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. In contrast to nearly all prior work, the paper focuses directly on fundamental worker skills – including a wide range of cognitive, people, and motor skills -- rather than on worker education. To identify these skills, we match occupation skill requirements as defined by the Dictionary of Occupational Titles with data from the Census and the National Longitudinal Survey of Youth.

The paper reaches four primary conclusions. First, the increase in productivity associated with agglomeration, as measured by the urban wage premium, is shown to be larger for workers with stronger cognitive skills. A one standard deviation increase in cognitive skills from the mean is associated with an increase of roughly one-fifth in the elasticity of wage with respect to MSA population. Second, the urban wage premium is also larger for a worker with strong people skills. 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. Clearly, soft skills are an essential aspect of agglomeration economies. Third, 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 additional elements of worker quality and also to a worker-MSA fixed effect specification. Fourth, turning to the issue of the allocation of skills to cities, we find that mean skill levels increase modestly with city size. Cities of different sizes are closer to equal in their skill endowments than in either their education levels or their breakdown by occupation or industry.

I. 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), Combes et al (2003), Lee (2005), or Rosenthal and Strange (2005). 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 fundamental worker 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) to characterize an occupation's requirements for a range of cognitive, motor, and people skills. There is no paper in the agglomeration literature that considers this sort of horizontal and vertical skill differentiation. Using these measures, we characterize the distribution of these fundamental 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 soft 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 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. Duranton and Charlot (2005a, 2005b) 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. Our result that interactive abilities are well rewarded in cities is complementary.

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

[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. This is referred to as the locus of internal control. See Rotter (1966). See Heckman et al (2006) for the importance to labor markets of "soft skills" such as those measured by the Rotter Index.

uniformity characterizes all sorts of skills, including individual and aggregate measures of cognitive, people, and motor skills.

It is important to point out, however, that our identification of the skill levels in differently sized cities depends on the use of the DOT to characterize worker skills based on the worker's occupation. When we look at heterogeneity within occupations using the AFQT and the Rotter Index, a very interesting result arises: in larger cities, the 90th percentile AFQT is higher (higher intelligence) and the 90th percentile Rotter score is lower (better social adjustment). Carrying out the same analysis for the 10th percentile reveals that the least skilled workers in an occupation have unusually low skills in precisely the situations where the most skilled have high skills. Thus, although mean level of AFQT and Rotter are roughly equal across city sizes, there is greater skill dispersion in larger cities as measured by AFQT and Rotter scores. Thus, although big cities have more of the most skilled workers calculated in this way, big cities also have more of the least skilled workers.

What can explain the surprising degree of skill uniformity? The obvious interpretation is that the high cognitive and social premiums earned in big cities by skilled workers are in equilibrium balanced by the high urban cost of living. This results in a greater absolute number of highly cognitive workers in the big city and an only marginally higher proportion. In a world where city formation is efficient – through Henderson's (1974) developers, for instance – the near uniformity of skills suggests that cities are more efficient when they all have approximately the same mix of skills. This is not to say that they have the same occupation or industry mixes. They do not. Rather, it is efficient for each city to have both highly skilled workers (whether engineers or financiers) and less skilled workers (whether taxicab drivers or waiters). If one instead considered a world where city formation depended on atomistic self-organization, our result would suggest that in a world where all cities are nearly equally skilled, there can be no benefit from migrating. This is not so strong as saying that it is efficient to have a particular spatial division of skills, but it does mean that it is difficult to upset the equilibrium where all cities have roughly the same mix. Put more concretely, financiers are not drawn to leave their banking cities to move to a city of engineers.[2]

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

[2] It is worth pointing out that the skill uniformity we have been discussing is the result that on average big cities have only slightly more skills than small cities. There is skill differentiation between cities within a given size category, although even in that case, the differentiation is typically not especially great.

II. Data

A. 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 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 2,453 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.[3] 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. DOT variables are described in Table 1.

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.[4]

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

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[3] 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 (2005), Wolff (2000, 2003) and Ingram and Neumann (2005).

[4] These categories or similar ones have been previously explored in the literature using the 1977 Fourth Edition DOT. See Miller et al. (1980), Edward Wolff (2003), and Ingram and Neumann (2005).

relative to the general population (*aptg*, *aptv*, and *aptg*). For instance, *gedm* measures mathematical development required 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 use all of the variables capturing the cognitive and motor demands of an occupation simultaneously. High collinearity makes precise estimation impossible. For some of our analysis, therefore, we work with skill indices created using principal component (factor) analysis.[5] In principal component analysis, the objective is to transform a given set of variables to a new set that will be pairwise uncorrelated. This is carried out by finding unit-length linear combinations of a given set of variables such that these variables' variance is maximized. The second subsequent factor is formed to maximize variance uncorrelated with the first factor, and so on. If we let X be the $n \times k$ matrix of DOT variables, where n denotes the number of DOT occupations with k the number of skill variables, the first factor is given by $z_1 = Xa_1$, where a_1 is a k-element vector. The objective is to choose a_1 to maximize $z_1'z_1$ subject to $a_1'a_1 = 1$. If we form the second factor, $z_2 = Xa_2$, we next wish to choose a_2 to maximize $z_2'z_2$ subject to $a_2'a_2 = 1$ and $a_1'a_2 = 0$. In practice, our skill indices are constructed from the first factor, as it tends to account for almost 100 percent of the variation.

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.[6] 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

[5] While we can generate skill measures from a joint factor analysis of the 44 DOT variables, an undesirable consequence of this procedure is that skill indices are orthogonal to each other by construction. To allow for skill complementarities we construct our skill indices based on textual definitions. Extensive robustness checks of this procedure are discussed in Bacolod and Blum (2005).

[6] 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.

requiring attainment of standards.[7] A higher value on the motor skills index indicates a job with greater manual demands. High complexity of the job in relation to things indicates that workers are required to set up and adjust machinery and to work it precisely. Lower values are assigned to jobs where workers have little or no involvement in selecting appropriate tools or in attainment of standards.

Finally, we measure the interpersonal skill requirements of jobs. There are a number of DOT measures that relate to the people skills involved in an occupation. 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 variable *people* measures the interpersonal interaction from most intensive to least (see Table 1). The ranking begins with mentorship being assigned more interpersonal skills than negotiation. This seems to us to be debatable. The ranking continues, moving down to receiving instructions. In our view, receiving and acting on instructions is a kind of interaction. So are mentorship, management, and the rest of the skills that we consider. While the ranking from leader down to follower may be useful for a potential employee to assess his or her skill fit with some occupation, it is not so useful for assessing the interactiveness of the occupation. We will not, therefore, employ this question in our preferred specifications. The variable *dcp* assesses the occupation's requirements regarding the direction, control, and planning of an activity. Again, the classification is designed to identify managerial people skills and not the more general interactive skills with which we are concerned. Similarly, the variable *influ* measures the occupation's requirement for exerting influence. The managerial bias is clear. We will, therefore, not include this measure in our preferred specifications either.

The variable *depl* is much more suitable for our purposes. It assesses the "adaptability to dealing with people beyond giving and receiving instructions." This is the only people skills question that escapes managerial bias. It is thus the only people skills question that we include in our preferred specifications. Having said that, we also estimated models employing other people skills measures and a people skills index.[8] The broad pattern of people skill results reported in the Introduction continues to hold 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

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

[8] Our people skills index is constructed from four DOT variables: complexity of the job in relation to people; adaptability to dealing with people; adaptability to accepting responsibility for direction, control or planning of an activity; adaptability to influencing people in their opinions.

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.

B. Census

Our wage and employment data come from the 1990 1% Census sample (IPUMS).[9] 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 1982-84.[10] 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.[11]

C. 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 the panel structure of this dataset. We use a confidential geocode version of the NLSY in order to identify county of residence.[12] Counties are converted to MSAs using the Census correspondence. Following Moretti (2004), we exclude the military supplemental samples from our analyses.[13] 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. Our data is then an unbalanced panel spanning the years 1979-1996, with a total of 110,659 individual-year observations with non-missing values for all the relevant variables. As with the Census, hourly wages are deflated by the CPI for All Urban Consumers, with base year 1982-84.

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[9] 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. We also do not use the 2000 Census as there is no direct mapping from 2000 Census occupational codes to 1991 DOT codes. Recall that the 1991 DOT was also collected over the 1980s, which may fail to fully characterize occupations in the 2000 Census.

[10] 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.

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

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

[13] The NLSY is comprised of three samples: a nationally representative cross-sectional sample, a set of supplemental samples designed to oversample minorities, and a military sample. All our analyses use weights to obtain nationally representative samples.

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. It thus proxies 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 1,971 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.[14] As a result, we are able to estimate the wage regressions with controls for college selectivity to account for elements of workers' unobserved ability.

III. The allocation of skills to cities

The method described in Section II allows us to describe 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

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[14] Respondents whose last college attended is coded as `unknown' either attended a two-year college or an institution classified by Barron's as special, e.g., art schools or music conservatories. The reason for combining 'special' 'two-year college' and 'non-competitive' to one category is that these are essentially the same in terms of selectivity. Moreover they apply to few NLS respondents (n=136 total).

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, motor, and strength. 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. The former is described in Table 4, which presents location quotients for a range of industries. As usual, these location quotients are defined to equal the share of a city's employment in an industry divided by the share of national employment in an industry. A location quotient greater than one indicates that the industry is over-represented, while a location quotient less than one indicates the reverse. Table 4 presents average values of location quotients by city size class Table 5 carries out the same exercise for occupations. It will become clear that 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.[15]

The second page of Table 3 present 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.[16] 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 have this skill. In medium sized cities, the figure 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.

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.[17,18]

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[15] *gedm* and *gedr* are coded on a six point scale. *gedl* is coded on a five point scale, with a sixth category included for symmetry. It is described as being the "same as category 5." We treat it as identical in constructing the cognitive skill index. The employment shares reported in Table 3 are based on the raw coding of occupations, which does include *gedl* values of both 5 and 6.

[16] 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).

[17] For completeness, we also calculated similar employment shares for the rest of the DOT skills. As can be seen at the bottom of Table 3, the pattern of skill uniformity persists.

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 (2003), Rosenthal and Strange (2005), and Lee (2005).[19]

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 briefly noted in the Introduction, the NLSY includes two variables that address worker quality that go beyond the Census. The best known of these is the AFQT, an intelligence test. The other is the Rotter Index, which measures the control of one's environment. 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 6 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 7 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,

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[18] We recalculated Table 3 excluding non-traded sectors, defined as those that are approximately constant for cities of different sizes. The results are available on request. The removal of these non-traded sectors does not change the pattern of skills and agglomeration.

[19] 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. Details are available on request.

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. Taken together, Tables 6 and 7 reconcile the skill uniformity result and the intuition that big cities are homes to highly-skilled workers. The dispersion shows that indeed some very highly skilled workers are in the most populous places. However, the average skill is not greater, because big cities are also home to some very low-skill workers within given occupations.

IV. A hedonic model of urban labor markets

The data described in Section II will be used to carry out a hedonic analysis of urban labor markets. The hedonic analysis of labor markets in general has a long history. Roy (1950), Tinbergen (1951, 1956, 1959) and Mandelbrot (1962) are seminal. There is also a large body of work carrying out what is in spirit a hedonic analysis of housing and land markets. Alonso (1964), Mills (1967), Muth (1969) are seminal in this literature. Roback (1982) considers both the housing and labor markets. In this section, we set out a simple hedonic model of urban labor markets. The focus of the section will be the properties of 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(-) 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 $w(\mathbf{z},I) = f(\mathbf{z_i},I) - c - r$.

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 how the implicit price of skills depend on agglomeration, $\partial^2 w(\mathbf{z},I)/\partial z_s\partial I$. This is new to this paper.

To understand how individual skills are likely to be impacted differentially by agglomeration, we will present a highly simplified model of the microfoundations of agglomeration economies. There are three broad ways that agglomeration economies might impact productivity, and so wages: matching, learning, and sharing (Duranton-Puga (2004)). The latter two effects involve respectively externalities and public goods.

Suppose that there are two broad elements to a worker's productivity, a baseline level and a bonus. The latter arises as a consequence of random urban synergies, as in Jacobs (1969) and others. It will be modeled here as a kind of matching. Formally, let the worker's marginal product equal

$$MP = A + \delta[\, a - b*d] *s. \tag{1}$$

A is the marginal product of labor unmodified for urban synergies. It includes any benefits from learning and sharing. δ is the probability that an opportunity presents itself to the worker. a is the inherent value of the opportunity if there is a perfectly matched partner with whom to cooperate. d is the distance in characteristic space from the best available partner. b is the cost of adjusting. We will ignore the case where the partner is so far away in characteristic space that the match generates negative surplus. s is the share of the benefits of the match that accrues to a given worker.

In order to explain how skill prices are impacted differently by agglomeration, we must consider how the various parts of the marginal productivity expression depend on a worker's skills. Beginning at the left, A will tend to be higher in a large city because of learning. Although the Silicon Valley is clearly a center of cognition, Marshall's story of cutlery workers argues that motor skills can also be enhanced by agglomeration. A will also tend to be higher in a large city because of sharing. As with learning, it is not difficult to conceive of stories where cognitive, social, and motor skills are all enhanced by urbanization.

Turning now to the second term in the marginal productivity expression, δ reflects the probability of randomly arising opportunities. To the extent that cognitively endowed workers can identify better opportunities, δ will be greater for such workers. Cities are for the smart. To the extent that socially endowed workers are better able to interact with other workers, δ may be higher for these workers as well. It is more difficult to argue that δ is higher for workers with strong motor skills. In any case, motor skills seem to be more closely associated with routine production than with random urban synergies. The variable a reflects the value of these random opportunities. As above, it seems more likely that these urban synergies involve making use of cognitive or social skills than motor skills. If so, then a would be larger for workers with high levels of cognitive and social skills. b is the cost of adaptation. This clearly has strong elements of both social and cognitive skills. Motor skills do not seem likely to help in this kind of adaptation. s is the share of the value of the random match that accrues to a given worker. Again, this is likely to be greater for a worker with cognitive or social skills. Motor skills do not seem especially beneficial.

Taking all of this analysis together, 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 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, there are many agglomerative forces that can impact the relationship between the hedonic price of a given skill and city size. As is common with empirical work on agglomeration, we are not able to separately identify these forces.

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 II, we observe wages and skills, but not rent. We have mentioned rent only in order to more completely characterize the equilibrium.

V. The urban skill premium: Census models

A. 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:

$$\ln w_{isjt} = \gamma_{st}^{'} z_{jt} + X_{ist}\beta_t + \varepsilon_{isjt}\,, \qquad (2)$$

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 skill. 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 II, 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 unobserved skills. Section VI 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.

B. Education and the urban wage premium

Results are reported in Table 8. The baseline model 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 will not report these coefficients in later tables.

The next model 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 (2005) 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.

C. Urbanization and hedonic prices of worker skills

Returning to Table 8, the third model includes cognitive skills. The hedonic price of cognitive skills is positive and significant. The fourth interacts cognitive skill with the logarithm of MSA population. The effect is positive and significant. If we take a worker with 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, -.066, and the interacted cognitive index coefficient, .122, evaluated at the cognitive skill mean of one. Increasing the level of cognitive skill by one standard deviation (.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, a result consistent with 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.

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. The cognitive urban wage premium that we have identified is also consistent with other sources of agglomeration economies. If a worker's cognitive abilities make the worker more specialized – this seems likely – then the urban wage premium associated with cognitive skills is also consistent with labor market pooling. Similarly, we cannot rule out a complementarity between cognitive skills and input sharing or even urban consumption opportunities.

Continuing with Table 8, the fifth column includes only a worker's people skills. These have a positive and significant effect on wage. The next model 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.[20]

Results for motor skills are presented in the seventh and eighth columns. 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 columns of Table 8 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.

D. 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 all the other variables. The results are reported in Table 9. The pattern of results found in Table 8 continues to hold.[21]

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

[20] 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.

[21] 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 8 again continues to hold.

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 10 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 10. First, the pattern of Table 8 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 the 20-40 quintile. 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. 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 10 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

E. 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 11. 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. The heart of our argument was that *depl* measures interactions, the ability to interact with people beyond giving and receiving instructions, while the other variables are oriented to a particular sort of people skills, the ability to manage. 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. Having said that, we do believe that it is worth considering the impacts of other sorts of people skills. We consider three addition variables, *people*, *influ*, and *dcp*. As described in Table 1, these relate respectively to the complexity of the jobs requirements for dealing with people (ranked from top level management down to being managed), the ability to lead, and the ability to direct, control, and plan. Table 10 also reports results on a people index constructed from these three and *depl* using the methods described in Section II.

As reported in Table 11, the results for the index, *people*, and *influ* are identical to the results 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 11 also reports individual skill models for motor skills and for two other DOT measures, specific vocational preparation (*svp*) and strength. The latter is obvious, while the former measures the degree of training and education required to perform a job. 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.

VI. Estimates using the National Longitudinal Survey of Youth.

A. 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 major source of omitted variables bias. Individuals in large cities in a given occupation may themselves be better workers than are workers 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, leading higher quality workers to move to larger cities. To the extent that such unobservable characteristics may be correlated to the amount of cognitive, people, and motor skills workers have, 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 social skills. 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.[22]

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 across MSAs. To exploit this possibility we employ a more general fixed effects specification

[22] See for example, Neal and Johnson (1996) on the AFQT, Bowles, Gintis, and Osborne (2001) on the Rotter score, and Black and Smith (2006) and Brewer, Eide, and Ehrenberg (1999) on college selectivity.

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.[23] 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.

