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Skills in the city ☆

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ABSTRACT

This paper documents the allocation of skills across cities and estimates the impact of agglomeration on the hedonic prices of worker skills. We find that large cities are more skilled than are small cities, but only to a modest degree. We also show that the increase in productivity associated with agglomeration, as measured by the urban wage premium, is larger for workers with stronger cognitive and people skills. In contrast, motor skills and physical strength are not rewarded to a greater degree in large cities. Urbanization thus enhances thinking and social interaction, rather than physical abilities. These results are robust to a variety of estimation strategies, including using NLSY variables that control for worker quality and a worker-MSA fixed effect specification.

1. Introduction

A skill is defined as a "proficiency, facility, or dexterity that is acquired or developed through training or experience" (Free Online Dictionary). Alternatively, it is "An art, trade, or technique, particularly one requiring use of the hands or body." These are broad definitions. They encompass the cognitive skills that allow a lawyer to write a complicated contract, the social skills that enable a teacher to motivate a class of six-year olds, and the motor skills used by a taxi-driver to negotiate congested city streets.

This sort of broad definition is entirely consistent with early conceptions of the role of skills in the economic development of cities. Marshall (1890), for instance, considers the possibility of industrial workers learning skills from each other ("the secrets of the trade"), the introduction of new skills through immigration, and the better matching of skills to needs allowed by a thick market. The examples he presents, including iron working and textile manufacturing, make it clear that he was thinking about many different sorts of skills, acquired through many different channels. Similarly, Jacobs' (1969) tales of urban synergy hinge crucially on how skills can be deployed to create "new work." An example of this is her discussion of the transmission of skills from airplane manufacturing to a range of other activities (i.e., sliding door production) in postwar Los Angeles. Again, the skills that allow the creation of new work are to be interpreted broadly.

The econometric analysis of skills in cities has taken a narrower approach, employing a vertical definition that equates a worker's skills with the level of education. See, for instance, the urban wage premium papers by Glaeser and Mare (2001), Wheeler (2001), Lee (2005), Combes et al. (2008), or Rosenthal and Strange (2008). This approach has the advantage of allowing the use of large datasets that track education but not skills. It has the disadvantage of missing both the horizontal differentiation of skills (i.e., cognitive vs. social vs. motor) and also the vertical differentiation not captured by a worker's achievement of a university degree.

This paper takes an entirely different approach to identifying worker skills. Specifically, in this paper we allow for horizontal as well as vertical differentiation, and we focus on the impact of agglomeration on the hedonic prices of skills. To do this, we make use of the Dictionary of Occupational Titles (DOT) and data from the US Census and National Longitudinal Survey of Youth (NLSY). The DOT characterizes the occupation's requirements for a range of cognitive, motor, and people skills. If one assumes that workers are assigned to jobs in a hedonic market clearing process, then one can infer a worker's skills from the occupation in which the worker is employed. Using these skill measures, we characterize the distribu-

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tion of worker skills across US cities and estimate a range of wage models, also including as regressors standard controls for worker education, family status, race, and gender.

The paper's analysis of urban wages reaches three primary conclusions. First, the urban wage premium is to an important extent a premium to cognitive skills. The hedonic prices of cognitive skills rise with MSA population in every specification we estimate. A broad range of cognitive skills are positively related to productivity, including verbal, numerical/mathematical, and logical/reasoning cognitive skills. In addition, the result holds for an index capturing a range of cognitive skills. The result that highly cognitive workers benefit most from urbanization is consistent with agglomeration theory. A high degree of cognitive skill may allow workers to learn more from their urban neighbors. It may also imply that matching is more important, since highly cognitive workers may be more specialized. See Fujita and Thisse (2002) and Duranton and Puga (2004) for surveys of the theoretical literature. The magnitudes are substantial. An increase of one standard deviation from the mean in cognitive skills increases the elasticity of wage with respect to MSA population by roughly one-fifth.

Second, there is also an urban people skills premium. Comparing a worker deemed able to interact well with others with one who is not, the interactive worker's population elasticity of wage is half again larger. Heckman et al. (2006) argue persuasively that non-cognitive skills such as this have important impacts on labor markets. Our people skills results show that soft skills are also an essential aspect of agglomeration economies, a result new to the literature.

The importance of people skills is interesting in light of the large body of research that has modeled cities as interactive systems. See for instance Beckmann (1976), Ogawa and Fujita (1980), Fujita and Ogawa (1982), or Fujita and Thisse (2002). In these papers, agents interact with each other over space, and the value of the interactions relative to the costs of interacting (transportation costs) determines urban spatial structure. Cities are denser when interaction is more valuable. Cities are more likely to be monocentric when interaction is valuable and transportation costs are low. Reducing the value of interacting can move the system to polycentricity, with minor centers developing at the city's edge. The literature thus highlights the forces that are important for the development of edge cities, sprawl, and the revival of traditional downtowns. Despite the maturity of the theoretical literature on urban interactions and the great importance of the issues it considers, there has been very little empirical work that has directly addressed urban interactions. The literature on the localization of patent citations following Jaffe et al. (1993) is one instance, albeit on only one sort of urban interaction. Charlot and Duranton (2004, 2006) consider more general interactions. They employ French survey data to show that workers in cities engage in more external communication and this is an important part of the urban productivity advantages. We find that interactive skills are highly rewarded in cities. This result is consistent with the primitive assumptions that underlie the theoretical literature.

Third, the prices of worker skills associated with physical labor do not increase with city size. Indeed, they typically decline. This is true for a range of motor skills (working with things, finger dexterity, motor coordination, eye–hand coordination, etc.). It is also true for an index that aggregates these various sorts of motor skill. The same is true for physical strength. In sum, cities raise the prices of cognitive and people skills, not the prices of physical skills such as strength and motor abilities. All three of these results are new to the literature. Prior work has considered how the differentiation of worker education impacts the urban wage premium, but it has not focused directly on worker skills.

This pattern of results holds for a range of specifications using both Census and NLSY data. Although it is much smaller than the Census sample, the NLSY is useful because it allows us to estimate several specifications that control in different ways for unobserved heterogeneity among workers. The first of these employs the Armed Forces Qualification Test and the Rotter Index to control further for worker ability. The AFQT is designed to measure intelligence, while the Rotter Index is designed to measure social skills.[1] The second NLSY specification employs a measure of university quality based on the SAT scores of accepted students to better capture the quality of a worker's education. The third exploits the panel nature of the NLSY, estimating worker-MSA fixed effects and so control for the entire range of unobserved worker skills. In all of these specifications, the pattern described above continues to hold: hedonic prices of cognitive and people skills rise with city size.

In addition to considering the urban wage premium, the paper also characterizes the spatial distribution of skills. Marshall (1890) argues that we should observe higher levels of skills in larger cities:

> In almost all countries there is a constant migration towards the towns. The large towns and especially London absorb the very best blood from all the rest of England; the most enterprising, the most highly gifted, those with the highest physique and the strongest characters go there to find scope for their abilities. (Marshall, 1890, 5.6)

There are good reasons to suspect that Marshall's analysis might continue to hold. High skill workers may be drawn disproportionately to large cities by high wages for their labor or for a taste for amenities associated with agglomeration. However, in order for Marshall's analysis to hold, the selection effects must be large enough to outweigh the high cost of living in large cities. High skill workers have high incomes, and housing is a normal good, so the urban cost-of-living effect will tend to work in the opposite direction of the wage and amenities effects.

With regard to the allocation of skills across cities, we find that large cities are more skilled than are small cities, but to a modest degree. The differences are smaller than are the differences in worker education across cities, which Berry and Glaeser (2005) argue are themselves not very large. The near uniformity characterizes all sorts of skills, including individual and aggregate measures of cognitive, people, and motor skills. When we look at within occupation heterogeneity using the AFQT and the Rotter Index, we also find roughly equal means.

The rest of the paper is organized as follows. Section 2 describes the data and our approach for characterizing a worker's skills using the DOT. Section 3 describes the allocation of skills across space. Section 4 sets out a simple hedonic model of an urban labor market. Section 5 presents the results of our Census data estimates of the urban skill premium. Section 6 presents results of NLSY models that address selection issues. Section 7 concludes by discussing the policy implications of our results.

2. Data

2.1. Dictionary of Occupational Titles

We employ data from the U.S. Census, the NLSY, and the DOT. The Census and the NLSY report worker occupations. The DOT characterizes the skill requirements of occupations. Matching the

[1] The index measures the degree to which an individual believes him- or herself to be in control of life circumstances, rather than being at the mercy of external forces (Rotter, 1966). The Rotter Index is not a measure of interactive skills *per se*, but it has been shown to be correlated with the individual's social skills (Lefcourt et al., 1985).

Table 1
Variables from the Dictionary of Occupational Titles.

DOT Variables	Description
Cognitive Skill Variables	
data	complexity at which worker performs job in relation to data, from highest to lowest: synthesizing, coordinating, analyzing, compiling, computing, copying, comparing
gedr	general educational development in *reasoning* required for job, ranging from being able to apply logical or scientific thinking to wide range of intellectual and practical problems, to being able to apply commonsense understanding to carry out simple instructions
gedm	general educational development in *mathematics* required to perform job, from knowledge of advanced calculus, modern algebra and statistics; algebra, geometry & shop math; to simple addition and subtraction
gedl	general educational development in *language* required, from reading literature, writing editorials & speeches, and conversant in persuasive speaking & debate; to reading at rate of 95–120 words per minute or vocabulary of 2500 words, and writing and speaking simple sentences
aptg	segment of the population possessing *intelligence* (or general learning ability) aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
aptv	segment of the population possessing *verbal* aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
aptn	segment of the population possessing *numerical* aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
People Skills Variables	
people	complexity at which worker performs job in relation to people, from highest to lowest: mentoring; negotiating; instructing; supervising; diverting; persuading; speaking-signaling; serving; taking instructions
dcp	adaptability to accepting responsibility for *d*irection, *c*ontrol or *p*lanning of an activity
influ	adaptability to *influ*encing people in their opinions, attitudes or judgments about ideas or things
depl	adaptability to *dealing with people* beyond giving and receiving instructions
Motor Skills Variables	
things	complexity at which worker performs job in relation to things, from highest to lowest: setting up; precision working; operating-controlling; driving-operating; manipulating; tending; feeding; handling
aptf	segment of the population possessing *finger dexterity* (ability to manipulate objects with fingers rapidly & accurately) aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
aptk	segment of the population possessing *motor coordination* aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
aptm	segment of the population possessing *manual dexterity* (ability to work with hands in turning and placing motions) aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
apte	segment of the population possessing *eye–hand–foot coordination* for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
apts	segment of the population possessing *spatial perception* aptitude (ability to think visually of geometric forms) for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
aptp	segment of the population possessing *form perception* (ability to perceive detail in objects) aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
aptc	segment of the population possessing *color discrimination* aptitude for the job: top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
sts	adaptability to situations requiring attainment of *s*et limits, *t*olerances or *s*tandards (e.g., operates a billing machine to transcribe from office records data; papers voter lists from official registration; measures dimensions of bottle to verify setup of bottlemaking conforms to standards)
Physical Strength Variable	
streng	degree of *strength* requirements of job as measured by involvement in standing, walking, sitting, lifting, carrying: from very heavy, heavy, medium, to light, sedentary

DOT with the Census and NLSY allows the characterization of worker skills. The period our study covers coincides well with information from the 1977 Fourth Edition and 1991 Revised Fourth Edition DOT. Information in the 1977 Fourth Edition were collected between 1966 and 1976, while data in the 1991 revision were collected between 1978 and 1990. Thus, DOT skill measures from the 1977 Fourth Edition describe in great detail the skill levels required to perform occupations in the 1970s (coinciding with the early years of NLSY respondents), while occupations in the 1980s (of both 1990 Census and NLSY respondents) are best described by the 1991 revised Fourth Edition. The revised Fourth Edition updated 2453 occupations out of the total of 12,742.

