

ESSAYS ON HUMAN CAPITAL HETEROGENEITY AND AGGLOMERATION

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ABSTRACT

This dissertation consists of three essays exploring how human capital heterogeneity within cities enhances individual productivity. Agglomeration theory suggests productivity is driven by rapid and frequent interactions with others in spatially-constrained areas. Using formal education data from the 2011 American Community Survey, we empirically test that theory by estimating the effects of local human capital stock characteristics on individual wages.

In essay one, we posit that some kinds of knowledge are harder to exchange remotely and thus workers possessing those knowledge types benefit more from close physical proximity to others. Our theoretical framework demonstrates the returns to finding a partner to exchange ideas with are heterogeneous across knowledge types. We propose agglomerative environments favor “soft skills” where creativity and informal networking are important. Our empirical results show people with non-STEM majors benefit more from locating within a city. Conversely, terminal degrees such as a J.D. or M.D. experience a smaller urban wage premium.

Essay two studies the role of specialization of human capital types for individual productivity. Glaeser et al. (1992) finds local industrial specialization has a non-increasing effect on employment and wage growth. Our empirical results indicate specialization of knowledge can play an important role in promoting productivity when simultaneously controlling for a population size effect via the urban wage premium. We find STEM-related knowledge benefits greatly from local specialization of knowledge. However, the urbanization effect from city population size often exceeds the specialization effect.

The third essay studies how workers in cities learn from one another in dense economic settings. Following Winters (2014), we estimate the impact of changes in the local stock of particular knowledge types on individual wages. The richness of our data allows us to estimate the productivity effects from over 400 different combinations of human capital interactions. We find most knowledge types are more productive when local STEM presence increases. The effect is strongest among workers with higher levels of educational attainment in the earlier stages of their careers. Similarly, areas such as government and psychology generate productivity gains among others. However, the lowest productivity gains occur from interactions with religious or education backgrounds.

DEDICATION

This dissertation is dedicated to the memory of Dr. Tyrone Ferdnance. You laid the foundation for everything I know in this discipline. I am forever grateful for your vision and encouragement.

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INTRODUCTION

This dissertation consists of three essays exploring the role of human capital heterogeneity on worker productivity within cities. Acknowledge human capital stock as a productive local amenity (Roback, 1982; Lucas, 1988), agglomeration theory suggests productivity is enhanced by rapid and frequent interactions with others in spatially constrained areas. Using formal education data from the 2011 American Community Survey, we empirically test that theory throughout this dissertation by estimating the effects of local human capital stock characteristics on individual wages. Specifically, we estimate wage premiums across 21 human capital types, defined by undergraduate major, accruing from frequent, specialized, and diverse interactions. We call these returns to interaction the urban wage premium, specialization premium, and composition premium, respectively.

The first essay, “Heterogeneous Returns to Knowledge Exchange: Evidence from the Urban Wage Premium”, we present a theoretical framework in which individuals randomly search for partners to exchange ideas. However, 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 empirically test this prediction, by regressing city population size on worker wages, controlling for demographic and regional productivity effects, and find that the urban wage premium varies considerably across majors. In line with the predictions of our model, people with non-STEM (soft) 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 J.D. or M.D. experience a smaller urban wage premium.

Essay two, “Productivity Gains from Spatial Concentration of Human Capital: Is Specialization or Diversity More Important?,” studies the role of local specialization of human capital types for individual productivity. This topic has generated large attention since Glaeser et al. (Journal of Political Economy, 1992) who find local industrial diversity augments employment and wage growth while specialization has a non-increasing effect. We mimic their data construction by aggregating data on formal education from the American Community Survey into “city-human capital type” observations to study the impact of own-type human capital specialization on wages. Our results indicate specialization of knowledge can play an important role in promoting productivity when simultaneously controlling for a population size effect via the urban wage premium. In particular, STEM-related knowledge benefits greatly from local specialization of knowledge. However, the urbanization effect from city population size often exceeds the specialization effect. Robustness checks via the use of instrumental variables and the estimation of density premiums are also included.

The third essay, “Productivity Gains from Knowledge Exchange across Different Types of Human Capital”, estimates the returns to cross-disciplinary interactions. In particular, we posit that cities promote informal exchange of knowledge between individuals with different types of human capital. Expanding on the work of Winters (2014), we construct employment shares for 21 different categories of majors across cities. We proceed by estimating how the impact of an increase in the local stock of particular types of knowledge affects wages across the distribution of human capital in cities. Notably, the richness of our data allows us to estimate the productivity

effects from over 400 different combinations of human capital interactions. We find that most knowledge types – regardless of their college major or their occupation – are more productive when local STEM presence increases, indicating that individuals learn the most from interacting with individuals who have STEM backgrounds. In particular, the effect is strongest among workers with higher levels of educational attainment in the earlier stages of their careers. In a similar manner, areas such as government and psychology generate productivity gains among others. However, the lowest productivity gains occur from interactions with religious or education backgrounds.

CHAPTER 1

HETEROGENEOUS RETURNS TO KNOWLEDGE EXCHANGE: EVIDENCE FROM THE URBAN WAGE PREMIUM

1.1 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 fronts 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, 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 in 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 sectors 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

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 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.

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 incorporate that the gains from information sharing 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 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 increase more) in larger 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 (2009) 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 this manner, our work complements recent contributions by Abel et al. (forthcoming) who find that larger labor markets better align an individual's job requirements to their previous human capital investments. The key observation behind our work is that the desire for better information sharing in urban settings depends on an individual's type of human capital.

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). The major serves as the empirical counterpart for an individual's type of knowledge in the model. The ACS geocodes respondents by Primary Use Microdata Area (PUMA) that we match to MSAs. MSA population size and its interactions with college major type are our principal independent variables of interest.

While individuals with hard science majors tend to earn more on average, the urban wage premium tends to be highest for individuals that majored in humanities or social sciences.² The five majors with the largest wage premiums had degrees that might typically be associated with soft skills: social science, history, media, liberal arts, and fine arts. Each of these majors likely depends on creativity, interpersonal skills, or informal networking capabilities, consistent with the findings of Bacolod, Blum and Strange (2009) that communication and human focused occupations enjoy larger urban wage premiums.³ Our results are also closely related to Abel et al. (2014) who observe that occupations in urban economies rely more on social skills and the ability to generate ideas than in rural areas. In addition, in our work, the lowest (and statistically significant) urban wage premiums are observed in STEM, agriculture, and architecture.

We also study how the urban wage premium varies by highest reported degree. We find that degrees that imply mastery of an existing cannon of knowledge such as a J.D. or M.D. and are likely associated with some type of certification or occupation license, experience a much smaller urban wage premium than do people with just a Bachelor's or Master's degree. The latter may require more on-the job training which may be accrued faster in cities.

In addition, we observe that the urban wage premium varies across major and highest degree. In particular, we find that many measures of lateral variation in human capital are significant at both the bachelor's and master's levels. However, regardless of the depth of human capital, the same basic insights emerge – majors related to soft skills are more highly rewarded than hard skills in dense economic environments.

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.

What accounts for our finding that STEM workers benefit less from city size? We explore a number of competing explanations. First, we look at whether some industries tend to favor non-STEM workers more than others. Using data at the 2-digit NAIC industry level, we find that within nearly half of the industries, the urban wage premium is statistically different between STEM and non-STEM workers. And, in each of these industries, the urban wage premium is smaller for STEM workers. This suggests that the wage differential is not driven by a small number of industries or other unobserved productive amenities that draw firms to larger, more expensive cities. We also find that even within similar occupations, workers with non-STEM majors often earn more than workers with more technical majors as the size of a city increases.

We then appeal to demographic differences in order to understand the source of the urban wage premium differential. To begin, we examine how the UWP varies by age. Strikingly, young workers (21-28 years of age) do not have statistically different urban wage premiums between STEM and non-STEM workers. However, the differential is positive and increases up to age 50, the prime working years. We think this finding is emblematic of our model in which there is worker learning in cities (rather than sorting to cities by unobserved ability). At the youngest parts of the lifecycle, there has not yet been much time to learn from others. However, over time, non-STEM workers acquire more human capital through their interactions in urban environments.

Further, on the basis of previous work on the role of foreign STEM workers in urban economies by Peri et al. (2015), we exclude foreign born workers. Again, the differential is in-line with the results from the full sample of workers. Next, we seek to inquire whether co-location issues within married households may be responsible. Consequently, we divide the

sample into three groups: 1) single individuals, 2) married respondents, and 3) married persons with spouses that work full-time. In all three cases, we find that the urban wage premium differential is present.

One might perceive that differential urban wage premium may be driven by unobserved heterogeneity. For example, if people with “hard” skills have less variance in unobserved ability than do people with “soft” skills, we might expect only the most talented soft skilled workers to pay the extra costs of moving to a big city. For the less skilled it simply wouldn’t be worth it. Stated differently, the UWP may be driven by sorting on ability, not knowledge sharing (Glaser and Mare, 2001). Thus, our gap in the STEM premium could also be driven by sorting if STEM workers are less heterogeneous in their ability (perhaps because people with STEM degrees have self-selected into more difficult majors). However, in the ACS, it is hard to control for unobserved ability as in Moretti (2004) and Glaeser and Mare (2001) because the ACS does not track individuals over time as in longitudinal data sets. Consequently, even though multiple years of the survey are available, it is not possible to estimate individual fixed effects which would help control for unobservable characteristics that might in some way be part of the explanation for the differences in the urban wage premium between STEM and non-STEM majors.

Nevertheless, if worker ability is observable to employers (but not the researcher) then we should not expect it to vary by how long they have lived in a large city. High-ability workers should command a premium as soon as they arrive in the city. Yet, they do not. This suggests that non-STEM workers learn more over time in urban environments than STEM workers as articulated by our modeling framework. Moreover, Baum-Snow and Pavan (2012) show that controlling for the level of education, there is little or even negative sorting to large cities based on unobserved ability.

None of these findings imply that STEM workers are unimportant in inventive activity or that spillovers do not occur in high-technology industries where large amounts of resources are allocated to developing new ideas. There are numerous prior contributions which focus on subsectors of the economy and measure spillovers through patent data, especially in high technology industries. For example, using patent citations, Jaffe et al. (1993) find that knowledge spillovers tend to be localized. In addition, Jaffe et al. (1996) study patent citations from work in federal labs and universities in the United States. See also Jaffe et al. (1998).

In terms of the linkages between inventive activity and the extent of agglomeration, Carlino et al. (2007) study the role of population density for innovative activity. In particular, both Carlino et al. and Grilliches (1990) point out that the extent of patenting activity varies across industries. In contrast to the importance of physical capital and skilled workers for R&D, we follow papers such as Ciccone and Hall (1996), Glaeser and Mare (2001), Rosenthal and Strange (2008), and Bacolod, Bloom, and Strange (2009) which look at the positive effects on overall output coming from the concentration of human capital.

Obviously, inventive activity depends on R&D and access to human capital as observed by Carlino et al. In those industries where patenting is more prominent, STEM majors are certainly important inputs. Consequently, there would be high social returns from the concentration of inputs into R&D in areas such as Silicon Valley.

By comparison, across the economy as a whole where patenting is not as important as the R&D-intensive sectors, we contend that STEM majors experience lower productivity gains from agglomeration than non-STEM individuals. This does not imply that STEM majors do not benefit from urbanization, just that the benefits are lower than the non-STEM category.

Admittedly, our paper does not address how individuals learn from others in R&D-intensive

industries. We also do not wish to imply that spillovers from STEM majors are non-existent – for example, Winters (2014) finds that STEM graduates generate larger spillovers to wages of other workers in metropolitan areas than non-STEM workers. However, we do find that the *returns to agglomeration* are higher among non-STEM workers.

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 and our robustness checks. There is a brief conclusion.

1.2 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.⁴ 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

⁴ See also Helsley and Strange (1990) who show that agglomeration economies enhance matches between firms and workers with heterogeneous skills.

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.

1.2.1 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 decreases. 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:

$$S(k, k') = q + k(1 - \delta(k, k')) \quad (1)$$

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.⁵ 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 $r > 0$.

1.2.2 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.⁶

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

⁵ 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.

⁶ The specification of the matching technology follows Glaeser (1999) for tractability.

will accept and exchange ideas. Given that the knowledge space has a circumference of I , 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 .

1.2.3 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 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 :

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

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:

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

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 :*

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

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

1.2.4 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:

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

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:

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

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:

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

1.2.5 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 $k > \bar{k} = \frac{2(r+\eta)q}{\alpha N}$.

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:

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

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

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 the urban wage premium varies according to individuals' base of knowledge.*

The balance of the paper is dedicated to finding empirical evidence of this. Under an alternative specification, one might posit that individuals with “soft” knowledge would have a large desire to share information regardless with whom they meet. Such a framework would not generate the same clear benefits from population density.

1.3 DESCRIPTION OF THE 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 U.S. 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.⁷

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 (using 2003 CBSA boundaries) that we believe best approximate a labor market and pool for knowledge exchange.⁸ We drop individuals not residing in an MSA. We use MSA population as our primary independent variable of interest, and use the MSA-level unemployment rate to control for local labor market conditions.⁹

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.¹⁰ Thus, we can study how the urban wage premium varies across rich dimensions of vertical human capital attainment among workers in the labor force.

⁷ 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.

⁸ 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.

⁹ We take the unemployment rate from Bureau of Labor Statistics via the FRED database of the Federal Reserve Bank of St. Louis.

¹⁰ 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.

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.¹¹ 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 occurs in the city, we use an indicator for, and sometimes exclude, people having recently moved to a MSA.¹² 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.¹³

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

¹¹ See, for example, Rauch (1993), Roback (1982), and Bacolod et al. (2009).

¹² 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.

¹³ Census region and division definitions are available at:
http://www.census.gov/econ/census07/www/geography/regions_and_divisions.html.

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.¹⁴

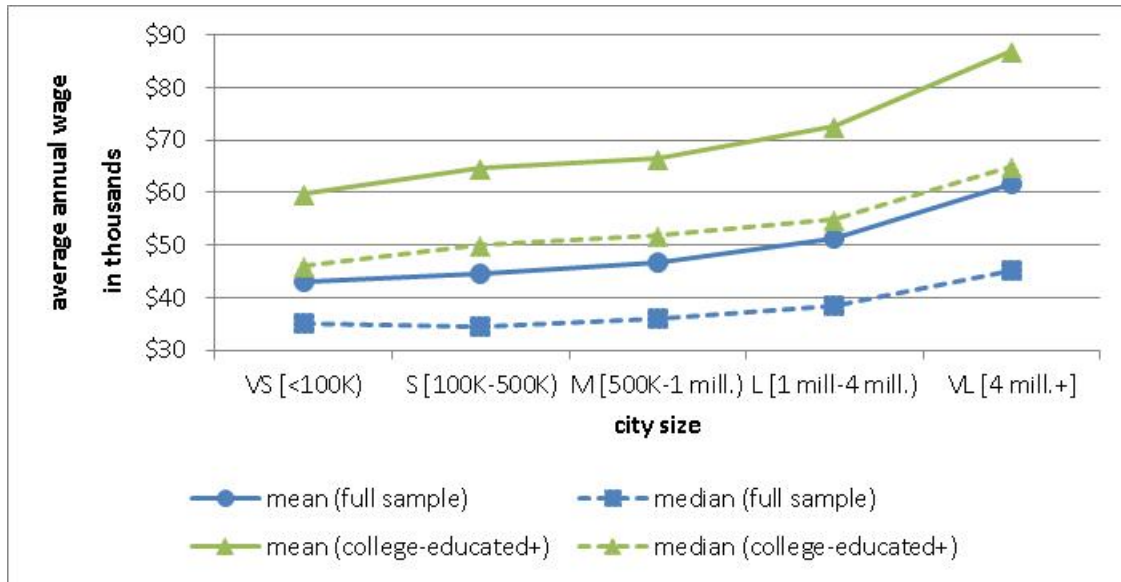
To gain a better understanding of the geographical distribution of our sample, we categorize MSA population size as follows: VS (very small, less than 100,000; example, Cheyenne, WY); S (small, 100,000 – 500,000; Tallahassee, FL); M (medium, 500,000 – 1 million; Birmingham, AL); L (large, 1 million – 4 million; Memphis, TN-AR-MS); and VL (very large, greater than 4 million; New York-Northern New Jersey-Long Island, NY-NJ-PA). 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. In all we identify 265 separate MSAs.

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.

¹⁴ 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%).

¹⁵ Percent representation in the full sample/% representation in the restricted sample.

Figure 1.1: 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 1.1, 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 1.1: 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.

1.4 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 from interacting with others is captured by the coefficient on 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 that choose to locate in high-wage/high-rent cities do so because workers are more productive there. Nevertheless, we allow for some regional variation in productivity by including dummy variables for Census division.¹⁶

Still, a central challenge to our econometric analysis is that if workers are completely mobile and indifferent across locations, why do we observe a mix of majors in every city? We posit that there is some heterogeneity in location preferences across individuals due to their desire to maintain social capital, community ties, or family relationships. For example, DiPasquale and Glaeser (1999) study the connections between limited mobility, homeownership, and social capital accumulation. In addition, Glaeser and Redlick (2008) contend that social capital does not transfer across locations. In particular, they develop a model in which social capital accumulation reduces the incentives for outward migration across locations.

In addition, co-location constraints (Costa and Kahn, 2000 and Compton and Pollak, 2007) may be a deterrent to labor market migration. Alternatively, differential tastes for urban amenities as in Black et al. (2009) can also prevent complete separation by knowledge type. Notably, if STEM workers prefer urban amenities more than non-STEM majors, then what would appear to us to be lower productive spillovers for large cities could instead be a compensating wage differential.

¹⁶ The south Atlantic division serves as the reference group.

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 Mincer (1974) equation:

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

where w_{is} is the annual wage earnings of individual i in city s . We include demographic variables, X_{is} , which includes age and age² 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 the workers current industry of employment and the respondent's weekly hours worked.¹⁷

While workers may gain knowledge from interacting with others like themselves, so too may firms. As discussed by Jaffe et al. (1993, 1998), this may come in the form of knowledge spillovers from research and development or through better matches between workers and firms as shown by Helsley and Strange (1990). Or, certain cities have some endowment such as better

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.

infrastructure or the presence of research universities and federal labs (Jaffe et al. 1996) that are particularly attractive to certain firms. These firm co-agglomerations could increase firm TFP but also worker wages. At the same time, the presence of these industry clusters and higher wages could attract additional workers which increase city population and introduce a spurious correlation between city size and wages. To control for this possibility, we also include the share of workers in the MSA in the same industry as the respondent. Combined with the industry fixed effects, we believe this variable controls for the effect of firm concentration on wages.

Our ultimate aim is to understand how types and levels of education interact with city size to raise observed wages and, by implication, worker productivity. Thus, we first incorporate the 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 stopped with 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:

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

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,

$$H_a: \varphi_{m=bus} \neq \varphi_{m \neq bus} .^{18}$$

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:

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

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 individuals' undergraduate and

¹⁸ We acknowledge that the model demonstrates that individuals receive higher wages through interactions with others. Admittedly, as in previous contributions in the agglomeration literature, we do not have observable information on contacts between people. However, better contacts between people lead to higher productivity. Our objective is to show that the returns to agglomeration (as measured in the form of labor productivity) vary across the different types of human capital as predicted by our modeling framework.

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 specifications where subsequent training may obscure the effects of undergraduate major.

1.5 DISCUSSION OF THE RESULTS

In this section we seek empirical validation of the 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 literature, we first replicate and extend some existing findings. Column 1 of Table 1.2 presents the coefficient estimate of (log) MSA population on a worker's wages. As expected, earnings increase with city size. Controlling for several demographic characteristics of the worker, their industry, the city's unemployment rate and census division, doubling the population size is associated with a 7.2 percent increase in wages for the average worker. This coefficient estimate is similar to the findings of Bacolod, Blum, and Strange (2009).

Next, we look at how the UWP varies with educational attainment. Rauch (1993) studies human capital externalities across cities based upon self-reported years of formal schooling which implies that each year generates the same returns in terms of labor productivity.¹⁹ Alternatively, Glaeser and Mare (2001) impose various educational dummies across years of schooling to impute the highest degree obtained. They also are unable to observe post-bachelor's educational attainment. The ACS actually contains nine different categories for levels of

¹⁹ 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.

schooling obtained and distinguishes between several types of graduate degrees. 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.

Column 2 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 3 of Table 1.2 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 do not 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 M.D. or a certificate as mechanic, as examples, 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 qualify them for a specific profession. Instead, these people are expected to learn more on-the-job. Thus, their earnings may depend more on developing industry specific knowledge or social capital that augments their careers. If this post-educational learning happens faster in cities, then that would explain the non-monotonic nature of the UWP with respect to the level of education. However, as we postulate in Section II, some knowledge may be easier to exchange in person than other types and so we may also see different UWPs across different types of undergraduate degrees. We explore the empirical evidence for this in the balance of the paper.

1.5.1 Horizontal Differentiation of Human Capital

We now turn to horizontal differences in human capital. This lateral variation in human capital is first introduced by dividing college graduates based on whether their undergraduate degree was in a STEM or non-STEM field. We then include twenty dummy variables for different types of undergraduate majors (business majors are the omitted category). We include the college major dummies into our earnings equation and interact them with city size, allowing each major to benefit differentially by 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 to working 333,524 individuals. Column 1 shows the UWP premium for these more educated workers is very similar to the UWP for all workers. Also, as discussed in the introduction, firms also likely benefit from

co-agglomeration of businesses within the same industry. Thus, in Table 1.3 we present the coefficient estimate for share of workers in the MSA that are in the same 2-digit NAIC industry as the respondent.²⁰ After controlling for national industry wages (with 2-digit industry fixed effects), own-industry share of employment captures the relative concentration of a particular industry within the MSA and the resulting coefficient estimate is positive and highly significant.

Column 2 of Table 1.3 presents the coefficient estimates when we divide college graduates into STEM and non-STEM majors. Despite being more compensated overall (STEM majors earn 17% more than other college graduates on average) they experience a significantly smaller urban wage premium. The coefficient estimate: $\hat{\varphi}_{m=STEM} = -0.017$ and is statistically different from zero at all standard cut-offs. We thus reject the null in favor of the alternative hypothesis: $H_a: \varphi_{m=STEM} < \varphi_{m \neq STEM}$, indicating that non-STEM majors appear to experience a larger UWP. This finding is consistent with the model presented in Section II and empirical work such as Lee (2010) and the rewards to “people skills” found in Bacolod, Blum and Strange (2009). However, there are a number competing explanations that we turn to shortly, but first we present the coefficient estimates for the UWP by majors in Column 3 of Table 1.3.

Disaggregating majors reveals some interesting nuances. The UWP is highest for social science, followed by mathematics, law, government, and history. Mathematics (perhaps consistent with the BBS (2009) finding with respect to cognitive skill) is the only STEM field in the top tercile and the only STEM field with an UWP statistically larger than business. People with degrees in science, medicine or engineering all have statistically smaller wage premiums

²⁰ We control for share of employment in respondent’s own industry throughout the analysis, but we present in Table 1.3 to acknowledge and control for an alternative source of agglomerative pressure that may drive the urban wage premium.

than business majors. Computer science majors appear to experience a similar UWP as business majors.

1.5.2 Multi-dimensional Variation in Human Capital

One concern with the estimates presented in Table 1.3 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 effect of undergraduate major (though it may not be in the field where the highest degree was obtained) is 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 net UWPs, the overall urban wage premium, $\hat{\delta}$, (for the omitted category, undergraduate-only business major) plus the specific major \times degree premium, $\hat{\varphi}_{mi}$, and convert the premiums to percentages and present the results in Table 1.4. These percentages can be interpreted as the expected increase in wages for a worker with a given educational endowment for moving to a city twice as large. Interacting the 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.

We are primarily interested in looking at the results for individuals with only bachelor's degrees since that is the most accurate information in terms of the highest type of human capital obtained. The results continue to buttress the 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. Media (4.98% ***), 4. Liberal Arts (4.85% **), and 5. Fine Arts (4.77% *). 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 is no longer statistically different from business.

However, we also find that undergraduate college major continues to be important at even higher levels of attainment. For example, at the master's level, the top fields appear to be dominated by soft skills: 1. Government (5.73% **), 2. Psychology (5.34% *), 3. Education (4.51% **), 4. Social Work (3.70% *), and 5. Science (3.75% ***). All of these measures of the urban wage premium but one (Social Work) 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. Though the evidence is not as strong among professional degree holders, it is still largely consistent with the results of our modeling framework: 1. Law (7.60% *), 2. Media (4.88% *), 3. Languages (4.33% **), 4. Agriculture (3.46% ***), 5. Fine Arts (2.90% ***), and 6. History (2.88% *). Though the ranking for Ph.D.s is not as consistent, three out of the top 5 are soft fields: 1. Mathematics (5.29% **), 2. Computer Science (4.84% *), 3. History (3.52% *), 4. Social Science (3.18% ***), and 5. Languages (2.57% ***).

One might argue that the results for Ph.Ds are less likely to be driven by incentives in our model as individuals with the highest levels of educational attainment may place a larger value on urban amenities. Interestingly, if one were to rank the different estimates of the urban wage premiums, the top premiums tend to occur in degrees that might be considered non-terminal (bachelor's and master's level.) The bottom quartile is dominated by Professional and Ph.D. degrees (our so-called terminal degrees).

1.5.3 Alternative Sources of the Smaller STEM Urban Wage Premium

While the empirical evidence presented so far is consistent with a model of agglomeration where “soft knowledge” is more easily shared through direct personal interaction afforded by big cities, or, alternatively that “hard knowledge” is more easily shared remotely, there are a number of competing explanations for the lower UWP earned by STEM workers. We address a number of these in turn below.

As previously mentioned (please see p. 22), the first, and most immediate explanation comes from work on the co-agglomeration of firms. The rise of industry clusters in certain cities such as information technology around San Jose or finance in New York could arise not from information sharing between workers in those cities but instead from backward or forward linkages in production, labor market pooling and search, or attributes of different cities such as the presence of research universities, a port or other critical pieces of infrastructure. This could raise firm and worker productivity, and attract workers to the city.

If certain industries need these co-agglomerations or city-specific amenities more than others they may crowd into larger cities. For example, Moretti (2013) considers that college graduates have consistently been drawn to cities with high costs of housing. One might believe that firms would increasingly need to compensate their employees for the additional housing and

commuting costs associated with larger cities, not because the workers are more productive, but because the firms are more productive and they need workers. If certain industries that benefit less from these co-agglomerative forces, say manufacturing, disproportionately employ STEM educated college workers then they will be less attracted to large cities and will not need to compensate their workers accordingly, perhaps generating a spuriously low UWP.

To address this concern we look at how the UWP varies across STEM/non-STEM majors *within* the same industry. Specifically, we estimate a triple interaction of the STEM major dummy, with our 2-digit NAICs industry dummies and city worker population. If the premium on city size simply reflects the needs of certain firms to be in larger cities, rather than the underlying skills of workers in large cities, we should expect that both STEM and non-STEM workers in the same industry would enjoy a similar UWP as those workers bid for the same houses and congest the same roads. Table 1.5 presents the coefficients for STEM and non-STEM workers within the same industry and the difference between them. For some industries, there is no statistical difference between both types of workers within the same industry. Within nearly half of the industries, the urban wage premium is statistically different between STEM and non-STEM workers. And, in each of these industries, the UWP for non-STEM workers is larger.

In a similar vein, we also look at the UWP within the same occupation categories. This specification is a little bit less transparent as it might be difficult to assign categories to occupations as requiring “hard” or “soft” skills. However, people with different educational backgrounds can and do end up doing the same job and they may, to some extent, use the knowledge they acquired as undergraduates to help them perform their jobs. An engineer still has to write reports and give presentations and a marketing executive still needs to understand a budget forecast. If larger cities afford greater sharing of soft knowledge, then if a non-STEM

worker has the same job as someone with a STEM major, we might expect them to get better at their job faster as they apply their non-STEM human capital and learn more from others in a big city.

We present the coefficient estimates for the triple interaction of occupation dummies and STEM status with city population size in Table 1.6. In a small number of occupations (managers, social workers, and lawyers/paralegals), individuals with STEM undergraduate majors earn statistically more in large cities than do non-STEM majors. However, there were eleven other occupations where the worker with a non-STEM degree had a statistically larger UWP. Thus, the majority of evidence continues to be supportive of the predictions from our modeling framework.

The small STEM urban wage premium could also be driven by unobserved heterogeneity. For example, if people with “hard” skills have less variance in unobserved ability than do people with “soft” skills, we might expect only the most talented soft skilled workers to pay the extra costs of moving to a big city. For the less skilled it simply would not be worth it. Stated differently, the UWP may be driven by sorting on ability, not knowledge sharing (Glaser and Mare, 2001). Thus, our gap in the STEM premium could also be driven by sorting if STEM workers are less heterogeneous in their ability (perhaps because people with STEM degrees have self-selected into more difficult majors). However, if worker ability is observable to employers (but not the researcher) then we should not expect it to vary by how long they have lived in a large city. High-ability workers should command a premium as soon as they arrive in the city. On the other hand, if the UWP premium is the result of knowledge exchange we might expect it to increase with exposure.

To that end, we now turn to whether demographic explanations may be behind the source of the UWP differential. First, we consider the role of the labor market lifecycle. While we know

little about the respondent's migration history in the ACS, other than whether they moved within the last year, which we control for, but we can infer that younger workers must have less experience in any city. Also, if most working age migration occurs at a relatively young age, before people have children or marry we may infer that many older workers we observe have spent their working lives in their current city of residence. Thus, we can assemble a rough test of the competing hypotheses. If the UWP and the STEM gap is the product of sorting by unobserved ability, we should expect the UWP and the wage gap to remain relatively constant over the life course. On the other hand, if the UWP is driven by knowledge exchange, we should expect it to grow over time.

Table 1.7 presents the UWP stratified by age cohorts. Workers 21-28 years of age, presumably early in their careers, have a relatively small UWP of 0.05, and the UWP for STEM workers is not statistically different from non-STEM workers. Workers between 29 and 35 have a larger UWP and the gap between the STEM UWP and non-STEM UWP is now statistically significantly smaller than the non-STEM worker's. The UWP is even larger, as is the associated gap between STEM and non-STEM workers for the 35-50 gap. For the oldest cohort of workers, age 51-65, the UWP is slightly smaller and STEM gap narrows, but remains statistically different from zero. The lower UWP and smaller STEM gap could be driven by older workers (perhaps in bridge-jobs) migrating to lower productivity, but amenity rich cities (Chen and Rosenthal, 2008).²¹

Next, based upon the work by Peri et al. (2015) on the role of non-native STEM workers, we exclude immigrants from our analysis. If immigrants are particularly reliant on these

²¹ Lee (2010) suggests that lower urban wage premiums would be expected of skilled workers who value amenities. See also Moretti (2013). Black et al. (2009) also contend that different urban wage premiums reflect the value of amenities.

networks which are often found in large cities, and STEM workers are favored for visas, then we might worry that these workers push down observed STEM wages in big cities either because they themselves accept lower wages or because they serve as a supply shock for native STEM workers.²² In Column 1 of Table 1.8 we limit the sample to native-born college educated workers. Restricting the sample actually increases our estimates of the UWP and the STEM gap.

Our final demographic specification looks at the role of marriage. For example, the differential may be driven by STEM workers who choose to live in big cities because it also provides a good labor market for their non-STEM major spouses. If so, then STEM workers may accept lower wages in order to raise household income. Column 2 of Table 1.8 focuses exclusively on individuals who are married. The results indicate that married individuals enjoy a slightly higher urban wage premium, but the STEM/Non-STEM differential is more negative.

In order to examine whether the co-location hypothesis plays a role, we proceed by studying married individuals who also have a spouse that works full time. Interestingly, the results in Column 3 indicate that the UWP further increases but the differential is about the same as the full sample of married respondents. Consequently, one might perceive that the differential primarily exists among married workers. To exclude this possibility, Column 4 looks at unmarried individuals. The STEM differential continues to be negative and highly significant. This might reflect that many single individuals are also relatively young so the differential (as suggested by the age cohort regressions in Table 1.7) would not be as strong. Nevertheless, demographics do not appear to be the reason why the UWP differential exists.

Finally, one might worry that the UWP is driven primarily by soft-major workers in the public sector. That is, individuals with a background in government and social science earn rents as

²² Note, however, that Peri et al. find that foreign STEM workers actually raise the wages of native STEM workers by raising city TFP. Perhaps their contribution to TFP comes via added knowledge exchange.

government employees in larger cities (sometimes referred to as the Leviathan Hypothesis).

However, our results are largely unchanged if we exclude government workers from the analysis as shown in the last column of Table 1.8.

1.6 CONCLUSION

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 to exchange knowledge 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 and the industry composition, we find that the urban wage premium varies considerably across majors. In line with the predictions of our model, non-STEM jobs experience a greater wage premium than do non-STEM majors. 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. However, the STEM dichotomy obscures some interesting variations within major. Consistent with Lee (2010), we find that people with an undergraduate degree in medicine (and also engineering) have relatively low wage premiums.

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 J.D. or M.D. experience a smaller urban wage premium. Among those that only have a Bachelor's or Master's degree, majors associated with softer skills seem to get the greatest wage boost from city size.

We wish to reiterate that cross-sectional evidence presented here is only consistent with differential learning by hard and soft skills, as posited in the model. The key empirical contribution of the paper is to utilize the previously unavailable information on advanced degrees and college majors provided in the ACS, but the ACS is only cross-sectional, so we are unable to follow workers over time or across cities. Thus, a number of competing phenomenon could also be at play that could generate the larger non-STEM premium.

Neither the model nor the empirics explicitly accounts for sorting across cities by workers or firms. Cities may have unobserved productive amenities that are particularly attractive to certain industries which, in turn, may cause those cities to be larger. Firms in these industries would then need to compensate workers to live in larger, more expensive cities. However, we control for the concentration of workers in the respondents industry and we observe a larger non-STEM urban wage premium even within the same industries and occupations suggesting that cities are benefiting particular workers.

Second, workers may be sorting themselves by unobserved ability. Again, if cities are expensive, and perhaps because of the relative lack of certification and credentialing in non-STEM fields, wages show more variation in those fields, only the most talented or ambitious will

pay the higher housing costs to live in large cities. In the absence of panel data, we can't replicate the wage growth and portability that Glaeser and Mare (2001) show to demonstrate productivity-enhancing learning has occurred in the city. However, we observe that the non-STEM premium is absent for younger workers but appears and grows larger for workers further along in their careers. If cities simply attracted better non-STEM workers, we might expect the wage premium to be evidenced throughout the age distribution. Finally, if, STEM workers disproportionately favor urban amenities, then they may crowd into large cities and depress wages in those fields relative to non-STEM workers. It is unclear to us why, for example, an engineer would prefer the opera to a social scientist. Nor is the distribution of majors by cities size presented in Table 1.1 isn't consistent with this STEM workers disproportionately concentrating in cities, however, if they do and those preference increase with age (or are stronger for older cohorts), it could generate a similar pattern of results. A more challenging concern is that if STEM majors benefit less from large cities why aren't they crowded out by non-STEM workers? We posit that the migration, even for highly skilled individuals, is costly. Perhaps because they're married to an equally highly skilled spouse, or, as in Costa and Kahn (2000) are looking for one. However, if there is sorting present, and non-STEM workers are crowding into large cities to realize the productive returns, but also competing with one another, then it suggests that our estimate of the non-STEM UWP is biased downward and the productivity of non-STEM workers from increasing the size of all cities, would be even greater.²³

Finally, in future research, we intend to study how different majors contribute to knowledge spillovers using information on patents. In this manner, our work would follow

²³ We thank an anonymous referee for pointing this out to us.

previous contributions on the localization of knowledge spillovers in R&D-intensive fields such as Jaffe et al. (1993, 1996, 1998) and Carlino et al. (2007). We believe such an exploration would be important for understanding the role of STEM majors in inventive activity and how individuals learn from each other in dense economic environments populated by high-technology industries.

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Table 1.2: Urban Wage Premium and Educational Attainment

	(1)	(2)	(3)
<i>Dependent variable: log of annual wages</i>	Population Size	Educational Attainment (highest degree)	Educational Attainment × Population Size
ln (MSA population)	0.072*** (0.006)	0.053*** (0.005)	0.009 (0.006)
<u>Educational Attainment (γ)</u>			
Less than High School		-0.181*** (0.011)	0.145 (0.090)
GED		-0.051*** (0.007)	-0.236*** (0.045)
Some College		0.123*** (0.004)	-0.041* (0.022)
Associate's degree		0.216*** (0.004)	0.134*** (0.041)
Bachelor's degree		0.459*** (0.007)	0.158*** (0.044)
Master's degree		0.658*** (0.009)	0.185*** (0.046)
Professional degree		0.910*** (0.011)	1.030*** (0.080)
Ph. D.		0.843*** (0.011)	0.810*** (0.078)
<u>Educational Attainment × ln(MSA population) (φ_d)</u>			
Less than High School			-0.022*** (0.006)
GED			0.013*** (0.003)
Some College			0.011*** (0.002)
Associate's degree			0.006* (0.003)
Bachelor's degree			0.020*** (0.003)
Master's degree			0.032*** (0.003)
Professional degree			-0.008 (0.006)
Ph. D.			0.002 (0.006)
Observations	859,007	859,007	859,007
R ²	0.345	0.461	0.462

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

<i>Dependent variable: log of annual wages</i>	UWP	UWP× STEM/ /non-STEM	(3) UWP× major (undergraduate)
In (MSA population)	0.069 *** (0.005)	0.076*** (0.006)	0.071 *** (0.007)
Own industry employment share	0.112 *** (0.011)	0.106*** (0.010)	0.107 *** (0.010)
<u>Major × ln(MSA population) (φ_m)</u>			
STEM majors		-0.017*** (0.005)	
Agriculture			-0.016 *** (0.007)
Architecture			-0.022 ** (0.011)
<i>Computer Science</i>			0.007 (0.010)
Education			-0.001 (0.007)
<i>Engineering</i>			-0.019 *** (0.007)
Fine Arts			0.002 (.004)
Fitness			-0.009 (0.011)
Government			0.019 ** (0.007)
History			0.010 ** (0.005)
Languages			0.01 (0.010)
Law			0.020 (0.025)
Liberal Arts			0.007 * (0.004)
<i>Mathematics</i>			0.020 *** (0.007)
Media			0.006 * (0.003)
<i>Medicine</i>			-0.010 * (0.005)
Psychology			0.004 (0.005)
Religion			-0.010 (0.010)
<i>Science</i>			-0.019 *** (0.005)
Social Science			0.020 *** (0.005)
Social Work			0.002 (0.010)
Observations	333,524	333,524	333,524
R ²	0.352	0.361	0.364

Note: Standard errors, clustered by MSA in parentheses. *, **, *** denote coefficient estimates statistically different from zero at the 10, 5, and 1 percent level respectively. A list of all included controls and full coefficient estimates available upon request.

Table 1.4: Total Urban Wage Premium by Undergraduate Major and Highest Degree

	Major	highest degree							
		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%	

Note: Ranking of expected wage premium for the urban wage premium by college major derived from the regression results presented in Table 1.2 ($\hat{\delta} + \hat{\varphi}_{mi}$), where $\hat{\delta}$ is UWP on the omitted category, business-bachelor's and $\hat{\varphi}_{mi}$ is the interaction of major-degree with log population. 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 1.5: Urban Wage Premium by Industry for STEM/Non-STEM majors

	STEM	Non-STEM	Difference	
Health care	-0.036	-0.025	0.011	**
Mining, quarrying, and oil and gas extraction	0.060	0.137	0.076	**
Utilities	-0.008	0.010	0.019	
Construction	-0.037	-0.017	0.021	*
Manufacturing	-0.019	-0.013	0.006	
Wholesale trade	-0.042	-0.015	0.027	
Retail trade	-0.061	-0.013	0.048	***
Transportation and warehousing	-0.068	-0.056	0.012	***
Information	0.013	0.001	-0.012	
Finance and insurance	0.022	0.015	-0.007	
Professional, scientific, and technical services	-0.027	-0.009	0.019	
Educational services	-0.009	-0.004	0.004	
Social Assistance	-0.030	-0.015	0.015	
Arts, entertainment, and recreation	-0.019	-0.018	0.002	
Other services	-0.037	-0.019	0.017	*
Public administration	-0.001	0.020	0.021	
Military	-0.061	-0.038	0.023	**
Agriculture, forestry, fishing and hunting	0.024	(omitted)	-0.024	

Note: The coefficients above come from a specification that also includes demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, the respondent's industry share of total MSA employment, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request. ***, ** and * indicates that the STEM/Non-STEM coefficient estimates are statistically different from one another at the 10, 5, and 1 percent level respectively.

Table 1.6: Urban Wage Premium by Occupation for STEM/Non-STEM majors

	STEM	Non-STEM	Difference	
Manager	0.018	0.008	-0.010	***
Finance worker	0.024	0.007	-0.017	
Computer Specialist (and Mathematics)	0.012	0.007	-0.005	
Engineering (and Architecture)	-0.027	-0.022	0.005	
Life, Physical and Social Scientists	0.000	0.002	0.001	
Social Worker	-0.008	-0.015	-0.007	**
Lawyer/para-legal	0.028	0.022	-0.006	**
Educator	-0.010	-0.004	0.006	
Entertainer	-0.011	0.016	0.027	***
Medical Professional	-0.027	-0.015	0.012	*
Nurse	-0.059	-0.029	0.030	***
Police	0.008	0.003	-0.005	
Cook	-0.050	-0.019	0.031	**
Cleaner	-0.046	-0.039	0.008	***
Personal Care	-0.079	-0.042	0.037	***
Salesman	-0.023	0.009	0.032	
Office workers	-0.016	-0.006	0.010	
Farming/Fishing	-0.005	0.004	0.008	
Construction worker	-0.051	-0.015	0.036	*
Miner/Oil worker	0.220	0.083	-0.136	
Repairman	-0.040	-0.021	0.019	**
Production worker	-0.035	-0.029	0.006	***
Transportation worker	-0.067	-0.057	0.009	***
Soldier	-0.057	-0.030	0.028	
Business	0.020	(ref)	0.020	**

Note: The coefficients above come from a specification that also includes demographic controls for race, sex, veteran status, immigrant status, recent mover, age (as a quadratic), working hours, MSA unemployment rate, the respondent's industry share of total MSA employment, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request. ***, ** and * indicates that the STEM/Non-STEM coefficient estimates are statistically different from one another at the 10, 5, and 1 percent level respectively.

Table 1.7: Urban Wage Premium by Age Cohort

<i>Dependent variable: log of annual wages</i>								
	21-28		29-35		36-50		51-65	
In(MSA population)	0.053	***	0.076	***	0.084	***	0.075	***
	(0.006)		(0.006)		(.006)		(0.007)	
STEM	-0.005		-0.012	**	-0.025	**	-0.016	***
	(.007)		(0.005)		(0.007)		(0.004)	
Observations	41,651		56,725		122,380		99,335	
R ²	0.34		0.29		0.32		0.30	

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, own-industry share, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request.

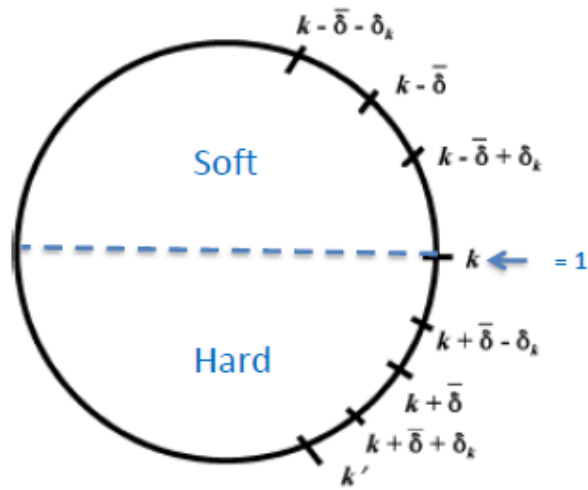
Table 1.8: Robustness Checks: Exclude Immigrants, Public Sector Workers, Restrict to Married

<i>Dependent variable: log of annual wages</i>	exclude immigrants		married		married working spouse ¹		single		exclude public sector	
	In(MSA population)	0.081	***	0.078	***	0.081	***	0.081	***	0.074
	(0.006)		(0.006)		(0.007)		(0.007)		(0.006)	
STEM	-0.021	***	-0.019	***	-.018	***	-0.018	***	-0.016	***
	(.004)		(0.006)		(0.006)		(0.006)		(0.005)	
Observations	279,572		219,138		96,909		96,909		308,028	
R ²	.377		0.339		0.276		0.276		0.364	

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, own-industry share, industry (2 digit NAICS) and census division dummies. Full coefficient estimates available upon request.

¹Limited to workers whose married spouse also works full time.

Figure 1.2 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 diligent 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.