B. 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 first two columns of Table 12 report estimates of wage regressions with the standard controls. They 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. The second column 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.

The third and fourth columns 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

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[23] 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.

examines the returns to "soft skills."[24] 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, Gintis, and Osborne (2001) and more recently, Heckman, Stixrud and Urzua 2006). Just as with AFQT scores, even though the Rotter Index is an important determinant of wages it does not explain the urban premium.

The remaining columns of Table 12 estimate models including the DOT measures of skills and their interactions with population size. Throughout Table 12 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.[25] 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.[26] 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.

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[24] This literature considers, for instance, the returns to beauty (Hamermesh and Biddle 1994), height (Persico, Postlewaite, and Silverman 2004), leadership (Kuhn and Weinberger 2002), and interpersonal skills (Borghans, ter Weel, and Weinberg 2006).

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

[26] 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 10.

The final measure of ability we use is the quality of the undergraduate institution that the NLSY worker last attended.[27] 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.[28]

Table 13 reports the results when we control for college quality. The baseline model 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. 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.

C. NLSY wage regressions with fixed effects

Table 14 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 characteristic 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

[27] This is the college from which they received their degree, as explained in Section II.
[28] See for instance Black and Smith (2006), Brewer et al (1999).

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.

VIII. 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 individual 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 (2006) show in a time series analysis that increases in the prices of cognitive and people skills are an important part of the phenomenon. Our results show 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.

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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 2,500 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
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; papres voter lists from official registration; measures dimensions of bottle to verify setup of bottlemaking conforms to standards
PEOPLE SKILLS VARIABLE:	
depl	adaptability to *dealing with people* beyond giving and receiving instructions.

Table 1. Variables from the Dictionary of Occupational Titles (continued)

DOT VARIABLES	DESCRIPTION
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.
Other DOT variables and Skill Measures:	
aptq	segment of the population possessing *clerical perception* (ability to proofread words & numbers, perceive detail in verbal or tabular material): top 10% of popn; top 1/3 except top 10%; middle third; lowest third except bottom 10%; lowest 10% of popn
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
fif	adaptability to situations involving interpretation of *f*eelings, *i*deas or *f*acts from personal viewpoint
influ	adaptabilty to *influ*encing people in their opinions, attitudes or judgments about ideas or things
sjc	adaptability to making evaluations or decisions based on *s*ensory or *j*udgmental *c*riteria
mvc	adaptability to making evaluations or decisions based on *m*easurable or *v*erifiable *c*riteria
repcon	adaptability to performing *repetitive work* or to continuously performing the same work
pus	adaptability to *performing under stress* when confronted with emergency or dangerous situations
varch	adaptability to performing a *var*iety of duties, often *ch*anging from one to another without loss of efficiency
climb	job requires climbing stairs, scaffolding, etc., &/or balancing
stoop	job requires stooping, kneeling, crouching, &/or crawling
out	job involves activities occuring outside with no protection from weather condition
see	job requires seeing
reach	job requires reaching, handling, fingering
talk	job requires talking and/or hearing
hazard	environmental conditions on job: extreme cold or heat; wet &/or humid; noise &/or vibration; hazards
svp	specific vocational *preparation* for the job: short demonstration; up to 30 days; 30 days-3 mos; 3-6 mos; 6 mos-1 yr; 1-2 yrs; 2-4 yrs; 4-10 yrs; 10+ yrs

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	Laywers	Religious Workers	Veterinarians	Car washers	Sales Person

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	0.270
Cognitive Skills				
GED-M				
Add-Subtract	0.268	0.252	0.221	0.252
Geometry	0.329	0.330	0.327	0.333
Algebra	0.212	0.217	0.231	0.215
Algebra+ Stats	0.162	0.168	0.181	0.167
Calculus	0.027	0.029	0.036	0.030
Advanced Calculus	2.5E-03	3.1E-03	4.1E-03	3.3E-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	0.320
Logical or scientific thinking	0.115	0.117	0.125	0.116
Deal w/very abstract concepts	0.023	0.025	0.027	0.027
GED-L				
2,500 words; simple sentences	0.186	0.172	0.143	0.167
5,000 - 6,000 words; compound	0.245	0.233	0.221	0.227
Read manuals; write essays	0.286	0.297	0.300	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	0.014	0.016	0.019	0.021
APTG				
lowest third except bottom 10%	0.333	0.312	0.277	0.306
middle third	0.436	0.443	0.444	0.436
top 1/3 except top 10%	0.212	0.223	0.253	0.232
top 10% of popn	0.019	0.022	0.025	0.025
APTV				
lowest 10% of popn	0.022	0.020	0.017	0.020
lowest third except bottom 10%	0.423	0.400	0.364	0.391
middle third	0.395	0.411	0.429	0.413
top 1/3 except top 10%	0.152	0.161	0.183	0.171
top 10% of popn	6.8E-03	7.0E-03	7.7E-03	5.6E-03
APTN				
lowest 10% of popn	0.115	0.103	0.086	0.104
lowest third except bottom 10%	0.475	0.466	0.448	0.471
middle third	0.353	0.365	0.384	0.350
top 1/3 except top 10%	0.055	0.063	0.079	0.072
top 10% of popn	2.2E-03	2.6E-03	3.6E-03	3.0E-03
DATA				
Comparing	0.198	0.182	0.156	0.180
Copying	0.082	0.078	0.070	0.075
Computing	0.147	0.145	0.143	0.148
Compiling	0.202	0.211	0.215	0.210
Analyzing	0.222	0.231	0.250	0.230
Coordinating	0.145	0.148	0.159	0.152
Synthesizing	4.0E-03	4.6E-03	6.4E-03	5.1E-03

Table 3. The distribution of skills across cities of different sizes (continued)

Skill Distribution- Share of Population				
	City Size			
	Small	Medium	Large	Very Large
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	0.370	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
APTF				
lowest 10% of popn	0.032	0.034	0.037	0.035
lowest third except bottom 10%	0.818	0.811	0.809	0.802
middle third	0.138	0.142	0.141	0.149
top 1/3 except top 10%	0.012	0.012	0.013	0.015
APTK				
lowest 10% of popn	0.029	0.032	0.036	0.033
lowest third except bottom 10%	0.785	0.78	0.779	0.777
middle third	0.184	0.186	0.182	0.189
top 1/3 except top 10%	2.40E-03	2.50E-03	2.30E-03	2.00E-03
APTM				
lowest 10% of popn	0.03	0.034	0.041	0.037
lowest third except bottom 10%	0.745	0.75	0.759	0.762
middle third	0.216	0.206	0.189	0.189
top 1/3 except top 10%	8.90E-03	9.80E-03	0.011	0.012
APTE				
lowest 10% of popn	0.888	0.89	0.901	0.899
lowest third except bottom 10%	0.095	0.093	0.082	0.084
middle third	0.017	0.017	0.017	0.017
top 1/3 except top 10%	1.30E-04	2.20E-04	2.60E-04	2.80E-04

Table 3. The distribution of skills across cities of different sizes (continued)

Skill Distribution- Share of Population				
	City Size			
	Small	Medium	Large	Very Large
APTS				
lowest 10% of popn	0.158	0.163	0.167	0.171
lowest third except bottom 10%	0.623	0.62	0.614	0.621
middle third	0.174	0.172	0.165	0.158
top 1/3 except top 10%	0.044	0.045	0.054	0.05
top 10% of popn	4.6E-04	4.1E-04	4.7E-04	2.3E-04
APTP				
lowest 10% of popn	0.019	0.022	0.027	0.027
lowest third except bottom 10%	0.735	0.732	0.724	0.731
middle third	0.225	0.225	0.226	0.219
top 1/3 except top 10%	0.02	0.021	0.023	0.023
APTC				
lowest 10% of popn	0.834	0.835	0.833	0.837
lowest third except bottom 10%	0.147	0.145	0.146	0.139
middle third	0.018	0.018	0.019	0.021
top 1/3 except top 10%	1.7E-03	1.8E-03	2.2E-03	2.7E-03
STS				
	0.422	0.419	0.406	0.411
MOTOR INDEX				
3 std deviations below mean	1.1E-03	1.3E-03	2.1E-03	1.7E-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
Specific Vocational Preparation				
short demonstration	0.016	0.014	0.012	0.014
up to 30 days	0.106	0.097	0.086	0.098
30 days - 3 months	0.169	0.163	0.142	0.161
3 - 6 months	0.127	0.131	0.134	0.137
6 months - 1 year	0.126	0.129	0.132	0.124
1 -2 years	0.196	0.194	0.191	0.187
2 - 4 years	0.224	0.234	0.259	0.235
4 - 10 years	0.037	0.039	0.044	0.043
Physical Strength				
STRENGTH				
sedentary	0.412	0.441	0.489	0.478
light	0.427	0.416	0.385	0.394
medium	0.158	0.139	0.123	0.124
heavy	3.10E-03	2.90E-03	2.90E-03	2.50E-03
very heavy	5.80E-04	6.10E-04	5.30E-04	8.00E-04
Other Skills				
SJC	0.616	0.627	0.656	0.619
REPCON	0.207	0.193	0.163	0.186
PUS	0.049	0.047	0.044	0.049
CLIMB	0.096	0.095	0.088	0.084
STOOP	0.292	0.271	0.245	0.245
OUT	0.155	0.144	0.133	0.119
SEE	0.988	0.989	0.99	0.99
REACH	0.996	0.996	0.997	0.997
TALK	0.707	0.727	0.756	0.735
HAZARD	0.305	0.28	0.242	0.249

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 on location quotient and Table 1 for definition of variables. See the text for a discussion of the categories for *gedl*.

Table 4. Spatial concentration of industries: location quotients

Average Location Quotient by Industry				
	City Size			
	Small	Medium	Large	Very Large
Manufacturing	1.09	1	0.91	1.07
Food	1.32	1.12	0.8	0.9
Textiles	1.44	1.5	0.66	0.68
Apparel	0.81	1.07	0.68	1.93
Paper and Pulp	1.39	1.15	0.74	0.92
Printing and Publishing	0.84	0.92	1.04	1.18
Chemicals	1.04	1.16	0.94	0.92
Petroleum	1.24	0.78	0.93	1.04
Rubber	1.28	1.25	0.76	0.91
Leather	1.36	0.88	0.81	1.06
Lumber	1.4	1.26	0.72	0.83
Clay and Glass Products	1.22	1.22	0.86	0.78
Metal	1.27	1.08	0.8	1.02
Machinery	1.17	0.92	1	0.82
Electrical Equipment	1.02	0.78	1.14	0.83
Transportation Equipment	0.97	0.81	0.91	1.41
Instruments	0.97	1.15	0.94	1.01
Mining	1.42	0.99	1.04	0.24
Construction	1.03	1.03	1.03	0.85
Transportation	0.86	0.98	1.06	1.04
Communications	0.82	0.91	1.14	1
Utilities	1.09	1.15	0.94	0.85
Wholesale Trade	0.88	0.95	1.06	1.05
Retail Trade	1.05	1	0.99	0.93
Finance, Insurance, and Real Estate	0.78	0.95	1.08	1.16
Business services	0.79	0.89	1.1	1.15
Professional services	1.01	1	0.98	1.02
Personal Services	0.99	1.06	0.98	0.98
Entertainment Services	0.87	0.96	0.94	1.33
Public admin.	0.99	1.07	1.06	0.77

Table 5. Spatial concentration of occupations: location quotients

Average Location Quotient by Occupation				
	City Size			
	Small	Medium	Large	Very Large
Managers	0.89	0.95	1.09	0.98
Engineers	0.89	0.91	1.14	0.91
Physicians	0.81	0.91	1.06	1.21
Dentists	0.91	1	1.03	1.06
Therapists	0.97	1	1	1.04
College Professors	1.25	1.14	0.88	0.8
Teachers	1.08	1.05	0.98	0.9
Sales Person	0.96	1	1.04	0.96
Food Services	1.08	1	0.97	0.96
Mechanics	1.12	1.06	0.95	0.91
Construction workers	1.06	1.05	0.99	0.89
Machine Operators	1.16	1.11	0.79	1.18
Janitors	1.07	1.02	0.94	1.03
Natural Scientists	0.98	0.95	1.16	0.69
Nurses	1.06	1.03	0.97	0.96
Social Workers	1.07	0.98	0.94	1.07
Technicians	0.97	1	1.07	0.87
Administrative Support	0.91	0.99	1.03	1.07
Personal Services	0.97	1.02	1	1.03

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 definition of location quotient.

Table 6. AFQT and Rotter Index for selected occupations

Panel A. Mean AFQT

	MSA Size				
Occupation	Small	Medium	Large	Very Large	Total
Managers	62.34 (3.09)	53.38 (4.59)	59.97 (2.31)	62.31 (0.84)	62.09 (0.62)
Engineers	72.30 (4.26)	83.22 (6.38)	76.52 (3.09)	75.85 (2.01)	75.97 (1.33)
Therapists	60.82 (5.48)	71.93 (5.78)	54.95 (4.47)	64.64 (3.04)	62.26 (2.02)
College Professors	77.75 (2.60)	72.33 (6.19)	79.25 (2.65)	73.91 (3.06)	75.57 (1.53)
Teachers	64.91 (4.02)	71.41 (4.13)	70.33 (2.79)	64.37 (1.50)	65.22 (1.07)
Sales Person	78.80 (5.25)	82.27 (4.35)	79.94 (5.08)	82.94 (2.29)	82.11 (1.69)
Food Services	53.91 (3.89)	43.32 (5.20)	47.23 (3.60)	44.30 (1.14)	44.57 (0.86)
Mechanics	48.43 (4.05)	45.16 (5.62)	47.93 (3.44)	42.17 (1.36)	42.82 (1.02)
Construction workers	48.91 (3.76)	37.08 (6.20)	40.95 (3.11)	37.34 (1.35)	37.73 (0.99)
Janitors	42.04 (4.42)	45.21 (8.01)	29.39 (2.73)	30.73 (1.63)	30.97 (1.16)
Natural Scientists	75.67 (7.82)	74.37 (4.59)	55.57 (9.55)	82.53 (2.52)	78.34 (2.45)
Nurses	58.26 (7.30)	64.75 (12.35)	70.56 (4.16)	67.16 (2.00)	67.61 (1.62)
Social Workers	48.87 (5.57)	54.71 (3.84)	63.76 (4.62)	56.36 (2.40)	56.85 (1.73)
Technicians	73.49 (3.28)	70.26 (4.06)	69.28 (3.33)	67.03 (1.27)	67.44 (0.93)
Administrative Support	45.87 (4.06)	55.13 (4.08)	56.09 (2.49)	49.55 (0.68)	49.78 (0.55)
Personal Services	65.80 (5.76)	48.67 (3.77)	45.86 (3.47)	43.10 (1.39)	44.03 (1.11)

Panel B. Mean Rotter Index

	MSA Size				
Occupation	Small	Medium	Large	Very Large	Total
Managers	0.50 (0.01)	0.49 (0.02)	0.54 (0.01)	0.51 (0.00)	0.51 (0.00)
Engineers	0.49 (0.02)	0.51 (0.03)	0.50 (0.01)	0.51 (0.01)	0.50 (0.01)
Therapists	0.57 (0.03)	0.60 (0.03)	0.53 (0.03)	0.51 (0.02)	0.52 (0.01)
College Professors	0.47 (0.02)	0.50 (0.03)	0.51 (0.01)	0.49 (0.01)	0.49 (0.01)
Teachers	0.52 (0.02)	0.48 (0.02)	0.51 (0.02)	0.51 (0.01)	0.51 (0.01)
Sales Person	0.50 (0.02)	0.42 (0.03)	0.48 (0.02)	0.51 (0.01)	0.50 (0.01)
Food Services	0.56 (0.02)	0.54 (0.02)	0.54 (0.01)	0.54 (0.00)	0.55 (0.00)
Mechanics	0.54 (0.02)	0.50 (0.02)	0.50 (0.01)	0.52 (0.01)	0.52 (0.00)
Construction workers	0.48 (0.02)	0.52 (0.04)	0.56 (0.01)	0.53 (0.01)	0.53 (0.00)
Janitors	0.53 (0.02)	0.57 (0.02)	0.55 (0.01)	0.56 (0.01)	0.55 (0.01)
Natural Scientists	0.52 (0.03)	0.48 (0.03)	0.48 (0.03)	0.51 (0.02)	0.50 (0.01)
Nurses	0.54 (0.04)	0.51 (0.05)	0.51 (0.02)	0.48 (0.01)	0.49 (0.01)
Social Workers	0.50 (0.02)	0.54 (0.04)	0.55 (0.02)	0.50 (0.01)	0.51 (0.01)
Technicians	0.51 (0.02)	0.49 (0.02)	0.52 (0.01)	0.52 (0.00)	0.51 (0.00)
Administrative Support	0.53 (0.02)	0.53 (0.02)	0.51 (0.01)	0.54 (0.00)	0.53 (0.00)
Personal Services	0.53 (0.02)	0.54 (0.01)	0.56 (0.02)	0.52 (0.01)	0.53 (0.00)

Notes: Weighted averages taken over all NLSY workers 1979-1996. Standard error in parentheses.

Table 7. 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 Person	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

Note: The first row reports the 10^{th} percentile, while the second row reports the 90^{th} percentile.

