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Agglomeration Effect of Skill-Based Local Labor Pooling: Evidence of South Korea

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Received: 25 March 2020; Accepted: 13 April 2020; Published: 15 April 2020

Abstract: Since workplace skills present diverse dimensions of a worker's ability, it has recently received renewed interest by researchers examining the growth of cities. The purpose of the paper explores the advantage of regional concentrations of workers specialized in different types of skills. Specifically, the analysis estimates the agglomeration effects of skill-based labor pooling on wage levels and wage growth in South Korea. To this end, it constructs skill-based labor pool indices for cognitive, social, technical, and physical skills at a provincial level. The indices show an uneven geographical distribution in varying degrees across four types of skills. The regression results indicate that the urban wage premium of skill-based local labor pooling varies according to types of skills. The greatest magnitude of benefit is incurred by workers in cognitive-skill-oriented occupations and moderate benefits are found in technical- and physical-skill-oriented occupations. An urban wage premium is non-existent in social-skill-oriented occupations. In addition, the wage growth model with job mobility shows that the urban wage premium immediately affects workers who change jobs and relocate to denser areas. As high-wage occupations earn higher wage premiums when workers in these occupations are concentrated, it supports patterns of the polarization of both skills and their effects.

Keywords: skill; local labor pooling; agglomeration; job mobility

1. Introduction

Studies related to workers' skills have highlighted their importance in fostering insight into the growth of cities and the divergence of regional economies [1,2]. While education, a conventional measure of a worker's human capital, indirectly represents the competency of a worker, skills are a more direct measure of the multi-dimensional aspects of the worker's ability to perform required tasks in the workplace [3]. As artificial intelligence and automation in industrial production advance and the gap between high- and low-skill cities widens, an examination of the nature of skills may provide a comprehensive understanding of the transforming features of urban economic growth [4].

The advantage of agglomeration economies in urban areas and wage premiums accrued by workers who change employers and work locations have been well documented in empirical studies [5,6]. Urban economic theorists have developed models related to the concentration of various firms and production factors in a city and their generation of urban advantages: sharing specialized production inputs, enhancing learning and spreading specific knowledge, and facilitating higher-quality matches between workers and firms [7]. In particular, a thick labor market represents a source of agglomeration economies by reducing employee search costs, increasing churning rates, and improving the likelihood of strong matches between workers and firms [8,9]. This line of study has indicated that a large local labor pool has a positive effect on both firms and workers during job searches and matching processes in populated urban areas. A local labor pool, however, is not a homogeneous entity. Workplace skills, including technical expertise, physical strength, knowledge field, and even the social/collaborative atmosphere vary across cities. Hence, a diverse composition of skill levels and types in a local labor pool is a key feature accounting for divergent regional advantages stemming from the agglomeration of workers [3]. Regardless of the recent diverging patterns of regional skills [4], only a few studies [10,11] have examined the effect of an agglomeration of workers with a variety of skill types and levels.

This paper explores the regional advantages of a nexus of skills and local workforces. It focuses on regional concentrations of workers with particular skill types. To this end, it presents an index of skill-based local labor pooling. While workplace skills in an occupation typically consist of multi-dimensional components, each occupation may be characterized by a main skill type, that is, one that is more frequently used in that occupation than in other occupations and needed in order to fulfill the tasks of that job. Hence, some occupations can be categorized into one group based on their main skills. By categorizing occupations based on their common characteristics of skillsets, this study constructs a skill-based labor pool index. This analysis takes into account four distinctive types of skills: cognitive, social, technical, and physical. The degree of regional concentration of workers with various skill types differs according to regional characteristics such as the industrial structure or the educational and vocational institutes. A prior study identified different spatial patterns among cognitive, technical, and manual skills [2]. Therefore, an examination of variations in cognitive-, social-, technical-, and physical-skill-based local labor pooling would provide valuable insights into our understanding of agglomerations and the future growth of cities.

The empirical analysis in this study estimates the effects of an agglomeration of skill-based labor pooling on wage levels as well as wage growth in South Korea. The first model examines how skill-based local labor pooling is associated with the productivity of local economies measured by wage levels. Typically, a more populated urban area has a wage premium due to self-selection and better allocation of workers and firms. The empirical model seeks to determine differences in the urban wage premium among four skill groups. It assumes that some occupations with some distinctive skills may gain greater benefits from local labor pooling than others. For example, if a worker tends to learn from interactions with co-workers with similar tasks, the concentration of workers with similar skills is more critical for that job. Possibly, cognitive and social skills are more likely to have been cumulatively acquired from work experience and interaction with others while physical and low technical skills related to manual tasks are much less likely to benefit from the experience and knowledge spillover from agglomerations.

The second model investigates how a skill-based local labor pool affects the return of job mobility. The expected return of job mobility, wage growth, heavily depends on how much a worker's accumulated skills are valued in a new job. If the required tasks of a new job differ markedly from those of past jobs, the skills acquired in the past job will be devalued, and job mobility will result in a significant decrease in wages. If vacancies that seek experience from previous jobs are limited in the local economy, a worker should choose to accept a less suitable local job or relocate to other cities. As occupational and regional mobility are a tradeoff [12], when a worker changes jobs to a location where similar-skill-content jobs are more available, such job mobility would lead to faster wage growth. Thus, an index of skill-based local labor pooling is a key factor that determines the return of job mobility.

For empirical analyses, we access three datasets. We use the Korea Network for Occupations and Workers (KNOW) and the Regional Employment Survey (RES) to construct skill-based local labor pool indices and then combine the indices with the Korean Labor and Income Panel Study (KLIPS) to estimate the effects of skill-based local labor pools.

The rest of the paper consists of five sections. Section 2 summarizes the existing literature that relates to the effects of local labor pools and discusses the contributions of the empirical analysis. Section 3 introduces a method of constructing indices of skill-based local labor pools and presents their features. Section 4 describes the panel data for wage and job mobility patterns, and Section 5 presents the analytical models and results. Section 6 concludes the paper and discusses the implications of the analysis.