Table 1.9: Field of Degree Category Components

<i>Agriculture</i>		
General Agriculture	Food Science	Forestry
Agriculture Production And Management	Plant Science And Agronomy	Natural Resources Management
Agricultural Economics	Soil Science	
Animal Sciences	Miscellaneous Agriculture	
	Environmental Science	
<i>Architecture</i>		
Architecture		
<i>Business</i>		
General Business		
Accounting	Marketing And Marketing Research	
Actuarial Science	Finance	Hospitality Management
Business Management And Administration	Human Resources And Personnel Management	Management Information Systems And Statistics
Operations Logistics And E-Commerce	International Business	Miscellaneous Business & Medical Administration
Business Economics		
Construction Services		
<i>Computer Science</i>		
Computer And Information Systems	Computer Science	Computer Networking And Telecommunications
Computer Programming And Data Processing	Information Sciences	
	Computer Administration	
	Management And Security	
<i>Education</i>		
General Education	Early Childhood Education	Teacher Education: Multiple Levels
Educational Administration And Supervision	Science And Computer Teacher Education	Language And Drama Education
School Student Counseling	Secondary Teacher Education	Art And Music Education
Elementary Education	Special Needs Education	Miscellaneous Education
Mathematics Teacher Education	Social Science Or History Teacher Education	
Physical And Health Education Teaching		
<i>Engineering</i>		
General Engineering	Chemical Engineering	Physics And Science
Aerospace Engineering	Civil Engineering	Environmental Engineering
Biological Engineering	Computer Engineering	Geological And Geophysical Engineering
Architectural Engineering	Electrical Engineering	Industrial And Manufacturing
Biomedical Engineering	Engineering Mechanics	

Engineering
Materials Engineering And
Materials Science
Mechanical Engineering
Metallurgical Engineering
Mining And Mineral
Engineering
Naval Architecture And
Marine Engineering

Fine Arts

Cosmetology Services And
Culinary Arts
Fine Arts
Drama And Theater Arts
Music

Fitness

Physical Fitness Parks Recreation And Leisure

Government

Criminal Justice And Fire
Protection
Public Administration
Public Policy

History

History
United States History

Languages

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

Law

Court Reporting

Liberal Arts

English Language And
Literature

Nuclear Engineering
Petroleum Engineering
Miscellaneous Engineering
Engineering Technologies
Engineering And Industrial
Management
Electrical Engineering
Technology
Industrial Production

Visual And Performing Arts
Commercial Art And Graphic
Design
Film Video And Photographic
Arts

Criminology
International Relations
Political Science And
Government

Composition And Rhetoric
Liberal Arts
Humanities

Technologies

Mechanical Engineering
Related Technologies
Miscellaneous Engineering
Technologies
Electrical, Mechanical, And
Precision Technologies And
Production

Art History And Criticism
Studio Arts
Miscellaneous Fine Arts

Transportation Sciences And
Technologies

Other Foreign Languages

Pre-Law And Legal Studies

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

CHAPTER 2

PRODUCTIVITY GAINS FROM SPATIAL CONCENTRATION OF HUMAN CAPITAL: IS SPECIALIZATION OR DIVERSITY MORE IMPORTANT?

2.1 INTRODUCTION

The ongoing debate in the human capital externality literature attempts to identify whether specialized or diverse economic environments are more productive. The industrial composition of an area is to some extent driven by the skill sets of the local human capital stock. Within cities, as members of the stock are exposed to more frequent interaction, they facilitate the agglomerative mechanism by learning from one another.²⁴ This idea is formalized in two recent papers—for example, both Berliant, Reed, and Wang (2006) and Cunningham, Patton, and Reed (2015) demonstrate that if random meetings in cities result in matches, productive knowledge exchange occurs as individuals of differing knowledge types apply what they learn from each other to their own work.²⁵ In contrast, the objective of this paper is to empirically identify which human capital types, as defined by level of educational attainment and college major, benefit the most from *specialized* interaction within cities.

Notably, Glaeser et al. (1992) are among the first to empirically investigate the relative importance of specialization and diversity. Motivated by the dynamic externality theories of

²⁴ Glaeser and Mare (2001) describe the agglomerative mechanism among human capital as a learning process by demonstrating wages rise with one's tenure in a city.

²⁵ The theoretical model of Cunningham, Patton, and Reed (2015) asserts agglomeration economies facilitate specialized interactions that in turn yield the greatest productivity benefits

Marshall, Arrow, and Romer (MAR) and Jacobs (1969), they construct a dataset of city-industry observations capturing the level of specialization (relative to the nation) and heterogeneity within the area.²⁶ They find specialization (or localization) externalities are either non-existent or counterproductive. Urbanization externalities generated by diverse industrial composition are a more significant factor in promoting economic growth.²⁷

Alternatively, Wheaton and Lewis (2002) isolate the effects of regional concentration and local specialization to confirm positive localization economies at the worker level within several sub-industry and occupational categories of the manufacturing sector.²⁸ Outside of manufacturing, Fu (2007) finds those in high-tech industries are also sensitive to specialization. In addition, math and computer-oriented occupations benefit from specialized interactions.²⁹

The literature largely focuses on industrial and occupational heterogeneity in the exploration of agglomeration externalities, neglecting analysis of the role of formal education in the foundational development of cognitive and technical skills used on the job. Even in cases where an individual does not work in their same field of study, one cannot assume the training received in school did not frame the way workers perceive, evaluate, plan around, and execute strategies toward various tasks and/or problems. The increased availability of more detailed data on educational background has allowed research in this area to explore new agglomerative channels. In particular, Rauch (1993), Fu (2007), Rosenthal and Strange (2008), and Abel et al.

²⁶ Marshall, 1890; Arrow, 1962; Romer, 1986; MAR argue high industry concentration within a city promotes economies between firms and consequently encourages industry growth. Additionally, local monopolization within an industry internalizes ideas and generates growth via an incubator effect.

²⁷ Jacobs cites several examples of innovations originating from cross-industry interaction, indicative of urbanization economies. Their results also identify positive effects from increased competition as proposed by Porter (1990).

²⁸ The results verify positive specialization externalities exist and tend to be larger at the industry level.

²⁹ Manufacturing and computer industries gain localization and urbanization economies. Management jobs benefit from interactions in all types of environments while creative jobs flourish and gain inspiration from diversity.

(2012) all devote a part of their analysis to the productive benefits of increased exposure to a college-educated labor pool. The results consistently show spatial concentration and growth of the college-educated portion of the workforce augments wages for *all* workers within a city.

Taking advantage of large-scale data sources, relatively recent research has only just begun to investigate the role of horizontal heterogeneity in educational types, and even still has focused largely on STEM knowledge exclusively. Our paper will advance the discussion on specialization externalities by uncovering the returns to knowledge type as captured by 21 different college majors. The uniqueness of our formal education data from the American Community Survey (ACS) will allow us to observe how local specialization strengthens individual productivity across multiple dimensions of human capital heterogeneity.

Drawing inspiration from Glaeser et al. (1992), we calculate city-knowledge type values to describe the composition of a city's human capital stock. This variable is the local employment share of a particular knowledge type among the college-educated workforce.³⁰ Our results initially support their findings, indicating the isolated specialization effect is largely either insignificant or counterproductive. We expand upon their analysis by using city size to estimate the urban wage premium which captures the influence of rapid, yet likely more diverse interaction within large cities. Doing so informs us that urbanization and specialization effects may be complementary as their joint estimation yields statistically significant positive and larger coefficients for both variables. Fields of knowledge such as business and media tend to be more productive in diversified and fast-paced areas, while STEM fields—computer science, in particular—thrive in specialized environments.

³⁰ This is the same specialization variable used on Wheaton and Lewis (2002) and Fu (2007)

The remainder of the paper is as follows. The next section will explain the construction of our dataset. Section 3 describes the empirical model. Section 4 provides interpretation of our results. We conclude and provide summary remarks in section 5.

2.2 DESCRIPTION OF THE DATA

The American Community Survey (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 undergraduate field of degree. As a result, the ACS is uniquely able to provide information about the level, type, and concentration of human capital across cities.³¹ We use this information to construct our variable of interest, local specialization of human capital types. The Census Bureau annually releases 1-, 3-, 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.

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 in the last year 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.

³¹ 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.

Lastly, we control for the Census-defined geographical division in which the individual resides.³² The ACS identifies residential location 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 assign individuals to Metropolitan Statistical Areas (MSAs) that we believe best approximate a local labor market and pool for knowledge exchange.³³ MSAs are areas of high socioeconomic integration, defined by commuting patterns. We drop individuals not residing in an MSA.

Our sample of college graduates has 339,724 observations. The demographic breakdown of the data is rather consistent across the years for which ACS data on field of degree is available. However, we study the 2011 sample in our analysis. 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.

2.2.1 Specialization and the Distribution of Human Capital Types

Our study seeks to determine how the rate of return to specialized interaction within cities varies across human capital types. Therefore, for each MSA, we construct city-level measures of specialization for various knowledge types, providing even finer analysis of the agglomerative benefits associated with human capital interaction. The responses to the ACS questions on educational attainment and undergraduate field of degree create a rich measure of the depth and

³²Census region and division definitions are available at:
http://www.census.gov/econ/census07/www/geography/regions_and_divisions.html.

³³ 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.

range of human capital in the US population. Specifically, the ACS allows us to construct four indicators for highest level of educational attainment: bachelor's degree, master's degree, professional degree, and Ph.D.³⁴ For individuals who have earned an undergraduate degree or higher, the ACS identifies which of 174 different majors a respondent studied. We aggregate the responses into twenty-one categories to represent horizontal variation in educational type. These areas of expertise in alphabetical order are: agriculture, architecture, business, computer science, education, engineering, fine arts, 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, individuals with a military science degree are dropped from the sample.

Following Glaeser et al. (1992), we construct measures of local specialization for city-major combinations. Our specialization measure for the local human capital stock is the same used in Wheaton and Lewis (2002) and Fu (2007). It is the MSA employment share of each knowledge type, l_{ej}/l_j .³⁵ As this measure is indexed on knowledge type e and location j , there are $e \times j$ unique specialization values that we merge with the existing dataset by unique city-major identifiers. Our study analyzes local specialization of both educational attainment and college major. Therefore, four post-secondary levels of degree and 258 MSAs give us 1,032

³⁴ 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. Many papers on wage premium models rely on a continuous measure of educational attainment or aggregate indicators for relatively coarse measures of educational attainment such as high school or college completion. Consider the work of Roback (1982), Rauch (1993), and Bacolod et al. (2009). 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.

³⁵ The employment counts for this variable were calculated using the person weight, PWGTP. It is recommended to use sample population weights to derive accurate descriptive measures of the population as a whole. A description of the derivation of person and housing unit weights is available at the following site: https://www.census.gov/acs/www/Downloads/survey_methodology/acs_design_methodology_ch11.pdf

unique values for local specialization of educational attainment. Likewise, 21 majors and 258 MSAs give us 5,418 values for local specialization of knowledge type. The mean rate of concentration across all workers in a city is 37.08% and 7.44% for level of educational attainment and college major, respectively.

To gain a better understanding of the geographical distribution of our sample, we categorize city size by MSA population 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).³⁶ Sample representation of the city size groups from very small to very large are: 0.28% (VS), 13.81% (S), 8.43% (M), 31.24% (L), and 46.24% (VL). Nearly half of the sample population lives in MSAs with more than 4 million people. Around 14% reside in MSAs with populations smaller than 500,000 people. Generally, we see that smaller cities tend to be more specialized. Consider the information presented in Table 2.1.

Table 2.1 provides examples of the most specialized cities for each human capital type represented in our dataset, and their corresponding local employment shares. For example, Dallas, TX is the most specialized very large city with the highest representation (68.8%) of bachelor's degree holders among their college-educated workforce. Likewise, out of very large cities, Houston, TX has the largest representation of STEM graduates (37.9%), which includes knowledge in the areas of computer science, engineering, mathematics, medicine, and science.

³⁶ A listing of all MSAs within each city size category is available upon request.

Table 2.1: Most Specialized Cities across Human Capital Types

	Very Small		Small		Medium		Large		Very Large	
	Less than 100,000		(100,000-500,000)		(500,000-1 million)		(1 million-4 million)		4 million+	
Bachelor's	Pocatello, ID	74.4	New London, CT	83.9	McAllen, TX	75.3	Charlotte, NC	71.0	Dallas, TX	68.8
Master's	Victoria, TX	32.7	Glens Falls, NY	40.9	Syracuse, NY	33.5	Buffalo, NY	32.2	Washington, DC	32.2
Professional	Owensboro, KY	9.8	Gadsden, AL	18.9	Harrisburg, PA	9.5	New Orleans, LA	10.9	Detroit, MI	8.3
Ph.D.	Owensboro, KY	10.8	Santa Fe, NM	15.7	Albuquerque, NM	8.0	Raleigh, NC	7.1	Boston, MA	6.7
STEM	Victoria, TX	35.4	Gadsden, AL	47.1	Dayton, OH	35.7	San Diego, CA	36.3	Houston, TX	37.9
Agriculture	Lawrence, KS	7.3	Columbia, MO	8.3	Fresno, CA	3.4	Portland, OR	3.0	San Francisco, CA	1.4
Architecture	Lawrence, KS	1.0	Laredo, TX	4.1	Tulsa, OK	1.4	West Palm Beach, FL	1.3	Los Angeles, CA	1.2
Business	Pine Bluff, AR	22.1	New London, CT	53.7	Birmingham, AL	28.1	Memphis, TN	30.2	Atlanta, GA	29.0
Computer Science	Owensboro, KY	4.8	Gadsden, AL	10.1	Colorado Springs, CO	7.2	Seattle, WA	5.3	San Francisco, CA	5.6
Education	Rapid City, SD	26.6	Yakima, WA	32.0	Youngstown, OH	22.6	Grand Rapids, MI	17.2	Philadelphia, PA	11.7
Engineering	Pocatello, ID	12.0	Richland, WA	20.6	Dayton, OH	13.5	San Diego, CA	12.3	Houston, TX	15.8
Fine Arts	Pittsfield, MA	9.3	Medford, OR	9.5	Albuquerque, NM	5.7	Portland, OR-WA	4.8	Los Angeles, CA	6.3
Fitness	Lawrence, KS	1.7	Yuma, AZ	5.8	McAllen, TX	2.2	Greensboro, NC	2.6	Houston, TX	1.2
Government	Pittsfield, MA	10.1	Yuma, AZ	19.0	Richmond, VA	7.1	Norfolk, VA	7.5	Washington, DC	8.7
History	Lawrence, KS	5.8	Yuma, AZ	9.9	Albany, NY	3.7	Providence, RI	3.9	Washington, DC	3.6
Languages	Pocatello, ID	2.4	Bloomington, IN	6.0	McAllen, TX	2.2	Salt Lake City, UT	1.8	Washington, DC	1.6
Law	--	--	Iowa City, IA	4.2	Springfield, MA	1.3	Minneapolis, MN	0.6	Boston, MA	0.3
Liberal Arts	Lawrence, KS	10.2	Visalia, CA	13.2	Bakersfield, CA	9.3	Louisville, KY-IN	6.3	Los Angeles, CA	5.6
Mathematics	Pine Bluff, AR	3.9	Yuba City, CA	7.9	Dayton, OH	2.2	Raleigh, NC	2.6	Boston, MA	2.1
Media	Rapid City, SD	6.3	Mansfield, OH	9.8	Charleston, SC	7.2	Louisville, KY-IN	6.0	Los Angeles, CA	5.2
Medicine	Victoria, TX	13.2	Punta Gorda, FL	26.6	Mobile, AL	13.3	San Antonio, TX	10.6	Detroit, MI	9.8
Psychology	Pocatello, ID	4.9	La Crosse, WI-MN	10.4	Springfield, MA	7.0	Hartford, CT	7.1	New York, NY	5.4
Religion	Lawrence, KS	3.7	Hattiesburg, MS	7.0	Stockton, CA	3.0	Memphis, TN	2.2	Los Angeles, CA	1.3
Science	Owensboro, KY	14.2	New London, CT	30.1	Bakersfield, CA	10.6	Raleigh, NC	12.8	Philadelphia, PA	10.5
Social Science	Rapid City, SD	8.1	Santa Barbara, CA	12.5	Colorado Springs, CO	8.5	Sacramento, CA	10.4	Los Angeles, CA	8.5
Social Work	Pine Bluff, AR	4.7	Eau Claire, WI	8.2	Fresno, CA	3.7	Milwaukee, WI	2.3	Detroit, MI	1.2

*Number values are in percentages, %.

**Majors in italics are aggregated into the STEM category

***City size based on year 2000 population counts and MSA boundary definitions

Some intuitive patterns surface within this table. For instance, across both educational dimensions, very small and small cities appear to have larger specialization values for many human capital types. This is likely due to the relatively limited capacity for smaller cities to support markets with sufficient demand for a wide variety of skill sets.

It is also worth noting the higher concentrations of individuals with not just graduate level, but terminal degrees within the lesser populated locations. Across the country, there are several examples of cities with flagship institutions of higher learning and research facilities in more isolated (but not necessarily rural) locations. These institutions have great demand for the specialized skills of the highly educated.

With regard to fields of study, agriculture tends to be more concentrated in smaller cities with a marked difference between Columbia, MO and San Francisco, CA with a respective 8.3%

and 1.4% representation of this knowledge set among the college-educated workforce. Focusing on more recognizable very large cities, there are several reasonable examples of places where the relatively high level of specialization in a specific knowledge type reflects the industrial composition of the area. For example, in Houston, there is an aggregation of STEM majors, specifically those with engineering degrees. This concentration of knowledge is likely due to the city's ties to NASA. Atlanta is capitalizing off of its central regional location to become a hub for the headquarters of many major companies that certainly employ workers with business backgrounds. Known for entertainment and creative production industries, Los Angeles, CA hosts many fine arts and media majors. Lastly, it is no surprise Washington, D.C., the seat of the federal government, attracts students of government, history, and languages to legislate, archive, and serve as global ambassadors for the United States.

Table 2.2 compares the human capital composition within cities of various sizes to the national distribution. The values in the table represent each human capital type's employment share of the college-educated workforce within each city size category. For example, in the subset for very small cities, 63.9% of college-educated workers have a bachelor's degree only. Among all college graduates across the nation, 62.7% hold a bachelor's degree. The human capital categories are ranked by national employment share. Regardless of location, employment share decreases with educational attainment. This relationship reflects the added cost in terms of time and forgone wages to obtain higher degrees. Very large cities have slightly less entry-level bachelor degree holders than the nation on average, but offset this deficiency with a higher than average presence of terminal Professional and Ph.D. degree recipients. STEM employment appears to be consistent across cities, representing 30% of the local college-educated workforce.

Table 2.2: Human Capital Composition within Cities

	VS	S	M	L	VL	U.S.
Bachelor's	63.9%	64.3%	63.6%	64.6%	60.9%	62.7%
Master's	27.1%	24.6%	25.8%	24.8%	27.3%	26.0%
Professional	5.1%	6.4%	6.5%	6.5%	7.2%	6.8%
Ph.D.	4.0%	4.7%	4.2%	4.1%	4.6%	4.4%
STEM	27.5%	29.5%	30.0%	30.0%	30.7%	30.3%
Business	16.3%	20.8%	21.8%	23.2%	22.3%	22.3%
Education	19.2%	14.1%	13.1%	10.8%	8.3%	10.3%
<i>Engineering</i>	7.1%	8.2%	9.1%	9.1%	10.1%	9.4%
<i>Science</i>	9.1%	8.7%	8.1%	8.4%	8.5%	8.5%
<i>Medicine</i>	7.6%	8.6%	8.9%	7.6%	6.6%	7.4%
Social Science	4.6%	5.4%	5.2%	5.8%	6.9%	6.2%
Government	3.6%	4.8%	5.0%	5.0%	5.4%	5.1%
Psychology	3.2%	4.5%	5.0%	4.8%	4.8%	4.8%
Liberal Arts	5.8%	4.1%	3.9%	4.1%	4.8%	4.4%
Media	3.4%	3.5%	3.7%	4.5%	4.2%	4.2%
Fine Arts	3.4%	3.0%	3.2%	3.6%	4.5%	3.9%
<i>Computer Science</i>	2.1%	2.7%	2.6%	3.6%	3.9%	3.5%
History	2.6%	2.0%	2.2%	1.8%	2.4%	2.1%
<i>Mathematics</i>	1.7%	1.3%	1.3%	1.4%	1.7%	1.5%
Agriculture	4.8%	2.4%	1.6%	1.3%	0.9%	1.3%
Religion	1.7%	1.6%	1.4%	1.2%	1.1%	1.3%
Social Work	1.4%	1.4%	1.3%	1.1%	0.9%	1.1%
Languages	1.1%	0.9%	1.0%	0.9%	1.1%	1.0%
Fitness	0.9%	1.2%	0.9%	0.9%	0.6%	0.8%
Architecture	0.4%	0.5%	0.6%	0.7%	0.9%	0.7%
Law	0.0%	0.2%	0.2%	0.2%	0.2%	0.2%

*Majors in italics are aggregated into the STEM category

In fact, three of the top five majors represented in cities are STEM-related. Business, education, engineering, science, and medicine fields maintain the highest representation within all but very large cities. Social science replaces medicine as the fifth largest group represented in the most populated cities. The distribution in large cities most closely resembles that of the nation at large.

2.3 EMPIRICAL MODEL

The objective of this paper is to identify which human capital types, as defined by level of educational attainment and college major, benefit the most from specialized interaction within cities. To accomplish this goal, we will combine analysis of human capital types with a spatial constraint variable. For example, Rosenthal and Strange (2008) measure externality attenuation associated with employment levels within concentric rings around places of work. They find for a subsample of college-educated individuals, wages increase by 5.16% when employment within five miles doubles. Similarly, wages also increase by 12% when local employment of college-educated workers doubles. The sample of those with less education also experience wage increases in response to these levels of employment, but at smaller magnitudes. In addition, Abel, Dey and Gabe (2012) show the density of “high” human capital within an MSA also has a significant positive effect on that area’s average productivity. In particular, productivity increases by 3.6% when population density doubles for areas where the college-educated share of the labor force is one standard deviation greater than the mean level representation. Several other studies make use of aggregate level measures of the human capital stock to determine significant channels for agglomeration, including depth of education, city size, degree of industrial diversity and concentration.³⁷

Our model and methodology utilizes various specifications of the wage premium model to estimate the magnitude and validity of the effect of city-level specialization on individual productivity. Our unique contribution starts with the data. We use information on formal education provided by the ACS to define concentration ratios for various human capital types. Compared to other studies that either focus on educational attainment or STEM versus non-

³⁷ Bacolod et al. (2009), Roback (1982), Rauch(1993), Cunningham, Patton, and Reed (2015), Glaeser et al. (1990), Fu (2007), Wheaton and Lewis (2002)

STEM comparisons, we increase the range of heterogeneity within formal education to levels commensurate with the variety studied among industrial and occupational categories in many other papers. We are able to identify four levels of educational attainment beyond post-secondary completion, and twenty-one categories of knowledge based on college major. These classifications capture both vertical and horizontal heterogeneity in human capital that allows for a more precise description of the composition of the local human capital stock within the model.

Like Abel et al. (2012), we interact a human capital type-based measure with MSA-specific descriptive variables of human capital stock in order to capture the effect of local human capital composition on productivity. However, our city-level term will predict individual wages rather than city-level productivity. Our benchmark results will show the average return to local specialization.

(1)

$$\ln(w)_{iej} = \alpha + X_i\beta + L_{ij}\theta + Z_{ie}\gamma + \ln(\text{local specialization})_{iej}\delta + \varepsilon_{iej}$$

In the above model specification, logged annual wages for individual i with human capital type e residing in MSA j are a function of standard demographics (X_i), local labor market conditions (L_{ij}), personal education (Z_{ie}), and the representation of the individual's knowledge type among the MSA's college-educated employment.³⁸ Local specialization is simply the MSA employment share of the human capital type, e_j . This MSA-level measure describes the distribution of each knowledge type within each city. Recall, e_j can represent either educational attainment or college

³⁸ See the data section for a list of all variables included. Note, matrix L includes MSA employment share of the individual's industry and is the occupational counterpart of local specialization.

major. The average return to specialization, δ , is estimated separately for each of these dimensions.³⁹ All standard errors are clustered at the MSA level.

Assuming the agglomerative effects of knowledge exchange are primarily facilitated through increased local population and specialization of the labor pool, specification (2) below attempts to disentangle the agglomerative effects of human capital stock *size* from human capital stock *composition*.⁴⁰ We add logged MSA population to provide the average urban wage premium (UWP) given by parameter λ below.⁴¹

(2)

$$\ln(w)_{iej} = \alpha + X_i\beta + L_{ij}\theta + Z_{ie}\gamma + \ln(\text{local specialization})_{iej}\delta + \ln(\text{MSA population})_{ij}\lambda + \varepsilon_{iej}$$

The role of MSA population size is to mitigate any bias that may accrue to specialization and vice-versa. The urban wage premium (UWP) is the signature mark of the existence of agglomeration externalities among labor. Previous research already explores wage elasticity across knowledge types in response to population size.⁴² Here, we use a similar methodology while focusing on direct comparisons between the specialization premium and the UWP. This allows us to verify the stability of the specialization premium across knowledge types.

Specification (3) distributes the specialization effect across the human capital types, yielding estimates of wage sensitivity to changes in local representation of the same type of knowledge possessed by individual i .

³⁹ $H_{01}: \delta = 0$

⁴⁰ $H_{02}: \lambda > \delta$

⁴¹ Note: The UWP is indexed on location, and the specialization premium is indexed on location *and* type.

⁴² See Bacolod et al. (2009) and Cunningham, Patton, and Reed (2015)

(3)

$$\ln(w)_{iej} = \alpha + X_i\beta + L_{ij}\theta + Z_{ie}\gamma +$$

$$\ln(\text{local specialization})_{iej}\delta + [\ln(\text{spec.})_{iej} \cdot Z_{ie}]\varphi + \varepsilon_{iej}$$

(4)

$$\ln(w)_{iej} = \alpha + X_i\beta + L_{ij}\theta + Z_{ie}\gamma +$$

$$\ln(\text{local specialization})_{iej}\delta + \ln(\text{MSA population})_{ij}\lambda + [\ln(\text{spec.})_{iej} \cdot Z_{ie}]\varphi + \varepsilon_{iej}$$

(5)

$$\ln(w)_{iej} = \alpha + X_{ij}\beta + L_j\theta + Z_{ie}\gamma + \text{local specialization}_{ej}\delta + \ln(\text{MSA population})_{ij}\lambda +$$

$$[\ln(\text{spec.})_{iej} \cdot Z_{ie}]\varphi + [\ln(\text{pop})_{ij} \cdot Z_{ie}]\eta + \varepsilon_{iej}$$

While δ is the specialization premium for our reference groups—either bachelor’s degree holders or business majors—the sum of coefficients δ and φ provide the size of the externality from interacting with others of similar knowledge. In other words, it is the specialization premium for type e .⁴³ Model (4) measures the specialization premium in the presence of the average UWP. Model (5) fully fleshes out the specialization and population effects across each human capital type. The sum of coefficients λ and η represents the UWP for each type and implicitly represents wage sensitivity to local increases or decreases in the representation of *any* type.⁴⁴ Here, λ represents the UWP for our reference groups. In order to provide a thorough comparison of the population and specialization effects, estimates of the UWP excluding specialization controls

⁴³ $H_{03}: \delta_{e=bach/bus} = \varphi_{e \neq bach/bus}$

⁴⁴ Additional analysis using population-weighted density will be discussed in the results section.

will also be provided in the results discussion. These results will be identified as specification (1') and (3') where local specialization is replaced with MSA population.

2.4 DISCUSSION OF RESULTS

2.4.1 Average Return to Agglomeration

The benchmark model highlights the average returns to specialization and city size. Table 2.3 shows a summary of these effects. Column a of specification (1) displays the attainment specialization premium in the presence of educational attainment indicators within matrix Z of the model.⁴⁵ Here, we find the return to interaction with someone possessing the same level of educational attainment is essentially zero. Meanwhile, in column b, interaction within a more specialized labor pool in terms of horizontal type of human capital has a positive and statistically significant (although underwhelming) effect. A doubling of local representation of own knowledge type enhances individual productivity by 1.37%.

Table 2.3: Average Returns to Agglomeration⁴⁶

Model Specification:	1				1'		2				
	Specialization Premium				Urban Wage Premium		Joint Specialization and Urban Wage Premiums				
	a	b	c	d	a	b	a	b	c	d	
Local Specialization of Educational Attainment with educational attainment controls: with college major controls:	-0.22		-11.21 ***				0.37			-11.00 ***	
Local Specialization of College Major with educational attainment controls: with college major controls:		1.37 ***		2.67 ***				2.60 ***			2.78 ***
MSA Population with educational attainment controls: with college major controls:					4.70 ***	4.99 ***	4.70 ***	5.03 ***	4.77 ***		4.73 ***

Note: Values represent the percent change in wages in response to a 100% increase in local specialization of own type.

⁴⁵ Column b of the same specification shows the major specialization premium in the presence of college major indicators.

⁴⁶ See Table 2.10 for corresponding formal results, as well as the average return to educational type. Average annual earnings increase with educational attainment. Also, STEM majors on average receive the largest return to their degree. The returns to fitness, law, social work, fine arts, and religion are consistently low in the ranking of average returns to knowledge type. The effects of all standard control variables are available upon request.

The diversity of the dataset allows us to observe “cross-effects” where local specialization of educational attainment may be measured in the presence of college major controls, and vice versa. In columns c and d of specification (1), we see an interesting difference between the premiums for each educational dimension. Holding fixed one’s undergraduate field of study, if specialization of the individual’s level of educational attainment doubles, wages actually decline significantly by 11%. On the other hand, for an individual with a particular level of educational attainment, doubling local representation of area of knowledge among the labor pool increases earnings by 2.7%. Within the context of returns to interaction, these cross effects tell us that individuals benefit from interacting with others with similar subject backgrounds, but not with others of the same depth of training. The contents of a discussion rather than its level of rigor provide greater productive benefit. For example, a professor can define new research ideas while engaging with students. However, depth of knowledge does not overcome the need to understand topical foundations in order to have a productive exchange. Regardless of one’s cognitive capacity, exchanges between someone who knows about fine arts and an individual with equal expertise in government may not be fruitful because the subjects are too different.⁴⁷

Compared to the specialization effect, specification (1’) shows the UWP varies only slightly when changing the contents of matrix Z. The UWP maintains its stability at 4.70% even during joint estimation of the average specialization premium, shown under specification (2). Specialization of educational attainment has no productive value without information on subject area. Even then, it has a negative return. Local specialization of college major, however, consistently displays a positive and statistically significant effect on wages, averaging around 2%. The UWP augments wages by at least 4.7% and tends to be larger than the specialization

⁴⁷ Cunningham, Patton, and Reed (2015) provide a theoretical model that suggests the returns to knowledge exchange are increasing with specialization of knowledge type.

premium on average. However, it is worthwhile to note that both the specialization and population premiums reach a maximum during joint estimation.⁴⁸

2.4.2 Return to Agglomeration across Educational Attainment

Next, we observe whether the specialization externality varies across educational levels. Table 2.4 shows the specialization premiums for each level of educational attainment in column (3), while sequentially increasing controls for the population effect in columns (4) and (5). The top portion displays premium estimates for specialization of educational attainment, while the bottom portion reports the analogous values from local specialization of college major. The relative relationships between the premiums for each level of attainment are consistent across model specifications. In model (3), bachelor's degree holders experience large negative returns to specialization of educational attainment, presumably from intense competition due to the substitutability of skills achieved with relatively generic degrees. However, that effect is reversed upon entering graduate study. A master's graduate benefits the most from an increase in the local representation of other master's degree holders, enjoying a wage increase up to 32%. The specialization premium for terminal degrees—professional and Ph.D.—are positive, but very small, hovering around 2%. When controlling for population effects in model (4), professional degree holders also experience negative returns to specialization.

The results for the college major specialization premium display much less fluctuation across levels of educational attainment. Professional degree and Ph.D. recipients effectively earn the same specialization premium as the reference group, bachelor's degree holders. In all model specifications, it is the master's group that once again receives the largest premium in response to increased local employment share of its own knowledge type. Therefore, master's degree

⁴⁸ See columns a and b of specification 2.

Table 2.4: Specialization Premium across Educational Attainment

	3		4		5	
	<i>w/o pop.</i>		<i>with avg. UWP</i>		<i>w/ UWP by type</i>	
<i>Specialization of Educational Attainment</i>						
Bachelor's	-36.74	***	-22.17	***	-22.59	***
Master's	32.24	***	18.96	***	15.89	***
Professional	2.33	***	-3.80	***	-1.44	***
Ph.D.	2.11	***	3.86	***	3.39	***
<i>Specialization of College Major</i>						
Bachelor's	2.53	***	2.56	***	2.56	***
Master's	2.98	**	3.24	***	3.31	***
Professional	2.45		2.67		2.54	
Ph.D.	3.28		3.62		3.60	

holders benefit the most from interacting with others that are exactly like them in terms of educational attainment and subject matter. This result is magnified in larger cities as the return to specialization of college major does increase with the addition of population controls in specifications (4) and (5).

Table 2.5 displays the urban wage premium results across educational attainment both without (3') and with (5) the specialization premium. These results substantiate the claim that master's degree holders benefit the most from agglomeration by earning the largest urban wage premium. Regardless of specification, the return to frequent interaction in larger cities is consistently smaller for terminal degrees. Specifically, professional degree holders benefit the least.

Table 2.5: UWP across Educational Attainment

	3'		5			
	<u>UWP alone</u>		<u>UWP with</u>			
			a: Specialization of Educational Attainment		b: Specialization of College Major	
Bachelor's	4.64	***	4.33	***	4.65	***
Master's	5.55	***	5.29	***	5.64	***
Professional	2.92	***	3.12	***	2.98	***
Ph.D.	3.45	***	3.64	**	3.46	***

The robustness of the urban wage premium across model specifications is impressive. The previous section discussed how the joint estimation of the urban wage premium and specialization premium enhanced both effects. However, for non-terminal degrees, the UWP only increases when controlling for college major specialization. Interestingly, joint estimation with the specialization premium for either educational dimension augments the UWP for terminal degrees. Comparison of the change in the UWP between columns (3') and (5a) and the change between (3') and (5b) shows terminal degree holders experience a larger change in the UWP when controlling for specialization of educational attainment.⁴⁹ These results suggest individuals with higher levels of expertise can more easily engage in multidisciplinary interaction and application in order to enhance their productivity within cities.

2.4.3 Return to Agglomeration across College Majors

At this point in the discussion, we will focus exclusively on the return to local specialization of college major. The detail afforded by this dataset will allow us to see precisely what types of human capital benefit more or less from city specialization, city size, or potentially, some other local productive amenity. Table 2.6 provides a ranking of the specialization premium across knowledge types as captured by undergraduate major. The results show changes in the specialization premium in response to gradually increasing population controls. On average—and independent of population effects—the specialization premiums for STEM fields and all other subject areas included in this study are the same, at 2.05%, as seen in column (3a).⁵⁰ Disaggregating the STEM category, however, tells a different story. Omission of population controls in specification (3b) of Table 2.6 yields either statistically insignificant or

⁴⁹ For example, for Ph.D. holders, the UWP only increases by 0.01 when estimated with specialization of college major; but increases by 0.19 when estimated with specialization of educational attainment. A similar effect occurs for Professional degree holders.

⁵⁰ See Table 2.11 for formal result.

negative specialization premiums. Outside of computer science, 12 of the 21 majors have a specialization premium of zero (since business is the reference group), and eight experience negative returns.

This result closely resembles that of Glaeser et al., who reject the MAR hypothesis due to negative and insignificant coefficient estimates of their industry specialization measure. While they normalized local specialization by the national employment distribution of the industry, their model did not include any population variables. Here lies an important contribution of this study, that the return to specialized interaction is biased when failing to control for city size. Recall from the data discussion, our dataset shows that smaller cities tend to be more specialized, and our results from Table 2.3—specifications (1') and (2)—show these locations will generally observe a smaller urban wage premium. The dominant nature of the population size effect in terms of robust statistical significance and relative size clouds the significant role of specialization within cities.

The top three significant fields are consistently STEM-related across model specifications. In column (3b), individuals with bachelor's degrees in computer science benefit the most from high local representation enjoying 15% greater productivity when employment share of this discipline doubles. Computer science is the only field that observes a positive specialization premium without the influence of population. When considering the population effect in models (4) and (5), that value settles around 10%.

Table 2.6: Ranking of Returns to Specialization across College Majors

	3 w/o pop.		4 with avg. UWP		5 w/ UWP by type		
	a	b					
STEM	1.45	<i>Computer Science</i>	15.68 *	<i>Computer Science</i>	10.02 ***	<i>Engineering</i>	10.25 ***
Other	2.05 ***	<i>Engineering</i>	12.7	<i>Engineering</i>	9.39 ***	<i>Computer Science</i>	9.97 ***
		<i>Government</i>	10.12	<i>Mathematics</i>	7.37 ***	<i>Mathematics</i>	6.16 **
		<i>Mathematics</i>	9.6	<i>Languages</i>	6.37 ***	<i>Languages</i>	6.09 ***
		<i>Social Science</i>	8.83	<i>Government</i>	6.19 **	<i>Government</i>	5.44 ***
		<i>Languages</i>	7.46	<i>Liberal Arts</i>	4.52 ***	<i>Law</i>	4.84 **
		<i>Media</i>	7.12	<i>Social Science</i>	4.48 **	<i>History</i>	3.83 **
		<i>History</i>	6.47	<i>History</i>	4.44 **	<i>Liberal Arts</i>	3.82 **
		<i>Fine Arts</i>	6.32	<i>Law</i>	3.42 *	<i>Psychology</i>	2.28 **
		<i>Business</i>	5.55	<i>Agriculture</i>	2.65 **	<i>Social Work</i>	2.1 **
		<i>Liberal Arts</i>	5.46	<i>Psychology</i>	2.53 **	<i>Social Science</i>	1.78
		<i>Law</i>	0.97	<i>Fitness</i>	1.85	<i>Education</i>	1.67
		<i>Architecture</i>	0.8	<i>Science</i>	1.67	<i>Agriculture</i>	1.66
		<i>Psychology</i>	-1.07 *	<i>Social Work</i>	1.25 *	<i>Fitness</i>	1.63
		<i>Science</i>	-2.64 *	<i>Education</i>	0.76	<i>Science</i>	0.6
		<i>Fitness</i>	-3.42 **	<i>Fine Arts</i>	0.13	<i>Architecture</i>	-0.09
		<i>Social Work</i>	-4.25 ***	<i>Media</i>	-0.2	<i>Fine Arts</i>	-0.78
		<i>Agriculture</i>	-4.5 ***	<i>Architecture</i>	-1.29	<i>Media</i>	-0.87
		<i>Religion</i>	-6.99 ***	<i>Medicine</i>	-1.8	<i>Business</i>	-2.75
		<i>Education</i>	-9.07 ***	<i>Religion</i>	-1.94	<i>Religion</i>	-3.09
		<i>Medicine</i>	-11.24 ***	<i>Business</i>	-2.92	<i>Medicine</i>	-4.34

Among other majors, it appears the role of population with this level of detail in human capital heterogeneity is to reverse its negative bias on the effect of local specialization. In specification (4), several fields of study gained positive and significant specialization premiums once the UWP was added to the model, including psychology, social work, and agriculture, which formerly exhibited negative returns. The shift of statistical significance from negative to highly ranked positive specialization premiums when estimated with population size suggests specialized interaction is desirable but costly to find in small, less diverse cities. Cities reduce that cost by affording individuals a greater probability of finding, meeting, and engaging with like-minded people.

Table 2.7 replicates the results of Table 2.6 displaying the population effect across knowledge types. Columns (3') and (5) provide rankings of the UWP across majors, independent of and in the presence of local specialization, respectively. As shown in column (3'a) STEM majors on average earn a lower UWP than other fields. Upon expanding the STEM category in columns (3'b) and (5), several fields consistently earn significant urban wage premiums, including: social science, government, mathematics, business, medicine, science, architecture, and engineering.

Table 2.7: Ranking of UWP across College Majors

		3' <i>UWP alone</i>			5 <i>UWP w/ specialization</i>		
	a		b				
Other	5.38 ***	Social Science	6.53 ***	Law		7.30	
STEM	4.16 ***	<i>Mathematics</i>	6.48 ***	Social Science		6.40 ***	
		Law	6.47	Government		6.39 ***	
		Government	6.47 ***	<i>Mathematics</i>		6.16 **	
		History	5.81 **	History		5.64	
		Languages	5.77	Languages		5.59	
		Liberal Arts	5.57 *	Social Work		5.57	
		<i>Computer Science</i>	5.56	Media		5.54	
		Media	5.47 *	Liberal Arts		5.40	
		Psychology	5.29	Fine Arts		5.35	
		Social Work	5.24	Psychology		5.29	
		Fine Arts	5.21	Education		5.26	
		Business	5.04 ***	Business		5.08 ***	
		Education	4.99	<i>Computer Science</i>		4.94	
		Fitness	4.43	Fitness		4.79	
		Religion	4.38	Agriculture		4.37	
		<i>Medicine</i>	4.28 *	Religion		4.08	
		Agriculture	3.86 **	<i>Medicine</i>		3.91 ***	
		<i>Science</i>	3.69 ***	<i>Science</i>		3.72 ***	
		<i>Engineering</i>	3.66 ***	Architecture		3.51 *	
		Architecture	3.47 **	<i>Engineering</i>		3.46 ***	

Note: In column 2 of model specification 3', statistically insignificant majors have a premium of 5.04%. In specification 5, statistically insignificant majors have an UWP of 5.08%.

To more clearly compare the relative effects of local human capital size to the composition of human capital, the results of model specification (5) are presented in Table 2.8. Column (5a) displays the specialization premium and column (5b) the UWP. The values are adjusted for statistical significance. Additionally, the rankings in this table are determined by the summed effects from city size and specialization for each human capital type, shown in the final column. To interpret these results, consider the reference group of our analysis—the business degree. The return to agglomeration for business majors equates to 5.08%; but, it is not driven by specialization, which generates no productivity effect at all for this type, as shown in column (5a). Rather, column (5b) shows that moving to cities twice as large allows rapid and frequent interaction with a variety of people to increase this human capital type’s productivity up to 5.08%.

Maximum gains in productivity from agglomeration come from a combination of fast, frequent interaction with others of similar knowledge. As previously discussed, across educational attainment levels, master’s degree holders benefit the most from agglomeration with a wage premium of 8.95% in the final column. 63% of that return comes from the urbanization effect of city size. Across majors, computer science, mathematics, and engineering benefit the most from interaction. Of these three majors, computer science and engineering experience dominant effects from specialization, while mathematics majors are equally sensitive to increases in both local population and specialization.

Table 2.8: Ranking of Combined Effects of Specialization and UWP

Human Capital Type	5		Combined effect of agglomeration
	Specialization of College Major a	UWP b	
Bachelor's	2.56	4.65	7.22
Master's	3.31	5.64	8.95
Professional	2.56	2.98	5.54
Ph.D.	2.56	3.46	6.02
<i>Computer Science</i>	9.97	5.08	15.05
<i>Engineering</i>	10.25	3.46	13.71
<i>Mathematics</i>	6.16	6.16	12.32
Government	5.44	6.39	11.84
Languages	6.09	5.08	11.17
Law	4.84	5.08	9.92
History	3.83	5.08	8.91
Liberal Arts	3.82	5.08	8.90
Psychology	2.28	5.08	7.36
Social Work	2.10	5.08	7.18
Social Science	0.00	6.40	6.40
Business	0.00	5.08	5.08
Education	0.00	5.08	5.08
Fitness	0.00	5.08	5.08
Agriculture	0.00	5.08	5.08
Media	0.00	5.08	5.08
Fine Arts	0.00	5.08	5.08
Religion	0.00	5.08	5.08
<i>Medicine</i>	0.00	3.91	3.91
<i>Science</i>	0.00	3.72	3.72
Architecture	0.00	3.51	3.51

*See Table 2.12 for formal results. The values reported above are adjusted for statistical significance, and represent the percent change in wages when the MSA employment share of a type doubles.

On average, STEM professionals benefit less from interaction; perhaps resulting from the insignificant specialization premium accruing to scientific and medical knowledge and low urban wage premiums assigned to engineering, science, and medicine. Nevertheless, the highest benefit from agglomeration—a 15.05% wage increase—goes to computer science, which is twice as responsive to interactions with other computer scientists (9.97%) as to frequent, random interactions in large, diverse cities (5.08%). Similarly, engineering and mathematics majors

maximize earnings by positioning themselves in large, specialized cities. Other STEM fields—specifically the hard sciences and medicine—showed no sensitivity to local specialization at all; yet, do display potential for greater productivity in bustling areas with an UWP of 3.91 and 3.72%, respectively.

