Heterogeneous Returns to Knowledge Exchange:

Evidence from the Urban Wage Premium

Chris Cunningham (Federal Reserve Bank of Atlanta)

Michaela C. Patton (University of Alabama)

Robert R. Reed (University of Alabama)

December, 2014

Abstract: We posit that some kinds of knowledge are harder to exchange remotely and thus certain types of workers trading in certain types of knowledge benefit more from close physical proximity to others. We first present a theoretical framework in which individuals randomly search for partners to exchange ideas, but that the returns to finding a partner are heterogeneous. In particular, some knowledge is more dependent on interpersonal exchange and most productive when shared with similar individuals. In this manner, we propose that agglomerative environments favor individuals with knowledge that is typically associated with "soft skills" where creativity and informal networking are important. We test this prediction using the most recent sample of the American Community Survey (ACS) in which college graduates are asked about their undergraduate major. Controlling for demographic and regional productivity effects and instrumenting for city size, we find that the urban wage premium varies considerably across majors. In line with the predictions of our model, people with non-STEM majors appear to benefit more from locating within a city. In the spirit of our results for majors, we also find that terminal degrees associated with the mastery of any existing cannon of knowledge such as a JD or MD experience a smaller urban wage premium.

Keywords: Human Capital, Wages, Agglomeration

JEL Codes: C78, J24, R12, J31, R23

[*]Cunningham, Federal Reserve Bank of Atlanta, 1000 Peachtree Street, NE, Atlanta, GA; Patton, Department of Economics, Finance, and Legal Studies, University of Alabama, 35487, (205) 348-8667, Reed, Department of Economics, Finance, and Legal Studies, University of Alabama, 35487, (205) 348-8667, rreed@cba.ua.edu.

Part of this work was completed while Reed was a Visiting Scholar at the Federal Reserve Bank of Atlanta. Patton thanks the CSWEP Summer Economic Fellows Program and the Federal Reserve Bank of Atlanta for financial support. We received valuable comments from Tony Braun, Todd Keister, Jordan Rappaport, Will Roberds and seminar participants at the Federal Reserve Bank of Atlanta, Southern Economic Association Meetings, the Urban Institute, and the Annual Meeting of the North American Regional Science Council. The views expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of Atlanta or the Federal Reserve System.

I. Introduction

There has been great progress towards understanding the determinants of agglomeration economies in recent years. Through this research, spillovers of knowledge have emerged as one of the major forces behind agglomerative behavior. The role of information sharing in cities was first posited by Marshall (1890), "Great are the advantages which people following the same skilled trade get from near neighborhood to one another." The seminal work of Jacobs (1969) also emphasizes that information sharing plays a large role in urbanization and Lucas (1988) stresses that cities provide a highly fertile environment for the transmission of information between individuals. Kuznets (1962) notes that "creative effort flourishes in a dense intellectual atmosphere..." suggesting that cities might be fonts for new ideas in particular.

Formal models of information sharing include Glaeser's (1999) construction of a theoretical framework in which cities promote the transmission of knowledge along the vertical dimension. That is, cities promote learning by younger, less skilled workers from older, skilled individuals. Berliant, Reed, and Wang (2006) develop a random matching model of spillovers between individuals with horizontally differentiated types of knowledge. In particular, they posit there is an optimal range of idea-diversity between people. Consequently, optimizing agents select a range of individuals with different types of knowledge to collaborate and share ideas.

Existing work on human capital and agglomeration economies recognizes that individuals are different – they either have different *types* of knowledge or different *levels* of knowledge. However, an important limitation was that knowledge was treated as *symmetric* and the *external gains from human capital were identical*. In this manner, existing theoretical models would predict that the tendency of firms to co-agglomerate would be the same across industries. However, a wide array of evidence demonstrates that there are differences in the potential to learn from others. For example, Bernstein and Nadiri (1989) find that there are substantial differences in R&D spillovers across industries.[1] In fact,

[1] In addition, Bernstein (1988) observes differences in intra-industry spillovers and inter-industry spillovers in Canadian data. Bernstein and Yan (1997) study differences in intra-national and international spillovers for manufacturing industries in Canada and Japan. Interestingly, they find that in some industries spillovers are more

Audretsch and Feldman (1996) point out that there are substantial differences in the tendency of innovations to cluster spatially across industries and this clustering increases with the number of skilled workers the industry. Moreover, both Ellison and Glaeser (1997) and Ellison, Glaeser, and Kerr (2010) show that there are sizable differences in the tendency of firms to co-agglomerate.

One might be inclined to believe that knowledge spillovers play the greatest role in promoting productivity in high technology where formal measures of human capital are an obvious input to production. Yet, Glaeser and Kahn (2001) find that high human-capital industries such as finance have a strong tendency to agglomerate. Conversely, Lee (2010) finds a flat or even negative urban wage premium for medical workers. However, Lucas conjectures "New York City's garment district, financial district, diamond district, advertising district, and many more are as much intellectual centers as is Columbia or New York University." As fashion and advertising are highly reliant on creativity and collaboration, Lucas also considers that agglomeration economies are likely to emerge in areas based upon "soft" skills. Arzaghi and Henderson (2008) explicitly focus on information sharing in the advertising sector in New York City where networking and creative vision are important.

The objective of this paper is to investigate the role of agglomeration according to an individual's human capital. In contrast to previous theoretical research, we allow the gains from information sharing to vary across individuals due to the different types of knowledge that they possess and may seek to exchange. As our primary focus is on horizontal differences in knowledge, we extend the framework of Berliant, Reed, and Wang by positing that the benefits of matching vary across individuals. In our framework, some individuals have types of knowledge with large potential gains from information sharing and others less so.

The heterogeneous returns to inter-person knowledge exchange could arise for a number of reasons. Some types of knowledge may only be acquired with diligent study or extensive laboratory work. Workers who specialize in this type of knowledge learn more from technical manuscripts and formal

likely to occur from Canada to Japan than Japan to Canada. In this vein, Holod and Reed (2009) examine the role of asymmetric spillovers across countries in a Lucas-type human capital model of economic growth.

education than social interactions. An alternative but functionally equivalent hypothesis is that the type of knowledge exchanged may depreciate at different rates. For example, medical knowledge may exhibit slow and steady but permanent advance whereas the entire stock of fashion knowledge from three years ago may be effectively worthless. In either case, it may be more important for some types of knowledge workers to meet than others. Our model allows the benefits of agglomeration economies to vary across the types of knowledge.

Our hypothesis is intuitive and motivated, in part, by existing evidence. Notably, Berger (1988) studies earnings growth from experience across individuals with different college majors. The strongest gains from experience occur amongst business and liberal arts majors. The smallest gains occur in science and education. In fact, the gains from experience in business and liberal arts are more than twice as large as the other two fields of study. The implication is that some people learn more and become more productive from on the job training than do others. We posit that this learning occurs faster (and productivity and compensation) in lager cities where match quality improves.

Following the equilibrium predictions of the model, we proceed to test it empirically. We build on the work of Glaeser and Mare (2001) and Bacolod, Blum, and Strange (2010) where productivity gains from agglomeration are manifest in the urban wage premium. If different types of human capital benefit more from good matches and match quality improves with city quality, then the urban wage premium should vary with an individual's type of knowledge.

In order to examine how the urban wage premium varies across types of human capital, we study individuals in the American Community Survey (ACS). The ACS is particularly well-suited for our question as it contains college graduates' field of degree (major) and asks specific questions about graduated degrees. By interacting college major with city population we can recover degree and major specific measure of the Urban Wage Premium (UWP).

We also attempt to address an unobserved heterogeneity problem not previously examined in the agglomeration literature which typically treats city size as exogenous with respect to wages. It is possible that both wages and total population simply reflect the underlying (unobserved) productivity of the city that attracts more workers and compensates them for the higher rents. We attempt to address these concerns by using the scarcity of developable land around the urban core (Saiz, 2010) as an instrument for population. This measure has been used in a number of papers as an instrument for house prices because it constrains the supply of developable land for housing. By extension we think it can serve as a supply shifter for population.

We make four empirical contributions to the literature. First, using the instrument for population size, we find an urban wage premium of 0.107. That is, doubling city size should raise the salary of average workers by just over ten percent. Second, the UWP does not increase monotonically with educational attainment. Workers with professional degrees and doctorates have salaries that are less sensitive to city size than workers with bachelor's or master's degrees. At the same time, workers with some college attendance but no degree have salaries more sensitive to city size than someone with an associate's degree, and a person with a GED gains from city more than a person with a high school diploma. We take this as evidence that learning afforded by big cities can substitute, to some degree, for the certification or credentialing of formal education.

Third, we find that the urban wage premium tends to be highest for individuals that majored in humanities or social sciences.[2] People with undergraduate majors in STEM fields had a statistically smaller UWP than non-STEM workers. When we look at people just with bachelor's degrees, the five majors with the largest wage premium had degrees that might typically be associated with soft skills: social science, history, languages, media, and liberal arts. Each of these majors likely depends on creativity, interpersonal skills, or informal networking capabilities. The majors that benefited the least from city size were religion, architecture, education, engineering and agriculture. Looking across majors and highest degree, we find that in general, bachelors or masters students with "soft" majors experience the greatest urban wage premium. These results are mostly consisted when we instrument for city population size (and its interactions with major and degree).

---

[2] Indeed, when aggregating the computer science, engineering, mathematics, medicine, and science fields into a STEM category the results clearly show that on average hard skills earn more and are less sensitive to city size.

The remainder of the paper is as follows. Section 2 presents the model that provides the theoretical underpinnings for our empirical work. Section 3 describes the data to be studied. Section 4 outlines the empirical model. Section 5 provides a detailed discussion of the empirical results. There is a brief conclusion.

II. Theoretical Model

The urban wage premium represents a source of uncompensated knowledge spillovers. As discussed in Duranton and Puga (2004), one of the ways that dense environments promote productivity is by information sharing. In particular, Berliant, Reed, and Wang (2006) develop a model of agglomeration economies in which individuals with different types of knowledge search for opportunities to exchange ideas. (Hereafter, we refer to Berliant, Reed, and Wang as BRW) In cities with a higher population size, search frictions are lower and support more productive intellectual exchange.[3] However, in their framework, all agents derive the same expected benefits from matching, and thus, the value of being in a city that affords intellectual exchange (typically large cities) is invariant to an individual's knowledge base. That is, in previous work, the external gains from knowledge exchange are identical across individuals.

The objective of this section is to provide a formal framework to demonstrate how the productivity gains from agglomeration vary across individuals with heterogeneous types of knowledge. Our framework builds on BRW, however, we consider that individuals vary according to their dependence on interpersonal exchange and information sharing. That is, the productivity gains from information sharing and matching depend upon the type of knowledge that an individual commands.

[3] See also Helsley and Strange (1990) who show that agglomeration economies enhance matches between firms and workers with heterogeneous skills.