2. Literature Review

A substantial number of studies have devoted efforts to examining the role of local labor pooling. Duranton and Puga [7] presented a theoretical foundation that shows that improving the quality and frequency of matching employees with firms serves as a channel through which local labor pooling contributes to the productivity of local firms. Abel and Deitz [8] provided empirical findings that a thick labor market helps college graduates in the United States find jobs that more closely match their education. Andini et al. [13] examined four aspects of local labor pools, including turnover, learning, matching, and hold up, and their Italian empirical analysis showed a positive association between turnover and on-the-job training and labor market density. Roca and Ruga [14] argued that workers accumulate their human capital in large cities. They showed empirical evidence of the accumulation and persistence of work experience by Spanish workers in large cities. A study by Bleakley and Lin [9] on the U.S. local labor market showed that although the overall turnover rate was lower in a denser labor market, it increased for young workers and played an important role in raising the wages of young workers. Andersson et al. [15] demonstrated the complementary relationship between worker and firm quality in the thick labor market, which led to an increase in productivity for both. These lines of theoretical and empirical research extensively support the significance of local labor pooling to the growth of cities.

Combining workplace skills and agglomeration has recently emerged in local labor market analyses. Gathmann and Schönberg [11] showed that some skills are portable and important sources of wage growth. In Germany, about 40% of wage growth was attributed to task-specific human capital. Bacolod et al. [3] analyzed how agglomeration affects the value of worker skills, including cognitive, social, and motor skills. The urban wage premium is greater in those with cognitive and social skills than in those with motor skills. Examining the relationship between skill clusters and mobility, Geel and Backers-Gellner [16] developed an indicator of a skill cluster and found that job mobility within a skill cluster led to higher wage gains than that between skill clusters.

Previous studies have provided abundant empirical evidence supporting the substantial influence of local labor pooling in terms of the accumulation of human capital and the positive wage effect. In addition, researchers have referred to skills to explain the increasing gap among regional economies, identify the transferability of human capital, and measure the agglomeration effect based on types of skills. In response to renewed interest in skills and agglomeration, this study extends the literature by building indices of local labor pooling based on diverse skill types, exploring geographical patterns of the nexus of skills and occupations, and measuring the differentiated impact of local agglomeration across various features of skills.

3. Geography of Skill-Based Local Labor Pooling

To understand the impact of the agglomeration effect of skill-based local labor pooling, we need to identify the types and levels of skills required for occupations and then draw a map for the geographical distribution of skills and labor. This section presents an approach to construct a skill-based local labor pool index using datasets from the KNOW and the RES and then discusses some spatial patterns of skill-based local labor indices. We follow three steps. First, as workplace skills are comprised of multiple dimensions, we need to reduce the number of dimensions by categorizing them into conceptualized factors. Through factor analysis, we identify four skill factors from the KNOW, which contains information about the importance and the level of 44 skill types required for each occupation. Second, the scores of the four skill factors are calculated through the two-digit Korean Standard Occupation Classification (KSOC). Finally, an index of skill-based local labor pools is computed in Equation (1) as follows:

$$\text{Skill-Based Local Labor Pool}_{is} = \sum_{j} \sum_{s} E_{ij} \times \mathrm{W}_{js} \tag{1}$$

where E_{ij} is the number of workers in occupation j and region i, and W_{js} is the score of skill *s* required for occupation *j*. The skill score indicates the effective use of a certain skill in an occupation compared to its use in other occupations. If the required importance and level of a certain skill in an occupation are more than average, that skill is effective and valuable for fulfilling the tasks of that occupation. The skill score, W_{js}, is zero when W_{js} is less than average. The skill-based local labor pool index is a sum of workers in similar skill-content occupations weighted by the effective use of skills.

Several key features about skill categorization and spatial patterns are presented below. To identify types of skills that fulfill the tasks of occupations, we employ the raw data of the KNOW surveyed from 2001 and 2015. The KNOW survey asks incumbents how important a particular type of skill is in an occupation and what level of that skill is required to fulfill the tasks of that occupation. The questionnaire includes 44 types of skills that comprehensively cover basic, cognitive, psychomotor, resource management, technical, sensory, and physical skills. To reduce the dimensions of skills, we perform a factor analysis, the results of which appear in Table 1. The table lists the 44 types of skills categorized into four factors whose eigenvalues exceed one.

Table 1. Factor Analysis for Ability and Skill Requirements.

Code	Ability and Skill Requirement	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
aq1	Reading Comprehension	0.788				0.331
aq2	Active Listening	0.779				0.305
aq3	Writing	0.754				0.356
aq4	Speaking	0.669		0.405		0.360
aq5	Mathematics	0.629				0.461
aq6	Logical Analysis	0.737				0.315
aq7	Critical Thinking	0.626				0.458
aq8	Category Flexibility	0.644				0.418
aq9	Memory	0.574				0.435
aq10	Spatial Perception	0.478				0.514
aq11	Reasoning	0.634				0.418
aq12	Learning Strategies	0.605		0.402		0.402
aq13	Attentiveness	0.552				0.422
aq14	Monitoring	0.490		0.501		0.423
aq15	Social Perceptiveness			0.648		0.345
aq16	Coordination			0.616		0.364
aq17	Persuasion	0.400		0.706		0.304
aq18	Negotiation			0.714		0.332
aq19	Instructing	0.450		0.499		0.456
aq20	Service Orientation			0.659		0.415
aq21	Complex Problem Solving	0.494		0.522		0.370
aq22	Judgment and Decision Making	0.444		0.571		0.373
aq23	Time Management			0.576		0.412
aq24	Management of Financial Resources			0.631		0.443
aq25	Management of Material Resources		0.482	0.502		0.446
aq26	Management of Personnel Resources			0.653		0.375
aq27	Troubleshooting		0.638			0.360
aq28	Technology Design		0.704			0.390
aq29	Equipment Selection		0.723			0.345
aq30	Installation		0.757			0.336
aq31	Programming		0.483			0.540
aq32	Quality Control Analysis		0.665			0.420
aq33	Operation and Control		0.733			0.332
aq34	Equipment Maintenance		0.775			0.283
aq35	Repairing		0.788			0.289
aq36	Operation Monitoring		0.777			0.289
aq37	Systems Analysis & Evaluation		0.516			0.480
aq38	Manual Dexterity		0.518		0.535	0.407
aq39	Control Movement Abilities		0.487		0.639	0.324
aq40	Reaction Time and Speed Abilities				0.681	0.330
aq41	Physical Strength Abilities				0.679	0.409
aq42	Flexibility, Balance, and Coordination				0.725	0.346
aq43	Visual Abilities				0.680	0.438
aq44	Auditory Abilities				0.686	0.411

According to the factor-loading values in Table 1, 44 types of skills are allocated to four factors. The first represents cognitive skills, consisting of reading comprehension, active learning, critical thinking, reasoning, attentiveness, and so on. The second factor comprises social skills and constitutes inter-personal and managerial elements, including persuasion, negotiation, instruction, service orientation, management, and so on. The third factor mainly includes technical skills such as equipment selection, installation, programming, operation monitoring, troubleshooting, and repairing. The final factor, physical skills, includes manual dexterity, reaction time and speed, and visual and auditory skills.