Table 8. Urban skill premiums: Basic models

	Dependent variable: Log of weekly wages									
	Baseline	Pop*Educ	Cog	+Pop*Cog	Peo	+Pop*Peo	Motor	+Pop*Motor	All Skills	+Pop*DOT
HS degree	0.30148	-0.13801	-0.19417	-0.07979	-0.15583	-0.05942	-0.14028	-0.13789	-0.18783	-0.05187
	[0.00454]***	[0.05246]***	[0.04599]***	[0.04336]*	[0.04998]***	[0.04628]	[0.05312]***	[0.05238]***	[0.04695]***	[0.04264]
College degree	0.67679	0.20066	-0.07638	0.21021	0.1376	0.33296	0.20734	0.25219	-0.05812	0.26702
	[0.00598]***	[0.07216]***	[0.06504]	[0.05721]***	[0.06982]**	[0.06493]***	[0.07382]***	[0.06994]***	[0.06674]	[0.05612]***
Female	-0.30702	-0.30716	-0.32768	-0.3277	-0.32885	-0.32873	-0.30247	-0.30227	-0.31343	-0.31333
	[0.00332]***	[0.00328]***	[0.00284]***	[0.00282]***	[0.00323]***	[0.00322]***	[0.00338]***	[0.00340]***	[0.00285]***	[0.00283]***
Age	0.06284	0.06287	0.05798	0.05798	0.06244	0.0624	0.06282	0.06281	0.05778	0.05774
	[0.00065]***	[0.00064]***	[0.00062]***	[0.00062]***	[0.00064]***	[0.00064]***	[0.00065]***	[0.00065]***	[0.00062]***	[0.00062]***
Age-squared	-0.00062	-0.00062	-0.00057	-0.00057	-0.00061	-0.00061	-0.00061	-0.00061	-0.00056	-0.00056
	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***	[0.00001]***
Married	0.10636	0.10649	0.08727	0.08738	0.10348	0.10356	0.10562	0.10562	0.08726	0.08736
	[0.00218]***	[0.00218]***	[0.00205]***	[0.00204]***	[0.00214]***	[0.00214]***	[0.00218]***	[0.00218]***	[0.00205]***	[0.00205]***
White	0.0889	0.08951	0.04892	0.04881	0.08473	0.08525	0.0875	0.08772	0.04776	0.04819
	[0.00415]***	[0.00409]***	[0.00356]***	[0.00356]***	[0.00403]***	[0.00406]***	[0.00415]***	[0.00414]***	[0.00360]***	[0.00357]***
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	0.03649	0.02318
		[0.00406]***	[0.00352]***	[0.01967]***	[0.00383]***	[0.00414]***	[0.00411]***	[0.02303]***	[0.00358]***	[0.02276]
ln(MSA Pop'n)*HS degree		0.07021	0.06326	-0.06573	0.06875	0.05359	0.07048	0.17298	0.06366	0.0406
		[0.00274]***	[0.00193]***	[0.01962]***	[0.00254]***	[0.00290]***	[0.00273]***	[0.02336]***	[0.00194]***	[0.02277]*
ln(MSA Pop'n)*College degree		0.07277	0.07019	-0.07107	0.07274	0.05055	0.07291	0.17239	0.06999	0.03347
		[0.00400]***	[0.00328]***	[0.02036]***	[0.00382]***	[0.00423]***	[0.00412]***	[0.02400]***	[0.00340]***	[0.02362]
Cognitive skills			1.67424	-0.04153					1.8397	0.95857
			[0.02086]***	[0.25141]					[0.02419]***	[0.29240]***
ln(MSA Pop'n) * Cognitive skills				0.12249						0.06287
				[0.01862]***						[0.02158]***
People Skills					0.10582	-0.30568			-0.07387	-0.39793
					[0.00562]***	[0.07000]***			[0.00551]***	[0.07103]***
ln(MSA Pop'n) *People skills						0.0294				0.0232
						[0.00524]***				[0.00526]***
Motor Skills							0.24009	1.69678	0.05826	0.84427
							[0.02381]***	[0.30636]***	[0.02142]***	[0.26614]***
ln(MSA Pop'n) *Motor skills								-0.10364		-0.05573
								[0.02286]***		[0.01968]***
Constant	-0.08231	0.31107	-1.1156	0.57633	0.34516	0.46053	0.06708	-1.37656	-1.3396	-1.15853
	[0.04206]*	[0.05830]***	[0.05060]***	[0.26528]**	[0.05520]***	[0.05869]***	[0.06308]	[0.31108]***	[0.05392]***	[0.30849]***
Observations	726277	726277	726277	726277	726277	726277	726277	726277	726277	726277
R-squared	0.22	0.22	0.25	0.25	0.22	0.22	0.22	0.22	0.25	0.25

Notes: Standard errors in brackets are clustered at the occupation/MSA level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9. Urban skill premiums: Models with all variables interacted with MSA population

	Dependent variable: Log of weekly wages									
	Baseline	Pop*Educ	Cog	+Pop*Cog	Peo	+Pop*Peo	Motor	+Pop*Motor	All Skills	+Pop*DOT
ln(MSA Pop'n)	0.03569									
	[0.01980]*									
ln(MSA Pop'n)*less than HS		0.03569	0.0264	-0.07757	0.03392	0.03757	0.03576	0.12561	0.02673	0.0167
		[0.01980]*	[0.01866]	[0.03006]**	[0.01967]*	[0.01920]*	[0.01986]*	[0.02709]***	[0.01859]	[0.02866]
ln(MSA Pop'n)*HS degree		0.06559	0.05238	-0.05947	0.06335	0.06186	0.06582	0.15556	0.05268	0.03385
		[0.01353]***	[0.01298]***	[0.02365]**	[0.01364]***	[0.01364]***	[0.01351]***	[0.02310]***	[0.01275]***	[0.02286]
ln(MSA Pop'n)*College degree		0.07068	0.06139	-0.06202	0.06984	0.06268	0.07076	0.15777	0.06108	0.02902
		[0.01500]***	[0.01363]***	[0.02488]**	[0.01492]***	[0.01492]***	[0.01509]***	[0.02441]***	[0.01350]***	[0.02400]
Cognitive skills			1.67312	0.01996					1.83793	0.74857
			[0.02732]***	[0.25148]					[0.02091]***	[0.19200]***
ln(MSA Pop'n) * Cognitive skills				0.11799						0.07766
				[0.01868]***						[0.01395]***
People Skills					0.10594	-0.21883			-0.07358	-0.29768
					[0.00687]***	[0.07043]***			[0.00548]***	[0.05742]***
ln(MSA Pop'n) *People skills						0.02319				0.01607
						[0.00528]***				[0.00427]***
Motor Skills							0.23883	1.49354	0.0575	0.84063
							[0.02352]***	[0.22171]***	[0.01467]***	[0.15159]***
ln(MSA Pop'n) *Motor skills								-0.08926		-0.05552
								[0.01644]***		[0.01078]***

Notes: Standard errors in brackets are clustered at the occupation/MSA level. * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions also include controls for age, age-squared, sex, marital status, race, dummies for high school graduate and college graduate, all interactions with ln(MSA Pop'n), and a constant.

Table 10. Urban skill premiums: Nonlinear models

	Baseline	POP*Educ	Cog	+Pop*Cog	Peo	+Pop*Peo	Motor	+Pop*Motor	All Skills	+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	0.036	0.034
		[0.00406]***	[0.00354]***	[0.00445]***	[0.00380]***	[0.00402]***	[0.00417]***	[0.00582]***	[0.00359]***	[0.00642]***
ln(MSA Pop'n)*HS		0.070	0.064	0.041	0.069	0.056	0.069	0.082	0.065	0.050
		[0.00274]***	[0.00209]***	[0.00366]***	[0.00253]***	[0.00281]***	[0.00257]***	[0.00439]***	[0.00195]***	[0.00584]***
ln(MSA Pop'n)*College		0.073	0.071	0.044	0.072	0.054	0.072	0.082	0.071	0.051
		[0.00400]***	[0.00358]***	[0.00477]***	[0.00378]***	[0.00404]***	[0.00381]***	[0.00506]***	[0.00351]***	[0.00636]***
Cognitive Skills										
20th - 40th pct			0.085	-0.238					0.082	-0.265
			[0.00571]***	[0.07225]***					[0.00669]***	[0.08705]***
40th - 60th pct			0.204	-0.223					0.191	-0.204
			[0.00570]***	[0.07476]***					[0.00607]***	[0.07947]**
60th - 80th pct			0.331	-0.230					0.339	-0.041
			[0.00676]***	[0.08352]***					[0.00756]***	[0.09538]
80th - 100th pct			0.434	0.126					0.444	0.286
			[0.00642]***	[0.07709]					[0.00719]***	[0.09087]***
People Skills					0.102	-0.225			-0.007	-0.192
					[0.00474]***	[0.05935]***			[0.00487]	[0.06389]***
Motor Skills										
20th - 40th pct							0.017	0.090	0.081	0.172
							[0.01005]*	[0.12642]	[0.00758]***	[0.08688]**
40th - 60th pct							-0.125	0.097	0.022	0.234
							[0.00632]***	[0.07821]	[0.00631]***	[0.07759]***
60th - 80th pct							0.012	0.249	0.099	0.329
							[0.00664]*	[0.08463]***	[0.00617]***	[0.07617]***
80th - 100th pct							0.041	0.390	0.089	0.394
							[0.00624]***	[0.07925]***	[0.00675]***	[0.08559]***

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

Table 10. Urban skill premiums: Nonlinear models (continued)

	Baseline	POP*Educ	Cog	+Pop*Cog	Peo	+Pop*Peo	Motor	+Pop*Motor	All Skills	+Pop*DOT
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]*
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]***
People* ln(MSA Pop'n)						0.023				0.013
						[0.00443]***				[0.00473]***
Constant	-0.082	0.311	0.456	0.634	0.350	0.438	0.368	0.173	0.392	0.420
	[0.04206]*	[0.05830]***	[0.05029]***	[0.06179]***	[0.05477]***	[0.05714]***	[0.06038]***	[0.07966]**	[0.05162]***	[0.08760]***
Observations	726277	726277	726277	726277	726277	726277	726277	726277	726277	726277
R-squared	0.22	0.22	0.25	0.25	0.22	0.22	0.22	0.22	0.25	0.25

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

Table 11. 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	-0.1197	DEPL	0.10582	-0.30568	THINGS	0.0051	0.16502
	[0.00378]***	[0.04807]**		[0.00562]***	[0.07000]***		[0.00351]	[0.04473]***
DATA* ln(MSA Pop’n)		0.02423	DEPL* ln(MSA Pop’n)		0.0294	THINGS* ln(MSA Pop’n)		-0.01139
		[0.00359]***			[0.00524]***			[0.00335]***
GEDR	0.47808	-0.09675	DCP	0.23521	0.12569	APTF	0.06085	0.56412
	[0.00687]***	[0.09250]		[0.00637]***	[0.07879]		[0.01275]***	[0.17170]***
GEDR* ln(MSA Pop’n)		0.0411	DCP* ln(MSA Pop’n)		0.00781	APTF * ln(MSA Pop’n)		-0.03582
		[0.00690]***			[0.00588]			[0.01282]***
GEDM	0.34803	0.00104	PEOPLE	1.03608	-0.50017	APTK	-0.05469	0.44226
	[0.00471]***	[0.05782]		[0.02770]***	[0.33810]		[0.01400]***	[0.19707]**
GEDM* ln(MSA Pop’n)		0.0248	PEOPLE* ln(MSA Pop’n)		0.10966	APTK * ln(MSA Pop’n)		-0.03532
		[0.00430]***			[0.02528]***			[0.01469]**
GEDL	0.34456	-0.13937				APTM	-0.20604	0.75809
	[0.00488]***	[0.05994]**					[0.01453]***	[0.18387]***
GEDL* ln(MSA Pop’n)		0.03461	OTHER SKILLS			APTM * ln(MSA Pop’n)		-0.0686
		[0.00446]***						[0.01372]***
APTG	0.72267	-0.10188	SVP	0.3724	0.03797	APTE	-0.084	0.18988
	[0.00993]***	[0.12200]		[0.00532]***	[0.06683]		[0.00718]***	[0.08814]**
APTG * ln(MSA Pop’n)		0.05886	SVP* ln(MSA Pop’n)		0.02389	APTE * ln(MSA Pop’n)		-0.01956
		[0.00905]***			[0.00498]***			[0.00659]***
APTV	0.58614	-0.29235	STRENGTH	-0.89681	0.66795	APTP	0.31743	0.92132
	[0.00842]***	[0.10174]***		[0.02740]***	[0.32492]**		[0.00973]***	[0.12608]***
APTV * ln(MSA Pop’n)		0.06279	STRENGTH* ln(MSA Pop’n)		-0.11162	APTP * ln(MSA Pop’n)		-0.04295
		[0.00755]***			[0.02427]***			[0.00939]***
APTN	0.55963	0.00258				APTC	-0.04671	0.25536
	[0.00778]***	[0.10066]					[0.00764]***	[0.09599]***
APTN * ln(MSA Pop’n)		0.03977				APTC * ln(MSA Pop’n)		-0.02149
		[0.00747]***						[0.00715]***
						STS	0.00957	0.13283
							[0.00416]**	[0.05223]**
						STS * ln(MSA Pop’n)		-0.00879
								[0.00392]**

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

Table 12. NLSY Wage models with controls for AFQT and Rotter Index

	Baseline	POP*Educ	+AFQT	+Rotter	+AFQT,Rotter	Cog	+Pop*Cog	People	+Pop*People	Motor	+Pop*Motor	All Skills	+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	0.03889	0.01386
		[0.00680]***	[0.00678]***	[0.00680]***	[0.00678]***	[0.00670]***	[0.02935]	[0.00677]***	[0.00703]***	[0.00673]***	[0.03317]***	[0.00666]***	[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	0.05314	0.02273
		[0.00399]***	[0.00401]***	[0.00399]***	[0.00401]***	[0.00351]***	[0.03018]	[0.00396]***	[0.00453]***	[0.00395]***	[0.03299]***	[0.00345]***	[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	0.06661	0.02906
		[0.00633]***	[0.00633]***	[0.00634]***	[0.00634]***	[0.00571]***	[0.03194]	[0.00628]***	[0.00743]***	[0.00659]***	[0.03314]***	[0.00593]***	[0.03769]
AFQT(i)-AFQT(occ)			0.00105		0.00101	0.00212	0.00212	0.00105	0.00104	0.001	0.001	0.00209	0.00209
			[0.00015]***		[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	-0.08563	-0.08502
				[0.02590]***	[0.02623]**	[0.02526]***	[0.02526]***	[0.02622]**	[0.02625]**	[0.02596]**	[0.02597]**	[0.02511]***	[0.02513]***
Cognitive Skills						1.65061	0.60257					1.88596	1.60439
						[0.04651]***	[0.40427]					[0.05281]***	[0.47567]***
Ln(MSA POP)*Cognitive skills							0.0733						0.01985
							[0.02844]***						[0.03317]
People Skills								0.02853	-0.28625			-0.12214	-0.46728
								[0.01107]***	[0.11438]**			[0.01201]***	[0.12306]***
Ln(MSA POP)*People									0.02204				0.02418
									[0.00816]***				[0.00866]***
Motor Skills										0.4673	1.21051	0.10603	0.12982
										[0.04967]***	[0.45959]***	[0.05038]**	[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.* significant at 10%; ** significant at 5%; *** significant at 1%. 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.

Table 13. NLSY Wage Models with controls for college quality

	Baseline	POP*Educ	+AFQT,Rotter	+AFQT,Rotter	+AFQT,Rotter	+Cog	+Pop*Cog	+Peo	+Pop*Peo	+Mot	+Pop*Mot	All Skills	+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	0.01316	0.19387
	[0.03070]***	[0.22557]	[0.22626]	[0.22595]	[0.22651]	[0.21757]	[0.21971]	[0.22624]	[0.22863]	[0.22869]	[0.22841]	[0.21851]	[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	0.1102	0.29339
	[0.02880]***	[0.23550]	[0.23494]	[0.23505]	[0.23466]	[0.22349]	[0.22669]	[0.23381]	[0.23861]	[0.23523]	[0.23553]	[0.22555]	[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	-0.31054	-0.1293
	[0.02550]***	[0.15158]	[0.15169]	[0.15162]	[0.15170]	[0.14596]**	[0.15096]	[0.15161]	[0.15556]	[0.15185]	[0.15186]	[0.14594]**	[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	-0.23979	-0.07123
	[0.02966]***	[0.20935]	[0.20884]	[0.20957]	[0.20905]	[0.19780]	[0.20301]	[0.20780]	[0.20787]	[0.21433]	[0.21209]	[0.20280]	[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	0.03891	0.0145
		[0.00680]***	[0.00678]***	[0.00680]***	[0.00678]***	[0.00670]***	[0.02932]	[0.00677]***	[0.00704]***	[0.00673]***	[0.03306]***	[0.00666]***	[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	0.05314	0.02334
		[0.00399]***	[0.00401]***	[0.00399]***	[0.00400]***	[0.00351]***	[0.03016]	[0.00396]***	[0.00453]***	[0.00395]***	[0.03287]***	[0.00345]***	[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	0.05232	0.01532
		[0.01395]***	[0.01403]***	[0.01399]***	[0.01405]***	[0.01325]***	[0.03386]	[0.01401]***	[0.01457]***	[0.01423]***	[0.03510]***	[0.01335]***	[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	0.05079	0.01359
		[0.01478]***	[0.01475]***	[0.01475]***	[0.01473]***	[0.01393]***	[0.03432]	[0.01469]***	[0.01553]**	[0.01479]***	[0.03545]***	[0.01408]***	[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	0.07808	0.04101
		[0.00797]***	[0.00800]***	[0.00799]***	[0.00801]***	[0.00747]***	[0.03234]	[0.00799]***	[0.00914]***	[0.00808]***	[0.03275]***	[0.00746]***	[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	0.07389	0.03767
		[0.01241]***	[0.01240]***	[0.01243]***	[0.01241]***	[0.01139]***	[0.03379]	[0.01227]***	[0.01261]***	[0.01291]***	[0.03591]***	[0.01189]***	[0.03952]
ln(MSA Pop'n)	0.05636												
	[0.00351]***												
Cognitive Skills						1.64752	0.60327					1.8826	1.59798
						[0.04650]***	[0.40393]					[0.05270]***	[0.47364]***
ln(MSA POP)*Cognitive skills							0.07304						0.02006
							[0.02841]**						[0.03302]
People Skills								0.02836	-0.28608			-0.1219	-0.46552
								[0.01103]**	[0.11420]**			[0.01199]***	[0.12275]***
ln(MSA POP)*People									0.02202				0.02408
									[0.00815]***				[0.00864]***
Motor Skills										0.46951	1.22406	0.10847	0.14381
										[0.04947]***	[0.45791]***	[0.05010]**	[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. * significant at 10%; ** significant at 5%; *** significant at 1%. Dependent variable: Log 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.