Outside of STEM, productivity among languages, law, history, liberal arts, psychology, and social work majors is stimulated by local specialization. Social science, business, education, fitness, agriculture, media, fine arts, religion, and architecture exhibit greater productivity based on city size alone. In total, ten areas of study are influenced by specialization, but, every subject area benefits from the urbanization effect of large cities.

2.4.4 Robustness of Results

Since the population effect plays a critical role in determining the influence of specialized interaction for many human capital types, it is important to adjust for any unobserved effects that can bias the wage premium results. In the literature, the endogeneity between wages and local population has been discussed as a simultaneity issue. Either wages increase due to the productive enhancement cities offer through the agglomerative mechanism, which we try to show here, or the observation of prevailing higher wages in the city induce immigration resulting in an increased labor supply. In this case, there is potential downward-bias on the estimates. We mimic the approach of Cunningham, Patton, and Reed (2015) by instrumenting for population size with the city's population in 1950 and with the Wharton Residential Urban Land Regulation Index (WRI) in our benchmark results. Lagging population by a large enough number of years should weaken any temporal biases against individual wages. While city size fifty years ago is a good indicator of which cities stand to enjoy sustained growth, it does not account for the technological and sociological evolutions that make today's society more productive.

WRI supplements lagged population by adding an element of spatial constraint to the analysis that population size alone is lacking. In particular, it addresses the rate of migration by quantifying the degree of regulation on residential development across U.S. cities. For example, land constrained cities with high housing prices may implement more (anti-growth) regulation to protect property values. Although land use regulation directly impacts the housing supply and subsequently the size of the resident population, its effect on wages is not as obvious, other than a cost of living adjustment due to higher housing costs.

The average specialization and urban wage premium results under IV estimation are slightly higher, and retain statistical significance.⁵¹ However, diagnostics suggest the IVs are weak when the premium is distributed across human capital types.⁵² Therefore, we further investigate the strength of the UWP by directly estimating the effects of spatial constraint using population-weighted density in its place. Our measure of density is the average population density across PUMAs within the MSA.⁵³ The results in Table 2.9 compare the effects of population size and population density on individual wages. Estimates of the density premium correspond to model specification (3'') in the table as density replaces population in the same manner that population replaces local specialization between specifications (3) and (3') in previous analysis. Formal results including the average density premium are available in table 2.15. We find MSA population and MSA weighted density display very similar effects on individual wages. One might even say they are almost interchangeable.⁵⁴

⁵¹ Formal results provided in Table 2.14.

⁵² Refer to Cunningham, Patton, and Reed (2015) for discussion of weak IV

⁵³ Finer density data based on census tracts is available, but, since the ACS only reports the PUMA, we had to settle for the broader density weight.

⁵⁴ Richard Florida discuss several benefits associated with the use of weighted-density measures in his Oct. 2012 article for Citylab. In it, he notes, "population-weighted density tracks closely with population size, being highest in metros with more than 5 million people (13,328 people per square mile), compared to 5,550 in metros with 2.5 to 5

Table 2.9: Returns to Weighted Density across College Majors

Human Capital Type	Density premium: 3''			UWP from 3'	
	a	b	c	a	b
Bachelor's	4.95 ***			4.64 ***	
Master's	5.82 ***			5.55 ***	
Professional	2.89 ***			2.92 ***	
Ph.D.	3.67 ***			3.45 ***	
STEM		4.32 ***			
Other		5.76 ***			
Agriculture			3.79 ***	3.86 **	
Architecture			3.02 ***	3.47 **	
Business			5.49 ***	5.04 ***	
Computer Science			5.70	5.56	
Education			5.26	4.99	
Engineering			3.65 ***	3.66 ***	
Fine Arts			5.72	5.21	
Fitness			4.55	4.43	
Government			6.90 **	6.47 ***	
History			5.95	5.81 **	
Languages			6.54	5.77	
Law			8.44 *	6.47	
Liberal Arts			6.13 *	5.57 *	
Mathematics			7.15 ***	6.48 ***	
Media			6.00 *	5.47 *	
Medicine			4.49 ***	4.28 *	
Psychology			5.62	5.29	
Religion			4.66	4.38	
Science			3.92 ***	3.69 ***	
Social Science			6.99 ***	6.53 ***	
Social Work			5.45	5.24	

Note: In specification 3'', statistically insignificant majors have an adjusted premium of 5.49%. In specification 3', statistically insignificant majors have an adjusted premium of 5.04%.

Focusing on the fully disaggregated listing of majors in column (3''c), statistically significant density premiums range from 3.02% for architecture students to 8.44% for law majors. In spite of the larger range in premium values (relative to the UWP in specification (3')),

million people, 3,489 in metros with 1 million people, and 1,597 in metros with less than 250,000 people". These values are weighted at the census tract level.

the ranking of wage premiums do not change drastically when we use density. Movement in the ranking occurs among the top three significant majors; law gains statistical significance under density, displacing social science and math majors as the types most sensitive to the population effect to the third and second rank, respectively. Also, agriculture and science switch places near the bottom of the ranking. History loses statistical significance with density. This minimal variation in wage premium estimates suggests the urban wage premium is quite stable, and maybe even slightly undervalued. More work is needed to identify strong instruments for population size. However, continuing work on creative new methods for data construction and estimation methodology steadily improve confidence in the predicted effects of population on wages.

2.5 CONCLUSION

Marshall (1890) argued the geographic concentration of individual industries facilitates the transmission of information via shared resources or even competitive imitation and espionage. On the other hand, Jacobs (1969) believed knowledge spillovers were the result of creative cross-industry application of innovation. The end game for both theories is competitive innovation that allows an industry to grow and thrive. Although Glaeser et.al do not find support for Marshall's hypothesis, the results are clear, here and in recent research, that the specialized interactions experienced within cities are productive.

We find that specialized interaction contributes to the wage premium evident within cities for half of the fields of knowledge studied. It has a dominant effect on productivity for fields such as computer science, engineering, and languages. The eleven majors with the lowest returns to agglomeration—including social science, business, and architecture—experience productive externalities exclusively generated from population size. Urbanization effects from city size are

crucial to the estimation of specialization externalities, and actually benefit *all* knowledge types. Nevertheless, the human capital size and composition effects are inextricably linked, and together maximize the earnings for individual workers. These findings are especially useful to governments and economic development authorities that seek to identify the industries that will flourish in the local economy given the human capital resources available within their city. For example, our results indicate it would be better to encourage population growth and *diversify* industry so that more individuals may benefit from the augmentation of the local human capital stock in terms of size and heterogeneity.

More direct estimation of the effects of diversity is warranted, by estimating wage sensitivity to concentration of knowledge types other than that of the individual. This exercise would also address the known occurrence of individuals working outside of their field of study. Assuming firms view skills from undergraduate degrees as substitutable and are willing to make significant investment in training, it would be helpful to know what majors specifically complement the firm's main subject area. For instance, should a software firm necessarily fill entry-level support staff positions with computer science majors to interact with their upper-level developers, or would interactions with math majors be just as beneficial for productivity?

Our findings made a significant contribution to the literature by highlighting the importance of population controls in models capturing agglomeration externalities. Therefore, future work will build on this momentum by testing new instruments for population size. Another addition to our analysis could be to directly estimate and compare the returns to education-based human capital within occupational or industrial classifications. This would provide more realistic modeling of the labor market by accounting for workers' skill sets from both education and employment.

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Table 2.10: Average Return to Agglomeration and Human Capital Type

	<i>Dependent variable: Log of annual wages</i>					
	<i>Educ. Attain.</i>		<i>Undergrad. Major</i>		<i>Cross-Effects</i>	
	<i>1</i>	<i>2</i>	<i>1</i>	<i>2</i>	<i>1</i>	<i>2</i>
In (local specialization of educational attainment)	-0.00314 0.0134	0.0054 0.0143				-0.172*** 0.00238
In (local specialization of major)			0.0196*** 0.0062	0.0370*** 0.00623	0.0380*** 0.00183	
In (MSA population)		0.0662*** 0.00501		0.0708*** 0.00529		
<i>Educational Attainment</i>						
Master's degree	0.188*** 0.0123	0.188*** 0.0134			0.194*** 0.00453	
Professional degree	0.417*** 0.0322	0.427*** 0.0344			0.431*** 0.00873	
Ph. D.	0.349*** 0.0366	0.369*** 0.0393			0.366*** 0.00935	
<i>Undergraduate Major</i>						
Agriculture			-0.0465** 0.0192	0.0320* 0.0189		-0.128*** 0.00857

Table Cont. (2)

Architecture	-0.0404 0.0282	0.013 0.0288	-0.115*** 0.017
Computer Science*	0.146*** 0.0166	0.179*** 0.0152	0.113*** 0.0115
Education	-0.0856*** 0.00797	-0.0616*** 0.00828	-0.110*** 0.00528
Engineering*	0.157*** 0.0113	0.175*** 0.0093	0.114*** 0.00947
Fine Arts	-0.136*** 0.0133	-0.115*** 0.0131	-0.181*** 0.00798
Fitness	-0.0500** 0.0207	0.0193 0.0198	-0.134*** 0.0117
Government	0.0390*** 0.0119	0.0605*** 0.0115	-0.0410*** 0.00914
History	0.0418** 0.0167	0.0760*** 0.0162	-0.0755*** 0.00878
Languages	0.0123 0.0204	0.0598*** 0.02	-0.106*** 0.0138
Law	-0.0224 0.0541	0.0605 0.0558	-0.163*** 0.0319
Liberal Arts	-0.0369*** 0.011	-0.0119 0.011	-0.110*** 0.00753
Mathematics*	0.170*** 0.0202	0.214*** 0.0202	0.0605*** 0.0101
Media	-0.0410*** 0.011	-0.0171 0.012	-0.0797*** 0.0056

Table Cont. (3)

Medicine*	0.127***	0.154***	0.0944***
	0.00997	0.0105	0.00639
Psychology	-0.00918	0.0165	-0.101***
	0.0119	0.0118	0.00673
Religion	-0.169***	-0.111***	-0.300***
	0.0211	0.0206	0.013
Science*	0.133***	0.154***	-0.00154
	0.00807	0.00653	0.00556
Social Science	0.0228	0.0402***	-0.0390***
	0.0141	0.0146	0.011
Social Work	-0.0819***	-0.0154	-0.169***
	0.022	0.0232	0.0124
Observations	333,524		
R ²	0.369	0.38	0.352
			0.364
			0.371
			0.378

* significant at 10%

** significant at 5%

*** significant at 1%

Table 2.11: Local Specialization Premiums Across Human Capital Types

	Dependent Variable: Log of annual wages					
	<u>3</u>			<u>4</u>		
	<i>i</i>	<i>ii</i>	<i>iii</i>	<i>i</i>	<i>ii</i>	<i>iii</i>
In (local specialization of educational attainment)	-0.661*** 1.6			-0.362*** 0.0933		
In (local specialization of major)		0.0293*** 0.0157	0.078 0.513		0.0308*** 0.00149	-0.0427 0.0302
In (MSA population)				0.0630*** 0.0041	0.0712*** 0.00536	0.0699*** 0.00529
<i>Local Specialization Premiums by type</i>						
Master's degree	1.064*** 2.54			0.612*** 0.141		
Professional degree	0.694*** 1.96			0.306*** 0.111		
Ph. D.	0.691*** 1.75			0.416*** 0.1		
STEM		-0.00857 0.0822			-0.00375 0.00628	
Agriculture			-0.144*** 0.522			0.0804** 0.0368
Architecture			-0.0665 0.631			0.0241 0.0482
Computer Science*			0.132* 0.76			0.181*** 0.0584
Education			-0.215*** 0.724			0.0537 0.0416
Engineering*			0.0945 0.661			0.172*** 0.0533

Table Cont. (2)

Fine Arts	0.0104	0.0446
	0.52	0.0362
Fitness	-0.128**	0.0692
	0.529	0.0431
Government	0.0611	0.129**
	0.876	0.0504
History	0.0126	0.105**
	0.778	0.0433
Languages	0.0259	0.132***
	0.765	0.0478
Law	-0.064	0.0912*
	0.648	0.0499
Liberal Arts	-0.00121	0.106***
	0.666	0.0401
Mathematics*	0.0543	0.145***
	0.742	0.0504
Media	0.0213	0.0398
	0.568	0.0373
Medicine*	-0.250***	0.0166
	0.633	0.0441
Psychology	-0.0935*	0.0788**
	0.489	0.0344
Religion	-0.183***	0.0145
	0.49	0.0389
Science*	-0.117*	0.0667
	0.633	0.0439
Social Science	0.0441	0.106**
	0.798	0.0479

Table Cont. (3)

Social Work			-0.141***			0.0607*
			0.519			0.0359
Observations	333,524					
R ²	0.371	0.349	0.354	0.38	0.362	0.365

* significant at 10%

** significant at 5%

*** significant at 1%

Table 2.12: Local Specialization and Urban Wage Premiums Across Human Capital Types

	<i>Dependent variable: Log of annual wages</i>					
	<i>i</i>		<i>5</i>		<i>iii</i>	
	<i>Spec.</i>	<i>UWP</i>	<i>Spec.</i>	<i>UWP</i>	<i>Spec.</i>	<i>UWP</i>
In (local specialization of educational attainment)	-0.369***					
	0.0967					
In (local specialization of major)			0.0310***		-0.0402	
			0.00147		0.0297	
In (MSA population)		0.0611***		0.0760***		0.0715***
		0.00432		0.00595		0.00649
<i>Premiums by type</i>						
Master's degree	0.582***	0.0133***				
	0.142	0.00256				
Professional degree	0.349***	-0.0168***				
	0.113	0.00479				
Ph. D.	0.418***	-0.00947**				
	0.106	0.0044				
STEM			-0.00566	-0.0167***		
			0.00683	0.00433		
Agriculture					0.064	-0.00971
					0.0422	0.0108
Architecture					0.0388	-0.0217*
					0.0461	0.0117
Computer Science*					0.177***	-0.00185
					0.0587	0.00867
Education					0.0641	0.00246
					0.0419	0.00752
Engineering*					0.181***	-0.0225***
					0.0504	0.00364

Table Cont. (2)

Fine Arts		0.0289	0.00366
		0.0336	0.0053
Fitness		0.0635	-0.004
		0.0403	0.0104
Government		0.117***	0.0179***
		0.0439	0.00681
History		0.0945**	0.00766
		0.0421	0.00529
Languages		0.125***	0.007
		0.0464	0.00902
Law		0.108**	0.0302
		0.052	0.0237
Liberal Arts		0.0943**	0.00437
		0.0398	0.00389
Mathematics*		0.126**	0.0147**
		0.0492	0.00694
Media		0.0275	0.00633
		0.0397	0.00386
Medicine*		-0.0239	-0.0161***
		0.0415	0.00558
Psychology		0.0727**	0.00287
		0.0341	0.00468
Religion		-0.00503	-0.0137
		0.0405	0.0102
Science*		0.0488	-0.0187***
		0.0413	0.00523
Social Science		0.0657	0.0180***
		0.044	0.0051

Table Cont. (3)

Social Work			0.0702**	0.00669
			0.0354	0.00998
Observations	333,524			
R-squared	0.381	0.362	0.365	

* significant at 10%

** significant at 5%

*** significant at 1%

Table 2.13: Urban Wage Premiums

	Dependent variable: Log annual wages				
		<u>1'</u> w/ undergrad. major controls	<u>3'</u>		
In (weighted density)	0.0662*** 0.00502	0.0703*** 0.00525	0.0654*** 0.00529	0.0756*** 0.00597	0.0709*** 0.00651
<i>UWP by Type</i>					
Master's degree			0.0125*** 0.00213		
Professional degree			-0.0238*** 0.00475		
Ph. D.			-0.0164*** 0.00417		
STEM				-0.0168*** 0.00479	
Agriculture					-0.0163** 0.00664
Architecture					-0.0217** 0.0106
Computer Science					0.00718 0.0104
Education					-0.00063 0.00684
Engineering					-0.0191*** 0.00693
Fine Arts					0.0024 0.00447
Fitness					-0.00843 0.0106
Government					0.0195*** 0.007
History					0.0105** 0.00475
Languages					0.0101 0.00935
Law					0.0196 0.0248
Liberal Arts					0.00723* 0.00374

Table Cont. (2)

Mathematics					0.0197***
					0.00653
Media					0.00595*
					0.00332
Medicine					-0.0104*
					0.00549
Psychology					0.0035
					0.00454
Religion					-0.00907
					0.0097
Science					-0.0186***
					0.00506
Social Science					0.0204***
					0.0048
Social Work					0.00281
					0.00971
Observations	333,524				
R-squared	0.38	0.364	0.38	0.361	0.365

Table 2.14: 2SLS Estimates of Average Returns to Agglomeration

	<i>Dependent variable: Log of annual wages</i>					
	<i>1'</i>		<i>2</i>			
In (local specialization of educational attainment)			-0.00799			-0.167***
			0.0114			0.00172
In (local specialization of major)				0.0478***	0.0402***	
				0.00499	0.00137	
In (MSA population)	0.0788***	0.0841***	0.0788***	0.0844***	0.0793***	0.0812***
	0.00134	0.00136	0.00134	0.00136	0.00134	0.00133
<i>Educational Attainment</i>						
Master's degree	0.186***		0.179***		0.190***	
	0.00271		0.0102		0.00271	
Professional degree	0.407***		0.389***		0.415***	
	0.00552		0.0257		0.00552	
Ph. D.	0.349***		0.328***		0.358***	
	0.00591		0.0305		0.00592	
<i>Undergraduate Major</i>						
Agriculture		-0.0812***		0.0597***		-0.110***
		0.0108		0.0181		0.0106
Architecture		-0.119***		0.0402*		-0.128***
		0.0132		0.0214		0.0133
Computer Science		0.113***		0.199***		0.115***
		0.00655		0.0111		0.00648
Education		-0.0914***		-0.0523***		-0.101***
		0.00471		0.00617		0.00463
Engineering		0.141***		0.181***		0.114***
		0.00482		0.00636		0.00476
Fine Arts		-0.180***		-0.0990***		-0.189***
		0.00621		0.0105		0.00614

Table Cont. (2)

Fitness		-0.0957***		0.0631***		-0.119***
		0.0125		0.0207		0.0122
Government		0.0102*		0.0794***		-0.0419***
		0.00592		0.0093		0.00579
History		-0.00562		0.105***		-0.0751***
		0.00856		0.0144		0.00835
Languages		-0.0507***		0.0950***		-0.107***
		0.0111		0.0189		0.011
Law		-0.106***		0.122***		-0.151***
		0.0279		0.0366		0.0267
Liberal Arts		-0.0696***		0.00686		-0.110***
		0.00605		0.01		0.00594
Mathematics		0.119***		0.247***		0.0626***
		0.00973		0.0165		0.00953
Media		-0.0788***		0.000476		-0.0831***
		0.00614		0.0103		0.00608
Medicine		0.113***		0.167***		0.101***
		0.00573		0.00804		0.0056
Psychology		-0.0394***		0.0340***		-0.0986***
		0.00582		0.00961		0.00571
Religion		-0.212***		-0.0729***		-0.286***
		0.0114		0.0184		0.0112
Science		0.115***		0.162***		0.000273
		0.00519		0.00708		0.00511
Social Science		-0.00054		0.0592***		-0.0366***
		0.00552		0.00833		0.00542
Social Work		-0.130***		0.0181		-0.155***
		0.011		0.0189		0.0107
Observations	282,668					
R-squared	0.376	0.361	0.376	0.361	0.378	0.385

Table 2.15: Density Premiums

	<i>Dependent variable: Log annual wages</i>			
	<i>w/ educ. attain. controls</i>	<u>1''</u> <i>w/ undergrad. major controls</i>	<u>3''</u>	
In (weighted density)	0.0700*** 0.00733	0.0745*** 0.00791	0.0697*** 0.007	0.0771*** 0.00808
Density Premiums by Type				
Master's degree			0.0118*** 0.00332	
Professional degree			-0.0286*** 0.00507	
Ph. D.			-0.0178*** 0.00476	
Agriculture				-0.0235*** 0.00684
Architecture				-0.0341*** 0.0104
Computer Science				0.00292 0.013
Education				-0.00307 0.00788
Engineering				-0.0253*** 0.00767
Fine Arts				0.00314 0.00513
Fitness				-0.0129 0.0124
Government				0.0192** 0.00822
History				0.00627 0.00618
Languages				0.0143 0.0122
Law				0.0398* 0.0219
Liberal Arts				0.00870* 0.00455

Table Cont. (2)

Mathematics				0.0225***
				0.00787
Media				0.00700*
				0.00403
Medicine				-0.0138***
				0.00489
Psychology				0.00174
				0.00507
Religion				-0.0114
				0.0113
Science				-0.0216***
				0.00545
Social Science				0.0205***
				0.00627
Social Work				-0.000495
				0.00954
Observations	333,524			
R-squared	0.378	0.362	0.378	0.362

CHAPTER 3

PRODUCTIVITY GAINS FROM KNOWLEDGE EXCHANGE ACROSS DIFFERENT TYPES OF HUMAN CAPITAL

3.1 INTRODUCTION

In this paper, we study how individuals learn from one another by identifying which human capital types generate the most productive knowledge spillovers. To do so, we study how knowledge exchange affects worker productivity across cities. In particular, we estimate individual wages in a series of regressions as a function of undergraduate major, city size, and employment share of a particular human capital type—either one’s own college major or another. By interacting these employment shares with indicators for an individual’s type of human capital, we can examine how worker productivity might be affected through interactions and exchange of knowledge. In particular, we use formal education data from the 2011 American Community Survey to identify over twenty fields of study at the undergraduate level. The richness of our data allows us to make a unique contribution to the literature by providing estimates of the productivity effects from over 400 different combinations of human capital interactions. Our findings suggest local STEM presence continues to have strong positive effects on most knowledge types. The effect is augmented with additional controls for the knowledge composition premium across industries. These results are robust at higher levels of education, and earlier stages of the labor market life cycle.

Within the segment of agglomeration literature regarding human capital externalities, studies verify the positive effects of larger and smarter human capital stocks. These effects are theorized to be productive externalities emanating from the frequent interactions individuals experience with one another inside of cities.⁵⁵ As a productive local amenity, a relatively specialized human capital stock should undoubtedly enhance the efficiency and performance of workers within the same industry or area of expertise. Existing research such as Wheaton and Lewis (2002) and Fu (2007) determines exposure to increased representation of one's own occupation or industry of employment within a geographic area has varying rates of return across human capital types. Specialized interaction between individuals of the same industry or job reduces friction in communication and allows for faster and/or more effective implementation of transferred knowledge. But, when you consider large cities, diversity often dominates the industrial landscape.⁵⁶ In cities, one inevitably encounters a variety of different types of interactions rather than repetitious patterns of contact.. What benefits, if any, come from that? Glaeser et al. (1992) find empirical support for Jacobs' dynamic externality theory that diverse cross-industry interaction within cities stimulates productivity and promotes growth.⁵⁷ This paper attempts to quantify the benefit of meeting others with different educational backgrounds.

The theoretical model of Berliant, Reed, and Wang (2007) suggests there is an optimal range of human capital one may experience within an agglomeration economy where individuals are randomly matched with others and engage in transfers of knowledge. If two individuals' knowledge backgrounds are too different, no productive exchange takes place. With the

⁵⁵ Roback (1982), Rauch (1993), Glaeser & Mare (2001), Fu (2007), Cunningham, Patton, & Reed (2015a)

⁵⁶ The data discussion of Cunningham, Patton, and Reed (2015b) shows that smaller cities tend to be more specialized. They conjecture this may be due to the limited capacity of small cities to support the demand for a wide variety of skill sets.

⁵⁷ Jacobs (1969)

availability of detailed data on level and subject of formal education, Cunningham, Patton, and Reed (2015a) expand upon this model by arguing the return to interactions with others varies by human capital type. Specifically, those with relatively soft skills/knowledge will benefit the most from specialized interaction in larger cities, as shown by the urban wage premium.

In related work, Winters (2014) estimates the effects of increased STEM presence on the wages of non-STEM workers and vice-versa. His study is the most closely related to our paper in terms of objective and methodology. Notably, Winters finds the increase in the percentage of STEM graduates in the local adult population has a larger positive effect than an increase in the percentage of non-STEM graduates on wages. However, these effects have greater influence on the wages of STEM workers. This paper will combine the rich heterogeneity of Cunningham, Patton, and Reed (2015b) with the cross-effect estimation of Winters.

The remainder of this paper is as follows. The next section will explain the construction of our dataset. Section 3 describes the empirical model. Section 4 provides interpretation of our results. We conclude and provide summary remarks in section 5.

3.2 DESCRIPTION OF THE DATA

The American Community Survey (ACS) provides a wealth of information on human capital accumulation in the United States. The U.S. 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. We focus on their formal education and industrial data for the purposes of this paper. In addition to various socioeconomic and demographic data, the ACS provides specific information regarding educational attainment, areas of study, and employment. We identify four levels of educational attainment within postsecondary education and aggregate undergraduate field of degree into 21 categories to

represent the depth and type of human capital possessed through formal education.⁵⁸ Our analysis also uses industry of employment information to determine the robustness of our results on knowledge composition premiums.⁵⁹ With the inclusion of eighteen indicators for industry we are able to determine if human capital composition externalities are significantly influenced by occupational knowledge.

We impose certain criteria to ensure we are conducting analysis on active labor market participants. We focus on employed college graduates aged 16 or older that earned at least \$10,000 in the last year. Additionally, each individual must reside within an MSA to best approximate an agglomerative environment where one faces a higher probability of face-to-face interaction with a wide variety of people.⁶⁰

The variables of interest are 21 aggregate measures of local specialization for each human capital type (college major, e). Local specialization is essentially the employment share of the college-educated workforce of each knowledge type, l_{ej}/l_j .⁶¹ These 21 specialization

⁵⁸ Field of degree information has been included in the ACS since 2009. We use the 2011 panel for the current analysis.

⁵⁹ The ACS allows us to construct four indicators for highest level of educational attainment: bachelor's degree, master's degree, professional degree, and Ph.D. We aggregate 174 different majors reported in the ACS into twenty-one categories to represent horizontal variation in educational type. 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. Similarly, we identify industry of employment at the 1-digit NAICS level and control for 18 industrial categories. They are: Agriculture/Forestry/Fishing and Hunting, Arts/Entertainment/Recreation, Construction, Educational Services, Finance and Insurance, Health Care, Information, Manufacturing, Military, Mining/Quarrying/Oil and Gas Extraction, Other Services, Professional/Scientific/Technical Services, Public Administration, Retail Trade, Social Assistance, Transportation and Warehousing, Utilities, and Wholesale Trade.

⁶⁰ The ACS reports location of residence at the Primary Use Microdata Area, a geographical unit characterized as 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. The Missouri Census Data Center's MABLE/Geocorr2K Geographic Correspondence Engine generates 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.

⁶¹ The employment counts for this variable were calculated using the person weight, PWGTP. It is recommended to use sample population weights to derive accurate descriptive measures of the population as a whole. A description of the derivation of person and housing unit weights is available at the following site: https://www.census.gov/acs/www/Downloads/survey_methodology/acs_design_methodology_ch11.pdf

variables vary by city (the Metropolitan Statistical Area, j), allowing up to 258 unique values for each term. Because we want to know the premiums associated with interacting with others of a different knowledge background, we additionally interact these employment shares across all majors. These interaction terms provide information about the sensitivity of an individual's wages to the presence of various educational backgrounds. For example, will the productivity of someone with an undergraduate degree in medicine be enhanced by a greater presence of computer science knowledge?

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. The final dataset has 339,724 observations. 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.

3.3 EMPIRICAL MODEL

The objective of this paper is to identify how individuals learn from one another within cities. Agglomeration theory tells us that the rapid and frequent rates of interaction between people allow them to learn and incorporate new knowledge into their own productive processes. Our data allows us the opportunity to determine who individuals of a certain knowledge type should interact with in order to receive the largest gains in productivity. For example, Rosenthal and Strange (2008) measure externality attenuation associated with employment levels within concentric rings around places of work and find wages increase by 12% when local employment of college-educated workers doubles. In addition, Winters (2014) estimates wages for STEM

graduates increase 1.6% when local STEM representation increases 1%. Several other studies make use of type-specific aggregate level measures of the human capital stock to determine significant channels for agglomeration, including depth of education, size, degree of diversity and concentration.⁶²

Our model and methodology utilizes specifications of the wage premium model to estimate the magnitude and validity of the effect of city-level human capital composition of various knowledge types on individual productivity. Using information on formal education provided by the ACS to define concentration ratios for several human capital types, we estimate wage sensitivity to changes in composition of the local human capital stock across very detailed categories of knowledge type. Specifically, we increase the range of heterogeneity within formal education to levels commensurate with the variety studied among industrial and occupational categories in many other papers.

Our benchmark results consist of twenty-one regressions that will show the knowledge composition premium for each major from increased exposure to a reference human capital type. All standard errors are clustered at the MSA level.

(1)

$$\ln(w)_{iej} = \alpha + X_i\beta + L_j\theta + W_{ij}\mu + Z_{ie}\gamma + \ln(\text{employment share of reference type})_j\delta + \ln(\text{MSA population})_{ij}\lambda + [\ln(\text{emp. share, ref. type})_{ij} \cdot Z_{ie}]\varphi + [\ln(\text{pop})_{ij} \cdot Z_{ie}]\eta + \varepsilon_{iej}$$

In the above model specification, logged annual wages for individual i residing in MSA j are a function of standard demographics (X_i), local labor market conditions (L_{ij}), industry of employment (W_{ij}), undergraduate education (Z_{ie}), and the representation of the reference group

⁶² Bacolod et al. (2009), Roback (1982), Rauch(1993), Cunningham, Patton, and Reed (2015a), Glaeser et al. (1990), Fu (2007), Wheaton and Lewis (2002)

knowledge type, e , among the MSA's college-educated employment. Local composition is simply the MSA employment share of the human capital type. This MSA-level measure describes the distribution of each knowledge type within each city. While δ is the composition premium for our reference group, the sum of coefficients δ and φ provide the size of the externality from interacting with others of a different knowledge type. In other words, it is the reference group composition premium for type e .⁶³

Assuming the agglomerative effects of knowledge exchange are facilitated through increased local population *and* specialization of the labor pool, we disentangle the agglomerative effects of human capital stock *size* from human capital stock *composition* with logged MSA population and its interactions across majors. The role of MSA population size is to control for the effects from standard agglomeration economies. The average urban wage premium (UWP) is represented by parameter λ , and $\lambda + \eta$ is the UWP for each individual major.

Furthermore, we expand model (1) to include interaction terms between the local representation of the reference group and industry of employment. This effectively provides estimates of the composition premium of the particular reference group across industries. In both models, the industry reference group is Agriculture. Therefore, in model (2), δ may be interpreted as the composition premium for individuals of the reference college major type who work in the agriculture sector.

⁶³ $H_0: \delta_{e=\text{reference group major}} = \varphi_{e \neq \text{ref.type}}$

(2)

$$\begin{aligned}
\ln(w)_{iej} = & \alpha + X_i\beta + L_j\theta + W_{ij}\mu + Z_{ie}\gamma + \ln(\text{emp. share, ref. type})_j\delta \\
& + \ln(\text{MSA population})_{ij}\lambda + [\ln(\text{emp. share, ref. type})_{ij} \cdot Z_{ie}]\varphi \\
& + [\ln(\text{emp. share, ref. type})_{ij} \cdot W_{ij}]\rho + [\ln(\text{pop})_{ij} \cdot Z_{ie}]\eta + \varepsilon_{iej}
\end{aligned}$$

The results will show composition effect may be potentially biased in a similar manner as discussed with population size. The literature up to the present has focused primarily on and proven the existence and robustness of externalities generated by industry and occupational type. So, while it is novel (and very interesting) to empirically verify similar effects based on formal education, it is unreasonable to ignore the effects of occupational training and knowledge. Additionally, we control for area of employment to address the significant probability that an individual may not work in a career directly related to their college major.

Endogeneity between wages and population is a well-documented issue within agglomeration literature, often stalled by the lack of strong instrumental variables to approximate city size. Although we are not necessarily concerned about the accurate value of the UWP in this study, we do know that population is a necessary determinant in the estimation of specialization effects.⁶⁴ In lieu of instrumental variables estimates, we acknowledge the potential bias and suggest our results be interpreted comparatively rather than in terms of strict causation.⁶⁵ To check the robustness of our estimates of the knowledge composition premium, we stratify our sample along educational attainment and labor market life cycle stages. It is our hope that consistent estimates of the composition effects across the aforementioned subsamples will validate our findings.

⁶⁴ Glaeser et al. (1992); Cunningham, Patton, Reed (2015b)

⁶⁵ Winters (2014)

3.4 DISCUSSION OF RESULTS

We estimate the effects of increased local representation of various knowledge types on individual wages to help us understand how people learn from one another in agglomeration economies. While we know workers generally benefit from the externalities provided by a larger human capital stock, as well as one that is specialized in a similar knowledge type, we do not yet know what effects on productivity occur when one interacts with others of a different human capital type. What does the artist gain from the engineer, and the mathematician from the minister? Here, we explicitly answer such questions and identify how the size and magnitude of those externalities vary across private and public sector employment, level of educational attainment and the labor market life cycle.

3.4.1 Benchmark Results

Our formal benchmark results—available in table 3.2—show considerable heterogeneity in the significance and size of productive externalities across the 21 college majors used in our analysis to represent human capital knowledge type. However, we can see some general persistent patterns. First, most majors are highly sensitive to the presence of STEM knowledge within the local labor force. Science, Engineering, and Computer Science tend to yield the highest composition premiums.

Table 3.1: Knowledge Composition Premiums across College Majors—Benchmark Results⁶⁶

MAJOR	% Change in annual wages given an increase in local employment share of																				
	Agriculture	Architecture	Business	Computer Science	Education	Engineering	Fine Arts	Fitness	Government	History	Languages	Law	Liberal Arts	Mathematics	Media	Medicine	Psychology	Religion	Science	Social Science	Social Work
Agriculture	0.00	0.00	-0.44	7.93	-10.73	-0.60	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-1.54	0.00	0.00	-4.21
Architecture	5.77	0.00	-8.57	7.93	-10.60	8.27	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	0.49	11.55	0.00	0.00
Business	3.49	0.00	-8.57	2.15	-8.44	1.72	-1.00	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-1.95	5.68	0.00	-2.56
Computer Science	6.78	0.00	-15.03	7.93	-14.14	8.27	-3.86	0.00	3.93	0.00	4.04	0.00	6.04	0.00	0.00	-14.81	0.00	-0.18	11.09	6.62	-4.43
Education	0.00	0.00	-8.57	-1.64	-4.00	-2.86	-0.45	0.00	3.93	0.00	4.04	0.00	3.22	0.00	0.00	-1.54	0.00	-0.43	0.00	0.00	0.00
Engineering	6.34	0.00	-8.57	7.93	-12.34	8.27	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-0.97	11.65	0.00	-5.24
Fine Arts	0.00	0.00	-8.57	1.45	-7.34	-0.43	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-2.66	0.00	-1.73	0.00	0.00	0.00
Fitness	0.00	0.00	5.02	1.30	-4.00	0.82	-3.86	0.00	3.93	0.00	-2.03	0.00	0.00	-6.17	6.26	0.55	-7.45	0.26	0.00	0.00	0.00
Government	4.57	0.00	-8.57	1.51	-11.02	1.23	-0.14	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-1.45	6.54	7.00	-3.38
History	3.38	0.00	-8.57	0.89	-8.37	8.27	0.26	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-0.69	5.71	0.00	-5.05
Languages	6.58	0.00	-8.57	7.93	-9.52	0.01	-3.86	0.00	3.93	5.06	4.04	0.00	0.00	0.00	7.27	-6.99	0.00	-5.95	8.86	9.95	0.00
Law	0.00	0.00	11.78	7.93	-4.00	-10.56	-3.86	0.00	3.93	-7.29	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-5.95	0.00	0.00	0.00
Liberal Arts	0.00	0.00	-8.57	0.84	-7.73	0.29	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-5.95	0.00	0.00	-2.86
Mathematics	6.54	0.00	-8.57	7.93	-11.97	8.27	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-5.95	10.53	7.30	-3.38
Media	3.44	0.00	-8.57	2.34	-8.83	2.39	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-1.12	5.52	0.00	-3.62
Medicine	3.39	0.00	-8.57	1.39	-11.29	1.55	-0.82	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-0.68	8.27	0.00	-3.48
Psychology	0.00	0.00	-8.57	1.20	-9.83	2.24	-3.86	0.00	3.93	0.00	4.04	0.00	3.07	0.00	0.00	-6.99	0.00	-2.07	6.29	3.38	0.00
Religion	0.00	0.00	-8.57	2.45	-10.72	8.27	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-5.95	12.58	0.00	0.00
Science	0.00	0.00	-0.64	2.91	-7.69	0.96	-3.86	0.00	3.93	0.00	4.04	0.00	0.00	-4.03	0.00	-3.56	0.00	-0.23	0.00	0.00	0.00
Social Science	0.00	0.00	-8.57	0.98	-4.00	-0.56	-3.86	0.00	3.93	3.18	4.04	0.00	0.00	0.00	0.00	-6.99	0.00	-1.19	6.39	0.00	0.00
Social Work	5.61	6.89	-15.33	-0.88	-11.66	-0.08	0.39	0.00	3.93	0.00	4.04	0.00	4.56	0.00	0.00	-6.99	0.00	0.85	0.00	0.00	0.00

Note: This table displays the benchmark knowledge composition premium results of 21 regressions (model specification 1). Each column indicates the reference human capital type for a regression, and therefore, the composition premium type. Each regression includes controls for standard demographics, local labor market characteristics, indicators for undergraduate major and industry of employment, and the urban wage premium interacted with each major.

⁶⁶ This table provides a grid of the knowledge composition premium results. The values should be interpreted as the percent change in wages for an individual with the row major, given a 100% increase in the local employment share of the column major. The tables in the appendix provide rankings of this same information and are arguably more intuitive in its presentation.

Secondly, mutually beneficial *and* premium-maximizing pairings exist and often include a STEM field. Thirdly, more often than not, increased exposure to your own knowledge type does not enhance productivity. Computer Science, Government, and Languages typically benefit from local specialization of their respective human capital types. Very few majors consistently experience a reduction in wage when local concentration of its own knowledge type increases.

Just over half (12 out of 21) of the knowledge types benefit the most from a STEM-related field.⁶⁷ For example, the first ranking in Table 3.4 shows Agriculture majors respond well to Computer Science information, receiving a 7.93% boost in productivity when CS majors double in local representation.⁶⁸ Similarly, those with History knowledge benefit from interaction with Engineering majors, earning a composition premium equal to 8.27%.

Science information enhances the productivity of several fields. They are: Architecture (11.55%), Business (5.68%), Computer Science (11.09%), Engineering (11.65%), Mathematics (10.53%), Media (5.52%), Medicine (8.27%), Psychology (6.29%), Religion (12.58%), and Social Science (6.39%). The Science discipline explains how we interact with the natural world and can understandably relate to the several fields listed above. Although Science does not benefit from increased local representation of its own type, it is interesting to note the strong effect—a minimum 8.3% wage increase—that Science bears on the other STEM fields. Its effect on STEM is only surpassed by the response of Religion, the historical antithesis of this discipline. Surprisingly, these two fields do not share a mutually beneficial relationship, as Religion actually diminishes productivity of scientists (-0.23%). For the scientist, facts trump

⁶⁷ The formal results for the benchmark model, excluding industry interactions with specialization, are presented in Appendix Table 1.

⁶⁸ Find this result in Agriculture row x Computer Science column in Table 1 above.

faith. On the other hand, students of Religion can produce books and sermons to motivate and defend faith in response to the findings of Science.

Outside of STEM, other high-yielding premiums come from increased local presence of Languages, Media, Social Science, Business, and Architecture majors. Business's effect on Law is the most intuitive and it, like many of the 441 estimated composition premiums, represents part of a lopsided relationship. Business specialization increases Law productivity by 11.8%, but Law presence has no effect on Business (or any other field's) productivity. Similarly, Fitness does not influence any other field and Government specialization has a uniform effect of 3.93% on all other majors.

There are pairings where both fields have maximized positive effects on each other. For instance, Agriculture benefits the most from Computer Science specialization. We would consider this pairing as mutually beneficial and "premium-maximizing" to the extent that Agriculture has its strongest effect on Computer Science (6.78%). Computer Science actually benefits the most from interaction with those possessing Science knowledge. Since Science does have a positive Computer Science composition premium, the Computer Science-Science match is mutually beneficial, but *not* premium-maximizing because Science exerts its strongest influence on Religion. Other "optimal" pairings include Government, Social Science, and Languages. Those with knowledge in Government and Languages should actively seek out areas with high representation of social scientists, and social scientists should welcome an influx of these human capital types even though they have a stronger preference for scientists.

There are cases in which pairings are completely counterproductive. All knowledge types experience a negative Education composition premium, ranging from -15.33 (Social Work) to -7.45% (Fitness). Religion, Fine Arts, Medicine, Computer Science, Engineering, Education, and

Business all return the favor. Meanwhile, Languages, Government, and Liberal Arts majors enhance the productivity of Education majors.

Education is one of the five fields of knowledge that experience negative returns to increased local representation of its own human capital type (-4%). This group additionally includes: Business (-8.57%), Fine Arts (-3.86), Medicine (-6.99), and Religion (-5.95). Business and Education tend to possess the largest representation within cities and their negative premiums may reflect competitive pressure within the labor market. Fine Arts and Religion are fields so deeply grounded in personal interpretation that interaction with *anyone* is likely to be counterproductive. In fact, Fine Arts only yield small positive composition premiums (less than 1%) for History and Social Work majors. The Fine Art premiums for all other majors are negative, effectively exhibiting the same behavior as those from Religion. Likewise, the Medicine composition premium is negative for all fields except Fitness (0.55%); however, it is a little more difficult to intuitively explain why those with knowledge in medicine ultimately do each other a disservice by interacting with one another.

Controlling for the effects of specialization across industries allows us to examine whether information exchange conditional on industry of employment enhances or deflates the knowledge composition premiums from formal education. The results and rankings are available in Tables 3.4 and 3.5, respectively. Under this specification, a STEM-related field—Engineering, specifically—possesses the highest ranking composition premium (17.2%) for just five majors: Architecture, Computer Science, Engineering, Mathematics, and Religion. Instead, Psychology and Government exert the greatest influence over the majority of the majors, while the influence of STEM shifts to the industry classifications. Workers in 13 of the 18 industries in our sample benefit the most from increased local representation of Engineering majors, receiving the same

17.2% premium. They are: Agriculture/Forestry/Fishing/Hunting, Construction, Finance/Insurance, Health Care, Information, Manufacturing, Other Services, Professional/Scientific/Technical Services, Public Administration, Retail Trade, Transportation/Warehousing, Utilities, and Wholesale Trade. Other high yielding premiums across industries originate from Agriculture (9.71%), Media (25.12%), and Psychology (13.8%) and are applied to the Military, Mining/Quarrying/Oil and Gas Extraction, and Social Assistance industries, respectively. The Engineering, Computer Science, and Languages majors positively influence all industries. Architecture, Business, Fitness, Law, Medicine, and Science knowledge have no effect on industrial productivity.

Failure to control for industry effects negatively biases the composition premium across majors. Even though Education *and* Religion now produce negative effects on all other majors, fields that formerly exhibited mixed effects such as Computer Science, Mathematics, and Psychology now join Government in producing strictly positive composition premiums. Only one major, Media, as opposed to two, fails to influence any of the other knowledge types. The most lucrative pairings when controlling for industry effects are: Engineering-Engineering, Psychology-Psychology, Computer Science-Engineering, Languages-Psychology, and Mathematics-Engineering. Notice how Engineering and Psychology benefit the most from specialized interaction with their own types. These results, along with the addition of Mathematics and Psychology to the list of fields that also benefit from specialized interaction, imply the industry effect enhances the role of own-type specialization. Likewise, the reduction in the number of fields that experience negative own-type premiums from five majors to two, Education (-6.19) and Religion (-10.33%), provides additional evidence of this augmented specialization effect.