We then calculate the average scores of the four factors—cognitive, social, technical, and physical skills—across the two-digit KSOC, including the 48 occupational groups displayed in Table 2, and normalize each score with a zero mean and one standard deviation. If the importance and skill level required in an occupation fall below the average of all other occupations, the skill score is negative. For example, while the scores of cognitive and technical skills in food service occupations are negative, those of social and physical skills are positive. This is because the main tasks of a restaurant server consist of taking orders accurately, engaging with customers in a friendly manner, preparing checks, and so forth.

Table 2. Skill Scores for the Two-Digit Korean Standard Occupation Classification (KSOC).

Two-Digit KSOC	Cognitive	Social	Technical	Physical	Type
Science Professionals and Related Occupations	0.815	−0.238	0.184	−0.408	Cognitive
Health-, Social-Welfare-, and Religion-Related Occupations	0.212	0.159	−0.343	0.255	
Education Professionals and Related Occupations	0.408	0.230	−0.333	0.056	
Legal and Administrative Occupations	0.786	0.517	−0.451	−0.263	
Business and Finance Professionals and Related Occupations	0.452	0.401	−0.121	−0.201	
Senior Public Officials and Senior Corporate Officials	0.312	1.028	−0.364	−0.332	Social
Public, Business Administration, and Marketing Management Occupations	0.072	0.708	−0.354	−0.411	
Professional Services Management Occupations	0.245	0.568	−0.202	−0.116	
Construction, Electricity, and Production-Related Managers	−0.370	0.135	0.436	−0.310	
Sales and Customer Service Managers	−0.311	0.589	−0.180	−0.117	
Administration and Accounting-Related Occupations	−0.052	0.223	−0.195	−0.258	
Financial Clerical Occupations	−0.015	0.403	−0.293	−0.064	
Legal and Inspection Occupations	0.154	0.232	−0.588	0.330	
Customer Service, Information Desk, Statistical Survey, and Other Clerical Occupations	−0.106	0.164	−0.642	−0.026	
Caregiving, Health, and Personal Service Workers	−0.408	0.143	−0.339	0.131	
Transport and Leisure Services Occupations	−0.225	0.254	−0.372	0.078	
Sales Occupations	−0.249	0.339	−0.154	−0.096	
Store Sales and Rental Sales Occupations	−0.357	0.239	−0.204	−0.044	
Information and Communication Professionals and Technical Occupations	−0.019	−0.206	0.613	−0.484	Technical
Engineering Professionals and Technical Occupations	0.189	−0.222	0.411	−0.412	
Skilled Forestry Occupations	−0.533	−0.167	−0.135	−0.193	
Wood- and Furniture-, Musical-Instrument-, and Signboard-Related Trade Occupations	−0.478	0.042	0.393	0.134	
Metal-Coremaker-Related Trade Occupations	−0.628	−0.455	0.388	0.135	
Transport- and Machine-Related Trade Occupations	−0.535	−0.382	0.647	0.226	
Electric- and Electronic-Related Trade Occupations	−0.500	−0.170	0.438	0.210	
Food-Processing-Related Machine Operating Occupations	−0.669	−0.423	0.363	0.037	
Textile- and Shoe-Related Machine Operating Occupations	−0.747	−0.273	0.198	0.045	
Chemical-Related Machine Operating Occupations	−0.433	−0.448	0.116	0.077	
Metal- and Nonmetal-Related Machine Operating Occupations	−0.529	−0.259	0.310	0.073	
Machine Production and Related Machine Operating Occupation	−0.440	−0.379	0.254	0.152	
Electrical- and Electronic-Related Machine Operating Occupations	−0.295	−0.405	0.414	0.099	
Water Treatment and Recycling-Related Operating Occupation	−0.455	−0.348	0.374	−0.005	
Wood, Printing, and Other Machine Operating Occupations	−0.560	−0.231	0.450	0.229	
Culture, Arts, and Sports Professionals and Related Occupations	0.095	0.050	−0.248	0.291	Physical
Police, Fire Fighting, and Security-Related Service Occupations	−0.122	0.085	−0.242	0.576	
Cooking and Food Service Occupations	−0.536	0.047	−0.301	0.133	
Agricultural and Livestock-Related Skilled Occupations	−0.656	−0.206	−0.018	0.111	
Skilled Fishery Occupations	−1.052	−0.316	−0.009	0.192	
Food-Processing-Related Trades Occupations	−0.660	−0.129	−0.002	0.049	
Textile-, Clothing-, and Leather-Related Trade Occupations	−0.363	−0.175	0.029	0.199	
Information-and-Communications-Technology-Related Occupations	−0.726	−0.326	0.139	0.360	
Other Technical Occupations	−0.480	−0.012	0.205	0.483	
Driving and Transport-Related Occupations	−0.712	−0.414	−0.121	0.428	
Construction and Mining-Related Elementary Occupations	−0.087	−0.462	0.177	0.948	
Cleaning and Guard-Related Elementary Occupations	−0.424	−0.108	−0.131	−0.072	
Household Helpers, Cooking Attendants, and Sales-Related Elementary Workers	−0.743	−0.140	−0.280	−0.008	
Armed Forces	−0.086	0.099	−0.087	0.368	
Agriculture, Forestry, Fishery, and Other Service Elementary Occupations	−0.583	−0.302	−0.060	0.107	