Table 14. NLSY wage models with individual*MSA fixed effects

	Baseline	POP*Educ	+Pop*Cog	+Pop*Peo	+Pop*Motor	+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	88759	88759	88759	88759	88759	88759
Number of ID*MSA	13776	13776	13776	13776	13776	13776
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. * significant at 10%; ** significant at 5%; *** significant at 1%.
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.

Urban Interactions: Soft Skills vs. Specialization

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Abstract

Agglomeration allows two quite different sorts of increasing returns: interactions among agents such as knowledge spillovers and a highly refined division of labor. A worker's "soft skills" enhance the former, but the specialization allowed by thick agglomerated markets may make soft skills less necessary. This paper considers the role of soft skills in cities and industry clusters in light of the different natures of the two sorts of agglomeration economy.

The paper begins by specifying a model of the microfoundations of agglomeration economies where soft skills allow agents to interact more productively with each other. The model shows that soft skills will be more valuable in cities and industry clusters if agglomeration provides agents with more opportunities to interact fruitfully. On the other hand, to the extent that agglomeration produces thick, specialized markets that make interaction easier, it may be a substitute for soft skills. The net effect of soft skills is thus theoretically ambiguous. If the opportunity effect dominates, there should be higher levels of soft skills in large cities and clusters. If the specialization effect dominates, the reverse will hold.

In order to consider the role of soft skills empirically, the paper matches several measures of soft skills from the Dictionary of Occupational Titles to Census data to evaluate the soft skills – agglomeration relationship. The within-industry average level of soft skills is found to be higher in cities but not in centers of an industry's activity. These results are consistent with the opportunity effect dominating for urbanization but not localization. Furthermore, large cities typically contain a disproportionate share of the industry's workers with both very high and very low levels of soft skills, a result consistent with the presence of both opportunity and specialization effects. Thus, the paper shows that cities are not unambiguously centers of soft-skill enabled interaction. Industry clusters are even less so.

I. Introduction

Like a long list of papers before it, this paper will deal with the role of interactions in cities. This paper's innovation will be the focus on the worker skills that allow interaction. These are known as "soft" skills, in contrast to the "hard" skills associated with cognitive or physical ability. There is growing recognition among economists that these skills are highly and increasingly valuable (Heckman et al (2006)).

There has long been recognition that the development and use of skills is one of the ways that cities and industry clusters create value. For instance, Marshall (1890) considers knowledge spillovers and the matching of skills to needs, while Jacobs (1969) considers the application of skills to "new work." Both Marshall and Jacobs recognize the importance of the specific class of skills that allow valuable interactions to take place. In other words, although neither uses the term, they both implicitly consider soft skills. It is typical for the interest of Marshall or Jacobs in an aspect of agglomeration to have launched a thousand intellectual ships, but it did not in this case. Although there has been a great amount of very valuable research on interactions (some of it reviewed below), there has not been either theoretical or empirical work that has focused primarily on soft skills.

The purpose of this paper is to specify a model of soft skills in a system of cities and to empirically evaluate its predictions. The model will involve an analysis that explicitly considers how soft skills are involved in the generation of agglomeration economies. The key assumption of the model is that soft skills facilitate interaction. To the extent that spatial concentration presents workers with more opportunities to interact, soft skills will be more valuable where activity is concentrated. We refer to this as the *opportunity effect.* This is not the only effect at work, however. One of the advantages of agglomeration is that it makes markets thicker. This allows better matching of workers to jobs (see Duranton-Puga (2004)). In this case, market thickness can potentially be a substitute for workers' soft skills. This *specialization effect* operates in the opposite direction of the opportunity effect. The relationship between soft skills and agglomeration is therefore ambiguous in theory.

We will make use of data from the Dictionary of Occupational Titles (DOT) and the 5% sample of the Census to help resolve this ambiguity. The DOT characterizes a large number of skills that are required to perform particular occupations. If one assumes that workers are assigned to jobs in some sort of hedonic market clearing process, then one can infer a worker's skills from the occupation in which the worker is employed. We use this hedonic imputation to characterize several sorts of worker soft skills. These include the worker's ability to interact outside of authority relationships (captured by the DOT variable *depl*), the worker's ability in direction, control, and planning (*dcp*), and the worker's ability to influence others (*influ*). The set of soft skill measures also includes the DOT measure of *people* skills, a ranking which goes from receiving instructions up to mentoring. Finally, we aggregate all these measures through factor analysis into a people skills index (*peoindx*). Taken as a group, these variables characterize a worker's interactiveness in a number of dimensions.

The DOT data are matched with the Census data to allow us to characterize the relationship between worker skills and agglomeration. We impute a worker's skills from the occupation the worker carries out. We consider the two traditional sorts of agglomeration, the formation of large cities (urbanization) and industry clusters (localization). We then estimate a range of models of the relationship between urbanization and localization and the soft skill measures described above. The most basic models are ordinary least squares (OLS) estimates of the relationship of mean skills to local characteristics controlling for industry fixed effects. More rigorous models involve a two-stage procedure where the effect of agglomeration on skill levels at various percentiles of a city-industry's skill distribution are calculated using feasible generalized least squares (GLS).

Taken as a group, the results are strongly consistent with the idea that cities and industry clusters are not simply centers of soft-skill enabled interaction. The OLS estimates of regressions of mean skill levels do show a higher average level of all of the soft skills in larger cities. These effects are statistically significant, but they are moderate in magnitude. The same estimates show, however, that the average skill level of an industry's workers is, in most cases, either statistically significantly lower where the industry is concentrated or is insignificant. These results are consistent with cities fostering soft-skill enabled interaction (a strong opportunity effect), but industry clusters not doing so (a strong specialization effect).

The two-stage regressions of the entire skill distribution clarify this distinction further. For most of the skill measures, an increase in city population increases the skill level at the 75th and 90th percentiles of the skill distribution, but decreases the skill level at the 10th and 25th percentiles. The increase in soft skills found in large cities is thus of a very particular form: the skills at the top end of the distribution. The low skill workers in large cities are by our measures even less skilled than the low skill workers in small cities. In industry clusters, in contrast, the skill level at the 75th and 90th percentiles tend to be lower, while the levels at the 10th and often the 25th are higher. This is the opposite pattern, where the tails of the distribution become thinner, and industry clusters are places for moderately skilled workers. All of this is consistent with the tensions in the theoretical model. Although concentrations of economic activity reward fluid and unplanned interaction, they also are associated with a refined division of labor where interaction requires lower levels of soft skills.

This analysis builds on several strands of research on the theory of agglomeration. First, it builds on models of spatial interactions (see Beckman (1976) or Helsley-Strange (2007)). These models allow for interaction and look at the implications for urban spatial structure. They do not consider soft skills directly. Second, it builds on models of the microfoundations of agglomeration economies, especially matching.   See Fujita and Thisse (2002) and Duranton and Puga (2004) for excellent surveys, the former at book length, the latter a long book chapter. Regarding matching, we build primarily on Helsley-Strange (1990, 1991, 2002). Third, the paper builds on models of systems of cities. See Henderson (1974) for a model with a black box production function and Helsley and Strange (1990) for a strategic model with an explicit matching microfoundation. Finally, and most importantly, we build on research that directly address the roles of flexibility and adaptation in the generation of urban increasing returns, including Vernon (1960), Duranton-Puga (2001), and Strange et al (2006).

The analysis also builds on a growing literature on skills in cities. Contributions here include Glaeser-Mare (2001), Wheeler (2001, 2006), Bacolod et al (2007), Elvery (2007), Lin (2007), Scott (2007) and Scott and Mantegna (2007). Glaeser and Mare (2001) and Wheeler (2001, 2006) document the existence of an urban wage premium. Fallick et al (2006) document a positive relationship between worker turnover and the concentration of the computer industry in the Silicon Valley. Elvery (2007) constructs a measure of worker skills based on an occupation's mean wage in medium sized cities. This measure is then employed to identify the skill intensity of establishments in small, medium, and large cities. Elvery's primary finding is that skill intensity increases with city size. Lin (2007) uses the changes in the DOT to identify "new work" as in Jacobs (1969). None of these papers directly consider soft skills. Scott (2007) and Scott and Mantegna (2007) do consider soft skills, among other things. The former finds a positive correlation between the DOT measure *people* (discussed below) and city size, while the latter shows a positive relationship between various measures of an occupation's behavioral requirements and city size.

The rest of the paper is organized as follows. Section II sets out a theoretical analysis of agglomeration that captures urbanization, localization, and both the opportunity and specialization effects. Section III discusses the matching of DOT and Census data to characterize the levels of a worker's soft skills. Section IV presents the results of the estimation of the within-industry relationship between soft skills and agglomeration. Section V concludes.

II. A model of soft skills and agglomeration

A. Overview

This section will carry out a theoretical analysis of soft skills and agglomeration. Agglomeration can take two forms, the formation large cities (urbanization) and industry clusters (localization). The analysis will address both the role of soft skills in a model of the microfoundations of agglomeration economies and the allocation of soft skills in a system of cities. This will generate predictions of the spatial distribution of soft skills that will be the foundation of the paper's later empirical work.

B. Basic model

We will begin with a basic model of agglomeration. There is one type of worker in the model, which we will call a production worker. These workers are assumed not to have soft skills. We conceive of these workers as engaging in routine tasks, the sort of activities that do not require soft skills. The workers choose between two cities, indexed j = {1, 2}, with the total number of production workers N being divided into city populations n_1 and n_2. The cities differ in their inherent productivity, θ_j. This can be seen as capturing both natural advantages and productivity enhancing historical accidents. The latter could include, for instance, the presence of unusually able local entrepreneurs whose businesses spin off entrepreneurs who are themselves unusually able. See Sorenson and Audia (2000) and Klepper (2007) for evidence of this sort of spinoff process for particular industries. We will adopt the notation that cities are ranked in decreasing inherent productivity, $\theta_1 > \theta_2$.

We suppose that there are agglomeration economies, so there exists a range of industry employment levels for the two cities over which the marginal product of a production worker is increasing in city's scale, which can be interpreted as either its population or as the employment in a given industry. In the latter case, N should be interpreted as an industry's total employment and n_i as the industry's employment in city i. We are interested in analyzing a case where there is a nontrivial system of cities in the sense that both cities are populated. We will therefore assume that a worker's marginal product is given by $f(n,\theta)$, with $\partial f/\partial n < 0$ and $\partial^2 f/\partial n^2 < 0$. We could have instead assumed that f(-) increased in n up to some sufficiently low level of population and decreased thereafter. In such a situation, as with all systems of cities models, both cities will be on the downward sloping side of the production worker marginal product curve. We make the global assumption to allow us to focus more tightly on soft skills, which is our real interest. We have included the city heterogeneity parameter θ to generate asymmetry in the equilibrium system. We therefore assume $\partial^2 f/\partial n \partial\theta > 0$. Finally, regarding the costs of agglomeration, we will suppose that each worker bears cost c(n), where c(-) is increasing and convex. We have suppressed rents here. One could conceive of c(-) as capturing the net costs of inhabiting a city of population n, where differential rents have been redistributed.[1]

In this situation, the utility of a production worker in city j with population n_j will be

$$u = f(n_j,\theta_j) - c(n_j). \quad (1)$$

[1] There is no reason that the asymmetry must be present only in f(-); it could be in c(-) also or instead, or there could be a separate term capturing the differences between locations.

An equilibrium in this model is a pair of city populations such that utility is equal in the two cities and all production workers are located somewhere. Substitution of the population adding up constraint $n_1 + n_2 = N$ into (1) gives the conditions that define equilibrium:

$$[f(n_1,\theta_1) - f(N\text{-}n_1,\theta_2)] – [c(n_1) - c(N\text{-}n_1)] = 0, \quad (2a)$$

$$n_2 = N - n_1. \quad (2b)$$

The key characteristic of the equilibrium in (2a) and (2b) is the asymmetric allocation of production workers in equilibrium. It is straightforward to show that $n_1 > N/2$ when $\theta_1 > \theta_2$ and that $dn_1/d\theta_1 > 0$. The better location will have more production workers, and the gap between the locations will grow with the quality of the better location, *ceteris paribus*. We believe that this captures the actual pattern of systems of cities and of industrial localization. Regarding the latter, the Silicon Valley is the heart of the computer software industry, but it is not the only location where the activity occurs. Hollywood is the heart of the film and television production industry, but movies and TV programs are created at other locations. We will now consider how workers with soft skills are attracted to core and peripheral locations in industries in a model with an explicit microfoundation of agglomeration.

Before doing so, it is useful to discuss how our very simple specification could be generalized or modified. The generalization of (2a) and (2b) to an arbitrary number of populated cities, J, is clear. For an arbitrary number of potential city sites, the marginal unpopulated city would offer utility at zero population insufficient to attract production workers from other cities. This is the familiar result that under autarkic city formation, city utility equals utility under autarky. If this were a system of cities governed by competitive developers (as in Henderson (1974)), the competition would be imperfect because of the heterogeneity of the sites. Free mobility would still give equal utility, but the price charged by the developer of the better city would be larger than in the inferior city, which would reduce the equilibrium n_1 and increase n_2. See Helsley and Strange (1993) for a model of this sort of imperfect competition. Since our goal is to set out a tractable model of a system of cities that allows the consideration of soft skills, having established the qualitative robustness of the key aspect of our analysis – the allocation of production workers to cities of asymmetric sizes in equilibrium – we will not comment further on different modeling approaches to city formation.

Finally, it is worth making a few observations regarding the model's interpretation. We want to have a simple model that generates predictions about both urbanization and localization. The urbanization interpretation, where n_j represents population, is clear. Similarly, if one were to suppose, following Henderson (1974), that the cities specialize, then the model is, without modification, also a model of the clustering of individual industries. The model would obviously become much more complicated if there were multiple industries co-agglomerating in cities. In this case, in order to characterize a city's attractiveness, one would need to consider both the positive agglomeration effects that spill across industry boundaries and inter-industry congestion. It would still be true that for any given industry, in equilibrium there would be more activity in the location that was more attractive for that industry. This asymmetry is all that is required to motivate our empirical exercises.

C. A simple model of adaptation and interaction

There is a long tradition of research in urban economics that has focused on the role of cities as centers of innovation. While it is sensible to consider patentable processes and products, as many have, it is obvious that much innovation is of a more mundane sort. Vernon (1960) writes of high-fashion dressmakers who require an ever-changing range of buttons. Such producers benefit from being able to work with local button producers, an obvious sort of adaptation. Jacobs' (1969) much repeated story of the invention of the brassiere also has adaptation at its core. The inventor, Ida Rosenthal, was a dressmaker. The adaptation was built on both the demands of customers and of the production capacities that a dressmaker possessed. Fashion is obviously a good example of an industry where adaptation is constant. Oscar Wilde writes that, "Fashion is a form of ugliness so intolerable that we have to alter it every six months." It is clearly not the only such industry. Jacobs' discussion of new work is all about adaptation:

> The process by which one sort of work leads to another must have happened millions of times in the whole history of human development...a cleaner of suede clothing is now starting to bottle and sell her cleaning fluid for people who want to clean their own suede; a chest and wardrobe manufacturer is starting, for a fee, to analyze what is wrong with one's household or office storage arrangements; a playground designer is starting to make and sell equipment for playgrounds and nursery schools; a sculptor is starting a line of costume jewelry; a designer of theater costumes is launching himself as a couturier; a couturier is starting a boutique; an importer of Italian marble is starting to manufacture marble-top tables; a clothing store is starting classes in teen-age grooming and dieting. (Jacobs (1969), pp. 53-54)

We will present a model of adaptation that will emphasize the role of soft skills. As in the above stories, adaptation is by its nature non-routine and nearly always involves working with other people. It thus requires soft skills. We therefore introduce another sort of worker to the model, referred to as analysts, a term that we intend be taken quite broadly. These are workers who have soft skills. Analysts include all workers who have soft skills and so take on non-routine tasks. This class of workers thus includes managers, entrepreneurs, and knowledge workers, among others. There are M of these workers, who will be divided between the two cities, with $M = m_1 + m_2$.

We assume that for analysts as for production workers, labor markets are competitive, and so analysts are paid their marginal products. In general, there are two elements to an analyst's marginal product. The first is the baseline level of productivity, reflecting the analyst's productivity in routine tasks. The second is based on the analyst's ability to carry out non-routine activities. It is these latter activities that will be the focus of the paper. We will therefore suppose for simplicity that analyst's wages depend only on the ability to carry out non-routine activities. Nothing would change were we to add to this a baseline of productivity in commonplace tasks. We also suppose that analysts must work as analysts rather than as production workers. Finally, we assume that employers are risk neutral, so that the uncertain elements of an analyst's marginal product are paid their expected values.

