Elements of Skill: Traits, Intelligences, and Agglomeration

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Abstract

There are many fundamental issues in regional and urban economics that hinge on worker skills. This paper builds on psychological approaches to learning to characterize the role of education and agglomeration in the skill development process. While the standard approach of equating skill to worker education can be useful, there are important aspects of skill that are missed. Using a measure of skill derived from hedonic attribution, the paper explores the geographic distribution of worker traits, intelligences, and skills and considers the role of urbanization and education in the skill development process.

I. Introduction

There are many fundamental issues in regional and urban economics that hinge on worker skills. A city's prosperity and growth depend crucially on its ability to attract productive workers, match them appropriately to jobs, and further develop their skills. The importance of skills goes back to the beginnings of urban economics, including Marshall (1890), Jacobs (1969), and Vernon (1960).hgh

Skills are central to a number of current lines of research as well, especially research on agglomeration and labor markets. Glaeser and Mare (2001) document a substantial urban wage premium, and show that a substantial fraction of it results from the sorting of high-skill workers into large cities. The importance of this selection effect is further reinforced by the panel estimates of Combes, Duranton, and Gobillon (2008). Regarding how the benefits of the urban wage premium accrue to workers of different skill levels, Wheeler (2001) finds that more educated workers enjoy a larger premium across a range of occupations, while Adamson et al (2004) find the opposite. Lee (2008), considering only health care workers, also finds that workers with less skill benefit more from agglomeration.

Skills are important as well in other urban and regional literatures. Rauch (1993) documents a relationship between the local level of human capital and wage. These human capital spillovers are considered further by Moretti (2004a, 2004b) and Ciccone and Peri (2006). The spatial dimension of human capital externalities and their impact on workers with different levels of education are considered by Rosenthal and Strange (2008). A relationship between a city's level of human capital and urban growth is found in Simon and Nardinelli (2002), Florida (2002), and Glaeser and Shapiro (2003). Furthermore, a relationship between local skill levels and innovation is found in Audretsch and Feldman (1996), while Andersson et al (2009) identify a relationship between the presence of a local university and innovation and productivity. Finally, agglomeration appears to impact the movement of skills across activities through job turnover (Freedman, 2008). In sum, skills matter.

In the large literature on skills in cities and regions, it is common to equate a worker's skill to the worker's education level. By this metric, all of the students in a class are equally skilled, as long as they all graduate. This does not really capture what Marshall, Jacobs, and Vernon had in mind. This is also a quite different approach than is taken in developmental psychology, a field in large part dedicated to understanding learning.

In this paper, we build on psychological approaches to learning to characterize the role of education and agglomeration in the skill development process. Very roughly, this approach posits that individual traits and intelligences interact with the environment to produce skills. Traits are stable personal characteristics, including such things as temperament and personality. Traits are determined by genetic endowment and early environment. Intelligences are defined as the ability to process contents of the world, including, for example, the ability to process words and logical relationships (verbal vs.

propositional intelligence) and the ability to arrange and rotate objects in space (spatial intelligence). Intelligences are thought to be somewhat more plastic than are traits, at least early in life. Like traits, intelligences are also produced by genetic endowment and environment, with traits also impacting the development of the abilities to process world content. Early acquisition of these abilities can in addition facilitate the further development of intelligences. Finally, skills are behavioral manifestations of intelligences and traits. For our purposes we will focus on the marketable or productive aspects of intelligences and traits. For example, creative thinking and flexible planning are skills that can be developed by people that have the necessary traits and intelligences and are exposed to the right environment. Education is an important part of the environment to which individuals are exposed. Urbanization is another one.

In this approach, education and skill are not equivalent. Education is instead part of the process determining a multi-dimensional package of skills.[1] Urban economists are manifestly aware of the limitations of the skill-equals-education approach, as is apparent from the many strategies employed to deal with unobserved heterogeneity in worker skill. These approaches are, however, often rather indirect. Sometimes, they involve including controls for worker traits that are related to skills. Sometimes, the approaches involve using fixed effects. Both approaches are appropriate ways to deal with the econometric problems associated with unobserved skill heterogeneity. Neither sheds light directly on the relationship between worker skills and agglomeration.