3.4.2 Private Sector Estimation

In order to determine if the results thus far are robust to one's sector of employment, we repeat our estimation methodology on a sample excluding public sector workers; i.e. those employed in the Public Administration and Military industries. In the benchmark results, Government was the only major to provide positive, nonzero composition premiums for all majors. It retains its behavior as a universal complement to other knowledge types among private sector employment and is joined by Social Science.⁶⁹ Controlling for industry effects, that group expands to include Computer Science, Mathematics, and Psychology, just like we observed in the benchmark results with the full sample. This model specification also mimics the benchmark results when Education and Religion maintain their absolute negative effect on private sector employment. Also, the results across industry are consistent, with the added influence of Government providing positive specialization economies for all majors. Regardless of model specification, Computer Science, Engineering, Government, Languages, and Mathematics benefit from own-type local specialization.⁷⁰

In this private sector sample, the strongest composition premiums emanate from fields of knowledge that facilitate the operation of the public sector such as Liberal Arts, Law, Social Science, Languages, and especially Government. With industry controls, two-thirds of the majors and one-third of the industries are most influenced by Government knowledge. Government knowledge offers more opportunity to maximize wage premiums through co-location. Specifically, Government, Languages, Mathematics, and Psychology majors potentially receive a 17.66% wage increase by seeking locations with high concentrations of Government

⁶⁹ See Table 3.5 for rankings of knowledge composition premiums.

⁷⁰ Without industry controls History, Law, Liberal Arts, and Social Science also benefit from specialized interaction while Business and Medicine experience negative returns to specialized interaction. When including industry controls Education and Religion experience negative returns.

knowledge.⁷¹ The strengthened roles of these fields of knowledge on this sample are most likely inflated due to the omission of the public sector industries. STEM still plays an important role in maximizing composition premiums. Half of the industries still benefit most from STEM fields (Computer Science, Engineering, and Mathematics), consistent with the results of the full sample. Also, there are instances where STEM fields maximize productivity through interactions with other STEM majors exclusively. These lucrative pairings include Computer Science-Computer Science (without industrial premium controls), Engineering-Engineering, and Computer Science-Engineering.

3.4.3 Knowledge Composition Premiums across Educational Attainment Samples

We further stratify the sample by level of educational attainment in order to see how the amount of human capital one possesses influences the composition premium. In appendix table 5, Bachelor's degree holders potentially benefit the most from local specialization of several fields of knowledge including: Computer Science, Liberal Arts, Government, Engineering, Mathematics, Social Science, Business, and Languages. However, with industry controls, that list dwindles to Government, Engineering, and Business. Business provides the largest specialization for one field, Law (32.92%), a result first observed in our benchmark results. Initially, only Government knowledge benefits all majors, while specialization in Education and Medicine lowers overall productivity.

When estimating industry effects, Computer Science, Engineering, and Mathematics join Government in providing strictly positive premiums to all majors. These are also the only fields that benefit from own-type specialization. Computer Science and Engineering knowledge

⁷¹ The results without industry controls additionally suggest mutually beneficial, high-premium pairings include: Government-Social Science, History-Government, Languages-Social Science, and Liberal Arts-Languages.

maintain that effect across industries as well.⁷² Once again, this expansion of complementarity illustrates a strengthening of the specialization effect with industry controls, as well as the reduction of strictly negative premiums coming from two fields of knowledge to just one, Religion. Religion is also the only major to experience a negative own-type composition premium (-5.33%).

Another interesting contribution from the results on Bachelor's degree holders is the heightened sensitivity to STEM. The most lucrative pairings as discussed in previous results in this sample include: History-Liberal Arts, Languages-Social Science, Media-Languages, Liberal Arts-Liberal Arts, Agriculture-Computer Science, Government-Mathematics, Computer Science-Engineering, Engineering-Engineering, and Mathematics-Engineering. The majority of these pairings involve a STEM field, and once industry controls are added, only the three pairs where STEM majors interact with one another persist.

Among Master's degree holders, Agriculture has a surprisingly stronger influence.⁷³ Prior to controlling for industry effects, Business (7.05%), Computer Science (12.95%), Government (11.85%), Languages (7.94%), Media (7.1%), Psychology (6.73%), and Social Work (12.34%) all benefited the most from more Agriculture majors. Of these fields, Business and Languages in particular are "optimal" matches for Agriculture.⁷⁴ Other fields generating high composition premiums for this sample are Business, Government, Mathematics, Computer Science, Engineering, and Religion. However, all of this heterogeneity disappears with industry controls. Under the expanded model specification the Agriculture composition premium becomes

⁷² Without industry controls, Agriculture, Fitness, History, Languages, Liberal Arts and Social Science also benefit from own-type specialization. Business, Education, Medicine, and Religion have negative own-type composition premiums.

⁷³ See Table 3.7 for rankings of knowledge composition premiums.

⁷⁴ Without industry controls, STEM pairings between Engineering and Computer Science, and Mathematics and Computer Science are also highly lucrative.

universally negative, and all majors benefit most from Psychology, Government, or Science presence.

All but four majors benefit the most from a larger presence of Psychology. Three industries, Agriculture/Forestry/Fishing/Hunting, Information, and Mining/Quarrying/Oil and Gas Extraction, benefit most from Psychology specialization (32.13%). The remaining industries are most influenced by STEM-related fields of knowledge (mostly Science). Psychology also has several matches for potentially maximizing the returns to specialization. Computer Science, History, Mathematics, Science, and Psychology majors should seek out location with high representation of Psychology knowledge to maximize productivity. Computer Science (11.39%), Engineering (8.07%), Languages (5.56%), and Mathematics (6.78%) benefit from own-type specialization.

With industry controls, the strong influence of Engineering and Languages is replaced by Government, Psychology, and Science. Only Business suffers a negative composition premium on itself in the absence of industry controls. Agriculture assumes that role in the expanded model.

The most interesting results for the Professional degree sample occur under the expanded model specification with industry controls. Professional degree holders receive generally large composition premiums, regardless of type.⁷⁵ Up to this point, such healthy, positive premiums would have come from knowledge types like Computer Science and Mathematics. Here, they have no effect at all.⁷⁶ In fact, every major benefits the most from increased local representation of Science knowledge, earning premiums well over 100%. This is the first instance where this

⁷⁵ See Table 3.8.

⁷⁶ Engineering has also yielded high, positive premiums, but now display a negative effect on many areas of knowledge.

influence is dominated by one field.⁷⁷ Business (189.97%), Languages (143.37%), Law (143.37%), and Media (199.52%) majors share a premium-maximizing relationship with Science knowledge. Given the performance of Science within this sample, it may be the case that the tendency to agglomerate, between STEM majors specifically, increases in strength at higher levels of attainment.

These results are also the first time we have seen every STEM field demonstrate maximum sensitivity to the presence of another STEM field. Half of the industries benefit most from the increased presence of Law knowledge. It makes sense that Science and Law would bear so much influence on this sample, as the M.D. and J.D. are the most common types of professional degrees.

Language (31.22%), Law (48.39%), Media (34.42%), and Science (143.37%) all benefit from own-type interactions. Another unique result from this sample is that none of the majors experience negative returns to specialized interaction. Languages, Law, and Science boost productivity of all majors while Media benefits all industries.

For the highest level of attainment, we continue to observe strong specialization effects from STEM fields.⁷⁸ Specifically, Science produces the highest premiums for every major except Architecture, which benefits the most from increased knowledge in Medicine (95.64%).⁷⁹ More than half of the industries also benefit most from Science specialization. In the sample, the magnitudes of the premiums are large, similar to those within the Professional degree sample. One reason we may see such a stark contrast in the size of composition premiums between the Bachelor's degree and Ph.D. is that workers with higher levels of attainment have greater

⁷⁷ Without industry controls, several fields yield high premiums across majors, just as seen in previous results. They include: Science, Agriculture, History, Social Science, Fine Arts, Religion, Government, and Business.

⁷⁸ See Table 3.9.

⁷⁹ These results are from the model with industry controls.

capacity or ability to absorb and utilize information from other disciplines. It may also be the case, that these high composition premiums are just reflecting the fact that those with a Professional degree or Ph.D. have made a career out of being an expert in a particular area, and therefore have mastered the ability to analyze detail and glean the most useful information out of interactions.

3.4.4 Knowledge Composition Premiums across Labor Market Life Cycle

The final set of results informs us of the role of specialization across the labor life cycle. We estimate knowledge composition premiums for three age spans: 21-35 years old, 36-50 years old, and 51-65 years. During the earliest age bracket, we expect most individuals will complete their formal education and begin their career. Therefore, it is interesting to see within this group 12 majors have no effect on industries at all. At such an early point in one's career, occupational knowledge is sparse, and firms may need to invest in additional training for new workers. Therefore, industries may not need to be as sensitive to the human capital composition of the local labor force if they will ultimately teach workers what they need to know.

Across majors, every field of knowledge (except Law which receives no positive composition premiums) benefits the most from exposure to Engineering knowledge, as seen in appendix table 9. Likewise, STEM knowledge provides the largest boost in productivity across industries as well. Only the Military differs by benefiting the most from Agriculture specialization (11.33%). However, this could be a function of many military facilities being located in small and/or remote locations where agriculture industries also thrive.

The mid-range of the labor market life cycle shows strong specialization externalities from Computer Science knowledge.⁸⁰ Computer Science benefits all majors and is the sole

⁸⁰ See Table 3.11.

positive premium for many major and industry categories. Computer Science is the only major within this age group that benefits from own-type interaction (12.18%), which happens to be the way this major can maximize its returns to specialization. Only the Languages majors do not benefit the most from Computer Science (or any other STEM field). Languages majors have the most productive interactions with social scientists (7.92%).

Within the later stage of the life cycle, workers nearing retirement become most productive from exchanges with Psychology majors.⁸¹ Optimal knowledge exchanges occur between Psychology and Computer Science, Government, Mathematics, and other Psychology majors (47.77%). The preference for Psychology is similar to the results within the Master's degree sample. With age come wisdom and more reflective thought that may increase one's penchant for armchair psychology. Therefore, this particular age group may actually value and internalize the information from this knowledge type more than their younger counterparts, resulting in higher productivity. Older workers may also be more likely to hold leadership positions which require better understanding of how to manage others; information the psychology discipline may offer.

3.5 CONCLUSION

This study set out to uncover how people learn from one another within cities. We successfully identified the most productive matches between human capital types. The rich data of this study provided equally rich results. We found that specialization effects are strong, especially for STEM-related disciplines. Local specialization of Computer Science, Engineering, and Science often generated the largest premiums across majors and industries alike. Other knowledge types that generally produced high composition premiums across all types of

⁸¹ See Table 3.12.

knowledge are Government and Psychology. Conversely, areas such as Religion, Education, Business, and Medicine often fail to provide positive composition premiums and actually reduce the productivity of most majors. These results are generally robust to model specification and sample composition.

Throughout the analysis we found the addition of terms that interacted local specialization with industry indicators augmented the composition premium. With these industry controls there were fewer instances of majors yielding zero, low, and/or type-invariant premiums, a reduction in the number of majors generating negative returns to specialization, and significant positive premiums for many industry categories. This suggests an omitted variable bias in specialization results that exclude industry controls. Ultimately, the most accurate results must account for the influences of occupational training and knowledge, even with such detailed data on formal education.

This study is exciting because it provides the foundation for identifying the optimal range of interaction referenced in the theory of Berliant, Reed, and Wang (2007) and Cunningham, Patton, and Reed (2015a). Using the rankings provided in the appendix, we can determine true complementarity between majors. Also, they provide insight into whether the optimal knowledge distance parameter is equal in magnitude in both the hard and soft skill directions from a specified field of knowledge. Secondly, future work can expand upon this line of research by incorporating dynamic analysis along the lines of Glaeser et al (1992) and Glaeser and Mare (2001). The availability of this education information extends back to 2009. The creation of a panel dataset or addition of growth terms to reflect change in the composition of the human capital stock would provide interesting results with respect to the relationship between productivity gains and an individual's tenure in cities.

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Table 3.2: Knowledge Composition Premiums Across College Majors

Knowledge Type	Dependent Variable: Log of Annual Wages						
	Specialization Type						
	Agriculture	Architecture	Business	Computer Science	Education	Engineering	Fine Arts
Agriculture	0.027 0.026	-0.010 0.040	0.035 0.051	-0.0865* 0.051	-0.134*** 0.029	-0.149*** 0.042	0.006 0.029
Architecture	0.053 0.040	-0.004 0.039	-0.117 0.085	-0.073 0.055	-0.126** 0.055	-0.074 0.050	-0.096 0.059
Business	0.007 0.021	-0.001 0.036	-0.0814** 0.038	-0.109*** 0.037	-0.0773** 0.030	-0.120*** 0.025	-0.002 0.019
Computer Science	0.065 0.040	0.025 0.040	-0.168*** 0.060	0.138*** 0.045	-0.189*** 0.042	0.008 0.038	0.005 0.035
Education	-0.0429* 0.024	-0.014 0.039	-0.015 0.046	-0.165*** 0.049	-0.042 0.027	-0.188*** 0.048	0.006 0.019
Engineering	0.0592* 0.031	0.023 0.035	-0.083 0.054	-0.034 0.028	-0.159*** 0.035	0.143*** 0.044	-0.004 0.034
Fine Arts	-0.017 0.023	-0.023 0.039	-0.038 0.035	-0.120*** 0.042	-0.075*** 0.021	-0.156*** 0.031	-0.018 0.024
Fitness	-0.034 0.035	-0.001 0.046	0.143** 0.055	-0.118** 0.052	-0.035 0.042	-0.134** 0.057	-0.0683* 0.038
Government	0.027 0.026	0.013 0.037	-0.109*** 0.034	-0.114*** 0.039	-0.129*** 0.021	-0.129*** 0.030	0.011 0.028
History	0.012 0.025	0.002 0.040	-0.004 0.046	-0.125*** 0.046	-0.088*** 0.026	-0.103** 0.041	0.022 0.024
Languages	0.0625** 0.031	0.028 0.039	-0.174*** 0.064	-0.0966** 0.046	-0.111*** 0.030	-0.145*** 0.044	-0.015 0.044
Law	-0.087 0.053	-0.166* 0.089	0.215* 0.122	-0.068 0.085	0.101 0.106	-0.322*** 0.076	0.056 0.112
Liberal Arts	-0.002 0.022	-0.001 0.038	-0.016 0.039	-0.129*** 0.046	-0.082*** 0.020	-0.141*** 0.037	-0.012 0.021
Mathematics	0.055 0.036	-0.020 0.042	-0.147*** 0.054	-0.057 0.041	-0.146*** 0.029	-0.0651** 0.032	0.020 0.038
Media	0.011 0.023	-0.005 0.037	-0.019 0.030	-0.106*** 0.036	-0.093*** 0.031	-0.114*** 0.025	-0.003 0.021
Medicine	0.007 0.025	0.016 0.037	-0.052 0.040	-0.121*** 0.036	-0.126*** 0.027	-0.123*** 0.025	0.002 0.023
Psychology	0.003 0.024	0.023 0.036	-0.0828** 0.037	-0.122*** 0.041	-0.111*** 0.025	-0.113*** 0.027	0.002 0.021
Religion	0.010 0.028	-0.006 0.038	-0.018 0.055	-0.103** 0.043	-0.126*** 0.044	-0.0894** 0.042	-0.030 0.034

Table Cont. (1)

Knowledge Type	Dependent Variable: Log of Annual Wages						
	Specialization Type						
	Agriculture	Architecture	Business	Computer Science	Education	Engineering	Fine Arts
Science	-0.025 0.024	-0.020 0.036	0.053 0.036	-0.0955** 0.039	-0.080*** 0.028	-0.126*** 0.026	-0.008 0.022
Social Science	-0.017 0.023	-0.039 0.035	-0.040 0.034	-0.122*** 0.042	-0.0631** 0.030	-0.151*** 0.033	-0.002 0.020
Social Work	0.039 0.034	0.059 0.043	-0.163*** 0.061	-0.156*** 0.046	-0.134*** 0.036	-0.148*** 0.043	0.030 0.031
Observations	332,732	319,975	333,521	332,367	333,521	333,518	332,948
R-squared	0.365	0.364	0.365	0.365	0.366	0.365	0.365

Table Cont. (2)

Knowledge Type	Dependent Variable: Log of Annual Wages						
	Specialization Type						
	Fitness	Government	History	Languages	Law	Liberal Arts	Mathematics
Agriculture	-0.034 0.034	-0.004 0.035	-0.038 0.028	-0.046 0.031	-0.0791* 0.042	0.018 0.030	-0.0612* 0.036
Architecture	-0.010 0.035	0.025 0.092	0.035 0.058	-0.002 0.043	-0.076 0.047	-0.013 0.057	-0.002 0.046
Business	-0.037 0.024	-0.0604*** 0.021	-0.015 0.021	-0.0627** 0.030	-0.0704* 0.042	-0.018 0.023	-0.0706** 0.030
Computer Science	-0.012 0.031	-0.0597* 0.034	-0.014 0.034	-0.010 0.035	-0.074 0.048	0.044 0.049	-0.013 0.037
Education	-0.0665** 0.028	-0.0678*** 0.025	-0.012 0.023	-0.0752*** 0.029	-0.058 0.042	-0.003 0.024	-0.048 0.034
Engineering	0.007 0.028	-0.0463* 0.025	-0.032 0.032	-0.039 0.035	-0.0809* 0.048	-0.020 0.043	-0.035 0.031
Fine Arts	-0.051 0.031	-0.024 0.025	0.001 0.026	-0.0675** 0.029	-0.055 0.041	-0.028 0.027	-0.0652** 0.032
Fitness	0.018 0.025	-0.030 0.050	-0.034 0.042	-0.115*** 0.039	-0.112** 0.046	-0.0827** 0.040	-0.133*** 0.040
Government	-0.0456* 0.025	0.0850*** 0.029	-0.007 0.022	-0.027 0.027	-0.065 0.042	-0.005 0.026	-0.052 0.033
History	-0.0781** 0.032	-0.029 0.029	0.066*** 0.024	-0.047 0.029	-0.0732* 0.043	-0.016 0.034	-0.0694** 0.032
Languages	0.002 0.036	0.014 0.040	0.049 0.035	0.0885*** 0.030	-0.0825* 0.047	-0.022 0.046	-0.028 0.040
Law	-0.086 0.067	0.081 0.112	-0.133** 0.066	-0.104 0.065	0.067 0.043	-0.067 0.106	-0.019 0.073
Liberal Arts	-0.0597** 0.025	-0.017 0.024	0.005 0.025	-0.0540* 0.029	-0.054 0.043	0.0673*** 0.024	-0.0701** 0.034
Mathematics	-0.046 0.039	-0.010 0.039	0.009 0.030	-0.038 0.038	-0.099** 0.048	0.024 0.047	0.0898*** 0.034
Media	-0.027 0.024	-0.0424* 0.023	-0.030 0.023	-0.0502* 0.030	-0.0715* 0.042	-0.025 0.027	-0.0722** 0.033
Medicine	-0.017 0.026	-0.0609** 0.029	-0.0423* 0.026	-0.0558* 0.031	-0.064 0.041	-0.003 0.026	-0.0826** 0.034
Psychology	-0.042 0.026	-0.028 0.026	-0.016 0.024	-0.050 0.031	-0.049 0.042	0.012 0.022	-0.0689** 0.033
Religion	-0.0561* 0.033	-0.022 0.042	0.003 0.031	-0.0491* 0.030	-0.075 0.049	0.016 0.040	-0.047 0.036

Table Cont. (3)

Knowledge Type	Dependent Variable: Log of Annual Wages						
	Specialization Type						
	Fitness	Government	History	Languages	Law	Liberal Arts	Mathematics
Science	-0.029 0.027	-0.0631*** 0.023	-0.056** 0.023	-0.0713** 0.029	-0.0728* 0.043	-0.0454* 0.025	-0.0908*** 0.034
Social Science	-0.0608** 0.028	-0.011 0.026	0.019 0.022	-0.040 0.029	-0.0705* 0.042	-0.012 0.028	-0.032 0.033
Social Work	-0.015 0.032	-0.0738** 0.034	0.006 0.027	-0.047 0.035	-0.054 0.048	0.030 0.038	-0.0620* 0.037
Observations	330,046	333,518	332,566	327,031	293,318	333,270	331,087
R-squared	0.365	0.365	0.365	0.365	0.362	0.365	0.365

Table Cont. (4)

Knowledge Type	Dependent Variable: Log of Annual Wages						
	Specialization Type						
	Media	Medicine	Psychology	Religion	Science	Social Science	Social Work
Agriculture	0.020 0.036	-0.052 0.044	-0.036 0.040	0.025 0.035	0.050 0.043	0.029 0.034	-0.0811*** 0.028
Architecture	-0.098 0.063	-0.056 0.081	-0.056 0.066	0.059 0.057	0.128* 0.074	0.034 0.055	-0.0808** 0.039
Business	-0.003 0.025	-0.020 0.026	-0.0583** 0.025	0.018 0.029	0.031 0.031	-0.008 0.020	-0.0537** 0.022
Computer Science	-0.032 0.034	-0.171*** 0.041	-0.030 0.040	0.040 0.036	0.128** 0.058	0.0716* 0.041	-0.0902*** 0.031
Education	-0.006 0.034	0.0682** 0.032	-0.031 0.024	0.039 0.031	-0.024 0.038	-0.020 0.024	-0.024 0.023
Engineering	-0.029 0.032	-0.0851*** 0.033	-0.059 0.037	0.026 0.033	0.142*** 0.041	0.020 0.035	-0.101*** 0.027
Fine Arts	-0.057 0.036	0.037 0.030	-0.040 0.029	0.028 0.031	0.013 0.034	0.015 0.024	-0.0460* 0.025
Fitness	0.051 0.037	0.0858* 0.046	-0.138*** 0.041	0.053 0.037	-0.066 0.055	-0.053 0.043	-0.038 0.030
Government	0.010 0.031	-0.048 0.034	-0.016 0.030	0.026 0.033	0.061 0.041	0.0730*** 0.023	-0.0685*** 0.022
History	-0.041 0.037	-0.0895** 0.040	-0.031 0.038	0.041 0.033	0.059 0.047	0.026 0.027	-0.0905*** 0.026
Languages	0.057 0.048	-0.026 0.058	0.000 0.055	0.006 0.035	0.111* 0.061	0.125*** 0.037	-0.040 0.028
Law	-0.036 0.108	0.105 0.119	-0.175 0.126	-0.035 0.083	-0.189 0.148	-0.096 0.093	0.041 0.059
Liberal Arts	-0.029 0.040	0.024 0.040	-0.022 0.029	0.003 0.030	0.037 0.038	0.018 0.028	-0.0606** 0.024
Mathematics	-0.036 0.047	-0.0863* 0.047	0.006 0.053	0.013 0.038	0.129** 0.052	0.0802** 0.039	-0.0674** 0.031
Media	-0.015 0.032	-0.0658** 0.030	-0.0730** 0.032	0.035 0.034	0.043 0.042	0.005 0.023	-0.0698*** 0.025
Medicine	-0.028 0.031	-0.0817*** 0.028	-0.008 0.026	0.036 0.033	0.0760** 0.031	0.009 0.030	-0.0668*** 0.021
Psychology	-0.030 0.036	-0.007 0.028	0.024 0.025	0.019 0.033	0.0613* 0.033	0.023 0.025	-0.0400* 0.022
Religion	0.003 0.040	-0.0776* 0.047	-0.025 0.048	-0.048 0.031	0.144** 0.058	0.001 0.031	-0.041 0.033
Science	0.005 0.035	0.023 0.023	-0.042 0.029	0.044 0.028	0.011 0.029	-0.013 0.026	-0.0538** 0.022

Table Cont. (5)

Knowledge Type	Dependent Variable: Log of Annual Wages						
	Specialization Type						
	Media	Medicine	Psychology	Religion	Science	Social Science	Social Work
Social Science	-0.012 0.032	-0.032 0.032	-0.035 0.034	0.032 0.031	0.069 0.044	0.0475* 0.027	-0.0423* 0.024
Social Work	-0.022 0.042	-0.003 0.039	-0.037 0.039	0.063 0.044	0.035 0.049	0.026 0.044	0.025 0.023
Observations	333,437	333,519	333,341	332,181	333,477	333,409	331,280
R-squared	0.365	0.365	0.365	0.365	0.365	0.365	0.365

Table 3.3: Knowledge Composition Premium Across College Majors and Industries

Dependent Variable: Log of Annual Wages							
<i>Specialization Type</i>							
	Agriculture	Architecture	Business	Computer Science	Education	Engineering	Fine Arts
<i>Knowledge Type</i>							
Agriculture	-0.032 0.047	-0.007 0.041	0.023 0.048	-0.0854* 0.048	-0.102*** 0.030	-0.142*** 0.037	-0.002 0.030
Architecture	0.042 0.039	-0.031 0.071	-0.103 0.086	-0.070 0.054	-0.0922* 0.050	-0.068 0.051	-0.0958* 0.056
Business	0.000 0.022	-0.002 0.036	0.005 0.153	-0.108*** 0.037	-0.0436** 0.020	-0.103*** 0.025	-0.008 0.020
Computer Science	0.056 0.040	0.022 0.040	-0.16*** 0.060	0.182*** 0.051	-0.149*** 0.037	0.016 0.036	-0.001 0.037
Education	-0.031 0.023	-0.013 0.037	-0.046 0.036	-0.126*** 0.046	-0.0922* 0.052	-0.120*** 0.036	-0.006 0.021
Engineering	0.049 0.031	0.022 0.035	-0.078 0.054	-0.037 0.027	-0.117*** 0.031	0.229*** 0.075	-0.009 0.031
Fine Arts	-0.025 0.023	-0.022 0.038	-0.045 0.034	-0.108*** 0.042	-0.050*** 0.017	-0.125*** 0.029	0.041 0.065
Fitness	-0.045 0.034	-0.001 0.044	0.124** 0.053	-0.0968** 0.049	-0.023 0.044	-0.0944* 0.055	-0.0618* 0.036
Government	0.021 0.026	0.011 0.036	-0.11*** 0.033	-0.108*** 0.036	-0.100*** 0.022	-0.107*** 0.028	0.007 0.028
History	0.006 0.025	0.001 0.040	-0.010 0.045	-0.108** 0.045	-0.068*** 0.023	-0.0698* 0.038	0.020 0.025
Languages	0.0610* 0.032	0.029 0.039	-0.19*** 0.062	-0.0822* 0.043	-0.094*** 0.032	-0.101** 0.042	-0.018 0.046
Law	-0.0942* 0.051	-0.171* 0.088	0.227* 0.124	-0.066 0.084	0.132 0.097	-0.310*** 0.073	0.051 0.112
Liberal Arts	-0.004 0.022	-0.002 0.037	-0.024 0.036	-0.112** 0.044	-0.063*** 0.021	-0.103*** 0.033	-0.017 0.023
Mathematics	0.059 0.036	-0.024 0.042	-0.16*** 0.053	-0.040 0.040	-0.118*** 0.027	-0.031 0.032	0.009 0.042
Media	0.003 0.022	-0.010 0.037	-0.010 0.031	-0.106*** 0.036	-0.0593** 0.025	-0.100*** 0.026	-0.006 0.021
Medicine	-0.028 0.026	0.015 0.037	-0.0724* 0.040	-0.0865** 0.034	-0.118*** 0.021	-0.0765*** 0.029	0.025 0.019
Psychology	-0.008 0.023	0.023 0.035	-0.098** 0.039	-0.0982** 0.040	-0.100*** 0.022	-0.0697*** 0.024	0.004 0.021

Table Cont. (1)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Agriculture	Architecture	Business	Computer Science	Education	Engineering	Fine Arts
Religion	-0.009 0.028	0.001 0.038	-0.012 0.059	-0.0908** 0.041	-0.111*** 0.040	-0.052 0.038	-0.010 0.032
Science	-0.0404* 0.024	-0.021 0.035	0.039 0.037	-0.0765** 0.037	-0.0575** 0.025	-0.0937*** 0.024	-0.003 0.021
Social Science	-0.022 0.024	-0.040 0.035	-0.046 0.033	-0.108*** 0.041	-0.0398* 0.022	-0.117*** 0.029	-0.005 0.020
Social Work	0.020 0.034	0.057 0.042	-0.18*** 0.062	-0.131*** 0.043	-0.121*** 0.037	-0.105** 0.042	0.036 0.030
<i>Industry</i>							
Agriculture, Forestry, Fishing and Hunting	-0.032 0.047	-0.031 0.071	0.005 0.153	0.182*** 0.051	-0.0922* 0.052	0.229*** 0.075	0.041 0.065
Arts, Entertainment, and Recreation	0.0829* 0.043	0.027 0.061	-0.029 0.162	-0.067 0.048	0.041 0.056	-0.151* 0.083	-0.048 0.064
Construction	0.0781* 0.046	0.021 0.063	-0.115 0.159	-0.042 0.044	0.015 0.059	-0.036 0.086	-0.103 0.070
Educational Services	0.031 0.042	0.025 0.062	-0.040 0.156	-0.0985** 0.045	0.064 0.051	-0.176** 0.077	-0.039 0.064
Finance and Insurance	0.020 0.052	0.067 0.063	-0.093 0.172	-0.015 0.050	-0.015 0.065	-0.138 0.105	0.013 0.080
Health Care	0.112*** 0.042	0.028 0.062	-0.064 0.155	-0.0869* 0.050	0.047 0.065	-0.136 0.086	-0.096 0.065
Information	0.075 0.049	0.070 0.067	-0.208 0.187	0.060 0.061	-0.072 0.065	0.016 0.104	-0.045 0.067
Manufacturing	0.0742* 0.041	0.033 0.060	-0.105 0.160	-0.027 0.048	-0.009 0.049	-0.062 0.085	-0.043 0.063
Military	0.134*** 0.050	-0.030 0.068	0.191 0.172	-0.161*** 0.056	0.193*** 0.057	-0.184** 0.081	-0.119* 0.064
Mining, Quarrying, and Oil and Gas Extraction	-0.139* 0.082	0.067 0.087	0.101 0.238	0.126** 0.049	-0.267*** 0.094	-0.074 0.108	0.307*** 0.106
Other Services	0.0952** 0.045	0.006 0.061	-0.161 0.162	-0.036 0.048	0.042 0.054	-0.124 0.077	-0.112* 0.065

Table Cont. (2)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Agriculture	Architecture	Business	Computer Science	Education	Engineering	Fine Arts
Professional, Scientific, and Technical Services	0.0806* 0.043	0.022 0.060	-0.122 0.159	-0.044 0.046	0.009 0.051	-0.070 0.082	-0.072 0.064
Public Administration	0.042 0.042	0.050 0.062	-0.144 0.158	-0.016 0.047	-0.018 0.048	-0.084 0.079	-0.023 0.066
Retail Trade	0.0943** 0.043	0.015 0.064	-0.079 0.173	-0.055 0.056	0.038 0.083	-0.097 0.097	-0.075 0.064
Social Assistance	0.0875** 0.041	0.017 0.058	-0.048 0.156	-0.0971** 0.047	0.068 0.046	-0.176** 0.074	-0.071 0.064
Transportation and Warehousing	0.129** 0.055	-0.073 0.065	0.027 0.160	-0.115** 0.048	0.157*** 0.059	-0.112 0.109	-0.179** 0.076
Utilities	0.020 0.046	0.067 0.063	0.004 0.165	-0.070 0.048	-0.008 0.049	-0.091 0.095	-0.039 0.072
Wholesale Trade	0.0863** 0.043	-0.025 0.065	-0.049 0.173	-0.074 0.049	0.050 0.072	-0.114 0.096	-0.089 0.067
Observations	332732	319975	333521	332367	333521	333518	332948
R-squared	0.365	0.364	0.365	0.365	0.366	0.365	0.365

Table Cont. (3)

		Dependent Variable: Log of Annual Wages						
		<i>Specialization Type</i>						
<i>Knowledge Type</i>		Fitness	Government	History	Languages	Law	Liberal Arts	Mathematics
Agriculture	-0.024 0.032	-0.010 0.033	-0.036 0.028	-0.052 0.032	-0.076* 0.042	0.024 0.030	-0.0647* 0.036	
Architecture	-0.005 0.035	0.022 0.093	0.024 0.055	-0.015 0.042	-0.071 0.046	-0.017 0.051	-0.009 0.046	
Business	-0.024 0.023	-0.0536** 0.021	-0.020 0.021	-0.0695** 0.030	-0.067 0.042	-0.021 0.021	-0.0739** 0.031	
Computer Science	0.001 0.031	-0.0634* 0.034	-0.022 0.034	-0.020 0.034	-0.072 0.047	0.042 0.046	-0.018 0.037	
Education	-0.0452* 0.025	-0.0405* 0.022	0.002 0.020	-0.0682** 0.027	-0.067 0.042	-0.007 0.025	-0.033 0.031	
Engineering	0.014 0.027	-0.0557** 0.025	-0.033 0.029	-0.047 0.035	-0.078* 0.046	-0.021 0.040	-0.041 0.033	
Fine Arts	-0.048 0.031	-0.004 0.024	0.009 0.026	-0.0704** 0.029	-0.054 0.041	-0.021 0.026	-0.0587* 0.032	
Fitness	0.001 0.068	0.000 0.044	-0.014 0.040	-0.108*** 0.037	-0.11** 0.047	-0.0756* 0.040	-0.117*** 0.039	
Government	-0.029 0.025	0.184*** 0.061	-0.011 0.021	-0.032 0.028	-0.062 0.043	-0.003 0.026	-0.0576* 0.034	
History	-0.065** 0.031	-0.022 0.029	0.081 0.054	-0.0499* 0.030	-0.073* 0.043	-0.014 0.034	-0.0663** 0.032	
Languages	0.010 0.036	0.022 0.044	0.056 0.036	0.100* 0.054	-0.084* 0.047	-0.018 0.045	-0.023 0.039	
Law	-0.071 0.068	0.091 0.114	-0.141** 0.066	-0.114* 0.066	0.046 0.054	-0.071 0.105	-0.034 0.074	
Liberal Arts	-0.0470* 0.024	-0.005 0.025	0.009 0.025	-0.0550* 0.029	-0.056 0.044	0.006 0.065	-0.0653* 0.033	
Mathematics	-0.026 0.038	-0.002 0.040	0.006 0.032	-0.042 0.037	-0.10** 0.049	0.018 0.047	0.119** 0.054	
Media	-0.019 0.024	-0.037 0.024	-0.034 0.023	-0.0578* 0.029	-0.071* 0.041	-0.023 0.026	-0.0747** 0.034	
Medicine	-0.042 0.029	-0.025 0.019	0.010 0.026	-0.041 0.029	-0.060 0.042	0.026 0.029	-0.051 0.033	
Psychology	-0.039 0.026	-0.011 0.025	0.001 0.024	-0.046 0.031	-0.050 0.042	0.020 0.022	-0.0545* 0.032	

Table Cont. (4)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Fitness	Government	History	Languages	Law	Liberal Arts	Mathematics
Religion	-0.0634* 0.033	-0.036 0.043	0.003 0.029	-0.0544* 0.031	-0.070 0.049	0.032 0.039	-0.042 0.039
Science	-0.034 0.027	-0.0470** 0.020	-0.032 0.023	-0.0668** 0.029	-0.0718* 0.042	-0.034 0.025	-0.0785** 0.033
Social Science	-0.0490* 0.027	-0.002 0.026	0.021 0.022	-0.043 0.029	-0.070 0.042	-0.012 0.027	-0.029 0.033
Social Work	-0.019 0.032	-0.0583* 0.032	0.026 0.027	-0.044 0.035	-0.056 0.048	0.039 0.040	-0.048 0.037
<i>Industry</i>							
Agriculture, Forestry, Fishing and Hunting	0.001 0.068	0.184*** 0.061	0.081 0.054	0.100* 0.054	0.046 0.054	0.006 0.065	0.119** 0.054
Arts, Entertainment, and Recreation	0.053 0.068	-0.189*** 0.064	-0.055 0.057	-0.035 0.046	0.005 0.044	0.042 0.060	-0.071 0.047
Construction	0.047 0.070	-0.112* 0.067	-0.034 0.061	-0.024 0.049	-0.011 0.047	0.083 0.068	-0.033 0.050
Educational Services	-0.017 0.068	-0.136** 0.060	-0.030 0.055	-0.024 0.044	0.037 0.044	0.073 0.060	-0.046 0.046
Finance and Insurance	-0.068 0.072	-0.104 0.065	0.070 0.068	0.012 0.050	0.017 0.048	0.156** 0.079	0.023 0.054
Health Care	0.062 0.067	-0.143** 0.060	-0.090 0.056	-0.035 0.045	0.015 0.044	0.021 0.062	-0.075 0.048
Information	0.010 0.068	-0.069 0.069	0.023 0.057	0.029 0.052	0.042 0.053	0.082 0.072	0.012 0.052
Manufacturing	0.010 0.064	-0.059 0.066	-0.014 0.053	0.007 0.045	0.027 0.049	0.078 0.061	-0.016 0.048
Military	0.038 0.072	-0.188** 0.080	-0.141** 0.058	-0.0930* 0.049	-0.021 0.051	-0.057 0.075	-0.125** 0.055
Mining, Quarrying, and Oil and Gas Extraction	-0.036 0.096	-0.178 0.136	-0.057 0.142	-0.046 0.100	-0.015 0.056	0.210** 0.104	0.068 0.080
Other Services	0.055 0.068	-0.009 0.075	0.013 0.065	0.012 0.048	0.004 0.041	0.024 0.066	-0.022 0.056

Table Cont. (5)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Fitness	Government	History	Languages	Law	Liberal Arts	Mathematics
Professional, Scientific, and Technical Services	0.016 0.066	-0.075 0.065	0.014 0.054	0.010 0.044	0.017 0.042	0.054 0.059	-0.012 0.048
Public Administration	-0.044 0.067	-0.064 0.073	0.022 0.056	0.015 0.047	0.028 0.048	0.089 0.062	0.021 0.048
Retail Trade	0.034 0.070	-0.186*** 0.063	-0.053 0.058	0.007 0.047	0.018 0.041	0.010 0.067	-0.050 0.049
Social Assistance	0.054 0.066	-0.119* 0.069	-0.042 0.053	-0.031 0.049	0.036 0.047	0.053 0.062	-0.0880* 0.047
Transportation and Warehousing	0.101 0.077	-0.185** 0.080	-0.148** 0.071	-0.0865* 0.052	-0.026 0.046	-0.082 0.079	-0.133** 0.064
Utilities	0.013 0.071	-0.076 0.066	-0.010 0.060	0.008 0.049	0.003 0.049	0.074 0.066	-0.035 0.053
Wholesale Trade	0.001 0.068	-0.115 0.072	-0.008 0.058	-0.028 0.048	0.025 0.044	0.020 0.071	-0.056 0.052
Observations	330046	333518	332566	327031	293318	333270	331087
R-squared	0.366	0.365	0.365	0.365	0.362	0.365	0.365

Table Cont. (6)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Media	Medicine	Psychology	Religion	Science	Social Science	Social Work
<i>Knowledge Type</i>							
Agriculture	0.016 0.034	-0.044 0.046	-0.052 0.040	0.031 0.035	0.058 0.044	0.033 0.033	-0.0823*** 0.029
Architecture	-0.089 0.064	-0.019 0.074	-0.055 0.066	0.052 0.056	0.116 0.071	0.030 0.053	-0.0710* 0.037
Business	-0.001 0.026	0.003 0.030	-0.0628*** 0.024	0.015 0.029	0.031 0.029	-0.012 0.021	-0.0491** 0.024
Computer Science	-0.029 0.035	-0.138*** 0.039	-0.034 0.042	0.035 0.036	0.113** 0.054	0.065 0.040	-0.0802*** 0.029
Education	-0.019 0.031	0.016 0.033	-0.0477** 0.023	0.029 0.031	0.032 0.032	-0.008 0.021	-0.0509** 0.023
Engineering	-0.039 0.032	-0.053 0.035	-0.0619* 0.032	0.022 0.032	0.114*** 0.038	0.012 0.033	-0.0855*** 0.026
Fine Arts	-0.059 0.036	0.034 0.034	-0.045 0.030	0.021 0.032	0.025 0.033	0.019 0.024	-0.0486* 0.026
Fitness	0.048 0.036	0.075 0.047	-0.138*** 0.040	0.045 0.037	-0.048 0.055	-0.040 0.042	-0.046 0.031
Government	0.011 0.030	-0.034 0.027	-0.016 0.031	0.027 0.032	0.0698* 0.040	0.0685*** 0.024	-0.0654*** 0.023
History	-0.041 0.037	-0.0883** 0.040	-0.037 0.037	0.037 0.033	0.074 0.045	0.027 0.027	-0.0960*** 0.027
Languages	0.050 0.047	-0.038 0.051	-0.003 0.055	-0.001 0.035	0.134** 0.060	0.127*** 0.036	-0.0509* 0.030
Law	-0.026 0.108	0.136 0.124	-0.183 0.126	-0.037 0.081	-0.198 0.144	-0.110 0.092	0.049 0.060
Liberal Arts	-0.032 0.039	0.019 0.038	-0.029 0.029	-0.004 0.030	0.055 0.038	0.020 0.028	-0.0709*** 0.026
Mathematics	-0.039 0.047	-0.0841* 0.044	-0.007 0.053	0.007 0.039	0.151*** 0.051	0.0778* 0.040	-0.0719** 0.030
Media	0.001 0.045	-0.049 0.035	-0.0794** 0.031	0.030 0.033	0.039 0.041	-0.001 0.023	-0.0661** 0.027
Medicine	-0.024 0.030	-0.049 0.094	0.011 0.027	0.023 0.033	0.0673** 0.032	0.033 0.029	-0.0652*** 0.022
Psychology	-0.032 0.035	-0.013 0.031	0.186* 0.108	0.010 0.032	0.0813** 0.032	0.030 0.025	-0.0453** 0.023

Table Cont. (7)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Media	Medicine	Psychology	Religion	Science	Social Science	Social Work
Religion	0.001 0.040	-0.061 0.043	-0.013 0.047	-0.157** 0.065	0.151*** 0.057	0.005 0.033	-0.048 0.034
Science	0.002 0.034	0.028 0.025	-0.041 0.029	0.035 0.029	-0.027 0.117	-0.005 0.025	-0.0540** 0.023
Social Science	-0.013 0.033	-0.030 0.034	-0.041 0.034	0.026 0.031	0.0863** 0.041	0.002 0.072	-0.0462* 0.024
Social Work	-0.022 0.041	-0.010 0.041	-0.031 0.039	0.051 0.042	0.049 0.048	0.031 0.043	0.050 0.042
<i>Industry</i>							
Agriculture, Forestry, Fishing and Hunting	0.001 0.045	-0.049 0.094	0.186* 0.108	-0.157** 0.065	-0.027 0.117	0.002 0.072	0.050 0.042
Arts, Entertainment, and Recreation	0.000 0.042	0.009 0.106	-0.153 0.109	0.131** 0.059	-0.016 0.117	0.011 0.069	-0.022 0.038
Construction	-0.031 0.045	0.011 0.104	-0.205* 0.114	0.130* 0.068	0.042 0.128	-0.001 0.069	-0.049 0.041
Educational Services	0.004 0.039	0.055 0.099	-0.135 0.108	0.122** 0.058	-0.047 0.114	0.031 0.067	0.019 0.038
Finance and Insurance	-0.032 0.045	-0.126 0.110	-0.104 0.118	0.111* 0.065	-0.033 0.127	0.103 0.080	-0.024 0.046
Health Care	-0.023 0.042	-0.041 0.100	-0.196* 0.111	0.128** 0.059	0.067 0.118	0.014 0.068	-0.033 0.041
Information	-0.014 0.056	-0.160 0.119	-0.121 0.115	0.112 0.069	0.169 0.131	0.116 0.079	-0.1000* 0.054
Manufacturing	0.009 0.046	-0.100 0.097	-0.142 0.107	0.107* 0.059	0.120 0.115	0.069 0.067	-0.061 0.042
Military	-0.0855* 0.048	0.109 0.110	-0.298** 0.121	0.145** 0.062	-0.092 0.128	-0.082 0.080	0.002 0.046
Mining, Quarrying, and Oil and Gas Extraction	0.323*** 0.080	-0.289 0.179	0.010 0.150	0.215** 0.091	0.122 0.208	0.266** 0.110	-0.027 0.050
Other Services	-0.012 0.043	-0.125 0.102	-0.195* 0.107	0.091 0.058	0.048 0.123	0.050 0.074	-0.014 0.043

Table Cont. (8)

