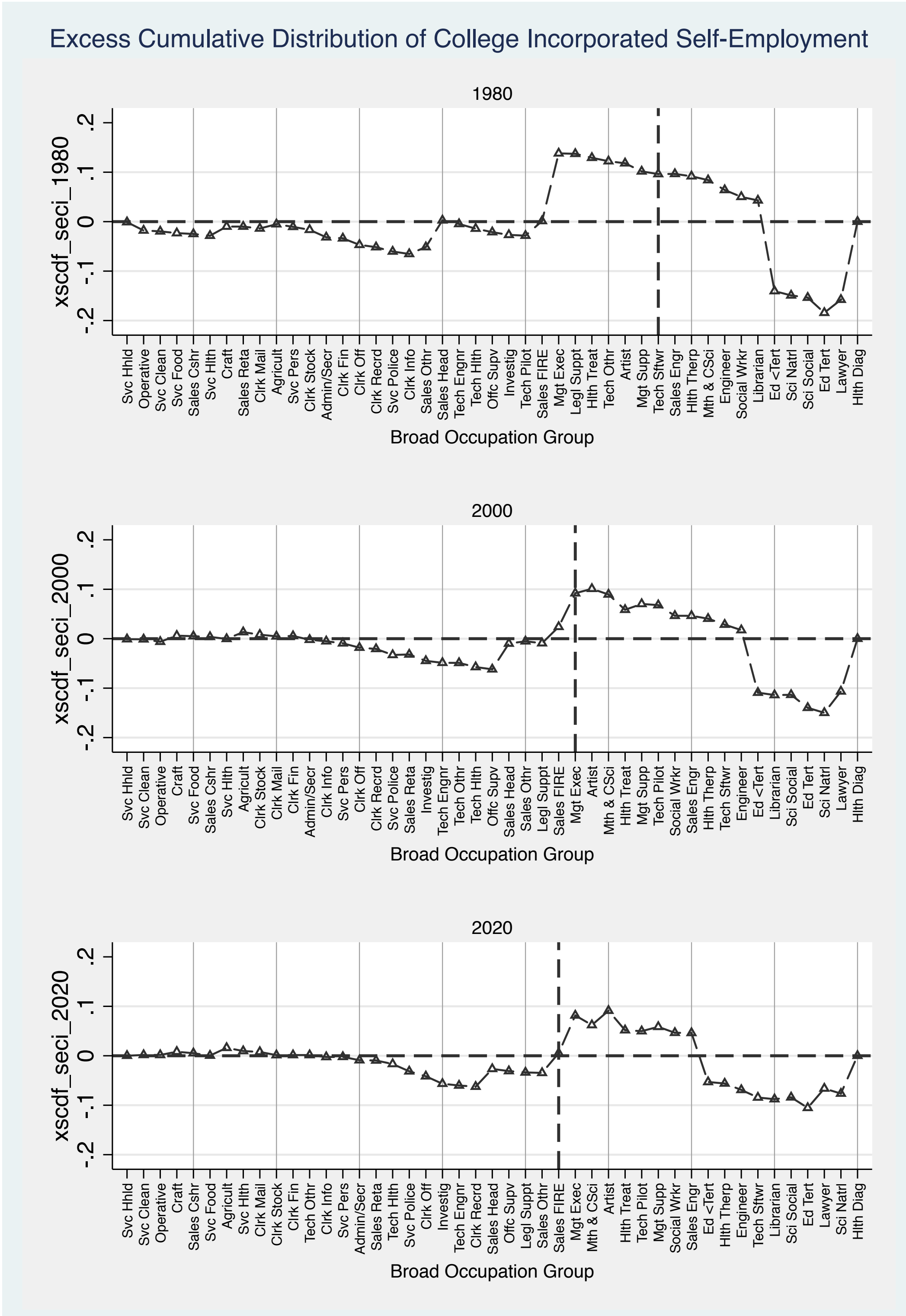

Figure 5: Excess Cumulative Distribution of Incorporated Self-Employment

Deviation between cumulative distribution of college-educated self-employment and overall college employment. Vertical line divides occupations with less than and more than 50% college graduates.

5 Geographic Distribution of Human Capital

The key human capital variables in my analysis are left- and right-tail college graduates as a fraction of total employment in city c and year t,

$$CG_{ct}^{\mathcal{L}} = C_{ct}^{\mathcal{L}}/E_{ct}; \quad CG_{ct}^{\mathcal{R}} = C_{ct}^{\mathcal{R}}/E_{ct}, \tag{14}$$

where $C_{ct}^{\mathcal{L}}$ and $C_{ct}^{\mathcal{R}}$ are the numbers of left and right-tail college graduates net of educators and E_{ct} is total employment. The overall fraction of employment that is college educated is

$$CG_{ct} = CG_{ct}^{\mathcal{L}} + CG_{ct}^{\mathcal{R}} + +CG_{ct}^{\mathcal{E}}, \tag{15}$$

where $CG_{ct}^{\mathcal{L}} = C_{ct}^{\mathcal{E}}/E_{ct}$ is equal to college graduates employed in education occupations as a fraction of total city employment.

5.1 Most and Least-Educated Cities

Table 1 shows the 20 most and least-educated cities as measured by the narrow measure of 1980 percent college graduates, CG, along with $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$ at $\theta = 50$ (I omit the city and year subscripts when doing so entails no ambiguity). Although educators have been removed, the most educated cities include a number of college towns, including Tallahassee (1), Charlottesville (3), Gainesville (7), and Bloomington (11). However, those cities tend to rank even higher when educators are included, as can be seen from the ranking for the broad measure (labeled "Broad"). The most educated large cities are Denver, CO (4), San Jose-San Francisco (5), Washington, DC (9), and Seattle (15). Notice, too, that San Diego, New York City, and Minneapolis rank 18 through 20 by the narrow measure, but would be excluded based on the broad measure. Most cities in the bottom 20 are small; the largest is Hickory, NC (rank 238, with a population of 305 thousand) and there is a smattering of cities with populations of 200-250 thousand.

5.2 Correlations Between Left and Right Tail Human Capital

The O-ring model of development of Kremer (1993) predicts that workers will sort geographically across the occupational spectrum. I begin investigation of this proposition by examining simple correlations among the human capital variables, seen in Table 2 along with their means. Statistics for the broad measures of human capital are contained in the upper half of the Table and those for the narrow measures, in the lower half. Considering the broad measures first, the first rows compare CG and a measure of percent college graduates constructed from county-level data, CG_{ct}^{A} (A for "Aggregate"). It makes sense that the means of CG, which are calculated for individuals age 25-54 who report an occupation, exceed those of CG^{A}, which is based on individuals age 25 and over and thus includes older (and hence less-educated) individuals and labor market non-participants. Ignoring 1960 (CG^A not available) and 1970 (CG available for just 108 cities), the correlations range between 0.87 and 0.91, which suggests that the geographic mapping of the microeconomic data is reasonable.

Means for and correlations between $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$ are shown for $\theta = 50$. The means rise from 4.3% and 5.3% in 1960 to 14.1% and 15.0% in 2020 (the means of $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$ differ because they are taken across cities and are not for the U.S. as a whole). The correlation between the two rises from 0.602 in 1960 to 0.882 in 2020, a pattern that holds at all θ.

Similar patterns are evident in the narrow measures, but the correlations between right and left-tail human capital are higher: for example, 0.725 versus 0.602 in 1960 and 0.913 versus 0.882 in 2020. Also seen are statistics for college-educated educators as a fraction of total employment, $CG^{\mathcal{E}}$. Although $CG^{\mathcal{E}}$ is positively correlated with the other measures, the correlations are much lower than those between $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$. This is not entirely surprising in that one would expect much less sorting of educators across cities either at the University level or below, which suggests that their location decisions are driven by factors beyond the models of Behrens et al. (2014) and Davis and Dingel (2020)

Additional detail on the correlations between right and left-tail human capital narrowly measured is contained in Table 3. Each entry in the Table is equal to the minimum correlation between left tail human capital at given left/right-threshold θ in each row, and right-tail human capital at given θ in each column; by "minimum," I mean the smallest value over the years 1960 through 2020. For example, the smallest correlation between left and right-tail human capital for a common threshold $\theta = 20$ equals 0.696, and the smallest correlation for a left-tail threshold of $\theta = 20$ and a right-tail threshold of $\theta = 80$ is 0.600. Virtually all of these correlations are large and statistically significant. As in Table 3, the correlations with respect to $CG^{\mathcal{E}}$, seen in the last row and column, are much smaller than those between the various measures of right and left tail human capital.[15] These results are consistent with those of Davis and Dingel (2020), but provide a somewhat different view of the data.[16]

[15] Although the correlations between left and right-tail human capital are high, there is no "collinearity problem." The data matrix is always of full rank, there remaining 21%-36% of linearly independent variation via which to identify their effects. There is no indication of the archetypal symptom: rejecting the null hypothesis jointly but failing to reject the null for either singly. Also, the estimated coefficients vary reasonably smoothly with θ at a point in time, and over time for given θ.

[16] They are also consistent with results in Wang (2020) that shows that (1) left-tail and right-tail human capital rise in city size and (2) within a city, left- and right-tail human capital are correlated across firms. Finally, the results are consistent with the findings of (Andersson et al., 2007) that high quality workers tended to locate in the same counties as high-quality firms

Table 1: 20 Most and Least-Educated Cities: CG, $CG^{\mathcal{L}}$, and $CG^{\mathcal{R}}$ at $\theta = 50$

Rank	City	CG	$CG^{\mathcal{L}}$	$CG^{\mathcal{R}}$	Broad	Pop
1	Tallahassee+, FL-GA	0.287	0.183	0.104	1	237305
2	Fort Collins, CO	0.254	0.174	0.080	5	149184
3	Charlottesville, VA	0.252	0.139	0.113	2	137523
4	Denver+, CO	0.251	0.159	0.092	8	1763831
5	San Jose+, CA	0.245	0.155	0.089	11	5740272
6	Burlington+, VT	0.241	0.134	0.106	6	154935
7	Gainesville+, FL	0.240	0.148	0.093	3	192514
8	Austin+, TX	0.239	0.145	0.094	7	585051
9	Washington+, DC-MD-VA-WV-PA	0.237	0.132	0.105	12	6043673
10	Santa Maria+, CA	0.223	0.141	0.082	14	298694
11	Lincoln+, NE	0.221	0.144	0.077	10	233129
12	Albuquerque+, NM	0.217	0.126	0.091	15	668097
13	Bloomington+, IN	0.215	0.144	0.071	4	157098
14	Boise City+, ID-OR	0.214	0.141	0.073	17	344218
15	Seattle+, WA	0.214	0.135	0.078	18	2559923
16	Bloomington+, IL	0.211	0.152	0.060	13	178638
17	Houston+, TX	0.205	0.129	0.076	29	3288864
18	San Diego+, CA	0.200	0.128	0.072	31	1861846
19	New York+, NY-NJ-CT-PA	0.200	0.121	0.079	25	19764358
20	Minneapolis+, MN-WI	0.200	0.129	0.071	24	2503343
233	Fort Smith, AR+, AR-OK	0.081	0.057	0.024	245	203511
234	Ocala, FL	0.080	0.047	0.033	242	122488
235	Brownsville+, TX	0.080	0.053	0.026	231	227222
236	Mankato+, MN	0.079	0.057	0.022	222	107888
237	Myrtle Beach+, SC-NC	0.079	0.054	0.025	236	179657
238	Hickory+, NC	0.079	0.053	0.025	244	305592
239	Quincy+, IL-MO	0.078	0.052	0.025	241	120072
240	Rocky Mount+, NC	0.078	0.052	0.025	239	264143
241	Houma+, LA	0.078	0.048	0.030	229	176876
242	Bloomsburg+, PA	0.078	0.041	0.036	235	245477
243	Altoona, PA	0.076	0.042	0.034	243	136621
244	Dixon+, IL	0.073	0.046	0.027	237	102298
245	Lima+, OH	0.072	0.043	0.029	247	223587
246	Jackson, TN	0.068	0.043	0.025	248	102214
247	Jacksonville, NC	0.068	0.042	0.026	234	112784
248	Danville, VA	0.065	0.039	0.026	250	111789
249	Beckley, WV	0.065	0.037	0.028	246	144684
250	Clarksville, TN+, TN-KY	0.063	0.040	0.023	251	159604
251	Poplar Bluff, MO	0.063	0.042	0.021	249	37693
252	Pottsville, PA	0.058	0.032	0.025	252	160630
253	Bowling Green+, KY	0.046	0.030	0.015	253	150475

The column labeled "Broad" shows the ranking when educators are included in CG.