We therefore propose as an alternative a direct measure of skills. It involves the construction of skill measures from the relatively new O-NET and from its predecessor, the Dictionary of Occupational Titles (DOT). These are designed to help a job searcher identify the skill requirements of jobs in order to plan a career. If the hedonic labor market equilibrium is frictionless in matching worker skills to jobs, then O-NET and the DOT can be used in reverse: as ways to identify the skills possessed by workers holding various jobs. An education measure identifies all graduating students as being equally skilled. This hedonic attribution measure separates graduates according to the positions that they fill after graduation. We merge these data with the panel data on the National Longitudinal Survey of Youth (NLSY79) to obtain workers' characteristics, including a number of measures of traits and intelligences.

This sort of approach has been employed previously by Bacolod, Blum, and Strange (2009a), who consider how urbanization impacts the hedonic prices of different skills and their spatial allocation. The approach is also employed in Bacolod, Blum, and Strange (2009b), who focus on the "soft" skills

[1] Elvery (2007) follows an alternate approach of associating the skills at an establishment with the industry level profiles of occupations. Another alternative is taken by Audretsch and Feldman (1996), who characterize local skills by the employment in professional and managerial occupations, plus craftspeople. Yet another parallel is found in the work of Agrawal-Kapur-McHale (2008) and Agrawal-Kapur-McHale (2009), who effectively identify skill through past innovative activity of "inventors."

associated with interaction.[2] This approach has also been used by Scott (2008) and Scott and Mantegna (2008), who also consider, among other things, the spatial allocation of skills.

Making use of the framework, the DOT skill attribution, and the new variables from the NLSY, we carry out an econometric analysis of the role of agglomeration in the manifestation of traits and abilities as marketable skills.[3] The analysis employs several variables that characterize worker traits and intelligences that are new to the urban and regional literatures. It explicitly considers education and urbanization as choice variables in the process of skill formation.[4] The key conclusion of this part of the paper is that urbanization, like education, has a positive relationship with cognitive and people skills. Urbanization is negatively correlated with motor skills. Therefore, there is not a monotonic mapping between the multidimensional vector of skills we use and the measure of worker's education, making it difficult to justify the use of education as a proxy for skills. Furthermore, there is strong evidence of selection, where highly capable workers choose larger cities.

The rest of the paper is organized as follows. Section II lays out the skill development framework around which our analysis is constructed. Section III discusses the data that is available for considering abilities, traits, and skills. Section IV makes use of some of these data sources to consider the impact of urbanization on the skill development process. Section V concludes.

II. Framework

A. Overview

This section will set out a framework that relates a worker's traits and intelligences to skills. Education will influence the relationship, and so will urbanization. Psychologists conceive of skills as arising from the traits and intelligences of workers, with additional influence coming from the worker's genetic endowment and the worker's environment. Figure 1 summarizes this approach to skill development. The arrows linking the boxes do not imply a deterministic relationship but rather one that is affected by the environment around the individual.

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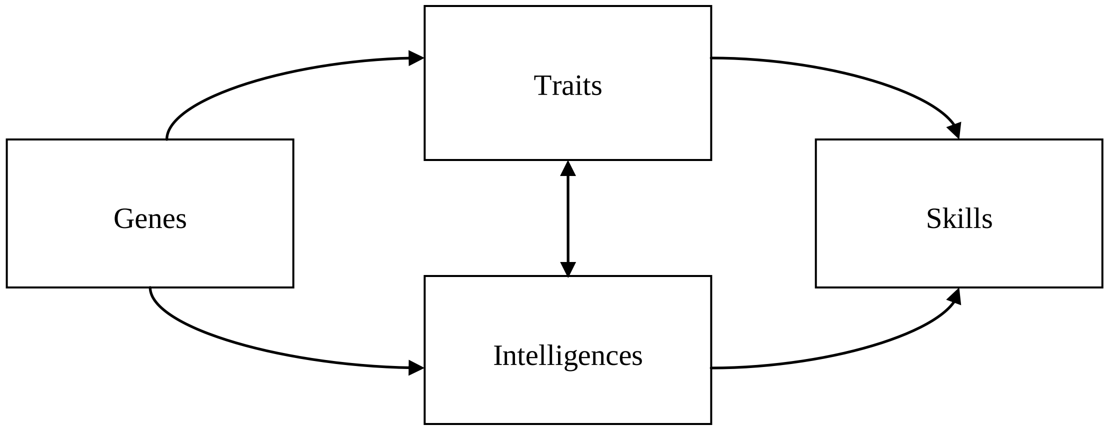
[2] Recent work on skills in labor economics has persuasively shown that it is important to acknowledge that skills are multi-dimensional, and thus not simply identical to education (Bowles et al (2001), Autor et al (2003), and Heckman et al (2006)).