Taking the highest and lowest scores of the four skill scores in an occupation, we rearranged all occupations as noted in the last column of Table 2. Since the common characteristics of each group of occupations were distinctive with regard to skill requirements, the table shows four skill-based occupational groups. The first consists of occupations that require the highest level cognitive skills, which are more valuable in scientific professions and related occupations, legal and administrative occupations, and business and finance professions and related occupations. They are categorized as cognitive-skill-oriented occupations. Second, for some occupations such as senior public officials and senior corporate officials; public, business administration, and marketing management occupations; professional service management occupations; sales and customer service managers; financial clerical occupations; and transport and leisure service occupations and others, the social skill scores are much higher than those of the other three skills, which are social-skill-oriented occupations. Third, occupations related to machine operations are categorized as technical-skill-oriented occupations, including engineering professionals and technical occupations, metal coremakers and related trade occupations, transport and machine-related trade occupations, electric and electronic-related trade occupations, and food processing-related machine operating occupations. The final group of occupations constitutes physical-skill-oriented occupations in which the physical skill scores are higher than those of other skills. These occupations with the higher physical skill scores include culture, arts, and sports professionals and related occupations; police, fire fighting, and security-related service occupations; cooking and food service occupations; construction and mining-related elementary occupations; cleaning and guard-related elementary occupations; and others.

Applying the results of the skill score calculations to Equation (1), we construct the local skill labor pooling index at a provincial level. Figure 1 and Table 3 present the provincial comparative advantage of a concentration of workers by skill types. They are a relative ratio between a provincial portion of a skill-based local labor pool index to a provincial portion of the population. It shows the relative concentration of workers in cognitive-, social-, technical-, and physical-skill-oriented occupations.

Table 3. Comparative Advantage of Province and Skill-based Local Labor Pooling.

Type	Province Name	Comparative Advantage of Local Skill Labor Pooling Index				Population Percent by Province
		Cognitive	Social	Technical	Physical	
Metro Province	Seoul	1.29	1.21	0.86	0.89	19.0%
	Busan	0.98	0.97	0.89	0.97	6.7%
	Daegu	0.97	1.06	0.87	0.97	4.8%
	Daejeon	1.30	1.09	1.01	0.96	2.9%
	Incheon	0.86	0.96	1.16	0.97	5.7%
	Gangju	1.11	1.02	0.94	1.02	2.8%
	Ulsan	0.75	0.82	1.43	1.11	2.3%
Non-Metro Province	Gyeonggi	1.09	1.03	1.17	0.94	24.9%
	Gangwon	0.74	0.84	0.63	1.17	3.0%
	Chungbuk	0.89	0.88	1.03	1.16	3.1%
	Chungnam	0.76	0.85	1.22	1.19	4.1%
	Jeonbuk	0.84	0.89	0.65	1.17	3.6%
	Jeonnam	0.61	0.76	0.71	1.10	3.7%
	Gyeongbuk	0.62	0.84	1.01	1.09	5.2%
	Gyeongnam	0.79	0.85	1.13	1.07	6.5%
Special District	Jeju	0.82	1.04	0.61	1.28	1.3%
	Sejong	1.66	0.98	0.86	0.66	0.5%
St. Dev. of Skill-based Indices		0.27	0.12	0.23	0.14	

We identify several patterns in the comparative advantages of skill-based local labor pooling. The capital city and adjacent provincial areas of Gyeonggi have an advantage in workforces with cognitive and social skills. The old southeastern industrialized belt, Ulsan and Gyeongnam, and the outskirts of capital areas such as Incheon and Chungnam are specialized in technically skilled workforces. The workforces of planned cities such as Sejong and Daejeon have a relative advantage in cognitive and social skills. Daejeon was designed for developing the science and technology cluster, and Sejong was built for relocating administrative functions from Seoul to Sejong. The less developed provinces and adjacent rural areas of Gangwon, Chungbuk, Jeonbuk, and Jeonnam show higher values in physical skill labor pooling. Jeju, which is specialized in tourism, has a large workforce with social and physical skills.