Table 2: Mean Left and Right-Tail Percent College Grads Across Cities for $\theta = 50$)

	1960	1970	1980	1990	2000	2010	2020
Broad Measures							
CG	0.096	0.135	0.183	0.203	0.231	0.260	0.291
CG^A	0.096	0.092	0.138	0.162	0.193	0.222	0.240
$\rho(CG, CG^A)$	1.000	0.804	0.901	0.907	0.872	0.878	0.905
$CG^{\mathcal{L}}$ $(\theta = 50)$	0.043	0.065	0.088	0.092	0.113	0.129	0.141
$CG^{\mathcal{R}}$	0.053	0.070	0.095	0.112	0.119	0.131	0.150
$\rho(CG^{\mathcal{L}}, CG^{\mathcal{R}})$	0.602	0.770	0.780	0.869	0.847	0.830	0.882
Obs	276	108	253	282	340	340	353
Narrow Measures							
CG	0.068	0.092	0.136	0.157	0.181	0.207	0.236
CG^A	0.096	0.092	0.138	0.162	0.193	0.222	0.240
CG^E	0.028	0.043	0.047	0.047	0.050	0.053	0.054
$\rho(CG, CG^A)$	0.943	0.732	0.896	0.885	0.856	0.862	0.899
$\rho(CG, CG^E)$	0.237	0.509	0.441	0.311	0.258	0.318	0.359
$CG^{\mathcal{L}}$ $(\theta = 50)$	0.043	0.063	0.086	0.087	0.108	0.122	0.134
$CG^{\mathcal{R}}$	0.026	0.029	0.050	0.069	0.073	0.084	0.103
$\rho(CG^{\mathcal{L}}, CG^{\mathcal{R}})$	0.725	0.844	0.850	0.907	0.897	0.879	0.913
$\rho(CG^{\mathcal{L}}, CG^{\mathcal{E}})$	0.204	0.509	0.402	0.320	0.244	0.271	0.329
$\rho(CG^{\mathcal{R}}, CG^{\mathcal{E}})$	0.246	0.452	0.461	0.286	0.261	0.350	0.376

CG is total percent college graduates, divided between the θ percent employed in lower-skilled ("left-tail") occupations ($CG^{\mathcal{L}}$) and 100-θ percent employed in higher-skill ("right-tail") occupations ($CG^{\mathcal{R}}$), all expressed as fractions of total employment. ρ is the correlation across cities between $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$. CG^A is percent college graduates calculated using county-level ("Aggregate") data, not available for 1960. Narrow measures of CG, $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$ exclude education occupations; see text for details. CG^A is included in both sections of the Table for convenience.

Table 3: Correlations, Left and Right-Tail Human Capital: Narrow Measures

Row = $\mathcal{L}$, Col = $\mathcal{R}$	$\theta = 20$	$\theta = 40$	$\theta = 50$	$\theta = 60$	$\theta = 80$	$CG^{\mathcal{E}}$
$\theta = 20$	0.696	0.663	0.643	0.602	0.600	0.252
$\theta = 40$	0.841	0.731	0.686	0.648	0.659	0.215
$\theta = 50$	0.907	0.787	0.725	0.669	0.673	0.204
$\theta = 60$	0.950	0.885	0.840	0.676	0.669	0.225
$\theta = 80$	0.972	0.914	0.876	0.746	0.671	0.242
$CG^{\mathcal{E}}$	0.216	0.227	0.246	0.216	0.117	1.000

Table shows correlations between narrow measures of left- and right-tail human capital across cities. Last column (row) of table shows correlation of left (right)-tail human capital with $CG^{\mathcal{E}}$. Data are taken from years 1960 through 2020; only the smallest correlations (across years) are shown. For example, the correlation between left ($\theta = 20$) and right ($\theta = 80$)-tail human capital is no smaller than 0.600.

6 Regression Analysis of City Size

I now examine whether larger cities are more highly skilled as measured by percent college graduates in various portions of the occupational skill distribution, a prediction of Behrens et al. (2014), Davis and Dingel (2020), and Kremer (1993). I eschew presentation of correlations and move immediately to regression analysis, which allows me to control for other factors that might be correlated with human capital. In addition, regression analysis permits me to test whether left-tail human capital has explanatory power, holding constant right-tail human capital, and vice versa. The regressions are of the form

$$\ln P_{ct} = \beta_0 + \beta_{\mathcal{L}} CG_{ct}^{\mathcal{L}} + \beta_{\mathcal{R}} CG_{ct}^{\mathcal{R}} + \beta_{\mathcal{E}} CG_{ct}^{\mathcal{E}} + \beta_X X_{ct} + \beta_A A_{ct} + \epsilon_{ct}, \tag{16}$$

where P_{ct} is the population, $CG_{ct}^{\mathcal{L}}$ and $CG_{ct}^{\mathcal{R}}$ are left-tail and right-tail college graduates as a fraction of total employment net of educators, $CG^{\mathcal{E}}$ is college-educated individuals in education-related occupations as a fraction of total employment, A_{ct} is a vector of natural amenities, X_{ct} contains control variables for the economic structure of the city, and ϵ_{ct} is an error term, all in city c in year t. Robust standard errors are reported throughout, clustered on city in regressions that pool the data for all years.

Amenities and Region College-educated workers may have higher demands for attractive amenities, which also may attract large numbers of people in general. I therefore control for natural amenities as measured by heating and cooling degree days, precipitation, and location on the coast. I also include Census division controls to capture other unmeasured time-invariant factors.[17]

Summary statistics for the variables in the regressions appear in Table 4.

[17] Other amenities may evolve endogenously as found by Diamond (2016). The model of (Behrens et al., 2014) is also consistent with a consumption variety model as in (Lee, 2010). However, I have chosen to focus on the production variety model for the purposes of discussion.

Table 4: Summary Statistics Across Cities

Variable	1960	1970	1980	1990	2000	2010	2020
Population	288,490	331,542	369,414	408,799	466,384	513,895	548,157
	(1,041,910)	(1,198,596)	(1,238,354)	(1,361,291)	(1,522,859)	(1,638,991)	(1,724,385)
Log Pop	11.291	11.377	11.535	11.595	11.701	11.769	11.793
	(1.364)	(1.392)	(1.370)	(1.396)	(1.415)	(1.442)	(1.471)
SE/E		0.014	0.021	0.026	0.031	0.033	0.034
		(0.004)	(0.006)	(0.007)	(0.010)	(0.012)	(0.011)
SE^C/E		0.003	0.007	0.008	0.010	0.012	0.012
		(0.001)	(0.002)	(0.003)	(0.005)	(0.006)	(0.006)
SE^N/E		0.011	0.014	0.018	0.021	0.021	0.021
		(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)
SE^C/C		0.026	0.039	0.040	0.044	0.047	0.042
		(0.011)	(0.012)	(0.011)	(0.014)	(0.016)	(0.015)
SE^N/N		0.012	0.018	0.022	0.028	0.029	0.031
		(0.004)	(0.005)	(0.006)	(0.009)	(0.011)	(0.011)
$BUSE$ (Bus Svc)	0.009	0.020	0.025	0.033	0.034	0.041	0.045
	(0.004)	(0.010)	(0.014)	(0.019)	(0.018)	(0.023)	(0.028)
MF (Manuf)	0.324	0.315	0.260	0.213	0.184	0.134	0.050
	(0.169)	(0.158)	(0.136)	(0.117)	(0.107)	(0.086)	(0.061)
TRD (Trade)	0.305	0.298	0.226	0.221	0.205	0.198	0.204
	(0.083)	(0.074)	(0.050)	(0.042)	(0.033)	(0.029)	(0.039)
Pat/Worker			0.001	0.001	0.002	0.002	0.002
			(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Obs	276	108	253	282	340	340	353

6.1 Ordinary Least Estimates: Pooled Data

Pooling the data allows me to present a wide variety of results without straining the reader. I present a limited number of results for each year separately later on. I focus on OLS estimation because I am not testing whether human capital exerts a causal effect. In particular, one might use instrumental variables (IV) because one is concerned that shocks to the error term ϵ_{ct} are causing shocks to the key explanatory variables, here $CG^{\mathcal{L}}_{ct}$ and $CG^{\mathcal{R}}_{ct}$. However, the framework of Behrens et al. (2014) *assumes* that sorting occurs so that Equation 5 holds in equilibrium. Indeed, there is no dependent variable per se. Because I am interested in comparing the explanatory power of left and right-tail human capital, it seems reasonable to specify city size as the dependent variable.

6.2 Single Measures of Human Capital Included

The results are contained in Table 5. I begin by showing estimates using both the broad and narrow measures of human capital. Column 1 shows the results of a simple OLS regression of log population on CG augmented solely by a set of year dummy variables. Looking at the broad human capital measures, seen in **Part A**, the estimated coefficient on CG is positive and statistically highly significant: 10.04 with a standard error of 1.02. The coefficient implies that a 10 percentage point increase in the fraction of college graduates in a city is associated with roughly a doubling in city size.

I next replace overall percent college graduates CG_{ct} with, alternatively, $CG^{\mathcal{L}}_{ct}$, seen in column 2 and $CG^{\mathcal{R}}_{ct}$ using a left/right threshold of $\theta = 50$, seen in column 3. As can be seen, the estimated coefficients on the left and right-tail human capital variables are nearly double in size, 18.90 (1.99) and 17.92 (2.22) and therefore are associated with even larger differences in city size.

6.3 Both Left- and Right-Tail Human Capital Included

I now consider whether there is independent information in left- and right-tail human capital. It is important to recognize that univariate analysis has already established that higher quality labor sorts into larger cities across the occupational skill spectrum, and that the quality of labor in the left portion of the skill distribution is positively correlated with quality of labor in the right portion.

The regression in column 4 includes both left- and right-tail human capital. As can be seen, the estimated coefficient (standard error) on $CG^{\mathcal{L}}_{ct}$ is 16.17 (3.69), which is positive and statistically significant, while the estimated coefficient on $CG^{\mathcal{R}}_{ct}$ is a small and statistically insignificant 3.47 (3.63). Clearly, one can reject the null hypothesis that $\beta_{\mathcal{R}} = \beta_{\mathcal{L}}$. Adding eight dummy controls for Census region, seen in column 5, the estimated coefficient on $CG^{\mathcal{L}}_{ct}$ rises to 21.27 (3.81) while the coefficient on $CG^{\mathcal{R}}_{ct}$ is now negative, -0.24 (3.43). The results are much the same with amenities added, seen in column 6.

Column 7 adds a complete set of city fixed effects and hence omits the division and amenity variables. The estimated coefficient on $CG^{\mathcal{L}}_{ct}$ is only about one-tenth its magnitude relative to OLS estimates but is a still statistically significant 2.55 (0.64). By contrast, the estimated coefficient on $CG^{\mathcal{R}}_{ct}$ is actually slightly more negative, -0.91, but only just slightly larger than its standard error of 0.71.

Table 5: Population Size, Basic Model, $\theta = 50$

	Pooled OLS						City FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				A. Broad HK Measures						
CG	10.04						0.82			
	(1.02)						(0.28)			
$CG^{\mathcal{L}}$		18.90		16.17	21.27	21.30		1.88		2.55
		(1.99)		(3.69)	(3.81)	(3.48)		(0.50)		(0.64)
$CG^{\mathcal{R}}$			17.92	3.47	-0.60	-0.24			0.99	-0.91
			(2.22)	(3.63)	(3.68)	(3.43)			(0.54)	(0.71)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division	No	No	No	No	Yes	Yes	No	No	No	No
Amenities	No	No	No	No	No	Yes	No	No	No	No
R-Square	0.26	0.27	0.22	0.27	0.40	0.46	0.56	0.57	0.56	0.57
Obs	1952	1952	1952	1952	1952	1952	1952	1952	1952	1952
				B. Narrow HK Measures						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CG	12.42						1.25			
	(1.06)						(0.32)			
$CG^{\mathcal{L}}$		19.68		-3.49	3.53	4.79		1.97		1.36
		(2.07)		(2.97)	(3.20)	(2.89)		(0.51)		(0.69)
$CG^{\mathcal{R}}$			28.37	32.15	30.10	29.17			2.48	2.31
			(2.16)	(3.91)	(3.65)	(3.36)			(0.70)	(0.96)
$CG^{\mathcal{E}}$					-35.56	-34.26				-7.02
					(3.26)	(2.87)				(1.26)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division	No	No	No	No	Yes	Yes	No	No	No	No
Amenities	No	No	No	No	No	Yes	No	No	No	No
R-Square	0.33	0.27	0.36	0.37	0.55	0.59	0.57	0.57	0.57	0.59
Obs	1952	1952	1952	1952	1952	1952	1952	1952	1952	1952

These regressions use a left-right threshold of $\theta = 50$. All regressions include year dummy variables. Years from 1960 through 2020 are included. The panels are not balanced. Numbers of cities in each year are seen in year-by-year regressions below.

Part B of Table 5 contains results using the narrow measures of human capital. The results in columns 1 and 2 do not differ appreciably from those in Part A. Notice, however, that when just right-tail human capital is included (column 3), the R-square is 0.36, more than 50% higher than the R-square of 0.22 using the broad measure. When left-tail human capital is added to the regression in column 4, its coefficient is a negative and statistically insignificant -3.49 (2.97) while the coefficient on right-tail human capital rises to 32.15 (3.91). The estimated coefficient on left-tail human capital turns positive when division dummy variables are added in column 5, and rises to a marginally significant 4.79 (2.89) when amenity controls are added in column 6. It is much smaller, however, than the estimated coefficient on right-tail human capital: 29.17 (3.36).