[3] As discussed later in the paper, DOT is a better match for the rest of the data we employ than is O-NET.

[4] This which means that they can be correlated for various reasons . For instance, if urbanization affects the process through which individuals acquire traits and intelligences, and traits and intelligences affect the individual's decision to acquire education, urbanization can impact skills via education.

Figure 1. Abilities, Traits and Skills



A personality trait is defined as an enduring personal characteristic that reveals itself in a particular pattern of behavior in a variety of situations (Carlson et al, 2005).[5] There are many personal characteristics that have been identified as personality traits in the sense that they affect an individual's patterns of behavior. Psychologists have used factor analysis to create a small number of linear combinations of them to capture the "main" aspects of personality traits. For instance, Eysenck (1970), proposes a 3 factor model, extroversion, neuroticism, and psychoticism, while Cattell's (1946) analysis includes 16 factors. The set of personality traits most frequently used by psychologists include five factors: openness (O), conscientiousness (C), extroversion (E), agreeableness (A), neuroticism (N) (see Costa and McCrae, 1998) and it is commonly referred as the big five.

Personality traits have been shown to be inheritable (see Bouchard and Hur, 1998) in studies that compare the personalities of identical and fraternal twins, twins that were raised together and twins that were raised apart, and biological and adopted relatives. Zuckerman (1991) concludes that between 50% and 70% of the individual variability in extroversion, neuroticism, and psychoticism is due to heredity. The same study compares identical twins raised together and separately to access if differences in the environment can account for the remaining 30% to 50%. It finds that the personalities of twins raised together are not more similar than the personalities of the ones raised apart. This suggests that it is not the general environment that accounts for the remaining 30%-50% in personality differences, but rather individual specific relationships that are possibly developed within the family.

All this evidence reinforces the notion that personality traits are very stable, at least over one's adult life. Indeed, Costa and McCrae (1988) show that after the age of 30 individuals personalities basically do not change further. Before that there is some evidence of personality changes, such as

[5] We will focus primarily on personality traits.

individuals becoming less emotional and thrill-seeking during their 20's, but there is little indication that the environment can have a big effect of these changes.

Intelligence is defined in different ways by different psychologists. Carlson et al (2005), for example, writes that "Most psychologists would define intelligence as a person's ability to learn and remember information, to recognize concepts and their relations, and to apply the information to their own behavior in an adaptive way." Gardner (1999), on the other hand, defines intelligence as the ability to process the contents of the world. The existence of different definitions for intelligence reflects, in part, different beliefs on if there is a single intelligence or if there are multiple more or less independent forms of intellectual abilities. Initial theories of intelligence conceived of a general form of intelligence, often referred to as the *g*-factor, which has been measured by different intelligence tests such as IQ tests. More recently, psychologists have conceived of multiple types of intelligences, as individuals may have different abilities to process distinct aspects of the world. Gardner (1983), for instance, uses biological isolation, i.e., the identification of distinct areas of the brain associated, to conclude that there are 8 types of intelligences, including logical-mathematical intelligence, linguistic intelligence, spatial intelligence, intrapersonal intelligence, and interpersonal intelligence. He then goes on to identify the specific skills and activities that individuals with large amounts of each type of intelligence can perform and the occupations they are likely to sort into.

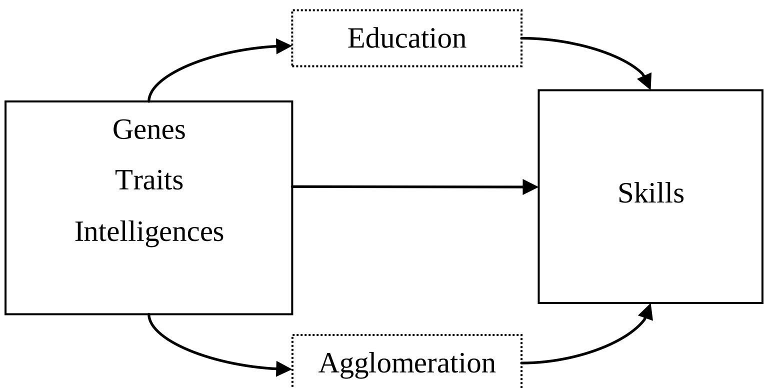
The roles of heredity and environment on intelligences are also controversial. Neisser at al (1996) summarize the evidence on the heritability of IQ and finds that about 45% of the variation in IQ scores in children is explained by genetic factors while for individuals at late adolescence this number goes up to 75%. Studies of the effects of special programs, such as the Head Start Program, show that they are successful in raising children’s IQ scores while they are participating on the program, but these effects are not long-lasting. However, the same studies find that these programs have a significant and lasting effect of other measures, such career paths, grade retention, and the probability of keeping a job. This has been suggested as evidence on the effects of these programs on non-cognitive types of intelligences. Even if all or some intelligences can be affected by the environment, it is important to understand when at an individual’s life this can happen. Jones and Bayley (1941) applied IQ tests on children annually during their childhood and adolescence. Scores at the ages of 18 and 6 were correlated at 0.77 while scores at the ages 18 and 12 were correlated at 0.89. When successive years were averaged to eliminate short run fluctuations, the correlations were even higher. More recent studies confirm these findings (e.g., Moffitt et al, 1993).