Specifically, we suppose that analysts create value by adapting to randomly arising opportunities. We will model this as matching. Suppose that each analyst has an address x on the unit circle that describes the activities that he or she is ideally suited to carry out. If an analyst carries out some other arbitrary activity y, there will be a loss in value that increases with the distance between the analyst's idiosyncratic abilities and the activity. We will suppose the loss to be linear, implying that the value of a analyst with skill x carrying out activity y is given by $a - b*|x-y| = a - b*d$. a and b are positive parameters, and d has the natural interpretation of the distance in the space of activities.

In this model, b captures an analyst's soft skills. An analyst with a lower level of b suffers a lower adaptation cost when required to perform a non-routine task. This interpretation fits well with managers, who must adapt the direction they give to other workers as the business environment changes. It fits also with entrepreneurs who must make choices of product positioning, production, and entry to best take advantage of fluctuating entrepreneurial opportunities. It fits as well with knowledge workers whose primary value-creating activity is in integrative thinking, the adaptation of a set of knowledge to new circumstances. The interpretation is also consistent with the stories of adaptation introduced above, both the adaptation carried out by Vernon's button makers and by Jacobs' synergistic creation of the brassiere.

The value of non-routine/adaptive activity depends on the arrival of opportunities to carry out this sort of activity. We suppose that the arrival of opportunities is related to the local economic environment. Specifically, we suppose that agglomeration increases an analyst's exposure to opportunities. Formally, we suppose that $\rho(n+m)$ represents the probability that an opportunity arises for a given analyst, where m is the number of analysts in the analyst's city, n is the number of production workers, and their sum is the degree of agglomeration. We further suppose that $\rho'(n+m) > 0$ and $\rho''(n+m) < 0$, implying that although clustering enhances opportunities for adaptation, it does so at a decreasing rate. It is worth reiterating that there are various aspects of the local environment that might impact adaptation opportunities.

Opportunities might be related to the overall scale of population in the worker's city. They might instead be related to the scale of the analyst's industry. The model is meant to capture both of these.

D. Soft skills and agglomeration economies: the opportunity and specialization effects.

Under the assumptions set out above, an analyst's wage will equal the analyst's expected value arising from random opportunities. This will depend on the expected adaptation distance associated with an opportunity. There are various ways that one might conceive of this. We will adopt a simple one that generates tractable closed form solutions. Suppose that analysts are evenly distributed on the unit circle. If there are m of them, then their addresses are {0,1/m, 2/m,...m-1,m}. Suppose that opportunities arise according to a uniform distribution on the unit circle. A given analyst with address x will be best-suited to respond to those opportunities whose address y is closer to x than to any other analyst. The expected distance will thus be the expectation of |x-y| conditional on y being closer to x than to any other analyst's address. In this setup, the expected distance from a given random opportunity to the nearest analyst who will act on it will be 1/2m. The worker will be closet to 1/m of total opportunities. As with production workers, we suppose that the increasing and convex function c(n+m) captures the costs of living in a concentrated environment.

In these circumstances, an analyst's expected value from adaptation equals

$$\nu = \rho(n+m)/m * [\, a - b*(1/2m)] - c(n+m). \tag{3}$$

This depends on the size of the market according to the probability of a worker having opportunities, $\rho(n+m)/m$, the value of a given adaptation, $[\, a - b*(1/2m)]$, and congestion costs, $c(n+m)$. In considering agglomeration effects, it is natural to consider the impact on analyst payoffs of increases in the scale of local activity. There are two elements of this, the population of local production workers and the population of local analysts. Regarding the former, we have

$$\partial\nu/\partial n = [(\rho'(n+m)/m^2] * [\, a - b*(1/2m)] - c'(n+m) > 0. \tag{4}$$

The assumptions we have made regarding the process of adaptation are sufficient to ensure a complementarity between production workers and analysts. More production workers create more opportunities for adaptation, and this increases the value of analysts. This tendency encourages agglomeration.

Regarding the latter soft skill workers, we have a much more interesting expression:

$$\partial \nu/\partial m = (\rho(n+m)/m) * [b*(1/2m^2)] \quad + [(\rho'(n+m)m - \rho(n+m)) /m^2]*[a - b*(1/2m)] \\ - c'(n+m). \qquad (5)$$

The congestion term is easy to understand and requires no further comment. The second term is parallel to the effect discussed above in the $\partial \nu/\partial n$ expression. The sign depends on the first term in brackets, equal to (d/dm) (ρ(n+m)/m)). If the flow of opportunities increases enough to outweigh the sharing of the opportunities more broadly (an effect absent above), then this term is positive.

The interesting and surprising result is found in the first expression, which is unambiguously positive. A thicker market decreases adaptation costs. While the result is well-known, the implications have not been fully thought out. The first expression means that an increase in the number of other soft skill workers reduces the necessity to carry out adaptation because the market's thickness ensures that analysts are highly specialized in the sense that they are closely matched to the tasks that they perform. This effect will be crucial below. The ambiguity of the second term (sharing vs. opportunities) and the opposite sign of the first term (specialization) together mean that the overall tendency to agglomeration is ambiguous. Soft skill workers benefit unambiguously from the opportunities created by production workers, but the effect associated with other analysts is unclear.

To see how the value of agglomeration depends on the level of soft skills, we obtain

$$\partial^2 \nu/\partial n \partial b = [(\rho'(n+m)/m^2]*[- (1/2m)] < 0 \qquad (6)$$

and

$$\partial^2 \nu/\partial m \partial b = (\rho(n+m)/m) *[(1/2n^2)] \quad + [(\rho'(n+m)m - \rho(m)) /m^2]*[- b*(1/2m)] \qquad (7)$$

The negative sign of $\partial^2 \nu/\partial n \partial b$ in (6) means that with more opportunities, workers with more soft skills (lower values of b), will have higher payoffs. This encourages agglomeration. As above, the situation is much more complicated when one considers the impact of the agglomeration of other analysts.
The expression for $\partial^2 \nu/\partial m \partial b$ in (7) captures the tendency of workers with increasing lower levels of soft skills (high b; costly adaptation) to agglomerate. If we suppose that (d/dm) (ρ(n+m)/m) > 0, the expression is ambiguous. The first term is positive. A larger market is thicker. Thickness allows specialization, which reduces the need to adapt. This, in turn, reduces the extra value that soft skills contribute. This *specialization effect* is opposed by the *opportunity effect* in the second term. When a

larger market allows more opportunities, soft skills are more valuable since they increase the value of adapting to opportunities.

We have thus uncovered a surprising ambiguity in the relationship between soft skills and agglomeration. Jacobs' (1969) analysis of new work in cities is filled with stories of fluid, unplanned, and informal interactions. Vernon (1960) likewise gives considerable emphasis to the "unstable" nature of the products in increasing returns industries. This is also the spirit of the elegantly formal treatments of agglomeration such as Ogawa and Fujita (1980) and Fujita and Ogawa (1982) and other papers of that sort. Although none of this work mentions soft skills explicitly, in every instance cities are presented as being centers of the sort of interaction that one would expect to be enhanced by soft skills. The microfoundations analysis that we have carried out here suggests that agglomeration is also important for a different reason. The additional force at work is the specialization allowed by market thickness. In thicker markets, analysts end-up only taking on tasks that are close to their ideal activities, and less adaptation is necessary.

Our analysis shows, therefore, that soft skills and specialization are, in a sense, substitutes. Soft skills are valuable because they allow adaptation, the more productive carrying out of non-routine activities. In contrast, specialization means that soft-skill enabled interaction is not necessary, since the thick division of labor reduces the need for adaptation. This substitutes relationship between soft skills and agglomeration means that workers with soft skills may not be unambiguously attracted to concentrations of economic activity. This will be the key issue addressed in our empirical analysis.

Before turning to the empirics, however, we must characterize the equilibrium of the system of cities with both analysts and production workers. Thus far, we have established the existence of conflicting tendencies for soft skills to be better rewarded in industry clusters. It should not be surprising that these conflicting tendencies will manifest themselves in the quantities of soft skills available in different places. To the extent that the opportunity effect dominates, we would expect to see a greater amount of soft skill in clusters. To the extent that the specialization effect dominates, we would expect the reverse.

Parallel to the case of production workers, we suppose that there are M analysts in total, and that each of them must be allocated between the two cities. An interior equilibrium in the system now requires four conditions be met:

$$[f(n_1,\theta_1) - f(N-n_1,\theta_2)] - [c(n_1+ m_1) - c(N-n_1+M- m_1)] = 0 \tag{8a}$$

$$n_2 = N - n_1 \tag{8b}$$

$$[\nu(m_1,n_1) - \nu(M-m_1,N-n_1)] = 0 \tag{8c}$$

$$m_2 = M - m_1. \tag{8d}$$

The first two conditions are minor modifications of (2a) and (2b), the conditions governing equilibrium in the production-workers only model above. The second two are the parallel conditions for analysts. They depend on the relative strengths of the opportunity and specialization effects. In the even that the specialization effect were to dominate, then it is possible that high soft skill workers would not be attracted to agglomerations. We will address this issue directly in our empirical work below.

A few final comments on specification are in order. First, we have assumed that opportunities to adapt arise symmetrically from the population of production workers and other analysts. This is not necessary. However, if opportunities were related more strongly to the other analysts, then more weight would be placed on the ambiguous $\partial v/\partial m$ effect, increasing the likelihood that soft skills are not attracted to concentrations of activity. Second, we included the local attractiveness parameter θ in order to generate an asymmetric system of cities. Our empirical work will be based on the existence of cities of different sizes and on a given industry being allocated in clusters of different sizes as well. In the model, it is straightforward to obtain the comparative static result that more productive locations would tend to have more of both kinds of worker. In contrast, if all sites were identical, then the equilibrium would be symmetric as in Henderson (1974).

The third comment is more subtle. We have established the existence of the specialization effect where soft skills and agglomeration are substitutes using a matching model of the microfoundations of agglomeration economies. It is important to note that the substitutes relationship applies rather generally across agglomeration forces. For instance, the matching model can quite naturally capture labor market pooling (Helsley and Strange (1990)). It also can capture input sharing (Helsley and Strange (2002)) or knowledge spillovers (Berliant et al (2006)). The general result that agglomeration and soft skills are substitutes will be present in all of these cases. Highly adaptable workers may be especially valuable outside of agglomerations, since it is unlikely that an employer can find a worker who closely fits the needs of the job. Inside of an agglomeration, finding a great fit will be much more likely. Highly adaptable workers can be very valuable in managing a complicated and flexible supply chain. They may not be required in a thick market where the local industrial system is highly refined. Highly adaptable workers may be crucial in innovating and in implementing new processes outside of an agglomeration, while adaptation may be less necessary in a thick market where everyone understands everyone else's activities.

The fourth and final comment concerns places where one might be most likely to find opportunity and specialization effects. There is no reason to believe that the opportunity and specialization effects will be the same for both urbanization and localization. Instead, it would be natural to suppose that the opportunity effect will tend to be more strongly associated with urbanization than with localization. This is clearly the spirit of the Jacobs' (1969) quote above. It is also consistent with the "nursery city" theory and evidence in Duranton and Puga (2001). Their finding that relocations of industry tend to be towards locations where the industry is concentrated suggests that cities are about adaptation while clusters are about routine. In a similar vein, it would also be natural to suppose that the opportunity effect would be more important for workers near the top of an industry's skill distribution than for those near the bottom. Taken together, these speculations suggest that the strongest evidence of an opportunity effect would be found in cities and at the top of the skill distribution, while the strongest evidence of specialization effects would be in industry clusters and at the bottom of the skill distribution. Before we can look for this sort of evidence, we must now describe the data that will allow our estimation.

III. Data

A. Overview

As mentioned in the Introduction, the DOT data describe the soft skill requirements of occupations. Our approach to identifying individual worker soft skills follows the approach taken in Autor et al (2003) and Bacold and Blum (2005) by supposing that in a labor market equilibrium workers are matched to jobs that require skills that they have. To be concrete, a worker currently employed as a janitor lacks the skill of direction, planning, and control (*dcp*). The analysis of soft skills is based on this hedonic imputation procedure.

As discussed at length in prior work, the hedonic equilibrium in labor markets has fractions, and so the hedonic imputation of worker skills from occupations is imperfect. It is, however, consistent with well-established economic theories of labor markets. Furthermore, there is no large dataset that directly measures the different aspects of workers soft skills. It is clear that creating such a dataset would be very costly, and it is not at all clear that a survey of workers' self-reported soft skills would really produce a better measure of, say, a worker's ability to direct, control, and plan than would the judgment of an employer. We thus believe that this approach is both reasonable and in case the best that can be done to allow one to analyze soft skills in large datasets. Nonetheless, we will occasionally comment below on problems that might arise from the hedonic imputation procedure.

B. Dictionary of Occupational Titles

The data used in this paper brings together information from the U.S. Census and the 1991 Revised Fourth Edition of the Dictionary of Occupational Titles (DOT). The DOT is a database that characterizes the skill requirements of occupations. In particular, it characterizes interpersonal skill requirements. Matching the DOT with the Census allows us to characterize the soft skills of workers by occupation, industry, and geographic location.

The Fourth Edition of the DOT released in 1977 provides measures of 44 different skills required to perform over 12,000 detailed occupations in the US labor market. These measures 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. Primarily, US Department of Labor occupational analysts "go out and collect reliable data which is provided to job interviewers so they may systematically compare and match the specifications of employer job openings with the qualifications of applicants who are seeking jobs through its facilities." (United States Department of Labor Office of Administrative Law Judges Law Library). For the Fourth Edition of the DOT approximately 75,000 on site job analysis studies were conducted. These studies are then supplemented by information obtained through extensive contacts with professional and trade associations.[2]

The Revised Fourth Edition was released in 1991 and used data collected throughout the 1980s to revise the skill requirements of occupations as well as to include new occupations. As a result, the information on 1,692 of the 12,742 occupations was changed (including some occupations that disappeared from the US labor market) and 761 new occupations were included in the dictionary. These new DOT titles were mostly computer-related jobs. 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 (2005), Wolff (2003) and Ingram and Neumann (2005).

Of the 44 different job characteristics available in the DOT, four capture distinct aspects of interpersonal skills (see Table 1, Panel A). The variable *dcp* assesses if an occupation requires direction, control, and planning of an activity. Clearly, this variable captures one element of soft skills, the ability to manage. Similarly, the variable *influ* measures if an occupation requires exerting influence. It therefore captures a different type of interpersonal skill that is also somewhat related to the ability to manage, although in this instance the "management" takes place outside of an authority relationship.

To make things more concrete, it is useful to consider some specific occupations. To that end, Panels A and B of Table 2 list some occupations that do or do not require these various soft skills. Beginning with the *dcp* and *influ* columns of Panel B, positions of authority such as financial managers and supervisors are required to engage in direction, control, and planning of activities (*dcp*=yes). However, financial managers and supervisors are not required to exert influence over others (*influ*=no). In contrast, teachers and lawyers are required to have influence over others (*influ*=yes), presumably over schoolchildren in the case of teachers and a jury or judge in the case of lawyers. But, while teachers are also required to direct, control, and plan activities (*dcp*=yes), lawyers are not (*dcp*=no).

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[2] For more information, see http://www.oalj.dol.gov/libdot.htm.

The third measure of interpersonal skills we use is the variable *depl*. It assesses an occupation's requirements of "adaptability to dealing with people beyond giving and receiving instructions." In our view, this variable captures the widest range of interactions among workers, and arguably is the one that fits best with the fluid, unplanned, and informal interactions usually thought to happen in cities and industry clusters. As the *depl* column in Panel B of Table 2 shows, the four occupations discussed in the previous paragraph require the ability to dealing with people beyond giving and receiving instructions, as do Physicians and Salespersons (*depl*=yes). Mathematicians, Insurance Underwriters, and Machine Operators do not require this skill (*depl*=no).

The last DOT measure of interpersonal skills we use is the *people* variable. Differently than the previous three variables, the *people* variable attempts to rank the *degree* of interpersonal interaction required by an occupation (see Table 1, Panel A). The ranking starts with mentorship being assigned more interpersonal skills than negotiation, and then continues moving down to receiving instructions. 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). While we do not see the ranking as being beyond dispute -- does mentorship really require more interpersonal skills than negotiation? -- we do view the arrangement of the people functions as being hierarchical in a more general sense. For instance, it seems hard to dispute that "instructing" people (*people*=7) involves a broader set of interactive skills than "taking instructions" (*people*=1).

We also employ factor analysis to construct an index of the people skills required by each DOT occupation by combining information from the four variables just described. The index *peoidx* is the first principal component formed from a weighted linear combination that maximizes the common variation across all four soft skills measures, subject to the constraint that the sum of the squared vector weights is equal to one. The variable is constructed to have mean of 100 and standard deviation of 10.[3] Panel A of Table 2 lists the top and bottom occupations requiring interactive skills, as defined by each of the soft skills measure we use, including the people skills index. 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 analysis in the next sections uses the five measures of interpersonal skills described above. In this way we aim at capturing, as much as the data available allows us, the multiple aspects of the interpersonal skills that are useful in the US labor market.

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[3] The index is constructed for occupations at the DOT level. See Bacolod and Blum (2005) or Bacolod et al (2007) for a somewhat more detailed discussion of the construction of the people index variable.

C. Census

Our employment data comes from the 2000 5% Census sample (IPUMS).[4] The sample we use includes employed individuals aged 25 to 70 not living in group quarters with positive weeks, hours, and wage income reports, whose occupational categories were merged with DOT information, and with non-missing or identifiable MSAs.