It is important to recognize that left-tail human capital is higher in larger cities, consistent with the sorting implications of the models of Behrens et al. (2014), Davis and Dingel (2020), and Kremer (1993). However, the results in columns 4-6 indicate that left-tail human capital has no explanatory power beyond, and indeed is dominated by right-tail human capital.

This conclusion, however, is somewhat altered when city fixed effects are added in column 7. There are two findings of note. First, the estimated coefficient on right-tail human capital is about a tenth the size, equal to 2.31 (0.96). Second, although the estimated coefficient on left-tail human capital is also smaller than in columns 4-6, it is about one-third as large: 1.36 (0.69), which is just statistically significant at the 5% level. In other words, left-tail human capital has explanatory power for city size in models that include city fixed effects.

It is worth reiterating the difference made by netting out educators from the left and right tail measures of human capital. According to the broad measures, it is left-tail human capital that dominates the city size-human capital relationship, whereas just the opposite is true using the narrow measures. Mechanically speaking, it is easy to see why: the estimated coefficient on $CG^{\mathcal{E}}$ in columns 5-7 are large, negative, and precisely estimated.

6.4 Population Size and Human Capital at Other Thresholds

Table 6 reports pooled fixed effects estimates for left/right thresholds varying from $\theta = 20$ to $\theta = 80$. In addition to year effects, I have included employment shares in three industries: business services, identified by Hendricks (2011) as a key source of agglomeration economies, manufacturing, and trade (retail and wholesale). The estimated coefficients on business service share are positive, as are the coefficients on manufacturing share. The estimated coefficients on trade share are negative but statistically insignificant.

The results in **Part A**, which exclude city fixed effects, reveal positive estimated effects of right-tail human capital across the board. The estimated effects of left-tail human capital are negative between $\theta = 20$ and $\theta = 50$. The estimated effects of left-tail human capital are positive at θ values of 60 and 80, but the relationship is dominated by the right tail, which coefficients are 2.5 to 3 times as large.

The story is somewhat changed when city fixed effects are included, seen in **Part B**. Left-tail human capital is positive and statistically significant at $\theta = 50$ and higher, and the coefficients on right-tail human capital are "only" twice as large. Again, the results indicate that left-tail human capital contains information above and beyond that of right-tail human capital, but not too far out in the left tail.

Table 6: Population Size: Pooled Fixed-Effects Estimates by Left/Right Threshold θ

	(1)	(2)	(3)	(4)	(5)
	$\theta = 20$	$\theta = 40$	$\theta = 50$	$\theta = 60$	$\theta = 80$
	A. Narrow HK Measures, OLS				
$CG^{\mathcal{L}}$	-31.37	-9.03	-1.64	7.26	9.47
	(3.25)	(3.28)	(3.11)	(2.72)	(1.70)
$CG^{\mathcal{R}}$	22.82	23.87	28.50	19.73	25.61
	(1.43)	(2.07)	(3.64)	(4.79)	(9.98)
$CG^{\mathcal{E}}$	-26.43	-29.38	-31.88	-30.90	-30.31
	(3.17)	(3.32)	(3.28)	(3.31)	(3.57)
Bus. Svc Shr	5.96	7.67	8.67	10.99	12.01
	(3.03)	(3.28)	(3.47)	(3.73)	(3.81)
Mfg Shr	-0.66	-0.68	-0.52	-0.30	-0.12
	(0.45)	(0.49)	(0.50)	(0.51)	(0.52)
Trade Shr	-4.73	-5.17	-5.49	-5.95	-5.90
	(1.05)	(1.14)	(1.19)	(1.24)	(1.24)
Year	Yes	Yes	Yes	Yes	Yes
R-Square	0.57	0.51	0.50	0.48	0.48
Obs	1945	1945	1945	1945	1945
	B. Narrow HK Measures, FE				
	(1)	(2)	(3)	(4)	(5)
$CG^{\mathcal{L}}$	-0.81	0.37	1.65	1.13	1.46
	(1.33)	(0.92)	(0.70)	(0.59)	(0.36)
$CG^{\mathcal{R}}$	2.23	2.33	1.66	2.66	3.60
	(0.44)	(0.58)	(0.85)	(1.06)	(1.80)
$CG^{\mathcal{E}}$	-5.61	-5.68	-5.81	-5.89	-5.95
	(1.05)	(1.04)	(1.06)	(1.05)	(1.07)
Bus. Svc Shr	1.45	1.51	1.66	1.53	1.59
	(0.63)	(0.62)	(0.65)	(0.63)	(0.65)
Mfg Shr	0.99	1.00	1.01	1.00	0.99
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
Trade Shr	-0.50	-0.45	-0.44	-0.47	-0.46
	(0.60)	(0.59)	(0.59)	(0.60)	(0.59)
Year	Yes	Yes	Yes	Yes	Yes
R-Square	0.65	0.65	0.65	0.65	0.65
Obs	1945	1945	1945	1945	1945

All regressions include year dummy variables. Years from 1960 through 2020 are included. The panels are not balanced. Numbers of cities in each year are seen in year-by-year regressions below.

6.5 Growth Restraints

Regulatory burdens have increased the cost of housing supply since the 1980s (Gyourko et al., 2008; Gyourko and Krimmel, 2019). In addition, the increasing geographic concentration of innovation since 1990 has coincided with steep rises in rents in a small number of "superstar cities" such as San Francisco, San Jose, Seattle, Los Angeles, and Boston (Andrews and Whalley, 2021; Chattergoon and Kerr, 2021). Because innovative industries employ intensively college graduates in the right tail of the occupational skill distribution, one might wonder whether their negative estimated effects are a spurious result of their concentration in cities that have highly regulated land use.

I briefly summarize the analysis detailed in Appendix E. I collect data on land use regulation as measured by the 2008 and 2018 Wharton Land Use Regulatory Indexes (Gyourko et al., 2008; Gyourko and Krimmel, 2019). I find that while more highly educated cities have higher levels of land use regulation, there is no evidence that the effects of left-tail and right-tail college graduates differ.

Estimates that exclude high-regulation cities from the sample are reported in Table 7. Both the OLS estimates in Panel A and the fixed effects estimates in Part B reinforce the findings in the sample as a whole. It does not appear that the estimated effects of left and right-tail human capital can be traced to land use regulation.

6.6 Year-by-Year Estimates

Finally, I present some year-by-year estimates for completeness in Table 8. **Part A** shows results for a left/right cutoff of $\theta = 50$. The pattern of results is considerably different than found using pooled data, and it is evident, too, that the estimated effects of left- and right-tail human capital differ over time. For example, in 1960 the estimated coefficient (standard error) on $CG^{\mathcal{L}}$ is a positive and statistically significant 26.60 (6.60) and the estimated coefficient on $CG^{\mathcal{R}}$ is just 11.77 (9.72). Over time, the estimated coefficients on $CG^{\mathcal{L}}$ fall, becoming insignificant in 2000, while those on $CG^{\mathcal{R}}$ rise and become statistically more significant. Evidently, left-tail human capital contained more independent information early on in the data. The evidence of independent explanatory power of $CG^{\mathcal{L}}$ is more apparent at $\theta = 60$, seen in **Part B**, and at $\theta = 80$, seen in **Part C**.

Table 7: Pooled Fixed-Effects Estimates, High Land Regulation Cities Excluded

	(1) $\theta = 20$	(2) $\theta = 40$	(3) $\theta = 50$	(4) $\theta = 60$	(5) $\theta = 80$
	A. Narrow HK Measures, OLS				
$CG^{\mathcal{L}}$	-15.411	2.704	7.748	14.174	12.606
	(4.096)	(3.462)	(2.930)	(2.255)	(1.517)
$CG^{\mathcal{R}}$	20.516	20.062	21.224	11.680	21.973
	(1.641)	(2.294)	(3.636)	(4.292)	(10.978)
$CG^{\mathcal{E}}$	-25.160	-28.003	-29.508	-28.402	-29.478
	(3.289)	(3.161)	(3.053)	(3.043)	(3.108)
Year	Yes	Yes	Yes	Yes	Yes
Division	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes
R-Square	0.65	0.62	0.62	0.62	0.62
Obs	1640	1640	1640	1640	1640
	B. Narrow HK Measures, FE				
$CG^{\mathcal{L}}$	-0.781	0.482	1.785	1.375	1.504
	(1.489)	(1.054)	(0.794)	(0.685)	(0.424)
$CG^{\mathcal{R}}$	2.277	2.340	1.525	2.274	3.308
	(0.514)	(0.704)	(1.022)	(1.282)	(2.009)
$CG^{\mathcal{E}}$	-5.038	-5.115	-5.170	-5.276	-5.326
	(1.208)	(1.196)	(1.214)	(1.221)	(1.236)
Year	Yes	Yes	Yes	Yes	Yes
R-Square	0.61	0.61	0.61	0.61	0.61
Obs	1640	1640	1640	1640	1640

All regressions include year dummy variables. Years from 1960 through 2020 are included. The panels are not balanced. Numbers of cities in each year are seen in year-by-year regressions below.

Table 8: Population Size, Year-by-Year Estimates

	(1) 1960	(2) 1970	(3) 1980	(4) 1990	(5) 2000	(6) 2010	(7) 2020
	A. Narrow HK Measures, $\theta = 50$						
$CG^{\mathcal{L}}$	26.60	30.00	12.49	9.90	-3.66	2.83	0.40
	(6.60)	(7.51)	(4.39)	(4.63)	(3.90)	(3.85)	(3.14)
$CG^{\mathcal{R}}$	11.77	16.61	17.83	19.20	34.33	24.77	32.99
	(9.72)	(21.02)	(7.37)	(5.78)	(5.72)	(5.71)	(4.03)
Division	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.56	0.54	0.55	0.66	0.70	0.69	0.72
Obs	269	108	253	282	340	340	353
	B. Narrow HK Measures, $\theta = 60$						
$CG^{\mathcal{L}}$	27.080	33.207	17.209	18.354	6.476	7.208	7.454
	(5.565)	(5.892)	(3.432)	(3.735)	(3.890)	(3.344)	(2.930)
$CG^{\mathcal{R}}$	-9.365	-19.068	3.142	2.575	23.783	23.920	28.588
	(16.757)	(27.837)	(10.079)	(8.828)	(8.995)	(8.026)	(5.479)
$CG^{\mathcal{E}}$	-30.420	-47.290	-34.915	-35.337	-32.838	-25.872	-27.803
	(6.700)	(10.803)	(5.496)	(4.749)	(4.528)	(3.505)	(3.558)
Division	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.56	0.55	0.55	0.66	0.68	0.68	0.70
Obs	269	108	253	282	340	340	353
	C. Narrow HK Measures, $\theta = 80$						
$CG^{\mathcal{L}}$	20.947	30.165	9.700	13.478	8.809	11.491	14.120
	(4.925)	(5.485)	(3.046)	(2.272)	(2.374)	(2.201)	(1.587)
$CG^{\mathcal{R}}$	18.736	-7.176	62.636	20.188	32.367	14.213	15.433
	(23.329)	(32.170)	(27.069)	(17.721)	(16.295)	(16.639)	(9.744)
$CG^{\mathcal{E}}$	-32.190	-50.782	-36.282	-37.057	-31.588	-22.575	-24.672
	(6.561)	(10.535)	(6.101)	(4.561)	(4.577)	(3.390)	(3.541)
Division	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.56	0.54	0.55	0.66	0.68	0.68	0.69
Obs	269	108	253	282	340	340	353

6.7 Size Regressions: Summing Up

The evidence indicates across the occupational skill spectrum, those more productive sort into larger cities. Right-tail human capital dominates left-tail human capital in regressions for log size, but both have explanatory power at thresholds θ greater than or equal to 50. These results suggest that left-tail human capital contribute to agglomeration economies arising from Equation 4.

7 Regression Analysis of Self-Employment

In the model of Behrens et al. (2014), entrepreneurs form an equal fraction of the workforce in every city in equilibrium. Thus, entrepreneurship and human capital composition are unrelated across cities. This is a result of the assumption that labor is perfectly mobile across cities, and is not unique. The same point was made by Glaeser et al. (2010), but they took the position that the question of whether human capital exerts a causal effect is ultimately empirical, which I adopt here.

Certainly, Chinitz (1961) thought that human capital differences deriving from historical specialization mattered and persisted. Implicitly, the knowledge gleaned in one city is not easily transferred to other cities, as in the equilibrium urban growth model ofBlack and Henderson (1999). For example, there seems to have been a historical home-town bias in entrepreneurship, albeit declining over time (Colaiacovo et al., 2022). At least for most of my 1960-2020 study period, it seems likely that human capital is less than perfectly geographically mobile. While the concern of these authors is on the propensity to become an entrepreneur, the arguments in Section 3 emphasize, too, the importance of human capital as a complementary input into the production process, particularly when the production process is new. In other words, human capital is a potentially important complementary input for entrepreneurs, as in Berry and Glaeser (2005).

7.1 Self-Employment Regressions: Specification

I estimate regressions of the form

$$SEI_{ct} = \beta_0 + \beta_L CG_{ct}^{\mathcal{L}} + \beta_R CG_{ct}^{\mathcal{R}} + \beta_E CG_{ct}^{\mathcal{E}} + \beta_X X_{ct} + \epsilon_{ct}, \tag{17}$$

where the dependent variable SEI_{ct} is one of several measures of incorporated self-employment intensity, and the other variables are as before.