This evidence sheds light on what kind of influence the urban environment can have. It seems to suggest little scope for the urban environment to affect cognitive intelligence, at least in adults. It suggests more potential scope for an urban influence on skills, which we define as behavior manifestations of traits and intelligences, with the environment potentially affecting the process.[6] We will consider exactly this later in the paper.

B. Skill formation.

Because of the lack of detail data on individuals' traits and intelligences in large datasets, we will not be able to make much of the trait /intelligence distinction. The framework in Figure 1 then collapses to the simpler Figure 2. If traits and intelligences are determined before individuals join the labor market, as seems likely given the evidence reviewed above, the framework in Figure 2 captures the process governing the labor market deployment of skills.

Figure 2. Skill Formation



As drawn, Figure 2 shows that both education and agglomeration influence the development / manifestation of skills. The role of education has been central to psychological approaches to skill development since the birth of psychology as a field of research. Binet's intelligence tests were designed explicitly to predict educational outcomes. The ensuing Stanford research and the notion of an intelligence quotient had a similar motivation. Although education is potentially important in developing traits and intelligences, it may also be important in the manifesting of abilities and traits as skills. For instance, education allows someone with mathematical intelligence to develop skills in engineering. It may also allow a worker with spatial intelligence to develop the skill required to engage in precision manufacturing.

It is well-known, of course, that formal education is not the only way that children develop abilities and traits into skills. There are numerous informal learning mechanisms. Urban and regional

[6] Clifford et al (2004), for example, shows that the skill of critical thinking is associated with cognitive intelligence and the trait of openness to new experiences.

economists have long been interested in the way that agglomeration -- both in cities and in industry clusters -- contributes to learning of both the formal and informal varieties. The possible impact of a worker's urban status on skill development is illustrated at the bottom of Figure 2. It is important to note that locations, like education, are chosen, and so may depend on worker traits and abilities. We will return to this issue below.

C. The spatial distribution of skills

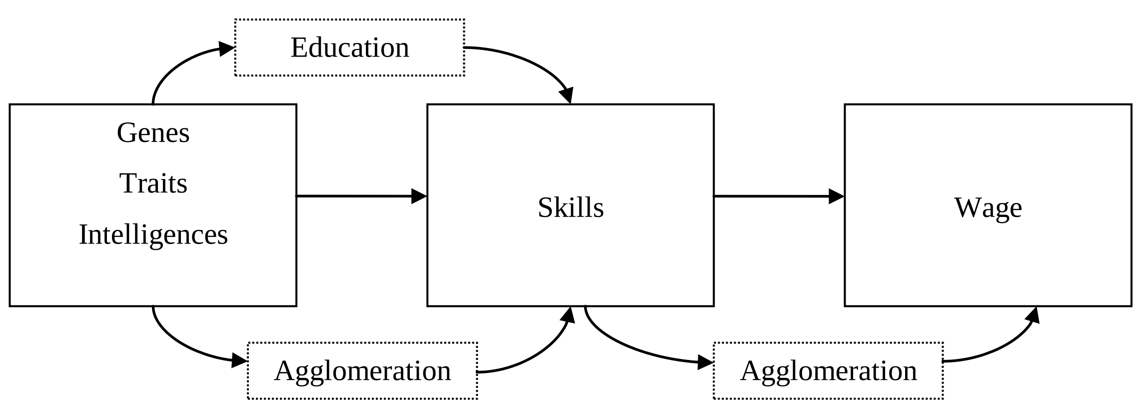
This section's framework has clear implications for thinking about the spatial distribution of skills. Education is an important input in the production of skills, so thinking about the spatial distribution of education is valuable. It is particularly valuable if one subscribes to the unique general intelligence view. If there is one skill produced with one intelligence, and education contributes to this process, then one can capture the spatial distribution of skill by using either the distribution of the general intelligence or by using education. Since skills are a monotonic transformation of education and traits, working with education is equivalent to working with skills.