	Dependent Variable: Log of Annual Wages						
	<i>Specialization Type</i>						
	Media	Medicine	Psychology	Religion	Science	Social Science	Social Work
Professional, Scientific, and Technical Services	-0.038 <i>0.044</i>	-0.104 <i>0.096</i>	-0.179* <i>0.109</i>	0.122** <i>0.061</i>	0.079 <i>0.118</i>	0.059 <i>0.066</i>	-0.046 <i>0.042</i>
Public Administration	0.005 <i>0.043</i>	-0.082 <i>0.105</i>	-0.143 <i>0.108</i>	0.079 <i>0.063</i>	0.021 <i>0.113</i>	0.094 <i>0.067</i>	-0.046 <i>0.040</i>
Retail Trade	-0.033 <i>0.043</i>	0.020 <i>0.110</i>	-0.172 <i>0.111</i>	0.0998* <i>0.059</i>	0.016 <i>0.121</i>	0.008 <i>0.075</i>	0.004 <i>0.044</i>
Social Assistance	-0.029 <i>0.042</i>	0.021 <i>0.104</i>	-0.174 <i>0.108</i>	0.166*** <i>0.060</i>	0.003 <i>0.121</i>	0.032 <i>0.068</i>	-0.012 <i>0.039</i>
Transportation and Warehousing	-0.067 <i>0.056</i>	0.131 <i>0.104</i>	-0.289** <i>0.133</i>	0.090 <i>0.069</i>	0.102 <i>0.137</i>	-0.066 <i>0.078</i>	-0.010 <i>0.051</i>
Utilities	0.017 <i>0.054</i>	-0.031 <i>0.099</i>	-0.153 <i>0.116</i>	0.083 <i>0.071</i>	0.078 <i>0.126</i>	0.066 <i>0.070</i>	-0.017 <i>0.042</i>
Wholesale Trade	-0.050 <i>0.055</i>	-0.012 <i>0.109</i>	-0.196* <i>0.116</i>	0.132** <i>0.064</i>	0.107 <i>0.126</i>	0.005 <i>0.074</i>	-0.030 <i>0.044</i>
Observations	333437	333519	333341	332181	333477	333409	331280
R-squared	0.365	0.366	0.365	0.365	0.365	0.365	0.365

Table 3.4: Ranking of Knowledge Composition Premiums across College Majors (Full Sample)

Estimates Excluding Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Computer Science	7.93	Science 11.55	Science 5.68	Science 11.09	Languages 4.04	Science 11.65	Languages 4.04
Languages	4.04	Engineering 8.27	Languages 4.04	Engineering 8.27	Government 3.93	Engineering 8.27	Government 3.93
Government	3.93	Computer Science 7.93	Government 3.93	Computer Science 7.93	Liberal Arts 3.22	Computer Science 7.93	Computer Science 1.45
Agriculture	0.00	Agriculture 5.77	Agriculture 3.49	Agriculture 6.78	Agriculture 0.00	Agriculture 6.34	Agriculture 0.00
Architecture	0.00	Languages 4.04	Computer Science 2.15	Social Science 6.62	Architecture 0.00	Languages 4.04	Architecture 0.00
Fitness	0.00	Government 3.93	Engineering 1.72	Liberal Arts 6.04	Fitness 0.00	Government 3.93	Fitness 0.00
History	0.00	Religion 0.49	Architecture 0.00	Languages 4.04	History 0.00	Architecture 0.00	History 0.00
Law	0.00	Architecture 0.00	Fitness 0.00	Government 3.93	Law 0.00	Fitness 0.00	Law 0.00
Liberal Arts	0.00	Fitness 0.00	History 0.00	Architecture 0.00	Mathematics 0.00	History 0.00	Liberal Arts 0.00
Mathematics	0.00	History 0.00	Law 0.00	Fitness 0.00	Media 0.00	Law 0.00	Mathematics 0.00
Media	0.00	Law 0.00	Liberal Arts 0.00	History 0.00	Psychology 0.00	Liberal Arts 0.00	Media 0.00
Psychology	0.00	Liberal Arts 0.00	Mathematics 0.00	Law 0.00	Science 0.00	Mathematics 0.00	Psychology 0.00
Science	0.00	Mathematics 0.00	Media 0.00	Mathematics 0.00	Social Science 0.00	Media 0.00	Science 0.00
Social Science	0.00	Media 0.00	Psychology 0.00	Media 0.00	Social Work 0.00	Psychology 0.00	Social Science 0.00
Business	-0.44	Psychology 0.00	Social Science 0.00	Psychology 0.00	Religion -0.43	Social Science 0.00	Social Work 0.00
Engineering	-0.60	Social Science 0.00	Fine Arts -1.00	Religion -1.00	Fine Arts -0.45	Religion -0.97	Engineering -0.43
Religion	-1.54	Social Work 0.00	Religion -1.95	Fine Arts -3.86	Medicine -1.54	Fine Arts -3.86	Religion -1.73
Fine Arts	-3.86	Fine Arts -3.86	Social Work -2.56	Social Work -4.43	Computer Science -1.64	Social Work -5.24	Medicine -2.66
Social Work	-4.21	Medicine -6.99	Medicine -6.99	Education -14.14	Engineering -2.86	Medicine -6.99	Fine Arts -3.86
Medicine	-6.99	Business -8.57	Education -8.44	Medicine -14.81	Education -4.00	Business -8.57	Education -7.34
Education	-10.73	Education -10.60	Business -8.57	Business -15.03	Business -8.57	Education -12.34	Business -8.57

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Media	6.26	Social Science 7.00	Engineering 8.27	Social Science 9.95	Business 11.78	Languages 4.04	Science 10.53
Business	5.02	Science 6.54	Science 5.71	Science 8.86	Computer Science 7.93	Government 3.93	Engineering 8.27
Government	3.93	Agriculture 4.57	Languages 4.04	Computer Science 7.93	Languages 4.04	Computer Science 7.93	Computer Science 7.93
Computer Science	1.30	Languages 4.04	Government 3.93	Media 7.27	Government 3.93	Engineering 0.29	Social Science 7.30
Engineering	0.82	Government 3.93	Agriculture 3.38	Agriculture 6.58	Agriculture 0.00	Agriculture 0.00	Agriculture 6.54
Medicine	0.55	Computer Science 1.51	Computer Science 0.89	History 5.06	Architecture 0.00	Architecture 0.00	Languages 4.04
Religion	0.26	Engineering 1.23	Fine Arts 0.26	Languages 4.04	Fitness 0.00	Fitness 0.00	Government 3.93
Agriculture	0.00	Architecture 0.00	Architecture 0.00	Government 3.93	Law 0.00	History 0.00	Architecture 0.00
Architecture	0.00	Fitness 0.00	Fitness 0.00	Engineering 0.01	Liberal Arts 0.00	Law 0.00	Fitness 0.00
Fitness	0.00	History 0.00	History 0.00	Architecture 0.00	Mathematics 0.00	Liberal Arts 0.00	History 0.00
History	0.00	Law 0.00	Law 0.00	Fitness 0.00	Media 0.00	Mathematics 0.00	Law 0.00
Law	0.00	Liberal Arts 0.00	Liberal Arts 0.00	Law 0.00	Psychology 0.00	Media 0.00	Liberal Arts 0.00
Liberal Arts	0.00	Mathematics 0.00	Mathematics 0.00	Liberal Arts 0.00	Science 0.00	Psychology 0.00	Mathematics 0.00
Science	0.00	Media 0.00	Media 0.00	Mathematics 0.00	Social Science 0.00	Science 0.00	Media 0.00
Social Science	0.00	Psychology 0.00	Psychology 0.00	Psychology 0.00	Social Work 0.00	Social Science 0.00	Psychology 0.00
Social Work	0.00	Fine Arts -0.14	Social Science 0.00	Social Work 0.00	Fine Arts -3.86	Social Work -2.86	Social Work -3.38
Languages	-2.03	Religion -1.45	Religion -0.69	Fine Arts -3.86	Education -4.00	Fine Arts -3.86	Fine Arts -3.86
Fine Arts	-3.86	Social Work -3.38	Social Work -5.05	Religion -5.95	Religion -5.95	Religion -5.95	Religion -5.95
Education	-4.00	Medicine -6.99	Medicine -6.99	Medicine -6.99	Medicine -6.99	Medicine -6.99	Medicine -6.99
Mathematics	-6.17	Business -8.57	Education -8.37	Business -8.57	History -7.29	Education -7.73	Business -8.57
Psychology	-7.45	Education -11.02	Business -8.57	Education -9.52	Engineering -10.56	Business -8.57	Education -11.97

Table Cont. (1)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>						
Science	5.52	Science	8.27	Science	6.29	Science	12.58	Languages	4.04	Science	6.39	Architecture	6.89
Languages	4.04	Languages	4.04	Languages	4.04	Engineering	8.27	Government	3.93	Languages	4.04	Agriculture	5.61
Government	3.93	Government	3.93	Government	3.93	Languages	4.04	Computer Science	2.91	Government	3.93	Liberal Arts	4.56
Agriculture	3.44	Agriculture	3.39	Social Science	3.38	Government	3.93	Engineering	0.96	History	3.18	Languages	4.04
Engineering	2.39	Engineering	1.55	Liberal Arts	3.07	Computer Science	2.45	Agriculture	0.00	Computer Science	0.98	Government	3.93
Computer Science	2.34	Computer Science	1.39	Engineering	2.24	Agriculture	0.00	Architecture	0.00	Agriculture	0.00	Religion	0.85
Architecture	0.00	Architecture	0.00	Computer Science	1.20	Architecture	0.00	Fitness	0.00	Architecture	0.00	Fine Arts	0.39
Fitness	0.00	Fitness	0.00	Agriculture	0.00	Fitness	0.00	History	0.00	Fitness	0.00	Fitness	0.00
History	0.00	History	0.00	Architecture	0.00	History	0.00	Law	0.00	Law	0.00	History	0.00
Law	0.00	Law	0.00	Fitness	0.00	Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00
Liberal Arts	0.00	Liberal Arts	0.00	History	0.00	Liberal Arts	0.00	Media	0.00	Mathematics	0.00	Mathematics	0.00
Mathematics	0.00	Mathematics	0.00	Law	0.00	Mathematics	0.00	Psychology	0.00	Media	0.00	Media	0.00
Media	0.00	Media	0.00	Mathematics	0.00	Media	0.00	Science	0.00	Psychology	0.00	Psychology	0.00
Psychology	0.00	Psychology	0.00	Media	0.00	Psychology	0.00	Social Science	0.00	Social Science	0.00	Science	0.00
Social Science	0.00	Social Science	0.00	Psychology	0.00	Social Science	0.00	Social Work	0.00	Social Work	0.00	Social Science	0.00
Religion	-1.12	Religion	-0.68	Social Work	0.00	Social Work	0.00	Religion	-0.23	Engineering	-0.56	Social Work	0.00
Social Work	-3.62	Fine Arts	-0.82	Religion	-2.07	Fine Arts	-3.86	Business	-0.64	Religion	-1.19	Engineering	-0.08
Fine Arts	-3.86	Social Work	-3.48	Fine Arts	-3.86	Religion	-5.95	Medicine	-3.56	Fine Arts	-3.86	Computer Science	-0.88
Medicine	-6.99	Medicine	-6.99	Medicine	-6.99	Medicine	-6.99	Fine Arts	-3.86	Education	-4.00	Medicine	-6.99
Business	-8.57	Business	-8.57	Business	-8.57	Business	-8.57	Mathematics	-4.03	Medicine	-6.99	Education	-11.66
Education	-8.83	Education	-11.29	Education	-9.83	Education	-10.72	Education	-7.69	Business	-8.57	Business	-15.33

PREMIUM TYPE (ADJUSTED)

Table Cont. (2)

Estimates Including Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Psychology	13.80	Engineering 17.20	Government 9.48	Engineering 17.20	Government 10.48	Engineering 17.20	Psychology 13.80
Government	13.63	Psychology 13.80	Engineering 9.14	Psychology 13.80	Psychology 10.09	Computer Science 13.44	Government 13.63
Languages	7.20	Government 13.63	Psychology 8.95	Computer Science 13.44	Mathematics 8.57	Government 9.32	Engineering 7.50
Computer Science	6.92	Computer Science 13.44	Computer Science 5.28	Government 8.74	Engineering 7.85	Psychology 9.01	Computer Science 5.25
Engineering	6.25	Mathematics 8.57	Mathematics 3.14	Mathematics 8.57	Computer Science 3.92	Mathematics 8.57	Mathematics 4.23
Mathematics	3.81	Languages 7.20	Languages 2.16	Science 8.17	Languages 2.25	Science 8.21	Languages 2.09
Agriculture	0.00	Agriculture 0.00	Agriculture 0.00	Languages 7.20	Agriculture 0.00	Languages 7.20	Agriculture 0.00
Architecture	0.00	Architecture 0.00	Architecture 0.00	Agriculture 0.00	Architecture 0.00	Agriculture 0.00	Architecture 0.00
Business	0.00	Business 0.00	Business 0.00	Architecture 0.00	Business 0.00	Architecture 0.00	Business 0.00
Fine Arts	0.00	Fitness 0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Business 0.00	Fine Arts 0.00
Fitness	0.00	History 0.00	Fitness 0.00	Fitness 0.00	History 0.00	Fine Arts 0.00	Fitness 0.00
History	0.00	Law 0.00	History 0.00	History 0.00	Law 0.00	Fitness 0.00	History 0.00
Liberal Arts	0.00	Liberal Arts 0.00	Law 0.00	Law 0.00	Liberal Arts 0.00	History 0.00	Law 0.00
Media	0.00	Media 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Media 0.00	Liberal Arts 0.00	Liberal Arts 0.00
Medicine	0.00	Medicine 0.00	Media 0.00	Media 0.00	Medicine 0.00	Media 0.00	Media 0.00
Science	0.00	Science 0.00	Medicine 0.00	Social Science 0.00	Science 0.00	Medicine 0.00	Medicine 0.00
Social Science	0.00	Social Science 0.00	Science 0.00	Social Work -5.41	Social Science 0.00	Social Science 0.00	Science 0.00
Law	-5.10	Social Work -4.80	Social Science 0.00	Medicine -9.10	Fitness -3.09	Law -5.25	Social Science 0.00
Social Work	-5.55	Fine Arts -6.43	Social Work -3.35	Religion -10.33	Social Work -3.47	Social Work -5.75	Social Work -3.31
Religion	-10.33	Religion -10.33	Education -8.98	Business -10.33	Education -6.19	Religion -10.33	Education -9.39
Education	-12.61	Education -12.00	Religion -10.33	Education -15.37	Religion -10.33	Education -13.47	Religion -10.33
	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Government	13.63	Psychology 13.80	Psychology 13.80	Psychology 13.80	Business 17.03	Psychology 13.80	Engineering 17.20
Engineering	9.78	Government 13.63	Government 13.63	Government 13.63	Psychology 13.80	Government 13.63	Psychology 13.80
Business	8.94	Engineering 8.81	Engineering 11.67	Science 9.74	Government 13.63	Engineering 9.15	Government 13.63
Computer Science	6.07	Languages 7.20	Computer Science 5.22	Engineering 9.26	Computer Science 13.44	Computer Science 4.95	Computer Science 13.44
Psychology	3.43	Computer Science 5.22	Mathematics 3.69	Social Science 9.24	Mathematics 8.57	Mathematics 3.76	Science 11.01
Mathematics	0.10	Science 4.96	Languages 3.55	Mathematics 8.57	Fine Arts 0.00	Languages 3.19	Mathematics 8.57
Agriculture	0.00	Social Science 4.86	Agriculture 0.00	Languages 7.20	Fitness 0.00	Agriculture 0.00	Languages 7.20
Architecture	0.00	Mathematics 4.31	Architecture 0.00	Computer Science 7.16	Law 0.00	Architecture 0.00	Social Science 5.54
Fitness	0.00	Agriculture 0.00	Business 0.00	Agriculture 4.32	Liberal Arts 0.00	Business 0.00	Agriculture 0.00
History	0.00	Architecture 0.00	Fine Arts 0.00	Architecture 0.00	Media 0.00	Fine Arts 0.00	Architecture 0.00
Media	0.00	Fine Arts 0.00	History 0.00	Fine Arts 0.00	Medicine 0.00	History 0.00	Fine Arts 0.00
Medicine	0.00	Fitness 0.00	Liberal Arts 0.00	Fitness 0.00	Science 0.00	Law 0.00	Fitness 0.00
Science	0.00	History 0.00	Media 0.00	History 0.00	Social Science 0.00	Liberal Arts 0.00	History 0.00
Social Science	0.00	Law 0.00	Science 0.00	Liberal Arts 0.00	Social Work 0.00	Media 0.00	Liberal Arts 0.00
Social Work	0.00	Liberal Arts 0.00	Social Science 0.00	Media 0.00	Languages -0.94	Medicine 0.00	Media 0.00
Languages	-0.52	Media 0.00	Fitness 0.00	Medicine -4.41	Engineering -5.45	Science 0.00	Social Work -4.86
Fine Arts	-4.19	Medicine 0.00	Law -4.95	Social Work -3.47	Education -6.19	Social Science 0.00	Medicine -5.67
Liberal Arts	-5.11	Social Work -4.43	Medicine -5.94	Law -5.63	Agriculture -6.32	Fitness -3.21	Law -6.67
Education	-6.19	Business -7.07	Social Work -6.44	Religion -10.33	History -9.29	Social Work -4.80	Business -10.31
Law	-7.30	Religion -10.33	Religion -10.33	Education -12.09	Religion -10.33	Education -10.21	Religion -10.33
Religion	-10.33	Education -12.45	Education -10.52	Business -12.15	Architecture -11.18	Religion -10.33	Education -13.54

Table Cont. (4)

	<u>Agriculture, Forestry, Fishing and Hunting</u>		<u>Arts, Entertainment, and Recreation</u>		<u>Construction</u>		<u>Educational Services</u>		<u>Finance and Insurance</u>		<u>Health Care</u>		
Engineering	17.20	Psychology	13.80	Engineering	17.20	Psychology	13.80	Engineering	17.20	Engineering	17.20	Engineering	17.20
Psychology	13.80	Computer Science	13.44	Computer Science	13.44	Mathematics	8.57	Psychology	13.80	Mathematics	8.57	Mathematics	8.57
Government	13.63	Mathematics	8.57	Mathematics	8.57	Languages	7.20	Government	13.63	Agriculture	8.10	Agriculture	8.10
Computer Science	13.44	Languages	7.20	Languages	7.20	Computer Science	5.95	Computer Science	13.44	Languages	7.20	Languages	7.20
Mathematics	8.57	Agriculture	5.92	Agriculture	5.56	Engineering	3.73	Liberal Arts	11.45	Computer Science	6.81	Computer Science	6.81
Languages	7.20	Engineering	5.53	Government	5.15	Government	3.37	Mathematics	8.57	Government	2.91	Government	2.91
Agriculture	0.00	Architecture	0.00	Architecture	0.00	Agriculture	0.00	Languages	7.20	Architecture	0.00	Architecture	0.00
Architecture	0.00	Business	0.00	Business	0.00	Architecture	0.00	Agriculture	0.00	Business	0.00	Business	0.00
Business	0.00	Fine Arts	0.00	Fine Arts	0.00	Business	0.00	Architecture	0.00	Fine Arts	0.00	Fine Arts	0.00
Fine Arts	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Business	0.00	Fitness	0.00	Fitness	0.00
Fitness	0.00	History	0.00	History	0.00	Fitness	0.00	Fine Arts	0.00	History	0.00	History	0.00
History	0.00	Law	0.00	Law	0.00	History	0.00	Fitness	0.00	Law	0.00	Law	0.00
Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	History	0.00	Liberal Arts	0.00	Liberal Arts	0.00
Liberal Arts	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Law	0.00	Media	0.00	Media	0.00
Media	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Media	0.00	Medicine	0.00	Medicine	0.00
Medicine	0.00	Science	0.00	Science	0.00	Medicine	0.00	Medicine	0.00	Science	0.00	Science	0.00
Science	0.00	Social Science	0.00	Social Science	0.00	Science	0.00	Science	0.00	Social Science	0.00	Social Science	0.00
Social Science	0.00	Social Work	0.00	Social Work	0.00	Social Science	0.00	Social Science	0.00	Social Work	0.00	Social Work	0.00
Social Work	0.00	Government	-0.36	Psychology	-1.31	Social Work	0.00	Social Work	0.00	Psychology	-0.65	Psychology	-0.65
Education	-6.19	Religion	-1.77	Religion	-1.87	Religion	-2.43	Religion	-3.18	Religion	-2.04	Religion	-2.04
Religion	-10.33	Education	-6.19	Education	-6.19	Education	-6.19	Education	-6.19	Education	-6.19	Education	-6.19

PREMIUM TYPE (ADJUSTED)

Table Cont. (5)

	<u>Information</u>		<u>Manufacturing</u>		<u>Military</u>	<u>Mining, Quarrying, and Oil and</u>		<u>Professional, Scientific, and</u>			
						<u>Gas Extraction</u>	<u>Other Services</u>	<u>Technical Services</u>			
Engineering	17.20	Engineering	17.20	Agriculture	9.71	Media	25.12	Engineering	17.20	Engineering	17.20
Psychology	13.80	Psychology	13.80	Education	7.26	Computer Science	23.82	Government	13.63	Government	13.63
Government	13.63	Government	13.63	Engineering	3.20	Fine Arts	23.72	Computer Science	13.44	Computer Science	13.44
Computer Science	13.44	Computer Science	13.44	Computer Science	1.48	Social Science	20.27	Mathematics	8.57	Mathematics	8.57
Mathematics	8.57	Mathematics	8.57	Languages	0.51	Engineering	17.20	Languages	7.20	Languages	7.20
Languages	7.20	Languages	7.20	Architecture	0.00	Liberal Arts	15.70	Agriculture	6.82	Agriculture	5.74
Agriculture	0.00	Agriculture	5.28	Business	0.00	Psychology	13.80	Architecture	0.00	Psychology	0.50
Architecture	0.00	Architecture	0.00	Fitness	0.00	Government	13.63	Business	0.00	Architecture	0.00
Business	0.00	Business	0.00	Law	0.00	Mathematics	8.57	Fitness	0.00	Business	0.00
Fine Arts	0.00	Fine Arts	0.00	Liberal Arts	0.00	Languages	7.20	History	0.00	Fine Arts	0.00
Fitness	0.00	Fitness	0.00	Medicine	0.00	Religion	4.07	Law	0.00	Fitness	0.00
History	0.00	History	0.00	Science	0.00	Architecture	0.00	Liberal Arts	0.00	History	0.00
Law	0.00	Law	0.00	Social Science	0.00	Business	0.00	Media	0.00	Law	0.00
Liberal Arts	0.00	Liberal Arts	0.00	Social Work	0.00	Fitness	0.00	Medicine	0.00	Liberal Arts	0.00
Media	0.00	Media	0.00	Government	-0.24	History	0.00	Science	0.00	Media	0.00
Medicine	0.00	Medicine	0.00	Mathematics	-0.47	Law	0.00	Social Science	0.00	Medicine	0.00
Science	0.00	Science	0.00	Religion	-0.86	Medicine	0.00	Social Work	0.00	Science	0.00
Social Science	0.00	Social Science	0.00	Media	-5.75	Science	0.00	Psychology	-0.61	Social Science	0.00
Education	-6.19	Social Work	0.00	Psychology	-7.47	Social Work	0.00	Education	-6.19	Social Work	0.00
Social Work	-6.70	Religion	-3.41	Fine Arts	-7.95	Agriculture	-9.19	Fine Arts	-7.44	Religion	-2.42
Religion	-10.33	Education	-6.19	History	-9.29	Education	-22.04	Religion	-10.33	Education	-6.19

PREMIUM TYPE (ADJUSTED)

Table Cont. (6)

PREMIUM TYPE (ADJUSTED)	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>		
	Engineering	17.20	Engineering	17.20	Psychology	13.80	Engineering	17.20	Engineering	17.20	Engineering	17.20	Engineering
Psychology	13.80	Psychology	13.80	Languages	7.20	Agriculture	9.38	Psychology	13.80	Government	13.63	Government	13.63
Government	13.63	Computer Science	13.44	Agriculture	6.25	Computer Science	4.74	Government	13.63	Computer Science	13.44	Computer Science	13.44
Computer Science	13.44	Mathematics	8.57	Computer Science	6.05	Education	4.58	Computer Science	13.44	Mathematics	8.57	Mathematics	8.57
Mathematics	8.57	Languages	7.20	Government	4.63	Languages	0.97	Mathematics	8.57	Languages	7.20	Languages	7.20
Languages	7.20	Agriculture	6.76	Engineering	3.77	Architecture	0.00	Languages	7.20	Agriculture	6.17	Agriculture	6.17
Agriculture	0.00	Architecture	0.00	Mathematics	2.14	Business	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00
Architecture	0.00	Business	0.00	Religion	0.63	Fitness	0.00	Architecture	0.00	Business	0.00	Business	0.00
Business	0.00	Fine Arts	0.00	Architecture	0.00	Law	0.00	Business	0.00	Business	0.00	Fine Arts	0.00
Fine Arts	0.00	Fitness	0.00	Business	0.00	Liberal Arts	0.00	Fine Arts	0.00	Fitness	0.00	Fitness	0.00
Fitness	0.00	History	0.00	Fine Arts	0.00	Media	0.00	Media	0.00	History	0.00	History	0.00
History	0.00	Law	0.00	Fitness	0.00	Medicine	0.00	Medicine	0.00	History	0.00	Law	0.00
Law	0.00	Liberal Arts	0.00	History	0.00	Science	0.00	Law	0.00	Law	0.00	Liberal Arts	0.00
Liberal Arts	0.00	Media	0.00	Law	0.00	Social Science	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Media	0.00
Media	0.00	Medicine	0.00	Liberal Arts	0.00	Social Work	0.00	Media	0.00	Media	0.00	Medicine	0.00
Medicine	0.00	Science	0.00	Media	0.00	Government	-0.03	Medicine	0.00	Medicine	0.00	Science	0.00
Science	0.00	Social Science	0.00	Medicine	0.00	Mathematics	-0.98	Science	0.00	Science	0.00	Social Science	0.00
Social Science	0.00	Social Work	0.00	Science	0.00	Psychology	-6.87	Social Science	0.00	Social Science	0.00	Social Work	0.00
Social Work	0.00	Government	-0.10	Social Science	0.00	History	-9.74	Social Work	0.00	Social Work	0.00	Psychology	-0.64
Education	-6.19	Religion	-3.91	Social Work	0.00	Religion	-10.33	Education	-6.19	Religion	-1.77	Religion	-1.77
Religion	-10.33	Education	-6.19	Education	-6.19	Fine Arts	-11.67	Religion	-10.33	Education	-6.19	Education	-6.19

Table 3.5: Ranking of Knowledge Composition Premiums across College Majors (Private Sector Sample)

Estimates Excluding Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Government	8.86	Computer Science	11.09	Liberal Arts	5.46	Computer Science	11.09
Languages	6.24	Science	9.85	History	4.77	Engineering	10.73
Liberal Arts	5.46	Government	8.86	Social Science	3.59	Science	9.76
History	4.77	Languages	6.24	Computer Science	2.01	Social Science	8.77
Social Science	3.59	Mathematics	5.69	Languages	1.79	Languages	6.24
Computer Science	3.50	Liberal Arts	5.46	Government	1.42	Mathematics	5.69
Mathematics	1.28	History	4.77	Engineering	1.32	Liberal Arts	5.46
Agriculture	0.00	Engineering	4.11	Mathematics	1.27	History	4.77
Architecture	0.00	Social Science	3.59	Agriculture	0.00	Government	1.83
Fine Arts	0.00	Agriculture	0.00	Architecture	0.00	Education	0.00
Fitness	0.00	Architecture	0.00	Fine Arts	0.00	Fine Arts	0.00
Media	0.00	Fitness	0.00	Fitness	0.00	Media	0.00
Psychology	0.00	Psychology	0.00	Media	0.00	Fitness	0.00
Religion	0.00	Religion	0.00	Religion	0.00	Religion	0.00
Science	0.00	Law	-0.32	Science	0.00	Science	0.00
Engineering	-1.05	Business	-4.82	Law	-0.23	Religion	0.00
Law	-1.20	Social Work	-5.09	Social Work	-3.03	Law	-0.72
Business	-4.82	Medicine	-5.57	Psychology	-4.38	Social Work	-5.78
Social Work	-4.97	Fine Arts	-7.23	Business	-4.82	Education	-12.72
Medicine	-5.57	Media	-7.78	Education	-5.37	Business	-16.03
Education	-8.88	Education	-7.98	Medicine	-5.57	Medicine	-16.99
						Business	-4.82
						Medicine	-11.63
						Medicine	-5.57

PREMIUM TYPE (ADJUSTED)

Table Cont. (1)

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>						
Government	8.86	Social Science	9.10	Government	8.86	Social Science	12.99	Computer Science	11.09	Languages	6.24	Science	10.24
Business	5.71	Government	8.86	Science	6.57	Government	8.86	Government	8.86	Law	5.94	Government	8.86
History	4.77	Science	6.95	Languages	6.24	Languages	6.24	Languages	6.24	Liberal Arts	5.46	Social Science	8.71
Social Science	3.59	Languages	6.24	Liberal Arts	5.46	Mathematics	5.69	Law	5.94	History	4.77	Languages	6.24
Medicine	1.66	Mathematics	5.69	History	4.77	Liberal Arts	5.46	Mathematics	5.69	Government	4.23	Engineering	5.75
Computer Science	1.28	Liberal Arts	5.46	Social Science	3.59	Agriculture	5.05	Liberal Arts	5.46	Social Science	3.59	Mathematics	5.69
Agriculture	0.00	History	4.77	Engineering	2.30	History	4.77	Social Science	3.59	Mathematics	1.44	Liberal Arts	5.46
Architecture	0.00	Computer Science	2.96	Computer Science	0.91	Computer Science	3.16	Agriculture	0.00	Computer Science	0.97	Computer Science	5.43
Education	0.00	Engineering	1.28	Mathematics	0.71	Engineering	0.66	Education	0.00	Engineering	0.21	History	4.77
Fitness	0.00	Agriculture	0.00	Agriculture	0.00	Architecture	0.00	Fine Arts	0.00	Agriculture	0.00	Agriculture	0.00
Media	0.00	Architecture	0.00	Architecture	0.00	Fine Arts	0.00	Fitness	0.00	Architecture	0.00	Architecture	0.00
Religion	0.00	Fine Arts	0.00	Fine Arts	0.00	Fitness	0.00	Media	0.00	Fine Arts	0.00	Fine Arts	0.00
Science	0.00	Fitness	0.00	Media	0.00	Media	0.00	Psychology	0.00	Media	0.00	Fitness	0.00
Social Work	0.00	Media	0.00	Psychology	0.00	Psychology	0.00	Religion	0.00	Psychology	0.00	Media	0.00
Engineering	-0.22	Psychology	0.00	Religion	0.00	Religion	0.00	Science	0.00	Religion	0.00	Psychology	0.00
Liberal Arts	-1.10	Religion	0.00	Law	-0.36	Science	0.00	Social Work	0.00	Science	0.00	Religion	0.00
Languages	-1.92	Law	-0.25	Business	-4.82	Social Work	0.00	Business	-4.82	Social Work	-3.68	Social Work	0.00
Mathematics	-3.29	Social Work	-4.95	Fitness	-5.11	Law	-1.36	Medicine	-5.57	Fitness	-3.78	Law	-2.34
Law	-3.48	Education	-9.02	Social Work	-5.53	Medicine	-5.57	History	-6.93	Business	-4.82	Education	-10.05
Fine Arts	-5.42	Business	-10.86	Education	-6.02	Education	-7.85	Architecture	-12.13	Medicine	-5.57	Medicine	-10.90
Psychology	-9.48	Medicine	-11.57	Medicine	-11.93	Business	-16.39	Engineering	-12.53	Education	-5.99	Business	-13.42

PREMIUM TYPE (ADJUSTED)

Table Cont. (2)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>
PREMIUM TYPE (ADJUSTED)							
Languages	6.24	Science 5.72	Languages 6.24	Science 12.16	Social Science 3.59	Government 8.86	Languages 6.24
Liberal Arts	5.46	Liberal Arts 5.46	Law 5.94	Government 8.86	Computer Science 2.88	Languages 6.24	Law 5.94
History	4.77	History 4.77	Liberal Arts 5.46	Mathematics 5.69	Government 1.74	Mathematics 5.69	Mathematics 5.69
Social Science	3.59	Social Science 3.59	Science 5.09	Liberal Arts 5.46	Liberal Arts 1.21	Liberal Arts 5.46	Liberal Arts 5.46
Government	2.71	Languages 2.18	History 4.77	History 4.77	Languages 0.77	Science 5.42	History 4.77
Engineering	2.14	Government 1.69	Government 4.33	Social Science 3.59	History 0.74	History 4.77	Social Science 3.59
Computer Science	1.94	Engineering 1.51	Social Science 3.59	Engineering 3.46	Engineering 0.63	Social Science 3.59	Government 1.38
Mathematics	1.38	Computer Science 1.29	Engineering 2.28	Languages 2.37	Agriculture 0.00	Computer Science 1.13	Agriculture 0.00
Agriculture	0.00	Mathematics 0.58	Mathematics 1.47	Computer Science 2.09	Architecture 0.00	Agriculture 0.00	Architecture 0.00
Architecture	0.00	Law 0.28	Computer Science 1.16	Agriculture 0.00	Fine Arts 0.00	Architecture 0.00	Fine Arts 0.00
Fine Arts	0.00	Agriculture 0.00	Agriculture 0.00	Architecture 0.00	Fitness 0.00	Fine Arts 0.00	Fitness 0.00
Fitness	0.00	Architecture 0.00	Architecture 0.00	Fine Arts 0.00	Media 0.00	Fitness 0.00	Media 0.00
Media	0.00	Fine Arts 0.00	Fine Arts 0.00	Fitness 0.00	Psychology 0.00	Media 0.00	Psychology 0.00
Religion	0.00	Fitness 0.00	Fitness 0.00	Media 0.00	Religion 0.00	Psychology 0.00	Religion 0.00
Science	0.00	Media 0.00	Media 0.00	Psychology 0.00	Science 0.00	Religion 0.00	Science 0.00
Law	-0.31	Psychology 0.00	Psychology 0.00	Religion 0.00	Law -0.39	Social Work 0.00	Social Work 0.00
Social Work	-4.28	Religion 0.00	Religion 0.00	Social Work 0.00	Mathematics -0.52	Law -0.09	Engineering -0.25
Business	-4.82	Social Work -3.94	Social Work 0.00	Law -0.92	Social Work -3.05	Engineering -0.64	Computer Science -1.37
Psychology	-5.40	Business -4.82	Medicine -5.57	Business -4.82	Business -4.82	Education -4.78	Medicine -5.57
Education	-6.44	Medicine -5.57	Education -7.61	Medicine -5.57	Education -5.08	Business -4.82	Education -8.45
Medicine	-9.42	Education -8.43	Business -10.41	Education -8.64	Medicine -5.57	Medicine -5.57	Business -13.79

Table Cont. (3)

Estimates Including Industry Interactions:

	<u>Agriculture</u>		<u>Architecture</u>		<u>Business</u>		<u>Computer Science</u>		<u>Education</u>		<u>Engineering</u>		<u>Fine Arts</u>	
	Government	17.66	Government	17.66	Government	9.76	Engineering	17.53	Government	10.92	Engineering	17.53	Government	17.66
	Psychology	14.22	Engineering	17.53	Engineering	9.07	Computer Science	14.47	Psychology	9.84	Computer Science	14.47	Psychology	14.22
	Languages	7.17	Computer Science	14.47	Psychology	8.80	Psychology	14.22	Mathematics	8.08	Government	9.40	Mathematics	8.08
	Computer Science	6.89	Psychology	14.22	Computer Science	5.24	Government	9.25	Engineering	7.91	Science	9.08	Engineering	7.37
	Engineering	5.72	Mathematics	8.08	Mathematics	3.43	Science	8.71	Computer Science	3.90	Psychology	8.57	Computer Science	5.63
	Mathematics	3.54	Languages	7.17	Languages	2.12	Mathematics	8.08	Languages	2.36	Mathematics	8.08	Languages	2.01
PREMIUM TYPE (ADJUSTED)	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Languages	7.17	Agriculture	0.00	Languages	7.17	Agriculture	0.00
	Architecture	0.00	Architecture	0.00	Architecture	0.00	Agriculture	0.00	Architecture	0.00	Agriculture	4.39	Architecture	0.00
	Business	0.00	Business	0.00	Business	0.00	Architecture	0.00	Business	0.00	Architecture	0.00	Business	0.00
	Fine Arts	0.00	Fitness	0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Business	0.00	Fine Arts	0.00
	Fitness	0.00	History	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Fitness	0.00
	History	0.00	Law	0.00	History	0.00	History	0.00	History	0.00	Fitness	0.00	History	0.00
	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	History	0.00	Law	0.00
	Media	0.00	Media	0.00	Media	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00
	Medicine	0.00	Medicine	0.00	Medicine	0.00	Social Science	0.00	Medicine	0.00	Media	0.00	Medicine	0.00
	Science	0.00	Science	0.00	Science	0.00	Social Work	-4.82	Science	0.00	Social Science	0.00	Science	0.00
	Social Science	0.00	Social Science	0.00	Social Science	0.00	Law	-6.23	Social Science	0.00	Medicine	-4.23	Social Science	0.00
	Social Work	-4.90	Social Work	-4.13	Social Work	0.00	Religion	-9.68	Social Work	-2.81	Social Work	-4.91	Social Work	0.00
	Law	-6.50	Education	-6.33	Law	-5.61	Medicine	-9.91	Law	-5.59	Law	-6.07	Media	-3.97
	Religion	-9.68	Fine Arts	-7.16	Education	-9.25	Business	-10.97	Education	-6.33	Religion	-9.68	Religion	-9.68
	Education	-12.89	Religion	-9.68	Religion	-9.68	Education	-15.80	Religion	-9.68	Education	-13.92	Education	-9.78

Table Cont. (4)

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Government	17.66	Government 17.66	Government 17.66	Government 17.66	Government 17.66	Psychology 14.22	Government 17.66
Business	9.69	Psychology 14.22	Psychology 14.22	Psychology 14.22	Computer Science 14.47	Government 13.29	Engineering 17.53
Engineering	9.32	Engineering 9.62	Engineering 11.47	Engineering 10.60	Psychology 14.22	Engineering 9.62	Computer Science 14.47
Medicine	6.67	Mathematics 8.08	Science 7.87	Science 9.97	Mathematics 8.08	Mathematics 8.08	Psychology 14.22
Computer Science	6.06	Science 7.34	Languages 7.17	Social Science 9.12	Languages 7.17	Science 5.43	Science 12.19
Psychology	3.36	Languages 7.17	Computer Science 5.29	Mathematics 8.08	Business 0.00	Computer Science 5.37	Mathematics 8.08
Mathematics	0.16	Computer Science 7.02	Mathematics 3.39	Computer Science 7.43	Fine Arts 0.00	Languages 3.33	Languages 7.17
Agriculture	0.00	Social Science 5.42	Agriculture 0.00	Languages 7.17	Fitness 0.00	Agriculture 0.00	Agriculture 4.71
Architecture	0.00	Agriculture 0.00	Architecture 0.00	Agriculture 5.03	Law 0.00	Architecture 0.00	Architecture 0.00
Fitness	0.00	Architecture 0.00	Business 0.00	Architecture 0.00	Liberal Arts 0.00	Business 0.00	Fine Arts 0.00
History	0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Media 0.00	Fine Arts 0.00	Fitness 0.00
Media	0.00	Fitness 0.00	History 0.00	Fitness 0.00	Medicine 0.00	Fitness 0.00	History 0.00
Science	0.00	History 0.00	Liberal Arts 0.00	History 0.00	Science 0.00	History 0.00	Liberal Arts 0.00
Social Science	0.00	Liberal Arts 0.00	Media 0.00	Liberal Arts 0.00	Social Science 0.00	Law 0.00	Media 0.00
Social Work	0.00	Media 0.00	Social Science 0.00	Media 0.00	Social Work 0.00	Liberal Arts 0.00	Social Science 0.00
Languages	-0.66	Social Work -4.71	Fitness -4.28	Medicine -4.28	Engineering -6.09	Media 0.00	Social Work -3.76
Fine Arts	-4.86	Law -5.60	Social Work -5.71	Social Work 0.00	Education -6.33	Medicine 0.00	Medicine -5.56
Liberal Arts	-5.73	Medicine -5.80	Law -6.01	Law -7.03	Agriculture -6.88	Social Science 0.00	Law -7.94
Education	-6.33	Business -6.61	Medicine -6.76	Religion -9.68	Religion -9.68	Social Work -4.22	Business -9.64
Law	-8.76	Religion -9.68	Religion -9.68	Education -12.71	History -11.58	Religion -9.68	Religion -9.68
Religion	-9.68	Education -13.35	Education -10.78	Business -12.87	Architecture -12.38	Education -10.80	Education -14.03

PREMIUM TYPE (ADJUSTED)

Table Cont. (5)

PREMIUM TYPE (ADJUSTED)	<u>Media</u>		<u>Medicine</u>		<u>Psychology</u>		<u>Religion</u>		<u>Science</u>		<u>Social Science</u>		<u>Social Work</u>	
	Government	11.03	Psychology	14.22	Government	17.66	Engineering	17.53	Psychology	14.22	Government	17.66	Psychology	14.22
Engineering	9.71	Government	12.43	Psychology	14.22	Psychology	14.22	Government	10.93	Psychology	14.22	Government	10.84	
Psychology	7.50	Engineering	11.64	Engineering	12.32	Science	12.97	Engineering	9.54	Engineering	8.47	Engineering	10.11	
Computer Science	5.08	Mathematics	8.08	Mathematics	8.08	Government	11.40	Computer Science	7.55	Mathematics	8.08	Mathematics	8.08	
Mathematics	3.54	Languages	7.17	Languages	7.17	Mathematics	8.08	Mathematics	2.77	Languages	7.17	Languages	7.17	
Languages	2.91	Computer Science	7.07	Science	6.74	Computer Science	6.08	Languages	1.93	Science	6.90	Computer Science	3.93	
Agriculture	0.00	Science	4.99	Computer Science	6.21	Languages	2.78	Agriculture	0.00	Computer Science	5.44	Agriculture	0.00	
Architecture	0.00	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Architecture	0.00	Agriculture	0.00	Architecture	0.00	
Business	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	Business	0.00	Architecture	0.00	Fine Arts	0.00	
Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Business	0.00	Fine Arts	0.00	Business	0.00	Fitness	0.00	
Fitness	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Fitness	0.00	Fine Arts	0.00	History	0.00	
History	0.00	History	0.00	History	0.00	History	0.00	History	0.00	Fitness	0.00	Law	0.00	
Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Liberal Arts	0.00	Media	0.00	History	0.00	Liberal Arts	0.00	
Media	0.00	Media	0.00	Liberal Arts	0.00	Media	0.00	Medicine	0.00	Liberal Arts	0.00	Media	0.00	
Medicine	0.00	Medicine	0.00	Media	0.00	Medicine	0.00	Science	0.00	Media	0.00	Medicine	0.00	
Science	0.00	Social Science	0.00	Medicine	0.00	Social Science	0.00	Social Science	0.00	Medicine	0.00	Science	0.00	
Social Science	0.00	Social Work	-3.57	Social Science	0.00	Social Work	0.00	Social Work	-2.81	Social Science	0.00	Social Science	0.00	
Social Work	-3.77	Business	-4.50	Social Work	0.00	Fitness	-3.78	Liberal Arts	-3.29	Social Work	0.00	Social Work	0.00	
Law	-5.92	Law	-5.18	Business	-6.86	Law	-6.22	Law	-5.96	Law	-5.71	Religion	-9.68	
Religion	-9.68	Religion	-9.68	Religion	-9.68	Religion	-9.68	Religion	-9.68	Education	-9.46	Business	-10.48	
Education	-10.29	Education	-13.73	Education	-12.68	Education	-13.48	Education	-9.71	Religion	-9.68	Education	-13.81	

Table Cont. (6)

	<u>Agriculture, Forestry, Fishing and Hunting</u>		<u>Arts, Entertainment, and Recreation</u>		<u>Construction</u>		<u>Educational Services</u>		<u>Finance and Insurance</u>		<u>Health Care</u>	
Government	17.66	Computer Science	14.47	Engineering	17.53	Psychology	14.22	Engineering	17.53	Mathematics	8.08	
Engineering	17.53	Psychology	14.22	Computer Science	14.47	Mathematics	8.08	Computer Science	14.47	Computer Science	7.78	
Computer Science	14.47	Mathematics	8.08	Government	8.65	Languages	7.17	Psychology	14.22	Agriculture	7.77	
Psychology	14.22	Languages	7.17	Mathematics	8.08	Computer Science	6.95	Liberal Arts	11.61	Languages	7.17	
Mathematics	8.08	Engineering	5.57	Languages	7.17	Government	6.70	Government	9.11	Engineering	6.69	
Languages	7.17	Agriculture	5.45	Agriculture	0.00	Engineering	3.77	Mathematics	8.08	Government	6.05	
Agriculture	0.00	Government	2.69	Architecture	0.00	Agriculture	0.00	Languages	7.17	Architecture	0.00	
Architecture	0.00	Architecture	0.00	Business	0.00	Architecture	0.00	Agriculture	0.00	Business	0.00	
Business	0.00	Business	0.00	Fine Arts	0.00	Business	0.00	Architecture	0.00	Fine Arts	0.00	
Fine Arts	0.00	Fine Arts	0.00	Fitness	0.00	Fine Arts	0.00	Business	0.00	Fitness	0.00	
Fitness	0.00	Fitness	0.00	History	0.00	Fitness	0.00	Fine Arts	0.00	Law	0.00	
History	0.00	History	0.00	Law	0.00	History	0.00	Fitness	0.00	Liberal Arts	0.00	
Law	0.00	Law	0.00	Liberal Arts	0.00	Law	0.00	History	0.00	Media	0.00	
Liberal Arts	0.00	Liberal Arts	0.00	Media	0.00	Liberal Arts	0.00	Law	0.00	Medicine	0.00	
Media	0.00	Media	0.00	Medicine	0.00	Media	0.00	Media	0.00	Science	0.00	
Medicine	0.00	Medicine	0.00	Science	0.00	Medicine	0.00	Medicine	0.00	Social Science	0.00	
Science	0.00	Science	0.00	Social Science	0.00	Science	0.00	Science	0.00	Social Work	0.00	
Social Science	0.00	Social Science	0.00	Social Work	0.00	Social Science	0.00	Social Science	0.00	Psychology	-0.19	
Social Work	0.00	Social Work	0.00	Psychology	-0.62	Social Work	0.00	Social Work	0.00	Religion	-1.18	
Education	-6.33	Religion	-0.89	Religion	-0.97	Religion	-1.57	Religion	-2.35	Education	-6.33	
Religion	-9.68	Education	-6.33	Education	-6.33	Education	-6.33	Education	-6.33	History	-6.35	