Heterogeneous Benefits of Knowledge Exchange

Our central hypothesis is that while all individuals benefit from matching, and the likelihood of matching improves with city size, those endowed with "soft knowledge" benefit more from matching than others with "hard knowledge." Moreover, individuals with soft knowledge benefit the most from exchanging ideas with agents who are also highly soft-knowledge based. As an example, an individual trained in the arts would benefit more from interactions with someone else trained in the arts. They can share information on techniques, identify trends in tastes (of art buyers, for example), and provide individuals with better connections or social capital. On the other hand, someone trained in the sciences or engineering can increase their productivity without as much personal interaction as they can acquire additional information from professional journals or technical manuscripts that they can easily obtain remotely. Or, conversely, they are less likely to learn anything useful through casual, face to face interactions. This is true of others who are also highly endowed with hard knowledge.

We consider an economy in which individuals are endowed with different types of knowledge. The types of knowledge are indexed by positions along a circle with unit circumference. An individual's position reflects their base of knowledge. As in BRW, κ represents the set of all types of knowledge. An individual's specific type of knowledge is denoted by $k \in \kappa$. For tractability, the population N of individuals is uniformly distributed across the knowledge space. Following BRW, we abstract from differences in levels of knowledge as doing so would generate multiple steady-state equilibria. In contrast to BRW, which allows for an optimal dissimilarity in agents' types of knowledge, we assume that the returns to matching are monotonically increasing as knowledge distance decrease. However, the principal theoretical innovation of this paper is to allow the productivity gains from matching to depend on the *type* of knowledge exchanged. In particular, the smaller an individual's 'location' in the knowledge space depicted in Figure 1, the lower the potential productivity gains from interaction. That is, such individuals place a lower value on interpersonal knowledge exchange and collaboration.

For example, an individual with a knowledge type at location '0' on the unit circle in Figure 1 places the lowest weight on exchanging ideas with others. However, individuals at higher locations are more dependent on interpersonal communication, but they also require more specialized interactions. Therefore, individuals endowed with higher amounts of 'soft' knowledge benefit the most from interactions with other agents who are also highly outward oriented. They gain very little from meetings with agents who are much different. In order to clarify how the productivity of information sharing depends upon the differences in types of knowledge, we use the Euclidean metric where $\delta(k, k')$ is the knowledge distance between two individuals with knowledge types k and k'.

The additional knowledge obtained by individual with knowledge type k in sharing ideas with someone of type k' is $S(k, k')$ and it is reflected as:

$$S(k, k') = q + k(1 - \delta(k, k')) \tag{1}$$

While q reflects the value of matching regardless of differences in knowledge, higher values of k reflect that individuals are endowed with more soft knowledge and therefore derive greater gains from information sharing. However, it is important to note that specialization and soft knowledge are complements in terms of generating ideas. The greater the differences in types of knowledge, the lower are the benefits of intellectual exchange. Nevertheless, individuals with hard skills benefit less from close matches. The additional knowledge obtained is temporary, but it immediately translates into higher income.[4] Moreover, the utility from meeting is equal to the additional knowledge obtained from exchanging ideas. Time in the model is continuous and the rate at which individuals discount future utility is $r > 0$.

[4] As previously emphasized, our primary goal is to study horizontal differences in knowledge on knowledge exchange and the implications for agglomeration economies. If matching would permanently affect individuals' human capital, the model generates multiple equilibria and non-stationary dynamics. Similar restrictions are also embedded in BRW.

Meetings and Matches

As previously mentioned, one of the primary benefits of agglomeration economies is an increase in the rate of interactions between individuals. In more dense environments, transactions costs are lower. Consequently, the flow probability of meetings in an economy is $\alpha(N)$ and it is increasing in the population mass.[5]

However, not all meetings result in a match between agents. This is because the additional knowledge generated from matching is decreasing in differences in knowledge between individuals. Moreover, there is complementarity between an agent's knowledge type and the degree of similarity between two individuals. Yet, because of search frictions, individuals will match with individuals who are different. As we will derive below, individuals will choose an optimal 'knowledge spread' of agents in which they will exchange ideas, $\delta(k, k')$. The knowledge spread represents the maximum knowledge distance that an individual of type *k* will accept and exchange ideas. Given that the knowledge space has a circumference of *1*, it also represents the fraction of individuals to collaborate. As the flow probability of a *meeting* is $\alpha(N)$, the flow probability of a *match* is $\alpha(N)\ \delta(k, k')$. Matches break-up with exogenous flow probability η.

Bellman Equations

At any point in time, an individual will either be unmatched or matched. Our primary attention focuses on activity in the steady-state where all variables are time-invariant. Individuals who are matched will generate income from sharing ideas and collaborating while others are seeking opportunities for intellectual exchange. Thus, they will have different streams of utility over time. The expected discounted utility of an agent of type *k* who is unmatched is $V_U(k, \hat{\delta}_k; N)$. For an agent that is matched, it depends

[5] The specification of the matching technology follows Glaeser (1999) for tractability.

on the quality of the collaboration. Hence, it is dependent on the individual's base of knowledge and the type of knowledge of their partner: $V_M(k,\delta;N)$.

We begin with the expected discounted utility of a matched agent with knowledge type *k*

$$rV_M(k,\delta;N) = \left[q + k(1-\delta(k,k'))\right] + \eta\left[V_U(k,\hat{\delta}_k;N) - V_M(k,\delta;N)\right] \tag{2}$$

As is standard in continuous-time search models, the flow value of a matched agent is the flow income they generate in addition to the expected capital loss that one would incur if the match breaks up. The derivation of the Bellman Equation follows directly from the discussion in BRW.

By comparison, the Bellman equation for unmatched agents is a bit different in that agents do not know ex-ante the quality of their match:

$$rV_U(k,\hat{\delta}_k;N) = \alpha(N)\int_0^{\hat{\delta}}\left[V_M(k,\delta;N) - V_U(k,\hat{\delta}_k;N)\right]d\delta \tag{3}$$

where $\hat{\delta}_k$ is the knowledge spread which is chosen to maximize an unmatched agent's expected lifetime utility. The flow value of an unmatched individual reflects the expected capital gain that occurs upon matching. The ex-post value of a match depends upon the knowledge distance between the two agents while the ex-ante measure reflects the range of agents that an individual selects to exchange ideas.

Based upon the Bellman equations for matched and unmatched agents, we obtain the following Lemma:

Lemma 1 *(Unmatched Value). An agent's unmatched value depends on the agent's type k:*

$$V_U(k;\hat{\delta}_k;N) = \frac{\left(\dfrac{\alpha(N)}{r}\right)\hat{\delta}_k\left[q + k\left(1 - \dfrac{1}{2}\hat{\delta}_k\right)\right]}{r + \eta + \alpha(N)\hat{\delta}_k} \quad \text{if } \hat{\delta} < 1$$

$$= \frac{\left(\frac{\alpha(N)}{r}\right)\left[q + \frac{k}{2}\right]}{r + \eta + \alpha(N)} \qquad \textit{otherwise} \tag{4}$$

Steady-State Populations

In the steady-state, the number of unmatched individuals must be constant. Since the search strategies vary across types of individuals, we begin by assuming that the population of unmatched agents of *each type* is constant. That is, in each period, the flow of individuals of type *k* who become unmatched is equal to the number of type *k* individuals who find a match:

$$\alpha(N)\hat{\delta}_k U_k = \eta M_k \tag{5}$$

At any point in time, there is a population of agents of type *k* who are not currently matched. This measure is equal to U_k. As the flow probability that each of these individuals will become matched is equal to $\alpha(N)\hat{\delta}_k$, the total number of agents of type *k* who become matched is $\alpha(N)\hat{\delta}_k U_k$. On the other side, $M_k = N - U_k$ agents will be in matches that are susceptible to breaking up.

Therefore, the steady-state population of unmatched agents for each knowledge type is:

$$U_k = \left(\frac{\eta}{\alpha(N)\hat{\delta}_k + \eta}\right) N \tag{6}$$

Note that as the knowledge spread for any type of agent is larger, the steady-state number of unmatched individuals for each type will be lower. Moreover, each type will choose different knowledge spreads. Therefore, the steady-state population of unmatched individuals across the entire economy is:

$$U = \int_0^1 U_k dk = \int_0^1 \left(\frac{\eta}{\alpha(N)\hat{\delta}_k + \eta}\right) dk \tag{7}$$

Steady-State Equilibrium

We now study the steady-state pure strategy Nash equilibrium for the economy. We first provide a formal definition for the steady-state equilibrium:

Definition. *(Steady-State Equilibrium). A non-degenerate steady-state equilibrium consists of* $\{\{R(k)_{k\in\kappa}, \hat{\delta}_k, U\}$ *satisfying the following conditions:*

(E-1) agents maximize their expected lifetime utilities through their choice of the knowledge spread, that is, $\hat{\delta}_k$ is the best response given $\hat{\delta}_{k'}, k' \in \kappa \setminus \{k\}$;

(E-2) equilibrium range of agents for *k* to exchange ideas, $R(k) = [k - \hat{\delta}_k, k + \hat{\delta}_k]$

(E-3) steady-state population, (7)

(E-4) there is interaction among agents (the steady-state equilibrium is non-degenerate); $\hat{\delta}_k > 0$.

Steady-state levels of interaction are reflected in the following:

Proposition *(Steady-State Knowledge Spread for type k) Let* $\alpha(N) = \alpha N$ *and* $k > \bar{k} = \dfrac{2(r+\eta)q}{\alpha N}$.

Suppose that a steady-state population mass for unmatched individuals exists and is unique. Then, the steady-state equilibrium knowledge spread of a type k agent solves the following quadratic equation:

$$\hat{\delta}_k^2 + \left(\frac{2(r+\eta)}{\alpha N}\right)\hat{\delta}_k - \left(\frac{2(r+\eta)}{\alpha N}\right)\left(\frac{q+k}{k}\right) = 0 \tag{8}$$

Moreover, $\dfrac{\partial \hat{\delta}_k}{\partial N} < 0, \dfrac{\partial \hat{\delta}_k}{\partial k} < 0,$ *and* $\dfrac{\partial^2 \hat{\delta}_k}{\partial N \partial k} < 0$. *If* $k \le \bar{k}$, $\hat{\delta}_k = 1$.

The first result is that the knowledge spread is generally decreasing in the population size. This reflects the lower degree of transactions costs in dense economic environments where frictions interfering with intellectual exchange are lower. In turn, individuals will select a more narrow range of individuals to exchange ideas and there are productivity gains from agglomeration. A similar result occurs in BRW.

However, in contrast to BRW, our framework recognizes that the gains from information sharing vary according to an individual's base of knowledge. As previously mentioned, a wide array of existing empirical evidence indicates that there are substantial differences in spillovers across industries and different tendencies for industries to co-agglomerate. Consequently, the knowledge spread is type-dependent in our framework as we postulate that there are differences in the potential to learn from others. Therefore, the second comparative static demonstrates that different types of agents will select different ranges of individuals for collaborations.