With multiple intelligences, education paints an incomplete picture. Education is related to general intelligence g, but there are other aspects of intelligence. Education is strongly related to cognitive skills, but not so strongly related to social skills. In this case, characterizing the spatial distribution of education will not be equivalent up to a monotonic transformation to the spatial distribution in skills.

D. Skills and agglomeration

We note above that there are a number of important issues in urban and regional economics that pertain to skills. One of these is the role of skill in the generation of and benefit from agglomeration economies, as manifested in the urban wage premium. This is depicted below in Figure 3.

Figure 3. Traits, Abilities, Skills, and Wages



As depicted in the figure, traits and intelligences lead to skills, with intermediation by education and agglomeration. Skills lead to wages, again impacted by agglomeration.

More formally, the graph suggests a simple model of skill development. The model builds loosely on Cunha and Heckman (2007). The key components of the model are as follows. Workers have primitive characteristics, both traits and intelligences. Let t give the initial vector. Skill development depends on initial traits and intelligences as well as on education and possibly local agglomeration. Let this relationship be given the vector-valued function $s = h(t,z,n)$ giving the vector of skills as a function of traits, abilities, education, and city population. Skills impact outcomes. In the Introduction, we mentioned a range of outcomes where skill development matters. The outcome we are concerned with here is wage. In addition to impacting the development of skills from traits and intelligences, urbanization also influences the application of skills to production. It thus impacts worker wages. Let this relationship be $w = q(s, n)$, where wage is an increasing function of a vector of worker skills s and n.[7]

This simple model illuminates specification issues in the estimation of the urban wage premium. Specifically, one can justify estimating models of the $q(s,n)$ relationship, but this requires data on skills. One could also justify estimating reduced form models $q(h(t,z,n),n)$. This would not require data on skills, but it would require data on traits. Estimating models with only education is potentially problematic. It is also important to recognize that theory suggests that urbanization has impacts in two places, both in skill development and in skill deployment in production. The reduced form model would present estimates of the net effect of both impacts.

To consider this relationship in more detail, we begin with the case of unique intelligence and skill. Specifically, we suppose for now that there is one characteristic, and this one characteristic predicts education, the one element of z, according to the one-to-one mapping $z = f(t)$. Education directly determines skill s according to the one-to-one mapping $s = h(z)$. We are assuming here that there is no direct impact of the trait on wage. Skills impact wage as above. Serially composing gives $w = q(s) = q(h(z)) = q(h(f(t)))$. Thus, in this very special case, one can estimate the effects of skills using direct measures of s if they are available or using the indirect measures z or t. There is no misspecification in this highly restrictive case. If we live in a world where characteristics such as general intelligence g predict education which itself predicts skills, then either skills or their proxies can be incorporated in estimation. The econometrician might have data on skills, education, and characteristics. Only one is

[7] We treat n as equaling city population throughout this discussion. There is no reason, however, that n could not instead measure instead the local activity in a worker's industry (Marshallian localization).

required. If the data are noisy, the least noisy data would be preferred. As we will argue below, it is plausible to argue that the data on education are the least noisy of the three.[8]

We turn now to a slightly less special case: unique intelligence plus direct impact of characteristics on skills. The model in this case is as above, except now s = h(z,t). In this case, serially composing gives $y = q(s) = q(h(z), f^{-1}(z))) = q(h(f(t)), t)$. Thus, in this special case as well, one can estimate the effects of skills using direct measures of s if they are available or using either of the indirect measures, z or t. There is no again misspecification in this also highly restrictive case. If we live in a world where characteristics such as general intelligence *g* predict education which itself predicts skills, then either skills or their proxies can be incorporated in estimation. The missing element in both of these special cases is the multidimensionality of intelligence and worker characteristics.

Turning now to this more general case with multidimensional intelligence and characteristics, the model is as above, except that now all of the vectors t, z, and s are potentially multi-dimensional. In this case, the only result is the limited one that there is a possibility of misspecification. To see this, let there be two characteristics (t_1, t_2). z is a scalar, with $z = f(t_1)$ as above. There are two skills, (s_1,s_2). $s_1=h(z,t_1)$ as above. $s_2 = \eta(t_2)$. In this situation, an estimate of q(s) using only z would be misspecified, as would an estimate using only t_1. Estimation using z and t_2 or t_1 and t_2 or direct measures of skills would be properly specified.