Occupational definitions in DOT are the result of comprehensive studies by trained occupational analysts of how jobs are performed in establishments across the nation and are composites of data collected from diverse sources.[2]. There are 44 different job characteristics available in the DOT. These fall into seven clusters: work functions; required General Educational Development (*ged*); aptitudes needed; temperaments needed; interests; physical demands; and working conditions in the environment. All these variables were re-scaled so that higher values denote higher requirements. Table 1 describes the DOT variables we use in the analysis and Bacolod and Blum (forthcoming) describe all the DOT variables.

Our first objective is to identify a plausible subset of these 44 DOT task measures and then to generate interpretable summary measures of occupational skill requirements. Using the textual definitions of the variables, we identify three broad skill categories in the DOT data for our analysis. These are: cognitive skills, motor skills, and people skills.[3]

There are many variables in the DOT dataset that capture aspects of cognitive skills. We will focus on seven of them. As described in detail in Table 1, these relate to the complexity of the data requirements of a worker's job (*data*), the reasoning required (*gedr*), the mathematics required (*gedm*), the language abilities required (*gedl*), and the intelligence, verbal, and numerical aptitudes required relative to the general population (*aptg*, *aptv*, and *aptg*). For instance, *gedm* measures mathematical development required

[2] For more information, see http://www.oalj.dol.gov/libdot.htm. While the main use of DOT information has been for job matching, employment counseling, occupational and career guidance, and labor market information services, a few economists also have used the information in DOT, including, Autor et al. (2003), Bacolod and Blum (forthcoming), Wolff (2003) and Ingram and Neumann (2006).

[3] These categories or similar ones have been previously explored in the literature using the 1977 Fourth Edition DOT. See Miller et al. (1980), Wolff (2003), and Ingram and Neumann (2006).

Table 2
Skill requirements of selected occupations.

Cognitive Skills		Motor Skills		People Skills	
Low	High	Low	High	Low	High
Garbage collectors	Physicists	Financial manager	Dentist	Data entry-keyers	Therapists
Machine feeders	Life scientists	Lawyers	Machinists	Machine operators	Secretaries
Laborers	Engineers	Social workers	Technicians	Assemblers	Social workers
Launderers	Physicians	Agents	Mechanics	Packers	Administrators
Packers	Lawyers	Religious workers	Veterinarians	Car washers	Sales person

for the job. At high *gedm* levels, workers are required to know advanced calculus, while at low levels, they are required only to know how to perform arithmetic. While more than a century of urban economic theory emphasizes the importance of worker skills, it does not definitively identify the sorts of skills that are enhanced by agglomeration. We will, therefore, work separately with all these measures for some of our analysis. The same is true of motor skills: there are many measures we will make use of in our empirical work (see Table 1).

It is not possible, of course, to make simultaneous use all of the variables capturing the cognitive and motor demands of an occupation. High collinearity makes precise estimation impossible. For some of our analysis, therefore, we work with skill indices created using principal component (factor) analysis.

We construct a cognitive index through factor analysis of the seven DOT cognitive skills listed in Table 1. As discussed earlier these are: complexity of the job in relation to data; educational development level in reasoning, mathematics and language for the job; and general intelligence, verbal, and numerical aptitudes.[4] A high value on this cognitive index indicates that substantive complexity is involved in carrying out the job. This and other indices reported are re-scaled to have a mean of 1 and a standard deviation of 0.1.

Likewise, we construct a motor skills index from nine DOT variables: complexity of the job in relation to things; aptitudes for manual dexterity, finger dexterity, motor coordination, eye–hand–foot coordination, spatial and form perception, and color discrimination; and adaptability to situations requiring attainment of standards.[5] A higher value on the motor skills index indicates a job with greater manual demands.

Finally, we measure the interpersonal skill requirements of jobs. There are four DOT measures that relate to the people skills involved in an occupation (see Table 1). In deciding how to make use of these occupational characteristics, our approach is to identify skill measures that fit best with the theory of urban interactions discussed in the Introduction. The first variable is *depl.* It assesses an occupation's requirements of "adaptability to dealing with people beyond giving and receiving instructions." This is our preferred measure, since as it captures the sorts of fluid, unplanned, and informal interactions that are considered in the spatial interactions literature (i.e., Jacobs, 1969 and successors). The variable *dcp* assesses if an occupation requires direction, control, and planning of an activity. Clearly, this variable focuses on one element of social interaction, the ability to manage. Similarly, the variable *influ* measures if an occupation requires exerting influence. It therefore focuses on a different type of social interaction that is also somewhat related to the ability to manage, although in this instance the "management" takes place outside of an authority relationship. We do not dispute the value of managerial ability, nor do we doubt that such ability may potentially be more valuable in a thick urban market. Our preference for *depl* is that it is a more inclusive variable. Finally, the *people* variable attempts to rank the *degree* of interpersonal interaction required by an occupation. The scale and structure of the ranking is intended to reflect a progression from simple to complex relations to people, such that each successive rank includes those that are simpler and excludes the more complex (Miller et al., 1980). It is not clear to us that the complexity of interactions is what is rewarded in a thick urban market. Having said that, we will estimate models employing all people skills measures as well as a people skills index constructed by factor analysis from the four measures discussed above. The broad pattern of people skill results reported in the Introduction holds for most specifications.

In order to make this discussion more concrete, it is useful to consider some specific occupations. To that end, Table 2 lists some occupations at the top and bottom of the cognitive and people skill requirement distributions. The occupations requiring the least people skills include data-entry keyers and machine operators. The occupations requiring the most include therapists, physicians, dentists, administrators and lawyers. Clearly, the latter group includes occupations that involve more interaction than does the former group. The table also lists the occupations that make the least cognitive demands on workers. These include garbage collectors and machine feeders. The most cognitively demanding occupations include physicists, life scientists, engineers, physicians, and lawyers. The distinction is again clear, with the latter group of occupations requiring much more cognition than the former group.

2.2. Census

Our wage and employment data come from the 1990 1% Census sample (IPUMS).[6] Our sample includes employed individuals aged 21–65 who were not living in group quarters, had non-missing occupational responses, and whose occupational categories were merged with DOT information. All wages are deflated by the CPI for All Urban Consumers, with base year 1982–1984.[7] Data on the size and density of the MSA are available from the Census. We match DOT skill measures to workers in the IPUMS using the mapping of 1991 DOT codes to 1990 Census classification codes from the National Crosswalk Service Center.[8]

2.3. NLSY79

We address the problem of unobserved ability by using individual measures of worker abilities available in the National Longitudinal Survey of Youth 1979 (NLSY) and by exploiting this data's panel structure. We use a confidential geocode version of the NLSY in order to identify county of residence.[9] Counties are converted to

[4] The first cognitive factor explains 100% of the variation in the seven cognitive variables, while each DOT variable loads about equally, with loadings ranging from 0.83 to 0.95.

[5] The first factor explains 95.4% of the variation in these nine variables.

[6] We also repeated all analysis using the 1980 1% Census samples from IPUMS. Since the results for 1980 and 1990 Census were very similar, we focus our discussion using only the 1990 Census.

[7] To be completely clear, the deflator is the same for all urban areas. We are estimating a nominal wage equation with the values scaled to 1982–1984.

[8] http://www.xwalkcenter.org/index.html.

[9] We thank the Bureau of Labor Statistics for making this version available.

MSAs using the Census correspondence. Following Moretti (2004), we exclude the military supplemental samples and use weights to make our sample nationally representative. Our sample includes individuals who worked in the last year, with non-missing hours, and whose occupational categories were merged with DOT information. As with the Census, we merged the relevant DOT edition information to the NLSY workers using the crosswalk from the National Crosswalk Service Center. Again, as with the Census, hourly wages are deflated by the CPI for All Urban Consumers, with base year 1982–1984.

The NLSY79 has two individual measures of worker abilities that allow us to directly address the sorts of unobserved ability with which we are concerned. One of these is the Armed Forces Qualification Test (AFQT), commonly argued to be a measure of the pre-labor market cognitive ability of the worker. The second is the Rotter Index, which measures an individual's self-perceived control over his or her life. As noted previously, the Rotter is a commonly used proxy for social skills that might impact labor market outcomes.

In addition, we can also measure the quality of the post-secondary institution attended by workers in the NLSY79 sample. NLSY79 respondents reported the actual names of colleges previously or currently attended during select survey year interviews. College Federal Interagency Committee on Education (FICE) codes were then assigned to each reported college by the Survey. We identified the institution last attended by the respondent as the college of attendance (as opposed to first or intervening). This is clearly the most relevant institution for labor markets. In most cases, this is the college or university from which the respondent obtained their degree. We use these FICE codes to match Barron's selectivity measures published in the 1982 issue of Barron's Profiles of American Colleges, a date when most NLSY79 respondents were attending or graduating from college. Barron's selectivity index classifies colleges into 7 categories: Most Competitive, Highly Competitive, Very Competitive, Competitive, Less Competitive, Non-Competitive, and Special (e.g., seminary, art). This single summary measure of selectivity is based on the entering class's SAT and ACT scores, class rank, high school grade point average, and the percentage of applicants who were accepted.

We were able to match college quality indicators for a total of 1971 NLSY respondents. Only a subset of these respondents is actively in the labor force in a given year, but we have several years of them working. Because there are few workers in some of the 7 categories described above, we aggregate them into 4 broader categories. These are: unknown to noncompetitive, less competitive, competitive, and very to most competitive.[10] As a result, we are able to estimate the wage regressions with controls for college selectivity to account for elements of workers' unobserved ability.

3. The allocation of skills to cities

The data described in Section 2 allow us to characterize the skills possessed by a city's workers. The skills are differentiated both horizontally (i.e., cognitive, motor, etc.) and also vertically (i.e., knowledge of algebra vs. knowledge of calculus). In contrast, prior work in this area has characterized skills by the level of education attained. Since our approach is new to the urban and regional economic literatures, before moving on to the hedonic estimation, we will describe the geography of worker skills, focusing on the relationship of city size to skills.

Table 3 characterizes the distribution of skills for four classes of cities, small cities (population between 100,000 and 500,000), medium-sized cities (population between 500,000 and 1,000,000), large cities (population between 1,000,000 and 4,000,000) and very large cities (population more than 4,000,000). The table gives the share of employment of workers with a particular level of skills on average for a city in a given size category. We present evidence on the distribution of skills within a city size category below. The shares of workers with college, high school, and less than high school are presented at the top of the table as a comparison.