We then match DOT skill measures to workers in the IPUMS. There is no direct mapping of 1991 DOT occupational codes to the 2000 census occupation codes. There is, on the other hand, a mapping of 1991 DOT codes to 1990 census occupation codes from the National Crosswalk Service Center.[5] IPUMS Census samples from 1950 onward happen to be coded with a uniform occupation coding scheme where, in particular, 2000 census occupation codes are mapped to common 1990 definitions (variable *occ1990*). We then match DOT skill measures to workers in the 2000 Census using the mapping of 1991 DOT codes to 1990 occupation codes further aggregated to the uniform classification scheme *occ1990*.[6] There are fewer census occupational categories (469 in 1990) than the nearly 13,000 DOT occupational categories. Therefore to create soft skill measures for the coarser census occupation classifications we first average our skill measures across DOT occupations within each census occupation.

One important point to note is that, by computing these averages without using employment weights, we are in effect assuming that each DOT occupation within a census occupation is equally important across local labor markets in the US. In the best of worlds this just adds noise to our measures and makes it less likely that we find statistically significant relationships between soft skills, agglomeration, and localization. If, however, the mis-measurements are correlated to city size or industry concentration, then they will actually bias the coefficients of any relationship we attempt to estimate. Fortunately, we can assess how relevant these mis-measurements are using a special version of the April 1971 CPS monthly file. This file was coded with both 1977 DOT and 1970 census occupation codes, and it was issued by the National Academy of Sciences (2001). In this file a committee of experts assigned individual DOT occupation codes to the 60,441 workers in the CPS sample. For the occupations in this special file we can compute our measures of interpersonal skills for each census occupation using CPS sampling weights.[7] We can then compare the employment weighted and the unweighted measures of soft skills and test if they are statistically different. For our purposes, it is not sufficient to assess whether weighted and unweighted averages of soft skills are different, but also whether or not they vary

[4] We have also carried out all of the analysis using the 1990 Census. The results are consistent with those that will be reported below.
[5] http://www.xwalkcenter.org/index.html
[6] With this procedure we are able to obtain a match for over 99% of the workers in the 2000 Census.

[7] For reference, 3,885 DOT occupations are represented in this special CPS sample.

systematically across SMSA status. For the 60,441 workers in that sample, we also know if they live in a SMSA or not. Therefore we can compute In/Out SMSA employment weighted measures of our interpersonal skills across census occupations, and use these to test if any mismeasurement in our soft skill measures due to the lack of employment weights is correlated to urbanization. We perform this analysis (the details are provided in Appendix A) and strongly reject the hypothesis that the weighted and the unweighted measures are statistically different across occupations. We also reject the hypothesis that In SMSA and the Out SMSA employment weighted measures are statistically different.

As a final note on this issue, it is worth asking why the weighted and unweighted measures are so similar. Upon inspection, we find that, even though different DOT occupations within a Census occupation have different employment weights, they usually have very similar interpersonal skill requirements. For instance, any of the different types of managers that are distinguished in the DOT but not in the Census is required to be able to deal with people beyond giving and receiving orders. Therefore, for many of the occupations employment weights do not matter at all, and for the remaining occupations they have a minor effect.

D. Descriptive statistics

Using the matched dataset, Tables 3 and 4 describe some broad characteristics of the soft skills composition of industries and cities, respectively. Table 3 shows the top and bottom five industries ranked by the share of workers in occupations that require interpersonal skill measures *depl, dcp,* and *influ*. In addition, Table 3 shows the top and bottom five industries ranked by workers' mean interpersonal skill measures *people* and *peoidx*.

There are several noteworthy features of Table 3. First, the same industries show up as the top and bottom five industries across the different soft skill measures. For instance, in manufacturing Apparel is the industry with the least share of workers in occupations that require *depl* (23% of the jobs in the industry require this skill), the least requiring *dcp* (16%), the lowest in *people,* and the lowest in *peoidx*. Similarly, Newspaper Publishing is the manufacturing industry with the highest share of jobs requiring *depl, influ, people,* and *peoidx*. However, Newspaper Publishing does not appear in the top 5 manufacturing industries requiring *dcp*. This is the second noteworthy point of Table 3. While there is commonality across soft skill measures in terms of its industry concentration, there is also variation across measures. By utilizing several measures to capture different aspects of interpersonal skills used in the labor market, we hope to have a better characterization of the relationship between soft skills and cities and industry clusters.

Finally, soft skills tend to be more or least concentrated in the industries we would expect. For instance, including all sectors of the economy, Child Care Services have a very high share of jobs requiring soft skills. So are Elementary and Secondary Schools (top 5 in all). This is what we would expect, since teachers and child care workers—whose people skills are to motivate, discipline, and/or educate children—also constitute a major factor in the production of child care services and education, the output of this sector.

Table 4 shows the top and bottom 5 MSAs ranked by the share of employment in occupations that require interpersonal skills or by the mean levels of soft skills measures. Similar to the first two points made above about Table 3, while the same MSAs show up as the top or bottom, there is also variation across measures. For instance, while Flint, MI is ranked among the cities requiring the least *dcp, influ, people,* and *peoidx*, it does not appear in the bottom 5 for *depl*. Also as expected, college towns—such as Gainesville, FL (home to University of Florida), State College, PA (Penn State), Bryan-College Station, TX (Texas A&M)—tend to have high concentrations of soft skills, in particular of *influ*, *people*, and *peoidx*. Perhaps most importantly for our purposes, we do not observe the country's biggest cities – New York, Los Angeles, and Chicago – anywhere in this table. Neither do we observe homes of well-known industry clusters such as San Jose or San Francisco. This begins to suggest that the relationship between soft skills and cities and clusters is not a simple monotonic one. The next section explores this issue more deeply.

IV. Estimation

A. Overview

A natural way to begin is to consider the relationship between a given worker's skill and the presence of activity in the worker's industry and total city population. This involves estimating the following regression:

$$\mathrm{DOT}_{ikm} = \delta_k + \alpha\ \mathrm{Cluster}_{km} + \beta\ \log(\mathrm{Pop}_m) + \nu_{ikm} \qquad (9)$$

DOT_{ikm} is the amount of soft skills (*depl*, etc.) of individual *i* working in industry *k* and living in MSA *m*. The right-hand-side contains measures of employment shares by industry and MSA (the *Cluster* variable) and MSA population.[8] Equation (9) includes controls for industry fixed-effects since the relationship predicted by the model operates within industries. Equation (9) is estimated for each of the soft skills discussed in Section III using Census individual weights. It is also estimated for measures of the workers' education like the number of years of schooling and the highest grade completed. Because of the grouped nature of the data, the standard errors are clustered at the industry-MSA level. Estimation is

[8] The logarithm of MSA population is used in order to capture the apparent non-linear relation between population and soft skills we find in the raw data. All results of the paper hold when MSA population is used instead.

carried out separately for manufacturing and for selected service sectors. The theory set out in Section II generates predictions of the location of a mobile industry. It is natural, therefore, to estimate (9) for manufacturing. The theory, of course, applies also to tradable service industries. We therefore also estimate (9) for select services whose outputs are plausibly at least partially tradable. We anticipate noisier estimates in these models.

The results for manufacturing sectors are presented in Table 5. Panel A presents the results on the education measures. In addition to being interesting by themselves, these results provide a benchmark against which we can compare the relationship between soft skills, agglomeration and localization. Larger cities have proportionally more workers with less than a high-school degree and with a college degree. Of course, they also have fewer workers with a high-school degree. This pattern echoes Berry and Glaeser (2005). In our data, we find that a doubling of MSA population corresponds to roughly 0.7 log points, which in turn is associated with a .027, -.032, and .015 point change in workers with less than high school, high school, and college degrees respectively. Given that by construction these education measures are {0,1}, one way to interpret these numbers is that doubling the MSA population raises the probability that a worker in that MSA will have less than a high school degree by 0.027 points. In our sample 11% of the workers have less than a high school degree (see Table 1 Panel B). Thus, doubling the MSA population raises the probability of finding a worker with less than a high school degree by about 25%. Doubling an MSA's population also increases the probability of finding a worker with college degree, but by only 5% and lowers the probability of finding a worker with high school degree by about 13%. Overall, larger cities have workers with fewer years of education, although the effect is small. Doubling the population lowers the average education by .07 years.

The effects of localization on education measures are fundamentally different. Industry clusters also have more college graduates, but fewer workers with a high-school diploma or less - although the effect for workers with less than high-school is not statistically significant. The effects are small in magnitude. Moving from a location with 1% of an industry's employment to one with 2% is associated with a decrease of roughly .4% in the probability of finding a worker with a HS degree, and an increase in the probability of finding a worker with a College degree of .6%.

Panel B of the same Table shows the results for the soft skills. On average, an industry's occupations that require soft skills are found in larger cities but not where the industry is clustered. A doubling of MSA population is associated with a .015 point change in *depl*. Given that 60% of workers are in occupations that require *depl*, a doubling of MSA population raises the probability of finding a worker in an occupation that requires *depl* by a about 2.5%. For the other {0,1} skill measures *influ* and *dcp*, the result of a population doubling is an increase in the analogous probability of about 5% and 2% respectively. These relationships are all statistically significant, but the magnitudes are relatively modest.

For the skill variable *people*, which runs from 1 to 9, the effect is roughly 0.5 points. To see what this means, recall that this variable ranks the complexity of a job in relation to people. A doubling of population is associated with an average increase in skills that is half of the difference between two consecutive ranks, for example instructing and negotiating or negotiating and mentoring. For the index of interpersonal skills (*peoindx*), the effect of doubling an MSA's population is to increase the mean value of the index by .30. This is roughly three one-hundreds of one standard deviation of the distribution of this index. In summary, although population size and average soft skills are positively correlated, none of the individual measures increases especially strongly with MSA population

In contrast, the within-industry relationship between soft skills and the presence of own-industry employment is not positive. In fact, for three of our measures of soft skills (*depl, influ*, and *peoidx*) industry clusters have less soft skills on average - although only the effect on *influ* is statistically significant. For this skill, the effect of moving from a location with 1% of an industry's employment to one with 2% is associated with a decrease of roughly 0.002 in the probability that an occupation requires it. This is a small effect. The effects on *dcp* and on *people* are positive but only statistically significant for *dcp*. Again, the magnitudes of the effects are small. In sum, the effects of the presence of own industry employment on the average level of soft skills are small, sometimes negative and sometimes positive.

These results establish the pattern that will appear in much of the subsequent estimation. Urbanization is associated with an increase in the average level of soft skills. Localization is not. This result is complementary to Duranton-Puga (2001) model of nursery cities. In this paper, theoretical analysis establishes the possibility that a large and diverse city is important in the development of prototypes, but the production of a settled product is more economically accomplished in a specialized industry cluster. Our result shows that large cities are associated with soft skills, which are presumably the sorts of abilities that would be useful in the experimental phases of production. Industry clusters are not associated with soft skills, which is consistent with the Duranton-Puga model of the production of a settled product and with our notion of a specialization effect that is inimical to soft skills.

Table 6 carries out more analysis in a similar vein, presenting the results for a sample with the following service sectors: FIRE[9], motion pictures and video industries, internet publishing and broadcasting, data processing, legal, accounting, advertising, architectural and engineering, design, computer system design, scientific, and technical consulting, scientific research and development, and management services. Clearly, the choice of where to locate different parts of the production process of and industry is only available for tradable sectors. This is why we focus on the subset of services sectors mentioned above. They are, at least on paper, potentially tradable.

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[9] FIRE includes: banking, savings institutions, non-depository credit, securities, commodities, funds, trusts, and other financial investments, insurance carriers, and real state.

Panel A shows the results for worker education. The pattern regarding agglomeration effects found in manufacturing sectors is also present in these services sectors: larger cities have more workers with less than high school and college degrees and less with high school degrees. The magnitude of the effects is very different, though. The effect on workers with less than a high school education is less than one-tenth of the one in manufacturing and the one on workers with a high school education is about one-half. On the other side, the effect on workers with college degrees is almost twice as large. Overall, larger cities have workers with more years of education in services sectors, but again, the effect is small. The effects of localization on education measures in the services sectors are very similar to the ones in manufacturing. Although the magnitudes are different, overall the effects are small.

Panel B of the same table shows the results for our soft skills. Like the manufacturing sectors, services sectors also locate their occupations that require soft skills in larger cities. These agglomeration effects are smaller than the effects estimated for manufacturing. In the case of *depl*, for example, it is 75% smaller than the effect in manufacturing which was itself not large. The effect of industry concentration is fundamentally different than the patterns found in manufacturing sectors. For all of our measures of soft skills industry clusters have less soft skills on average, but the effects continue to be small.

As a group, these results are consistent with the key patterns from manufacturing in the soft skill - agglomeration relationship. There is evidence consistent with both opportunity and specialization effects. The former appear to dominate for urbanization, while the latter are strongest for localization.

C. The distribution of skills

Although illustrative, the evidence from means does not paint a complete picture of the role of soft skills in cities. Section II's theory gives us reason to wonder whether the upper and lower tails of an industry's skill distribution are affected in the same way that the mean is. Does a production worker in manufacturing have the same opportunities for adaptation that a manager does in a large city or industry cluster? Do the tasks performed by both sorts of worker become highly specific as the division of labor becomes more refined in a city or cluster? These questions can only be answered by considering the entire distribution of worker skills.

In this section, we will look at the distribution of skills by industries across locations. As noted above, it is essential that any estimates of this distribution must consider the tendency of the industry to employ workers with soft skills. The predictions of our model are about the allocation of soft skills within industries. The mean model in (9) does so by including fixed effects. Estimating a similar model for the percentiles of the skill distribution would have the usual incidental parameters problem of estimating fixed effects in a nonlinear model (see Arellano and Honore 2001 and Koenker 2004). Because of this problem, we do not estimate a quantile model. Since the explanatory variables of interest only vary at the MSA-industry level, and because we want the industry fixed effects to have a pure location shift effect on the skill distribution, we use a 2-stage procedure that groups the individual data at the MSA-industry level.[10] Under the usual assumptions of exogeneity of the regressors, the estimates of the model described below can be shown to be consistent.

In the first stage we net out the industry-specific component of the distribution of the soft skill and calculate percentile values of the skills by industry and MSA:

$$\mathrm{DOT}_{ikm} = \delta_k + \sum_q \alpha_{km}^q d_{km}^q + \eta_{ikm}. \tag{10}$$

In (10), d_{km}^q equals one if the individual is at the q^{th} percentile of the skill distribution in industry k and MSA m and zero otherwise. In the second stage we then use $\hat{\alpha}_{km}^q$ to estimate the relationship between the percentile values of the distribution of skills and industry concentration and agglomeration at the MSA-industry level. For q={10, 25, 50, 75, 90}, we estimate:

$$\begin{bmatrix} \hat{\alpha}_{km}^{10} \\ \hat{\alpha}_{km}^{25} \\ \hat{\alpha}_{km}^{50} \\ \hat{\alpha}_{km}^{75} \\ \hat{\alpha}_{km}^{90} \end{bmatrix} = \begin{bmatrix} \kappa^{10} \\ \kappa^{25} \\ \kappa^{50} \\ \kappa^{75} \\ \kappa^{90} \end{bmatrix} + \begin{bmatrix} \gamma^{10} \\ \gamma^{25} \\ \gamma^{50} \\ \gamma^{75} \\ \gamma^{90} \end{bmatrix} * \mathrm{Cluster}_{km} + \begin{bmatrix} \lambda^{10} \\ \lambda^{25} \\ \lambda^{50} \\ \lambda^{75} \\ \lambda^{90} \end{bmatrix} * \log(\mathrm{Popn}_m) + \begin{bmatrix} \varepsilon_{km}^{10} \\ \varepsilon_{km}^{25} \\ \varepsilon_{km}^{50} \\ \varepsilon_{km}^{75} \\ \varepsilon_{km}^{90} \end{bmatrix} \tag{11}$$

The system of equations above is estimated jointly by feasible GLS to allow for correlation of the residuals. The standard errors are bootstrapped to take into account the fact that the LHS variables are estimated parameters. This approach also allows for clustering of the standard errors at the MSA level. An additional issue is that in some industry/MSA-pairs the number of workers sampled can be very small. This is because employment in these industries and MSAs is itself small. In these cases the estimated percentile values should be very noisy and not carry much information. We deal with this by restricting the sample to industry/MSA-pairs for which there are at least 20 workers sampled. We would argue that this sample restriction is a sensible way to consider the soft skills - cities/clusters relationship.[11]

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[10] The 2-stage approach used in Moretti (2004) is similar to the one employed here, except that it aggregates up to the MSA level and focuses only on mean values.
[11] None of the results are driven by this restriction.

This quantile approach imposes very little structure on the relationship between the skill distribution and agglomeration. As an alternative, we also estimate the effects of urbanization and localization on the 90th-10th and the 75th-25th percentile differences:

$$\left(\hat{\alpha}_{km}^{90}-\hat{\alpha}_{km}^{10}\right)=\kappa^{90,10}+\gamma^{90,10}*\text{Cluster}_{km}+\lambda^{90,10}*\log\left(\text{Popn}_m\right)+\varepsilon_{km}^{90,10}$$
$$\left(\hat{\alpha}_{km}^{75}-\hat{\alpha}_{km}^{25}\right)=\kappa^{75,25}+\gamma^{90,10}*\text{Cluster}_{km}+\lambda^{75,25}*\log\left(\text{Popn}_m\right)+\varepsilon_{km}^{75,25} \quad (12)$$

The equations above are estimated separately and, as before, the standard errors are bootstrapped and clustered at the MSA level. The sample is also restricted to industry/MSA-pairs for which there are at least 20 workers sampled. This approach will allow us to test the relationship of agglomeration to extreme levels of skills.