PREMIUM TYPE (ADJUSTED)

Table Cont. (7)

PREMIUM TYPE (ADJUSTED)	<u>Information</u>		<u>Manufacturing</u>		<u>Mining, Quarrying, and Oil and Gas Extraction</u>		<u>Other Services</u>		<u>Professional, Scientific, and Technical Services</u>		<u>Retail Trade</u>	
		Government	17.66	Government	17.66	Computer Science	25.00	Government	17.66	Government	17.66	Engineering
	Engineering	17.53	Engineering	17.53	Media	24.88	Computer Science	14.47	Engineering	17.53	Computer Science	14.47
	Computer Science	14.47	Computer Science	14.47	Fine Arts	23.16	Mathematics	8.08	Computer Science	14.47	Psychology	14.22
	Psychology	14.22	Psychology	14.22	Social Science	20.18	Engineering	7.71	Psychology	14.22	Mathematics	8.08
	Mathematics	8.08	Mathematics	8.08	Government	17.66	Languages	7.17	Mathematics	8.08	Languages	7.17
	Languages	7.17	Languages	7.17	Engineering	17.53	Agriculture	6.41	Languages	7.17	Agriculture	6.30
	Agriculture	0.00	Agriculture	4.79	Liberal Arts	15.50	Architecture	0.00	Agriculture	5.25	Government	3.11
	Architecture	0.00	Architecture	0.00	Psychology	14.22	Business	0.00	Architecture	0.00	Architecture	0.00
	Business	0.00	Business	0.00	Mathematics	8.08	Fitness	0.00	Business	0.00	Business	0.00
	Fine Arts	0.00	Fine Arts	0.00	Languages	7.17	History	0.00	Fine Arts	0.00	Fine Arts	0.00
	Fitness	0.00	Fitness	0.00	Religion	4.68	Law	0.00	Fitness	0.00	Fitness	0.00
	History	0.00	History	0.00	Architecture	0.00	Liberal Arts	0.00	History	0.00	History	0.00
	Law	0.00	Law	0.00	Business	0.00	Media	0.00	Law	0.00	Law	0.00
	Liberal Arts	0.00	Liberal Arts	0.00	Fitness	0.00	Medicine	0.00	Liberal Arts	0.00	Liberal Arts	0.00
	Media	0.00	Media	0.00	History	0.00	Science	0.00	Media	0.00	Media	0.00
	Medicine	0.00	Medicine	0.00	Law	0.00	Social Science	0.00	Medicine	0.00	Medicine	0.00
	Science	0.00	Science	0.00	Medicine	0.00	Social Work	0.00	Science	0.00	Science	0.00
	Social Science	0.00	Social Science	0.00	Science	0.00	Psychology	-0.09	Social Science	0.00	Social Science	0.00
	Education	-6.33	Social Work	0.00	Social Work	0.00	Education	-6.33	Social Work	0.00	Social Work	0.00
	Social Work	-6.69	Religion	-2.59	Agriculture	-9.46	Fine Arts	-7.39	Religion	-1.55	Religion	-3.06
	Religion	-9.68	Education	-6.33	Education	-22.11	Religion	-9.68	Education	-6.33	Education	-6.33

Table Cont. (8)

	<u>Transportation and</u>							
	<u>Social Assistance</u>		<u>Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>	
Psychology	14.22	Engineering	17.53	Government	17.66	Engineering	17.53	
Government	7.74	Agriculture	8.80	Engineering	17.53	Computer Science	14.47	
Languages	7.17	Computer Science	5.77	Computer Science	14.47	Government	8.31	
Computer Science	7.06	Education	4.42	Psychology	14.22	Mathematics	8.08	
Agriculture	5.86	Government	3.12	Mathematics	8.08	Languages	7.17	
Engineering	3.68	Languages	0.94	Languages	7.17	Agriculture	5.61	
Mathematics	1.56	Architecture	0.00	Agriculture	0.00	Psychology	0.03	
Religion	1.50	Business	0.00	Architecture	0.00	Architecture	0.00	
Architecture	0.00	Fitness	0.00	Business	0.00	Business	0.00	
Business	0.00	Law	0.00	Fine Arts	0.00	Fine Arts	0.00	
Fine Arts	0.00	Liberal Arts	0.00	Fitness	0.00	Fitness	0.00	
Fitness	0.00	Media	0.00	History	0.00	History	0.00	
History	0.00	Medicine	0.00	Law	0.00	Law	0.00	
Law	0.00	Science	0.00	Liberal Arts	0.00	Liberal Arts	0.00	
Liberal Arts	0.00	Social Science	0.00	Media	0.00	Media	0.00	
Media	0.00	Social Work	0.00	Medicine	0.00	Medicine	0.00	
Medicine	0.00	Mathematics	-1.56	Science	0.00	Science	0.00	
Science	0.00	Psychology	-6.30	Social Science	0.00	Social Science	0.00	
Social Science	0.00	Religion	-9.68	Social Work	0.00	Social Work	0.00	
Social Work	0.00	History	-9.94	Education	-6.33	Religion	-0.94	
Education	-6.33	Fine Arts	-11.53	Religion	-9.68	Education	-6.33	

PREMIUM TYPE (ADJUSTED)

Table 3.6: Ranking of Knowledge Composition Premiums across College Majors (Bachelor's Degree Sample)

Estimates Excluding Industry Interactions:

	<u>Agriculture</u>		<u>Architecture</u>		<u>Business</u>		<u>Computer Science</u>		<u>Education</u>		<u>Engineering</u>		<u>Fine Arts</u>	
Computer Science	8.62	Computer Science	8.62	Liberal Arts	6.46	Engineering	9.16	Liberal Arts	6.46	Engineering	9.16	Liberal Arts	6.46	
Mathematics	7.81	Mathematics	7.81	Languages	6.22	Computer Science	8.62	History	5.23	Computer Science	8.62	Government	5.91	
Liberal Arts	6.46	Liberal Arts	6.46	History	5.23	Mathematics	7.81	Social Science	4.03	Mathematics	7.81	History	5.23	
Languages	6.22	Languages	6.22	Agriculture	5.04	Liberal Arts	6.46	Government	2.44	Science	7.60	Social Science	4.03	
Government	5.91	Government	5.91	Social Science	4.03	Languages	6.22	Mathematics	1.42	Languages	6.22	Mathematics	2.63	
History	5.23	History	5.23	Computer Science	1.99	History	5.23	Agriculture	0.72	History	5.23	Computer Science	1.86	
Agriculture	5.04	Agriculture	5.04	Engineering	1.63	Agriculture	5.04	Languages	0.64	Agriculture	5.04	Languages	1.30	
Social Science	4.03	Social Science	4.03	Government	1.52	Social Science	4.03	Architecture	0.00	Social Science	4.03	Agriculture	1.29	
Fitness	2.88	Fitness	2.88	Mathematics	1.39	Fitness	2.88	Fine Arts	0.00	Fitness	2.88	Engineering	1.07	
Architecture	0.00	Religion	2.20	Architecture	0.00	Government	1.23	Law	0.00	Government	1.65	Architecture	0.00	
Fine Arts	0.00	Engineering	0.64	Fine Arts	0.00	Architecture	0.00	Media	0.00	Liberal Arts	1.13	Fine Arts	0.00	
Media	0.00	Architecture	0.00	Law	0.00	Fine Arts	0.00	Psychology	0.00	Architecture	0.00	Law	0.00	
Psychology	0.00	Fine Arts	0.00	Media	0.00	Law	0.00	Science	0.00	Fine Arts	0.00	Media	0.00	
Science	0.00	Law	0.00	Psychology	0.00	Media	0.00	Engineering	-0.35	Law	0.00	Psychology	0.00	
Engineering	-0.51	Media	0.00	Science	0.00	Psychology	0.00	Medicine	-1.36	Media	0.00	Science	0.00	
Religion	-5.33	Psychology	0.00	Fitness	-1.54	Science	0.00	Computer Science	-1.63	Psychology	0.00	Fitness	-2.74	
Business	-5.51	Science	0.00	Social Work	-4.56	Religion	-5.33	Fitness	-1.89	Religion	-5.33	Social Work	-4.91	
Law	-5.56	Social Work	0.00	Religion	-5.33	Social Work	-5.45	Social Work	-3.86	Business	-5.51	Religion	-5.33	
Social Work	-5.57	Business	-5.51	Business	-5.51	Education	-12.33	Religion	-5.33	Social Work	-6.15	Business	-5.51	
Medicine	-6.39	Education	-5.58	Education	-5.58	Business	-12.48	Business	-5.51	Medicine	-6.39	Education	-5.58	
Education	-12.37	Medicine	-6.39	Medicine	-6.39	Medicine	-14.91	Education	-5.58	Education	-10.96	Medicine	-6.39	
	<u>Fitness</u>		<u>Government</u>		<u>History</u>		<u>Languages</u>		<u>Law</u>		<u>Liberal Arts</u>		<u>Mathematics</u>	
Government	5.91	Mathematics	7.81	Liberal Arts	6.46	Social Science	11.30	Business	24.75	Liberal Arts	6.46	Engineering	9.16	
History	5.23	Liberal Arts	6.46	Government	5.91	Media	10.92	Computer Science	8.62	Languages	6.22	Computer Science	8.62	
Agriculture	5.04	Languages	6.22	History	5.23	Computer Science	8.62	Mathematics	7.81	Government	5.91	Mathematics	7.81	
Social Science	4.03	Government	5.91	Fine Arts	4.17	Mathematics	7.81	Government	5.91	History	5.23	Liberal Arts	6.46	
Fitness	2.88	History	5.23	Social Science	4.03	Liberal Arts	6.46	Fitness	2.88	Agriculture	5.04	Languages	6.22	
Business	2.29	Agriculture	5.04	Languages	1.60	Languages	6.22	Fine Arts	0.00	Social Science	4.03	Government	5.91	
Computer Science	1.48	Social Science	4.03	Computer Science	1.48	Government	5.91	Law	0.00	Engineering	0.56	History	5.23	
Religion	0.53	Computer Science	1.53	Agriculture	1.07	History	5.23	Media	0.00	Mathematics	0.32	Agriculture	5.04	
Engineering	0.17	Engineering	1.31	Engineering	1.06	Agriculture	5.04	Science	0.00	Computer Science	0.25	Social Science	4.03	
Liberal Arts	0.09	Architecture	0.00	Mathematics	0.71	Fitness	2.88	Social Work	0.00	Architecture	0.00	Fitness	2.88	
Architecture	0.00	Fine Arts	0.00	Religion	0.68	Architecture	0.00	Languages	-3.76	Fine Arts	0.00	Architecture	0.00	
Fine Arts	0.00	Law	0.00	Architecture	0.00	Fine Arts	0.00	Religion	-5.33	Law	0.00	Fine Arts	0.00	
Media	0.00	Media	0.00	Law	0.00	Law	0.00	History	-5.33	Media	0.00	Media	0.00	
Science	0.00	Psychology	0.00	Media	0.00	Psychology	0.00	Engineering	-5.45	Psychology	0.00	Psychology	0.00	
Mathematics	-1.13	Science	0.00	Psychology	0.00	Science	0.00	Education	-5.58	Science	0.00	Science	0.00	
Languages	-1.97	Fitness	-2.50	Science	0.00	Engineering	-0.39	Medicine	-6.39	Fitness	-1.99	Social Work	0.00	
Social Work	-4.09	Social Work	-4.65	Fitness	-4.72	Religion	-5.33	Agriculture	-6.77	Religion	-5.33	Religion	-5.33	
Education	-5.58	Religion	-5.33	Business	-5.51	Social Work	-5.73	Architecture	-8.93	Business	-5.51	Business	-5.51	
Psychology	-5.79	Business	-5.51	Medicine	-6.39	Medicine	-6.39	Liberal Arts	-10.83	Social Work	-5.51	Education	-5.58	
Law	-6.34	Medicine	-6.39	Social Work	-7.78	Education	-10.85	Social Science	-11.84	Medicine	-6.39	Law	-6.22	
Medicine	-6.39	Education	-9.02	Education	-9.81	Business	-17.95	Psychology	-17.31	Education	-9.21	Medicine	-6.39	

Table Cont. (1)

PREMIUM TYPE	<u>Media</u>		<u>Medicine</u>		<u>Psychology</u>		<u>Religion</u>		<u>Science</u>		<u>Social Science</u>		<u>Social Work</u>	
Languages	6.22	Liberal Arts	6.46	Mathematics	7.81	Engineering	9.16	Liberal Arts	6.46	Mathematics	7.81	Mathematics	7.81	
Government	5.91	Languages	6.22	Liberal Arts	6.46	Liberal Arts	6.46	Languages	6.22	Liberal Arts	6.46	Liberal Arts	6.46	
History	5.23	Agriculture	5.04	Languages	6.22	Languages	6.22	Government	5.91	Languages	6.22	Languages	6.22	
Agriculture	5.04	Social Science	4.03	Government	5.91	Government	5.91	History	5.23	Government	5.91	Government	5.91	
Social Science	4.03	Government	2.02	History	5.23	History	5.23	Agriculture	5.04	History	5.23	History	5.23	
Engineering	2.74	History	1.44	Agriculture	5.04	Agriculture	5.04	Social Science	4.03	Social Science	4.03	Agriculture	5.04	
Computer Science	2.55	Computer Science	1.42	Social Science	4.03	Social Science	4.03	Computer Science	3.91	Computer Science	2.48	Social Science	4.03	
Liberal Arts	1.34	Engineering	1.35	Fitness	2.88	Computer Science	2.04	Engineering	1.89	Agriculture	0.79	Fitness	2.88	
Mathematics	1.23	Mathematics	0.25	Computer Science	1.19	Mathematics	0.77	Mathematics	1.73	Architecture	0.00	Engineering	0.28	
Architecture	0.00	Architecture	0.00	Engineering	1.19	Architecture	0.00	Architecture	0.00	Fine Arts	0.00	Architecture	0.00	
Fine Arts	0.00	Fine Arts	0.00	Architecture	0.00	Fine Arts	0.00	Fine Arts	0.00	Law	0.00	Fine Arts	0.00	
Law	0.00	Law	0.00	Fine Arts	0.00	Law	0.00	Law	0.00	Media	0.00	Law	0.00	
Media	0.00	Media	0.00	Law	0.00	Media	0.00	Media	0.00	Psychology	0.00	Media	0.00	
Science	0.00	Psychology	0.00	Media	0.00	Psychology	0.00	Psychology	0.00	Science	0.00	Psychology	0.00	
Fitness	-0.91	Science	0.00	Psychology	0.00	Science	0.00	Science	0.00	Religion	-0.10	Science	0.00	
Psychology	-4.16	Fitness	-0.34	Science	0.00	Fitness	-3.35	Fitness	-2.20	Engineering	-0.50	Social Work	0.00	
Social Work	-4.91	Religion	-5.33	Social Work	0.00	Religion	-5.33	Social Work	-4.15	Fitness	-1.62	Computer Science	-1.51	
Religion	-5.33	Social Work	-5.94	Religion	-0.41	Business	-5.51	Religion	-5.33	Social Work	-4.41	Religion	-5.33	
Business	-5.51	Medicine	-6.39	Medicine	-6.39	Medicine	-6.39	Business	-5.51	Business	-5.51	Education	-5.58	
Education	-5.58	Business	-12.13	Education	-9.58	Social Work	-7.00	Medicine	-6.39	Education	-5.58	Medicine	-6.39	
Medicine	-6.39	Education	-12.28	Business	-9.91	Education	-15.14	Education	-9.22	Medicine	-6.39	Business	-19.03	

Table Cont. (2)

Estimates Including Industry Interactions:

	<u>Agriculture</u>		<u>Architecture</u>		<u>Business</u>		<u>Computer Science</u>		<u>Education</u>		<u>Engineering</u>		<u>Fine Arts</u>	
Government	11.86	Government	11.86	Engineering	7.96	Engineering	14.43	Government	11.86	Engineering	14.43	Government	11.86	
Computer Science	9.80	Computer Science	9.80	Government	7.63	Computer Science	9.80	Mathematics	9.17	Computer Science	9.80	Mathematics	9.17	
Mathematics	9.17	Mathematics	9.17	Computer Science	3.47	Mathematics	9.17	Engineering	7.03	Mathematics	9.17	Engineering	7.24	
Engineering	4.50	Engineering	5.17	Mathematics	2.67	Government	6.48	Computer Science	2.24	Government	6.84	Computer Science	3.56	
Agriculture	0.00	Agriculture	0.00	Architecture	0.00	Agriculture	0.00	Architecture	0.00	Science	6.16	Architecture	0.00	
Architecture	0.00	Architecture	0.00	Business	0.00	Architecture	0.00	Business	0.00	Agriculture	0.00	Business	0.00	
Business	0.00	Business	0.00	Education	0.00	Fine Arts	0.00	Education	0.00	Architecture	0.00	Education	0.00	
Fine Arts	0.00	Education	0.00	Fine Arts	0.00	Fitness	0.00	Fine Arts	0.00	Business	0.00	Fine Arts	0.00	
Fitness	0.00	Fine Arts	0.00	History	0.00	History	0.00	History	0.00	Fine Arts	0.00	History	0.00	
History	0.00	Fitness	0.00	Languages	0.00	Languages	0.00	Law	0.00	Fitness	0.00	Law	0.00	
Languages	0.00	History	0.00	Law	0.00	Law	0.00	Liberal Arts	0.00	Languages	0.00	Liberal Arts	0.00	
Liberal Arts	0.00	Languages	0.00	Media	0.00	Liberal Arts	0.00	Media	0.00	Law	0.00	Medicine	0.00	
Media	0.00	Law	0.00	Medicine	0.00	Media	0.00	Medicine	0.00	Media	0.00	Psychology	0.00	
Medicine	0.00	Liberal Arts	0.00	Psychology	0.00	Psychology	0.00	Psychology	0.00	Medicine	0.00	Science	0.00	
Psychology	0.00	Media	0.00	Science	0.00	Science	0.00	Science	0.00	Psychology	0.00	Social Science	0.00	
Science	0.00	Medicine	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Media	-4.24	
Social Science	0.00	Psychology	0.00	Agriculture	-3.12	Social Work	-4.56	Fitness	-4.23	History	-3.80	Agriculture	-4.45	
Law	-5.19	Science	0.00	Liberal Arts	-3.13	Education	-5.47	Agriculture	-4.59	Education	-3.92	Social Work	-4.71	
Social Work	-5.43	Social Science	0.00	Fitness	-3.57	Business	-6.50	Languages	-4.86	Social Work	-5.03	Languages	-4.85	
Education	-5.96	Social Work	0.00	Social Work	-4.15	Medicine	-7.71	Social Work	-4.92	Liberal Arts	-5.10	Fitness	-5.51	
Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	
	<u>Fitness</u>		<u>Government</u>		<u>History</u>		<u>Languages</u>		<u>Law</u>		<u>Liberal Arts</u>		<u>Mathematics</u>	
Government	11.86	Government	11.86	Government	11.86	Government	11.86	Business	32.92	Government	11.86	Engineering	14.43	
Business	8.06	Mathematics	9.17	Engineering	7.70	Media	10.62	Government	11.86	Engineering	7.07	Government	11.86	
Engineering	6.94	Engineering	7.68	Fine Arts	4.01	Computer Science	9.80	Computer Science	9.80	Computer Science	2.46	Computer Science	9.80	
Computer Science	3.86	Computer Science	3.25	Computer Science	3.92	Mathematics	9.17	Mathematics	9.17	Mathematics	2.15	Mathematics	9.17	
Mathematics	1.12	Architecture	0.00	Mathematics	2.43	Science	8.80	Engineering	0.32	Agriculture	0.00	Agriculture	0.00	
Agriculture	0.00	Business	0.00	Architecture	0.00	Social Science	7.18	Education	0.00	Architecture	0.00	Architecture	0.00	
Architecture	0.00	Education	0.00	Business	0.00	Engineering	6.24	Fine Arts	0.00	Business	0.00	Business	0.00	
Education	0.00	Fine Arts	0.00	Education	0.00	Agriculture	0.00	Fitness	0.00	Fine Arts	0.00	Education	0.00	
Fine Arts	0.00	History	0.00	History	0.00	Architecture	0.00	Law	0.00	History	0.00	Fine Arts	0.00	
Fitness	0.00	Languages	0.00	Law	0.00	Fine Arts	0.00	Media	0.00	Languages	0.00	Fitness	0.00	
History	0.00	Law	0.00	Liberal Arts	0.00	Fitness	0.00	Medicine	0.00	Law	0.00	History	0.00	
Media	0.00	Liberal Arts	0.00	Media	0.00	History	0.00	Science	0.00	Liberal Arts	0.00	Languages	0.00	
Medicine	0.00	Media	0.00	Medicine	0.00	Languages	0.00	Social Work	0.00	Media	0.00	Liberal Arts	0.00	
Science	0.00	Medicine	0.00	Psychology	0.00	Law	0.00	Architecture	-9.04	Medicine	0.00	Media	0.00	
Social Science	0.00	Psychology	0.00	Science	0.00	Liberal Arts	0.00	Languages	-9.90	Psychology	0.00	Psychology	0.00	
Social Work	-4.22	Science	0.00	Social Science	0.00	Medicine	0.00	History	-10.77	Science	0.00	Science	0.00	
Psychology	-5.68	Social Science	0.00	Languages	-4.26	Psychology	0.00	Agriculture	-11.55	Social Science	0.00	Social Science	0.00	
Liberal Arts	-5.86	Agriculture	-3.50	Agriculture	-4.55	Education	-4.86	Religion	-13.66	Education	-2.94	Social Work	0.00	
Law	-6.12	Fitness	-4.26	Fitness	-6.88	Social Work	-6.06	Social Science	-15.61	Fitness	-4.25	Law	-6.09	
Languages	-7.49	Social Work	-4.38	Social Work	-7.84	Business	-12.90	Liberal Arts	-16.36	Social Work	-5.69	Medicine	-7.31	
Religion	-8.70	Religion	-13.66	Religion	-8.43	Religion	-13.66	Psychology	-17.46	Religion	-13.66	Religion	-13.66	

Table Cont. (3)

PREMIUM TYPE	<u>Media</u>		<u>Medicine</u>		<u>Psychology</u>		<u>Religion</u>		<u>Science</u>		<u>Social Science</u>		<u>Social Work</u>	
Government	11.86	Government	8.68	Government	11.86	Engineering	14.43	Government	11.86	Government	11.86	Engineering	14.43	
Engineering	8.31	Engineering	8.17	Mathematics	9.17	Government	11.86	Engineering	7.95	Mathematics	9.17	Government	11.86	
Computer Science	3.71	Computer Science	3.96	Engineering	8.01	Mathematics	9.17	Computer Science	5.81	Engineering	6.15	Mathematics	9.17	
Mathematics	2.28	Mathematics	2.45	Computer Science	3.55	Computer Science	3.81	Mathematics	3.38	Computer Science	4.62	Computer Science	1.02	
Architecture	0.00	Agriculture	0.00	Architecture	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	
Business	0.00	Architecture	0.00	Fine Arts	0.00	Architecture	0.00	Business	0.00	Business	0.00	Education	0.00	
Education	0.00	Fine Arts	0.00	Fitness	0.00	Business	0.00	Education	0.00	Education	0.00	Fine Arts	0.00	
Fine Arts	0.00	History	0.00	History	0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Fitness	0.00	
History	0.00	Languages	0.00	Languages	0.00	History	0.00	History	0.00	History	0.00	History	0.00	
Languages	0.00	Law	0.00	Law	0.00	Languages	0.00	Languages	0.00	Languages	0.00	Languages	0.00	
Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Law	0.00	Law	0.00	Law	0.00	
Media	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	
Medicine	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Media	0.00	Media	0.00	Media	0.00	
Science	0.00	Psychology	0.00	Psychology	0.00	Medicine	0.00	Medicine	0.00	Medicine	0.00	Medicine	0.00	
Social Science	0.00	Science	0.00	Science	0.00	Psychology	0.00	Psychology	0.00	Psychology	0.00	Psychology	0.00	
Fitness	-3.17	Social Science	0.00	Social Science	0.00	Science	0.00	Science	0.00	Science	0.00	Science	0.00	
Agriculture	-3.37	Fitness	-3.79	Social Work	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	
Psychology	-4.10	Social Work	-4.88	Education	-3.35	Fitness	-6.35	Social Work	-3.68	Fitness	-3.81	Social Work	0.00	
Social Work	-4.45	Education	-5.25	Agriculture	-4.09	Social Work	-7.53	Agriculture	-3.86	Social Work	-4.44	Agriculture	-5.28	
Liberal Arts	-4.80	Business	-6.51	Business	-4.29	Education	-9.54	Fitness	-4.87	Agriculture	-4.61	Business	-13.39	
Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	Religion	-13.66	

Table Cont. (5)

PREMIUM TYPE	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>		
Engineering	14.43	Engineering	14.43	Government	11.86	Engineering	14.43	Engineering	14.43	Engineering	14.43	Engineering	14.43
Government	11.86	Computer Science	9.80	Computer Science	9.80	Mathematics	9.17	Government	11.86	Government	11.86	Government	11.86
Social Science	10.75	Mathematics	9.17	Mathematics	9.17	Agriculture	8.31	Social Science	11.66	Computer Science	9.80	Computer Science	9.80
Computer Science	9.80	Agriculture	5.82	Agriculture	6.89	Education	7.03	Computer Science	9.80	Mathematics	9.17	Mathematics	9.17
Mathematics	9.17	Government	2.83	Engineering	3.26	Computer Science	2.92	Mathematics	9.17	Agriculture	0.00	Agriculture	0.00
Agriculture	0.00	Architecture	0.00	Religion	0.53	Architecture	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00
Architecture	0.00	Business	0.00	Architecture	0.00	Business	0.00	Architecture	0.00	Business	0.00	Business	0.00
Business	0.00	Education	0.00	Business	0.00	Fine Arts	0.00	Business	0.00	Education	0.00	Education	0.00
Education	0.00	Fine Arts	0.00	Education	0.00	Fitness	0.00	Education	0.00	Fine Arts	0.00	Fine Arts	0.00
Fine Arts	0.00	Fitness	0.00	Fine Arts	0.00	Languages	0.00	Fine Arts	0.00	Fitness	0.00	Fitness	0.00
Fitness	0.00	History	0.00	Fitness	0.00	Law	0.00	Fitness	0.00	History	0.00	History	0.00
History	0.00	Languages	0.00	History	0.00	Liberal Arts	0.00	History	0.00	Languages	0.00	Languages	0.00
Languages	0.00	Law	0.00	Languages	0.00	Media	0.00	Languages	0.00	Law	0.00	Law	0.00
Law	0.00	Liberal Arts	0.00	Law	0.00	Medicine	0.00	Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00
Liberal Arts	0.00	Media	0.00	Liberal Arts	0.00	Psychology	0.00	Liberal Arts	0.00	Media	0.00	Media	0.00
Media	0.00	Medicine	0.00	Media	0.00	Science	0.00	Media	0.00	Medicine	0.00	Medicine	0.00
Medicine	0.00	Psychology	0.00	Medicine	0.00	Social Science	0.00	Medicine	0.00	Psychology	0.00	Psychology	0.00
Psychology	0.00	Science	0.00	Psychology	0.00	Social Work	0.00	Psychology	0.00	Science	0.00	Science	0.00
Science	0.00	Social Science	0.00	Science	0.00	Government	-0.95	Science	0.00	Social Science	0.00	Social Science	0.00
Social Work	0.00	Social Work	0.00	Social Science	0.00	History	-8.69	Social Work	0.00	Social Work	0.00	Social Work	0.00
Religion	-13.66	Religion	-6.42	Social Work	0.00	Religion	-13.66	Religion	-4.62	Religion	-2.92	Religion	-2.92

Table 3.7: Ranking of Knowledge Composition Premiums across College Majors (Master's Degree Sample)

Estimates Excluding Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Business	16.02	Government 15.37	Agriculture 7.05	Agriculture 12.95	Mathematics 6.78	Computer Science 11.39	Computer Science 0.67
Engineering	8.07	Computer Science 11.39	Mathematics 6.78	Computer Science 11.39	Languages 0.66	Agriculture 10.49	Agriculture 0.00
Languages	5.56	Agriculture 11.13	Languages 5.56	Social Science 9.07	Agriculture 0.00	Engineering 8.07	Architecture 0.00
Agriculture	0.00	Engineering 8.07	Computer Science 2.66	Engineering 8.07	Architecture 0.00	Mathematics 6.78	Fine Arts 0.00
Architecture	0.00	Mathematics 6.78	Engineering 0.68	Mathematics 6.78	Education 0.00	Languages 5.56	Fitness 0.00
Education	0.00	Languages 5.56	Architecture 0.00	Languages 5.56	Fine Arts 0.00	Architecture 0.00	Government 0.00
Fine Arts	0.00	Architecture 0.00	Fine Arts 0.00	Architecture 0.00	Fitness 0.00	Fine Arts 0.00	History 0.00
Fitness	0.00	Fine Arts 0.00	Fitness 0.00	Fine Arts 0.00	Government 0.00	Fine Arts 0.00	Law 0.00
Government	0.00	Fitness 0.00	Government 0.00	Fitness 0.00	History 0.00	Government 0.00	Liberal Arts 0.00
History	0.00	History 0.00	History 0.00	Government 0.00	Law 0.00	History 0.00	Media 0.00
Law	0.00	Law 0.00	Law 0.00	History 0.00	Liberal Arts 0.00	Law 0.00	Medicine 0.00
Liberal Arts	0.00	Liberal Arts 0.00	Liberal Arts 0.00	Law 0.00	Media 0.00	Liberal Arts 0.00	Religion 0.00
Media	0.00	Media 0.00	Media 0.00	Liberal Arts 0.00	Medicine 0.00	Religion 0.00	Science 0.00
Medicine	0.00	Medicine 0.00	Medicine 0.00	Media 0.00	Psychology 0.00	Science 0.00	Social Science 0.00
Psychology	0.00	Psychology 0.00	Psychology 0.00	Psychology 0.00	Religion 0.00	Social Science 0.00	Social Work 0.00
Religion	0.00	Religion 0.00	Religion 0.00	Religion 0.00	Science 0.00	Media -5.54	Languages -0.69
Social Science	0.00	Science 0.00	Science 0.00	Science 0.00	Social Science 0.00	Social Work -5.56	Mathematics -2.13
Social Work	0.00	Social Science 0.00	Social Science 0.00	Social Work 0.00	Social Work 0.00	Psychology -5.74	Engineering -4.26
Computer Science	-1.56	Business -5.96	Social Work 0.00	Business -5.96	Computer Science -1.85	Business -5.96	Education -4.62
Mathematics	-7.08	Social Work -9.76	Business -5.96	Medicine -9.88	Engineering -4.52	Medicine -10.07	Business -5.96
Science	-14.03	Education -15.16	Education -6.95	Education -13.85	Business -5.96	Education -11.73	Psychology -9.79
	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Computer Science	11.39	Agriculture 11.85	Engineering 8.07	Agriculture 7.94	Religion 29.58	Engineering 8.07	Computer Science 11.39
Business	10.85	Science 8.81	Agriculture 7.80	Mathematics 6.78	Fine Arts 21.02	Mathematics 6.78	Agriculture 10.48
Engineering	8.07	Social Science 8.43	Mathematics 6.78	Languages 5.56	Computer Science 11.39	Languages 5.56	Engineering 8.07
Agriculture	0.00	Engineering 8.07	Languages 5.56	Computer Science 1.41	Mathematics 6.78	Computer Science 2.49	Mathematics 6.78
Architecture	0.00	Mathematics 6.78	Computer Science 1.25	Architecture 0.00	Languages 5.56	Agriculture 0.00	Languages 5.56
Education	0.00	Languages 5.56	Architecture 0.00	Fine Arts 0.00	Agriculture 0.00	Architecture 0.00	Architecture 0.00
Fine Arts	0.00	Computer Science 1.80	Fine Arts 0.00	Fitness 0.00	Architecture 0.00	Fine Arts 0.00	Fine Arts 0.00
Fitness	0.00	Architecture 0.00	Fitness 0.00	Government 0.00	Education 0.00	Fitness 0.00	Fitness 0.00
Government	0.00	Fine Arts 0.00	Government 0.00	History 0.00	Fitness 0.00	Government 0.00	Government 0.00
History	0.00	Fitness 0.00	History 0.00	Law 0.00	Government 0.00	History 0.00	History 0.00
Law	0.00	Government 0.00	Law 0.00	Liberal Arts 0.00	History 0.00	Law 0.00	Law 0.00
Media	0.00	History 0.00	Liberal Arts 0.00	Media 0.00	Law 0.00	Liberal Arts 0.00	Liberal Arts 0.00
Medicine	0.00	Law 0.00	Media 0.00	Medicine 0.00	Liberal Arts 0.00	Media 0.00	Media 0.00
Psychology	0.00	Liberal Arts 0.00	Medicine 0.00	Psychology 0.00	Media 0.00	Medicine 0.00	Medicine 0.00
Religion	0.00	Media 0.00	Psychology 0.00	Religion 0.00	Medicine 0.00	Psychology 0.00	Psychology 0.00
Science	0.00	Psychology 0.00	Religion 0.00	Science 0.00	Psychology 0.00	Religion 0.00	Religion 0.00
Social Work	0.00	Religion 0.00	Science 0.00	Social Science 0.00	Science 0.00	Science 0.00	Science 0.00
Languages	-3.71	Social Work 0.00	Social Science 0.00	Social Work 0.00	Social Science 0.00	Social Science 0.00	Social Science 0.00
Mathematics	-9.41	Medicine -5.88	Social Work 0.00	Engineering -0.65	Social Work 0.00	Social Work 0.00	Social Work -5.12
Liberal Arts	-9.98	Education -12.28	Business -5.96	Business -5.96	Business -5.96	Business -5.96	Education -9.26
Social Science	-10.87	Business -20.31	Education -8.46	Education -7.49	Engineering -15.48	Education -7.95	Business -13.98

Table Cont. (1)

PREMIUM TYPE	<u>Media</u>		<u>Medicine</u>		<u>Psychology</u>		<u>Religion</u>		<u>Science</u>		<u>Social Science</u>		<u>Social Work</u>	
	Agriculture	7.10	Engineering	8.07	Agriculture	6.73	Computer Science	11.39	Engineering	8.07	Mathematics	6.78	Agriculture	12.34
Mathematics	6.78	Mathematics	6.78	Languages	5.56	Business	9.59	Computer Science	3.24	Languages	5.56	Mathematics	6.78	
Languages	5.56	Languages	5.56	Computer Science	1.10	Engineering	8.07	Agriculture	0.00	Computer Science	0.17	Languages	5.56	
Computer Science	2.52	Computer Science	0.87	Engineering	0.52	Mathematics	6.78	Architecture	0.00	Agriculture	0.00	Engineering	0.29	
Engineering	1.33	Agriculture	0.00	Mathematics	0.12	Agriculture	0.00	Fine Arts	0.00	Architecture	0.00	Computer Science	0.06	
Architecture	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	Fitness	0.00	Fine Arts	0.00	Architecture	0.00	
Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Education	0.00	Government	0.00	Fitness	0.00	Fine Arts	0.00	
Fitness	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	History	0.00	Government	0.00	Fitness	0.00	
Government	0.00	History	0.00	Government	0.00	Fitness	0.00	Law	0.00	History	0.00	Government	0.00	
History	0.00	Law	0.00	History	0.00	Government	0.00	Liberal Arts	0.00	Law	0.00	History	0.00	
Law	0.00	Liberal Arts	0.00	Law	0.00	History	0.00	Media	0.00	Liberal Arts	0.00	Law	0.00	
Liberal Arts	0.00	Media	0.00	Liberal Arts	0.00	Law	0.00	Medicine	0.00	Media	0.00	Liberal Arts	0.00	
Media	0.00	Medicine	0.00	Media	0.00	Liberal Arts	0.00	Psychology	0.00	Medicine	0.00	Media	0.00	
Medicine	0.00	Psychology	0.00	Medicine	0.00	Media	0.00	Religion	0.00	Psychology	0.00	Medicine	0.00	
Psychology	0.00	Religion	0.00	Psychology	0.00	Medicine	0.00	Science	0.00	Religion	0.00	Psychology	0.00	
Religion	0.00	Science	0.00	Religion	0.00	Psychology	0.00	Social Science	0.00	Science	0.00	Religion	0.00	
Science	0.00	Social Science	0.00	Science	0.00	Religion	0.00	Social Work	0.00	Social Science	0.00	Science	0.00	
Social Science	0.00	Social Work	0.00	Social Science	0.00	Science	0.00	Languages	-0.74	Social Work	0.00	Social Science	0.00	
Social Work	0.00	Business	-5.96	Social Work	0.00	Social Work	0.00	Mathematics	-0.99	Engineering	-0.30	Social Work	0.00	
Business	-5.96	Education	-6.88	Business	-5.96	Languages	-1.17	Business	-5.96	Education	-3.93	Business	-5.96	
Education	-8.34	Government	-7.88	Education	-8.31	Social Science	-9.86	Education	-8.85	Business	-5.96	Education	-13.15	

Table Cont. (2)

Estimates Including Industry Interactions:

	<u>Agriculture</u>		<u>Architecture</u>		<u>Business</u>		<u>Computer Science</u>		<u>Education</u>		<u>Engineering</u>		<u>Fine Arts</u>	
PREMIUM TYPE	Government	26.62	Government	44.71	Psychology	32.13	Psychology	32.13	Psychology	32.13	Science	31.07	Science	31.07
	Business	21.41	Science	31.07	Science	31.07	Science	31.07	Science	31.07	Government	26.62	Government	26.62
	Psychology	20.21	Mathematics	19.69	Government	26.62	Government	26.62	Government	26.62	Psychology	23.01	Computer Science	18.83
	Science	10.68	Computer Science	18.83	Mathematics	19.69	Mathematics	19.69	Mathematics	19.69	Mathematics	19.69	Psychology	18.19
	Computer Science	5.52	Psychology	16.51	Computer Science	10.01	Computer Science	18.83	Computer Science	8.07	Computer Science	18.83	Mathematics	11.08
	Mathematics	3.55	Architecture	0.00	Architecture	0.00	Social Science	8.38	Architecture	0.00	Architecture	0.00	Architecture	0.00
	Architecture	0.00	Business	0.00	Business	0.00	Architecture	0.00	Business	0.00	Business	0.00	Business	0.00
	Education	0.00	Engineering	0.00	Fine Arts	0.00	Business	0.00	Education	0.00	Engineering	0.00	Education	0.00
	Engineering	0.00	Fine Arts	0.00	Fitness	0.00	Engineering	0.00	Engineering	0.00	Fine Arts	0.00	Fine Arts	0.00
	Fine Arts	0.00	Fitness	0.00	History	0.00	Fine Arts	0.00	Fine Arts	0.00	Fitness	0.00	Fitness	0.00
	Fitness	0.00	History	0.00	Law	0.00	Fitness	0.00	Fitness	0.00	History	0.00	History	0.00
	History	0.00	Languages	0.00	Liberal Arts	0.00	History	0.00	History	0.00	Languages	0.00	Law	0.00
	Languages	0.00	Law	0.00	Media	0.00	Languages	0.00	Languages	0.00	Law	0.00	Liberal Arts	0.00
	Law	0.00	Liberal Arts	0.00	Medicine	0.00	Law	0.00	Law	0.00	Liberal Arts	0.00	Media	0.00
	Liberal Arts	0.00	Media	0.00	Religion	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Media	0.00	Medicine	0.00
	Media	0.00	Medicine	0.00	Social Science	0.00	Media	0.00	Media	0.00	Religion	0.00	Religion	0.00
	Medicine	0.00	Religion	0.00	Social Work	0.00	Medicine	0.00	Medicine	0.00	Social Science	0.00	Social Science	0.00
	Religion	0.00	Social Science	0.00	Education	-4.30	Religion	0.00	Religion	0.00	Social Work	-4.59	Social Work	0.00
	Social Science	0.00	Agriculture	-8.02	Languages	-5.20	Social Work	0.00	Social Science	0.00	Medicine	-5.83	Languages	-5.40
	Social Work	0.00	Social Work	-9.36	Engineering	-5.87	Agriculture	-6.35	Social Work	0.00	Agriculture	-8.24	Engineering	-7.46
	Agriculture	-16.43	Education	-13.26	Agriculture	-11.04	Education	-10.63	Agriculture	-16.43	Education	-9.10	Agriculture	-16.43
	PREMIUM TYPE		<u>Fitness</u>		<u>Government</u>		<u>History</u>		<u>Languages</u>		<u>Law</u>		<u>Liberal Arts</u>	
Psychology		32.13	Psychology	32.13	Psychology	32.13	Psychology	32.13	Psychology	32.13	Psychology	32.13	Psychology	32.13
Science		31.07	Science	31.07	Science	31.07	Science	31.07	Science	31.07	Science	31.07	Science	31.07
Government		26.62	Government	26.62	Government	26.62	Government	26.62	Religion	29.40	Government	26.62	Government	26.62
Computer Science		18.83	Mathematics	19.69	Mathematics	19.69	Mathematics	19.69	Government	26.62	Mathematics	19.69	Mathematics	19.69
Mathematics		3.12	Computer Science	9.78	Computer Science	18.83	Computer Science	9.63	Mathematics	19.69	Computer Science	18.83	Computer Science	18.83
Architecture		0.00	Social Science	8.20	Architecture	0.00	Architecture	0.00	Fine Arts	19.32	Architecture	0.00	Architecture	0.00
Business		0.00	Architecture	0.00	Business	0.00	Business	0.00	Computer Science	18.83	Engineering	0.00	Engineering	0.00
Education		0.00	Engineering	0.00	Engineering	0.00	Engineering	0.00	Architecture	0.00	Fine Arts	0.00	Fine Arts	0.00
Engineering		0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Business	0.00	Fitness	0.00	Fitness	0.00
Fine Arts		0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00	Education	0.00	History	0.00	History	0.00
Fitness		0.00	History	0.00	History	0.00	History	0.00	Fitness	0.00	Languages	0.00	Languages	0.00
History		0.00	Languages	0.00	Languages	0.00	Languages	0.00	History	0.00	Law	0.00	Law	0.00
Law		0.00	Law	0.00	Law	0.00	Law	0.00	Languages	0.00	Liberal Arts	0.00	Liberal Arts	0.00
Liberal Arts		0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Media	0.00	Media	0.00
Media		0.00	Media	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Medicine	0.00	Medicine	0.00
Medicine		0.00	Medicine	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Religion	0.00	Religion	0.00
Religion		0.00	Religion	0.00	Religion	0.00	Religion	0.00	Medicine	0.00	Social Science	0.00	Social Science	0.00
Social Work		0.00	Social Work	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Work	0.00	Social Work	-5.40
Languages		-7.87	Agriculture	-6.60	Social Work	0.00	Social Work	0.00	Social Work	0.00	Education	-6.92	Education	-6.98
Social Science		-9.46	Education	-10.44	Education	-7.23	Education	-6.14	Agriculture	-16.43	Business	-7.87	Agriculture	-7.15
Agriculture		-16.43	Business	-16.22	Agriculture	-9.72	Agriculture	-9.42	Engineering	-21.18	Agriculture	-10.92	Business	-10.27

Table Cont. (4)

