Shape of Jobs and Urban Wage Premium

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Division of labor among workers is one of the key drivers of productivity growth, and specialization generates experts who "know more and more about less and less" (Smith 1937; Becker and Murphy 1992). Urban areas are especially suited for stronger division of labor and have more such experts. In addition to the direct benefit of lower coordination costs resulting from density, there is also a selection effect: workers with higher human capital have higher returns from specialization and are attracted to cities by the lower coordination costs. This complementarity between knowledge and coordination cost is highlighted in Becker and Murphy [1992], who argue that "this analysis explains, among other things, why earnings are usually higher in large cities even after adjusting for observable measures of human capital—such as years of schooling and experience."

In this project, we aim to provide empirical evidence on the role of selection and unobserved worker quality in determining the urban wage premium. We argue that workers in bigger cities are not only better in terms of their observable characteristics such as education and experience, but also better in other human capital characteristics that are not traditionally observed. A key dataset that enables this analysis is job postings. In order to quickly match with the best candidates, firms specify the skill requirements and other job characteristics explicitly in the job ads.

We use a comprehensive dataset of online job postings from the three biggest job search platforms in China. The dataset covers more than 130 million job postings from 2014 to 2020 and includes information such as firm name, location, position description, job requirements in terms of education, experience, gender, age, and job benefits. By using information extracted from the text of the job description, we can pinpoint the skills and technologies used in jobs in cities of different sizes and show that larger cities have better workers, even after controlling for industry, occupation, education, and experience.

To define "better workers," we need to define the technology or skill frontier in a given occupation. There are two methods. One is within-sample and another is outside-sample. For the outside-sample method, we will use the skill requirements in O*NET dataset, assuming that the United States is closer to the technology frontier than China during this time period. For within-sample analysis, we can use the skill requirement for positions in an occupation and industry that requires the highest level of education. Then we can construct the distance between the skill requirements of each posting and the frontier.

To illustrate the idea of the within-sample method, we first present a simple example using a preliminary analysis of a subsample of the data. Let's take two cities, Beijing and Chengdu, as an example. According to the 2010 population census, the size of the population in the urban areas of Beijing

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is about 1.5 times the population in Chengdu. As shown in Table 1, there is more highly skilled labor in Beijing compared to Chengdu, when skill is measured by the education level. For example, among the working-age population (aged 16-65), 35% in Beijing have junior college or college, and the share is 20% in Chengdu.

Table 1: Comparing Beijing and Chengdu, using the 2010 population census data

	Beijing	Chengdu
No schooling	0.6%	1%
Primary school	5%	19%
Junior high school	31%	39%
Secondary school	24%	19%
Junior college	15%	11%
College	20%	9%
Graduate or higher	5%	0.2%

Note: The data is from the 2010 population census 4% individual sample. Only people aged between 16 and 65 are included.

Then we extract the job posting in July 2018 in these two cities and focus on IT service providers on one of the three online job platforms. Table 2 shows the distribution of education requirements in this industry in the two cities. When we look at the jobs that require junior college, the mean monthly wage in the job postings is 6,974 yuan in Beijing and 3,614 yuan in Chengdu.

Table 2: Comparing Beijing and Chengdu, using the July 2018 job postings on one major online job platforms, IT service provider (system/data/maintenance)

	% of job postings		Mean wage (unit: yuan)	
	Beijing	Chengdu	Beijing	Chengdu
No restriction	28%	8%		
Secondary school	0.5%	0.3%		
Technical secondary school	11%	8%		
Junior college	36%	79%	6,974	3,614
College	22%	4%		
Master	3%	0.2%		

Note: the data is from www.zhilian.com, which is one of the three major online job platforms in China.

Why is the wage for junior college graduates higher in Beijing than in Chengdu, despite the abundance of skilled labor in Beijing? One possibility is that the skills entailed in jobs in Beijing are different from the ones in Chengdu, *even for the same industry and same education requirement.* One measure of the skill requirements is the programming skills and knowledge of software. For simplicity, we extract the English words in the job descriptions and these word clouds are shown in Figure 1. The larger the text size, the more frequently the word shows up in the pool of words.

Figure 1: The world clouds for skill requirements in English for IT service providers, in Beijing and in Chengdu, by required education level