The table exhibits a striking pattern. There is a positive but weak relationship between city size and worker skills for all of the skill categories that we examine, cognitive, people, and motor. The difference in average skills between small and large cities is small compared to variations in education (also Table 3). The difference is also small compared to differences in industrial and occupation localization (see the Online Appendix to this paper). Thus, both industries and occupations are much more unevenly distributed across city size categories than are worker skills.

Returning to Table 3, we will begin at the top of the table. 26.8% of the workers in a small city have only the minimum mathematical skills (*gedm*) of addition and subtraction. 32.9% of workers in a small city also understand geometry, and so on. The highest level of mathematical development, advanced calculus, is possessed by 0.25% of a small city's workers. Aggregating workers with algebra or more, the very large cities have 4% more (1 percentage point) than the small cities. The large cities have 15% more (just under 3 percentage points). For college education, the difference with very large cities is 22% (five percentage points), and the difference with large cities is 29% (slightly above 6 percentage points). Thus, for this particular cognitive skill, there is only modest variation by city size.

For other cognitive skills, the pattern is the same. The variable *gedr* measures reasoning skills. At the highest level, the percentage difference between the largest and small cities is only slightly less than the difference for education. However, the absolute numbers of workers who "deal with very abstract concepts" is tiny, roughly 2.5% of the workforce across worker categories. For workers with more common reasoning skills, there is virtually no difference across city size categories. The case of *gedl*, language skills is quite similar, as are the cases for the rest of the cognitive skills.[11]

Table 3 also presents employment shares at various points on the distribution for the cognitive skill index. The virtue of the index is that it aggregates the various dimensions of cognitive skill into a single measure, clarifying the geographic allocation of skills.[12] Given the robustness of the pattern described above, it should be no surprise that it reappears for the skill index. There is very little difference in skill endowment between the largest and smallest cities, except at the very highest end of the skill distribution (workers who are three standard deviations above the mean, a group that contains 7–8% of the population). Even for this group, the difference is comparable to the relatively small differences in the percentage of the populations that are college educated.

For people skills, there is even less difference across city sizes. Our primary people skills measure, *depl*, characterizes the worker's "adaptability to dealing with people beyond giving and receiving instructions." As discussed earlier, it captures the kinds of interactions that are presumably involved in the tacit exchange of knowledge, an interaction considered fundamental in research on the geography of innovation. In the smallest cities, 53.3% of workers are in jobs that require this skill. In medium sized cities, the figure

[10] The category labeled as "unknown" includes two-year colleges and institutions classified by Barron's as special, e.g., art schools or music conservatories. The results of the paper are robust to excluding the "unknown" category.

[11] See the Online Appendix for the distribution across city sizes of a much larger list of DOT variables.

[12] It is important to point out, however, that the index is a cardinal score computed from the ordinal codings of occupation skill requirements. It thus treats the difference between Calculus and Algebra (categories 5 and 4) as being the same as the difference between Advanced Calculus and Calculus (categories 6 and 5).

Table 3
The distribution of skills across cities of different sizes.

Skill Distribution – Share of Population	City Size			
	Small	Medium	Large	Very Large
Education				
Less than HS	0.125	0.119	0.105	0.147
HS Degree	0.653	0.639	0.609	0.583
College Degree	0.221	0.242	0.285	0.27
Cognitive Skills				
GED-M				
Add–Subtract	0.268	0.252	0.221	0.252
Geometry	0.329	0.33	0.327	0.333
Algebra	0.212	0.217	0.231	0.215
Algebra + Statistics	0.162	0.168	0.181	0.167
Calculus	0.027	0.029	0.036	0.03
Advanced Calculus	2.50E–03	3.10E–03	4.10E–03	3.30E–03
GED-R				
Carry out simple instructions	0.056	0.052	0.047	0.053
Commonsense understanding	0.191	0.179	0.153	0.171
Carry out detailed instructions	0.317	0.313	0.306	0.314
Solve practical problems	0.298	0.315	0.342	0.32
Logical or scientific thinking	0.115	0.117	0.125	0.116
Deal with very abstract concepts	0.023	0.025	0.027	0.027
GED-L				
2500 words; simple sentences	0.186	0.172	0.143	0.167
5000–6000 words; compound sentences	0.245	0.233	0.221	0.227
Read manuals; write essays	0.286	0.297	0.3	0.293
Read novels; write business reports	0.184	0.195	0.224	0.207
Read & write literature	0.085	0.086	0.092	0.085
Same as level 5[a]	0.014	0.016	0.019	0.021
COGNITIVE INDEX				
2 std deviations below mean	0.028	0.025	0.022	0.025
1 std deviation below mean	0.238	0.222	0.191	0.217
1 std deviation above mean	0.377	0.376	0.37	0.372
2 std deviations above mean	0.292	0.306	0.332	0.306
3 std deviations above mean	0.066	0.071	0.085	0.079
People Skills				
depl: Adaptability to dealing with people beyond giving and receiving instructions	0.533	0.552	0.576	0.561
dcp: Adaptability to accepting responsibility for direction, control, and planning	0.282	0.288	0.307	0.283
influ: Adaptability to influencing people in their opinions and judgments	0.113	0.117	0.124	0.118
PEOPLE INDEX				
1 std deviation below mean	0.395	0.374	0.341	0.361
1 std deviation above mean	0.272	0.282	0.295	0.297
2 std deviations above mean	0.217	0.226	0.247	0.226
3 std deviations above mean	0.116	0.118	0.117	0.117
Motor Skills				
THINGS				
Handling	0.413	0.423	0.445	0.436
Feeding	0.129	0.128	0.124	0.132
Tending	0.072	0.067	0.061	0.061
Manipulating	0.082	0.081	0.08	0.075
Driving-Operating	0.102	0.102	0.094	0.098
Operating-Controlling	0.166	0.168	0.167	0.168
Precision Working	0.035	0.031	0.029	0.031
Setting Up	7.10E–04	6.90E–04	6.70E–04	5.40E–04
MOTOR INDEX				
3 std deviations below mean	1.10E–03	1.30E–03	2.10E–03	1.70E–03
2 std deviations below mean	0.177	0.185	0.194	0.191
1 std deviation below mean	0.419	0.419	0.422	0.429
1 std deviation above mean	0.268	0.259	0.245	0.239
2 std deviations above mean	0.114	0.114	0.113	0.118
3 std deviations above mean	0.021	0.022	0.023	0.022

Notes. Small city size: population between 100,000 and 500,000; Medium: between 500,000 and 1 million; Large: between 1 million and 4 million; Very Large: more than 4 million. See text for more discussion and Table 1 for definition of variables.

[a] *gedm* and *gedr* are coded on a 6-point scale; *gedl* is on a five point scale, with a sixth for symmetry described as being the "same as category 5." We treat it as identical in constructing the cognitive skill index. The employment shares reported in the table are based on the raw coding of occupations, which does include *gedl* values of both 5 and 6.

rises to 55.2%. In the two largest size categories, the percentages of workers with people skills are 57.6% and 56.1%. The percentage differences between these and the share in a small city are less than 10%.

The differences are smaller still for the other measures of people skills and for the people skills index. For the DOT measure *dcp*, control and planning, there is essentially no difference across size classes, except for the large cities. For large cities, there are less than 10% more workers with this people skill than in small cities. The pattern is the same for the DOT measure *influ*, measuring the ability to influence people. The people index also exhibits considerable uniformity across city size categories.

Table 4
AFQT and Rotter Index for selected occupations.

	Panel A. Mean AFQT Score					Panel B. Mean Rotter Score				
	MSA Size					MSA Size				
Occupation	Small	Medium	Large	Very Large	Total	Small	Medium	Large	Very Large	Total
Managers	62.34	53.38	59.97	62.31	62.09	62.09	0.5	0.49	0.54	0.51
Engineers	72.3	83.22	76.52	75.85	75.97	75.97	0.49	0.51	0.5	0.51
Therapists	60.82	71.93	54.95	64.64	62.26	62.26	0.57	0.6	0.53	0.51
College Professors	77.75	72.33	79.25	73.91	75.57	75.57	0.47	0.5	0.51	0.49
Teachers	64.91	71.41	70.33	64.37	65.22	65.22	0.52	0.48	0.51	0.51
Sales Person	78.8	82.27	79.94	82.94	82.11	82.11	0.5	0.42	0.48	0.51
Food Services	53.91	43.32	47.23	44.3	44.57	44.57	0.56	0.54	0.54	0.54
Mechanics	48.43	45.16	47.93	42.17	42.82	42.82	0.54	0.5	0.5	0.52
Construction Workers	48.91	37.08	40.95	37.34	37.73	37.73	0.48	0.52	0.56	0.53
Janitors	42.04	45.21	29.39	30.73	30.97	30.97	0.53	0.57	0.55	0.56
Natural Scientists	75.67	74.37	55.57	82.53	78.34	78.34	0.52	0.48	0.48	0.51
Nurses	58.26	64.75	70.56	67.16	67.61	67.61	0.54	0.51	0.51	0.48
Social Workers	48.87	54.71	63.76	56.36	56.85	56.85	0.5	0.54	0.55	0.5
Technicians	73.49	70.26	69.28	67.03	67.44	67.44	0.51	0.49	0.52	0.52
Administrative Support	45.87	55.13	56.09	49.55	49.78	49.78	0.53	0.53	0.51	0.54
Personal Services	65.8	48.67	45.86	43.1	44.03	44.03	0.53	0.54	0.56	0.52

Notes. Weighted averages taken over all NLSY workers 1979–1996. Small MSA size: population between 100,000 and 500,000; Medium: between 500,000 and 1 million; Large: between 1 million and 4 million; Very Large: more than 4 million.

Motor skills also do not appear to be allocated in radically different proportions across city size categories. For *things*, the complexity of the job as it relates to objects, there is slightly less skill in the large cities at the highest skill category. For the other motor skills and for the motor skills index, the pattern across city size classes is quite uniform.[13]

The weakness of the relationship between skills and city size is surprising. The introduction presented a quote from Marshall to the effect that there is a "constant migration" of the "very best blood" to towns and to London. The idea of a selection of the highly skilled into cities is central to the modern literature on agglomeration as well. Glaeser and Mare (2001), for instance, attribute a substantial fraction of the urban wage premium to the selection of highly productive workers to large cities. The issue is also prominent in Combes et al. (2008), Rosenthal and Strange (2008), and Lee (2005).[14]

One way to interpret the result is that the technology of production does not allow a very fine spatial division of labor by skills. This can be seen as being consistent with some explanations of Zipf's Law, the power law that holds that the rank of a city in the urban system multiplied by its population is roughly constant. Gabaix (1999) has showed that this regularity can be obtained if city populations grow ergodically. If the system of cities were composed of cities with roughly equal skill distributions, then ergodic growth of the populations of workers at various skill levels would generate ergodic growth of the city. Our result is thus consistent with Zipf's Law.

One concern with the result that skills are relatively uniform is that occupations are defined nationally, so any coding of an occupation's skill requirements may have error associated with the deviation between the occupation's skill requirements in a particular size of city and the national average requirements. Our characterization of the city-size/skill relationship would be incorrect if larger cities had workers whose skills were systematically greater than the national average.