Before presenting the results, it is worth noting that the interpretation of the analysis of the percentiles of the skill distributions for variables that can only assume values {0,1} – *depl, influ, dcp* - is slightly different than for continuous variables, but carries the same message. For instance, a positive and significant coefficient for the 75th percentile of *dcp* with respect to city population indicates that the 75th percentile of the distribution of *dcp* is more likely to be an occupation that requires direction control and planning in a large than in a small city.

Table 7 reports the estimates for the manufacturing sector. The first panel shows the effect of urbanization and localization on the values of the different percentiles of the distribution of years of education. Larger cities' most educated workers clearly have more years of education. The coefficients are all highly significant. A similar pattern emerges for industry clusters, with locations with greater shares of an industry's activity having more educated workers. However, the cluster estimates are quite noisy, and many are insignificant. Table 7 also shows the effect of urbanization and localization on the inter-percentile values of the distribution of years of education. Larger cities are more unequal in the way education is distributed across workers. For instance, doubling a city's population is associated to an increase of .5 years in the difference between the number of years of education of the 90th percentile and the 10th percentile worker. Industry concentration has a significant and positive effect on the 75th-25th percentile difference, but an insignificant positive effect on the 90th-10th difference.

The remaining panels of Table 7 relate to soft skills. The clear pattern in the estimates is that the distribution of soft skills is wider in large cities and more concentrated in the clusters. For MSA population (urbanization), the *depl, influ,* and *dcp* skill values are significantly greater for both the 75th and 90th percentiles and lower for the 10th and 25th percentiles. The results are mixed for the 50th percentile, with a significant positive coefficient for *depl* and *dcp,* and a significant negative coefficient for *influ*. In contrast, for the Cluster variable (localization), the coefficients are negative and significant for the 75th and 90th percentiles and positive for the 10th and 25th for the three variables in every instance but one (the 90th percentile for *dcp*), and that coefficient is still negative but insignificant. For the 50th percentile, the coefficient for *depl* is negative and significant, while for *dcp* and *influ* the coefficients are positive and significant. The entire pattern makes it very clear that soft skills are related to urbanization very differently than to localization. While we are not able to identify the opportunity and specialization effects themselves, the results are consistent with the discussion at the end of Section III.

The results for *people* and *peoindx* are similar. The only difference is that the tendency for urbanization to be associated with a decrease in soft skills at the bottom of an industry's skill distribution is less pronounced, affecting the tenth percentile of the distributions but not the twenty-fifth percentile.

Table 8 reports the estimates for the sample of potentially tradable service sectors discussed in the previous section. The pattern in Table 8 is much less clear than the pattern in Table 7. The distribution of education and soft skills in these service sectors is much less affected by industry concentration and urbanization. If we focus on the effects on the 90th-10th difference, we find that the same patterns found in manufacturing hold for services as well. For all five measures of soft skills urbanization increases the spread of the distribution, with the estimated parameters statistically significant in 3 of the 5 cases. For four of the soft skill measures localization reduces the spread of the skill distribution (all except *depl*), although in this case the parameter estimates are not statistically significant. Overall, the results for service sectors are similar to manufacturing, but are less sharp.[12]

V. Conclusion

This paper has considered the role of soft skills in cities and industry clusters. The analysis has focused on a tension between two ways that agglomeration can produce increasing returns. One is that agglomeration facilitates fluid and unplanned interactions among agents such as knowledge spillovers. Since soft skills are likely to facilitate this sort of interaction, cities and industry clusters may prove to be attractive for workers who possess these skills. However, the other sort of increasing return is that cities allow a highly refined division of labor. In this situation, a worker's role in the industrial system is specialized, not requiring much in the way of flexibility and adaptation. This may tend to make cities and clusters less attractive to workers who are endowed with soft skills. The relationship between soft skills and agglomeration is thus ambiguous in theory. Furthermore, it is theoretically unclear whether the relevant dimension of agglomeration is the concentration of an industry or the aggregation of population.

[12] One possible explanation for this is that many of the service sectors do not tend to cluster. If this is because agglomeration economies are weak, then we would expect to find a weaker soft skills - agglomeration relationship. As a robustness check, we re-estimated Table 8 for a more restrictive set of service industries that exhibit tendencies to agglomeration. We obtain strong results confirming that urbanization widens the distribution of soft skills.

Having set out a theoretical model that establishes the existence of this tension between cities as centers of soft-skill enabled interaction and cities as refined divisions of specialized labor, the paper then carries out an empirical analysis of the relationship. To do so, the paper matches data from the Dictionary of Occupational Titles to Census data. The within-industry average level of soft skills is found to be higher in cities but not in centers of an industry's activity. The former is consistent with a dominant opportunity effect, while the latter is consistent with a dominant specialization effect. Furthermore, large cities typically contain a disproportionate share of the industry's workers with both very high and very low levels of soft skills, a result consistent with the presence of both opportunity and specialization effects. In contrast, in industry clusters there is greater concentration around the mean. This is more easily seen as a manifestation of a specialization effect.

All of this leads to the paper's main conclusion: cities are not unambiguously centers of soft-skill enabled interaction. Industry clusters are even less so.

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Table 1. Data Description

Panel A. Description of Soft Skill Measures from the Dictionary of Occupational Titles

DOT VARIABLES	DESCRIPTION
depl	adaptability to *dealing with people* beyond giving and receiving 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
people	complexity at which worker performs job in relation to human beings; also animals dealt with on an individual basis as if they were human. From highest to lowest: 9. Mentoring: Dealing with individuals in terms of their total personality in order to advise, counsel, and/or guide them with regard to problems that may be resolved by legal, scientific, clinical, spiritual, and/or other professional principles. 8. Negotiating: Exchanging ideas, information, and opinions with others to formulate policies and programs and/or arrive jointly at decisions, conclusions or solutions. 7. Instructing: Teaching subject matter to others, or training others (including animals) through explanation, demonstration, and supervised practice; or making recommendations on the basis of technical disciplines. 6. Supervising: Determining or interpreting work procedures for a group of workers, assigning specific duties to them, maintaining harmonious relations among them, and promoting efficiency. A variety of responsibilities is involved in this function. 5. Diverting: Amusing others, usually accomplished through the medium of stage, screen, television, or radio. 4. Persuading: Influencing others in favor of a product, service or point of view. 3. Speaking-Signaling: Talking with and/or signaling people to convey or exchange information. Includes giving assignments and/or directions to helpers or assistants. 2. Serving: Attending to the needs or requests of people or animals or the expressed or implicit wishes of people. Immediate response is involved. 1. Taking Instructions-Helping: Helping applies to "non-learning" helpers. No variety of responsibility is involved in this function.

Panel B. Descriptive Statistics from the 1990 5% IPUMS merged with 1991 DOT

Variable	Mean	Std Dev	p10	p25	p50	p75	p90
Years of Schooling	13.592	2.784	12	12	13	16	16
Less than HS	0.106	0.308	0	0	0	0	1
HS Grad	0.24	0.427	0	0	0	0	1
Some College	0.316	0.465	0	0	0	1	1
College+	0.338	0.473	0	0	0	1	1
depl91	0.604	0.396	0	0.2	0.778	0.972	1
dcp91	0.358	0.396	0	0	0.167	0.826	1
influ91	0.15	0.269	0	0	0	0.15	0.6
people91	3.505	1.849	1.375	2	3	4.529	6.519
peoidx_91	107.949	9.933	94.681	98.317	106.669	116.205	121.612
Industry Share	0.015	0.026	0.001	0.003	0.007	0.016	0.032
ln(MSA pop'n)	14.208	1.164	12.487	13.344	14.318	15.033	15.916
No. of Workers	3,556,261						
No. of MSA's	297						
No. of Industries	264						

Note: Sample includes only workers aged 25-70 with positive hours, weeks, wage income, with identifiable MSA and occupation codes matched to the DOT. Statistics are weighted to reflect U.S. population.

Table 2. Soft Skill Content of Various Occupations

Panel A. Top and Bottom 5 Occupations for Soft Skill Measures

DCP91*		**INFLU91***	
Low	**High**	**Low**	**High**
Janitors	Financial managers	Geologists	Subject instructors (HS/college)
Stevedores	Chief executives	Chemical engineers	Primary schoolteachers
Packers	Speech therapists	Optometrists	Door-to-door sales vendors
Typists	Primary schoolteachers	Industrial engineers	Public relations managers
Dental technicians	Secondary schoolteachers	Bartenders	Advertising sales jobs

DEPL91*		**PEOPLE**	
Low	**High**	**Low**	**High**
Postal Mail Carriers	Speech therapists	Data entry-keyers	Therapists
Movie Projectionists	Salespersons	Machine operators	Secretaries
Ship crews	Funeral directors	Asssemblers	Social Workers
Miners	Subject instructors (HS/college)	Packers	Aministrators
Engravers	Receptionists	Car washers	Salespersons

People Skills Index	
Low	**High**
Bakers	Speech therapists
Oil well drillers	Primary schoolteachers
Upholsterers	Chief executives
Garbage collectors	Physicians
Stevedores	Educational counselors

Panel B. Soft Skills for Select Occupations

	DEPL		INFLU		DCP		PEOPLE
	YES	NO	YES	NO	YES	NO	
Financial Managers	x			x	x		Supervising
Chemical Engineers		x		x	x		Speaking-Signaling
Insurance underwriters		x		x		x	Speaking-Signaling
Mathematicians		x		x		x	Speaking-Signaling
Physicians	x			x	x		Mentoring
Subject Instructors (HS/College)	x		x		x		Instructing
Social Workers	x		x		x		Supervising
Lawyers	x		x			x	Negotiating
Technicians		x		x		x	Servicing
Salesperson	x			x		x	Persuading
Secretaries	x			x		x	Speaking-Signaling
Supervisors	x			x	x		Supervising
Cook		x		x		x	Servicing
Waiter/Waitress	x			x		x	Servicing
Machine Operators		x		x		x	Taking Instructions
Promotion Agents	x		x		x		Instructing

Note: *There are actually more than 5 occupations in the top and bottom, in that several have values equal to 0 or 1. See text for more description of data.

Table 3. Industry Concentration of Soft Skills

DEPL		DCP		INFLU	
BOTTOM 5	**TOP 5**	**BOTTOM 5**	**TOP 5**	**BOTTOM 5**	**TOP 5**
MANUFACTURING		**MANUFACTURING**		**MANUFACTURING**	
Apparel, except Knit (23%)	Newspaper Publishing (62.8%)	Apparel, except Knit (16%)	Guided Missiles (46.7%)	Logging (2.1%)	Newspaper Publishing (30.7%)
Tires and Inner Tubes (24.8%)	Computer Equipment (56%)	Carpets and Rugs (16.7%)	Drugs (42.2%)	Ship and Boat Building (3.4%)	Publishing, Except Newspaper (16.3%)
Knitting Mills (25%)	Drugs (53.6%)	Meat Products (17.4%)	Agricultural Chemicals (42%)	Iron and Steel Foundries (4%)	Beverage Industries (14.4%)
Meat Products (26.7%)	Publishing, Except Newspaper (49%)	Knitting Mills (18.8%)	Radio, TV & Communication (41%)	Railroad Equipment (4.1%)	Drugs (14.2%)
Yarn and Fabric Mills (27.4%)	Radio, TV & Communication (49%)	Yarn and Fabric Mills (20.7%)	Computer Equipment (41%)	Aircraft and Parts (4.2%)	Paints, Varnishes & Related (12.8%)
ALL INDUSTRIES		**ALL INDUSTRIES**		**ALL INDUSTRIES**	
Shoe Repair Shops (18.7%)	Barber Shops (98%)	Barber Shops (2.5%)	Elem. and Sec. Schools (74.3%)	Barber Shops (0.3%)	Elem. and Sec. Schools (55.5%)
Fishing, Hunting, Trapping (21.1%)	Offices of Dentists (93%)	Taxicab Service (7.4%)	Educational Services (64.8%)	Taxicab Service (0.9%)	Direct Selling Establishments (43.3%)
Miscellaneous Repair Services (22%)	Beauty Shops (90%)	Beauty Shops (7.5%)	Child Care Services (64.5%)	Offices of Dentists (1%)	Colleges and Universities (39.4%)
Apparel, except Knit (23%)	Child Care Services (89%)	U.S. Postal Service (9.9%)	Colleges and Universities (58.1%)	Beauty Shops (1.1%)	Drugs (39.3%)
Automotive Repair (24%)	Elem. And Sec. Schools (86%)	Shoe Repair Shops (11%)	Management Services (57.8%)	U.S. Postal Service (1.4%)	Religious Organizations (36.9%)

PEOPLE		PEOPLE INDEX	
BOTTOM 5	**TOP 5**	**BOTTOM 5**	**TOP 5**
MANUFACTURING		**MANUFACTURING**	
Apparel, except Knit (2.15)	Newspaper Publishing (3.52)	Apparel, except Knit (99.8)	Newspaper Publishing (108.2)
Meat Products (2.3)	Drugs (3.4)	Meat Products (100.5)	Drugs (107.5)
Knitting Mills (2.31)	Agricultural Chemicals (3.31)	Knitting Mills (100.6)	Computer Equipment (107.4)
Tires and Inner Tubes (2.31)	Computer Equipment (3.3)	Tires and Inner Tubes (100.7)	Agricultural Chemicals (106.7)
Carpets and Rugs (2.35)	Paints, Varnishes and Related (3.2)	Carpets and Rugs (101)	Guided Missiles and Parts (106.4)
ALL INDUSTRIES		**ALL INDUSTRIES**	
Taxicab Service (2)	Religious Organizations (5.8)	Shoe Repair Shops (98.9)	Elem. and Sec. Schools (119.4)
Shoe Repair Shops (2.1)	Elem. & Sec. schools (5.76)	Taxicab Service (99)	Educational services (116.4)
Barber Shops (2.1)	Education Services (5.3)	Miscellaneous Repair Services (99.7)	Religious Organizations (115.3)
Apparel, except Knit (2.15)	Colleges and Universities (5)	Apparel, except Knit (99.8)	Colleges and Universities (115.2)
Miscellaneous Repair Services (2.2)	Legal services (4.9)	U.S. Postal Service (100.5)	Child Care Services (114.7)

Note: Percentages reflect percent of workers in that industry requiring that skill; other figures in parentheses are means. Statistics are weighted to add up to the U.S. population.

Table 4. Location Concentration of Soft Skills

DEPL		DCP	
BOTTOM 5	**TOP 5**	**BOTTOM 5**	**TOP 5**
Kokomo, IN (46.4%)	Stamford, CT (70.6%)	Williamsport, PA (25.9%)	Bryan-College Station, TX (45.7%)
Hickory-Morgantown, NC (46.7%)	Barnstable-Yarmouth, MA (67.7%)	Flint, MI (26.1%)	Boulder-Longmont, CO (44.6%)
Janesville-Beloit, WI (47.2%)	Tallahassee, FL (67.3%)	Danville, VA (26.8%)	Stamford, CT (44%)
Danville, VA (47.3%)	Boulder-Longmont, CO (65.9%)	Waterbury, CT (27.3%)	Santa Fe, NM (43.6%)
Decatur, AL (48.3%)	Boston, MA (65.8%)	Hickory-Morgantown, NC (27.6%)	Danbury, CT (43.3%)

INFLU		PEOPLE	
BOTTOM 5	**TOP 5**	**BOTTOM 5**	**TOP 5**
Kokomo, IN (9.1%)	Stamford, CT (20.9%)	Kokomo, IN (2.9)	Stamford, CT (3.97)
Danville, VA (10%)	Bloomington, IN (20.7%)	Flint, MI (2.97)	Bryan-College Station, TX (3.96)
Flint, MI (10.2%)	Bryan-College Station, TX (20.5%)	Danville, VA (2.98)	Iowa City, IA (3.95)
Jacksonville, NC (10.5%)	State College, PA (19.9%)	Hickory-Morgantown, NC (3)	Gainesville, FL (3.94)
Hickory-Morgantown, NC (10.8%)	Champaign-Urbana-Rantoul, IL (19.4%)	Janesville-Beloit, WI (3.1)	Columbia, MO (3.89)

PEOPLE INDEX	
BOTTOM 5	**TOP 5**
Kokomo, IN (104.6)	Stamford, CT (110.68)
Danville, VA (104.7)	Bryan-College Station, TX (110.2)
Hickory-Morgantown, NC (104.8)	Iowa City, IA (110)
Flint, MI (104.97)	Gainesville, FL (110)
Janesville-Beloit, WI (105)	Tallahassee, FL (109.9)

Note: Percentages reflect percent of workers in that industry requiring that skill; other figures in parentheses are means. Statistics are weighted to add up to the U.S. population.