Human capital composition of the city can affect self-employment via (1) an own-education channel and (2) the complementarity channel discussed in Section 3.4. I begin with broad measures of SEI_{ct}, namely total, college and non-college self-employment per worker. I then move on to narrower measures that condition on education and occupational skill level that help to distinguish between the roles played by the two channels.

7.2 Female Educational Attainment as an Instrument

It is beyond the scope of this paper to causally link entrepreneurship to equilibrium city size or growth. However, Faggio and Silva (2014) found that self-employment and the formation of new enterprise are closely related in the UK. Similarly, self-employment per worker is positively correlated with growth in employment and population, shown in Appendix Table C1 to save space, visualized for selected measures in Appendix Figure C1. Concern therefore arises that better-educated individuals are more mobile and hence could be over-represented in faster-growing cities Duranton and Puga (2014) (40) .

I address the possibility that human capital is endogenous by using instrumental variables. Typically, researchers (e.g., Shapiro (2006)) have used Moretti's (2004a) land grant institution indicator as an instrument, described in Appendix A.3. However, this instrument is not usable in panel estimation that includes city fixed effects. In addition, at least two instruments are required in the presence of two potentially endogenous variables, $CG^{\mathcal{L}}_{ct}$ and $CG^{\mathcal{R}}_{ct}$.[18]

I constructed instruments based on lags of the human capital variables, the maintained hypothesis being that past location decisions are uncorrelated with entrepreneurship or population shocks a decade in the future. Furthermore, the instruments are constructed using data on women age 36 and higher, whose location decisions are less likely to reflect career concerns, at least among those who were married. The reason for the age restriction is that Costa and Kahn (2000) and Simon (2018) found that the college degree of the wife affected the location and migration decisions of younger couples. Thus, the instruments are 10 or 20-year lags of $CG^{\mathcal{FL}}_{ct}$ and $CG^{\mathcal{FR}}_{ct}$, where the superscript $\mathcal{F}$ denotes the use of data on older women.

7.3 Self Employment Regressions: Main Results

The specifications are similar to those used for the analysis of log size, but augment the list of explanatory variables to include log population. I again start with OLS estimates for a left/right threshold of $\theta = 50$ and move on to variations in θ and IV estimation below. All specifications control for year dummy variables, and standard errors are clustered on city.

Part A of Table 9 reports the basic results for incorporated self-employment per worker. Recall that college self-employment per worker is equal to SE_c/E_c, where SE_c is total incorporated self-employment and E_c is total employment in city c. Columns 1, 2, and 3 containing just a single human capital indicator, CG, $CG^{\mathcal{L}}$, and $CG^{\mathcal{R}}$, respectively. The estimated coefficients on the human capital variables are all positive and statistically significant.

When both $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$ are included, seen in column 4, the estimated coefficient on $CG^{\mathcal{L}}$ is positive and statistically significant and the estimated coefficient on $CG^{\mathcal{R}}$ is negative and statistically significant, a pattern that persists when division and amenity indicators are added to the model, seen in columns 5 and 6. Adding a complete set city dummy variables, seen in column 7, reduces the magnitude of the estimated coefficient on $CG^{\mathcal{L}}$ in half, but it remains statistically highly significant, while the estimated coefficient on $CG^{\mathcal{R}}$ turns positive and is statistically significant at about the 12% level.

Parts B reports results for college self-employment per worker, equal to SE^C_c/E_c , where SE^C_c. The sign pattern on the human capital variables are similar to those for overall self-employment per worker in Part A, but the estimated coefficients on both $CG^{\mathcal{L}}$ $CG^{\mathcal{R}}$ are statistically significant when city fixed effects are included, and the magnitude of the coefficient on $CG^{\mathcal{R}}$ is larger than on $CG^{\mathcal{L}}$.

Results for non-college self-employment per worker, equal to SE^N_c/E_c, reported in Part C, are markedly different. The estimated coefficient on CG_c in column 1 is positive but is tiny and statistically insignificant: 0.002 with a standard error of 0.004. When $CG^{\mathcal{L}}$ enters alone in column 2, its coefficient is 0.016 – much smaller than for the other two measures – and with a standard error of 0.009 is only marginally significant. When $CG^{\mathcal{R}}$ enters alone in column 3, its coefficient is negative and significant: -0.017 (.008). When both $CG^{\mathcal{L}}$ and $CG^{\mathcal{R}}$ are included, the former enters positively and the latter negatively, a pattern that persists when city fixed effects are included in column 7.

[18] Angrist and Pischke (2009) recommend against IV with more than one endogenous variable. Winters (2012) eschewed IV due to the difficulty of instrumenting for STEM and non-STEM college graduates, nor did Broxterman and Yezer (2020) instrument for human capital entered as a quadratic.

Doms et al. (2010) estimated a positive relationship between the probability that an individual was self-employed and the percentage of college graduates in the city's workforce, but that this positive effect went away once they controlled for individual's levels of education. The fact that I find non-college self-employment per worker to be higher in cities with higher fractions of college graduates is not consistent with their finding. However, there are a number of important differences between our studies. First, I am studying a time period from 1970 through 2020, whereas they studied just the Census year 2000. Second, my measure of self-employment differs from theirs in that I include only incorporated self-employed whereas they included all self-employed workers who reported working full time.

Table 9: Incorporated Self Employment, Basic Model, $\theta = 50$

	Pooled OLS						City FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Self Employment per Worker							
CG	0.050						
	(0.007)						
$CG^{\mathcal{L}}$		0.106		0.245	0.201	0.179	0.081
		(0.015)		(0.033)	(0.032)	(0.030)	(0.018)
$CG^{\mathcal{R}}$			0.073	-0.192	-0.130	-0.121	0.029
			(0.012)	(0.033)	(0.031)	(0.030)	(0.019)
$CG^{\mathcal{E}}$					-0.125	-0.103	-0.104
					(0.026)	(0.023)	(0.028)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division	No	No	No	No	Yes	Yes	No
Amenities	No	No	No	No	No	Yes	No
R-Square	0.67	0.69	0.65	0.72	0.76	0.79	0.86
Obs	1952	1952	1952	1952	1952	1952	1952
B. Coll Self-Emp per Worker							
CG	0.048						
	(0.003)						
$CG^{\mathcal{L}}$		0.090		0.116	0.104	0.099	0.048
		(0.006)		(0.017)	(0.017)	(0.016)	(0.008)
$CG^{\mathcal{R}}$			0.090	-0.036	-0.017	-0.015	0.067
			(0.006)	(0.017)	(0.016)	(0.016)	(0.008)
$CG^{\mathcal{E}}$					-0.043	-0.038	-0.041
					(0.011)	(0.010)	(0.012)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division	No	No	No	No	Yes	Yes	No
Amenities	No	No	No	No	No	Yes	No
R-Square	0.71	0.74	0.66	0.74	0.78	0.79	0.84
Obs	1952	1952	1952	1952	1952	1952	1952
C. Non-Coll Self-Emp per Worker							
CG	0.002						
	(0.004)						
$CG^{\mathcal{L}}$		0.016		0.129	0.097	0.080	0.034
		(0.009)		(0.018)	(0.017)	(0.015)	(0.012)
$CG^{\mathcal{R}}$			-0.017	-0.156	-0.113	-0.106	-0.038
			(0.008)	(0.019)	(0.017)	(0.016)	(0.013)
$CG^{\mathcal{E}}$					-0.082	-0.065	-0.064
					(0.017)	(0.014)	(0.019)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division	No	No	No	No	Yes	Yes	No
Amenities	No	No	No	No	No	Yes	No
R-Square	0.62	0.62	0.62	0.66	0.71	0.75	0.82
Obs	1952	1952	1952	1952	1952	1952	1952

These regressions use a left-right threshold of $\theta = 50$. All regressions include year dummy variables. Years from 1960 through 2020 are included. The panels are not balanced. Numbers of cities in each year are seen in year-by-year regressions below.

7.3.1 Self Employment: Additional Results

Fixed Effect Estimates by θ Columns 1-5 of Table 11 show the sensitivity of the results to different values of θ in models that include city fixed-effects, along with controls for city size and employment shares in manufacturing, trade, and business services. The estimated effects of left-tail human capital are all positive, largest at $\theta = 20$ with a coefficient (standard error) of 0.164 (0.029) and gradually declining to 0.038 (0.009) at $\theta = 80$. The estimated coefficients on right-tail human capital are mostly positive but are not as statistically significant as in Table 9. The estimated coefficients on both left- and right-tail human capital have positive and statistically significant effects on college self-employment in Part B, of comparable magnitude except at $\theta = 80$. The estimated effect of left-tail human capital on non-college self employment, seen in Part C, is positive and significant but declining between $\theta = 20$ and $\theta = 60$, but is negative and insignificant at $\theta = 80$. By contrast, the estimated effect of right-tail human capital is negative across the board, and is statistically significant except for $\theta = 80$.

IV Fixed-Effects by θ Columns 6-10 of Table 11 report fixed-effects IV estimates of the same models. Before turning to the second stage, consider the first stage results in Table 10. The first stages for left tail human capital are contained in columns 1-5, and for right tail human capital in columns 6-10. The estimated coefficients on lag $CG^{\mathcal{FL}}$ are all positive and statistically highly significant in the first stages for left tail human capital, while the estimated coefficients on lag $CG^{\mathcal{FR}}$ are of mixed sign and significance. Interestingly, both instruments enter positively and significantly in the first stages for right tail human capital. Manufacturing and trade shares tend to enter with negative coefficients, and business service share is generally positive.

Moving to the second stage results in Table 11, the Kleiberger-Paap statistics are sufficiently large to assuage concerns of weak instruments, and most of the endogeneity tests reject the null hypothesis of exogeneity. The pattern of estimated coefficients on the human capital variables is much the same as in columns 1-5.[19]

Estimates by Year Finally, Table 12 contains OLS and IV estimates of college and non-college self-employment for each sample year at a left/right threshold of $\theta = 50$. As I no longer need to contend with city fixed effects, I am able to add the land grant indicator as an instrument, which permits me to carry out tests of overidentification. The Kleiberger-Paap statistics are not particularly impressive for most years. There is only scattered evidence of endogoneity bias, but the over-identifying restrictions are not rejected.

Statistical significance is sometimes lower than in the pooled fixed-effects models, but the overall sign pattern of coefficients is much the same as in the pooled models, with positive estimated coefficients on $CG^{\mathcal{L}}$ and negative coefficients on $CG^{\mathcal{R}}$. The main consequence of IV estimation relative to OLS is to increase the magnitudes of the estimated coefficients on human capital as well as their statistical significance, with the possible exception of non-college self-employment in 1990.

[19] As there are two potentially endogenous variables and I have just two instruments, I am not able to carry out tests of overidentification. However, I am able to include as an instrument the land-grant institution indicator in models estimated for each year separately, to be seen shortly, and it will be seen that the null hypothesis that the instruments do not belong in the model are not rejected.

Table 10: Incorporated Self Employment, IV Fixed Effects First Stage Estimates by θ

	Left Tail					Right Tail				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\theta = 20$	$\theta = 40$	$\theta = 50$	$\theta = 60$	$\theta = 80$	$\theta = 20$	$\theta = 40$	$\theta = 50$	$\theta = 60$	$\theta = 80$
Lag $CG^{F\mathcal{L}}$	0.240	0.290	0.355	0.459	0.559	0.450	0.386	0.346	0.274	0.052
	(0.035)	(0.034)	(0.036)	(0.037)	(0.043)	(0.079)	(0.048)	(0.028)	(0.020)	(0.007)
Lag $CG^{F\mathcal{R}}$	0.019	0.043	0.127	-0.073	-0.138	0.517	0.463	0.257	0.251	0.255
	(0.013)	(0.024)	(0.048)	(0.069)	(0.223)	(0.040)	(0.038)	(0.038)	(0.043)	(0.046)
$CG^{\mathcal{E}}$	0.312	0.524	0.704	0.785	1.053	0.929	0.720	0.539	0.451	0.181
	(0.036)	(0.057)	(0.089)	(0.101)	(0.151)	(0.166)	(0.152)	(0.117)	(0.110)	(0.058)
$\ln Pop$	0.002	0.005	0.011	0.012	0.015	0.014	0.011	0.006	0.005	0.002
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Mfg Shr	-0.021	-0.032	-0.055	-0.069	-0.092	-0.076	-0.064	-0.041	-0.023	-0.003
	(0.005)	(0.008)	(0.009)	(0.011)	(0.013)	(0.011)	(0.009)	(0.007)	(0.005)	(0.002)
Trade Shr	-0.034	-0.036	-0.061	-0.085	-0.105	-0.073	-0.071	-0.047	-0.020	-0.002
	(0.010)	(0.015)	(0.019)	(0.023)	(0.027)	(0.024)	(0.019)	(0.013)	(0.011)	(0.005)
Bus. Svc Shr	-0.005	0.030	0.068	0.091	0.154	0.199	0.166	0.129	0.112	0.040
	(0.013)	(0.021)	(0.042)	(0.038)	(0.063)	(0.060)	(0.053)	(0.032)	(0.037)	(0.009)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1761	1761	1761	1761	1761	1761	1761	1761	1761	1761

See text.