PREMIUM TYPE	<u>Arts, Entertainment, and</u>											
	<u>Agriculture</u>		<u>Recreation</u>		<u>Construction</u>		<u>Educational Services</u>		<u>Finance and Insurance</u>		<u>Health Care</u>	
Psychology	32.13	Computer Science	18.83	Medicine	32.19	Computer Science	7.24	Science	31.07	Science	31.07	
Science	31.07	Psychology	5.73	Computer Science	6.48	Mathematics	5.21	Mathematics	19.69	Computer Science	6.14	
Government	26.62	Mathematics	0.04	Mathematics	6.04	Psychology	2.25	Computer Science	18.83	Mathematics	1.51	
Mathematics	19.69	Government	0.00	Psychology	1.42	Government	1.40	Psychology	5.19	Architecture	0.00	
Computer Science	18.83	Architecture	0.00	Architecture	0.00	Architecture	0.00	Government	3.31	Business	0.00	
Architecture	0.00	Business	0.00	Business	0.00	Business	0.00	Architecture	0.00	Education	0.00	
Business	0.00	Education	0.00	Education	0.00	Education	0.00	Business	0.00	Engineering	0.00	
Education	0.00	Engineering	0.00	Engineering	0.00	Engineering	0.00	Education	0.00	Fitness	0.00	
Engineering	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Engineering	0.00	History	0.00	
Fine Arts	0.00	History	0.00	History	0.00	Fitness	0.00	Fine Arts	0.00	Languages	0.00	
Fitness	0.00	Languages	0.00	Languages	0.00	History	0.00	Fitness	0.00	Law	0.00	
History	0.00	Law	0.00	Law	0.00	Languages	0.00	History	0.00	Liberal Arts	0.00	
Languages	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Languages	0.00	Media	0.00	
Law	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Law	0.00	Medicine	0.00	
Liberal Arts	0.00	Medicine	0.00	Religion	0.00	Media	0.00	Liberal Arts	0.00	Religion	0.00	
Media	0.00	Religion	0.00	Social Science	0.00	Medicine	0.00	Media	0.00	Social Science	0.00	
Medicine	0.00	Social Science	0.00	Social Work	0.00	Religion	0.00	Medicine	0.00	Social Work	0.00	
Religion	0.00	Social Work	0.00	Government	-0.67	Social Science	0.00	Religion	0.00	Agriculture	-0.87	
Social Science	0.00	Agriculture	-3.11	Science	-3.26	Social Work	0.00	Social Science	0.00	Psychology	-0.95	
Social Work	0.00	Science	-5.43	Agriculture	-16.43	Science	-5.90	Social Work	0.00	Government	-1.04	
Agriculture	-16.43	Fine Arts	-16.98	Fine Arts	-16.68	Agriculture	-6.94	Agriculture	-6.68	Fine Arts	-17.21	

PREMIUM TYPE	<u>Mining, Quarrying, and Oil</u>											
	<u>Information</u>		<u>Manufacturing</u>		<u>Military</u>		<u>and Gas Extraction</u>		<u>Other Services</u>		<u>Professional, Scientific, and</u>	
Psychology	32.13	Science	31.07	Medicine	37.09	Psychology	32.13	Science	31.07	Science	31.07	
Science	31.07	Computer Science	18.83	Mathematics	0.43	Government	26.62	Government	26.62	Computer Science	18.83	
Mathematics	19.69	Mathematics	8.50	Business	0.00	Mathematics	19.69	Computer Science	18.83	Mathematics	7.72	
Computer Science	18.83	Government	7.14	Education	0.00	Computer Science	18.83	Mathematics	6.10	Government	7.45	
Government	3.62	Psychology	4.06	Engineering	0.00	Agriculture	2.97	Architecture	0.00	Psychology	0.99	
Agriculture	1.37	Architecture	0.00	Fitness	0.00	Architecture	0.00	Business	0.00	Architecture	0.00	
Architecture	0.00	Business	0.00	History	0.00	Business	0.00	Education	0.00	Business	0.00	
Business	0.00	Education	0.00	Languages	0.00	Education	0.00	Engineering	0.00	Education	0.00	
Education	0.00	Engineering	0.00	Law	0.00	Engineering	0.00	Fitness	0.00	Engineering	0.00	
Engineering	0.00	Fine Arts	0.00	Liberal Arts	0.00	Fine Arts	0.00	History	0.00	Fitness	0.00	
Fine Arts	0.00	Fitness	0.00	Media	0.00	Fitness	0.00	Languages	0.00	History	0.00	
Fitness	0.00	History	0.00	Religion	0.00	History	0.00	Law	0.00	Languages	0.00	
History	0.00	Languages	0.00	Social Science	0.00	Languages	0.00	Liberal Arts	0.00	Law	0.00	
Languages	0.00	Law	0.00	Social Work	0.00	Law	0.00	Media	0.00	Liberal Arts	0.00	
Law	0.00	Liberal Arts	0.00	Computer Science	-0.19	Liberal Arts	0.00	Medicine	0.00	Media	0.00	
Liberal Arts	0.00	Media	0.00	Agriculture	-1.74	Media	0.00	Religion	0.00	Medicine	0.00	
Media	0.00	Medicine	0.00	Psychology	-1.98	Medicine	0.00	Social Science	0.00	Religion	0.00	
Medicine	0.00	Religion	0.00	Government	-3.57	Religion	0.00	Social Work	0.00	Social Science	0.00	
Religion	0.00	Social Science	0.00	Science	-4.54	Social Science	0.00	Agriculture	-1.41	Social Work	0.00	
Social Science	0.00	Social Work	0.00	Architecture	-12.18	Social Work	0.00	Psychology	-2.73	Agriculture	-0.73	
Social Work	-12.51	Agriculture	-4.61	Fine Arts	-17.64	Science	-15.16	Fine Arts	-18.97	Fine Arts	-17.60	

Table Cont. (5)

PREMIUM TYPE	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>	
	Science	31.07	Science	31.07	Science	31.07	Science	31.07	Science	31.07	Science	31.07
	Mathematics	19.69	Computer Science	18.83	Computer Science	4.40	Computer Science	18.83	Computer Science	3.22	Mathematics	19.69
	Computer Science	18.83	Mathematics	4.55	Mathematics	3.89	Government	3.82	Mathematics	0.65	Computer Science	18.83
	Government	7.92	Psychology	1.18	Government	1.95	Mathematics	1.17	Government	0.15	Government	3.96
	Psychology	2.74	Architecture	0.00	Business	0.00	Business	0.00	Architecture	0.00	Agriculture	3.04
	Architecture	0.00	Business	0.00	Education	0.00	Education	0.00	Business	0.00	Business	0.00
	Business	0.00	Education	0.00	Engineering	0.00	Engineering	0.00	Education	0.00	Education	0.00
	Education	0.00	Engineering	0.00	Fitness	0.00	Fitness	0.00	Engineering	0.00	Engineering	0.00
	Engineering	0.00	Fine Arts	0.00	History	0.00	History	0.00	Fitness	0.00	Fitness	0.00
	Fine Arts	0.00	Fitness	0.00	Languages	0.00	Languages	0.00	History	0.00	History	0.00
	Fitness	0.00	History	0.00	Law	0.00	Law	0.00	Languages	0.00	Languages	0.00
	History	0.00	Languages	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Law	0.00
	Languages	0.00	Law	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00
	Law	0.00	Liberal Arts	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Media	0.00
	Liberal Arts	0.00	Media	0.00	Religion	0.00	Religion	0.00	Medicine	0.00	Medicine	0.00
	Media	0.00	Medicine	0.00	Social Science	0.00	Social Science	0.00	Religion	0.00	Religion	0.00
	Medicine	0.00	Religion	0.00	Social Work	0.00	Social Work	0.00	Social Science	0.00	Social Science	0.00
	Religion	0.00	Social Science	0.00	Psychology	-2.64	Agriculture	-0.74	Social Work	0.00	Social Work	0.00
	Social Science	0.00	Social Work	0.00	Agriculture	-4.11	Architecture	-13.01	Psychology	-4.27	Psychology	-0.27
	Social Work	0.00	Agriculture	-0.63	Architecture	-11.10	Psychology	-16.97	Agriculture	-16.43	Architecture	-13.38
	Agriculture	-4.34	Government	-9.08	Fine Arts	-17.13	Fine Arts	-25.23	Fine Arts	-20.67	Fine Arts	-19.10

Table 3.8: Ranking of Knowledge Composition Premiums across College Majors (Professional Degree Sample)

Estimates Excluding Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Science	29.90	Science 32.70	Science 18.06	Agriculture 42.44	Science 24.00	Agriculture 14.96	History 12.85
Agriculture	0.00	History 12.85	History 12.85	History 12.85	Religion 12.46	Government 6.91	Government 6.91
Architecture	0.00	Government 6.91	Social Science 10.85	Government 6.91	History 2.97	History 0.13	Agriculture 0.00
Business	0.00	Agriculture 0.00	Agriculture 10.59	Architecture 0.00	Agriculture 0.00	Architecture 0.00	Architecture 0.00
Computer Science	0.00	Architecture 0.00	Architecture 0.00	Business 0.00	Architecture 0.00	Business 0.00	Business 0.00
Education	0.00	Business 0.00	Business 0.00	Computer Science 0.00	Business 0.00	Computer Science 0.00	Computer Science 0.00
Engineering	0.00	Computer Science 0.00	Computer Science 0.00	Education 0.00	Computer Science 0.00	Education 0.00	Education 0.00
Fine Arts	0.00	Education 0.00	Education 0.00	Engineering 0.00	Education 0.00	Engineering 0.00	Engineering 0.00
Fitness	0.00	Engineering 0.00	Fine Arts 0.00	Fine Arts 0.00	Engineering 0.00	Fine Arts 0.00	Fine Arts 0.00
Languages	0.00	Fine Arts 0.00	Fitness 0.00	Fitness 0.00	Fine Arts 0.00	Fitness 0.00	Fitness 0.00
Law	0.00	Fitness 0.00	Languages 0.00	Languages 0.00	Fitness 0.00	Languages 0.00	Languages 0.00
Liberal Arts	0.00	Languages 0.00	Law 0.00	Law 0.00	Languages 0.00	Liberal Arts 0.00	Law 0.00
Mathematics	0.00	Law 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Law 0.00	Mathematics 0.00	Liberal Arts 0.00
Media	0.00	Mathematics 0.00	Mathematics 0.00	Mathematics 0.00	Liberal Arts 0.00	Media 0.00	Mathematics 0.00
Medicine	0.00	Medicine 0.00	Medicine 0.00	Medicine 0.00	Mathematics 0.00	Medicine 0.00	Media 0.00
Psychology	0.00	Psychology 0.00	Psychology 0.00	Psychology 0.00	Media 0.00	Psychology 0.00	Medicine 0.00
Religion	0.00	Religion 0.00	Religion 0.00	Religion 0.00	Psychology 0.00	Religion 0.00	Psychology 0.00
Social Science	0.00	Social Science 0.00	Social Work 0.00	Science 0.00	Social Science 0.00	Science 0.00	Religion 0.00
Social Work	0.00	Social Work 0.00	Government -1.82	Social Science 0.00	Social Work 0.00	Social Science 0.00	Science 0.00
History	-4.65	Liberal Arts -21.86	Engineering -13.73	Social Work 0.00	Government -1.73	Social Science 0.00	Social Science 0.00
Government	-7.09	Media -30.29	Media -21.38	Media -38.27	Medicine -10.38	Law -14.64	Social Work 0.00
	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Agriculture	0.00	Social Science 17.06	Social Science 15.30	Social Science 30.03	Fine Arts 68.88	History 12.85	History 12.85
Business	0.00	Agriculture 11.57	History 12.85	Government 26.39	Education 22.23	Government 6.91	Government 6.91
Computer Science	0.00	Government 6.91	Agriculture 11.96	History 12.85	Government 6.91	Agriculture 0.00	Agriculture 0.00
Education	0.00	History 2.57	Government 6.91	Agriculture 0.00	Agriculture 0.00	Architecture 0.00	Architecture 0.00
Engineering	0.00	Architecture 0.00	Architecture 0.00	Architecture 0.00	Architecture 0.00	Business 0.00	Business 0.00
Fine Arts	0.00	Business 0.00	Business 0.00	Business 0.00	Business 0.00	Computer Science 0.00	Computer Science 0.00
Fitness	0.00	Computer Science 0.00	Computer Science 0.00	Computer Science 0.00	Computer Science 0.00	Education 0.00	Education 0.00
Languages	0.00	Education 0.00	Education 0.00	Education 0.00	Fitness 0.00	Fine Arts 0.00	Engineering 0.00
Liberal Arts	0.00	Fine Arts 0.00	Fine Arts 0.00	Engineering 0.00	Languages 0.00	Fitness 0.00	Fine Arts 0.00
Mathematics	0.00	Fitness 0.00	Fitness 0.00	Fine Arts 0.00	Law 0.00	Languages 0.00	Fitness 0.00
Media	0.00	Languages 0.00	Languages 0.00	Fitness 0.00	Liberal Arts 0.00	Law 0.00	Languages 0.00
Medicine	0.00	Law 0.00	Law 0.00	Languages 0.00	Mathematics 0.00	Liberal Arts 0.00	Law 0.00
Religion	0.00	Liberal Arts 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Media 0.00	Mathematics 0.00	Liberal Arts 0.00
Science	0.00	Mathematics 0.00	Mathematics 0.00	Mathematics 0.00	Medicine 0.00	Media 0.00	Mathematics 0.00
Social Science	0.00	Medicine 0.00	Psychology 0.00	Medicine 0.00	Psychology 0.00	Medicine 0.00	Medicine 0.00
Social Work	0.00	Psychology 0.00	Religion 0.00	Psychology 0.00	Religion 0.00	Psychology 0.00	Psychology 0.00
History	-13.03	Religion 0.00	Science 0.00	Religion 0.00	Science 0.00	Religion 0.00	Religion 0.00
Government	-13.54	Science 0.00	Social Work 0.00	Science 0.00	Social Science 0.00	Science 0.00	Science 0.00
Law	-16.46	Social Work 0.00	Medicine -12.81	Social Work 0.00	Social Work 0.00	Social Science 0.00	Social Science 0.00
Architecture	-24.89	Engineering -11.69	Engineering -13.18	Law -17.94	History -11.51	Social Work 0.00	Social Work 0.00
Psychology	-41.60	Media -19.59	Media -22.70	Media -21.90	Engineering -39.49	Engineering -13.28	Media -28.16

Table Cont. (1)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>
Religion	23.41	Government 6.91	History 1.80	Science 22.27	Business 15.37	Government 6.91	Agriculture 31.40
Social Science	15.89	History 1.46	Agriculture 0.00	Social Science 17.48	Government 6.91	History 0.15	History 12.85
Agriculture	15.43	Agriculture 0.00	Architecture 0.00	Agriculture 14.37	Agriculture 0.00	Agriculture 0.00	Government 6.91
History	12.85	Architecture 0.00	Business 0.00	History 12.85	Architecture 0.00	Architecture 0.00	Architecture 0.00
Government	6.91	Business 0.00	Computer Science 0.00	Government 6.91	Computer Science 0.00	Business 0.00	Business 0.00
Architecture	0.00	Computer Science 0.00	Education 0.00	Architecture 0.00	Education 0.00	Computer Science 0.00	Computer Science 0.00
Business	0.00	Education 0.00	Engineering 0.00	Business 0.00	Fine Arts 0.00	Education 0.00	Education 0.00
Computer Science	0.00	Engineering 0.00	Fine Arts 0.00	Computer Science 0.00	Fitness 0.00	Engineering 0.00	Engineering 0.00
Education	0.00	Fine Arts 0.00	Fitness 0.00	Education 0.00	Languages 0.00	Fine Arts 0.00	Fine Arts 0.00
Fine Arts	0.00	Fitness 0.00	Languages 0.00	Engineering 0.00	Law 0.00	Fitness 0.00	Fitness 0.00
Fitness	0.00	Languages 0.00	Liberal Arts 0.00	Fine Arts 0.00	Liberal Arts 0.00	Languages 0.00	Languages 0.00
Languages	0.00	Law 0.00	Mathematics 0.00	Fitness 0.00	Mathematics 0.00	Liberal Arts 0.00	Law 0.00
Law	0.00	Liberal Arts 0.00	Medicine 0.00	Languages 0.00	Media 0.00	Mathematics 0.00	Liberal Arts 0.00
Liberal Arts	0.00	Mathematics 0.00	Psychology 0.00	Law 0.00	Medicine 0.00	Medicine 0.00	Mathematics 0.00
Mathematics	0.00	Medicine 0.00	Religion 0.00	Liberal Arts 0.00	Psychology 0.00	Psychology 0.00	Media 0.00
Media	0.00	Psychology 0.00	Science 0.00	Mathematics 0.00	Religion 0.00	Religion 0.00	Medicine 0.00
Psychology	0.00	Religion 0.00	Social Science 0.00	Media 0.00	Science 0.00	Science 0.00	Psychology 0.00
Science	0.00	Science 0.00	Social Work 0.00	Medicine 0.00	Social Science 0.00	Social Science 0.00	Religion 0.00
Social Work	0.00	Social Science 0.00	Government -8.46	Psychology 0.00	Social Work 0.00	Social Work 0.00	Science 0.00
Engineering	-20.31	Social Work 0.00	Law -13.05	Religion 0.00	History 0.00	Law -12.03	Social Science 0.00
Medicine	-26.18	Media -20.81	Media -24.08	Social Work 0.00	Engineering -9.64	Media -20.84	Social Work 0.00

PREMIUM TYPE

Table Cont. (2)

Estimates Including Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Science	217.85	Science 226.21	Science 189.97	Science 143.37	Science 209.65	Science 143.37	Science 143.37
Law	48.39	Law 48.39	Law 48.39	Law 48.39	Law 48.39	Media 34.42	Law 48.39
Media	34.42	Languages 31.22	Languages 31.22	Agriculture 41.23	Media 34.42	Languages 31.22	Media 34.42
Languages	31.22	Agriculture 18.91	Agriculture 11.54	Languages 31.22	Languages 31.22	Law 26.11	Languages 31.22
Agriculture	0.00	Architecture 0.00	Media 6.27	Architecture 0.00	Agriculture 0.00	Social Science 14.69	Agriculture 0.00
Architecture	0.00	Business 0.00	Architecture 0.00	Business 0.00	Architecture 0.00	Agriculture 14.54	Architecture 0.00
Business	0.00	Computer Science 0.00	Business 0.00	Computer Science 0.00	Business 0.00	Architecture 0.00	Business 0.00
Computer Science	0.00	Education 0.00	Computer Science 0.00	Education 0.00	Computer Science 0.00	Business 0.00	Computer Science 0.00
Education	0.00	Engineering 0.00	Education 0.00	Engineering 0.00	Education 0.00	Computer Science 0.00	Education 0.00
Fine Arts	0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Engineering 0.00	Education 0.00	Engineering 0.00
Fitness	0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	Fine Arts 0.00	Engineering 0.00	Fine Arts 0.00
Government	0.00	Government 0.00	History 0.00	Government 0.00	Fine Arts 0.00	Fine Arts 0.00	Fitness 0.00
Liberal Arts	0.00	History 0.00	Liberal Arts 0.00	History 0.00	History 0.00	Fitness 0.00	Government 0.00
Mathematics	0.00	Mathematics 0.00	Mathematics 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Government 0.00	History 0.00
Medicine	0.00	Medicine 0.00	Medicine 0.00	Mathematics 0.00	Mathematics 0.00	Liberal Arts 0.00	Liberal Arts 0.00
Psychology	0.00	Psychology 0.00	Psychology 0.00	Medicine 0.00	Medicine 0.00	Mathematics 0.00	Mathematics 0.00
Religion	0.00	Religion 0.00	Religion 0.00	Psychology 0.00	Psychology 0.00	Medicine 0.00	Medicine 0.00
Social Science	0.00	Social Science 0.00	Social Science 0.00	Religion 0.00	Religion 0.00	Psychology 0.00	Psychology 0.00
Social Work	0.00	Social Work 0.00	Social Work 0.00	Social Science 0.00	Social Science 0.00	Religion 0.00	Religion 0.00
Engineering	-13.69	Media -7.21	Government -8.09	Media -14.62	Social Work 0.00	Social Work 0.00	Social Science 0.00
History	-15.08	Liberal Arts -25.84	Engineering -15.90	Social Work -23.83	Government -10.57	History -11.10	Social Work 0.00

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Science	143.37	Science 143.37	Science 143.37	Science 143.37	Science 143.37	Science 143.37	Science 143.37
Media	34.42	Law 48.39	Law 48.39	Languages 31.22	Fine Arts 65.46	Law 48.39	Law 48.39
Languages	31.22	Languages 31.22	Languages 31.22	Social Science 29.95	Law 48.39	Media 34.42	Languages 31.22
Law	23.48	Social Science 14.86	Social Science 14.17	Law 20.52	Media 34.42	Languages 31.22	Agriculture 0.00
Agriculture	0.00	Agriculture 12.43	Agriculture 12.34	Government 18.87	Languages 31.22	Education 10.27	Architecture 0.00
Business	0.00	Media 6.76	Media 3.23	Media 4.30	Education 30.35	Agriculture 0.00	Business 0.00
Computer Science	0.00	Architecture 0.00	Architecture 0.00	Agriculture 0.00	Agriculture 0.00	Architecture 0.00	Computer Science 0.00
Education	0.00	Business 0.00	Business 0.00	Architecture 0.00	Architecture 0.00	Business 0.00	Education 0.00
Engineering	0.00	Computer Science 0.00	Computer Science 0.00	Business 0.00	Business 0.00	Computer Science 0.00	Engineering 0.00
Fine Arts	0.00	Education 0.00	Education 0.00	Computer Science 0.00	Computer Science 0.00	Fine Arts 0.00	Fine Arts 0.00
Fitness	0.00	Fine Arts 0.00	Fine Arts 0.00	Education 0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00
Government	0.00	Fitness 0.00	Fitness 0.00	Engineering 0.00	Government 0.00	Government 0.00	Government 0.00
Liberal Arts	0.00	Government 0.00	Government 0.00	Fine Arts 0.00	Liberal Arts 0.00	History 0.00	History 0.00
Mathematics	0.00	Liberal Arts 0.00	History 0.00	Fitness 0.00	Mathematics 0.00	Liberal Arts 0.00	Liberal Arts 0.00
Medicine	0.00	Mathematics 0.00	Liberal Arts 0.00	History 0.00	Medicine 0.00	Mathematics 0.00	Mathematics 0.00
Religion	0.00	Medicine 0.00	Mathematics 0.00	Liberal Arts 0.00	Psychology 0.00	Medicine 0.00	Medicine 0.00
Social Science	0.00	Psychology 0.00	Medicine 0.00	Mathematics 0.00	Religion 0.00	Psychology 0.00	Psychology 0.00
Social Work	0.00	Religion 0.00	Psychology 0.00	Medicine 0.00	Social Science 0.00	Religion 0.00	Religion 0.00
History	-20.33	Social Work 0.00	Religion 0.00	Psychology 0.00	Social Work 0.00	Religion 0.00	Social Science 0.00
Architecture	-22.98	History -9.85	Social Work 0.00	Religion 0.00	History -22.45	Social Work 0.00	Social Work 0.00
Psychology	-40.09	Engineering -14.59	Engineering -15.73	Social Work 0.00	Engineering -41.73	Engineering -14.17	Media -0.95

Table Cont. (3)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>
Science	199.52	Science 143.37	Science 143.37	Science 199.19	Science 143.37	Science 143.37	Science 143.37
Law	48.39	Law 48.39	Languages 31.22	Law 48.39	Law 48.39	Languages 31.22	Law 48.39
Media	34.42	Languages 31.22	Law 28.40	Media 34.42	Media 34.42	Law 29.93	Media 34.42
Languages	31.22	Media 8.77	Media 5.37	Languages 31.22	Languages 31.22	Education 10.85	Languages 31.22
Religion	20.57	Agriculture 0.00	Agriculture 0.00	Social Science 14.43	Business 16.57	Media 7.31	Agriculture 0.00
Social Science	16.24	Architecture 0.00	Architecture 0.00	Agriculture 0.00	Social Science 11.22	Agriculture 0.00	Architecture 0.00
Agriculture	15.27	Business 0.00	Business 0.00	Architecture 0.00	Agriculture 0.00	Architecture 0.00	Business 0.00
Architecture	0.00	Computer Science 0.00	Computer Science 0.00	Business 0.00	Architecture 0.00	Business 0.00	Computer Science 0.00
Business	0.00	Education 0.00	Education 0.00	Computer Science 0.00	Computer Science 0.00	Computer Science 0.00	Education 0.00
Computer Science	0.00	Engineering 0.00	Engineering 0.00	Education 0.00	Education 0.00	Fine Arts 0.00	Engineering 0.00
Education	0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Engineering 0.00	Fitness 0.00	Fine Arts 0.00
Fine Arts	0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	Fine Arts 0.00	Government 0.00	Fitness 0.00
Fitness	0.00	Government 0.00	Liberal Arts 0.00	Government 0.00	Fitness 0.00	Liberal Arts 0.00	Government 0.00
Government	0.00	History 0.00	Mathematics 0.00	History 0.00	Government 0.00	Mathematics 0.00	History 0.00
History	0.00	Liberal Arts 0.00	Medicine 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Medicine 0.00	Liberal Arts 0.00
Liberal Arts	0.00	Mathematics 0.00	Psychology 0.00	Mathematics 0.00	Mathematics 0.00	Psychology 0.00	Mathematics 0.00
Mathematics	0.00	Medicine 0.00	Religion 0.00	Medicine 0.00	Medicine 0.00	Religion 0.00	Medicine 0.00
Psychology	0.00	Psychology 0.00	Social Science 0.00	Psychology 0.00	Psychology 0.00	Social Science 0.00	Psychology 0.00
Social Work	0.00	Religion 0.00	Social Work 0.00	Religion 0.00	Religion 0.00	Social Work 0.00	Religion 0.00
Engineering	-22.02	Social Science 0.00	History -8.28	Social Work 0.00	Social Work 0.00	History -11.01	Social Science 0.00
Medicine	-23.77	Social Work 0.00	Government -13.01	Engineering -15.52	History -8.53	Engineering -14.60	Social Work 0.00

PREMIUM TYPE

Table Cont. (5)

PREMIUM TYPE	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>	
	Law	48.39	Medicine	100.84	Liberal Arts	75.57	Science	143.37	Business	192.44	Liberal Arts	74.18
Media	34.42	Law	48.39	Law	48.39	Media	3.53	Media	34.42	Law	48.39	
Languages	31.22	Media	34.42	History	45.54	Agriculture	0.00	Science	6.06	Media	34.42	
Architecture	18.23	Languages	31.22	Media	34.42	Architecture	0.00	Agriculture	0.00	Languages	31.22	
Agriculture	0.00	Agriculture	0.00	Languages	31.22	Business	0.00	Architecture	0.00	Science	13.94	
Business	0.00	Architecture	0.00	Science	1.55	Computer Science	0.00	Computer Science	0.00	Agriculture	0.00	
Computer Science	0.00	Business	0.00	Agriculture	0.00	Education	0.00	Education	0.00	Architecture	0.00	
Education	0.00	Education	0.00	Architecture	0.00	Engineering	0.00	Engineering	0.00	Business	0.00	
Engineering	0.00	Engineering	0.00	Business	0.00	Fitness	0.00	Fitness	0.00	Computer Science	0.00	
Fine Arts	0.00	Fine Arts	0.00	Computer Science	0.00	Government	0.00	Government	0.00	Education	0.00	
Fitness	0.00	Fitness	0.00	Education	0.00	History	0.00	History	0.00	Engineering	0.00	
Government	0.00	Government	0.00	Engineering	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Fine Arts	0.00	
History	0.00	History	0.00	Fine Arts	0.00	Medicine	0.00	Mathematics	0.00	Fitness	0.00	
Liberal Arts	0.00	Liberal Arts	0.00	Fitness	0.00	Psychology	0.00	Medicine	0.00	Government	0.00	
Mathematics	0.00	Mathematics	0.00	Government	0.00	Religion	0.00	Psychology	0.00	History	0.00	
Medicine	0.00	Psychology	0.00	Mathematics	0.00	Social Science	0.00	Social Science	0.00	Mathematics	0.00	
Psychology	0.00	Religion	0.00	Medicine	0.00	Social Work	0.00	Social Work	0.00	Medicine	0.00	
Religion	0.00	Social Science	0.00	Psychology	0.00	Languages	-2.43	Languages	-6.33	Psychology	0.00	
Social Science	0.00	Social Work	0.00	Religion	0.00	Law	-3.51	Law	-16.74	Religion	0.00	
Social Work	0.00	Science	-2.76	Social Science	0.00	Mathematics	-36.67	Religion	-32.32	Social Science	0.00	
Science	-13.55	Computer Science	-26.38	Social Work	0.00	Fine Arts	-44.81	Fine Arts	-39.89	Social Work	0.00	

Table 3.9: Ranking of Knowledge Specialization Premiums across College Majors (Ph. D. Sample)

Estimates Excluding Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Architecture	29.07	Medicine 90.45	Architecture 31.71	Engineering 10.53	Agriculture 0.00	Architecture 27.51	Agriculture 0.00
Engineering	10.53	Social Work 63.67	Liberal Arts 17.31	Agriculture 0.00	Architecture 0.00	Engineering 10.53	Architecture 0.00
Agriculture	0.00	Education 33.62	Engineering 10.53	Architecture 0.00	Business 0.00	Agriculture 0.00	Business 0.00
Business	0.00	Architecture 0.00	Agriculture 0.00	Business 0.00	Computer Science 0.00	Business 0.00	Computer Science 0.00
Computer Science	0.00	Business 0.00	Business 0.00	Computer Science 0.00	Education 0.00	Computer Science 0.00	Education 0.00
Fine Arts	0.00	Fine Arts 0.00	Computer Science 0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00
Fitness	0.00	Fitness 0.00	Fine Arts 0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00
Government	0.00	Government 0.00	Fitness 0.00	Government 0.00	History 0.00	Government 0.00	Government 0.00
History	0.00	History 0.00	Government 0.00	History 0.00	Languages 0.00	History 0.00	History 0.00
Languages	0.00	Languages 0.00	History 0.00	Languages 0.00	Law 0.00	Languages 0.00	Languages 0.00
Law	0.00	Law 0.00	Languages 0.00	Law 0.00	Liberal Arts 0.00	Law 0.00	Law 0.00
Liberal Arts	0.00	Liberal Arts 0.00	Law 0.00	Liberal Arts 0.00	Mathematics 0.00	Liberal Arts 0.00	Liberal Arts 0.00
Mathematics	0.00	Mathematics 0.00	Mathematics 0.00	Mathematics 0.00	Media 0.00	Mathematics 0.00	Mathematics 0.00
Media	0.00	Media 0.00	Media 0.00	Media 0.00	Medicine 0.00	Media 0.00	Media 0.00
Medicine	0.00	Psychology 0.00	Medicine 0.00	Psychology 0.00	Psychology 0.00	Medicine 0.00	Medicine 0.00
Psychology	0.00	Religion 0.00	Psychology 0.00	Religion 0.00	Religion 0.00	Psychology 0.00	Religion 0.00
Religion	0.00	Science 0.00	Religion 0.00	Science 0.00	Science 0.00	Religion 0.00	Science 0.00
Science	0.00	Social Science 0.00	Science 0.00	Social Science 0.00	Social Science 0.00	Science 0.00	Social Science 0.00
Social Science	0.00	Agriculture -19.71	Social Science 0.00	Social Work 0.00	Social Work 0.00	Social Science 0.00	Social Work 0.00
Social Work	0.00	Computer Science -37.63	Social Work 0.00	Education -18.62	Engineering -6.37	Social Work 0.00	Engineering -7.15
Education	-14.85	Engineering -40.77	Education -13.22	Medicine -27.90	Government -9.89	Education -12.55	Psychology -24.54
	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Engineering	10.53	Social Science 12.93	Engineering 10.53	Agriculture 22.74	Fitness 402.30	Medicine 17.31	Liberal Arts 20.03
Agriculture	0.00	Engineering 10.53	Agriculture 0.00	Engineering 10.53	Agriculture 213.91	Engineering 10.53	Science 19.04
Architecture	0.00	Agriculture 0.00	Architecture 0.00	Architecture 0.00	Mathematics 193.36	Agriculture 0.00	Social Science 12.44
Business	0.00	Architecture 0.00	Business 0.00	Business 0.00	Languages 121.08	Architecture 0.00	Engineering 10.53
Computer Science	0.00	Business 0.00	Computer Science 0.00	Computer Science 0.00	Engineering 57.16	Business 0.00	Agriculture 0.00
Education	0.00	Computer Science 0.00	Education 0.00	Education 0.00	Architecture 47.84	Computer Science 0.00	Architecture 0.00
Fine Arts	0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Business 0.00	Education 0.00	Business 0.00
Fitness	0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	Computer Science 0.00	Fitness 0.00	Computer Science 0.00
Government	0.00	Government 0.00	Government 0.00	Government 0.00	Government 0.00	Government 0.00	Fine Arts 0.00
Languages	0.00	History 0.00	History 0.00	History 0.00	History 0.00	Languages 0.00	Fitness 0.00
Law	0.00	Languages 0.00	Languages 0.00	Languages 0.00	Law 0.00	Law 0.00	History 0.00
Liberal Arts	0.00	Law 0.00	Law 0.00	Law 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Languages 0.00
Media	0.00	Liberal Arts 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Media 0.00	Mathematics 0.00	Law 0.00
Medicine	0.00	Mathematics 0.00	Mathematics 0.00	Mathematics 0.00	Medicine 0.00	Media 0.00	Mathematics 0.00
Religion	0.00	Media 0.00	Media 0.00	Media 0.00	Psychology 0.00	Psychology 0.00	Media 0.00
Science	0.00	Medicine 0.00	Medicine 0.00	Medicine 0.00	Religion 0.00	Religion 0.00	Medicine 0.00
Social Science	0.00	Psychology 0.00	Psychology 0.00	Psychology 0.00	Science 0.00	Science 0.00	Psychology 0.00
Social Work	0.00	Religion 0.00	Religion 0.00	Religion 0.00	Social Science 0.00	Social Science 0.00	Religion 0.00
Mathematics	-21.92	Science 0.00	Science 0.00	Science 0.00	Social Work 0.00	Social Work 0.00	Social Work 0.00
History	-27.47	Social Work 0.00	Social Science 0.00	Social Science 0.00	Education -27.64	History -11.19	Government -11.64
Psychology	-27.93	Education -24.05	Social Work 0.00	Social Work 0.00	Fine Arts -66.71	Fine Arts -12.88	Education -15.37

Table Cont. (1)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>						
Architecture	32.66	Science	14.31	Science	10.75	Mathematics	12.63	Engineering	1.49	Engineering	10.53	Religion	38.29
Medicine	20.87	Agriculture	0.00	Engineering	10.53	Engineering	10.53	Agriculture	0.00	Agriculture	0.00	Engineering	10.53
Engineering	10.53	Architecture	0.00	Agriculture	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00	Agriculture	0.00
Agriculture	0.00	Business	0.00	Architecture	0.00	Architecture	0.00	Business	0.00	Business	0.00	Architecture	0.00
Business	0.00	Computer Science	0.00	Business	0.00	Business	0.00	Computer Science	0.00	Computer Science	0.00	Business	0.00
Computer Science	0.00	Education	0.00	Computer Science	0.00	Computer Science	0.00	Education	0.00	Fine Arts	0.00	Computer Science	0.00
Education	0.00	Fine Arts	0.00	Fine Arts	0.00	Education	0.00	Fine Arts	0.00	Fitness	0.00	Education	0.00
Fine Arts	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00	Government	0.00	Fine Arts	0.00
Fitness	0.00	Government	0.00	Government	0.00	Government	0.00	History	0.00	History	0.00	Fitness	0.00
History	0.00	History	0.00	History	0.00	History	0.00	Languages	0.00	Languages	0.00	Government	0.00
Languages	0.00	Languages	0.00	Languages	0.00	Languages	0.00	Law	0.00	Law	0.00	History	0.00
Law	0.00	Law	0.00	Law	0.00	Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Languages	0.00
Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Mathematics	0.00	Mathematics	0.00	Law	0.00
Mathematics	0.00	Mathematics	0.00	Mathematics	0.00	Media	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00
Media	0.00	Media	0.00	Media	0.00	Medicine	0.00	Medicine	0.00	Medicine	0.00	Mathematics	0.00
Psychology	0.00	Medicine	0.00	Medicine	0.00	Psychology	0.00	Religion	0.00	Psychology	0.00	Media	0.00
Religion	0.00	Psychology	0.00	Psychology	0.00	Religion	0.00	Science	0.00	Religion	0.00	Medicine	0.00
Science	0.00	Religion	0.00	Religion	0.00	Science	0.00	Social Science	0.00	Science	0.00	Psychology	0.00
Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Work	0.00	Social Science	0.00	Science	0.00
Social Work	0.00	Social Work	0.00	Social Work	0.00	Social Work	0.00	Psychology	-8.19	Social Work	0.00	Social Science	0.00
Government	-13.45	Engineering	-0.99	Education	-14.55	Fine Arts	-12.86	Government	-9.84	Education	-10.56	Social Work	0.00

PREMIUM TYPE

Table Cont. (3)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>
Science	109.88	Science	100.43	Science	96.72	Science	73.21
Architecture	47.97	Agriculture	0.00	Architecture	39.22	Architecture	41.02
Medicine	24.95	Architecture	0.00	Liberal Arts	12.19	Agriculture	0.00
Agriculture	0.00	Business	0.00	Agriculture	0.00	Business	0.00
Business	0.00	Computer Science	0.00	Business	0.00	Computer Science	0.00
Computer Science	0.00	Engineering	0.00	Computer Science	0.00	Education	0.00
Education	0.00	Fine Arts	0.00	Engineering	0.00	Engineering	0.00
Engineering	0.00	Fitness	0.00	Fine Arts	0.00	Fitness	0.00
Fine Arts	0.00	Government	0.00	Fitness	0.00	Government	0.00
Fitness	0.00	History	0.00	Government	0.00	History	0.00
Languages	0.00	Languages	0.00	History	0.00	Languages	0.00
Law	0.00	Law	0.00	Languages	0.00	Law	0.00
Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Liberal Arts	0.00
Media	0.00	Media	0.00	Media	0.00	Media	0.00
Psychology	0.00	Medicine	0.00	Medicine	0.00	Religion	0.00
Religion	0.00	Psychology	0.00	Psychology	0.00	Social Science	0.00
Social Science	0.00	Religion	0.00	Religion	0.00	Social Work	0.00
Social Work	0.00	Social Science	0.00	Social Science	0.00	Engineering	-6.59
History	-13.33	Social Work	0.00	Social Work	0.00	Government	-9.32
Government	-13.66	Education	-10.20	Education	-14.12	Psychology	-9.35
Mathematics	-21.96	Mathematics	-21.96	Mathematics	-21.96	Mathematics	-21.96

PREMIUM TYPE

Table Cont. (4)

PREMIUM TYPE	<u>Arts, Entertainment, and</u>											
	<u>Agriculture</u>		<u>Recreation</u>		<u>Construction</u>		<u>Educational Services</u>		<u>Finance and Insurance</u>		<u>Health Care</u>	
Science	73.21	History	31.37	Science	73.21	History	24.98	Science	73.21	History	21.60	
Agriculture	0.00	Mathematics	20.78	History	45.22	Mathematics	0.81	History	58.54	Agriculture	0.00	
Architecture	0.00	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Psychology	56.42	Architecture	0.00	
Business	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	Mathematics	35.28	Business	0.00	
Computer Science	0.00	Business	0.00	Business	0.00	Business	0.00	Government	31.90	Computer Science	0.00	
Education	0.00	Computer Science	0.00	Computer Science	0.00	Computer Science	0.00	Languages	30.09	Education	0.00	
Engineering	0.00	Education	0.00	Education	0.00	Education	0.00	Computer Science	25.99	Engineering	0.00	
Fine Arts	0.00	Engineering	0.00	Engineering	0.00	Engineering	0.00	Agriculture	0.00	Fine Arts	0.00	
Fitness	0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Architecture	0.00	Fitness	0.00	
Government	0.00	Government	0.00	Fitness	0.00	Fitness	0.00	Business	0.00	Government	0.00	
History	0.00	Languages	0.00	Government	0.00	Government	0.00	Education	0.00	Languages	0.00	
Languages	0.00	Law	0.00	Languages	0.00	Languages	0.00	Engineering	0.00	Law	0.00	
Law	0.00	Liberal Arts	0.00	Law	0.00	Law	0.00	Fine Arts	0.00	Liberal Arts	0.00	
Liberal Arts	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Media	0.00	
Media	0.00	Medicine	0.00	Media	0.00	Media	0.00	Liberal Arts	0.00	Medicine	0.00	
Medicine	0.00	Psychology	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Psychology	0.00	
Psychology	0.00	Religion	0.00	Psychology	0.00	Psychology	0.00	Medicine	0.00	Religion	0.00	
Religion	0.00	Social Science	0.00	Religion	0.00	Religion	0.00	Religion	0.00	Social Science	0.00	
Social Science	0.00	Social Work	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Work	0.00	
Social Work	0.00	Science	-17.85	Social Work	0.00	Social Work	0.00	Social Work	0.00	Mathematics	-3.59	
Mathematics	-21.96	Fitness	-29.18	Mathematics	-21.96	Science	-4.90	Fitness	-29.99	Science	-6.66	
PREMIUM TYPE	<u>Mining, Quarrying, and Oil</u>											
	<u>Information</u>		<u>Manufacturing</u>		<u>Military</u>		<u>and Gas Extraction</u>		<u>Other Services</u>		<u>Professional, Scientific, and Technical Services</u>	
Science	73.21	Science	73.21	Government	85.17	Government	349.74	Science	73.21	Science	73.21	
Computer Science	45.03	History	34.39	Science	73.21	Media	183.22	History	35.29	History	26.46	
Agriculture	0.00	Mathematics	6.89	Mathematics	26.65	History	178.51	Mathematics	8.45	Mathematics	5.65	
Architecture	0.00	Agriculture	0.00	Agriculture	0.00	Psychology	148.70	Agriculture	0.00	Agriculture	0.00	
Business	0.00	Architecture	0.00	Architecture	0.00	Computer Science	100.66	Architecture	0.00	Architecture	0.00	
Education	0.00	Business	0.00	Computer Science	0.00	Social Science	89.25	Business	0.00	Business	0.00	
Engineering	0.00	Computer Science	0.00	Education	0.00	Science	73.21	Computer Science	0.00	Computer Science	0.00	
Fine Arts	0.00	Education	0.00	Engineering	0.00	Fine Arts	71.76	Education	0.00	Education	0.00	
Fitness	0.00	Engineering	0.00	Fine Arts	0.00	Mathematics	63.45	Engineering	0.00	Engineering	0.00	
Government	0.00	Fine Arts	0.00	Fitness	0.00	Languages	49.55	Fine Arts	0.00	Fine Arts	0.00	
History	0.00	Fitness	0.00	History	0.00	Agriculture	0.00	Fitness	0.00	Fitness	0.00	
Languages	0.00	Government	0.00	Languages	0.00	Architecture	0.00	Government	0.00	Government	0.00	
Law	0.00	Languages	0.00	Law	0.00	Education	0.00	Languages	0.00	Languages	0.00	
Liberal Arts	0.00	Law	0.00	Liberal Arts	0.00	Law	0.00	Law	0.00	Law	0.00	
Media	0.00	Liberal Arts	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Liberal Arts	0.00	
Medicine	0.00	Media	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Media	0.00	
Psychology	0.00	Medicine	0.00	Psychology	0.00	Religion	0.00	Medicine	0.00	Medicine	0.00	
Social Science	0.00	Psychology	0.00	Religion	0.00	Social Work	0.00	Psychology	0.00	Psychology	0.00	
Social Work	0.00	Religion	0.00	Social Science	0.00	Fitness	-44.01	Religion	0.00	Religion	0.00	
Mathematics	-21.96	Social Science	0.00	Social Work	-18.61	Engineering	-47.17	Social Science	0.00	Social Science	0.00	
Religion	-29.54	Social Work	0.00	Business	-63.56	Business	-53.21	Social Work	0.00	Social Work	0.00	

Table Cont. (5)