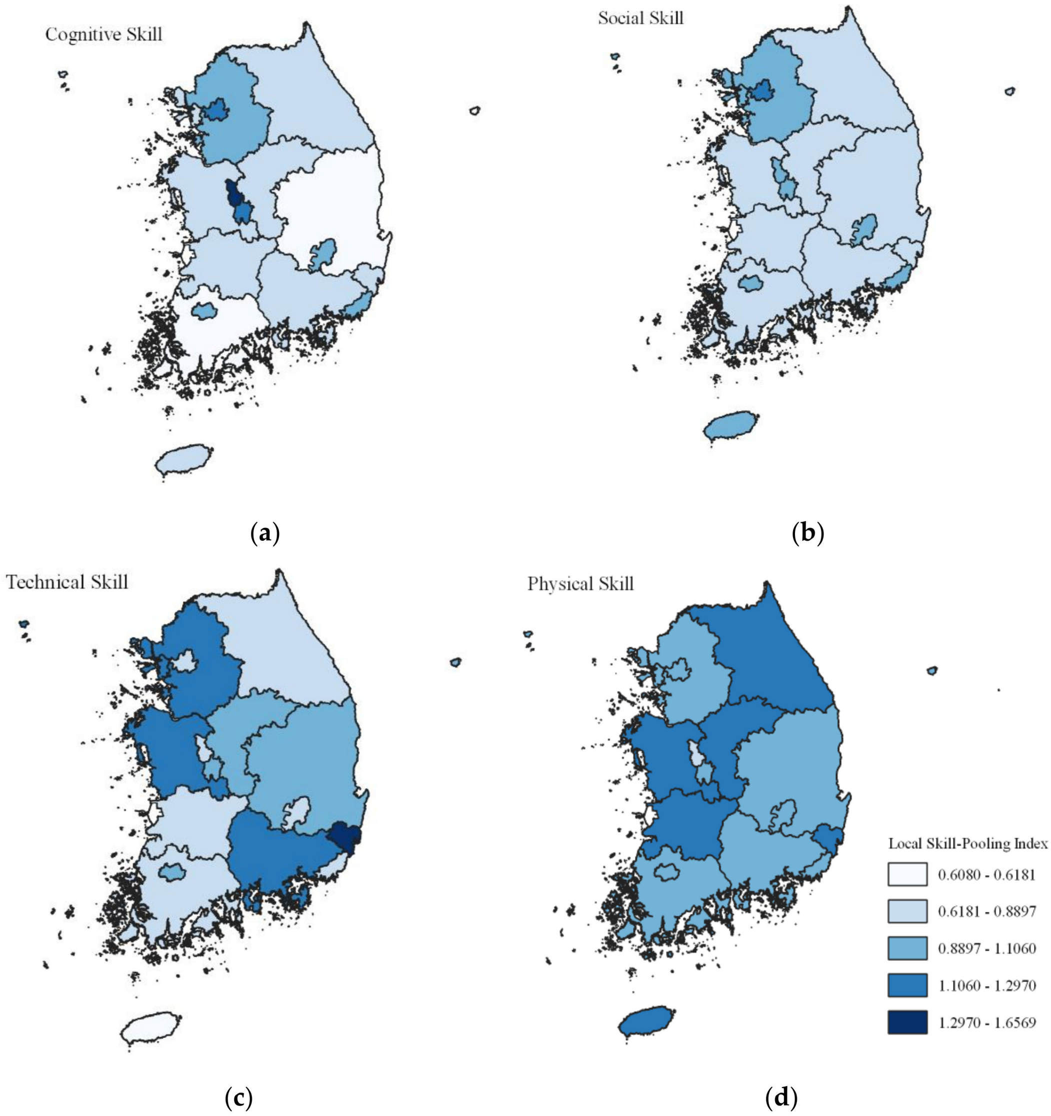

Figure 1. Geographical distribution of skill-based local labor pooling. (**a**) Cognitive-skill-based local labor pool index, (**b**) social-skill-based local labor pool index, (**c**) technical-skill-based local labor pool index, and (**d**) physical-skill-based local labor pool index.

One important aspect is the extent to which skilled workers with unique skillsets are geographically concentrated or evenly distributed. Displayed at the bottom of Table 3 are the standard deviations of the four skill indices across the provinces: 0.27 for cognitive skills, 0.12 for social skills, 0.23 for technical skills, and 0.14 for physical skills. Workforces with cognitive and technical skills are relatively more concentrated while those with social and physical skills are more evenly distributed.

4. Data Description

To estimate the agglomeration effect of skill-based local labor pooling, we combine the index of the skill-based local labor pool and panel data from the Korean Labor and Income Panel Study (KLIPS) in the analysis. The KLIPS traced employment status and income level for individual households and their members during 20 waves from 1998 to 2017. It provides a work history that covers every job status during the surveyed period. The work history includes job-related information such as the sequence of jobs, the type of jobs (permanent, temporary, or daily job), type of payment, main job or not, occupation, age, education attainment, size of firm, location of firm, job mobility, and monthly wage. We use the KLIPS work history information about individuals working between 2013 to 2017 because the provincial-level occupational statistics are available for only those periods in South Korea. The provincial occupational statistics are drawn from the Regional Employment Survey (RES). The analysis is restricted to the cases observed in consecutive five years and permanent workers. Year to year, 10,443 individuals were observed. Some moved between unemployed and employed statuses, and data for the year of unemployment were eliminated because they did not contain wage information. The survey asks individuals whether they held the same job in a previous year. This question enables us to accurately identify job mobility on an annual basis. When the employed status was held for two consecutive years and the job of a current year is not the same as that of a previous year, it is identified as job mobility.

The variables employed in this analysis are listed in Table 4. They are grouped as personal-, job-, and province-related variables. The average age of the sample is 46 and the percentage of male workers is 57.3%. Regarding education attainment, the sample consists of 35.0% with a high school diploma, 17.6% with a two-year vocational college degree, and 30.4% with a four-year university or higher degree. Job-related variables include monthly wage, firm size, job mobility or no job mobility, and scores for cognitive, social, technical, and physical skills. The share of workers who changed employers is 8.7% in the sample. The province-related variables are population, population density, and cognitive-, social-, technical-, and physical-skill-based labor pool indices.

Table 4. Variables Description.

Variable		Mean	Std. Dev.	Min	Max
Personal-related	Gender	0.573	0.495	0	1
	Age	46	12	18	88
	Share of High School	0.350	0.477	0	1
	Share of 2-Year Vocational College	0.176	0.381	0	1
	Share 4-Year University or More	0.304	0.460	0	1
Job-related	Wage	237	156	4	4200
	Firm Size	248	2530	0	60,000
	Share of Job Mobility	0.087	0.282	0	1
	Cognitive Skill Score	−0.294	0.366	−1.052	1.021
	Social Skill Score	−0.026	0.351	−1.315	1.028
	Technical Skill Score	−0.091	0.354	−0.694	0.822
	Physical Skill Score	0.020	0.303	−0.848	1.159
Province-related	Population	6,207,050	4,525,717	210,884	12,900,000
	Population Density	4483	6147	92	16,761
	Cognitive Skill Labor Pool Index	193	158	0	412
	Social Skill Labor Pool Index	386	302	0	786
	Technical Skill Labor Pool Index	227	177	0	545
	Physical Skill Labor Pool Index	323	223	0	678

Furthermore, the patterns of job mobility are displayed in Tables 5–7. Table 5 shows how the rate of job mobility differs across individual characteristics. Female workers are slightly more mobile than male workers. While the rate of job mobility of females is 9.1%, that of males is 8.4%. The younger the worker is, the higher the probability of job mobility, which is consistent with previous empirical analysis that found that young workers tend to experience a period of job shopping and then settle down in a career job [17]. The rate of job mobility is 14.3% for ages 20–29, 9.1% for ages 30–39, and 8.2% for ages 40–49. The job mobility rate stabilizes at about age 50 at 7.7%. Regarding educational attainment, job mobility rates do not appear to significantly differ: for high school graduates, it is 9.3%, for 2-year vocational college graduates 9.1%, and for four-year university or more 8.0%.

Tables 6 and 7 show the job mobility patterns by occupation and location. Job mobility within a one-digit occupation was slightly higher than that between one-digit occupations. The percentage within a one-digit occupation was 52.1%. Within-occupation mobility is more frequent in occupations that include managers, professionals and related workers, and craft and related trade workers. Between-occupation job mobility more commonly occurs in occupations that include service worker and sales worker occupations. As these workers change occupations, they are more likely to lose job-specific human capital, experiencing greater wage losses than other workers.

Table 5. Frequency of Job Mobility Across Individual Characteristics.