To consider this issue, we make use of the NLSY sample. As noted above, the NLSY variables AFQT and Rotter go beyond the Census in addressing worker quality. The AFQT ranges from 0–100, with a higher score indicating greater intelligence, while the Rotter Index ranges from 0–1, with a lower score indicating greater control of one's social environment. Table 4 reports mean scores by occupation. The mean AFQT scores do not vary much across city sizes. There are some occupations with higher skill levels in big cities (i.e., sales), but there are others with lower scores (i.e., personnel services). The same is true for the Rotter Index, with means quite similar across city size categories.

Table 5 presents 10th and 90th percentiles by city size class for the AFQT and Rotter Index for a range of occupations. Panel A reports the AFQT results. There is a very clear pattern. In a larger city, the lowest AFQT workers have much lower scores than in a smaller city. In contrast, the highest AFQT workers have much higher scores. Put concretely, in a very large city, the top-end lawyers are on average smarter than in a small city using the AFQT measure of intelligence. So are the doctors, and so on. However, it is also true that in a large city the low-end lawyers are on average less intelligent than in a small city, as are doctors and others. This is consistent with larger cities have a more refined division of labor. This result helps to reconcile the skill uniformity result with the intuition that big cities are homes to highly-skilled workers. There are, indeed, some very highly skilled workers are in the most populous places. The average skill is not greater because big cities are also home to some very low-skill workers.

4. A hedonic model of urban labor markets

The data described in Section 2 will be used to carry out a hedonic analysis of urban labor markets. This section will explore the relationship between city size and the equilibrium function giving an occupation's wages as a function of its skills.

We begin by taking a city's population as fixed. Specifically, we suppose that a city contains I workers, indexed i. Each worker is characterized by a skill vector $\mathbf{z}_i$. Firms employ worker skills under a fixed proportions technology. For each worker the firm employs, the firm must employ one unit of land at cost r and also incur non-land costs equal to c. The worker's output is treated as numeraire, the firms have identical production technologies, and the worker's production is given by $f(\mathbf{z}_i, I)$. $f(\text{-})$ is increasing and convex in skills. The firm's profit from employing the worker equals $f(\mathbf{z}_i, I) - c - r - w(\mathbf{z}_i)$, where the function $w(\mathbf{z})$ gives the wage for a worker with skills $\mathbf{z}$. Firms compete for labor, implying zero profits, and resulting in the usual derived demand condition $w(\mathbf{z}, I) = f(\mathbf{z}_i, I) - c - r$.

[13] See the Online Appendix for a more complete characterization of the geography of skills. The pattern discussed in the paper continues to hold.

[14] We have also calculated the 10th and 90th percentiles of the skill distribution for the city size categories. Not only are the distributions of average skill levels relatively even across cities, but so are the extreme values. See the Online Appendix.

Table 5
Agglomeration and the AFQT and Rotter scores: Distributions for selected occupations and city size categories.

	Panel A. 10th & 90th Percentiles of AFQT Score				*Panel B. 10th & 90th Percentiles of Rotter Score*			
	MSA Size				MSA Size			
Occupation	Small	Medium	Large	Very Large	Small	Medium	Large	Very Large
Managers	51.99	42.02	36.37	24.6	0.47	0.46	0.43	0.37
	69.65	64.81	82.29	91.72	0.55	0.52	0.65	0.68
Engineers	62.92	79.22	62.95	49.67	0.47	0.49	0.42	0.41
	79.22	86.96	87.59	94.93	0.53	0.53	0.58	0.63
Therapists	60.75	70.92	44.98	41.62	0.57	0.6	0.49	0.42
	60.9	72.93	60.03	82.56	0.57	0.6	0.62	0.62
College Professors	74.1	59.79	70.4	45.13	0.45	0.47	0.46	0.4
	81.43	81.77	88.25	93.61	0.49	0.6	0.55	0.6
Teachers	60.32	63.82	50.88	34.51	0.51	0.45	0.43	0.38
	68.81	75.67	81.96	86.44	0.54	0.52	0.62	0.62
Sales Persons	69.74	82.27	62.92	66.41	0.49	0.42	0.44	0.42
	81.45	82.27	86.18	96.12	0.56	0.42	0.5	0.59
Food Services	47.48	21.05	27.21	10.71	0.53	0.49	0.42	0.38
	58.01	54.9	64.57	80.6	0.58	0.64	0.66	0.7
Mechanics	39.73	29.72	24.13	12.71	0.51	0.45	0.41	0.38
	57.01	61.59	67.99	74.14	0.56	0.55	0.62	0.68
Construction Workers	42.4	26.8	15.22	8.89	0.46	0.48	0.46	0.39
	51.75	42.58	63.56	68.33	0.51	0.58	0.7	0.69
Janitors	34.54	35.99	11.83	5.55	0.52	0.48	0.43	0.4
	45.41	55.4	53.21	64.15	0.55	0.63	0.67	0.72
Natural Scientists	75.67	53.53	47.25	63.06	0.52	0.45	0.47	0.44
	75.67	77.7	58.03	92.92	0.52	0.51	0.49	0.6
Nurses	57.33	61.02	61.97	51.23	0.53	0.48	0.46	0.41
	58.88	65.34	76.31	83.92	0.54	0.51	0.59	0.57
Social Workers	38.52	54.14	57.37	34.1	0.49	0.52	0.53	0.4
	52.54	57.04	69.24	77.37	0.5	0.54	0.58	0.63
Technicians	67.28	52.01	46.84	30.44	0.47	0.42	0.42	0.38
	79.89	81.6	85.74	93.88	0.55	0.61	0.62	0.67
Administrative Support	34.18	37.9	34.05	14.65	0.49	0.45	0.41	0.37
	55.98	70.32	75.89	83.85	0.6	0.62	0.62	0.7
Personal Services	60.54	34.46	19.58	14.74	0.51	0.5	0.44	0.39
	68.11	57.92	65.6	73.21	0.56	0.59	0.67	0.68
Total	56.78	52.77	44.92	33.86	0.5	0.48	0.45	0.4
	66.61	69.49	74	84.39	0.54	0.56	0.6	0.65

Notes. The first row reports the 10th percentile, while the second row reports the 90th percentile. Small MSA size: population between 100,000 and 500,000; Medium: between 500,000 and 1 million; Large: between 1 million and 4 million; Very Large: more than 4 million.

There are S skills, indexed by s. In this setup, the implicit price of a particular skill is given by $\partial w(\mathbf{z}, I)/\partial z^s$. The total impact of agglomeration on a particular worker's wage is given by $\partial w(\mathbf{z}, I)/\partial I$. Both of these have been studied previously. We are interested in something previously ignored: how the implicit price of skills depend on agglomeration, $\partial^2 w(\mathbf{z}, I)/\partial z^s \partial I$.

In order to understand how skill prices depend on agglomeration, it is natural to turn to the vast literature on the microfoundations of agglomeration economies. The literature clearly shows that there are numerous ways that agglomeration economies might increase productivity, and so wages. In their survey of research on microfoundations, Duranton and Puga (2004) identify three broad categories: learning, matching, and sharing.[15]

How might these sorts of agglomeration economy impact the prices of cognitive, people, and motor skills? It is easy to see that there are many channels by which the price of cognitive skills might be affected. A worker with a high level of cognitive skills, for instance, probably would be better able to learn from others. It is also plausible that highly cognitive workers would tend to be specialized, and so benefit from the improved match allowed by a thick labor market. Finally, it is also reasonable to believe that highly cognitive workers would benefit from complementary resources available in large markets (in other words, from sharing). The cognitive dimension of agglomeration is very clear in Vernon's (1960) analysis of "increasing returns industries" in the New York Metropolitan Area. He describes these industries as involving "unstable" products, with improvements being made continually. Although Vernon does not explicitly note that agglomeration is highly valuable for cognitive workers, his analysis is certainly consistent with such a finding.

Turning to people skills, it is again likely that all three sorts of agglomeration economies will tend to raise the price of such skills in large cities. Learning depends on interaction, which requires people skills. Matching is inherently mutual, and sharing is by its nature social. In both cases, there is a clear role for people skills. There is a long tradition of considering the role of interactions in cities, with Jacobs (1969) being probably the classic reference. Again, Jacobs does not explicitly mention people skills, but she clearly paints a picture of cities as places where there are rewards to being good at interacting.[16]

Motor and other physical skills are a different matter. It is certainly true that when Marshall (1890) set out his famous trinity of knowledge spillovers, labor market pooling, and input sharing, he used examples from occupations requiring motor and physical skills. Sheffield's cutlery workers is one such example. And it is easy to see how the value of physical skills might be enhanced by improved matches in thick urban markets or by complementary resources that can be shared. On the other hand, possessing

[15] In contrast, an increase in local amenities will tend to decrease wage, since workers will accept a discount to live in a desirable location. See Roback (1982).

[16] This list only scratches the surface. For instance, a referee suggested that workers with high levels of cognitive or people skills might experience a smaller increase in search friction as a market gets larger. This sort of labor market pooling would also tend to generate a positive relationship between city size and the prices of cognitive and people skills.

a physical skill is not so naturally linked to learning as are cognitive and social skills.

In sum, there are many ways that cognitive and social skills may become more valuable in large cities. The case for an increase in the value of motor skills is somewhat weaker. We expect, therefore, to see the hedonic prices of cognitive and social skills increase with city size more than will the prices of motor skills. Of course, we are not able to separately identify which microfoundation is responsible for a relationship between city size and skill price, since there are many explanations that share this prediction. Duranton and Puga (2004) have labeled this problem, "Marshallian equivalence."

One point worth underlining in conclusion is that the capitalization into wages of productivity differences associated with agglomeration is an entirely nominal exercise. A firm does not care about the cost of living a worker incurs in a particular city, although the worker does.

We have thus far focused on wage hedonics. To consider the hedonics of rents, we would allow workers to migrate between cities. Assuming that the number of cities is large enough that the system may be modeled as open, a worker with a given set of skills must achieve the same level of utility in every city where such a worker is located. Defining $K^{z'}$ to be the set of cities k where an occupation with skills z' can be found, the equal utility condition is $v(w(z), r; a) = v^*(z)$ for $k \in K^{z'}$. Together, the zero-profit condition, the adding-up of skills, and the equal utility condition define the equilibrium rent r and wage function $w(z)$. As described in Section 2, we observe wages and skills, but not rent. We have mentioned rent only in order to more completely characterize the equilibrium.[17]

5. The urban skill premium: Census models

5.1. Specification

In this section, we estimate hedonic models of the impact of urbanization on the prices of worker skills. As noted above, urbanization is captured by MSA population. The basic empirical model is specified as:

$$\ln w_{isjt} = \gamma'_{st} z_{jt} + X_{ist}\beta_t + \varepsilon_{isjt}, \qquad (1)$$

where w_{isjt} is the annual (Census) or hourly (NLSY) wage earnings of individual i in occupation j residing in SMSA s at time t. All models have a set of standard controls for worker characteristics (X_{ist}). These include dummies for having a college degree and having a high school degree. They also include dummies for the sex (1 for a female), race (1 for white), and marital status (1 for married). The worker's age and age squared are also included.

The vector z_{jt} denotes DOT characteristics required to perform occupation j and proxy for the workers' skills in that occupation, whose hedonic prices are allowed to vary across location s. As discussed above, the data allow us to identify a range of worker skills. We will focus on three sorts of skill: cognitive, people and motor.