As demonstrated in the Proposition, an individual's knowledge spread will be smaller if they have a higher value of *k*. That is, individuals with a greater soft-knowledge base will select more specialized interactions. In contrast to soft-knowledge types of individuals, individuals with a lower value of *k* are not sensitive to knowledge gained from matching and would meet with any agent. However, they accomplish relatively little in interpersonal exchange.

The final comparative static provides the key empirical prediction of our model. In particular, the model demonstrates that $\frac{\partial^2 \hat{\delta}_k}{\partial N \partial k} < 0$, indicating that individuals with more soft-knowledge will become even more selective as the population is higher. Because the quality of information sharing improves in more dense environments, *the productivity from matching will be higher among those with soft knowledge rather than hard knowledge. In this manner, the model demonstrates that worker productivity among those with soft knowledge will increase more in agglomerative environments than those with hard knowledge. Therefore, the model implies that that the urban wage premium varies according to individuals' base of knowledge*. The balance of the paper is dedicated to finding empirical evidence of this.

III. Data

We look for evidence consistent with the model in the American Community Survey (ACS). The ACS provides a cross-sectional look at various socioeconomic, demographic and housing characteristics of the United States population. In particular, it provides detailed information on individuals' educational attainment and, since 2009, undergraduate field of degree. The responses to these questions provide a rich measure of the depth and types of human capital in the US population. For individuals who have earned an undergraduate degree or higher, the ACS identifies which of 174 different majors a respondent obtains. We aggregate the responses into twenty-one categories. These areas of expertise in alphabetical order are: agriculture, architecture, arts, business, computer science, education, engineering, fitness, government, history, languages, law, liberal arts, mathematics, medicine, media, psychology, religion, science, social science, and social work. As we are primarily interested in studying civilian labor markets, majors with a military science degree are dropped from the sample of college majors.

The ACS is also large, as it is intended to replace the long-form from the decennial census. The Census Bureau annually releases 1-year, 3-year, and 5-year panels of this large dataset. 1-year releases are the results from a 1% sampling of the population and contain over 3 million observations. Thus, the ACS is uniquely able to inform questions about the level, type, and concentration of human capital across cities.[6]

The large sample size, in turn, allows the ACS to provide relatively fine geocoding at the Primary Use Microdata Area (PUMA). PUMA boundaries encompass contiguous census tracts, counties, and places consisting of 100,000 to approximately 200,000 people, and are redefined each decade according to decennial census population estimates. Using PUMA geocodes we are able to assign individuals to MSAs that we believe best approximate a labor market and pool for knowledge exchange.[7] We drop

---

[6] Since new data is available each year, the 1-year estimates only sample from areas with a population of 65,000 or greater. The 3 and 5-year estimates reach smaller populations.
[7] The Missouri Census Data Center's MABLE/Geocorr2K Geographic Correspondence Engine streamlines the process by generating customized, downloadable reports of the relationship between PUMAs and MSAs based on year 2000 boundaries and population size. This resource provides the corresponding MSA name and code, and population for each PUMA.

individuals not residing in an MSA. We use MSA population as our primary independent variable of interest, and use MSA-level unemployment rate to control for local labor market conditions.[8]

The theoretical framework that we seek to test focuses on horizontal differences in human capital accumulation. One might also be concerned that any of our empirical results for college majors are biased because some majors tend to serve as pathways towards post-baccalaureate education. An advantage of the ACS is that it also asks about advanced degrees. Specifically, the ACS allows us to construct nine indicators for educational attainment: less than high school, GED, high school, some college, associate's degree, bachelor's degree, master's degree, professional degree, and Ph.D.[9] Thus, we can study how the urban wage premium varies across rich dimensions of vertical human capital attainment among workers in the labor force. We view that such analysis is also warranted as many papers on wage models rely on a continuous measure of educational attainment or aggregate responses or relatively coarse measures of educational attainment such as high school or college completion.[10] Results from these methods unrealistically imply either the return to human capital investment is constant, or that individuals with the same years of education should expect the same return in wages.

In order to study individuals who are active labor market participants, we focus on individuals age 16 or older that earned at least $10,000 and completed a bachelor's degree. Along with human capital, we control for standard demographic information such as gender, marital status, white/non-white race, veteran status, immigrant status, and age which we enter as a quadratic expression. Other variables include occupational controls for weekly hours worked, indicators for industry in which the individual is employed, and industry share of MSA employment. As we expect the urban wage premium to reflect, in part, the learning that's occurring in the city, we use an indicator for, and sometimes exclude, for people

[8] We take the unemployment rate from Bureau of Labor Statistics via the FRED database of the Federal Reserve Bank of St. Louis.
[9] Bacolod et al. (2009) only study three categories of educational attainment: less than high school, high school, and a college degree. However, in comparison to our work, they also control for quality of undergraduate institution.
[10] See, for example, Rauch (1993), Roback (1982), and Bacolod et al. (2009).

having recently moved MSA.[11] Unfortunately, we do not observe the previous residence of recent movers. Lastly, we control for the Census-defined geographical division in which the individual resides.[12]

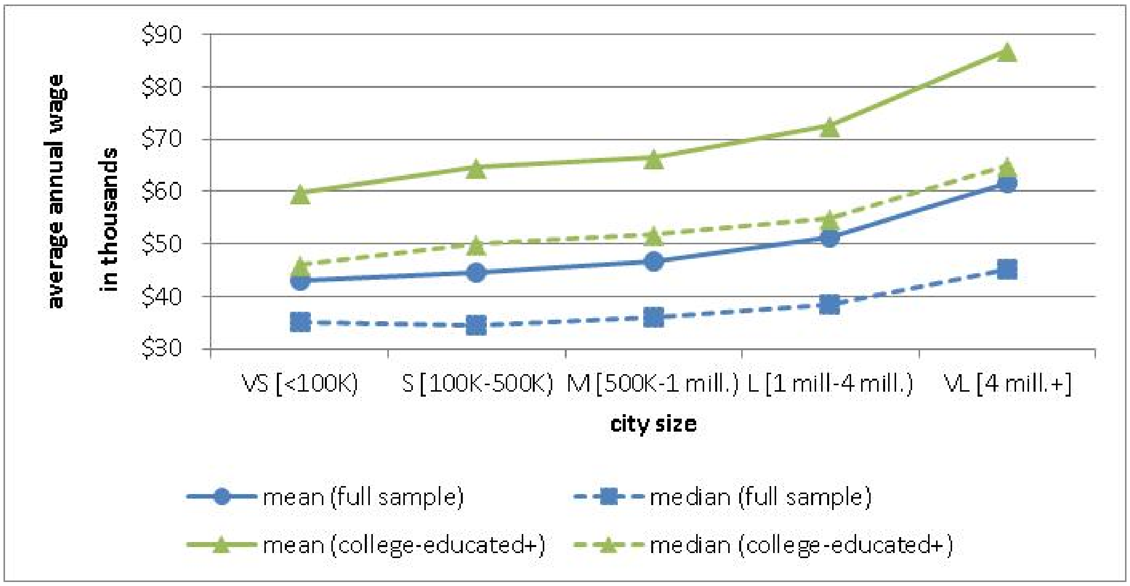
We obtain two samples. The unrestricted sample for 2011 includes individuals with any level of educational attainment and has 875,255 observations. Our subsample of college graduates has 339,724 observations. The demographic breakdown of the data is rather consistent across 2009-2011, the years for which ACS data on field of degree is available. However, we study the most recent sample in our analysis. Each year, about half the dataset is female. Eighty percent of the population is white, and two-thirds are married. The average age of the sample is around 43 years old. Approximately 7% in the sample are veterans.[13]

To gain a better understanding of the geographical distribution of our sample, we categorize MSA population size as follows: VS (very small, less than 100,000; example, Cheyenne, WY); S (small, 100,000 – 500,000; Tallahassee, FL); M (medium, 500,000 – 1 million; Birmingham, AL); L (large, 1 million – 4 million; Memphis, TN-AR-MS); and VL (very large, greater than 4 million; New York-Northern New Jersey-Long Island, NY-NJ-PA).[14] Sample representation of the city size groups from very small to very large are: 0.38%/0.28% (VS), 17.38%/13.81% (S), 9.74%/8.43% (M), 31.64%/31.24% (L), and 40.86%/46.24% (VL).[15] Nearly half of the full sample population lives in MSAs with more than 4 million people. Less than 20% reside in MSAs with populations smaller than 500,000 people. Limiting the sample to the college educated causes us to have fewer individuals in small towns and more in very large cities relative to the population as a whole.

[11] The migration PUMA (MIGPUMA) identifies the PUMA of residence one year ago. As discussed, PUMAs are aggregated to the MSA-level by population. The difference in the relative size of cities follows our previous definitions.
[12]Census region and division definitions are available at: http://www.census.gov/econ/census07/www/geography/regions_and_divisions.html.
[13] In 2011, these values hold between the full and restricted samples as well, with the exception that the college-educated are more likely to be married (66% vs. 60%) and less likely to serve in the military (7% vs. 9%).
[14] See appendix table 1 for a listing of all MSAs within each city size category.
[15] Percent representation in the full sample/% representation in the restricted sample.

Consistent with previous work, we find strong evidence for the urban wage premium in the ACS. Average annual wages in very small cities are less than $45,000. By comparison, in the largest cities, average annual income is over 40% larger (at $61,487). The average premium for workers with at least a bachelor's degree was similar at 46%, equivalent to an increase in average earnings from $59,732 to $86, 965. In fact, average (and median) annual wages for all workers and for workers with at least a bachelor's degree are monotonically increasing with city size.

Figure 1: Average Earnings Across City Sizes



However, the distribution of educational attainment within each city size reveals very small, small and medium cities are largely composed of individuals with some college experience. The modal level of educational attainment in large and very large cities is the bachelor's degree.

In Table 1, we look at how people sort themselves across cities. Education, business, science, and engineering fields maintain the highest representation within all city size groups. Education dominates in very small cities, while the business degree is the most prevalent everywhere else. After grouping science, engineering, medicine, computer science, and mathematics into the STEM category, we see STEM fields are the largest group of majors consisting of at least 25% of college-educated population in all city sizes. Education, business, and social science follow STEM.