		Frequency of Job Mobility	Percentage of Job Mobility	Total Observations
Gender	Male	1033	8.4%	12,314
	Female	839	9.1%	9191
Age Group	20–29	221	14.3%	1547
	30–39	483	9.1%	5312
	40–49	526	8.2%	6427
	50–59	377	7.7%	4888
	60–69	182	7.7%	2378
Education	Less Than High School	298	8.2%	3642
	High School	703	9.3%	7536
	2-Year Vocational College	346	9.1%	3787
	More Than 4-Year University	525	8.0%	6540
	Sum	1872	8.7%	21,505

Table 6. Frequency of Job Mobility within and between Occupational Groups.

	Frequency of Job Mobility		Percentage of Job Mobility		Total
	within 1-Digit Occupation	between 1-Digit Occupations	within 1-Digit Occupation	between 1-Digit Occupations	
Managers	14	12	53.8%	46.2%	26
Professionals and Related Workers	261	124	67.8%	32.2%	385
Clerks	104	116	47.3%	52.7%	220
Service Workers	99	133	42.7%	57.3%	232
Sales Workers	102	143	41.6%	58.4%	245
Skilled Agricultural, Forestry, and Fishery Workers	2	36	5.3%	94.7%	38
Craft and Related Trades Workers	102	74	58.0%	42.0%	176
Equipment, Machine Operating, and Assembling Workers	118	107	52.4%	47.6%	225
Elementary Workers	156	136	53.4%	46.6%	292
Sum	958	881	52.1%	47.9%	1839

Table 7. Frequency of Job Mobility within and between Provinces.

		Frequency of Job Mobility		Percentage of Job Mobility		Total
		within Province	between Provinces	within Province	between Provinces	
Metro Province	Seoul	259	90	74.2%	25.8%	349
	Busan	136	21	86.6%	13.4%	157
	Daegu	72	19	79.1%	20.9%	91
	Daejeon	40	15	72.7%	27.3%	55
	Incheon	70	31	69.3%	30.7%	101
	Gwangju	38	14	73.1%	26.9%	52
	Ulsan	41	7	85.4%	14.6%	48
Non-Metro Province	Gyeonggi	348	83	80.7%	19.3%	431
	Gangwon	24	4	85.7%	14.3%	28
	Chungbuk	61	12	83.6%	16.4%	73
	Chungnam	87	24	78.4%	21.6%	111
	Jeonbuk	49	5	90.7%	9.3%	54
	Jeonnam	44	10	81.5%	18.5%	54
	Gyeongbuk	72	25	74.2%	25.8%	97
	Gyeongnam	143	18	88.8%	11.2%	161
	Jeju	9	0	100.0%	0.0%	9
	Sum	1493	378	79.8%	20.2%	1871

Regarding within- and between-province job mobility, the within-province job mobility is more common than the between-province job mobility. The ratio of within-province job mobility was almost 80%. As job mobility with relocation incurs additional moving costs, the higher rate of within-province job mobility is a predictable pattern. There is some variation in between-province job mobility across provinces, however. The between-province job mobility rates tend to be higher in the metro provinces such as Seoul, Daegu, Incheon, and Gwangju while the within-province job mobility rate is higher in non-metro provinces, including Gangwon, Chungbuk, Jeonbuk, and Gyeongnam. If the moving costs of between-province job mobility were compensated for, the return of job mobility from some metro provinces may become higher than others.

5. Analysis and Results

The analysis begins with an examination of the urban wage premium hypothesis with skill-based local labor pool indices. The analytical model for estimating the urban wage premium is expressed in Equation (2).

$$\ln(W_{kit}) = \beta X_{kit} + \delta L_{ist} + \phi_k + \varepsilon_{kt} \quad (2)$$

where the dependent variable is the log of the monthly wage of individual k in province i at time t, X_{kit} denotes the characteristics of individual k in province i at time t, including age, gender, education attainment, and L_{ist} is the skill-based local labor pool index for skill s in province i at time t. ϕ_k represents unobserved individual characteristics such as innate intelligence and ability. The model follows the estimate approach of Glaeser and Mare [5], in which OLS regression constrains ϕ to be zero. While the application of an individual fixed-effect model may correct the omitted bias of unobserved individual characteristics, this application loses most of the variation in individual characteristics in this analysis.

The results of the estimations of urban wage premium models with the skill-based local labor pool indices are shown in Table 8. With respect to conventional variables for urban wage premium in models 1 and 2, workers obtain higher wages in denser, larger urban areas. Two variables, population and population density, are statistically significant at a 1% level. The elasticity of population density and size to worker's wage level was 0.022 and 0.032. The sign of the variables of individual characteristics is congruent to the expected. The wages of male workers are 37.5% higher than those of female workers. The wage curve is convex over age with a negative sign of an age-squared variable. Education attainment explains the variation in wages. All three dummies for education attainment are statistically significant. Compared to the wages of individuals who have not graduated from high school, the wages of high school, 2-year vocational college, and 4-year or more university graduates are 8.7%, 23.7%, and 26.9% higher, respectively. The variable of firm size is also significant, and the elasticity of firm size to wage level is 0.090. As a whole, the estimate results of the conventional urban wage premium model are highly consistent with those of previous empirical studies.

Models 3, 4, 5, and 6 in Table 8 show the results of estimates with a subset of samples with similar skill-content occupations, as noted in Table 2. The main interest of the analysis is the significance and magnitude of the variables of the skill-based local labor pooling indices. In model 3, the wage level of workers specialized in cognitive skills is significantly higher in areas in which workers with these skills are concentrated. One percentage increase of a cognitive skill labor pool index is associated with a 0.075 percentage increase of wage level. The cognitive skill score variable representing the price of cognitive skill and education dummies are not significant, partly because the prerequisite of jobs requiring high-level cognitive skills is at least four years of university study, and their productivity is not simply assessed by quantitatively measured scores. Their activities may consist of far more than routine tasks. The firm size variable is significant and its magnitude is higher than that of other models. The wage level of workers in cognitive-skill-oriented occupations is highly related to the features of the workplace, that is, the firm size and its location.