7.4 Self-Employment Results: Summing Up

Taken as a whole, the results indicate that self-employment per worker is positively related to left-tail human capital but negatively related to right-tail human capital. This suggests that college graduates in the left tail of the occupational skill distribution are important complements to entrepreneurship in the city.

Table 11: Incorporated Self Employment, OLS and IV Fixed Effects Estimates by θ

	OLS Fixed Effects					IV Fixed Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\theta = 20$	$\theta = 40$	$\theta = 50$	$\theta = 60$	$\theta = 80$	$\theta = 20$	$\theta = 40$	$\theta = 50$	$\theta = 60$	$\theta = 80$
A. SE per Worker										
$CG^{\mathcal{L}}$	0.164	0.111	0.073	0.083	0.038	0.594	0.494	0.660	0.166	0.073
	(0.029)	(0.020)	(0.017)	(0.014)	(0.009)	(0.123)	(0.118)	(0.303)	(0.060)	(0.031)
$CG^{\mathcal{R}}$	0.017	0.010	0.012	-0.026	0.118	-0.020	-0.084	-0.457	-0.074	-0.085
	(0.010)	(0.012)	(0.019)	(0.023)	(0.045)	(0.023)	(0.042)	(0.261)	(0.073)	(0.203)
$CG^{\mathcal{E}}$	-0.041	-0.039	-0.033	-0.026	-0.039	-0.140	-0.169	-0.189	-0.070	-0.035
	(0.023)	(0.024)	(0.024)	(0.025)	(0.024)	(0.037)	(0.047)	(0.085)	(0.033)	(0.034)
Log Pop	0.008	0.008	0.008	0.008	0.008	0.008	0.007	0.004	0.007	0.008
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Mfg Shr	0.009	0.008	0.008	0.009	0.007	0.013	0.013	0.020	0.012	0.009
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endog						0.000	0.000	0.000	0.016	0.403
K-P						18.08	16.75	2.42	15.52	13.84
Obs	1945	1945	1945	1945	1945	1761	1761	1761	1761	1761
B. College SE per Worker										
$CG^{\mathcal{L}}$	0.061	0.054	0.045	0.050	0.043	0.202	0.155	0.111	0.040	0.047
	(0.013)	(0.009)	(0.007)	(0.007)	(0.004)	(0.056)	(0.048)	(0.092)	(0.026)	(0.013)
$CG^{\mathcal{R}}$	0.049	0.049	0.059	0.053	0.134	0.048	0.039	0.028	0.096	0.205
	(0.005)	(0.005)	(0.008)	(0.010)	(0.018)	(0.010)	(0.016)	(0.078)	(0.032)	(0.086)
$CG^{\mathcal{E}}$	-0.008	-0.007	-0.007	-0.007	-0.013	-0.055	-0.056	-0.041	-0.023	-0.034
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.018)	(0.019)	(0.025)	(0.014)	(0.013)
Log Pop	0.004	0.004	0.004	0.004	0.004	0.003	0.003	0.003	0.004	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mfg Shr	0.005	0.005	0.005	0.005	0.004	0.007	0.007	0.006	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endog						0.000	0.001	0.007	0.004	0.015
K-P						18.08	16.75	2.42	15.52	13.84
Obs	1945	1945	1945	1945	1945	1761	1761	1761	1761	1761
C. Non-College SE per Worker										
$CG^{\mathcal{L}}$	0.102	0.057	0.028	0.032	-0.005	0.392	0.339	0.548	0.126	0.026
	(0.020)	(0.013)	(0.012)	(0.009)	(0.006)	(0.088)	(0.088)	(0.246)	(0.046)	(0.024)
$CG^{\mathcal{R}}$	-0.032	-0.039	-0.047	-0.079	-0.016	-0.068	-0.123	-0.486	-0.170	-0.291
	(0.007)	(0.008)	(0.013)	(0.015)	(0.034)	(0.016)	(0.031)	(0.213)	(0.057)	(0.164)
$CG^{\mathcal{E}}$	-0.033	-0.031	-0.026	-0.019	-0.025	-0.084	-0.113	-0.148	-0.047	-0.000
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.025)	(0.034)	(0.069)	(0.025)	(0.028)
Log Pop	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.001	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Mfg Shr	0.004	0.004	0.004	0.004	0.003	0.006	0.007	0.013	0.008	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endog						0.002	0.000	0.000	0.031	0.150
K-P						18.08	16.75	2.42	15.52	13.84
Obs	1945	1945	1945	1945	1945	1761	1761	1761	1761	1761

Table 12: Incorporated Self Employment by Year, $\theta = 50$

	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2010	(6) 2020
			A. Coll SE, OLS			
$CG^{\mathcal{L}}$	0.050	0.060	0.077	0.137	0.152	0.106
	(0.013)	(0.011)	(0.015)	(0.025)	(0.018)	(0.019)
$CG^{\mathcal{R}}$	-0.033	-0.002	-0.011	-0.043	-0.038	0.032
	(0.034)	(0.019)	(0.018)	(0.028)	(0.021)	(0.019)
$CG^{\mathcal{E}}$	-0.016	-0.032	-0.038	-0.086	-0.019	-0.051
	(0.016)	(0.015)	(0.012)	(0.021)	(0.019)	(0.019)
Division	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.45	0.56	0.65	0.70	0.72	0.70
Obs	108	253	282	340	340	353
			B. Coll SE, IV			
$CG^{\mathcal{L}}$	0.030	0.088	0.204	0.189	0.293	0.205
	(0.040)	(0.032)	(0.152)	(0.065)	(0.046)	(0.038)
$CG^{\mathcal{R}}$	-0.077	-0.032	-0.153	-0.154	-0.241	-0.117
	(0.104)	(0.069)	(0.193)	(0.095)	(0.069)	(0.056)
$CG^{\mathcal{E}}$	0.025	-0.038	-0.044	-0.052	0.038	-0.027
	(0.029)	(0.030)	(0.031)	(0.028)	(0.036)	(0.037)
Division	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes
Endog	0.228	0.477	0.691	0.055	0.000	0.004
Overid J	0.43	0.33	0.04	0.46	0.99	0.38
K-P	2.36	4.23	0.76	4.13	4.17	13.90
Obs	106	236	231	267	338	320
			C. Non-Coll SE, OLS			
$CG^{\mathcal{L}}$	0.021	0.038	0.066	0.114	0.121	0.037
	(0.023)	(0.021)	(0.031)	(0.023)	(0.022)	(0.023)
$CG^{\mathcal{R}}$	-0.051	-0.070	-0.098	-0.145	-0.132	-0.013
	(0.081)	(0.035)	(0.036)	(0.033)	(0.028)	(0.031)
$CG^{\mathcal{E}}$	-0.005	-0.071	-0.068	-0.087	-0.105	-0.124
	(0.038)	(0.029)	(0.026)	(0.030)	(0.029)	(0.028)
Division	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.46	0.37	0.44	0.52	0.50	0.47
Obs	108	253	282	340	340	353
			D. Non-Coll SE, IV			
$CG^{\mathcal{L}}$	0.124	0.193	-0.003	0.294	0.344	0.198
	(0.072)	(0.083)	(0.217)	(0.112)	(0.089)	(0.056)
$CG^{\mathcal{R}}$	-0.442	-0.333	0.048	-0.503	-0.470	-0.233
	(0.201)	(0.159)	(0.284)	(0.171)	(0.136)	(0.086)
$CG^{\mathcal{E}}$	0.036	-0.045	-0.130	0.013	-0.003	-0.098
	(0.070)	(0.068)	(0.049)	(0.063)	(0.060)	(0.050)
Division	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	Yes	Yes	Yes	Yes	Yes	Yes
Endog	0.052	0.060	0.243	0.011	0.000	0.002
Overid J	0.84	0.78	0.12	0.96	0.36	0.84
K-P	2.36	4.23	0.76	4.13	4.17	13.90
Obs	106	236	231	267	338	320

8 Conclusion

While a number of theoretical contributions have emphasized the importance of human capital heterogeneity in generating economies of agglomeration and in the success of entrepreneurial ventures, empirical analysis has yet to catch up. My paper is a first attempt in this direction. I find evidence consistent with sorting of more highly skilled individuals into larger cities in the left and right portions of the occupational skill distribution. This is consistent with the notion that agglomeration economies deriving from human capital as in Behrens et al. (2014) do not merely derive from college graduates who are employed in occupations that "require" a college degree. It is also consistent with the prediction of the O-ring theory of development of Kremer (1993) in the presence of matching imperfections that there is strategic complementarity in human capital acquisition: it pays more to acquire human capital when one lives in a larger, more highly skilled city.

I also present evidence that entrepreneurship is positively related to the concentration of college graduates in the left portion of the occupational skill distribution, but generally negatively related to the concentration of college graduates in the right portion. These findings are consistent with the view expressed by Glaeser (1999) in the epigraph and by Strange (2004) that the human capital of an extraordinary few is not a substitute for human capital in the remainder of the skill distribution. They are also consistent with the notion of Lazear (2005) that entrepreneurs tend to have balanced skill sets while specialists with high levels of analytic ability who might be expected to fill out the right portion of the skill distribution, will have higher opportunity costs of entrepreneurship. Finally, they are consistent with the notion that college-educated workers in the left portion are a valuable resource, increasing entrepreneurship via the complementarity channel.

There are many possible extensions. In work in progress (Simon, 2022), I am examining cross-city data for evidence of human capital complementarities across occupations within an industry, and across industries. Also of interest is to examine the evolution of the occupational skill distribution of college graduates over time across cities. Another idea is to examine the startup and growth of employment by industry using Business Dynamics or County Business Patterns data, or using Census and ACS micro data, which have the advantage of allowing disaggregation by both industry *and* occupation.

References

Jaison R. Abel and Richard Deitz. *Underemployment in the Early Careers of College Graduates following the Great Recession*, pages 149–181. University of Chicago Press, April 2017.

Zoltan Acs and Catherine Armington. *Entrepreneurship, Geography, and American Economic Growth*. 01 2006. doi: 10.1017/CBO9780511510816.

Fredrik Andersson, Simon Burgess, and Julia I. Lane. Cities, matching and the productivity gains of agglomeration. *Journal of Urban Economics*, 61(1):112 – 128, 2007. ISSN 0094-1190. doi: https://doi.org/10.1016/j.jue.2006.06.005. URL `http://www.sciencedirect.com/science/article/pii/S0094119006000623`.

Michael J. Andrews and Alexander Whalley. 150 years of the geography of innovation. *Regional Science and Urban Economics*, page 103627, 2021.

Joshua Angrist and Jörn-Steffen Pischke. *Mostly Harmless Econometrics*. Princeton University Press, 2009.

Mikaela Backman and Janet E. Kohlhase. Labor force diversity and new firm formation. *The Annals of Regional Science*, 68(1):9–28, 2022. doi: 10.1007/s00168-021-01084-9. URL `https://doi.org/10.1007/s00168-021-01084-9`.

Marigee Bacolod, Bernardo S. Blum, and William C. Strange. Skills in the city. *Journal of Urban Economics*, 65(2):136 – 153, 2009.

Paul Beaudry, Mark Doms, and Ethan Lewis. Should the personal computer be considered a technological revolution? evidence from u.s. metropolitan areas. *Journal of Political Economy*, 118(5):988–1036, 2010.

Kristian Behrens, Gilles Duranton, and Frédéric Robert-Nicoud. Productive cities: Sorting, selection, and agglomeration. *Journal of Political Economy*, 122(3):507–553, 2014.

Christopher R. Berry and Edward L. Glaeser. The divergence of human capital levels across cities. *Papers in Regional Science*, 84(3):407–444, 2005.

Barbara Biasi, David J Deming, and Petra Moser. Education and innovation. Working Paper 28544, National Bureau of Economic Research, March 2021.

Duncan Black and Vernon Henderson. A theory of urban growth. *Journal of Political Economy*, 107(2): 252–284, 1999.

Daniel A. Broxterman and Anthony M. Yezer. Measuring human capital divergence in a growing economy. *Journal of Urban Economics*, 118:103255, 2020.

Kristy Buzard, Gerald A. Carlino, Robert M. Hunt, Jake K. Carr, and Tony E. Smith. Localized knowledge spillovers: Evidence from the spatial clustering of R& D labs and patent citations. *Regional Science and Urban Economics*, 81:103490, 2020.

Brad Chattergoon and William R Kerr. Winner takes all? tech clusters, population centers, and the spatial transformation of u.s. invention. Working Paper 29456, National Bureau of Economic Research, November 2021.

Benjamin Chinitz. Contrasts in agglomeration. *American Economic Review*, 51(2):279–289, 1961.

Brian Clark, Clément Joubert, and Arnaud Maurel. The career prospects of overeducated americans. *IZA Journal of Labor Economics*, 6(1):3, 2017.

Innessa Colaiacovo, Margaret G Dalton, Sari Pekkala Kerr, and William R Kerr. The transformation of self employment. Working Paper 29725, National Bureau of Economic Research, February 2022.