Table 1: Field of Undergraduate Major Distribution within Cities

	VS	S	M	L	VL	U.S.
Education	17.83	15.21	13.5	11.08	8.56	10.7
Business	16.35	19.91	20.93	22.49	21.36	21.46
Science*	9.39	8.75	8.19	8.54	8.75	8.64
Engineering*	7.7	8.1	8.9	8.96	10.09	9.35
Medicine*	7.59	8.54	8.64	7.4	6.56	7.27
Liberal Arts	5.27	4.18	4.28	4.2	4.97	4.56
Social Science	5.06	5.48	5.54	6.15	7.15	6.46
Arts	4.43	2.99	3.28	3.62	4.39	3.86
Agriculture	4.32	2.61	1.68	1.38	0.98	1.4
Government	3.9	4.85	4.82	4.98	5.32	5.11
Comp. Sci.*	3.06	2.42	2.39	3.17	3.54	3.17
Psychology	2.95	4.49	4.94	4.84	4.84	4.8
Media	2.53	3.35	3.51	4.49	4.16	4.09
History	2.43	2.09	2.3	2	2.55	2.29
Math*	1.69	1.34	1.46	1.46	1.81	1.61
Social Work	1.58	1.36	1.33	1.07	0.82	1.01
Languages	1.27	0.94	0.99	0.97	1.24	1.09
Religion	1.16	1.61	1.61	1.39	1.26	1.38
Fitness	0.95	1.11	0.87	0.87	0.59	0.78
Architecture	0.53	0.53	0.68	0.78	0.9	0.79
Law	0	0.15	0.17	0.17	0.16	0.16
*STEM	29.43	29.15	29.58	29.53	30.75	30.04

STEM is the sum of values for the fields marked with an asterisk within each city size.

IV. Empirical Model

As in Lucas (1988) we assume that wages measure an individual's productivity and that it reflects both the individual's initial human capital (education, skill, innate ability) but also the positive productive externalities they accrue from interacting with others. Empirically, this premium is captured by the coefficient for local population size. For example, Roback (1982) identifies population size as a productive amenity in her spatial equilibrium model of wages and rents. In particular, population size drives up firm demand for land. Consistent with Roback (1982) and the subsequent literature, we assume free mobility for workers and firms and do not control for cost of living or amenities across cities. The iso-utility constraint for spatial equilibrium assumes the individual is indifferent across locations after controlling for the cost of housing and local amenities. Therefore, individuals' preferences for the local amenities compensate for higher rent or lower wages. Firms that choose to locate in high-rent (or low-amenity) cities must compensate workers for living there by paying a higher wage. Firms choose to locate in high-wage cities if workers are more productive there. Nevertheless, we allow for some regional variation in productivity by including dummy variables for Census division.[16]

Bacolod, Blum and Strange (2009) expanded the wage regression by incorporating educational attainment and indices of minimum occupational skill requirements. Standard educational attainment captures one form of human capital while the indices for cognitive, people, and motor skills capture horizontal variation. They then interact these measures of human capital with population size to determine which skills are rewarded in larger cities. Similarly, we regress (log) wages on a set of demographic controls and education and interact education with city population size. Our initial contribution is to control for educational attainment with much finer measures than were available to earlier researchers.

We specify the following regression:

$$ln(w_{is}) = \alpha + X_{is}\beta + L_{is}\theta + pop_s\delta + D_{id}\gamma + M_{im}\mu + (pop_s \times D_{id})\varphi_d + \varepsilon_{is} \tag{9}$$

where w_{is} is the annual wage earnings of individual i in city s . We include demographic variables, X_{is}, which includes age and age^2 and a dummy indicator for race (white = 1), marital status (married = 1), gender (female = 1), immigrant status (foreign-born = 1), and veteran status (veteran = 1). We also control for local labor market conditions, L_{is}, with MSA-level unemployment rates, seventeen indicators of industry of employment, own-industry share of employment in the MSA. We also control for the respondent's weekly hours worked.[17] Our ultimate aim is to understand how types and levels of education interact with city size to raise worker productivity and observed wages. Thus, we first incorporate the

[16] The south Atlantic division serves as the reference group.
[17] The represented industries are: agriculture (reference group), extraction, utilities, construction, manufacturing, wholesale trade, retail, transportation, information, finance, professional services, administrative services, educational services, social assistance, entertainment, military, medical, and other services.

vector matrix D_{id}, that contains nine dummies for highest degree obtained in the full sample specification for the urban wage premium. The omitted category is people that only obtained a high school diploma.

We also want to understand how the urban wage premium varies across types of knowledge. To do so, we substitute a vector of college majors, M_{im} for highest degree and limit the specification to respondents with a bachelor's degree or higher:

$$ln(w_{is}) = \alpha + X_{is}\beta + L_{is}\theta + pop_s\delta + M_{im}\mu + (\text{pop}_s \times M_{im})\varphi_m + \varepsilon_{is}. \quad (10)$$

Business, the most common undergraduate major, is omitted. To find which majors appear to be most productive from living in larger cities, we interact the 21 college majors with city population size. Our coefficients of interest are denoted by the vector φ_m.

Drawing on the theoretical discussion in Section II, we first collapse the field of degree vector to a dummy variable for STEM majors and our testable hypothesis becomes: $H_0: \varphi_{m=STEM} \geq \varphi_{m \neq STEM}$ against our alternative hypothesis that non-STEM majors benefit more from city size, $H_a: \varphi_{m=STEM} < \varphi_{m \neq STEM}$. We then relax the dichotomization and simply test whether individual majors experience different urban wage premiums than do other majors. Specifically, our null hypothesis is that all majors enjoy the same urban wage premium. Recalling that the omitted major is business, $H_0: \varphi_{m=bus} = \varphi_{m \neq bus}$. Our alternative hypothesis is that workers with different undergraduate degrees earn more when living in larger cities, $H_a: \varphi_{m=bus} \neq \varphi_{m \neq bus}$.

Finally, we wish to understand how the returns to knowledge exchange vary with the depth of training. As a person learns more through formal education they may select into professions that require less informal learning that accrues in cities. On the other hand, more education may facilitate greater specialization in a specific field and the ability to find close matches as city size increases is at the heart of the theoretical exercise in Section II. To explore these potentially competing forces we create a matrix of 21 fields of degree interacted with four measures of educational attainment: bachelor's, master's, professional and Doctorate degrees. The omitted category is now individuals that stopped with a bachelor's degree in business. The full specification is:

$$ln(w_{is}) = \alpha + X_i\beta + L_s\theta + pop_s\delta + M_{im}\mu + (\text{pop}_s \times M_{im} \times D_{id})\varphi_{md} + \varepsilon_{is} \quad (11)$$

where the coefficients φ_{md} capture the urban wage premium for different college majors with different highest degrees earned.

Interacting undergraduate majors with highest degrees also allows us to address one of the data limitations of the model. While we believe that most individual's undergraduate and graduate programs have considerable overlaps in their types of knowledge, especially graduate STEM programs where training in math or science would be clear prerequisites, the fact that we don't observe the type of post-bachelor's education remains a concern. For example, a science undergraduate could still pursue a master's of Fine Art or a mathematics major could get a Ph.D. in economics. By looking within majors across highest degrees we can at least isolate the amount of possible measurement error.

Controlling for Endogenous City Population

Work on the urban wage premium has typically treated population as an exogenous determinant of wages. While population agglomerations are quite persistent and may in some cases be artifacts of history (Bleakley and Lin, 2012), treating population as persistent and exogenous is inconsistent with our assumption of free mobility. Thus, in some specifications, we instrument for population size with a measure of land supply elasticity. Specifically, we use Saiz's (2010) measure of developable land around cities which is the share of land surrounding a city center that is not either covered with water or steep slopes. A number of papers have used this land supply elasticity as an instrument for house prices or house price appreciation including work by Mian and Sufi (2009) and Chetty and Szeidl (2010). However it is new construction that limits price increases, so land availability should, even more directly, explain population levels. The key assumption is that the amount of buildable land does not otherwise affect the productivity of workers with a college degree or higher. Oceans, lakes and mountains could also be amenities that appeal differentially to skilled workers and affect wages. However, our key findings, presented below, reveal much more nuanced variation across levels of types of knowledge. The instrument for education population interactions is education*land constraint.

V. Empirical Results

In this section, we seek to empirically test the primary prediction from our theoretical model. That is, we want to study how the urban wage premium varies according to an individual's horizontally differentiated base of knowledge. However, to ground our analysis in the existing literature, we first replicate education and city size, but with our richer measure educational attainment. For example, Rauch (1993) studies human capital externalities across cities based upon years of formal schooling which implies that each year generates the same returns in terms of labor productivity. [18] Alternatively, Glaeser and Mare (2001) impose various educational dummies across years of schooling in an attempt to mimic different classes of educational attainment. However, as previously outlined, the ACS contains nine different measures of educational attainment. Thus, we begin by looking at the relationship between the urban wage premium and these vertical measures of human capital. The omitted indicator for the level of human capital attainment is a high school diploma. In our first wage regression, the logarithm of MSA population reflects the urban wage premium. The full set of coefficient estimates is available upon request.

Column 1 of Table 2 presents the coefficient estimate on logged MSA population, the baseline urban wage premium for all workers. Column 2 shows the coefficient estimates when we instrument for MSA population size using land scarcity. While the F statistic for this specification is under 10 (a common rule of thumb for first stage power) we present the coefficient estimates for consistency with subsequent specifications. Column 3 presents the coefficient estimates of the urban wage premium when we include measures of educational attainment. Controlling for respondent's highest degree obtained reduces our estimate for the urban wage premium by around 30 percent, reflecting the greater concentration of educated workers in larger cities. Also, note that worker earnings increase monotonically with educational attainment up to a professional degree. Column 4 instruments for population size, and

[18] Rauch (1993) follows Roback by estimating social returns from human capital accumulation. In particular, Rauch finds that an individual's wage is higher in MSAs with higher average years of education.

has an F statistic >10. Similar to OLS, controlling for individual highest degree lowers the urban wage premium by almost 25 percent.

Column 5 of Table 2 presents the coefficient estimates when we interact highest degree and city size. Estimated coefficients are denoted by φ_d in equation 9. Note that unlike previous work that only measured the interaction of education and the UWP up to a bachelor's degree, using finer measures of education reveals a highly non-monotonic relationship with respect to city size.

People with professional degrees and Ph.D.s don't see their wages grow with city size any faster than someone with a High School diploma (the omitted category). One possibility is that people with high amounts of human capital differentially prefer urban amenities, lowering their (relative) reservation wages. However, people with master's degrees do earn more in big cities than do those with just a bachelor's, so the amenity value itself would have to be highly non-linear by education. Also, when we look at individuals with less education we see a similar pattern. Someone with only a GED earns more with city size than does someone with a High School diploma. Moreover, a person with only some college education, but no diploma gains an additional 1 percent in wages with city size, but the person that actually obtains an associate's degree has half the relative urban wage premium.

We postulate that, to a certain extent, an associate's degree, a professional degree and a Ph.D. can be thought of as terminal degrees that confer the mastery of a certain skill set or cannon of knowledge. Someone with an associate's degree or a D.D.S for example have clear career trajectories. By comparison, a person with a bachelor's or master's degree has demonstrated some overall ability and exposure to a range of ideas, but obtaining the degree does not immediately open the door to certain vocations the way an M.D. or J.D. does. Instead these people are expected to learn more on-the-job, or, to be more precise, post-formal education. Their earnings may depend on developing industry specific knowledge or social capital that augments their careers and may benefit more from the knowledge exchange that bigger cities allow. However, as we postulate in Section II, some knowledge may be easier exchange in person than other types and so we may also see different UWPs across different types of undergraduate degree. We explore the empirical evidence for this in the balance of the paper.