Regarding social-skill-oriented occupations, the social skill local labor pool index is not significant while the social skill score is a statistically significant variable in model 4 of Table 8. Social-skill-oriented occupations are more heterogeneous compared to other occupational groups. From an occupational hierarchy perspective, some employees, such as senior officials, business managers, and professional service managers, are on a higher order than customer service, sales, and personal service workers. The social skill scores in this group vary markedly, shown in Table 2. Social skill scores are a key explanatory variable for determining the wage levels of this group. However, from a spatial perspective, social-skill-oriented occupations are the most evenly distributed, so wage differences across provinces are not found by the empirical model.

Table 8. Regression Results for Urban Wage Premiums with Skill-Based Local Labor Pooling.

	Conventional Urban Wage Premium Model				**Skill-Based Local Labor Pooling Model**							
	Model 1		**Model 2**		**Model 3 (Cognitive-Skill-Oriented Occupations)**		**Model 4 (Social-Skill-Oriented Occupations)**		**Model 5 (Technical-Skill-Oriented Occupations)**		**Model 6 (Physical-Skill-Oriented Occupations)**	
Individual Variables												
Gender	0.375 ***	(0.011)	0.372 ***	(0.011)	0.261 ***	(0.033)	0.372 ***	(0.020)	0.427 ***	(0.030)	0.343 ***	(0.024)
Age	0.070 ***	(0.003)	0.069 ***	(0.003)	0.034 ***	(0.009)	0.051 ***	(0.006)	0.103 ***	(0.008)	0.053 ***	(0.007)
Sq. Age	−0.001 ***	(0.000)	−0.001 ***	(0.000)	−0.000 ***	0.000	−0.001 ***	0.000	−0.001 ***	0.000	−0.001 ***	0.000
Education Dummy												
High School	0.087 ***	(0.020)	0.091 ***	(0.020)	−0.147	(0.106)	0.225 ***	(0.060)	0.139 ***	(0.044)	−0.003	(0.027)
2-Year Vocational College	0.237 ***	(0.023)	0.243 ***	(0.023)	0.024	(0.107)	0.322 ***	(0.062)	0.258 ***	(0.051)	0.140 ***	(0.045)
4-Year University or More	0.269 ***	(0.022)	0.275 ***	(0.022)	−0.045	(0.107)	0.350 ***	(0.061)	0.395 ***	(0.047)	0.173 ***	(0.046)
Firm Size	0.090 ***	(0.003)	0.090 ***	(0.003)	0.141 ***	(0.009)	0.088 ***	(0.005)	0.072 ***	(0.006)	0.066 ***	(0.008)
Provincial Variables												
Population Density	0.022 ***	(0.003)										
Population Size			0.032 ***	(0.006)								
Skill Score												
Cognitive					−0.028	(0.062)						
Social							0.461 ***	(0.091)				
Technical									0.140 **	(0.063)		
Physical											0.210 ***	(0.058)
Skill-Based Local Labor Pool												
Cognitive					0.075 ***	(0.014)						
Social							0.014	(0.010)				
Technical									0.025 **	(0.012)		
Physical											0.031 **	(0.015)
Intercept	3.065 ***	(0.081)	2.745 ***	(0.127)	3.693 ***	(0.229)	3.332 ***	(0.152)	2.216 ***	(0.207)	3.565 ***	(0.193)
Observations	4503		4503		752		1565		970		1051	
R-square	0.448		0.445		0.408		0.447		0.445		0.411	

Note: Numbers in parentheses are standard errors. *** significant at 1% level, ** at 5% level, and * at 10% level.

Model 5 shows that both the technical skill score and technical skill local labor pool index are statistically significant variables. One percentage increase of a technical skill labor pool index led to a 0.025 percentage increase of the wage level of technically skilled workers. Information and communication, transport and machine, and electric and electronic occupations are those requiring higher technical skill levels. The variables of gender, age, and educational level are statistically significant. In particular, the gender wage gap is the widest in technical-skill-oriented occupations.

Finally, the physical skill score and physical skill local labor pool index are also significant, shown in model 6. Jobs that require stronger physical skills are police, fire fighting, and security, construction and mining, and driving and transport. For this group of occupations, an urban wage premium is found, but the elasticity of a physical skill labor pool index to the wage level is relatively lower than that of cognitive-skill-oriented occupations. In addition, the benefits of education for those in physical-skill-oriented occupations are modest. In short, the empirical analysis of South Korea showed that the urban wage premium is mostly found in occupations that require different sets of skills, except social-skill-oriented occupations. The magnitudes of the urban wage premium, in order from high to low, are cognitive-, physical-, and technical-skill-oriented occupations.

The next analytical model examines how the return of job mobility differs across provinces where the skill-based local labor pool varies. The analysis employs the wage growth model with interactive variables expressed in Equation (3).

$$\ln(\Delta Wage_{kti}) = \beta X_{kti} + \theta M_{ktji} + \delta\left(M_{ktji} \times \Delta L_{jist}\right) + \varepsilon_{kt} \quad (3)$$

where the dependent variable is the growth in monthly wages from year to year of individual k in province i at time t, X_{kti} is a time-varying variable of individual k in province i at time t, M_{ktji} is the job mobility of individual k from province j to i at time t, and $M_{ktji} \times \Delta L_{ist}$ is an interactive variable that represents the change in skill-based local labor pool indices between province j and i (ΔL_{jist}) related to job mobility (M_{ktji}). For example, if a technically skilled worker relocates from a rural area to an industrialized urban area, the interactive variable has a positive value; it is expected that this type of job change, along with relocation, is associated with faster wage growth.

Model 1 in Table 9 shows the effect of job mobility on wage growth on average. Job mobility itself is positively associated with wage growth. The wage growth of those who change jobs is 4.3% higher than those who do not. Model 2 takes into account cases of those who change jobs and locations simultaneously. The interactive variable of job mobility*population size change is the difference between the population sizes of the prior and present provinces where they work. Model 2 indicates a statistically positive sign of the interactive variable. Migration associated with job changes to more populated areas increases the likelihood of faster wage growth. Models 3 to 6 show the effects of job mobility on wage growth by four occupational groups. The effects, however, are not significant for all occupational groups. The effects are positive only in cognitive- and technical-skill-oriented occupations but not in social- and physical-skill-oriented occupations. The wage growth rates of those who changed jobs in the cognitive- and technical-oriented occupation groups are 5.4% and 4.9% higher, respectively.