Dora L. Costa and Matthew E. Kahn. Power couples: Changes in the locational choice of the college educated, 1940-1990. *The Quarterly Journal of Economics*, 115(4):1287–1315, 2000.

Donald R. Davis and Jonathan I. Dingel. The comparative advantage of cities. *Journal of International Economics*, 123:103291, 2020.

Banu Demir, Ana Cecilia Fieler, Daniel Xu, and Kelly Kaili Yang. O-ring production networks. Working Paper 28433, National Bureau of Economic Research, February 2021.

Rebecca Diamond. The determinants and welfare implications of U.S. workers' diverging location choices by skill: 1980-2000. *American Economic Review*, 106(3):479–524, March 2016.

Mark Doms, Ethan Lewis, and Alicia Robb. Local labor force education, new business characteristics, and firm performance. *Journal of Urban Economics*, 67(1):61–77, 2010. Special Issue: Cities and Entrepreneurship.

Gilles Duranton and Diego Puga. Diversity and specialisation in cities: Why, where and when does it matter? *Urban Studies*, 37(3):533–555, 2000.

Gilles Duranton and Diego Puga. Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, 91(5):1454–1477, December 2001.

Gilles Duranton and Diego Puga. Chapter 5 - The Growth of Cities. In Philippe Aghion and Steven N. Durlauf, editors, *Handbook of Economic Growth*, volume 2, pages 781 – 853. Elsevier, 2014.

Fabian Eckert, Teresa C. Fort, Peter K. Schott, and Natalie J. Yang. Imputing missing values in the U.S. Census Bureau's County Business Patterns. Technical report, National Bureau of Economic Research, 2021.

Philipp Ehrl and Leonardo Monasterio. Spatial skill concentration agglomeration economies. *Journal of Regional Science*, 53(11), 2019.

Giulia Faggio and Olmo Silva. Self-employment and entrepreneurship in urban and rural labour markets. *Journal of Urban Economics*, 84:67–85, 2014.

Sarah Flood, Miriam King, Steven Ruggles, and J. Robert Warrren. *Integrated Public Use Microdata Series, USA: Version 10.0. [dataset].* University of Minnesota, Minneapolis, Minnesota, 2020.

Richard Freeman. *The Overeducated American.* Academic Press, 1976. (Japanese translation, 1977). Chapter 8 reprinted in Readings in Labor Economics and Labor Relations. ed. by L. Reynolds, S. Masters, and C. Moser, Prentice Hall, Inc., 1978. Reprinted in Kenkysusha Modern English Readers. (Tokyo 1982).

Edward L Glaeser. Learning in cities. *Journal of Urban Economics*, 46(2):254 – 277, 1999.

Edward L. Glaeser. Entrepreneurship and the city, 2007.

Edward L. Glaeser and William R. Kerr. Local industrial conditions and entrepreneurship: How much of the spatial distribution can we explain? *Journal of Economics & Management Strategy*, 18(3):623–663, 2009.

Edward L. Glaeser and Albert Saiz. The rise of the skilled city. *Brookings-Wharton Papers on Urban Affairs*, pages 47–105, 2004.

Edward L. Glaeser, Hedi D. Kallal, José A. Scheinkman, and Andrei Shleifer. Growth in cities. *Journal of Political Economy*, 100(6):1126–1152, 1992.

Edward L. Glaeser, JoséA. Scheinkman, and Andrei Shleifer. Economic growth in a cross-section of cities. *Journal of Monetary Economics*, 36(1):117 – 143, 1995.

Edward L. Glaeser, William R. Kerr, and Giacomo A.M. Ponzetto. Clusters of entrepreneurship. *Journal of Urban Economics*, 67(1):150–168, 2010. Special Issue: Cities and Entrepreneurship.

Edward L. Glaeser, Sari Pekkala Kerr, and William R. Kerr. Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines. *The Review of Economics and Statistics*, 97(2):498–520, 05 2015.

Benjamin Goldman, Thomas Klier, and Thomas Walstrum. Within-industry agglomeration of occupations: Evidence from census microdata. *Journal of Regional Science*, 59(5):910–930, 2019.

Peter Gottschalk and Michael Hansen. Is the proportion of college workers in noncollege jobs increasing? *Journal of Labor Economics*, 21(2):449–471, 2003.

Hartley J. Gyourko, J. and J. Krimmel. The Local Residential Land Use Regulatory Environment Across U.S. Housing Markets: Evidence from a New Wharton Index. Working Paper 26573, National Bureau of Economic Research, September 2019.

Joseph Gyourko, Albert Saiz, and Anita Summers. A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, 45(3):693–729, 2008.

Michael R. Haines, Inter university Consortium for Political, and Social Research. Historical, demographic, economic, and social data: The United States, 1790-2002. 2010.

Robert W. Helsley and William C. Strange. Innovation and input sharing. *Journal of Urban Economics*, 51(1):25 – 45, 2002.

Robert W. Helsley and William C. Strange. Entrepreneurs and cities: Complexity, thickness and balance. *Regional Science and Urban Economics*, 41(6):550–559, 2011.

Lutz Hendricks. The skill composition of U.S. cities. *International Economic Review*, 52(1):1–32, 2011.

J. Jacobs. *The Economy of Cities*. Knopf Doubleday Publishing Group, 2016. ISBN 9780525432869. URL `https://books.google.com/books?id=OaydDAAAQBAJ`.

Adam B. Jaffe, Manuel Trajtenberg, and Rebecca Henderson. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations*. *The Quarterly Journal of Economics*, 108(3):577–598, 08 1993.

Ryan Nunn Jay Shambaugh and Becca Portman. Eleven facts about innovation and patents. Technical report, The Hamilton Project, 2017.

Geoffrey Jones. Entrepreneurship in the natural food and beauty categories before 2000: Global visions and local expressions. Working Paper 13-024, Harvard Business School, 2012.

Michael Kremer. The O-Ring Theory of Economic Development*. *The Quarterly Journal of Economics*, 108 (3):551–575, 08 1993. ISSN 0033-5533. doi: 10.2307/2118400. URL `https://doi.org/10.2307/2118400`.

Edward P. Lazear. Entrepreneurship. *Journal of Labor Economics*, 23(4):649–680, 2005.

Sanghoon Lee. Ability sorting and consumer city. *Journal of Urban Economics*, 68(1):20 – 33, 2010.

Ross Levine and Yona Rubinstein. Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More? *The Quarterly Journal of Economics*, 132(2):963–1018, 11 2016.

Ross Levine and Yona Rubinstein. Selection into entrepreneurship and self-employment. *National Bureau of Economic Research Working Paper Series*, No. 25350, December 2018.

Audrey Light and Robert Munk. Business ownership versus self-employment. *Industrial Relations: A Journal of Economy and Society*, 57(3):435–468, 2018.

Shimeng Liu. Agglomeration, urban wage premiums, and college majors. *Journal of Regional Science*, 57 (4):611–630, 2017.

Enrico Moretti. Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, 121(1):175 – 212, 2004a.

Enrico Moretti. Workers' education, spillovers, and productivity: Evidence from plant-level production functions. *American Economic Review*, 94(3):656–690, June 2004b.

Enrico Moretti. The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, 111(10):3328–75, October 2021.

National Bureau of Economic Research. Census U.S. intercensal county population data, 1970-2014. 2014. URL `https://data.nber.org/data/census_popest.html`.

National Center for Educational Statistics. Complete data files, 2019. URL `https://nces.ed.gov/ipeds/use-the-data`.

National Oceanographic and Atmospheric Administration. Divisional inventory files. 2019. URL `ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/`.

Christopher John Ody and Thomas N. Hubbard. *County Business Patterns , 1962, 1964-1970: U.S. Summary, State, and County Data: ICPSR 25984*. Inter-university Consortium for Political and Social Research, Ann Arbor, MI, 2011.

Ni Qin and Dongmin Kong. Human capital and entrepreneurship. *Journal of Human Capital*, Forthcoming, 2021.

Raul Ramos, Jordi Surinach, and Manuel Artís. Regional economic growth and human capital: The role of over-education. *Regional Studies*, 46(10):1389–1400, 2012.

Christopher Robinson. Occupational mobility, occupation distance, and specific human capital. *Journal of Human Resources*, 53(2), Spring 2018.

Jesse M Shapiro. Smart cities: Quality of life, productivity, and the growth effects of human capital. *The Review of Economics and Statistics*, 88(2):324–335, 2006.

Curtis J Simon. Human capital and metropolitan employment growth. *Journal of Urban Economics*, 43 (2):223–243, 1998.

Curtis J Simon. Migration and career attainment of power couples: the roles of city size and human capital composition. *Journal of Economic Geography*, 19(2):505–534, 03 2018.

Curtis J. Simon. The skill intensity of cities: Complements welcome. May 2022.

Curtis J Simon and Clark Nardinelli. Human capital and the rise of American cities, 1900–1990. *Regional Science and Urban Economics*, 32(1):59 – 96, 2002.

Curtis J. Simon and Mallika Pung. The effect of career displacement: A task-specific human capital approach. May 2021.

William Strange, Walid Hejazi, and Jianmin Tang. The uncertain city: Competitive instability, skills, innovation and the strategy of agglomeration. *Journal of Urban Economics*, 59(3):331 – 351, 2006.

William C. Strange. Comment, Edward L. Glaeser and Alberto Saiz, Rise of the Skilled City. *Brookings-Wharton Papers on Urban Affairs*, pages 47–105, 2004.

United States Census Bureau. County population by characteristics. 2019.

United States Census Bureau. American community survey tables and tools. 2021. URL `https://www.census.gov/acs/www/data/data-tables-and-tools/`.

U.S. Department of Agriculture. *Land-Grant University Website Directory*. U.S. Department of Agriculture, 2021. URL `https://nifa.usda.gov/land-grant-colleges-and-universities-partner-website-directory`.

Nico Voigtländer. Skill bias magnified: Intersectoral linkages and white-collar labor demand in U.S. manufacturing. *The Review of Economics and Statistics*, 96(3):495–513, 2021/02/08 2013.

Yang Wang. Skill complementarity in teams: Matching, sorting and agglomeration in china. January 2020.

John V. Winters. Human capital externalities and employment differences across metropolitan areas of the USA. *Journal of Economic Geography*, 13(5):799–822, 12 2012.

John V. Winters. Stem graduates, human capital externalities, and wages in the U.S. *Regional Science and Urban Economics*, 48:190 – 198, 2014.

Cui Zhang. Skill diversity of cities and entrepreneurship. *Regional Studies*, 54(3):403–414, 2020.

A Data Appendix

A.1 Individual-Level Data

Individual-level data from Flood et al. (2020) are used to calculate the occupational composition of employment. I use 5% samples of 1960, 1980, 1990, and 2000 decennial Censuses, but am able to construct only a 2% sample for 1970 using two 1% metro samples of the 1970 decennial Census.[20] For years beyond 2000, I use 5-year samples of the American Community Surveys: 2007-2011 for the year 2010 (to avoid a change in PUMA definition that starts in 2012) and 2015-2019 for the year 2020. The key human capital measures, college graduates employed in left and right-tail occupations in a city, are calculated by assigning to each individual in these samples a city via a crosswalk between either the PUMA (1960, 1990 onward) or county group (1970 and 1980).

My instrumental variable strategy requires lags of the human capital and occupation variables. I generally use 10-year lags, but samples for the 1950 and 1970 Censuses are too small for this purpose. I use 1940 Census data, for which a 100% sample is available, to construct instruments for 1960, and I use the 1960 data to construct instruments for 1980. Individuals in the 1940 Census data are assigned to cities based on their reported county of residence, available only for that year.[21]

The 1940 Census data include information on IPUMS 1950 occupation, but not on IPUMS 1990 occupation, which start with the 1960 Census. I translate the 1950 codes to IPUMS 1990 occupation codes via a crosswalk constructed from the 1960 Census, sub-dividing data into industry and education groups to avoid conflicts when possible.

A.2 Geographic Unit of Observation

My unit of observation is the Consolidated Statistical Area or Core-Based Statistical Area, whichever is larger.[22] To smooth the exposition I refer to these CSA/CBSA units as "cities." Most of these crosswalks are generated from the Missouri Geocorr Datacenter.[23] I generate crosswalks from PUMA to 2013 Consolidate Business Statistical Areas (CBSA); from 2010 county to 2013 CBSA; and from 2013 CBSA to 2013 Consolidated Statistical Area (CSA).[24] County groups in 1970 and

[20] A September 2013 post clarifies that the various 1970 samples were selected by an independent random draw with replacement, and as such, may overlap. I ignore the potential for duplicates, and divide the resulting person weights by 2 to form the sample. The link is at https://forum.ipums.org/t/it-it-okay-to-combine-the-six-1-samples-of-the-1970-us-census-into-a-6-sample/276.

[21] Beaudry et al. (2010) used the 1% sample of the 1940 Census to instrument for 1980s human capital ("before any experimental electronic computers had been developed", 990-991).

[22] The unit of observation is therefore different from the one used by Berry and Glaeser (2005) and Broxterman and Yezer (2020) (who used the same one): the 1990 Standard for Metropolitan and Primary Metropolitan Statistical Areas (MSAs/PMSAs) as established on June 30, 1999 and, in New England States, New England County Metropolitan (NECMA) definitions. See `https://socds.huduser.gov/Census/Census_Home.html`.