Column 6 presents the same specification instrumenting for city size. The associated F statistic on city size is 17.2. Instrumenting for city population weakens statistical significance in some instances, but doesn't alter the same basic underlying pattern. Workers with GEDs earn more than those with an actual diploma. Professional and Ph.D. degree holders don't appear to command a larger urban wage premium than do high school graduates.

Horizontal Differentiation of Human Capital

We now turn to horizontal differences in human capital. This lateral variation in human capital comes in the form of twenty dummy variables for undergraduate major (business majors are the omitted category). We introduce these college majors into our earnings equation and then interact them with city size. As we only have data on this category for those who have acquired at least a bachelor's degree, the sample is restricted. Prior to looking at measures of the urban wage premium across fields, we note the average return to major. As can be observed in the first two columns of Table 3, STEM majors earn about 17% more than all other college graduates on average. Columns 4 and 5 show earnings premiums for all fields of degree categories. The top five statistically significant fields are STEM-related. Though lower than someone with a business degree, other high-earning areas are psychology, languages, and liberal arts. The lowest-earning fields are religion, fine arts, and social work – all earning at least 10% less than someone with a business major.

Table 4 presents the estimated urban wage premium for different college majors and contains the principal empirical finding of the paper. Column 1 presents the coefficient estimates when we divide college graduates into STEM and non-STEM majors. Consistent with the model presented in Section II, STEM majors experience a significantly smaller urban wage premium. The coefficient estimate: $\hat{\varphi}_{m=STEM} = -0.17$ and is statistically different from zero (non-STEM) at all standard cut-offs.

We thus reject the null in favor of the alternative hypothesis: $H_a: \varphi_{m=STEM} < \varphi_{m\neq STEM}$. Thus, non-STEM workers with soft skills appear to become relatively more productive in big cities.

In Column 2, we attempt to instrument for population size. Our coefficient estimates for the UWP (effectively non-STEM majors) and our STEM majors are not statistically different from zero, however the magnitude of estimate for the UWP is similar. Rather, the standard errors have grown suggesting a weak instrument may be keeping us from rejecting the null.

Column 3 present the coefficient estimates for all 20 wage categories relative to business and Table 4 presents the net percentage wage premiums for each major ($\hat{\delta} + \hat{\varphi}_m$) ranked by their urban wage premium. Disaggregating majors reveals some interesting nuances. The top five degrees are Social Science (6.45%***), Mathematics (6.41***), Law(6.34**), Government 6.27** and History (5.48**). Thus, a worker with a degree in a Social Science could expect to see their salary increase by 6.45% if their city size doubled. Mathematics is the only STEM field in the top tercile and the only STEM field with a UWP statistically larger than business. People with degrees in science, medicine or engineering all have statistically smaller wage premiums than business majors. Computer science majors experience a similar UWP as business majors.

Finally, in column 4 of Table 3 (and column 2 of the rankings presented in Table 4) we attempt to address the endogeneity of population size by using land scarcity as an instrument for population. The results between OLS and IV estimation differ in a few ways. After instrumenting for population, the only majors to have a statistically greater urban wage premium are psychology (6.95**), government (6.55%*), social science (4.69%*) and media (4.2%*). We highlight again that we treat the IV as more of a robustness check against one possible challenge to identification, rather than the definitive specification. We do not have a good instrument for the distribution of majors across cities. For example, if larger cities disproportionately attract certain majors, those workers might experience more competitive wage pressure. However, it's unclear, given our observed results, why STEM majors would tend to value urban amenities relative to social science or history majors. It's also worth returning to Table 1 to recall that STEM majors do not appear to be disproportionately concentrated in large or very large cities.

Multi-dimensional Variation in Human Capital

One concern with the estimates presented in Tables 3 and 4 is that the apparent wage premium accruing to some majors may be confounded by subsequent education in unrelated fields. In this section we present the results for the urban wage premium when we interact vertical levels of educational attainment with undergraduate majors. In this manner, we aim to demonstrate that the results without highest degree are largely robust to controls for depth of human capital. The omitted category is people with only a bachelor's degree in business. For ease of exposition, we present the OLS derived net UWPs, the overall urban wage premium, $\hat{\delta}$, (for the omitted category, undergraduate business) plus the specific major×degree premium, $\hat{\varphi}_{mi}$, and convert the premiums to percentages in Table 5 below. Interacting four categories for advanced degrees with 21 categories for majors generates 84 separate wage premiums. Obviously, some of these cells are quite thin, even for the ACS and will not generate statistically significantly different UWPs from the omitted category nor certainly from major-degrees with a similar wage premium. A fuller set of coefficient estimates is available in Appendix Table 2.

Looking at workers with only a bachelor's degree buttresses our theme that workers with "soft" majors appear to gain the most productivity from working in cities and is strongly consistent with the model presented in Section II. The top five fields at the bachelor's ranking among all fields are: 1. Social Science (5.46%***), 2. History (5.20%**), 3. Language (5.01**), 4. Media (4.98%***), 4. Liberal Arts (4.85%**). This ranking is very much in line with the previous results, highlighting the higher level of productivity of individuals with soft skills in agglomerative settings. Mathematics which was inconsistent with our model when we grouped all degrees across majors drops to the second tercile as does computer science and is no longer statistically different from business.

At the master's level, the ranking based upon OLS is: 1. Social Science (7.57%***), 2. Languages (6.05%**), 3. Liberal Arts (5.93%**), 4. Government (5.83%**), and 5. History (5.48%*). All of these measures of the urban wage premium are greater than their bachelor's level counterparts. Again, the ranking is highly consistent with earlier comparisons – fields related to creativity, interpersonal communication, and informal networking, generate high returns in dense economic environments. The relationship becomes somewhat less pronounced when we examine workers that have obtained professional degrees or Ph.Ds. Liberal Arts majors that go on to obtain a Ph.D. (in something) actually earn less as city size increases. Consistent with the findings of Lee (2010) undergraduate majors in medicine or science that go on to get professional degrees experience a flat or even negative urban wage premium.

In Table 6 we present the same coefficients but rank them across major-degree pairs. We also include results where we instrument for city size but these estimates tend to be less precisely identified. This reveals that all of the statistically significant premiums in the top quartile have degrees that might be considered non-terminal (bachelor's and master's level.)[19] The bottom quadrant is dominated by professional and Ph.D. degrees (our so-called terminal degrees). Both STEM and non-STEM Ph.D.s are well represented in the bottom UWP quadrant. For example, a history major with a bachelor's degree is in the top UWP quadrant, whereas as history major with a Ph.D. is in the bottom. Presumably the bachelor's student is not working as a historian, but has instead used their general college education to learn some industry specific skill post-graduation and learned it better or faster in a big city. On the other hand, the undergraduate history major with a Ph.D. may actually be a working historian that would learn very little from the fast interactions the city affords.

[19] Formal results can be found in appendix table 4.

VI. Conclusions

This paper explores whether different types of knowledge experience greater returns to agglomeration. Specifically, we posit that some kinds of knowledge are harder to exchange remotely and thus certain workers benefit more from close physical proximity to others. We first present a theoretical framework in which individuals randomly search for partners to exchange ideas, but that the returns to finding a partner are heterogeneous. In particular, some individuals have knowledge which is not only dependent on interpersonal exchange but is also the most productive when shared with similar individuals. In this manner, we propose that agglomerative environments favor individuals with knowledge that is typically associated with "soft skills" where creativity and informal networking are important.

We test this prediction using the most recent sample of the American Community Survey (ACS) in which college graduates are asked about their undergraduate major. Controlling for demographic and regional productivity effects and instrumenting for city size, we find that the urban wage premium varies considerably across majors. In line with the predictions of our model, the highest wage premiums are observed in majors linked to soft skills. This finding is consistent with the notion that large cities are particularly good at facilitating informal networking and promoting creativity whereas majors typically associated with "hard" skills tend to experience a smaller urban wage premium. We also study how the urban wage premium varies by highest degree. Our estimates imply that the largest urban wage premium is associated with a master's degree. In the spirit of our results for majors, terminal degrees associated with the mastery of any existing cannon of knowledge such as a JD or MD experience a smaller urban wage premium. Among those that only have a bachelor's or master's degree, majors associated with softer skills (perhaps excepting mathematics) seem to get the greatest wage boost from city size.

References

Arzaghi, M. and J.V. Henderson, 2008. Networking off Madison Avenue. Review of Economic Studies 75, 1011-1038.

Audretsch, D.B., M. P. Feldman, 1996. R&D spillovers and the geography of innovation and production, American Economic Review 86, 630-640.

Bacolod, M., Blum, B. S., and W.C. Strange, 2009. Skills in the City. Journal of Urban Economics, 136-153.

Berger, M.C., 1988. Predicted Future Earnings and Choice of College Major. Industrial and Labor Relations Review 41, 418-429.

Berliant, M., R. Reed, and P. Wang, 2006. Knowledge Exchange, Matching, and Agglomeration. Journal of Urban Economics 60, 69-95.

Bernstein, J.I., 1988. Costs of Production, Intra- and Interindustry R&D Spillovers: Canadian Evidence. Canadian Journal of Economics 21, 324-47.

Bernstein, J.I. and N. Nadiri, 1989. Research and Development and Intra-Industry Spillovers: An Empirical Application of Dynamic Duality. Review of Economic Studies 56, 249-67.

_____, and X. Yan, 1997. Costs of Production, Intra- and Interindustry R&D Spillovers: Canadian Evidence. Canadian Journal of Economics 21, 324-47.

Bleakley, H., & Lin, J., 2012. Portage and path dependence. Quarterly Journal of Economics, *127*(2) 587-644.

Duranton, G. and D. Puga, 2004. "Micro-foundations of Urban Agglomeration Economies," in J.V. Henderson and J.F. Thisse (eds.), Handbook of Regional and Urban Economics, ed. 1, vol. 4, ch. 48, 2063-2117.

Ellison, G., and E.L. Glaeser, 1997. Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach. Journal of Political Economy 105, 889-927.

_____, _____, and William R. Kerr. 2010. What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns. American Economic Review 100, 1195-1213.

Glaeser, E.L., 1999. Learning in cities. Journal of Urban Economics 46, 254-277.

_____, and M. Kahn, 2001. Decentralized Employment and the Transformation of the American City. NBER Working Paper #8117.

_____, and Mare, D. C., 2001. Cities and Skills. Journal of Labor Economics, 316-342.

Heckman, J., J. Stixrud, and S. Urzua, 2006. The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. Journal of Labor Economics 24, 411-483.

Helsley, R.W., W.C. Strange, 1990. Matching and Agglomeration Economies in a System of Cities, Regional Science and Urban Economics 20, 189-212.

Holod, D. and R. Reed, 2009. Regional External Economies and Economic Growth under Asymmetry. Southern Economic Journal 75, 1123-1140.

Jacobs, J., The Economy of Cities, Random House, New York 1969.

Kuznets, S., Population change and aggregate output in: Demographic and Economic Change in Developed Countries, Princeton University Press, Princeton, 1962, pp. 324-340.