Table 10 presents the effects of skill-based labor pooling on wage growth from job mobility. As a whole, these regression models show that the return of job mobility differs across occupational groups and that it is affected by the degree of skill-based labor pooling. Significant effects of skill-based labor pooling on wage growth from job mobility occurs in the cognitive-, technical-, and physical-skill-oriented occupational groups. The magnitude of the effects of skill-based labor pooling on wage growth is the highest in the technical-skill-oriented occupational groups. When workers change to occupations whose main tasks required technical skills and relocate to areas with a denser population of technically skilled workers, their wage growth rates are 15.4% higher. The magnitudes of cognitive and physical skill labor pool indices in wage growth from job mobility are 13.8% and 11.8%, respectively.

Table 9. Regression Result for Effect of Job Mobility.

	Model 1 (All Occupations)		Model 2 (All Occupations)		Model 3 (Cognitive-Skill-Oriented Occupations)		Model 4 (Social-Skill-Oriented Occupations)		Model 5 (Technical-Skill-Oriented Occupations)		Model 6 (Physical-Skill-Oriented Occupations)	
Time-Varying Variables												
Age	−0.001 ***	0.000	−0.001 ***	0.000	0	(0.001)	−0.001	(0.001)	−0.001 **	(0.001)	−0.001 **	(0.001)
Firm-Size	0.002	(0.002)	0.002	(0.002)	0.004	(0.006)	−0.001	(0.003)	0.002	(0.004)	0.011 **	(0.005)
Effect of Job Mobility												
Job Mobility Dummy	0.043 ***	(0.011)			0.054 *	(0.030)	0.028	(0.019)	0.049 **	(0.024)	0.036	(0.022)
Job Mobility × Population Size Change			0.069 ***	(0.022)								
Intercept	0.080 ***	(0.016)	0.090 ***	(0.015)	0.046	(0.046)	0.071 ***	(0.026)	0.098 ***	(0.037)	0.069 **	(0.031)
Observations	4120		4120		669		1430		910		958	
Adj. R-square	0.006		0.005		0.001		0.001		0.007		0.01	

Note: Numbers in parentheses are standard errors. *** significant at 1% level, ** at 5% level, and * at 10% level.

Table 10. Regression Result for Effect of Interactive Variables between Job Mobility and Skill-Based Local Labor Pooling.

	Model 1 (Cognitive-Skill-Oriented Occupations)		Model 2 (Social-Skill-Oriented Occupations)		Model 3 (Technical-Skill-Oriented Occupations)		Model 4 (Physical-Skill-Oriented Occupations)	
Time-Varying Variables								
Age	0.000	(0.001)	−0.001	(0.001)	−0.002 **	(0.001)	−0.001 **	(0.001)
Firm-Size	0.003	(0.006)	−0.001	(0.003)	0.001	(0.004)	0.010 **	(0.005)
Interactive Variables								
Cognitive × Job Mobility	0.138 ***	(0.052)						
Social × Job Mobility			−0.006	(0.038)				
Technical × Job Mobility					0.154 ***	(0.044)		
Physical × Job Mobility							0.118 **	(0.056)
Intercept	0.062	(0.045)	0.077 ***	(0.026)	0.110 ***	(0.036)	0.080 ***	(0.030)
Observations	669		1430		910		958	
Adj. R-square	0.001		0.001		0.007		0.01	

Note: Numbers in parentheses are standard errors. *** significant at 1% level, ** at 5% level, and * at 10% level.

In summary, the analytical models provide evidence of differentiated urban wage premiums based on workplace skills in South Korea. First, the elasticity of population density and size to wages ranges from 0.022 to 0.032, lower than those reported in previous studies [18]. These relatively small magnitudes are somewhat surprising because economic growth has simultaneously occurred with rapid urbanization in South Korea, and urban areas typically provide better job opportunities. It can be explained partly by the spatial unit of analysis, the province, where a large portion of variations is condensed. In addition, the urban wage premium varies considerably according to types of skills. The analysis finds the highest wage premium in cognitive-skill-oriented occupations but only a moderate urban wage premium in the technical and physical-skill-oriented occupations and no urban wage premium in the social-skill-oriented occupations. As the wage levels of cognitive-skill-oriented occupations are high, the benefits of urbanization are more likely to be accrued by those with higher-quality jobs. The job mobility analysis shows immediate benefits to workers who move to denser areas. Those who change jobs and relocate to places with a concentration of similar skill-content workers experience faster wage growth. Particularly, the analysis finds a strong positive effect of cognitive, technical, and physical skill labor pooling on wage growth from job mobility. As a result, this analysis demonstrates that skill-based labor pooling is a significant factor in wage levels and wage growth in South Korea.

6. Conclusions

The paper explored the agglomeration effect of skill-based labor pooling on wage levels and growth in the case of South Korean regional economies. To this end, we developed skill-based labor pooling indices involving cognitive-, social-, technical-, and physical-skill-oriented occupations at a provincial level. These indices showed uneven geographical distributions of four types of skills; cognitive and technical skills were more concentrated while social skills were evenly distributed over the provinces. Then, the analytical model estimated the effect of skill-based labor pooling indices on wage levels and wage growth. The results showed that the wage premium stemming from local labor pooling significantly varied according to the types of skills. The magnitude of benefits was the largest in cognitive-skill-oriented occupations, modest in technical- and physical-skill-oriented occupations, and non-existent in social-skill-oriented occupations. Finally, the analysis also discovered that the agglomeration effect of skill-based labor pooling was immediate to those who changed jobs and relocated to denser areas.

From this study, we suggest several directions of research. For one, the study categorized 44 abilities and skill requirements into four skill types; however, several variations occur within each group, particularly in social skills, which would require a more thorough investigation of the nature of workplace skills and a more nuanced skill classification. In addition, the analysis did not account for the accumulation of workplace skills, or experience. As work experience is an essential element for establishing close matches between workers and firms, a future study could separate young workers from older workers in an examination of the agglomeration effect. Another research topic relates to the relationship between skill-based labor pooling and regional economic performance. Since skill-based labor pooling proffers a regional economic advantage, it impacts region-wide economies and may lead to polarization of regional economies. Thus, skill-based labor pooling could explain the path of regional economic growth.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

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