Table 5: Mean Regressions: Manufacturing Sectors - 2000

Panel A: Education Measures

	Less Than HS	HS Grad.	Some Coll.	Coll. Grad.	Years Educ.
Log(Pop)	0.02761	-0.03212	-0.01117	0.01569	-0.10531
	[0.00207]***	[0.00135]***	[0.00123]***	[0.00169]***	[0.01709]***
Cluster	-0.19409	-0.38227	-0.01736	0.59372	2.97929
	[0.12582]	[0.05383]***	[0.08326]	[0.11850]***	[1.26085]**
Constant	-0.24497	0.78437	0.40706	0.05354	14.41533
	[0.03107]***	[0.02496]***	[0.01993]***	[0.03074]*	[0.26823]***
Observations	521344	521344	521344	521344	521344
R-squared	0.07	0.04	0.01	0.09	0.11

Panel B: Soft Skills

	depl91	influ91	dcp91	peoidx_91	people91
Log(Pop)	0.02112	0.01127	0.00839	0.43778	0.0692
	[0.00134]***	[0.00060]***	[0.00110]***	[0.03188]***	[0.00505]***
Cluster	-0.06813	-0.17637	0.26327	0.33354	-0.19757
	[0.11517]	[0.04565]***	[0.08779]***	[2.82576]	[0.46368]
Constant	0.09272	-0.07341	0.17545	97.72663	1.87457
	[0.02512]***	[0.00948]***	[0.02035]***	[0.58980]***	[0.09280]***
Observations	521344	521344	521344	521344	521344
R-squared	0.04	0.02	0.04	0.04	0.03

Notes: Standard errors in brackets are clustered by industry/MSA. * significant at 10%; ** significant at 5%; *** significant at 1%. Dependent variables in Panel A are for first four columns are percent of workers in each education level. Years of schooling is created from reported categorical schooling. See text for further details.

Table 6: Mean Regressions: Selected Services Sectors - 2000

Panel A: Education Measures

	Less Than HS	HS Grad.	Some Col.	Col. Grad.	Years Educ.
Log(Pop)	0.00236	-0.01465	-0.01551	0.0278	0.10129
	[0.00087]***	[0.00131]***	[0.00259]***	[0.00283]***	[0.01225]***
Cluster	0.00597	-0.02636	-0.33109	0.35149	1.37786
	[0.02928]	[0.06220]	[0.16916]*	[0.17153]**	[0.66296]**
Constant	0.00971	0.35682	0.60207	0.0314	12.62561
	[0.01657]	[0.02018]***	[0.04440]***	[0.04709]	[0.20990]***
Observations	535342	535342	535342	535342	535342
R-squared	0.02	0.03	0.02	0.07	0.11

Panel B: Soft Skills

	depl91	influ91	dcp91	peoidx_91	people91
Log(Pop)	0.00584	0.00326	0.0089	0.19788	0.03156
	[0.00105]***	[0.00103]***	[0.00125]***	[0.02799]***	[0.00481]***
Cluster	-0.13322	-0.08631	-0.09609	-3.5854	-0.63429
	[0.03467]***	[0.04166]**	[0.05093]*	[1.01362]***	[0.18985]***
Constant	0.57046	0.08704	0.32038	106.7346	3.29971
	[0.01942]***	[0.01845]***	[0.02103]***	[0.51527]***	[0.08583]***
Observations	535342	535342	535342	535342	535342
R-squared	0.11	0.11	0.07	0.05	0.08

Notes: Standard errors in brackets are clustered by industry/MSA. * significant at 10%; ** significant at 5%; *** significant at 1%. Dependent variables for first four columns are percent of workers in each education level. Years of schooling is created from reported categorical schooling. See text for further details.

Table 7: Skill Distribution Regressions for Manufacturing – 2000

	Years of Education						
	p10	p25	p50	p75	P90	P90-P10	P75-P25
Log(Pop)	-0.4933	-0.13292	0.06562	0.19226	0.21925	0.71255	0.32517
	[0.11076]***	[0.05954]**	[0.02315]***	[0.02782]***	[0.02215]***	[0.11838]***	[0.04758]***
Cluster	-2.90358	-2.95245	2.39304	2.26955	1.01576	3.91934	5.22201
	[4.64636]	[2.47529]	[1.25971]*	[1.24515]*	[1.07822]	[4.74641]	[2.15272]**
Constant	4.4016	0.88263	-0.9794	-1.38428	-0.26276	-4.66436	-2.26691
	[1.48317]***	[0.80276]	[0.31073]***	[0.37179]***	[0.30077]	[1.57928]***	[0.64223]***
Observations	4852	4852	4852	4852	4852	4852	4852
	DEPL						
	p10	p25	p50	p75	P90	P90-P10	P75-P25
Log(Pop)	-0.00563	-0.00009	0.05381	0.08075	0.02087	0.0265	0.08084
	[0.00106]***	[0.00152]	[0.00715]***	[0.00665]***	[0.00181]***	[0.00198]***	[0.00501]***
Cluster	0.21557	0.17847	-0.78113	-1.40998	-0.18728	-0.40285	-1.58846
	[0.06755]***	[0.07259]**	[0.25029]***	[0.23729]***	[0.08638]**	[0.06237]***	[0.23819]***
Constant	-0.28477	-0.3396	-0.88911	-0.74618	0.28159	0.56636	-0.40659
	[0.01465]***	[0.02059]***	[0.09525]***	[0.09180]***	[0.02526]***	[0.02743]***	[0.06922]***
Observations	4852	4852	4852	4852	4852	4852	4852
	INFLU						
	p10	p25	p50	p75	P90	P90-P10	P75-P25
Log(Pop)	-0.00227	-0.00226	-0.0015	0.01694	0.07611	0.07838	0.01921
	[0.00036]***	[0.00036]***	[0.00034]***	[0.00213]***	[0.00827]***	[0.00789]***	[0.00221]***
Cluster	0.10208	0.10158	0.07018	-0.40093	-2.03934	-2.14143	-0.50252
	[0.02147]***	[0.02146]***	[0.02304]***	[0.05860]***	[0.22509]***	[0.24032]***	[0.08266]***
Constant	-0.04718	-0.04725	-0.05588	-0.25571	-0.81044	-0.76326	-0.20846
	[0.00497]***	[0.00495]***	[0.00464]***	[0.02817]***	[0.10985]***	[0.10368]***	[0.02875]***
Observations	4852	4852	4852	4852	4852	4852	4852
	DCP						
	p10	p25	p50	p75	P90	P90-P10	P75-P25
Log(Pop)	-0.00313	-0.0031	0.00934	0.06041	0.02621	0.02934	0.06351
	[0.00091]***	[0.00080]***	[0.00339]***	[0.00850]***	[0.00311]***	[0.00340]***	[0.00846]***
Cluster	0.13544	0.15686	0.24198	-0.98373	-0.19166	-0.3271	-1.14059
	[0.07825]*	[0.07337]**	[0.14223]*	[0.33946]***	[0.11863]	[0.11125]***	[0.40319]***
Constant	-0.23912	-0.23461	-0.33828	-0.57725	0.25825	0.49736	-0.34264
	[0.01285]***	[0.01075]***	[0.04616]***	[0.11455]***	[0.04353]***	[0.04754]***	[0.11540]***
Observations	4852	4852	4852	4852	4852	4852	4852

Table 7: Skill Distribution Regressions for Manufacturing - 2000 (continued)

PEOPLE VARIABLE

	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	-0.00717	0.02229	0.14072	0.26822	0.10846	0.11563	0.24593
	[0.00400]*	[0.00678]***	[0.01776]***	[0.02512]***	[0.01458]***	[0.01583]***	[0.02197]***
Cluster	0.67371	0.58366	-1.91946	-5.98579	-2.11834	-2.79204	-6.56945
	[0.22123]***	[0.32915]*	[0.65038]***	[0.76098]***	[0.67555]***	[0.69890]***	[0.73470]***
Constant	-1.449	-1.61077	-2.53962	-2.63576	1.09691	2.54591	-1.02498
	[0.05396]***	[0.09272]***	[0.24218]***	[0.33979]***	[0.20007]***	[0.21348]***	[0.29633]***
Observations	4852	4852	4852	4852	4852	4852	4852

PEOPLE INDEX

	p10	p25	P50	p75	p90	P90-P10	P75-P25
Log(Popn)	-0.0863	0.07553	0.99239	1.70546	0.70433	0.79063	1.62992
	[0.02330]***	[0.04572]*	[0.13440]***	[0.16713]***	[0.07104]***	[0.07575]***	[0.12584]***
Cluster	4.5658	5.41171	-12.87682	-33.97261	-5.31527	-9.88106	-39.38432
	[1.71285]***	[1.96822]***	[4.32622]***	[4.84255]***	[2.87713]*	[2.79915]***	[5.39760]***
Constant	-7.82363	-9.05869	-17.45963	-16.24744	5.69491	13.51854	-7.18875
	[0.31690]***	[0.60719]***	[1.79573]***	[2.26485]***	[0.99301]***	[1.04703]***	[1.67938]***
Observations	4852	4852	4852	4852	4852	4852	4852

Note: Boostrapped standard errors in brackets clustered at the MSA level. * significant at 10%; ** significant at 5%; *** significant at 1%. See text for further details.

Table 8: Skill Distribution Regressions for Selected Services – 2000

	Years of Education						
	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	-0.03048	-0.00103	0.16684	0.05072	-0.09209	-0.06161	0.05175
	[0.02561]	[0.05531]	[0.05274]***	[0.03094]	[0.02940]***	[0.02475]**	[0.03767]
Cluster	2.9375	8.98974	9.54685	3.53227	3.32265	0.38515	-5.45747
	[4.08811]	[8.67178]	[6.54395]	[3.46430]	[3.60128]	[2.05139]	[5.70073]
Constant	-2.04656	-1.7523	-2.46927	0.69979	3.11018	5.15675	2.45209
	[0.32517]***	[0.70546]**	[0.68308]***	[0.40439]*	[0.38204]***	[0.33107]***	[0.48365]***
Observations	2926	2926	2926	2926	2926	2926	2926
	DEPL						
	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	0.00055	0.00842	0.01012	0.00744	0.00337	0.00283	-0.00097
	[0.00429]	[0.00448]*	[0.00254]***	[0.00206]***	[0.00154]**	[0.00458]	[0.00429]
Cluster	0.01935	-0.02229	-0.17586	-0.12093	0.15281	0.13346	-0.09865
	[0.51881]	[0.47476]	[0.23798]	[0.23648]	[0.22058]	[0.41595]	[0.43238]
Constant	-0.44715	-0.30896	-0.08412	0.13699	0.27264	0.7198	0.44595
	[0.05594]***	[0.05846]***	[0.03333]**	[0.02689]***	[0.01991]***	[0.06086]***	[0.05703]***
Observations	2926	2926	2926	2926	2926	2926	2926
	INFLU						
	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	0.00682	0.00184	-0.0102	-0.00721	0.03118	0.02436	-0.00905
	[0.00147]***	[0.00158]	[0.00171]***	[0.00392]*	[0.00502]***	[0.00625]***	[0.00574]
Cluster	0.0026	0.07637	0.17745	-0.08744	-1.02023	-1.02283	-0.16381
	[0.22645]	[0.22247]	[0.12170]	[0.47710]	[0.54521]*	[0.79729]	[0.90243]
Constant	-0.26738	-0.19476	0.04807	0.20171	-0.0889	0.17849	0.39647
	[0.01894]***	[0.02061]***	[0.02327]**	[0.05145]***	[0.06476]	[0.08066]**	[0.07328]***
Observations	2926	2926	2926	2926	2926	2926	2926
	DCP						
	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	-0.01214	-0.01225	0.01971	0.02987	0.0101	0.02224	0.04212
	[0.00126]***	[0.00366]***	[0.00398]***	[0.00493]***	[0.00367]***	[0.00331]***	[0.00463]***
Cluster	0.12605	0.59872	0.13699	0.07279	0.10778	-0.01827	-0.52593
	[0.12516]	[0.60478]	[0.39739]	[0.65283]	[0.48001]	[0.36439]	[0.45848]
Constant	-0.23173	-0.16117	-0.33011	-0.13288	0.32889	0.56062	0.02829
	[0.01679]***	[0.04691]***	[0.05277]***	[0.06517]**	[0.04808]***	[0.04443]***	[0.06187]
Observations	2926	2926	2926	2926	2926	2926	2926

Table 8: Skill Distribution Regressions for Selected Services – 2000 (continued)

	PEOPLE VARIABLE						
	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	0.01285	0.02661	0.00286	0.01401	0.02031	0.00746	-0.0126
	[0.01341]	[0.00876]***	[0.01235]	[0.01325]	[0.01189]*	[0.02021]	[0.01661]
Cluster	0.39253	0.42311	0.35716	-0.34609	-1.37383	-1.76636	-0.7692
	[1.59612]	[0.87848]	[1.07025]	[0.79037]	[0.73589]*	[2.17256]	[1.08999]
Constant	-1.7229	-1.30061	-0.3195	0.65841	1.43729	3.16019	1.95902
	[0.17749]***	[0.11649]***	[0.16489]*	[0.17846]***	[0.15955]***	[0.26509]***	[0.22430]***
Observations	2926	2926	2926	2926	2926	2926	2926
	PEOPLE INDEX						
	p10	p25	p50	p75	p90	P90-P10	P75-P25
Log(Popn)	-0.08857	0.14666	0.24984	0.31138	0.22978	0.31835	0.16472
	[0.09769]	[0.08838]*	[0.06582]***	[0.07840]***	[0.04893]***	[0.09953]***	[0.07887]**
Cluster	8.23197	3.91512	-1.40975	-0.45806	2.84214	-5.38983	-4.37318
	[13.43306]	[10.88833]	[4.10896]	[7.68876]	[4.66355]	[10.63926]	[6.99583]
Constant	-8.66792	-7.27604	-3.81166	0.89106	6.63048	15.29839	8.1671
	[1.26458]***	[1.15905]***	[0.88814]***	[1.04010]	[0.64787]***	[1.31048]***	[1.04914]***
Observations	2926	2926	2926	2926	2926	2926	2926

Note: Boostrapped standard errors in brackets clustered at the MSA level. * significant at 10%; ** significant at 5%; *** significant at 1%. See text for further details.

Appendix A. Sensitivity of Weighted vs Unweighted Soft Skill Measures

As discussed in the text, to create soft skill measures for the coarser census occupations, we average DOT skill measures across DOT occupations in each census category. Computing these averages without weighting by actual employment in that DOT sub-occupation in effect assumes that each DOT sub-occupation within a census occupation has equal weight. These averages could be distorted if, for instance, one particular DOT sub-occupation can actually be found with more frequency in the labor force than other DOT sub-occupations within the same census occupation code. To date, however, there is only one labor force data that has been coded with both DOT and census occupation codes. A special version of the April 1971 CPS monthly file was issued by the National Academy of Sciences (2001), in which a committee of experts assigned individual DOT occupation codes and measures to the 60,441 workers in that sample. In this special CPS sample 3,885 DOT occupations are represented. To convert this special CPS sample into DOT skill measures by census occupation cells, we calculate weighted means (using CPS sampling weights) and unweighted means (treating each DOT sub-occupation equally). The correlation across weighted and unweighted means for each soft skills measure is 0.999.[13]

To explain this very high correlation, we took a closer look at the DOT sub-occupations within census occupations. Even though DOT sub-occupations within a census occupation do have different employment weights, soft skill measures tend to be the same or very similar across these DOT sub-occupations. This highlights that the DOT classifications are really very fine sub-occupational classifications. For instance, "registered nurses" in the census are comprised of "school nurses," "nurse practitioners," "nurse-midwife," "nurse anesthetist," etcetera in the DOT. However, all these nurse titles in the DOT are required to have *depl*. Thus, regardless of how many school nurses versus nurse practitioners there are actually in the labor force, the weighted and unweighted averages for *depl* among "registered nurses" in the census are going to be exactly the same.

For our purposes, we are not only concerned with whether or not weighting by employment preserves the ranking of soft skills across occupations, but also whether or not weighting leads to a systematic variation in soft skills across location. To examine this, we test to see whether or not employment-weighted averages of soft skills within census occupations vary systematically by SMSA status.

We specified this test in two different ways. First, at the worker level, we run a regression of the various soft skill measures on census occupation dummies, an indicator for whether the worker is an MSA, and an indicator for whether the worker is not in an MSA. This is reported in Panel A of Table A-1. The second panel of Table A-1 reports a regression of the difference in average soft skills in MSA minus outside MSA at the census. Across these soft skills measures, we uniformly fail to reject the

[13] Specifically, the correlation in weighted and unweighted averages of *people* across 419 census occupation cells in the April 1971 CPS is 0.9994; *depl* is 0.9995; *dcp* is 0.9984; *influ* is 0.9997.

hypothesis that the measures vary systematically across location. In other words, employment weighted averages of soft skills do not vary systematically inside and outside an MSA.

Table A-1. Testing for Difference in Soft Skill Measures In and Out of MSA

Panel A. Worker Level

	influ	dcp	people	depl
in SMSA	0.02203***	0.72503***	2.76535***	0.60730***
	[0.00637]	[0.02137]	[0.03881]	[0.02722]
notSMSA	0.01935***	0.72390***	2.74865***	0.60910***
	[0.00658]	[0.02144]	[0.03965]	[0.02726]
Observations	53457	53457	52919	53457
R-squared	0.729	0.772	0.905	0.876
Test SMSA=notSMSA	2.00381	0.29055	2.3057	0.59945
p-value	0.15691	0.58987	0.12891	0.43879

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1. Regressions are weighted by CPS sampling weights and also include occupation dummies, without a constant. Data used is the April 1971 CPS special release with 1977 DOT titles.

Panel B. Occupation Level

	influ(inMSA)-influ(outMSA)	dcp(inMSA)-dcp(outMSA)	people(inMSA)-people(outMSA)	depl(inMSA)-depl(outMSA)
Constant	-0.00381	0.00681	0.02385	0.00013
	[0.00496]	[0.00602]	[0.02434]	[0.00785]
T-statistic	-0.77	1.13	0.98	0.02
p-value	0.443	0.259	0.328	0.987
Observations	388	388	388	388

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1. Regressions are weighted by CPS sampling weights and also include occupation dummies, without a constant. Data used is the April 1971 CPS special release with 1977 DOT titles.