Lee, S., 2010. Ability sorting and consumer city, Journal of Urban Economics, Volume 68, Issue 1, 20-33.

Lucas, R. E., 1988. On the Mechanics of Economic Development. Journal of Monetary Economics, 3-42.

Marshall, A., Principles of Economics, Macmillan and Co., London 1895.

Mian, Atif R., and Amir Sufi. (2009). House prices, home equity-based borrowing, and the US household leverage crisis. No. w15283. National Bureau of Economic Research, 2009.

Rauch, J. E., 1993. Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities. Journal of Urban Economics, 380-400.

Roback, J., 1982. Wages, Rents, and the Quality of Life. Journal of Political Economy, 1257-1278.

Rosenthal, S.S. and W. C. Strange, 2008. The Attenuation of Human Capital Spillovers. Journal of Urban Economics 64, 373-389.

Saiz, Albert, 2010. The Geographic Determinants of Housing Supply. Quarterly Journal of Economics 125.3, 1253-1296.

Table 2: Urban Wage Premium and Educational Attainment

Dependent variable: log of annual wages	Urban Wage Premium		Educational Attainment (Highest Degree)		Urban Wage Premium and Highest Degree	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln (MSA population)	0.072***	0.107**	0.053***	0.077**	0.009	0.013
	(0.006)	(0.050)	(0.005)	(0.034)	(0.006)	(0.035)
Educational Attainment (γ)						
Less than High School			-0.181***	-0.187***	0.145	0.179
			(0.011)	(0.013)	(0.090)	(0.248)
GED			-0.051***	-0.046***	-0.236***	-0.887***
			(0.007)	(0.009)	(0.045)	(0.274)
Some college			0.123***	0.128***	-0.041*	-0.158
			(0.004)	(0.004)	(0.022)	(0.148)
Associate's degree			0.216***	0.216***	0.134***	-0.028
			(0.004)	(0.006)	(0.041)	(0.189)
Bachelor's degree			0.459***	0.463***	0.158***	0.316
			(0.007)	(0.007)	(0.044)	(0.377)
Master's degree			0.658***	0.664***	0.185***	-0.080
			(0.009)	(0.008)	(0.046)	(0.449)
Professional degree			0.910***	0.902***	1.030***	1.373**
			(0.011)	(0.012)	(0.080)	(0.574)
Ph. D.			0.843***	0.841***	0.810***	0.302
			(0.011)	(0.012)	(0.078)	(0.557)
Educational Attainment ×ln(MSA population) (φ_d)						
Less than high school					-0.022***	-0.024
					(0.006)	(0.016)
GED					0.013***	0.056***
					(0.003)	(0.018)
Some college					0.011***	0.019*
					(0.002)	(0.010)
Associate's degree					0.006*	0.016
					(0.003)	(0.013)
Bachelor's degree					0.020***	0.010
					(0.003)	(0.025)
Master's degree					0.032***	0.049*
					(0.003)	(0.029)
Professional degree					-0.008	-0.031
					(0.006)	(0.038)
Ph. D.					0.002	0.035
					(0.006)	(0.037)
Observations	859,007	696,130	859,007	696,130	859,007	696,130
R^2	0.345	0.345	0.461	0.463	0.462	0.463

Note: Standard errors, clustered by MSA in parentheses. *,**,*** denote coefficient estimates statistically different from zero at the 10, 5, and 1 percent level respectively. Specifications also include demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, industry (2 digit NAICS) and census division dummies. Full set of coefficient estimates available upon request.

Table 3: Urban Wage Premium by Field of Degree (undergraduate major)

Dependent variable: log of annual wages	STEM/Non-STEM		Fields of Degree (major)	
	(1) OLS	(2) IV	(3) OLS	(4) IV
ln (MSA population)	0.049***	0.048	0.045***	0.024
	(0.007)	(0.045)	(0.007)	(0.048)
Major × ln(MSA population) (φ_m)				
STEM majors	-0.017***	0.000		
	(0.005)	(0.029)		
Agriculture			-0.019***	-0.006
			(0.007)	(0.026)
Architecture			-0.021**	-0.041
			(0.011)	(0.054)
Computer Science			*0.008*	*0.067*
			(0.010)	*(0.053)*
Education			-0.006	0.018
			(0.007)	(0.029)
Engineering			*-0.019***	*-0.014*
			(0.008)	*(0.046)*
Fine Arts			0.005	0.023
			(0.005)	(0.015)
Fitness			-0.009	-0.053
			(0.011)	(0.041)
Government			0.018**	0.041*
			(0.008)	(0.023)
History			0.010**	0.027
			(0.005)	(0.019)
Languages			0.009	0.034
			(0.010)	(0.033)
Law			0.018	-0.085
			(0.025)	(0.071)
Liberal Arts			0.007*	0.027
			(0.004)	(0.023)
Mathematics			*0.019****	*0.029*
			(0.007)	*(0.026)*
Media			0.008**	0.022*
			(0.003)	(0.014)
Medicine			*-0.013***	*0.031*
			(0.006)	*(0.022)*
Psychology			0.002	0.045**
			(0.005)	(0.020)
Religion			-0.011	0.008
			(0.010)	(0.027)
Science			*-0.021****	*0.011*
			(0.006)	*(0.020)*
Social Science			0.019***	0.023*
			(0.005)	(0.013)
Social Work			0.000	0.046
			(0.010)	(0.028)
Observations	333,530	282,668	333,530	282,668
R^2	0.360	0.356	0.364	0.360

Note: Standard errors, clustered by MSA in parentheses. *,**,*** denote coefficient estimates statistically different from zero at the 10, 5, and 1 percent level respectively. Specifications also include demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request.

Table 4: Ranking of Urban Wage Premium by Field of Degree

	Field of Degree (undergraduate major)			
	OLS		IV	
1	Social Science	6.45%***	*Computer Science*	9.08%
2	*Mathematics*	6.41%***	Social Work	7.01%
3	Law	6.34%	Psychology	6.95%**
4	Government	6.27%**	Government	6.55%*
5	History	5.48%**	Languages	5.81%
6	Languages	5.46%	*Medicine*	5.53%
7	Media	5.31%**	*Mathematics*	5.28%
8	*Computer Science*	5.29%	History	5.13%
9	Liberal Arts	5.17%*	Liberal Arts	5.12%
10	Fine Arts	4.97%	Fine Arts	4.72%
11	Psychology	4.73%*	Social Science	4.69%*
12	Social Work	4.54%*	Media	4.65%*
13	Business	4.52%	Education	4.20%
14	Education	3.90%	*Science*	3.54%
15	Fitness	3.59%	Religion	3.18%
16	Religion	3.39%	Business	2.43%
17	*Medicine*	3.22%**	Agriculture	1.80%
18	Agriculture	2.65%***	*Engineering*	1.00%
19	*Engineering*	2.61%**	Architecture	-1.71%
20	Architecture	2.41%**	Fitness	-2.91%
21	*Science*	2.41%***	Law	-6.08%

Note: Ranking of expected wage premium for the urban wage premium by college major derived from the regression results presented in Table 3 above ($\hat{\delta} + \hat{\varphi}_m$). Full coefficient estimates available upon request. *,**,*** denote coefficient estimates statistically different from business majors at the 10, 5, and 1 percent level respectively. Specifications also include demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request. *Italics* indicate STEM fields.

Table 5: Urban Wage Premium by Undergraduate Major and Highest Degree (OLS)
Note: Ranking of expected wage premium for the urban wage premium by college major derived from the

		highest degree							
	Major	Bachelor's		Master's		Professional		Ph.D.	
1	Social Science	5.46%	***	7.50%		3.14%		3.18%	***
2	History	5.20%	**	5.39%		2.88%	*	3.52%	*
3	Languages	5.01%		5.98%		4.33%	**	2.57%	**
4	Media	4.98%	***	4.97%		4.88%	***	1.43%	
5	Liberal Arts	4.85%	**	5.84%		3.11%	**	-0.08%	**
6	Social Work	4.78%		3.70%	*	-14.26%		4.96%	
7	Fine Arts	4.77%	*	4.87%		2.90%	***	1.42%	
8	Government	4.64%		5.73%	**	6.89%		3.41%	
9	Psychology	4.25%		5.34%	*	1.43%	*	0.97%	
10	*Computer Science*	4.14%		4.69%		5.95%		4.84%	*
11	Business	3.93%	***	4.51%		4.10%		-0.28%	
12	Law	3.90%		9.35%		7.60%	*	-6.66%	**
13	*Mathematics*	3.64%		8.01%		6.07%		5.29%	**
14	*Science*	3.60%		3.75%	***	-2.76%		0.61%	
15	*Medicine*	3.50%		2.98%	***	-2.91%		3.43%	
16	Fitness	3.37%		2.99%	*	-1.98%	***	-1.32%	
17	Religion	3.11%		2.18%		1.43%		0.83%	
18	Architecture	2.36%		2.57%		0.00%	***	-6.11%	
19	Education	2.04%	***	4.51%	**	1.03%	***	3.63%	
20	*Engineering*	1.51%	***	2.75%		2.94%		1.27%	
21	Agriculture	1.38%	***	5.09%		3.46%	***	-3.68%	

regression results presented in Appendix Table 2 ($\hat{\delta} + \hat{\varphi}_{mi}$). Full coefficient estimates available upon request. *,**,*** denote coefficient estimates statistically different from business majors with only a bachelor's degree at the 10, 5, and 1 percent level respectively. Specifications also include demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request.