The most important econometric issues that we face are that worker skills are measured with error and that there is unobserved heterogeneity among workers that is related to city size. Turning first to the measurement of skills, as described in Section 2, we attribute skills to workers by making use of the DOT characterization of occupation skill requirements. These requirements are described in the DOT code book as minimums. It is possible, therefore, that workers will have skills that exceed the DOT requirements for their jobs. In this case, we would underestimate worker skills. If this error were unrelated to city size, no bias would be introduced into the estimation, although the estimation would become less precise. Also, if workers were not compensated for excess skills, there would be no bias introduced. Our estimates would be biased if excess skills were both rewarded and also somehow correlated with city size. To the extent that workers with high levels of unmeasured skills are attracted to large cities, there would be a positive bias in our measures of the urban skill premium. On the other hand, if the skill space were compact and if all skills had a positive hedonic price, then there would be no possibility of unmeasured skills. This compactness assumption is obviously never met exactly. It is, however, almost certainly closer to correct in large cities than in small cities, since large cities have thicker labor markets. This would imply a downward bias in our measures of the urban wage premium. Our estimates would also be biased if workers in big cities had more of some unobserved characteristic and this characteristic was correlated with observed skills. Section 6 is entirely devoted to addressing these issues.

An additional econometric issue is that within an MSA and occupation our measure of the interaction between these two variables does not vary by worker. Because of that we face the classical Moulton (1990) problem of estimating the effects of aggregate variables on individual outcomes. We deal with this by having the standard errors clustered at the occupation/MSA level.

5.2. Education and the urban wage premium

Results are reported in Table 6. The baseline model (column (1)) establishes the existence of an urban wage premium. The elasticity of wage with respect to population is 6.7%, a result that is broadly consistent with prior work. The controls for worker characteristics have the expected pattern of sign and significance. Females earn lower wages, while married workers and white workers earn higher wages. Age has an increasing and concave effect on wages. This pattern persists in the rest of the paper's wage models. To conserve space, we report these coefficients in the Online Appendix only.

The next model, column (2), allows the effect of MSA population to differ depending on worker education. The results are consistent with Wheeler's (2001) MSA level estimation and also with Rosenthal and Strange's (2008) geographic model. The effect of urbanization increases monotonically with worker education. However, the effect is almost identical on workers with college and high school degrees. The effect on workers without a high school degree is slightly greater than half as large as the effect on more educated workers. This difference is significant.

5.3. Urbanization and hedonic prices of skills

Returning to Table 6, column (3) includes cognitive skill, as measured by the cognitive index. The hedonic price of cognitive skills, as imputed from worker occupations, is positive and significant. Column (4) interacts cognitive skill with the logarithm of MSA population. The effect is positive and significant. If we take a worker at the mean level of cognitive skill (i.e., a cashier with a high school degree), a doubling of MSA population increases wage by 5.4%. Mechanically, this value is the sum of the interacted education coefficient, −0.066, and the interacted cognitive index coefficient, 0.122, evaluated at the cognitive skill mean of one. Increasing the level of cognitive skill by one standard deviation (0.1, to the level of an artist) increases the elasticity of wage with respect to MSA population by 1.2 percentage points, slightly more than one-fifth of the elasticity for a worker of mean cognition. This result suggests that urbanization is especially valuable for workers with high levels of cognitive skill and is consistent

[17] We have focused here on the relationship between skills and wages. Skills also influence the matching of workers to jobs (e.g., Andersson et al., 2007) and turnover (e.g., Fallick et al., 2006).

Table 6
Urban skill premiums: Basic models.

	Dependent variable: Log of weekly wages								
	(1) Baseline	(2) Pop*Educ	(3) Cog	(4) +Pop*Cog	(5) Peo	(6) +Pop*Peo	(7) Motor	(8) +Pop*Motor	(9) +Pop*DOT
ln(MSA Pop'n)	0.06695								
	[0.00264]***								
ln(MSA Pop'n)*less than HS		0.03897	0.03602	−0.08478	0.03792	0.02966	0.03905	0.14173	0.02318
		[0.00406]***	[0.00352]***	[0.01967]***	[0.00383]***	[0.00414]***	[0.00411]***	[0.02303]***	[0.02276]
ln(MSA Pop'n)*HS degree		0.07021	0.06326	−0.06573	0.06875	0.05359	0.07048	0.17298	0.0406
		[0.00274]***	[0.00193]***	[0.01962]***	[0.00254]***	[0.00290]***	[0.00273]	[0.02336]***	[0.02277]*
ln(MSA Pop'n)*College degree		0.07277	0.07019	−0.07107	0.07274	0.05055	0.07291	0.17239	0.03347
		[0.00400]***	[0.00328]***	[0.02036]***	[0.00382]***	[0.00423]***	[0.00412]***	[0.02400]***	[0.02362]
Cognitive Skills			1.67424	−0.04153					0.95857
			[0.02086]***	[0.25141]					[0.29240]***
ln(MSA Pop'n)*Cognitive Skills				0.12249					0.06287
				[0.01862]***					[0.02158]***
People Skills					0.10582	−0.30568			−0.39793
					[0.00562]***	[0.07000]***			[0.07103]***
ln(MSA Pop'n)*People Skills						0.0294			0.0232
						[0.00524]***			[0.00526]***
Motor Skills							0.24009	1.69678	0.84427
							[0.02381]***	[0.30636]***	[0.26614]***
ln(MSA Pop'n)*Motor Skills								−0.10364	−0.05573
								[0.02286]***	[0.01968]***
Observations	726,277	726,277	726,277	726,277	726,277	726,277	726,277	726,277	726,277
R-squared	0.22	0.22	0.25	0.25	0.22	0.22	0.22	0.22	0.25

Notes. Standard errors in brackets are clustered at the occupation/MSA level. Regressions also include controls for age, age-squared, sex, marital status, race, two indicators for highest grade completed: high school degree, college degree, and a constant. Cognitive skills measured by the cognitive index, motor skills measured by the motor index, and people skills measured by *depl*.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

with many sorts of agglomeration economies, including Marshallian knowledge spillovers. Workers with a greater level of cognitive skill are better able to apprehend the knowledge that is "in the air" around them, and so earn a greater urban wage premium than do workers with less cognitive skill. Of course, as much as we might wish to have pierced the veil of Marshallian equivalence and conclusively identified the sources of agglomeration economies, we cannot make such a claim. As noted in Section 4, the cognitive urban wage premium that we have identified is also consistent with other sources of agglomeration economies.

Continuing with Table 6, column (5) includes only a worker's people skills, as measured by our preferred measure *depl*. These have a positive and significant effect on wage. Column (6) interacts people skills with MSA population. The key result is that the hedonic price of being able to interact with people beyond giving and receiving instructions increases with city size. For a college educated worker without the ability to interact ($depl = 0$, a statistician or actuary), the elasticity of wage with respect to MSA population is 5.1%. A worker with a college education and with the ability to interact has an elasticity that is 2.9 percentage points higher, or more than half again as large. Heckman et al. (2006) and others have shown soft skills to be important in understanding labor markets. This result – which subsequent estimation will show to be quite robust – shows that soft skills are also important in understanding the agglomeration economies that give rise to the urban wage premium.

The result that the value of people skills increases with urbanization is consistent with the large theoretical literature on spatial interactions (see Fujita and Thisse, 2002 for a survey). In this literature, agents interact with each other, and the interactions add more value if the agents are close to each other. The attenuation of interaction value with distance is sometimes modeled as exogenous decay with an un-modeled microfoundation and sometimes modeled as an exogenous transportation cost, reducing the net benefit of interactions. It has also been modeled as an endogenous reduction in the amount of interacting that an agent does resulting from a greater cost of interacting at greater distance. In all cases, agglomeration is about interacting. A worker's people skill is one aspect of the worker's interaction potential. Our result on the importance of people skills is to the best of our knowledge entirely new to the empirical agglomeration literature.[18]

Columns (7) and (8) present the results when motor skills are measured by the motor index. The key result is that motor skills have a hedonic price that decreases with MSA population. This suggests that the urban wage premium is related to either cognitive or social skills, but not to more physical skills.

The last column of Table 6 present stacked models that jointly include cognitive, people, and motor skills. The key results persist. There is a strong cognitive element to the urban wage premium. People skills are also associated with the urban wage premium.

5.4. Nonlinear models

We consider two sorts of non-linearity. First, we consider a broader set of possible interactions between worker characteristics and city size. In the models estimated so far, the only variables allowed to have their coefficients to vary with city size were the DOT skills and the education dummies. It is possible that the effect of some of the other personal characteristics included as controls in the regressions also vary with city size. If these personal characteristics were correlated to the DOT measures, this would bias parameter estimates. In order to deal with this, we estimate the wage equation including interactions between MSA population and

[18] It is worth pointing out that including people skills in the regression has almost no effect on the coefficients of population interacted with worker education. In contrast, when cognitive skills are interacted with population, the variables interacting population with education no longer have direct effects on wages. This suggests that our measures of people skills capture something quite different than what is captured by worker education.

Table 7
Urban skill premiums: Nonlinear models.

	(1) Baseline	(2) POP*Educ	(3) Cog	(4) +Pop*Cog	(5) Peo	(6) +Pop*Peo	(7) Motor	(8) +Pop*Motor	(9) +Pop*DOT
ln(MSA Pop'n)	0.067								
	[0.00264]***								[0.00264]***
ln(MSA Pop'n)*Less than HS		0.039	0.036	0.023	0.038	0.032	0.037	0.051	0.034
		[0.00406]***	[0.00354]***	[0.00445]***	[0.00380]***	[0.00402]***	[0.00417]***	[0.00582]***	[0.00642]***
ln(MSA Pop'n)*HS		0.070	0.064	0.041	0.069	0.056	0.069	0.082	0.050
		[0.00274]***	[0.00209]***	[0.00366]***	[0.00253]***	[0.00281]***	[0.00257]***	[0.00439]***	[0.00584]***
ln(MSA Pop'n)*College		0.073	0.071	0.044	0.072	0.054	0.072	0.082	0.051
		[0.00400]***	[0.00358]***	[0.00477]***	[0.00378]***	[0.00404]***	[0.00381]***	[0.00506]***	[0.00636]***
Cognitive Skills									
20th–40th pct			0.085	−0.238					−0.265
			[0.00571]***	[0.07225]***					[0.08705]***
40th–60th pct			0.204	−0.223					−0.204
			[0.00570]***	[0.07476]***					[0.07947]**
60th–80th pct			0.331	−0.230					−0.041
			[0.00676]***	[0.08352]***					[0.09538]
80th–100th pct			0.434	0.126					0.286
			[0.00642]***	[0.07709]					[0.09087]***
People Skills					0.102	−0.225			−0.192
					[0.00474]***	[0.05935]***			[0.06389]***
Motor Skills									
20th–40th pct							0.017	0.090	0.172
							[0.01005]*	[0.12642]	[0.08688]**
40th–60th pct							−0.125	0.097	0.234
							[0.00632]***	[0.07821]	[0.07759]***
60th–80th pct							0.012	0.249	0.329
							[0.00664]*	[0.08463]***	[0.07617]***
80th–100th pct							0.041	0.390	0.394
							[0.00624]***	[0.07925]***	[0.08559]***
Cognitive*ln(MSA Pop'n)									
20th–40th pct				0.023					0.025
				[0.00539]***					[0.00651]***
40th–60th pct				0.031					0.028
				[0.00557]***					[0.00591]***
60th–80th pct				0.040					0.027
				[0.00621]***					[0.00707]***
80th–100th pct				0.022					0.011
				[0.00572]***					[0.00673]*
People*ln(MSA Pop'n)						0.023			0.013
						[0.00443]***			[0.00473]***
Motor*ln(MSA Pop'n)									
20th–40th pct								−0.005	−0.006
								[0.00943]	[0.00643]
40th–60th pct								−0.016	−0.015
								[0.00583]***	[0.00577]***
60th–80th pct								−0.017	−0.016
								[0.00632]***	[0.00567]***
80th–100th pct								−0.025	−0.022
								[0.00590]***	[0.00636]***
Observations	726,277	726,277	726,277	726,277	726,277	726,277	726,277	726,277	726,277
R-squared	0.22	0.22	0.25	0.25	0.22	0.22	0.22	0.22	0.25