[23] The link is http://mcdc.missouri.edu/applications/geocorr2014.html.

[24] The resulting crosswalk seems consistent with the official OMB delineation file at https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/delineation-files.html.

1980 are crosswalked to cities via their composite counties, and 1960 PUMAs are crosswalked to cities by using the IPUMS-provided mapping from 1960 PUMAs to 2000 PUMAs. When a county group or PUMA map into more than one city, it is assigned to the largest city. I recognize that the geographies so constituted in the individual-level data will vary over time, but this is bound to be the case regardless of how the data are mapped. While this assignment procedure is imperfect, the resulting measures of human capital are quite closely related to measures of human capital assembled from county-level data, which are not subject to such errors.

A.3 Other Data

Climate data are from the National Oceanic and Atmospheric Administration, by year and county (National Oceanographic and Atmospheric Administration, 2019).

Coastal cities are identified using data from the Bureau of the Census (Coastline Counties).

Dictionary of Occupational Titles (DOT) Data DOT 1991 data (generously provided by Robinson (2018)) are matched to March Current Population Survey data as in Simon and Pung (2021); 20 DOT scores are rescaled into deciles; averaged by IPUMS 1990 occupation; matched to the microdata; averaged by occupation group; and reduced to the 3 factors shown in Table B1.

Employment (Citywide) Citywide employment data are built up from county-level data taken mostly from the County and City Data Books (Haines et al., 2010), and supplemented with data based 5-year averages of American Community Survey data downloaded from the Census website.

Industry Employment Shares

County Business Patterns (CBP) data on Manufacturing MF and Trade TRD are available for all years. I use CBP NAICS 2012 industry data corrected for imputations from Eckert et al. (2021) for 1980 and after, and CBP data from Ody and Hubbard (2011) for 1960 and 1970. .

Hendricks (2011) defined Business Services to include the 1950 IPUMS industry definition of Business Services plus Legal Services. However, most of my industry composition data make use of the harmonized NAICS 2012 based County Business Patterns data constructed by Eckert et al. (2021), which 2-digit sector 54 corresponds well with a modern notion of Business Services. It includes the industries in Hendricks (2011) plus Architecture, Engineering, Specialized and Computer Design, Management Consulting, and Scientific Research and Development. CBP data on Business Services ($BUSE$) are available only from 1980 on; I therefore construct Business Service shares for 1960 and 1970 using microdata (IPUMS 1990 codes 12, 721, 841, 882, 890, 892)

Land grant institutions are constructed from institutional data supplied by National Center for Educational Statistics (2019). The name of the data set is HD2019, downloaded from `https://nces.ed.gov/ipeds/datacenter/DataFiles.aspx?goToReportId=7`. These data include institutions added in the 1994 expansion to a number of tribal colleges and universities. I remove those institutions using information from U.S. Department of Agriculture (2021), and correct one omission (Central State University).

Patent data are taken from the Bulk Data Products page of the U.S. Patent and Trademark Office. I use four data sets: location, patent, application, and patent inventor data sets. Each patent is traced to its inventors, and each inventor is assigned (when possible) to a U.S. county. I assign to each inventor an equal fraction of the patented invention, which is then summed to the year-county level. Patents for growth regressions with base year t are sums of patents in years $t-4$ through t.

Percent College Graduates, Aggregate Data As a check, I construct city percent college graduates, CG^A, from county-level data taken mainly from the County and City Data Books (Haines et al., 2010), supplemented with recent data from the American Community Survey (United States Census Bureau, 2021).

Population The population are initially at the county level, taken mostly from the National Bureau of Economic Research (2014), with recent years using data provided by United States Census Bureau (2019).

B Human Capital Appendix

B.1 More on the Quimby-Madison Effect

Strange (2004) draws inspiration from a passage in (Jacobs, 2016).

> From only a few days gleanings in the women's pages, one learns that a cleaner of suede clothing is now starting to bottle and sell her cleaning fluid for people who want to clean their own suede; a chest and wardrobe manufacturer is starting, for a fee, to analyze what is wrong with one's household or office storage arrangements; a playground designer is starting to make and sell equipment for playgrounds and nursery schools; a sculptor is starting a line of costume jewelry; a designer of theater costumes is launching himself as a couturier; a couturier is starting a boutique; an importer of Italian marble is starting to manufacture marble-top tables; a clothing store is starting classes in teen-age grooming and dieting (53-4).

The Quimby-Madison effect discussed in Section 3.1 is named after two individuals who would likely would have been considered over-educated early on in their careers.[25] There are other examples. **Frank Ford**, a graduate of Texas A&M University, started as a "dirt farmer," beginning with "a stone-mill, a 1939 tractor, and an old railroad car as their office" before founding Arrowhead Mills (Jones, 2012). **Michio and Aveline Kushi** graduated from Japanese Universities and studied at University of Illinois and Columbia University after emigrating to the US. They opened a "small below-street level macrobiotic and natural foods store" in 1966 before going on to found Erewhon (Jones, 2012).[26] **Yvon Chouinard**, who only went to junior college, started a business making pitons for use in Yosemite Valley, first out of hardened steel and then aluminum, selling them out of the back of his car, before founding Patagonia.[27] Finally, **Carlo Bartolucci** graduated from Connecticut College in 1988. She and her husband ran a small sandwich shop in Mystic Connecticut, but eventually partnered with the Italian company Bionaturae to sell organic Italian products. She went on to cofound Jovial Foods in 2010, a multi-million dollar brand.[28].

B.2 Skill Intensity of Occupations

[25] The information on Roxanne Quimby is from https://unity.edu/faculty/roxanne-quimby/, https://en.wikipedia.org/wiki/Burt's_Bees, and https://www.npr.org/2021/08/19/1029305404/burts-bees-roxanne-quimby-2019; for Stacy Madison, from https://www.americanexpress.com/en-us/business/trends-and-insights/articles/the-story-behind-stacys-pita-chips/ and https://www.npr.org/2021/08/04/1024913084/stacys-pita-chips-stacy-madison-2019; and for Douglas Tompkins, see https://en.wikipedia.org/wiki/Douglas_Tompkins.

[26] See, too, https://en.wikipedia.org/wiki/Aveline_Kushi and https://en.wikipedia.org/wiki/Michio_Kushi

[27] Education background at https://www.nndb.com/people/878/000217227/. See, too, https://en.wikipedia.org/wiki/Yvon_Chouinard

[28] See https://www.theday.com/article/20150805/ENT04/150809654 and https://www.npr.org/2021/06/03/1002962059/jovial-foods-carla-bartolucci

Table B1: Occupational Percent College Graduates and DOT Factor Scores

		Coll Grads			DOT Scores		
Rank	Occ	1960	1980	2000	Cogn	People	Motor
1	Hlth Diagnost	0.951	0.961	0.992	0.939	0.947	2.013
2	Lawyers	0.913	0.953	0.984	1.231	1.575	-1.972
3	Tert Ed	0.940	0.908	0.912	0.891	1.684	-0.378
4	Oth Ed	0.758	0.833	0.748	1.354	1.721	-1.180
5	Soc Sci	0.798	0.817	0.907	0.860	1.004	-1.067
6	Natural Sci	0.673	0.805	0.925	0.794	-0.086	1.219
7	Libr	0.555	0.709	0.825	1.333	0.895	-0.639
8	Soc Wrkrs	0.625	0.666	0.667	1.556	1.590	-1.133
9	Engnrs	0.562	0.625	0.744	0.663	-0.398	1.165
10	Math and Com Sci	0.561	0.584	0.544	0.557	-0.008	-0.571
11	Hlth Therap	0.562	0.583	0.699	0.697	0.810	1.405
12	Sales Engnrs	0.530	0.574	0.672	0.558	0.970	1.162
13	Software Developers		0.508	0.711	0.898	-0.019	-0.502
14	Mgt Spprt	0.275	0.438	0.564	0.506	0.409	-0.985
15	Artists	0.401	0.437	0.536	1.020	0.245	0.867
16	Techn, Oth	0.121	0.399	0.225	-0.177	-0.544	1.172
17	Hlth Trtmnt	0.213	0.389	0.555	1.013	0.448	1.428
18	Legal Support		0.378	0.381	0.896	-0.299	-0.556
19	Mgt Execs	0.166	0.376	0.505	0.308	1.128	-0.677
20	Sales FIRE	0.211	0.359	0.458	0.622	1.001	-1.285
21	Pilots etc	0.180	0.349	0.595	-0.196	-0.050	1.279
22	Invstgtrs	0.250	0.261	0.223	0.223	0.433	-1.030
23	Office Spvsrs		0.220	0.249	0.154	1.131	-0.275
24	Techn, Hlth	0.085	0.201	0.242	0.196	-0.835	1.367
25	Techn, Eng	0.096	0.193	0.223	-0.908	-0.931	1.671
26	Sales Heads	0.062	0.183	0.253	-0.276	0.632	-1.469
27	Sales Oth	0.078	0.182	0.351	-0.359	0.694	-0.681
28	Clerks, Info	0.047	0.125	0.154	0.162	-0.320	-1.239
29	Police	0.027	0.124	0.199	-0.324	-0.187	-0.107
30	Clerks, Record	0.186	0.120	0.183	-0.277	-0.694	-0.653
31	Clerks, Office	0.058	0.111	0.167	-0.258	-0.593	-0.137
32	Clerks, Fin	0.039	0.094	0.136	-1.869	-1.686	0.256
33	Secretaries	0.047	0.088	0.142	0.655	-0.466	0.591
34	Clerks, Stock	0.021	0.085	0.108	-1.452	-1.015	-0.375
35	Svc, Prsnl	0.008	0.079	0.157	-0.553	-0.440	0.047
36	Agr	0.016	0.078	0.095	-0.903	-0.922	0.475
37	Clerks, Mail	0.024	0.065	0.114	-0.538	-0.909	-0.297
38	Sales, Rtl		0.060	0.209	-0.278	0.719	-0.214
39	Craft	0.018	0.058	0.066	-1.233	-0.976	1.519
40	Svc, Hlth	0.017	0.054	0.079	-1.063	-0.766	0.218
41	Sales, Cshrs	0.015	0.043	0.070	-1.580	-0.409	0.032
42	Svc, Food	0.008	0.042	0.068	-1.254	-0.964	-0.016
43	Svc, Clnrs etc	0.009	0.031	0.042	-1.334	-1.388	-0.064
44	Oprtvs	0.006	0.028	0.044	-1.650	-1.615	0.504
45	Svc, HHld	0.015	0.019	0.031	-1.601	-1.516	-0.891

DOT scores taken from Dictionary of Occupational Titles. See text for details.

C Entrepreneurship and City Growth

All three measures (overall, college, and non-college) incorporated self-employment per worker are positively correlated with log population growth over the subsequent decade (past decade for 2020), seen in Table C1. The correlations are modest, concentrated between 0.2 and 0.5, but visualization in Figure C1 suggests that the relationships are not driven by outliers.

Table C1: Incorporated Self-Employment: Correlations with Growth

	1970	1980	1990	2000	2010	2020
			A. Means			
All	0.014	0.021	0.021	0.031	0.033	0.034
College	0.003	0.007	0.008	0.010	0.012	0.012
Non-College	0.011	0.014	0.018	0.021	0.021	0.021
			B. Correlations			
All	0.114	0.402	0.402	0.355	0.488	0.480
College	0.178	0.402	0.390	0.396	0.541	0.553
Non-College	0.064	0.316	0.190	0.253	0.350	0.307

Growth over subsequent decade except 2020, which uses past decade.

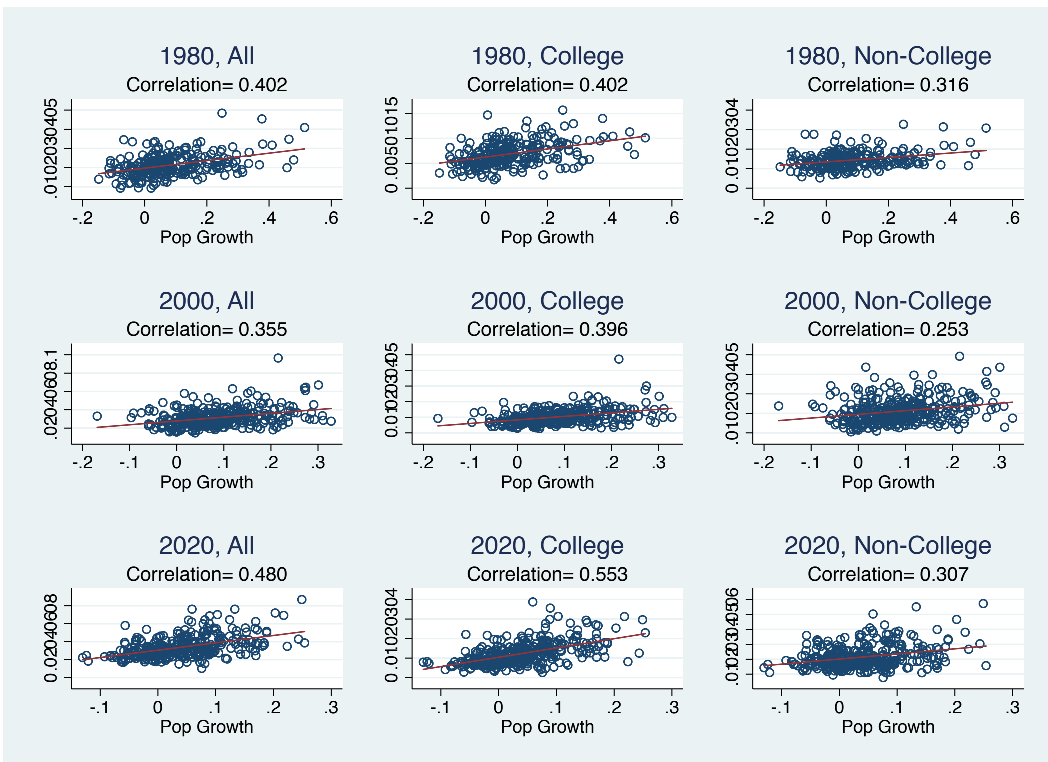

Figure C1: Self-Employment and City Growth

See text for details.