PREMIUM TYPE	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>		
History	30.61	Science	73.21	Science	73.21	Science	73.21	Science	73.21	Science	73.21	Science	73.21
Mathematics	13.32	History	44.90	Government	36.40	Social Work	28.98	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00
Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Mathematics	1.40	Architecture	0.00	Architecture	0.00	Architecture	0.00
Architecture	0.00	Architecture	0.00	Architecture	0.00	Agriculture	0.00	Computer Science	0.00	Business	0.00	Business	0.00
Business	0.00	Business	0.00	Business	0.00	Architecture	0.00	Education	0.00	Education	0.00	Computer Science	0.00
Computer Science	0.00	Computer Science	0.00	Computer Science	0.00	Business	0.00	Engineering	0.00	Engineering	0.00	Education	0.00
Education	0.00	Education	0.00	Education	0.00	Computer Science	0.00	Fine Arts	0.00	Fine Arts	0.00	Engineering	0.00
Engineering	0.00	Engineering	0.00	Engineering	0.00	Education	0.00	Government	0.00	Government	0.00	Fine Arts	0.00
Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Engineering	0.00	History	0.00	History	0.00	Fitness	0.00
Government	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Languages	0.00	Languages	0.00	Government	0.00
Languages	0.00	Government	0.00	History	0.00	Fitness	0.00	Law	0.00	Law	0.00	History	0.00
Law	0.00	Languages	0.00	Languages	0.00	Government	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Languages	0.00
Liberal Arts	0.00	Law	0.00	Law	0.00	History	0.00	Media	0.00	Media	0.00	Law	0.00
Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Languages	0.00	Medicine	0.00	Medicine	0.00	Liberal Arts	0.00
Medicine	0.00	Media	0.00	Media	0.00	Law	0.00	Psychology	0.00	Psychology	0.00	Media	0.00
Psychology	0.00	Medicine	0.00	Medicine	0.00	Liberal Arts	0.00	Religion	0.00	Religion	0.00	Medicine	0.00
Social Science	0.00	Psychology	0.00	Psychology	0.00	Media	0.00	Social Science	0.00	Social Science	0.00	Psychology	0.00
Social Work	0.00	Religion	0.00	Social Science	0.00	Medicine	0.00	Social Work	0.00	Social Work	0.00	Religion	0.00
Science	-8.82	Social Science	0.00	Social Work	0.00	Psychology	0.00	Mathematics	-21.96	Mathematics	-21.96	Social Science	0.00
Fitness	-19.24	Social Work	0.00	Mathematics	-0.35	Religion	0.00	Business	-29.70	Business	-29.70	Social Work	0.00
Religion	-24.71	Mathematics	-2.81	Religion	-28.58	Social Science	0.00	Fitness	-31.59	Fitness	-31.59	Mathematics	-21.96

Table 3.10: Ranking of Knowledge Composition Premiums across College Majors (Age 21-35 Sample)

Estimates Including Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Engineering	3.42	Engineering 23.16	Engineering 13.99	Engineering 23.16	Engineering 13.13	Engineering 23.16	Engineering 23.16
Agriculture	0.00	Computer Science 0.90	Computer Science 3.40	Science 14.47	Science 8.37	Computer Science 7.29	Computer Science 4.07
Architecture	0.00	Agriculture 0.00	Agriculture 0.00	Computer Science 14.46	Computer Science 1.53	Agriculture 0.00	Agriculture 0.00
Business	0.00	Architecture 0.00	Architecture 0.00	Social Science 12.32	Agriculture 0.00	Architecture 0.00	Architecture 0.00
Education	0.00	Business 0.00	Business 0.00	Agriculture 8.30	Architecture 0.00	Business 0.00	Business 0.00
Fine Arts	0.00	Education 0.00	Education 0.00	Architecture 0.00	Education 0.00	Fine Arts 0.00	Education 0.00
Fitness	0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00	Fitness 0.00	Fine Arts 0.00
Government	0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	History 0.00	Fitness 0.00
History	0.00	Government 0.00	History 0.00	Government 0.00	Government 0.00	Liberal Arts 0.00	Government 0.00
Law	0.00	History 0.00	Liberal Arts 0.00	History 0.00	History 0.00	Mathematics 0.00	History 0.00
Liberal Arts	0.00	Languages 0.00	Mathematics 0.00	Languages 0.00	Law 0.00	Media 0.00	Law 0.00
Mathematics	0.00	Law 0.00	Media 0.00	Law 0.00	Liberal Arts 0.00	Science 0.00	Liberal Arts 0.00
Media	0.00	Liberal Arts 0.00	Medicine 0.00	Liberal Arts 0.00	Mathematics 0.00	Social Science 0.00	Mathematics 0.00
Medicine	0.00	Mathematics 0.00	Science 0.00	Mathematics 0.00	Media 0.00	Social Work 0.00	Media 0.00
Psychology	0.00	Medicine 0.00	Social Science 0.00	Media 0.00	Medicine 0.00	Government -3.81	Medicine 0.00
Science	0.00	Psychology 0.00	Social Work 0.00	Psychology 0.00	Psychology 0.00	Languages -5.11	Psychology 0.00
Social Science	0.00	Science 0.00	Government -3.54	Social Work 0.00	Social Science 0.00	Psychology -5.23	Science 0.00
Social Work	0.00	Social Science 0.00	Psychology -5.02	Religion -9.92	Religion -9.92	Law -5.62	Social Science 0.00
Computer Science	-0.43	Social Work 0.00	Law -5.30	Education -13.29	Languages -6.24	Medicine -6.80	Social Work 0.00
Languages	-5.91	Religion -9.92	Languages -6.67	Medicine -15.89	Business -7.68	Education -7.82	Languages -5.28
Religion	-9.92	Media -12.07	Religion -9.92	Business -16.39	Religion -9.92	Religion -9.92	Religion -9.92

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Engineering	23.16	Engineering 14.88	Engineering 23.16	Engineering 14.81	Agriculture 0.00	Engineering 13.93	Engineering 23.16
Computer Science	4.06	Science 5.99	Fine Arts 5.10	Computer Science 14.46	Architecture 0.00	Computer Science 0.64	Computer Science 14.46
Agriculture	0.00	Computer Science 1.40	Computer Science 2.00	Social Science 14.03	Business 0.00	Agriculture 0.00	Agriculture 0.00
Architecture	0.00	Agriculture 0.00	Agriculture 0.00	Agriculture 6.50	Education 0.00	Architecture 0.00	Architecture 0.00
Business	0.00	Architecture 0.00	Architecture 0.00	Architecture 0.00	Fine Arts 0.00	Business 0.00	Business 0.00
Education	0.00	Business 0.00	Business 0.00	Fine Arts 0.00	Fitness 0.00	Fine Arts 0.00	Education 0.00
Fine Arts	0.00	Fine Arts 0.00	Education 0.00	Fitness 0.00	Government 0.00	Fitness 0.00	Fine Arts 0.00
Fitness	0.00	Fitness 0.00	Fitness 0.00	Government 0.00	History 0.00	Government 0.00	Fitness 0.00
Government	0.00	Government 0.00	Government 0.00	History 0.00	Law 0.00	History 0.00	Government 0.00
History	0.00	History 0.00	History 0.00	Languages 0.00	Liberal Arts 0.00	Languages 0.00	History 0.00
Liberal Arts	0.00	Law 0.00	Liberal Arts 0.00	Law 0.00	Mathematics 0.00	Law 0.00	Liberal Arts 0.00
Mathematics	0.00	Liberal Arts 0.00	Mathematics 0.00	Liberal Arts 0.00	Media 0.00	Liberal Arts 0.00	Mathematics 0.00
Media	0.00	Mathematics 0.00	Media 0.00	Mathematics 0.00	Medicine 0.00	Mathematics 0.00	Media 0.00
Medicine	0.00	Media 0.00	Medicine 0.00	Media 0.00	Science 0.00	Medicine 0.00	Medicine 0.00
Science	0.00	Medicine 0.00	Psychology 0.00	Medicine 0.00	Social Science 0.00	Psychology 0.00	Psychology 0.00
Social Science	0.00	Psychology 0.00	Science 0.00	Psychology 0.00	Social Work 0.00	Science 0.00	Science 0.00
Social Work	0.00	Social Science 0.00	Social Science 0.00	Science 0.00	Computer Science -0.66	Social Science 0.00	Social Science 0.00
Law	-8.33	Social Work 0.00	Social Work 0.00	Social Work 0.00	Engineering -4.95	Social Work 0.00	Social Work 0.00
Languages	-9.51	Education -4.68	Law -6.69	Education -8.16	Religion -9.92	Education -3.72	Law -7.48
Religion	-9.92	Languages -6.24	Languages -9.34	Religion -9.92	Languages -13.86	Media -6.43	Languages -9.76
Psychology	-10.07	Religion -9.92	Religion -9.92	Business -21.19	Psychology -19.83	Religion -9.92	Religion -9.92

Table Cont. (1)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>						
Engineering	15.45	Engineering	23.16	Engineering	16.56	Engineering	15.47	Engineering	13.82	Engineering	15.32	Engineering	23.16
Computer Science	4.12	Science	7.00	Science	5.71	Science	11.34	Business	5.83	Computer Science	1.61	Computer Science	5.31
Agriculture	0.00	Computer Science	3.63	Computer Science	2.27	Liberal Arts	8.92	Computer Science	3.10	Agriculture	0.00	Agriculture	0.00
Architecture	0.00	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00
Business	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	Business	0.00	Business	0.00
Education	0.00	Business	0.00	Fine Arts	0.00	Business	0.00	Education	0.00	Education	0.00	Education	0.00
Fine Arts	0.00	Fine Arts	0.00	Fitness	0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00
Fitness	0.00	Fitness	0.00	Government	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00
Government	0.00	History	0.00	History	0.00	Government	0.00	History	0.00	Government	0.00	Government	0.00
History	0.00	Law	0.00	Law	0.00	History	0.00	Law	0.00	History	0.00	History	0.00
Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Mathematics	0.00	Liberal Arts	0.00	Law	0.00	Languages	0.00
Liberal Arts	0.00	Mathematics	0.00	Mathematics	0.00	Media	0.00	Mathematics	0.00	Liberal Arts	0.00	Liberal Arts	0.00
Mathematics	0.00	Medicine	0.00	Media	0.00	Medicine	0.00	Media	0.00	Mathematics	0.00	Mathematics	0.00
Media	0.00	Psychology	0.00	Medicine	0.00	Psychology	0.00	Medicine	0.00	Medicine	0.00	Media	0.00
Science	0.00	Social Science	0.00	Psychology	0.00	Social Science	0.00	Psychology	0.00	Psychology	0.00	Medicine	0.00
Social Science	0.00	Social Work	0.00	Social Science	0.00	Social Work	0.00	Science	0.00	Science	0.00	Psychology	0.00
Social Work	0.00	Government	-4.50	Social Work	0.00	Computer Science	-2.31	Social Science	0.00	Social Science	0.00	Science	0.00
Psychology	-5.78	Media	-4.79	Education	-4.42	Law	-6.84	Social Work	0.00	Social Work	0.00	Social Science	0.00
Medicine	-6.28	Languages	-6.00	Languages	-4.69	Languages	-8.30	Government	-4.75	Media	-5.77	Social Work	0.00
Languages	-7.46	Education	-6.28	Business	-5.76	Education	-9.85	Languages	-8.06	Languages	-6.59	Law	-5.55
Religion	-9.92	Religion	-9.92	Religion	-9.92	Religion	-9.92	Religion	-9.92	Religion	-9.92	Religion	-9.92

PREMIUM TYPE (ADJUSTED)

Table Cont. (3)

	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>	
Engineering	23.16	Engineering	23.16	Computer Science	14.46	Medicine	20.51	Engineering	23.16	Computer Science	14.46	
Computer Science	14.46	Computer Science	14.46	Engineering	4.47	Computer Science	14.46	Social Science	15.46	Agriculture	10.83	
Social Science	12.22	Agriculture	8.94	Agriculture	0.00	Agriculture	9.11	Computer Science	14.46	Engineering	5.84	
Agriculture	0.00	Architecture	0.00	Architecture	0.00	Engineering	3.74	Religion	0.39	Architecture	0.00	
Architecture	0.00	Business	0.00	Business	0.00	Architecture	0.00	Agriculture	0.00	Business	0.00	
Business	0.00	Education	0.00	Education	0.00	Business	0.00	Architecture	0.00	Education	0.00	
Education	0.00	Fine Arts	0.00	Fine Arts	0.00	Education	0.00	Fine Arts	0.00	Fine Arts	0.00	
Fine Arts	0.00	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Fitness	0.00	Fitness	0.00	
Fitness	0.00	Government	0.00	Government	0.00	Fitness	0.00	Government	0.00	Government	0.00	
Government	0.00	History	0.00	History	0.00	Government	0.00	History	0.00	History	0.00	
History	0.00	Languages	0.00	Languages	0.00	History	0.00	Languages	0.00	Languages	0.00	
Languages	0.00	Law	0.00	Law	0.00	Languages	0.00	Law	0.00	Law	0.00	
Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	
Liberal Arts	0.00	Mathematics	0.00	Mathematics	0.00	Liberal Arts	0.00	Mathematics	0.00	Mathematics	0.00	
Mathematics	0.00	Media	0.00	Media	0.00	Mathematics	0.00	Media	0.00	Media	0.00	
Media	0.00	Medicine	0.00	Medicine	0.00	Media	0.00	Medicine	0.00	Medicine	0.00	
Medicine	0.00	Psychology	0.00	Psychology	0.00	Psychology	0.00	Psychology	0.00	Psychology	0.00	
Psychology	0.00	Science	0.00	Science	0.00	Science	0.00	Science	0.00	Science	0.00	
Science	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Work	0.00	Social Science	0.00	
Social Work	0.00	Social Work	0.00	Social Work	0.00	Social Work	0.00	Education	-9.58	Social Work	0.00	
Religion	-9.92	Religion	-9.92	Religion	-0.49	Religion	-9.92	Business	-24.63	Religion	-9.92	

PREMIUM TYPE (ADJUSTED)

Table 3.11: Ranking of Knowledge Composition Premiums across College Majors (Age 36-50 Sample)

Estimates Including Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Computer Science	12.18	Computer Science 12.18	Computer Science 5.03	Computer Science 12.18	Medicine 8.98	Computer Science 12.18	Medicine 10.71
Agriculture	0.00	Agriculture 0.00	Agriculture 0.00	Agriculture 0.00	Computer Science 5.37	Science 8.70	Computer Science 5.21
Architecture	0.00	Architecture 0.00	Architecture 0.00	Architecture 0.00	Agriculture 0.00	Social Science 5.33	Architecture 0.00
Business	0.00	Business 0.00	Business 0.00	Business 0.00	Architecture 0.00	Agriculture 0.00	Business 0.00
Engineering	0.00	Education 0.00	Education 0.00	Engineering 0.00	Business 0.00	Architecture 0.00	Education 0.00
Fine Arts	0.00	Engineering 0.00	Fine Arts 0.00	Fine Arts 0.00	Education 0.00	Engineering 0.00	Fine Arts 0.00
Fitness	0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00	Fine Arts 0.00	Fine Arts 0.00	Fitness 0.00
Government	0.00	Government 0.00	Government 0.00	Government 0.00	Fitness 0.00	Fitness 0.00	Government 0.00
History	0.00	History 0.00	Languages 0.00	Languages 0.00	Government 0.00	Government 0.00	History 0.00
Languages	0.00	Languages 0.00	Law 0.00	Law 0.00	History 0.00	History 0.00	Languages 0.00
Law	0.00	Liberal Arts 0.00	Media 0.00	Liberal Arts 0.00	Languages 0.00	Languages 0.00	Liberal Arts 0.00
Liberal Arts	0.00	Media 0.00	Medicine 0.00	Mathematics 0.00	Law 0.00	Law 0.00	Media 0.00
Mathematics	0.00	Medicine 0.00	Psychology 0.00	Media 0.00	Mathematics 0.00	Liberal Arts 0.00	Psychology 0.00
Media	0.00	Psychology 0.00	Religion 0.00	Medicine 0.00	Media 0.00	Mathematics 0.00	Religion 0.00
Medicine	0.00	Religion 0.00	Science 0.00	Psychology 0.00	Psychology 0.00	Media 0.00	Science 0.00
Psychology	0.00	Science 0.00	Social Science 0.00	Religion 0.00	Religion 0.00	Medicine 0.00	Social Science 0.00
Religion	0.00	Social Science 0.00	Social Work 0.00	Science 0.00	Science 0.00	Psychology 0.00	Social Work 0.00
Science	0.00	Social Work 0.00	History -4.36	Social Science 0.00	Social Science 0.00	Religion 0.00	Agriculture -4.79
Social Science	0.00	Law -7.22	Liberal Arts -5.71	History -4.93	Social Work 0.00	Social Work -6.13	Law -5.98
Social Work	-5.93	Mathematics -8.60	Engineering -6.90	Social Work -5.33	Liberal Arts -5.12	Education -9.47	Mathematics -8.71
Education	-10.31	Fine Arts -12.73	Mathematics -7.04	Education -9.14	Engineering -7.99	Business -10.52	Engineering -11.91

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Medicine	15.32	Computer Science 6.36	Science 12.75	Social Science 7.92	Computer Science 12.18	Computer Science 12.18	Computer Science 12.18
Computer Science	1.27	Social Science 5.78	Computer Science 12.18	Computer Science 3.79	Agriculture 0.00	Agriculture 0.00	Science 11.30
Agriculture	0.00	Agriculture 0.00	Agriculture 0.00	Agriculture 0.00	Architecture 0.00	Architecture 0.00	Social Science 8.04
Architecture	0.00	Architecture 0.00	Architecture 0.00	Architecture 0.00	Business 0.00	Business 0.00	Agriculture 0.00
Business	0.00	Business 0.00	Business 0.00	Business 0.00	Education 0.00	Fine Arts 0.00	Architecture 0.00
Education	0.00	Fine Arts 0.00	Fine Arts 0.00	Education 0.00	Engineering 0.00	Fitness 0.00	Engineering 0.00
Engineering	0.00	Fitness 0.00	Government 0.00	Engineering 0.00	Fine Arts 0.00	Government 0.00	Fine Arts 0.00
Fitness	0.00	Government 0.00	History 0.00	Fine Arts 0.00	Fitness 0.00	History 0.00	Fitness 0.00
History	0.00	History 0.00	Languages 0.00	Fitness 0.00	Government 0.00	Languages 0.00	Government 0.00
Languages	0.00	Languages 0.00	Law 0.00	Government 0.00	Languages 0.00	Law 0.00	History 0.00
Law	0.00	Law 0.00	Media 0.00	History 0.00	Law 0.00	Liberal Arts 0.00	Languages 0.00
Mathematics	0.00	Mathematics 0.00	Medicine 0.00	Languages 0.00	Liberal Arts 0.00	Media 0.00	Liberal Arts 0.00
Media	0.00	Media 0.00	Psychology 0.00	Mathematics 0.00	Mathematics 0.00	Medicine 0.00	Mathematics 0.00
Psychology	0.00	Medicine 0.00	Religion 0.00	Media 0.00	Media 0.00	Psychology 0.00	Media 0.00
Religion	0.00	Psychology 0.00	Social Science 0.00	Medicine 0.00	Medicine 0.00	Religion 0.00	Medicine 0.00
Science	0.00	Religion 0.00	Fitness -5.38	Psychology 0.00	Psychology 0.00	Science 0.00	Psychology 0.00
Social Science	0.00	Science 0.00	Mathematics -5.42	Religion 0.00	Religion 0.00	Social Science 0.00	Religion 0.00
Social Work	0.00	Social Work 0.00	Social Work -6.17	Science 0.00	Science 0.00	Social Work -5.44	Social Work 0.00
Fine Arts	-6.73	Liberal Arts -5.34	Engineering -6.54	Social Work 0.00	Social Science 0.00	Engineering -6.61	Education -6.27
Government	-7.51	Engineering -6.94	Liberal Arts -6.68	Law -8.83	Social Work 0.00	Mathematics -6.80	Law -8.08
Liberal Arts	-8.59	Education -8.50	Education -9.22	Liberal Arts -10.30	History -12.06	Education -7.85	Business -11.20

Table Cont. (1)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>						
Computer Science	5.23	Computer Science	12.18	Computer Science	6.52	Computer Science	12.18	Computer Science	12.18	Computer Science	6.41	Computer Science	1.03
Agriculture	0.00	Social Science	7.45	Social Science	5.95	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00
Architecture	0.00	Agriculture	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00
Business	0.00	Architecture	0.00	Architecture	0.00	Business	0.00	Business	0.00	Education	0.00	Engineering	0.00
Fine Arts	0.00	Business	0.00	Business	0.00	Engineering	0.00	Fine Arts	0.00	Fine Arts	0.00	Fine Arts	0.00
Fitness	0.00	Fine Arts	0.00	Engineering	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00	Fitness	0.00
Government	0.00	Fitness	0.00	Fine Arts	0.00	Government	0.00	Government	0.00	Government	0.00	Government	0.00
Languages	0.00	Government	0.00	Fitness	0.00	History	0.00	History	0.00	History	0.00	History	0.00
Law	0.00	History	0.00	Government	0.00	Languages	0.00	Languages	0.00	Languages	0.00	Languages	0.00
Media	0.00	Languages	0.00	History	0.00	Law	0.00	Liberal Arts	0.00	Law	0.00	Law	0.00
Medicine	0.00	Law	0.00	Languages	0.00	Mathematics	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00
Psychology	0.00	Liberal Arts	0.00	Law	0.00	Media	0.00	Medicine	0.00	Mathematics	0.00	Mathematics	0.00
Religion	0.00	Mathematics	0.00	Liberal Arts	0.00	Medicine	0.00	Psychology	0.00	Media	0.00	Media	0.00
Science	0.00	Media	0.00	Mathematics	0.00	Psychology	0.00	Religion	0.00	Medicine	0.00	Medicine	0.00
Social Science	0.00	Medicine	0.00	Media	0.00	Religion	0.00	Science	0.00	Psychology	0.00	Psychology	0.00
Education	-4.64	Psychology	0.00	Medicine	0.00	Science	0.00	Social Science	0.00	Religion	0.00	Religion	0.00
History	-4.89	Religion	0.00	Psychology	0.00	Social Science	0.00	Social Work	0.00	Science	0.00	Science	0.00
Social Work	-5.51	Science	0.00	Religion	0.00	Social Work	0.00	Engineering	-4.68	Social Science	0.00	Social Science	0.00
Liberal Arts	-6.03	Engineering	-4.87	Science	0.00	Fine Arts	-7.69	Law	-5.66	Social Work	0.00	Social Work	0.00
Engineering	-6.99	Social Work	-5.21	Social Work	0.00	Liberal Arts	-9.31	Education	-7.06	Business	-6.81	Education	-10.02
Mathematics	-7.97	Education	-12.29	Education	-7.37	Education	-12.09	Mathematics	-7.13	Engineering	-7.01	Business	-12.59

PREMIUM TYPE (ADJUSTED)

Table Cont. (3)

	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>	
PREMIUM TYPE (ADJUSTED)	Computer Science	12.18	Computer Science	12.18	Religion	12.97	Computer Science	12.18	Computer Science	12.18	Computer Science	12.18
	Agriculture	0.00	Agriculture	0.00	Computer Science	12.18	Agriculture	0.00	Agriculture	0.00	Agriculture	0.00
	Architecture	0.00	Architecture	0.00	Agriculture	0.00	Architecture	0.00	Architecture	0.00	Architecture	0.00
	Business	0.00	Business	0.00	Architecture	0.00	Business	0.00	Business	0.00	Business	0.00
	Education	0.00	Education	0.00	Business	0.00	Education	0.00	Education	0.00	Education	0.00
	Engineering	0.00	Engineering	0.00	Education	0.00	Engineering	0.00	Engineering	0.00	Engineering	0.00
	Fine Arts	0.00	Fine Arts	0.00	Engineering	0.00	Fine Arts	0.00	Fine Arts	0.00	Fitness	0.00
	Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Fitness	0.00	Fitness	0.00	Government	0.00
	Government	0.00	Government	0.00	Fitness	0.00	Government	0.00	Government	0.00	History	0.00
	History	0.00	History	0.00	Government	0.00	History	0.00	History	0.00	Languages	0.00
	Languages	0.00	Languages	0.00	History	0.00	Languages	0.00	Languages	0.00	Law	0.00
	Law	0.00	Law	0.00	Languages	0.00	Law	0.00	Law	0.00	Liberal Arts	0.00
	Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	Mathematics	0.00
	Mathematics	0.00	Mathematics	0.00	Liberal Arts	0.00	Mathematics	0.00	Mathematics	0.00	Media	0.00
	Media	0.00	Media	0.00	Mathematics	0.00	Media	0.00	Media	0.00	Medicine	0.00
	Medicine	0.00	Medicine	0.00	Media	0.00	Medicine	0.00	Medicine	0.00	Psychology	0.00
	Psychology	0.00	Psychology	0.00	Medicine	0.00	Psychology	0.00	Psychology	0.00	Religion	0.00
	Religion	0.00	Religion	0.00	Psychology	0.00	Religion	0.00	Religion	0.00	Science	0.00
	Science	0.00	Science	0.00	Science	0.00	Science	0.00	Science	0.00	Social Science	0.00
	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Science	0.00	Social Work	0.00
	Social Work	0.00	Social Work	0.00	Social Work	0.00	Social Work	0.00	Social Work	0.00	Fine Arts	-12.68

Table 3.12: Ranking of Knowledge Composition Premiums across College Majors (Age 51-65 Sample)

Estimates Including Industry Interactions:

	<u>Agriculture</u>	<u>Architecture</u>	<u>Business</u>	<u>Computer Science</u>	<u>Education</u>	<u>Engineering</u>	<u>Fine Arts</u>
Psychology	47.77	Psychology 47.77	Psychology 36.27	Psychology 47.77	Psychology 40.05	Psychology 37.22	Psychology 47.77
Government	22.55	Government 22.55	Mathematics 16.34	Government 22.55	Mathematics 16.34	Mathematics 16.34	Government 22.55
Mathematics	16.34	Mathematics 16.34	Government 13.26	Mathematics 16.34	Government 15.15	Engineering 14.98	Mathematics 16.34
Computer Science	9.47	Engineering 14.98	Computer Science 9.47	Engineering 14.98	Computer Science 9.47	Science 10.16	Computer Science 9.47
Religion	7.86	Computer Science 9.47	Engineering 6.68	Computer Science 9.47	Engineering 5.89	Computer Science 9.47	Engineering 6.18
Engineering	2.02	Architecture 0.00	Architecture 0.00	Architecture 0.00	Architecture 0.00	Government 9.17	Architecture 0.00
Architecture	0.00	Fine Arts 0.00	Business 0.00	Fine Arts 0.00	Business 0.00	Architecture 0.00	Business 0.00
Business	0.00	Fitness 0.00	Fine Arts 0.00	Fitness 0.00	Fine Arts 0.00	Business 0.00	Fine Arts 0.00
Fine Arts	0.00	History 0.00	Fitness 0.00	History 0.00	Fitness 0.00	Fine Arts 0.00	Fitness 0.00
Fitness	0.00	Languages 0.00	History 0.00	Languages 0.00	History 0.00	Fitness 0.00	History 0.00
History	0.00	Law 0.00	Languages 0.00	Law 0.00	Law 0.00	History 0.00	Languages 0.00
Law	0.00	Liberal Arts 0.00	Law 0.00	Liberal Arts 0.00	Liberal Arts 0.00	Languages 0.00	Law 0.00
Liberal Arts	0.00	Media 0.00	Liberal Arts 0.00	Media 0.00	Media 0.00	Law 0.00	Liberal Arts 0.00
Media	0.00	Medicine 0.00	Media 0.00	Medicine 0.00	Medicine 0.00	Liberal Arts 0.00	Media 0.00
Medicine	0.00	Religion 0.00	Medicine 0.00	Religion 0.00	Religion 0.00	Media 0.00	Medicine 0.00
Science	0.00	Science 0.00	Religion 0.00	Science 0.00	Science 0.00	Medicine 0.00	Religion 0.00
Social Science	0.00	Social Science 0.00	Science 0.00	Social Science 0.00	Social Science -5.36	Religion 0.00	Science 0.00
Languages	-6.35	Social Work -8.47	Social Science -5.34	Social Work 0.00	Languages -5.75	Social Science -6.11	Social Science 0.00
Social Work	-6.47	Agriculture -9.23	Social Work -5.35	Agriculture -9.23	Social Work -6.84	Social Work -6.91	Social Work 0.00
Agriculture	-9.23	Business -14.38	Agriculture -9.23	Business -13.63	Agriculture -9.23	Agriculture -9.23	Agriculture -9.23
Education	-15.00	Education -24.06	Education -17.53	Education -20.46	Education -15.00	Education -19.85	Education -15.00

	<u>Fitness</u>	<u>Government</u>	<u>History</u>	<u>Languages</u>	<u>Law</u>	<u>Liberal Arts</u>	<u>Mathematics</u>
Psychology	47.77	Psychology 47.77	Psychology 47.77	Psychology 47.77	Psychology 47.77	Psychology 36.23	Psychology 47.77
Government	22.55	Government 22.55	Government 11.09	Government 22.55	Medicine 46.56	Government 22.55	Government 22.55
Engineering	14.98	Mathematics 16.34	Business 11.02	Mathematics 16.34	Government 22.55	Mathematics 16.34	Mathematics 16.34
Computer Science	9.47	Computer Science 9.47	Computer Science 9.47	Science 15.38	Mathematics 16.34	Computer Science 9.47	Engineering 14.98
Mathematics	3.57	Social Science 4.75	Mathematics 7.70	Computer Science 9.47	Computer Science 9.47	Engineering 6.61	Science 10.91
Architecture	0.00	Engineering 4.67	Engineering 6.36	Engineering 4.21	Architecture 0.00	Architecture 0.00	Computer Science 9.47
Business	0.00	Architecture 0.00	Fine Arts 6.22	Architecture 0.00	Business 0.00	Business 0.00	Architecture 0.00
Fine Arts	0.00	Fine Arts 0.00	Architecture 0.00	Business 0.00	Fine Arts 0.00	Fine Arts 0.00	Fine Arts 0.00
Fitness	0.00	Fitness 0.00	Fitness 0.00	Fine Arts 0.00	Fitness 0.00	Fitness 0.00	Fitness 0.00
History	0.00	History 0.00	History 0.00	Fitness 0.00	Law 0.00	History 0.00	History 0.00
Languages	0.00	Languages 0.00	Languages 0.00	History 0.00	Liberal Arts 0.00	Languages 0.00	Languages 0.00
Law	0.00	Law 0.00	Law 0.00	Languages 0.00	Media 0.00	Law 0.00	Law 0.00
Liberal Arts	0.00	Liberal Arts 0.00	Liberal Arts 0.00	Law 0.00	Religion 0.00	Liberal Arts 0.00	Liberal Arts 0.00
Media	0.00	Media 0.00	Media 0.00	Liberal Arts 0.00	Social Science 0.00	Media 0.00	Media 0.00
Medicine	0.00	Medicine 0.00	Medicine 0.00	Media 0.00	Social Work 0.00	Medicine 0.00	Religion 0.00
Religion	0.00	Religion 0.00	Religion 0.00	Religion 0.00	Agriculture -9.23	Religion 0.00	Social Science 0.00
Social Science	0.00	Science 0.00	Science 0.00	Social Science 0.00	Engineering -11.38	Science 0.00	Social Work -7.43
Social Work	0.00	Agriculture -2.96	Social Science 0.00	Agriculture -1.44	Education -15.00	Social Science 0.00	Agriculture -9.23
Agriculture	-9.23	Social Work -5.24	Social Work -6.81	Social Work -7.93	History -24.02	Social Work -6.24	Medicine -9.90
Education	-15.00	Business -12.61	Agriculture -9.23	Medicine -12.85	Languages -29.57	Agriculture -9.23	Business -12.64
Science	-17.09	Education -19.94	Education -15.00	Education -15.00	Science -41.63	Education -15.00	Education -22.71

Table Cont. (1)

	<u>Media</u>	<u>Medicine</u>	<u>Psychology</u>	<u>Religion</u>	<u>Science</u>	<u>Social Science</u>	<u>Social Work</u>
Psychology	47.77	Psychology	47.77	Psychology	47.77	Psychology	47.77
Mathematics	16.34	Government	22.55	Mathematics	16.34	Government	22.55
Government	15.23	Mathematics	16.34	Engineering	14.98	Mathematics	16.34
Computer Science	9.47	Computer Science	9.47	Government	13.36	Computer Science	9.47
Engineering	6.49	Engineering	6.56	Computer Science	9.47	Engineering	6.81
Architecture	0.00	Architecture	0.00	Engineering	8.09	Architecture	0.00
Business	0.00	Business	0.00	Architecture	0.00	Architecture	0.00
Fine Arts	0.00	Fine Arts	0.00	Business	0.00	Business	0.00
Fitness	0.00	Fitness	0.00	Fine Arts	0.00	Fine Arts	0.00
History	0.00	History	0.00	Fitness	0.00	Fitness	0.00
Languages	0.00	Languages	0.00	History	0.00	History	0.00
Law	0.00	Law	0.00	Languages	0.00	Languages	0.00
Liberal Arts	0.00	Liberal Arts	0.00	Law	0.00	Law	0.00
Media	0.00	Media	0.00	Liberal Arts	0.00	Liberal Arts	0.00
Medicine	0.00	Medicine	0.00	Media	0.00	Media	0.00
Religion	0.00	Religion	0.00	Medicine	0.00	Medicine	0.00
Science	0.00	Science	0.00	Religion	0.00	Religion	0.00
Social Science	0.00	Social Science	0.00	Science	0.00	Science	0.00
Social Work	0.00	Social Work	0.00	Social Science	0.00	Social Science	0.00
Agriculture	-9.23	Agriculture	-9.23	Social Work	-5.16	Social Work	-5.49
Education	-15.00	Education	-18.96	Business	-9.15	Agriculture	-9.23
				Agriculture	-9.23	Education	-15.00
				Education	-22.22		
				Education	-15.00		
				Education	-17.97		
				Education	-19.32		

PREMIUM TYPE (ADJUSTED)

Table Cont. (2)

	<u>Agriculture, Forestry, Fishing and Hunting</u>		<u>Arts, Entertainment, and Recreation</u>		<u>Construction</u>		<u>Educational Services</u>		<u>Finance and Insurance</u>		<u>Health Care</u>	
Psychology	47.77	Engineering	14.98	Mathematics	16.34	Engineering	14.98	Government	22.55	Engineering	14.98	
Government	22.55	Psychology	9.27	Engineering	14.98	Government	7.10	Mathematics	16.34	Computer Science	9.47	
Mathematics	16.34	Government	7.53	Computer Science	9.47	Psychology	6.45	Engineering	14.98	Government	7.70	
Engineering	14.98	Mathematics	5.36	Government	7.42	Mathematics	6.32	Computer Science	9.47	Mathematics	4.13	
Computer Science	9.47	Agriculture	2.15	Agriculture	1.70	Computer Science	0.91	Psychology	2.89	Psychology	3.07	
Architecture	0.00	Computer Science	0.06	Architecture	0.00	Architecture	0.00	Architecture	0.00	Agriculture	1.53	
Business	0.00	Architecture	0.00	Business	0.00	Business	0.00	Business	0.00	Architecture	0.00	
Fine Arts	0.00	Business	0.00	Fitness	0.00	Fine Arts	0.00	Fine Arts	0.00	Business	0.00	
Fitness	0.00	Fine Arts	0.00	History	0.00	Fitness	0.00	History	0.00	Fine Arts	0.00	
History	0.00	Fitness	0.00	Languages	0.00	History	0.00	Languages	0.00	Fitness	0.00	
Languages	0.00	History	0.00	Law	0.00	Languages	0.00	Law	0.00	Languages	0.00	
Law	0.00	Languages	0.00	Liberal Arts	0.00	Law	0.00	Liberal Arts	0.00	Law	0.00	
Liberal Arts	0.00	Law	0.00	Medicine	0.00	Liberal Arts	0.00	Medicine	0.00	Liberal Arts	0.00	
Media	0.00	Liberal Arts	0.00	Religion	0.00	Media	0.00	Religion	0.00	Medicine	0.00	
Medicine	0.00	Media	0.00	Science	0.00	Medicine	0.00	Science	0.00	Religion	0.00	
Religion	0.00	Medicine	0.00	Social Science	0.00	Religion	0.00	Social Science	0.00	Science	0.00	
Science	0.00	Religion	0.00	Social Work	0.00	Science	0.00	Social Work	0.00	Social Science	0.00	
Social Science	0.00	Science	0.00	Psychology	-7.46	Social Science	0.00	Agriculture	-1.36	Social Work	0.00	
Social Work	0.00	Social Science	0.00	Fine Arts	-11.17	Social Work	0.00	Fitness	-9.92	Media	-9.32	
Agriculture	-9.23	Social Work	0.00	Media	-11.66	Agriculture	-9.23	Media	-10.53	History	-9.56	
Education	-15.00	Education	-15.00	Education	-15.00	Education	-15.00	Education	-15.00	Education	-15.00	
	<u>Information</u>		<u>Manufacturing</u>		<u>Military</u>		<u>Mining, Quarrying, and Oil and Gas Extraction</u>		<u>Other Services</u>		<u>Professional, Scientific, and Technical Services</u>	
Government	22.55	Government	22.55	Psychology	47.77	Computer Science	21.61	Government	22.55	Government	22.55	
Mathematics	16.34	Mathematics	16.34	Government	22.55	Liberal Arts	21.34	Mathematics	16.34	Mathematics	16.34	
Engineering	14.98	Engineering	14.98	Mathematics	16.34	Media	16.47	Engineering	14.98	Engineering	14.98	
Computer Science	9.47	Computer Science	9.47	Engineering	14.98	Mathematics	16.34	Computer Science	9.47	Computer Science	9.47	
Psychology	6.05	Psychology	4.86	Architecture	0.00	Engineering	14.98	Agriculture	0.29	Psychology	6.16	
Architecture	0.00	Agriculture	0.64	Business	0.00	Psychology	13.64	Psychology	0.04	Agriculture	0.71	
Business	0.00	Architecture	0.00	Fine Arts	0.00	Government	1.02	Architecture	0.00	Architecture	0.00	
Fine Arts	0.00	Business	0.00	Fitness	0.00	Architecture	0.00	Business	0.00	Business	0.00	
Fitness	0.00	Fine Arts	0.00	History	0.00	Business	0.00	Fine Arts	0.00	Fine Arts	0.00	
History	0.00	Fitness	0.00	Languages	0.00	Fine Arts	0.00	Fitness	0.00	Fitness	0.00	
Languages	0.00	History	0.00	Law	0.00	Fitness	0.00	History	0.00	History	0.00	
Law	0.00	Languages	0.00	Liberal Arts	0.00	History	0.00	Languages	0.00	Languages	0.00	
Liberal Arts	0.00	Law	0.00	Media	0.00	Languages	0.00	Law	0.00	Law	0.00	
Media	0.00	Liberal Arts	0.00	Medicine	0.00	Law	0.00	Liberal Arts	0.00	Liberal Arts	0.00	
Medicine	0.00	Media	0.00	Religion	0.00	Medicine	0.00	Media	0.00	Medicine	0.00	
Religion	0.00	Medicine	0.00	Science	0.00	Religion	0.00	Medicine	0.00	Religion	0.00	
Science	0.00	Religion	0.00	Social Science	0.00	Science	0.00	Religion	0.00	Science	0.00	
Social Science	0.00	Science	0.00	Social Work	0.00	Social Science	0.00	Science	0.00	Social Science	0.00	
Social Work	0.00	Social Science	0.00	Agriculture	-9.23	Social Work	0.00	Social Science	0.00	Social Work	0.00	
Agriculture	-1.38	Social Work	0.00	Computer Science	-12.15	Agriculture	-9.23	Social Work	0.00	Media	-8.81	
Education	-15.00	Education	-15.00	Education	-15.00	Education	-15.00	Education	-15.00	Education	-15.00	

Table Cont. (3)

	<u>Public Administration</u>		<u>Retail Trade</u>		<u>Social Assistance</u>		<u>Transportation and Warehousing</u>		<u>Utilities</u>		<u>Wholesale Trade</u>	
	Government	22.55	Engineering	14.98	Government	22.55	Engineering	14.98	Government	22.55	Government	22.55
	Mathematics	16.34	Computer Science	9.47	Engineering	14.98	Computer Science	9.47	Engineering	14.98	Engineering	14.98
	Engineering	14.98	Government	7.38	Psychology	5.58	Agriculture	3.37	Computer Science	9.47	Psychology	10.75
	Computer Science	9.47	Mathematics	4.21	Agriculture	1.67	Education	2.22	Psychology	2.73	Computer Science	9.47
	Psychology	5.35	Psychology	3.10	Computer Science	0.04	Architecture	0.00	Mathematics	2.65	Mathematics	4.12
	Architecture	0.00	Agriculture	1.02	Architecture	0.00	Business	0.00	Architecture	0.00	Architecture	0.00
	Business	0.00	Education	0.28	Business	0.00	Fitness	0.00	Business	0.00	Business	0.00
	Fine Arts	0.00	Architecture	0.00	Fine Arts	0.00	Languages	0.00	Fine Arts	0.00	Fine Arts	0.00
	History	0.00	Business	0.00	Fitness	0.00	Law	0.00	Fitness	0.00	Fitness	0.00
	Languages	0.00	Fitness	0.00	Languages	0.00	Liberal Arts	0.00	History	0.00	History	0.00
	Law	0.00	History	0.00	Law	0.00	Media	0.00	Languages	0.00	Languages	0.00
	Liberal Arts	0.00	Languages	0.00	Liberal Arts	0.00	Medicine	0.00	Law	0.00	Law	0.00
	Media	0.00	Law	0.00	Medicine	0.00	Religion	0.00	Liberal Arts	0.00	Liberal Arts	0.00
	Medicine	0.00	Liberal Arts	0.00	Religion	0.00	Science	0.00	Media	0.00	Medicine	0.00
	Religion	0.00	Medicine	0.00	Science	0.00	Social Science	0.00	Medicine	0.00	Religion	0.00
	Science	0.00	Religion	0.00	Social Science	0.00	Social Work	0.00	Religion	0.00	Science	0.00
	Social Science	0.00	Science	0.00	Social Work	0.00	Government	-0.65	Science	0.00	Social Science	0.00
	Social Work	0.00	Social Science	0.00	Mathematics	-0.01	Mathematics	-2.02	Social Science	0.00	Social Work	0.00
	Agriculture	-9.23	Social Work	0.00	Education	-2.08	Psychology	-10.07	Social Work	0.00	Agriculture	-0.26
	Fitness	-11.64	Fine Arts	-9.31	History	-9.66	History	-13.21	Agriculture	-9.23	Media	-9.74
	Education	-15.00	Media	-10.29	Media	-10.97	Fine Arts	-15.32	Education	-15.00	Education	-15.00

PREMIUM TYPE (ADJUSTED)

CONCLUSION

This dissertation explores whether different types of knowledge experience greater returns to agglomeration. 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. While controlling for demographic and regional productivity and the industry composition, our essay one results show that the urban wage premium varies considerably across majors. In line with the predictions of our model, non-STEM jobs experience a greater wage premium than do non-STEM majors. 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 J.D. or M.D. experience a smaller urban wage premium. Among those that only have a Bachelor’s or Master’s degree, majors associated with softer skills seem to get the greatest wage boost from city size. We believe this pattern is a result of the tradeoff in the intensity of on-the-job training as educational attainment increases.

In essay 2, we aimed to disentangle the agglomerative mechanism by directly estimating premiums for specialized interactions. Specialized interaction contributes to the wage premium

evident within cities for half of the 21 fields of knowledge studied. It has a dominant effect on productivity for fields such as computer science, engineering, and languages. The eleven majors with the lowest returns to agglomeration—including social science, business, and architecture—experience productive externalities exclusively generated from population size.

Urbanization effects from city size are crucial to the estimation of specialization externalities, and actually benefit *all* knowledge types. Nevertheless, the human capital size and composition effects are inextricably linked, and together maximize the earnings for individual workers. These findings are especially useful to governments and economic development authorities that seek to identify the industries that will flourish in the local economy given the human capital resources available within their city. For example, our results indicate it would be better to encourage population growth and *diversify* industry so that more individuals may benefit from the augmentation of the local human capital stock in terms of size and heterogeneity.

Lastly, in essay three, we successfully identified the most productive matches between human capital types. We found that specialization effects are strong, especially for STEM-related disciplines. High local composition of Computer Science, Engineering, and Science often generated the largest premiums across majors and industries alike. Other knowledge types that generally produced high composition premiums across all types of knowledge are Government and Psychology. Conversely, areas such as Religion, Education, Business, and Medicine often reduce the productivity of most majors.

Future work on this topic can potentially extend in many directions. Firstly, our findings made a significant contribution to the literature by highlighting the importance of population controls in models capturing agglomeration externalities. Therefore, future work will build on

this momentum by testing new instruments for population size. Secondly, we can also expand upon this line of research by incorporating dynamic analysis along the lines of Glaeser et al (1992) and Glaeser and Mare (2001). The creation of a panel dataset or addition of growth terms to reflect change in the composition of the human capital stock would provide interesting results with respect to the relationship between productivity gains and an individual's tenure in cities. Thirdly, we can use the results of this dissertation to determine the true complementarity between majors along the lines of Berliant, Reed, and Wang (2007). Specifically, we have the information to construct the optimal ranges of interaction for several knowledge types. Lastly, another addition to our analysis could be to directly estimate and compare the returns to education-based human capital within occupational or industrial classifications. This would provide more realistic modeling of the labor market by accounting for workers' skill sets from both education and employment.