Notes. Standard errors in brackets are clustered at the occupation/MSA level. Dependent variable: Log weekly wage. Regressions also include controls for age, age-squared, sex, marital status, race, two indicators for highest grade completed: high school degree, college degree, and a constant. Cognitive skills measured by the cognitive index, motor skills measured by the motor index, and people skills measured by *depl*.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

all the other variables. These results are reported in the Online Appendix. The pattern of results found in Table 6 continues to hold.[19]

The second type of non-linearity that we consider concerns the specification of the skill premium. In the results discussed so far, cognitive and motor skills are assumed to have a constant marginal effect on wage. This assumption is worth questioning, since the marginal contribution to a worker's wage of being able to add and subtract is likely to be different than the marginal contribution of being able to use calculus, for example. Table 7 presents results when we allow for different returns to cognitive and motor skills at different points of the skills' distributions.

Three conclusions should be drawn from Table 7. First, the pattern of Table 6 continues to hold, and so is not an artifact of the linear specification. The hedonic prices of cognitive and people skills rise with MSA population while the hedonic price of motor skills does not. Second, the direct returns to cognitive skills, not interacted with population, are much greater for more skilled workers. Specifically, the marginal return to an increase in cognitive skills in the top quintile (80–100) is five times as large as in

[19] As an alternative approach, we also estimated DOT prices separately for each MSA in our sample, clustering standard errors at the occupation level. We then regressed the vector of DOT prices on MSA population and bootstrapped the standard errors. The pattern from Table 6 again continues to hold.

Table 8
Urban skill premiums for individual skills.

Cognitive Skills	Skill Only	Skill*Pop	People Skills	Skill Only	Skill*Pop	Motor Skills	Skill Only	Skill*Pop
DATA	0.21881 [0.00378]***	−0.1197 [0.04807]**	DEPL	0.10582 [0.00562]***	−0.30568 [0.07000]***	THINGS	0.0051 [0.00351]	0.16502 [0.04473]***
DATA*ln(MSA Pop'n)		0.02423 [0.00359]***	DEPL*ln(MSA Pop'n)		0.0294 [0.00524]***	THINGS*ln(MSA Pop'n)		−0.01139 [0.00335]***
GEDR	0.47808 [0.00687]***	−0.09675 [0.09250]	DCP	0.23521 [0.00637]***	0.12569 [0.07879]	APTF	0.06085 [0.01275]***	0.56412 [0.17170]***
GEDR*ln(MSA Pop'n)		0.0411 [0.00690]***	DCP*ln(MSA Pop'n)		0.00781 [0.00588]	APTF*ln(MSA Pop'n)		−0.03582 [0.01282]***
GEDM	0.34803 [0.00471]***	0.00104 [0.05782]	PEOPLE	1.03608 [0.02770]***	−0.50017 [0.33810]	APTK	−0.05469 [0.01400]***	0.44226 [0.19707]**
GEDM*ln(MSA Pop'n)		0.0248 [0.00430]***	PEOPLE*ln(MSA Pop'n)		0.10966 [0.02528]***	APTK*ln(MSA Pop'n)		−0.03532 [0.01469]**
GEDL	0.34456 [0.00488]***	−0.13937 [0.05994]**	INFLU	0.03763 [0.04925]	−0.30568 [0.15343]**	APTM	−0.20604 [0.01453]***	0.75809 [0.18387]***
GEDL*ln(MSA Pop'n)		0.03461 [0.00446]***	INFLU*ln(MSA Pop'n)		0.027 [0.01079]**	APTM*ln(MSA Pop'n)		−0.0686 [0.01372]***
APTG	0.72267 [0.00993]***	−0.10188 [0.12200]	PEO INDEX	0.92124 [0.17393]***	−0.84354 [0.42042]***	APTE	−0.084 [0.00718]***	0.18988 [0.08814]**
APTG*ln(MSA Pop'n)		0.05886 [0.00905]***	PEO INDEX*ln(MSA Pop'n)	0.12605 [0.02942]***		APTE*ln(MSA Pop'n)		−0.01956 [0.00659]***
APTV	0.58614 [0.00842]***	−0.29235 [0.10174]***				APTP	0.31743 [0.00973]***	0.92132 [0.12608]***
APTV*ln(MSA Pop'n)		0.06279 [0.00755]***	STRENGTH STRENGTH	−0.89681 [0.02740]***	0.66795 [0.32492]**	APTP*ln(MSA Pop'n)		−0.04295 [0.00939]***
APTN	0.55963 [0.00778]***	0.00258 [0.10066]	STRENGTH*ln(MSA Pop'n)		−0.11162 [0.02427]***	APTC	−0.04671 [0.00764]***	0.25536 [0.09599]***
APTN*ln(MSA Pop'n)		0.03977 [0.00747]***				APTC*ln(MSA Pop'n)		−0.02149 [0.00715]***
						STS	0.00957 [0.00416]**	0.13283 [0.05223]**
						STS*ln(MSA Pop'n)		−0.00879 [0.00392]**

Notes. Standard errors in brackets are clustered at the occupation/MSA level. Dependent variable: Log weekly wage. Regressions also include controls for age, age-squared, sex, marital status, race, dummies for high school graduate and college graduate, and a constant.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

the 20–40 quintile (column (3)). In fact, the marginal returns increase monotonically moving across the quintiles, and all of the differences are significant. Third, although the marginal returns to skills are greatest for the most skilled, the urban skill premium takes on an inverted-U shaped pattern. The marginal returns to skills are essentially equal at the top and bottom of the cognitive skill distribution (column (4)). The marginal returns to skills are greatest in the 60–80 quintile, where skill prices are roughly twice as large as at the bottom and the top, a significant difference. Thus, the urban skill premium is not enjoyed by only the very most highly cognitive of the economy's workers. In these estimates, it is the workers near the top who benefit most. One might speculate that this is consistent with a model of learning, but since our model does not identify the channels by which the urban wage premium manifests itself, one should be cautious in such speculation. Finally, it is interesting to draw a parallel to Marshall, who exemplified increasing returns by referring to skilled workers such as cutlery manufacturers. In our estimates, these fourth quintile workers seem to occupy a similar position in the economy. They are legal assistants rather than lawyers, near the top, rather than at the top.

The results in Table 7 are also helpful in illustrating the magnitude of the effect of agglomeration on skill prices. Relative to a worker in the first quintile of the cognitive distribution (i.e. Janitor) a worker in second quintile (i.e. Hairdresser) makes 8% higher wages, even after controlling for all other observed characteristics. Workers in the third (i.e. Secretary), fourth (i.e. Legal Assistant), and fifth (i.e. Lawyer) quintiles make 20%, 33%, and 43% more respectively.

5.5. Individual skill models and alternative approaches to people skills

The analysis thus far has employed indices of cognitive and motor skills, rather than including the individual skills themselves. As noted above, we have taken this approach because the correlations between individual skills make it impossible to estimate precisely if a long list of individual skills is included. In order to better understand the centrality of cognitive and people skills in the urban wage premium, we have also estimated hedonic models individually for all of the cognitive skills in the DOT.

The results are reported in Table 8. The cognitive skill results are reported in the left two columns. Two models were estimated for each skill. The first includes only the skill itself, as well as the usual controls for worker characteristics and the interactions between worker education and MSA population. This enables us to comment on the total effect of the skill on wage. The second model includes the skill itself and the interaction between the skill and MSA population. The results for the other coefficients follow the pattern of previous models.

The results are completely consistent with the results that we have reported thus far for the cognitive skill index. For each individual measure of cognitive skill, the coefficient on the skill itself in the first model is positive, so the net value of the skill is positive. More importantly, for each individual measure, the coefficient on the skill interacted with population is positive and significant. This means that the urban cognition premium depends on a range of skills, mathematical/numerical as well as verbal and logical.

We have thus far considered people skills using the DOT variable *depl*. We have made the theoretical case for this choice above. Here, we consider the urban premium paid to the three other people skill variables in the DOT, *people*, *influ*, and *dcp*, and to a people index constructed from these three and *depl* using the methods described in Section 2. As reported in Table 8, the results for the index, and the *people* and *influ* variables confirm the findings reported thus far. The results for *dcp* have the same pattern of sign – most importantly a positive interaction with population – but are insignificant. Our interpretation of these results is that they are further evidence of the role of people skills in the urban wage premium.

Table 8 also reports individual skill models for motor skills and for physical strength. All of the individual elements of the motor skill index have coefficients that follow the pattern of the index itself. Motor skills are less valuable in large cities, not more valuable. The results for *strength* are the same. Taken as a group, the results paint a very clear picture. Urbanization does not raise the value of the sorts of physical skills that are associated with manufacturing. Instead, urbanization raises the value of cognitive and people skills.

6. Estimates using the National Longitudinal Survey of Youth

6.1. Overview

The previous section's analysis was built on the attribution of skills to occupations using the DOT, where skill measures are occupational minimums. If the actual skills required by an occupation vary systematically across city sizes, then the estimates of the skill components of the urban wage premium will be biased. For instance, it is possible that workers in large cities in a given occupation need to be more skilled than workers in the same occupation in small cities. Lawyers in large cities may be more likely to be involved in highly demanding corporate law, while lawyers in small cities might be more involved with routine law such as that involved in buying a house. If this were true across occupations, then the coefficient on cognitive skills times MSA population would be biased upwards. Similar concerns apply to people and motor skills.

In addition to measurement error in DOT skills that might be systematically related to city size, unobserved worker heterogeneity is potentially a source of omitted variables bias. Individuals in large cities in a given occupation may be better workers than others in the same occupation in small cities. The big-city corporate lawyer may be different in some unobservable dimension than the small-town attorney. This sorting can happen if larger cities are associated with a higher return to such unobserved ability or if the high ability workers are attracted to big city amenities. To the extent that such unobservable characteristics may be correlated to the amount of cognitive, people, and motor skills as measured by the DOT, our estimates of the urban effect on skill prices will be biased.