D Computer Adoption

It is well known that better-educated workers are more likely to use a computer at work. College-educated workers could use computers more frequently than those less-educated for two reasons. First, they could be more likely to be employed in high-skill occupations that are more likely to require a computer. Alternatively, they could be more likely to use a computer conditional on occupation.

I explore this question using data from the Computer Use Supplements of the Current Population Surveys 1984-2003 reveal that college graduates are more likely to use computers at work than non-graduates over most of the occupational skill distribution, seen in Figure D1 (top) for 1993 (the graphs for other years look similar). College graduates are also more highly represented among computer users than in total employment (middle graph). Finally, the cumulative distribution of college-educated computer users closely mirrors that of overall employment (bottom graph), meaning that computer use among college graduates is not skewed towards more highly-skilled occupations.

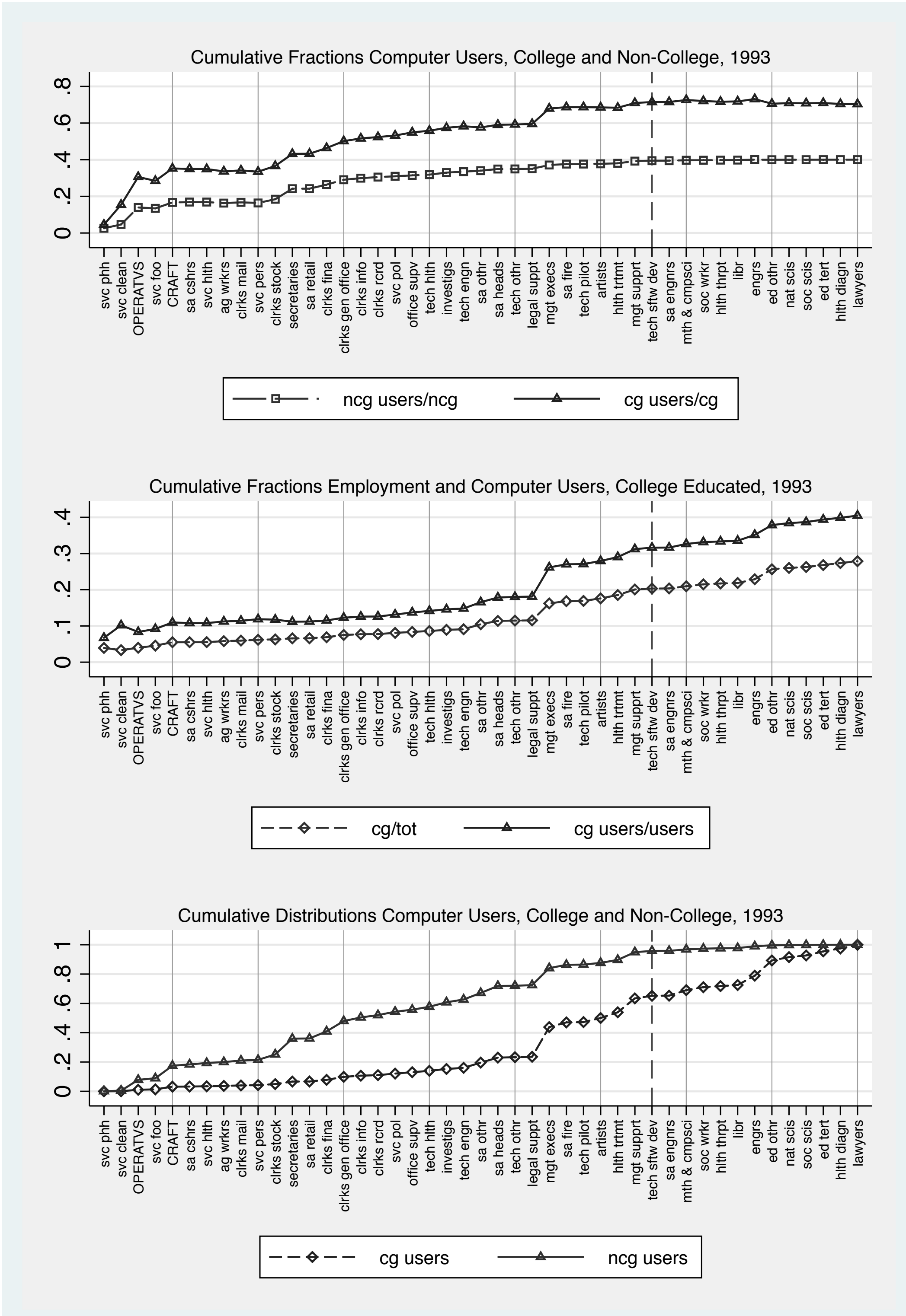

Figure D1: Cumulative Fraction College Graduates:
Total Employment and Total Computer Users

See text for details.

E Cities with Highly Regulated Land Use

Section 6.5 considers whether the negative estimated effects of right-tail college graduates arises spuriously as a result of high levels of regulation on land use in cities where they live. I match my data to the Wharton Residential Land Use Regulation (WRLURI) Indexes (Gyourko et al., 2008; Gyourko and Krimmel, 2019). Both the 2008 and 2018 indexes are reported at the FIPS place or county subdivision level. I match each location to its county and cross-walk the counties to cities. City-level indexes are calculated using both the full and metro weight, and the maximum of the full-weighted and metro-weighted 2008 and 2018 indexes is assigned to the city.

Table E1 lists highly regulated cities, defined as cities with a 2008 index of 0.74 or higher, taken from the third quartile value reported in Table 7 in Gyourko et al. (2008), or a 2018 value of 0.64 or higher, taken from the third quartile value reported in Table 2 in Gyourko and Krimmel (2019). Gyourko and Krimmel (2019) report little change over the period in the roughly 500 entities in common between the 2007 and 2018 samples (5-6). One might get the opposite impression from Table E1, with a correlation of -0.53 between the full-weighted 2008 and 2018 indexes (54 cities) and -0.51 between the metro-weighted 2008 and 2018 indexes (37 cities). However, the correlation between the 2008 and 2018 full-weighted indexes is 0.26 across the 265 cities for which they are available in both years, and the correlation between the metro-weighted indexes is 0.31.

E.1 Land Use Regulation and Human Capital

I examine whether regulation is higher in more highly educated cities. The controls are the same as in Equation 16. I measure regulation both using a continuous WRLURI index, equal to the maximum of the 2008 and 2018 values, and using an indicator equal to one if the city is highly regulated as defined above and zero otherwise. Note that the dependent variables are the same across years; only the values of the explanatory variables change. Cities for which WRLURI is not available are excluded from the analysis. Because I am interested only in correlation and not causation, all regressions are estimated using Ordinary Least Squares.

The results are suppressed to reduce clutter. Summarizing briefly, there is some indication that larger cities with higher percent college graduates (narrow measure) have higher WRLURI indexes. However. there was virtually no systematic relationship between either the WRLURI indexes or the indicator for high levels of regulation, on the one hand, and left or right-tail human capital on the other. This likely explains why the relationship between city size and human capital does not change much when high-regulation cities are excluded from the analysis.

Table E1: Cities with Highly Regulated Land Use

City	Pop 1980	$WRLURI^{M}_{2008}$	$WRLURI^{F}_{2008}$	$WRLURI^{M}_{2018}$	$WRLURI^{F}_{2018}$
Pinehurst+, NC	50505		0.138	0.640	0.610
Twin Falls, ID	67767			0.650	0.645
Salt Lake City+, UT	1216751	0.039	0.017	0.651	0.658
Los Angeles+, CA	11497568	0.552	0.542	0.663	0.659
Reno+, NV	260163	-0.306	-0.006	0.664	0.623
Florence, SC	172880	-0.428	-0.428	0.667	0.673
Rochester+, MN	188434		-0.048	0.673	0.650
Waterloo+, IA	177147	-0.840	-0.840	0.674	0.689
Champaign+, IL	200238	-0.391	-0.391	0.691	0.697
Bemidji, MN	30982			0.699	0.699
Killeen+, TX	226661	-1.009	-1.004	0.723	0.723
Harrisburg+, PA	936413	0.721	0.741	0.187	0.182
Denver+, CO	1763831	0.744	0.697	0.284	0.256
Springfield+, MA	646148	0.749	0.721	0.207	0.186
Jacksonville, NC	112784			0.678	0.761
Lincoln+, NE	233129	0.761	-0.721		
Washington+, DC-MD-VA-WV-PA	6043673	0.710	0.772	0.262	0.234
State College+, PA	196338	0.774	0.182	-0.497	-0.448
San Diego+, CA	1861846	0.402	0.386	0.784	0.768
Kennewick+, WA	144469	0.789	0.789	-0.081	-0.101
Hermiston+, OR	66380		-0.134	0.791	0.786
Bloomington+, IN	157098			0.804	0.796
Fort Collins, CO	149184	0.824	0.828	0.286	0.297
Medford+, OR	191311	0.848	0.848	0.257	0.271
Cullowhee, NC	25811			0.855	0.855
Salina, KS	54876			0.867	0.867
Jackson, WY+, WY-ID	12252		0.886		
Claremont+, NH-VT	175638		0.888	-0.362	-0.377
Tallahassee+, FL-GA	237305		0.889	0.851	0.810
Fresno+, CA	577737	0.908	0.891	0.193	0.194
Colorado Springs, CO	317458	0.868	0.921	-0.252	-0.252
Chico, CA	143851	0.940	0.931	-1.193	-1.193
Philadelphia+, PA-NJ-DE-MD	6060018	0.979	0.965	0.365	0.361
Seattle+, WA	2559923	0.989	0.985	0.460	0.436
North Port+, FL	428192	0.922	1.007	-0.198	-0.163
Roseburg, OR	93748		-0.521	0.970	1.021
Albuquerque+, NM	668097	0.253	0.255	1.019	1.028
North Wilkesboro, NC	58657		-1.666	1.056	1.056
Edwards+, CO	46172		1.093	0.208	0.235
Prescott, AZ	68145	1.106	0.882	-0.140	-0.103
Fergus Falls, MN	51937		-0.686	1.116	1.116
Jackson, OH	30592			1.130	1.130

Continued on next page

Table E1 – continued from previous page

City	Pop 1980	$WRLURI^M_{2008}$	$WRLURI^F_{2008}$	$WRLURI^M_{2018}$	$WRLURI^F_{2018}$
Coldwater, MI	40188		-0.300	1.152	1.019
Memphis+, TN-MS-AR	1036855	1.181	0.970	0.311	0.257
Clarksburg, WV	101727		-0.216	1.186	1.186
San Jose+, CA	5740272	0.731	0.744	1.149	1.197
Burlington+, VT	154935	1.177	1.228	-0.053	-0.060
Salisbury, MD+, MD-DE	212621	1.255	1.255	0.231	0.242
Sterling, CO	19800		-1.069	1.271	1.271
Portland+, ME	483907	1.286	1.252	-0.186	-0.194
Greenville+, NC	130501	1.391	0.720	-0.506	-0.513
Amarillo+, TX	210952	-0.399	-0.814	1.517	1.517
Tucson+, AZ	551902	1.517	1.574	0.347	0.357
Breckenridge, CO	8848		1.574	-0.435	-0.445
Santa Maria+, CA	298694	0.872	0.869	1.605	1.603
Lafayette+, LA	507249	-1.034	-1.019	1.662	1.662
Dixon+, IL	102298		-1.089	1.724	1.724
Boston+, MA-RI-NH-CT	6664763	1.789	1.739	0.141	0.139
Pottsville, PA	160630		0.347	1.743	1.818
Key West, FL	63188		2.010	0.000	0.000
Vineyard Haven, MA	8942		2.025		
San Luis Obispo+, CA	155435	1.115	1.064	2.072	2.081
Bozeman, MT	42865		0.663	2.191	2.191
Flagstaff, AZ	75008	-0.418	-0.418	2.488	2.488
El Centro, CA	92110			2.982	2.982

Note: Metro-weighted indexes are denoted by a superscript M and full-weighted indexes are denoted by a superscript F.