Table 6: Ranking of Urban Wage Premium for Field of Degree-Educational Attainment Interactions

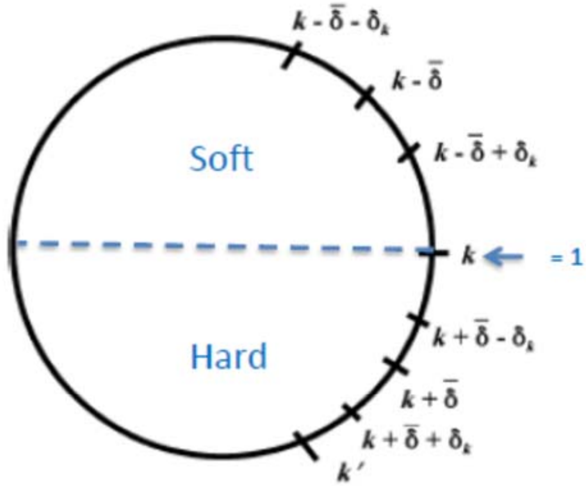
		OLS			IV		
1		Law*master’s	9.35%		Business*Ph. D.	21.60%	*
2		_Mathematics*master’s_	8.01%	***	_Computer Science*Ph. D._	19.54%	
3		Law*Professional	7.60%		_Mathematics*Ph. D._	17.44%	**
4		Social Science*master’s	7.50%	***	Agriculture*master’s	15.54%	*
5		Government*Professional	6.89%	**	_Computer Science*master’s_	12.79%	
6		_Mathematics*Professional_	6.07%		Government*Ph. D.	11.00%	
7		Languages*master’s	5.98%	**	Social Science*Ph. D.	10.34%	
8		_Comp. Science*Professional_	5.95%		Social Work*bachelor’s	9.21%	**
9		Liberal Arts*master’s	5.84%	**	Religion*Professional	8.60%	
10		Government*master’s	5.73%	**	Government*master’s	8.50%	*
11	Q4	Social Science*bachelor’s	5.46%	***	Religion*bachelor’s	8.15%	
12		History*master’s	5.39%	*	_Engineering*Ph. D._	8.02%	
13		Psychology*master’s	5.34%	**	_Mathematics*master’s_	7.96%	**
14		_Mathematics*Ph. D._	5.29%		Media*master’s	7.94%	*
15		History*bachelor’s	5.20%	**	Liberal Arts*master’s	7.89%	**
16		Agriculture*master’s	5.09%		Languages*bachelor’s	7.81%	**
17		Languages*bachelor’s	5.01%		Languages*master’s	7.77%	**
18		Media*bachelor’s	4.98%	***	Social Science*master’s	7.67%	***
19		Media*master’s	4.97%		_Science*master’s_	7.23%	*
20		Social Work*Ph. D.	4.96%		Social Work*master’s	6.54%	
21		Media*Professional	4.88%		_Engineering*Professional_	5.95%	
22		Fine Arts*master’s	4.87%		Psychology*master’s	5.88%	**
23		Liberal Arts*bachelor’s	4.85%	**	Education*master’s	5.76%	
24		_Computer Science*Ph. D._	4.84%		_Medicine*bachelor’s_	5.68%	*
25		Social Work*bachelor’s	4.78%		Psychology*bachelor’s	5.10%	**
26		Fine Arts*bachelor’s	4.77%	*	Fine Arts*master’s	5.04%	
27		_Computer Science*master’s_	4.69%		History*Ph. D.	4.78%	
28		Government*bachelor’s	4.64%		History*bachelor’s	4.74%	**
29		Education*master’s	4.51%		Languages*Ph. D.	4.33%	
30		Business*master’s	4.51%	*	Government*bachelor’s	4.29%	
31		Languages*Professional	4.33%		Liberal Arts*bachelor’s	4.21%	*
32	Q3	Psychology*bachelor’s	4.25%		_Science*bachelor’s_	4.20%	
33		_Computer Science*bachelor’s_	4.14%		_Medicine*master’s_	3.98%	
34		Business*Professional	4.10%		_Comp. Science*bachelor’s_	3.48%	
35		Business*bachelor’s	3.93%	***	Fine Arts*bachelor’s	3.46%	*
36		Law*bachelor’s	3.90%		Government*Professional	3.21%	
37		_Science*master’s_	3.75%		Psychology*Ph. D.	2.79%	
38		Social Work*master’s	3.70%		Psychology*Professional	2.66%	
39		_Mathematics*bachelor’s_	3.64%		Social Science*bachelor’s	2.64%	
40		Education*Ph. D.	3.63%		_Engineering*master’s_	2.64%	
41		_Science*bachelor’s_	3.60%		Media*bachelor’s	2.52%	
42		History*Ph. D.	3.52%		Business*master’s	2.46%	

Table 6 (cont): Ranking of Urban Wage Premium for Major-Educational Attainment

		OLS			IV		
43		*Medicine*bachelor's*	3.50%		*Medicine*Professional*	2.23%	
44		Agriculture*Professional	3.46%		Fine Arts*Professional	2.22%	
45		*Medicine*Ph. D.*	3.43%		*Medicine*Ph. D.*	1.46%	
46		Government*Ph. D.	3.41%		History*master's	1.45%	
47		Fitness*bachelor's	3.37%		Business*bachelor's	0.79%	
48		Social Science*Ph. D.	3.18%		Education*bachelor's	0.59%	
49		Social Science*Professional	3.14%		Business*Professional	0.58%	
50		Liberal Arts*Professional	3.11%		Education*Ph. D.	0.16%	
51		Religion*bachelor's	3.11%		*Mathematics*Professional*	-0.71%	
52		Fitness*master's	2.99%		Architecture*bachelor's	-1.00%	
53	Q2	*Medicine*master's*	2.98%	*	*Comp. Sci*Professional*	-1.01%	
54		*Engineering*Professional*	2.94%		Liberal Arts*Ph. D.	-1.07%	
55		Fine Arts*Professional	2.90%		History*Professional	-1.93%	
56		History*Professional	2.88%		Religion*Ph. D.	-2.11%	
57		*Engineering*master's*	2.75%		Law*master's	-2.38%	
58		Languages*Ph. D.	2.57%		Fitness*Ph. D.	-2.89%	
59		Architecture*master's	2.57%		Architecture*master's	-2.91%	
60		Architecture*bachelor's	2.36%		Media*Ph. D.	-3.14%	
61		Religion*master's	2.18%		*Science*Ph. D.*	-3.43%	
62		Education*bachelor's	2.04%	***	Fitness*bachelor's	-3.61%	
63		*Engineering*bachelor's*	1.51%	***	Agriculture*Bachleor's	-3.68%	
64		Religion*Professional	1.43%		*Science*Professional*	-4.04%	
65		Media*Ph. D.	1.43%		*Engineering*bachelor's*	-4.17%	
66		Psychology*Professional	1.43%	*	*Mathematics*bachelor's*	-4.86%	
67		Fine Arts*Ph. D.	1.42%		Agriculture*Ph. D.	-4.93%	
68		Agriculture*Bachleor's	1.38%	***	Media*Professional	-5.07%	
69		*Engineering*Ph. D.*	1.27%	**	Social Sci.*Professional	-5.18%	
70		Education*Professional	1.03%	**	Fitness*master's	-5.63%	
71		Psychology*Ph. D.	0.97%	***	Fine Arts*Ph. D.	-6.78%	
72		Religion*Ph. D.	0.83%		Agriculture*Professional	-7.63%	
73		*Science*Ph. D.*	0.61%	***	Liberal Arts*Professional	-8.06%	
74	Q1	Architecture*Professional	0.00%		Education*Professional	-8.31%	
75		Liberal Arts*Ph. D.	-0.08%	***	Religion*master's	-8.36%	***
76		Business*Ph. D.	-0.28%	*	Architecture*Ph. D.	-8.40%	
77		Fitness*Ph. D.	-1.32%		Fitness*Professional	-8.63%	
78		Fitness*Professional	-1.98%	*	Law*bachelor's	-10.89%	
79		*Science*Professional*	-2.76%	***	Languages*Professional	-13.31%	
80		*Medicine*Professional*	-2.91%	***	Law*Ph. D.	-13.60%	
81		Agriculture*Ph. D.	-3.68%	***	Architecture*Professional	-14.52%	*
82		Architecture*Ph. D.	-6.11%		Law*Professional	-16.67%	
83		Law*Ph. D.	-6.66%		Social Work*Professional	-40.34%	**
84		Social Work*Professional	-14.26%	*	Social Work*Ph. D.	-43.22%	

Note: Ranking of urban wage premium by college major and field of degree. Full coefficient estimates available upon request. *,**,*** denote coefficient estimates statistically different from business majors with a bachelor's degree at the 10, 5, and 1 percent level, respectively. Specifications also include demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, industry (2 digit NAICS) and census division dummies.

Figure 1. The Knowledge Space of the Economy



This figure represents the knowledge space of individuals within the economy where k is one's endowment of relatively "soft" skills. Lower values of k are associated with "hard" skills in which mastery can be attained through dilligent independent study in books, for example. Those with relatively hard skills do not experience as large productivity gains from interaction as outwardly-oriented individuals with larger endowments of soft skills.

Appendix Table 1: Field of Degree Category Components

Agriculture

- General Agriculture
- Agriculture Production And Management
- Agricultural Economics
- Animal Sciences
- Food Science
- Plant Science And Agronomy
- Soil Science
- Miscellaneous Agriculture
- Environmental Science
- Forestry
- Natural Resources Management

Architecture

- Architecture

Business

- General Business
- Accounting
- Actuarial Science
- Business Management And Administration
- Operations Logistics And E-Commerce
- Business Economics
- Construction Services
- Marketing And Marketing Research
- Finance
- Human Resources And Personnel Management
- International Business
- Hospitality Management
- Management Information Systems And Statistics
- Miscellaneous Business & Medical Administration

Computer Science

- Computer And Information Systems
- Computer Programming And Data Processing
- Computer Science
- Information Sciences
- Computer Administration Management And Security
- Computer Networking And Telecommunications

Appendix Table 1: Field of Degree Category Components (continued)

Education

- General Education
- Educational Administration And Supervision
- School Student Counseling
- Elementary Education
- Mathematics Teacher Education
- Physical And Health Education Teaching
- Early Childhood Education
- Science And Computer Teacher Education
- Secondary Teacher Education
- Special Needs Education
- Social Science Or History Teacher Education
- Teacher Education: Multiple Levels
- Language And Drama Education
- Art And Music Education
- Miscellaneous Education

Engineering

- General Engineering
- Aerospace Engineering
- Biological Engineering
- Architectural Engineering
- Biomedical Engineering
- Chemical Engineering
- Civil Engineering
- Computer Engineering
- Electrical Engineering
- Engineering Mechanics Physics And Science
- Environmental Engineering
- Geological And Geophysical Engineering
- Industrial And Manufacturing Engineering
- Materials Engineering And Materials Science
- Mechanical Engineering
- Metallurgical Engineering
- Mining And Mineral Engineering
- Naval Architecture And Marine Engineering
- Nuclear Engineering
- Petroleum Engineering
- Miscellaneous Engineering
- Engineering Technologies
- Engineering And Industrial Management
- Electrical Engineering Technology
- Industrial Production Technologies
- Mechanical Engineering Related Technologies
- Miscellaneous Engineering Technologies
- Electrical, Mechanical, And Precision Technologies And Production

Fine Arts

- Cosmetology Services And Culinary Arts
- Fine Arts
- Drama And Theater Arts
- Music
- Visual And Performing Arts
- Commercial Art And Graphic Design
- Film Video And Photographic Arts
- Art History And Criticism
- Studio Arts
- Miscellaneous Fine Arts

Fitness

- Physical Fitness Parks Recreation And Leisure

Government

- Criminal Justice And Fire Protection
- Public Administration
- Public Policy
- Criminology
- International Relations
- Political Science And Government
- Transportation Sciences And Technologies

History

- History
- United States History

Languages

- Linguistics And Comparative Language And Literature
- French German Latin And Other Common Foreign Language Studies
- Other Foreign Languages

Law

- Court Reporting
- Pre-Law And Legal Studies

Liberal Arts

- English Language And Literature
- Composition And Rhetoric
- Liberal Arts
- Humanities
- Library Science

Mathematics

- Mathematics
- Applied Mathematics
- Statistics And Decision Science
- Mathematics And Computer Science