In this section, we address these empirical concerns using the NLSY79. As noted earlier, The NLSY79 has individual measures of worker abilities that the Census does not which allow us to directly address the sorts of unobserved ability and measurement error with which we are concerned. Specifically, the AFQT measures cognitive ability, while the Rotter Index captures non-cognitive ability that has been shown to be correlated with people skills (e.g., Lefcourt et al., 1985). The third measure we use is the quality of the undergraduate institution the worker attended – more specifically, the selectivity of that undergraduate institution. Of course, this last measure is only available for workers who attended college. All these three proxies for workers' skills have been shown in prior work to account for sizeable shares of wage variation.[20]

[20] See for example, Neal and Johnson (1996) on the AFQT, Bowles et al. (2001) on the Rotter score, and Black and Smith (2006) and Brewer et al. (1999) on college selectivity.

In addition to providing additional measures of workers' skills, the panel structure of the NLSY allows us to account for time-invariant unobserved factors that make a worker permanently more productive. To exploit this possibility we employ a more general fixed effects specification similar to the one used in Moretti (2004), and estimate a wage model including individual*MSA fixed effects. In this case the identification of the urban premium comes exclusively from changes in MSA population over time.[21] That is, conditional on a worker-MSA, the hedonic price estimates capture what happens to the returns to skills as the population around him/her changes. With this specification we can control for individuals' unobserved ability as well as for variation in the returns to the unobserved ability of individuals across MSAs.

6.2. The urban premium in the NLSY data with individual measures of skills

In this section we use the additional individual-level measures of skills available in the NLSY. The results reported in Table 9 confirm that the usual results hold in the NLSY data. The first column presents the results of the baseline model. The magnitude of the urban wage premium is close to previously reported estimates from Census data, which are themselves similar to the estimates in the literature. Column (2) includes education variables. The agglomeration returns to high-school graduates are smaller in the NLSY than in the Census data, but the general pattern of results hold.

Columns (3) and (4) of Table 9 add AFQT and Rotter scores to the model. We use the de-meaned scores on the AFQT and the Rotter Index so that individual scores are relative to the occupational average. The rationale for de-meaning is that we are concerned with the selection of unusually skilled workers in a given occupation into large cities. We are thus not concerned with the levels of the AFQT and Rotter variables *per se*, since occupation specific variables in the regressions already capture the fact that people with high AFQT scores usually become lawyers instead of janitors.

As expected, a worker with an unusually high AFQT for his or her occupation has a significantly higher wage. This is consistent with much of the empirical literature that has found positive wage returns to cognitive skills as measured by the AFQT. Interestingly, controlling for workers' AFQT scores does not affect the magnitude of the urban wage premium (see columns (3) and (5)). This is consistent with Glaeser and Mare (2001), who find that including AFQT makes little difference in the estimated magnitude of the urban wage premium but contrasts to findings in Neal and Johnson (1996) where the white-black wage gap can be explained by differences in AFQT scores.

A worker with an unusually high Rotter Index (low perceived control over environment) has a significantly lower wage. This result confirms the findings of an emerging empirical literature that examines the returns to "soft skills."[22] In particular, it confirms a number of studies that find significant returns to behavior or personality traits on wages and earnings, where such traits are measured by the Rotter index (see Table 1 in the survey by Bowles et al., 2001 and more recently, Heckman et al., 2006). Just as with AFQT scores, even though the Rotter Index is an important determinant of wages it does not explain the urban premium.

[21] The NLSY records worker location by county. We use the county-MSA correspondence provided by the US Census Bureau to allocate workers to MSAs. We use the definition based on application of 1980 metropolitan areas standards to 1980 census data. This correspondence is available at: http://www.census.gov/population/www/estimates/pastmetro.html.

[22] This literature considers, for instance, the returns to beauty (Hamermesh and Biddle, 1994), height (Persico et al., 2004), leadership (Kuhn and Weinberger, 2005), and interpersonal skills (Borghans et al., 2006).

Table 9
NLSY wage models with controls for AFQT and Rotter Index.

	(1) Baseline	(2) POP*Educ	(3) +AFQT	(4) +Rotter	(5) +AFQT,Rotter	(6) Cog	(7) +Pop*Cog	(8) People	(9) +Pop*People	(10) Motor	(11) +Pop*Motor	(12) +Pop*DOT
Ln(MSA Pop'n)	0.0569											
	[0.00354]***											
Ln(MSA POP)*Less than HS		0.04341	0.04322	0.04308	0.04299	0.03757	−0.03479	0.04254	0.03629	0.04372	0.09497	0.01386
		[0.00680]***	[0.00678]***	[0.00680]***	[0.00678]***	[0.00670]***	[0.02935]	[0.00677]***	[0.00703]***	[0.00673]***	[0.03317]***	[0.03671]
Ln(MSA POP)*HS degree		0.05499	0.05618	0.05488	0.05605	0.05197	−0.02403	0.05567	0.0454	0.05665	0.10781	0.02273
		[0.00399]***	[0.00401]***	[0.00399]***	[0.00401]***	[0.00351]***	[0.03018]	[0.00396]***	[0.00453]***	[0.00395]***	[0.03299]***	[0.03710]
Ln(MSA POP)*College degree		0.06962	0.06973	0.06961	0.06971	0.06589	−0.01711	0.06946	0.05444	0.07051	0.12057	0.02906
		[0.00633]***	[0.00633]***	[0.00634]***	[0.00634]***	[0.00571]***	[0.03194]	[0.00628]***	[0.00743]***	[0.00659]***	[0.03314]***	[0.03769]
AFQT(i)-AFQT(occ)			0.00105		0.00101	0.00212	0.00212	0.00105	0.00104	0.001	0.001	0.00209
			[0.00015]***		[0.00015]***	[0.00015]***	[0.00015]***	[0.00015]***	[0.00015]***	[0.00015]***	[0.00015]***	[0.00015]***
ROTTER(i)-ROTTER(occ)				−0.08099	−0.05684	−0.08099	−0.08148	−0.05647	−0.05579	−0.0552	−0.05435	−0.08502
				[0.02590]***	[0.02623]**	[0.02526]***	[0.02526]***	[0.02622]**	[0.02625]**	[0.02596]**	[0.02597]**	[0.02513]***
Cognitive Skills						1.65061	0.60257					1.60439
						[0.04651]***	[0.40427]					[0.47567]***
Ln(MSA POP)*Cognitive Skills							0.0733					0.01985
							[0.02844]***					[0.03317]
People Skills								0.02853	−0.28625			−0.46728
								[0.01107]***	[0.11438]**			[0.12306]***
Ln(MSA POP)*People									0.02204			0.02418
									[0.00816]***			[0.00866]***
Motor Skills										0.4673	1.21051	0.12982
										[0.04967]***	[0.45959]***	[0.49657]
Ln(MSA POP)*Motor Skills											−0.0517	−0.00145
											[0.03237]	[0.03466]

Notes. Robust standard errors in brackets are clustered at the occupation/MSA level. Dependent variable: Log hourly wage. Regressions also include controls for age, age-squared, sex, race, highest grade completed, highest grade squared, dummies for high school graduate and college graduate, missing indicators, AFQT and Rotter scores deviated from occupational average, and a constant. Cognitive skills measured by the cognitive index, motor skills measured by the motor index, and people skills measured by *depl*.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

The remaining columns of Table 9 estimate models including the DOT measures of skills and their interactions with population size. Throughout Table 9 the de-meaned AFQT scores remain positive and significant. In fact, the coefficient on de-meaned AFQT actually becomes larger, with the standard error remaining roughly the same. The coefficients on the de-meaned Rotter Index remain negative, although not significant in some specifications.

The most important results, of course, are those of the DOT skills interacted with population. Cognitive skills have a positive and significant effect on the urban wage premium when entered alone, but the coefficient is not statistically significant when all skills enter together. This result is different than what we obtained with the Census data, where cognitive skills were statistically more valuable in large cities even when we had all skills entered together in the regression. However, this change appears to be due to the smaller number of observations in the NLSY data since statistical significance is lost even before we control for AFQT and Rotter scores.[23] People skills, on the other hand, continue to be worth more in larger cities in all specifications. Endowing a worker with the ability to interact (moving from $depl = 0$ to $depl = 1$) adds 2.2 percentage points to the elasticity of wage with respect to MSA population. This is an increase of roughly one third for a college-educated worker. Finally, motor skills continue to be worth less in large cities but, differently than what we had with the Census data, these results are not statistically significant in the NLSY. Again, the coefficient on motor skills becomes statistically insignificant even before we control for the AFQT and Rotter scores, suggesting that statistical significance is lost due to the smaller sample in the NLSY and not because the previous finding was only due to unobserved abilities.[24] In sum, both AFQT and Rotter scores are useful measures of worker ability in the sense that they explain wage variation even among workers in the same occupation. However, they cannot explain the urban premium. They also cannot account for cognitive and people skills being more valuable in large cities.

The final measure of ability we use is the quality of the undergraduate institution that the NLSY worker last attended.[25] This measure – the selectivity of one's undergraduate institution – has been shown in the literature to account for a significant portion of the wage variation of workers, where workers who attend higher quality colleges are better compensated.[26]

Table 10 reports the results when we control for college quality. The baseline model (column (1)) shows that attendance at a higher quality college is associated with higher wages. More interesting, however, is the finding that attending a high quality college is significantly better rewarded in large cities, as can be seen in the second column. In other words, there is an urban premium associated with the quality of one's degree in addition to the one associated with holding a degree.[27] With respect to the urban premium on the DOT skills, the results previously obtained continue to hold. Even after controlling for college quality, cognitive and people skills are worth more in large cities while motor skills are worth less.

[23] Although not shown here, these results are available upon request.

[24] We have also estimated NLSY wage equations for all the skills in the DOT individually, controlling for AFQT and Rotter scores. The results are consistent with the individual skill results presented in Table 8.

[25] This is the college from which they received their degree, as explained in Section 2.

[26] See for instance Black and Smith (2006), Brewer et al. (1999).

[27] It is possible that selection might explain the college quality urban premium. More able (potentially high-earning) individuals may not only more be likely to attend more selective colleges, they may also be more likely to reside in larger cities once they graduate. We thank a referee for pointing this out.

6.3. NLSY wage regressions with fixed effects

Table 11 reports the results when the wage equation is estimated with MSA*individual fixed effects. The standard errors are clustered at the MSA-occupation-time level. By estimating a worker-MSA fixed effect, we control for all time-invariant individual worker-MSA unobserved characteristics that might affect wages. These include unobserved worker ability as well as differences in the returns to such unobserved worker ability across MSAs. This specification is more general than an individual fixed effect approach. In this specification the interacted skill*population effects are identified by changes in population over time.

The first interesting finding is that, with worker-MSA fixed effects, the urban premium is smaller for workers with less than a high-school degree, is slightly higher for workers with a high-school degree, and almost doubles for workers with college degrees. This suggests that the effect of agglomeration on wages is even greater on workers with more education once we account for individual and MSA specific unobserved characteristics.

With respect to the urban premium of cognitive, people, and motor skills, cognitive skills are worth more in large cities. This result is statistically significant in all specifications. Therefore, the result that the urban wage premium is in part a cognitive premium is highly robust. People skills are worth more in large cities in all specifications as well, except when all skills enter together in the specification with individual and MSA fixed effects. However, it is important to recognize that this general fixed effect specification is asking a lot of the data. Given the many other specifications where people skills are significant, our reading of the overall pattern is that people skills are also an important part of the urban wage premium. Finally, motor skills are worth less in large cities in all specifications, but this result is not statistically significant. While across specifications it is frequently the case that the estimate for the urban premium paid to motor skills is not statistically significant, the point estimates consistently indicate that motor skills are worth less in large cities.