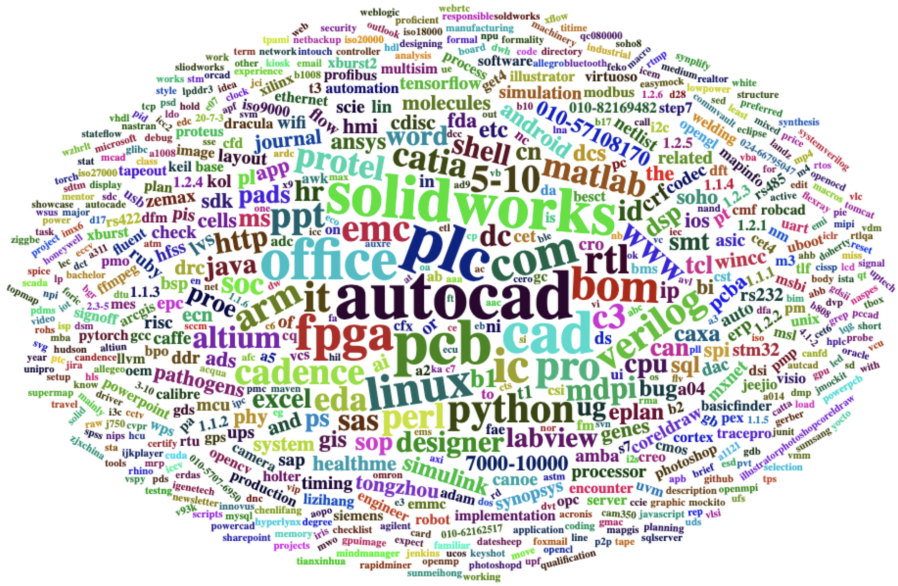
(1.a) Beijing, junior college degrees



(1.b) Chengdu, junior college degrees



(2) College degrees



How do we understand the differences between skill requirements in Beijing and Chengdu, for positions that require *junior college*? The top two figures show the English word clouds for these jobs, (1.a) for Beijing and (1.b) for Chengdu. First, we see some common words, such as "java," "autocad," "solidworks." These are important software for engineers and designers. Second, to show the difference in skill requirements, we compare both (1.a) and (1.b) with jobs that need *college degree*. Given the small share of jobs in Chengdu that require a college degree (4%), we focus on job postings in Beijing that need college degrees (22%) to construct the pool of keywords that signal high-skill requirements. Figure (2) depicts the English word clouds for jobs in Beijing that require college degrees, with some additional high-frequency words: "fpga," "linux," "verilog," and "python." If we assume that only high-skill workers can master the technology embodied in these four keywords, then we can use the frequency of these four keywords in different word clouds to measure their skill requirements. In other words, we want to benchmark keyword frequencies in (1.a) and (1.b) with keyword frequencies in (2) to demonstrate the difference between (1.a) and (1.b).

When we conduct this analysis we find that these four words are 4.7% of the total number of words in job ads in Beijing that require college degrees, 2.7% for Beijing jobs that require junior college, and 1.3% for Chengdu jobs that require junior college. Thus, using the detailed information from the job descriptions, we find evidence that even within the *same* industry (IT services) and *same* degree requirement (junior college), the jobs in Beijing require *twice* as much skills than jobs in Chengdu using this frequency measure. This evidence cannot come from existing alternative data sources.

The analysis above is cross-sectional. The complementarity between knowledge and coordination cost can also be tested using changes in industries over time. During the 2014 and 2020 period, a few industries in China experienced substantial growth, such as information and communication technology and renewable energy. In these industries, the amount of knowledge expanded substantially. Thus, we would expect to see a faster increase in the division of labor among these industries compared to more traditional industries and an even faster increase in bigger cities. We measure the expansion in knowledge in an industry using the number of new patents filed by firms in an industry, and we will investigate (a) whether industries with faster growth in knowledge are increasingly sorted into larger cities, (b) whether in these industries, the increase in the number of occupations is larger, and (c) whether in these industries, the selection of high-skilled workers into larger cities is stronger. To address the potential concern that urban areas facilitated the growth in knowledge in certain industries, we will use (i) the spread of technology from abroad and (ii) the increase in demand on the international market to instrument for changes in technologies in Chinese industries.

Understanding the worker selection effect on urban wage premiums is important for policy analysis, especially in developing countries. For example, it helps us better understand the potential gains from internal migration. The literature has documented insufficient rural-to-urban migration in developing countries (e.g., Lagakos 2020, Lagakos et al. 2023, and Tian forthcoming). Accurately depicting job tasks and specific skill requirements can help us understand whether rural-to-urban migration is limited because seemingly identical jobs have different skill requirements in urban and rural areas, and that the selection of high-skilled labor is the main channel for city premium. In this case, the policies that intend to encourage urbanization and structural transformation, and to reduce income inequality should focus on (a) increasing the equality of education opportunities and occupation training to narrow the skill gap, and (b) reduction in coordination costs in rural areas by expansion of information and communication technology and improvement in enforcement of contracts through law and order.

Our analysis is closely related to a growth literature that uses job posting texts to document technological changes (Atalay et al. 2018, 2020), the geographical spread of new technologies (Bloom et al. 2021), the implication of geography of tasks on wages (Atalay et al. forthcoming), and the impact of skill changes on earnings dynamic (Deming and Noray 2020). We complement these papers by (a) focusing on a developing country context, (b) highlighting the selection channel with a well-defined measure of better workers, and (c) utilizing recent growth in industries to study the change in specialization patterns.

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