Media

- Communications
- Journalism
- Mass Media
- Advertising And Public Relations
- Communication Technologies

Medicine

- General Medical And Health Services
- Communication Disorders Sciences And Services
- Health And Medical Administrative Services
- Medical Assisting Services
- Medical Technologies Technicians
- Health And Medical Preparatory Programs
- Nursing
- Pharmacy Pharmaceutical Sciences And Administration
- Treatment Therapy Professions
- Community And Public Health
- Miscellaneous Health Medical Professions

Psychology

- Cognitive Science And Biopsychology
- Psychology
- Educational Psychology
- Clinical Psychology
- Counseling Psychology
- Industrial And Organizational Psychology
- Social Psychology
- Miscellaneous Psychology

Religion

- Philosophy And Religious Studies
- Theology And Religious Vocations

Science

- Biology
- Biochemical Sciences
- Botany
- Molecular Biology
- Ecology
- Genetics
- Microbiology
- Pharmacology
- Physiology
- Zoology
- Neuroscience
- Miscellaneous Biology
- Nutrition Sciences
- Physical Sciences
- Astronomy And Astrophysics
- Atmospheric Sciences And Meteorology
- Chemistry
- Geology And Earth Science
- Geosciences
- Oceanography
- Physics
- Materials Science
- Multi-Disciplinary Or General Science
- Nuclear, Industrial Radiology, And Biological Technologies

Social Science

- Area Ethnic And Civilization Studies
- Family And Consumer Sciences
- Multi/Interdisciplinary Studies
- Intercultural And International Studies
- Interdisciplinary Social Sciences
- General Social Sciences
- Economics
- Anthropology And Archeology
- Geography
- Sociology
- Miscellaneous Social Sciences

Social Work

- Human Services And Community Organization
- Social Work

Appendix Table 2: Urban Wage Premium for Field of Degree-Educational Attainment Interactions

dependent variable ln(earnings)	OLS	IV
ln (MSA population)	0.039***	0.008
	(0.007)	(0.048)
Agriculture*Bachleor's*ln(MSA pop)	-0.025***	-0.045
	(0.008)	(0.039)
Agriculture*master's*ln(MSA pop)	0.012	0.147
	(0.014)	(0.084)
Agriculture*Professional*ln(MSA pop)	-0.005	-0.084
	(0.023)	(0.111)
Agriculture*Ph. D.*ln(MSA pop)	-0.076***	-0.057
	(0.021)	(0.171)
Architecture*bachelor's*ln(MSA pop)	-0.016	-0.018
	(0.010)	(0.048)
Architecture*master's*ln(MSA pop)	-0.014	-0.037
	(0.022)	(0.100)
Architecture*Professional*ln(MSA pop)	-0.039	-0.153
	(0.035)	(0.088)
Architecture*Ph. D.*ln(MSA pop)	-0.100	-0.092
	(0.078)	(0.219)
Business*master's*ln(MSA pop)	0.006*	0.017
	(0.003)	(0.013)
Business*Professional*ln(MSA pop)	0.002	-0.002
	(0.014)	(0.067)
Business*Ph. D.*ln(MSA pop)	-0.042*	0.208
	(0.025)	(0.160)
Computer Science*bachelor's*ln(MSA pop)	0.002	0.027
	(0.008)	(0.030)
Computer Science*master's*ln(MSA pop)	0.008	0.120
	(0.019)	(0.081)
Computer Science*Professional*ln(MSA pop)	0.020	-0.018
	(0.043)	(0.193)
Computer Science*Ph. D.*ln(MSA pop)	0.009	0.188
	(0.027)	(0.148)
Education*bachelor's*ln(MSA pop)	-0.019***	-0.002
	(0.007)	(0.029)
Education*master's*ln(MSA pop)	0.006	0.050
	(0.008)	(0.033)
Education*Professional*ln(MSA pop)	-0.029**	-0.091
	(0.012)	(0.060)
Education*Ph. D.*ln(MSA pop)	-0.003	-0.006
	(0.013)	(0.058)
Engineering*bachelor's*ln(MSA pop)	-0.024***	-0.050

Appendix Table 2 (continued)	OLS	IV
Engineering*master's*ln(MSA pop)	-0.012	0.018
	(0.008)	(0.055)
Engineering*Professional*ln(MSA pop)	-0.010	0.052
	(0.019)	(0.088)
Engineering*Ph. D.*ln(MSA pop)	-0.027**	0.072
	(0.012)	(0.051)
Fine Arts*bachelor's*ln(MSA pop)	0.008*	0.027*
	(0.005)	(0.015)
Fine Arts*master's*ln(MSA pop)	0.009	0.043
	(0.009)	(0.038)
Fine Arts*Professional*ln(MSA pop)	-0.010	0.014
	(0.031)	(0.080)
Fine Arts*Ph. D.*ln(MSA pop)	-0.025	-0.076
	(0.020)	(0.089)
Fitness*bachelor's*ln(MSA pop)	-0.006	-0.044
	(0.008)	(0.033)
Fitness*master's*ln(MSA pop)	-0.009	-0.064
	(0.019)	(0.067)
Fitness*Professional*ln(MSA pop)	-0.059*	-0.094
	(0.032)	(0.196)
Fitness*Ph. D.*ln(MSA pop)	-0.053	-0.037
	(0.084)	(0.177)
Government*bachelor's*ln(MSA pop)	0.007	0.035
	(0.007)	(0.029)
Government*master's*ln(MSA pop)	0.018**	0.077*
	(0.008)	(0.044)
Government*Professional*ln(MSA pop)	0.030**	0.024
	(0.012)	(0.051)
Government*Ph. D.*ln(MSA pop)	-0.005	0.102
	(0.024)	(0.097)
History*bachelor's*ln(MSA pop)	0.013**	0.040**
	(0.006)	(0.019)
History*master's*ln(MSA pop)	0.015*	0.007
	(0.008)	(0.028)
History*Professional*ln(MSA pop)	-0.010	-0.028
	(0.013)	(0.080)
History*Ph. D.*ln(MSA pop)	-0.004	0.040
	(0.019)	(0.129)
Languages*bachelor's*ln(MSA pop)	0.011	0.070**
	(0.010)	(0.035)
Languages*master's*ln(MSA pop)	0.020**	0.070**
	(0.010)	(0.034)
Languages*Professional*ln(MSA pop)	0.004	-0.141
	(0.034)	(0.193)

Appendix Table 2 (continued)		
Languages*Ph. D.*ln(MSA pop)	-0.014	0.035
	(0.031)	(0.089)
Law*bachelor's*ln(MSA pop)	0.000	-0.117
	(0.027)	(0.098)
Law*master's*ln(MSA pop)	0.054	-0.032
	(0.038)	(0.177)
Law*Professional*ln(MSA pop)	0.037	-0.175
	(0.059)	(0.273)
Law*Ph. D.*ln(MSA pop)	-0.106	-0.144
	(0.121)	(0.775)
Liberal Arts*bachelor's*ln(MSA pop)	0.009**	0.034*
	(0.004)	(0.018)
Liberal Arts*master's*ln(MSA pop)	0.019**	0.071**
	(0.008)	(0.036)
Liberal Arts*Professional*ln(MSA pop)	-0.008	-0.089
	(0.014)	(0.088)
Liberal Arts*Ph. D.*ln(MSA pop)	-0.040***	-0.019
	(0.012)	(0.053)
Mathematics*bachelor's*ln(MSA pop)	-0.003	-0.056
	(0.012)	(0.036)
Mathematics*master's*ln(MSA pop)	0.041***	0.072**
	(0.008)	(0.028)
Mathematics*Professional*ln(MSA pop)	0.021	-0.015
	(0.037)	(0.088)
Mathematics*Ph. D.*ln(MSA pop)	0.014	0.167 **
	(0.018)	(0.081)
Media*bachelor's*ln(MSA pop)	0.010***	0.017
	(0.003)	(0.013)
Media*master's*ln(MSA pop)	0.010	0.072*
	(0.008)	(0.041)
Media*Professional*ln(MSA pop)	0.010	-0.059
	(0.019)	(0.119)
Media*Ph. D.*ln(MSA pop)	-0.025	-0.039
	(0.034)	(0.133)
Medicine*bachelor's*ln(MSA pop)	-0.004	0.049 *
	(0.007)	(0.027)
Medicine*master's*ln(MSA pop)	-0.010*	0.032
	(0.006)	(0.024)
Medicine*Professional*ln(MSA pop)	-0.068***	0.014
	(0.013)	(0.052)
Medicine*Ph. D.*ln(MSA pop)	-0.005	0.007
	(0.017)	(0.065)
Psychology*bachelor's*ln(MSA pop)	0.003	0.043**
	(0.005)	(0.020)

Appendix Table 2 (continued)		
Psychology*master's*ln(MSA pop)	0.014**	0.051**
	(0.007)	(0.022)
Psychology*Professional*ln(MSA pop)	-0.025*	0.019
	(0.014)	(0.067)
Psychology*Ph. D.*ln(MSA pop)	-0.030***	0.020
	(0.011)	(0.056)
Religion*bachelor's*ln(MSA pop)	-0.008	0.074
	(0.012)	(0.050)
Religion*master's*ln(MSA pop)	-0.018	-0.091**
	(0.012)	(0.040)
Religion*Professional*ln(MSA pop)	-0.025	0.078
	(0.020)	(0.101)
Religion*Ph. D.*ln(MSA pop)	-0.031	-0.029
	(0.019)	(0.060)
Science*bachelor's*ln(MSA pop)	-0.003	0.034
	(0.004)	(0.021)
Science*master's*ln(MSA pop)	-0.002	0.064*
	(0.008)	(0.036)
Science*Professional*ln(MSA pop)	-0.067***	-0.048
	(0.014)	(0.046)
Science*Ph. D.*ln(MSA pop)	-0.033***	-0.042
	(0.007)	(0.028)
Social Science*bachelor's*ln(MSA pop)	0.015***	0.019
	(0.005)	(0.016)
Social Science*master's*ln(MSA pop)	0.036***	0.069***
	(0.008)	(0.026)
Social Science*Professional*ln(MSA pop)	-0.008	-0.060
	(0.013)	(0.068)
Social Science*Ph. D.*ln(MSA pop)	-0.007	0.096
	(0.010)	(0.078)
Social Work*bachelor's*ln(MSA pop)	0.008	0.084**
	(0.014)	(0.036)
Social Work*master's*ln(MSA pop)	-0.002	0.058
	(0.010)	(0.036)
Social Work*Professional*ln(MSA pop)	-0.182*	-0.411**
	(0.098)	(0.200)
Social Work*Ph. D.*ln(MSA pop)	0.010	-0.440
	(0.036)	(0.529)
Observations	333,530	282,668
R^2	0.394	0.388

Note: Standard errors, clustered by MSA in parentheses. *,**,*** denote coefficient estimates statistically different from zero at the 10, 5, and 1 percent level respectively. Specifications also include demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request.