Overall, the results obtained after we control for time-invariant unobserved individual and MSA specific characteristics lend further support to our findings that cognitive and people skills are worth more in large cities while motor skills are worth less in large cities. These results suggest that unobserved individual ability is not what is driving the main findings of this paper.

7. Conclusions

This paper has employed DOT evaluations of the skill requirements of occupations in order to characterize worker skills. This allows us to characterize the geographic distribution of worker skills and to estimate the impact of population on the hedonic prices of skills. We show that worker skills are surprisingly evenly distributed. Values for indices of cognitive, people, and motor skills vary only modestly across city sizes. The same is true for the shares of workers with high levels of different aspects of cognitive, people, and motor skills. The paper also shows that the urban wage premium is greater for workers with high cognitive and people skills, but not for workers with high levels of motor skills. These results are consistent with models of the microfoundations of agglomeration economies that stress the importance of worker skills and learning. The results are also consistent with models of agglomeration that stress the importance of spatial interaction.

We believe that these results are relevant to a broad range of public policy issues, including labor market issues, education, and, of course, urban policy. Arguably, the salient economic policy issue today is inequality, in particular, the increase in inequality in labor income. Bacolod and Blum (forthcoming) show in a time series analysis that increases in the prices of cognitive and people skills

Table 10
NLSY wage models with controls for college quality.

	(1) Baseline	(2) POP*Educ	(3) +AFQT,Rotter	(4) +AFQT,Rotter	(5) +AFQT,Rotter	(6) +Cog	(7) +Pop*Cog	(8) +Peo	(9) +Pop*Peo	(10) +Mot	(11) +Pop*Mot	(12) +Pop*DOT
College degree												
Non-competitive (Eq1)	0.24268	0.07198	0.05162	0.06184	0.04526	−0.001	0.14904	0.04027	0.16744	0.0423	0.05597	0.19387
	[0.03070]***	[0.22557]	[0.22626]	[0.22595]	[0.22651]	[0.21757]	[0.21971]	[0.22624]	[0.22863]	[0.22869]	[0.22841]	[0.22316]
Less-competitive College (Eq2)	0.3253	0.15393	0.15558	0.14806	0.15129	0.0837	0.23235	0.14453	0.27383	0.18192	0.20346	0.29339
	[0.02880]***	[0.23550]	[0.23494]	[0.23505]	[0.23466]	[0.22349]	[0.22669]	[0.23381]	[0.23861]	[0.23523]	[0.23553]	[0.23066]
Competitive College (Eq3)	0.32115	−0.12872	−0.14736	−0.13179	−0.14872	−0.30091	−0.15239	−0.151	−0.02311	−0.13876	−0.12059	−0.1293
	[0.02550]***	[0.15158]	[0.15169]	[0.15162]	[0.15170]	[0.14596]**	[0.15096]	[0.15161]	[0.15556]	[0.15185]	[0.15186]	[0.15409]
Very to Most Selective (Eq4)	0.36557	−0.16304	−0.16923	−0.1769	−0.1789	−0.22619	−0.06567	−0.17654	−0.0634	−0.16466	−0.14753	−0.07123
	[0.02966]***	[0.20935]	[0.20884]	[0.20957]	[0.20905]	[0.19780]	[0.20301]	[0.20780]	[0.20787]	[0.21433]	[0.21209]	[0.20574]
ln(MSA POP)*Less than HS		0.04338	0.0432	0.04305	0.04297	0.03759	−0.03452	0.04253	0.03628	0.04371	0.09574	0.0145
		[0.00680]***	[0.00678]***	[0.00680]***	[0.00678]***	[0.00670]***	[0.02932]	[0.00677]***	[0.00704]***	[0.00673]***	[0.03306]***	[0.03671]
ln(MSA POP)*HS degree		0.05498	0.05613	0.05487	0.056	0.05196	−0.02377	0.05562	0.04536	0.0566	0.10854	0.02334
		[0.00399]***	[0.00401]***	[0.00399]***	[0.00400]***	[0.00351]***	[0.03016]	[0.00396]***	[0.00453]***	[0.00395]***	[0.03287]***	[0.03711]
ln(MSA POP)*College degree												
ln(MSA POP)*Eq1		0.05525	0.05665	0.05552	0.05678	0.05218	−0.03046	0.05669	0.0416	0.05846	0.10955	0.01532
		[0.01395]***	[0.01403]***	[0.01399]***	[0.01405]***	[0.01325]***	[0.03386]	[0.01401]***	[0.01457]***	[0.01423]***	[0.03510]***	[0.03919]
ln(MSA POP)*Eq2		0.05527	0.05508	0.05535	0.05514	0.05156	−0.03098	0.05518	0.03991	0.05467	0.10524	0.01359
		[0.01478]***	[0.01475]***	[0.01475]***	[0.01473]***	[0.01393]***	[0.03432]	[0.01469]***	[0.01553]**	[0.01479]***	[0.03545]***	[0.04015]
ln(MSA POP)*Eq3		0.07438	0.07526	0.07415	0.07506	0.0763	−0.00621	0.07474	0.05956	0.076	0.12679	0.04101
		[0.00797]***	[0.00800]***	[0.00799]***	[0.00801]***	[0.00747]***	[0.03234]	[0.00799]***	[0.00914]***	[0.00808]***	[0.03275]***	[0.03786]
ln(MSA POP)*Eq4		0.07922	0.07887	0.07972	0.07924	0.07227	−0.01111	0.07867	0.0645	0.07988	0.13074	0.03767
		[0.01241]***	[0.01240]***	[0.01243]***	[0.01241]***	[0.01139]***	[0.03379]	[0.01227]***	[0.01261]***	[0.01291]***	[0.03591]***	[0.03952]
ln(MSA Pop'n)	0.05636											
	[0.00351]***											
Cognitive Skills						1.64752	0.60327					1.59798
						[0.04650]***	[0.40393]					[0.47364]***
ln(MSA POP)*Cognitive Skills							0.07304					0.02006
							[0.02841]**					[0.03302]
People Skills								0.02836	−0.28608			−0.46552
								[0.01103]**	[0.11420]**			[0.12275]***
ln(MSA POP)*People									0.02202			0.02408
									[0.00815]***			[0.00864]***
Motor Skills										0.46951	1.22406	0.14381
										[0.04947]***	[0.45791]***	[0.49290]
ln(MSA POP)*Motor Skills											−0.05249	−0.00225
											[0.03225]	[0.03441]

Notes. Robust standard errors in brackets are clustered by occupation/MSA. Dependent variable: Log hourly wage. Regressions also include controls for age, age-squared, sex, race, highest grade completed, highest grade squared, dummies for high school graduate and college graduate, missing indicators, AFQT and Rotter scores deviated from occupational average, and a constant. Cognitive skills measured by the cognitive index, motor skills measured by the motor index, and people skills measured by *depl*.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 11
NLSY wage models with individual*MSA fixed effects.

	(1) Baseline	(2) POP*Educ	(3) +Pop*Cog	(4) +Pop*Peo	(5) +Pop*Motor	(6) +Pop*DOT
ln(MSA Pop'n)	0.0646					
	[0.01249]***					
ln(MSA POP)*Less than HS		0.04085	−0.03841	0.03527	0.06081	−0.009
		[0.01668]**	[0.02602]	[0.01669]**	[0.02495]**	[0.02869]
ln(MSA POP)*HS degree		0.05447	−0.02938	0.04849	0.0746	0.00159
		[0.01258]***	[0.02503]	[0.01266]***	[0.02303]***	[0.02786]
ln(MSA POP)*College degree		0.11415	0.02294	0.10606	0.13364	0.05295
		[0.01438]***	[0.02689]	[0.01445]***	[0.02358]***	[0.02917]*
ln(MSA POP)*Cognitive Skills			0.08375			0.0771
			[0.02213]***			[0.02760]***
ln(MSA POP)*People Skills				0.016		0.00717
				[0.00535]***		[0.00638]
ln(MSA POP)*Motor Skills					−0.02075	−0.02734
					[0.02024]	[0.02334]
Constant	−1.65271	−1.34721	−0.57991	−1.26963	−1.76133	−1.10331
	[0.29629]***	[0.34936]***	[0.43749]	[0.34876]***	[0.44157]***	[0.47414]**
Observations	88,759	88,759	88,759	88,759	88,759	88,759
Number of ID*MSA	13,776	13,776	13,776	13,776	13,776	13,776
R-squared	0.56	0.56	0.56	0.56	0.56	0.56

Notes. Robust standard errors in brackets, clustered at MSA/occupation/year. Dependent variable: Log hourly wage. Regressions also include controls for age, age-squared, highest grade completed, highest grade squared, dummies for high school graduate and college graduate, missing indicators. Cognitive skills measured by the cognitive index, motor skills measured by the motor index, and people skills measured by *depl*.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

are an important part of the phenomenon. Our results show that a similar phenomenon is operating in cross-section, an increase in the prices of cognitive and social skills as a worker moves to a larger city. In a sense, then, the movement to a city is a movement from old to new economy in the same way as the time series movement analyzed by Bacolod and Blum.

What do these results say about urban policy? Most directly, the results are not favorable to attempts to preserve declining industrial cities by somehow propping up manufacturing and other sectors that draw heavily on motor skills. Our results show clearly that cities are complementary to cognitive and social skills, implying that development strategies ought to lever this complementarity. Retaining a shipyard in a large city like Philadelphia will preserve jobs demanding substantial motor skills, skills not well-rewarded in big cities. Retaining cognitive workers such as lawyers will be easier, since their occupations involve the better rewarded and hence more productive cognitive and social skills. In other words, big city urban development policy needs to recognize the cognitive and social bias in the agglomeration economies that are the foundation for urbanization.

Of course, our results also have implications for urban development policy in small cities. The key implication is that there is no one-size-fits-all urban development policy. While large cities have an advantage in attracting activities that stress thinking and interaction, small cities have a comparative advantage in activities that stress motor and other physical skills. A small city may find it easier to retain manufacturing activity than to develop a biotechnology cluster. This does not, of course, mean that there is no place for cognitive skills in a small city or for motor skills in a large one. The descriptive part of the paper makes it clear that the division of labor across city sizes is not very sharp. All sizes of cities appear to require fairly similar levels of cognitive, social, and motor skill. Instead, we are arguing that at the margin it will be relatively easier for small cities to attract and retain motor-intensive activities and for large cities to retain cognitive- and social-intensive activities.

With regard to cognitive and social skills, it is important to recognize that our results show that essentially every measured type of cognitive or social skill has its price increased by urbanization. So saying that cities are cognitive does not at all mean that they are involved in frontier science, as with the Silicon Valley or with Boston. Mathematical skills, reasoning skills, and language skills are all rewarded to a greater degree in large cities. So too are general intelligence and the overall complexity of the occupation. This means that in designing education systems, while one can make a case for the rigors of science education, there is an equally strong case for other sorts of education that stress language and general critical thinking. In recent years, Canada's education policy has been skewed towards the sciences. To the extent that the goal is to provide the skills needed for cities' new economies, our results suggest that this focus may be overly narrow.

Supplementary material

The online version of this article contains additional supplementary material.

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