The main implication of this section's framework is that skill and education are not equivalent. This has several corollaries. First, data on skills, traits, and intelligences are needed in order to estimate outcomes such as the urban wage premium. Second, estimates of disaggregated urban skill premiums obviously require skill data. Third, data on skills also allow the estimation of the impact of agglomeration on skill development. In all three cases, it is clear that data on skills has the potential to be very useful. The remainder of the paper will build on these conclusions by setting out a procedure for estimating worker skills and by estimating a model of skill development.

III. Data

The previous section deals with theoretical issues involved in the measurement of traits, intelligences, and skills. This section will be more applied. It will consider the measures that are actually available, and it will discuss their use in light of the theoretical framework developed above. We will focus on U.S. data.

It is natural to begin with the standard approach, where education is treated as being identical to skills. Education variables are available in individual worker level datasets most commonly used in urban

[8] There are, of course, many econometric issues other than the measurement of skills (i.e., simultaneity). We have ignored these.

and regional economics, including notably the Census and the National Longitudinal Survey of Youth 1979 (NLSY79). Since the geocoded NLSY79 reports the College Federal Interagency Committee (FICE) codes for individual colleges and universities, it is possible to go further by evaluating the quality of the institution of workers who went to college. This can be done by matching the institution's FICE code to the selectivity categories reported by Barron's Profiles of American Colleges. This procedure still ranks all graduates equally, but now only within a college or university.

Measures of traits and intelligences are much harder to obtain. While the readily available Census does have data on family circumstances, age, and so on, it does not have variables that capture relatively stable characteristics of workers that contribute to skill formation.[9] The NLSY79 is a much richer resource with information on multiple traits and intelligences. Respondents in the NLSY79 were administered the Armed Forces Qualification Tests (AFQT), which is generally agreed to capture cognition. In addition, the NLSY79 includes several measures of traits and abilities that capture aspects of social adjustment and interaction. One of these is the Rotter (1966) Scale administered to respondents in 1979. The Rotter Internal-External Locus of Control Scale is designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal), as opposed to the extent that the environment (i.e., chance, fate, luck) controls their lives (external). This measure of one's sense of self-control has been shown to be correlated with the individual's social skills (Lefcourt et al (1985)). NLSY respondents were also administered the Pearlin Mastery instrument in 1992, which is related to Rotter's locus of control.[10] We rescale the Rotter Control Scale and the Pearlin Mastery Scale scores to be positively oriented, so a larger value indicates a more adjusted personality. The Rosenberg Self-Esteem Scale is a personality assessment administered in 1980 of perceived self-esteem, describing a degree of self-approval or disapproval (Rosenberg, 1965). All three of these measures are calculated from responses to psychometric tests. Sociability, is the only one that is not test-based in that it comes from respondents' direct response to interviewers' asking them whether they were extremely or somewhat shy or outgoing at age 6. To make this measure comparable to the other measures that are oriented on a positive scale, we created a Sociability indicator equaling one if a respondent was not extremely nor somewhat shy, and zero otherwise.[11]

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[9] The closest measure of traits is a disability indicator (physical or mental condition impairing work or mobility).
[10] Rotter is measured on a two dimensional scale while Pearlin is uni-dimensional.
[11] These measures have been used previously: the AFQT and/or its components to capture cognitive ability (Neal and Johnson (1996) and Heckman, Stixrud, and Urzua (2006), among many others); the Rotter to capture personality traits or non-cognitive ability (see the various studies listed in Table 1 of the survey by Bowles, Gintis and Osborne (2001) and more recently Heckman, Stixrud, and Urzua (2006)); self-esteem (Murnane et al 1997); and Sociability (Borghans, ter Weel, and Weinberg 2007). We include all these measures in our analyses as the quality and amount of information may possibly vary from measure to measure.

The NLSY79 thus includes data on worker traits and intelligences, as well as data on education.[12] These are all part of the skill development process, but they are not themselves measures of skills. The paper has already dealt with the circumstances under which one can deal with urban and regional skill issues without direct measures of skills. We will illustrate such an approach in the next section. However, the previous discussion of skill development makes a strong case for the value of direct measures of skill. Such measures can be helpful in understanding the urban wage premium, and they are essential to computing more disaggregated urban skill premiums.

This leads naturally to the question: given the absence of skill data, how can one directly address skills? One approach is to infer skills from the occupations that worker's pursue. The motivation for this hedonic imputation procedure is straightforward: there is great variation in skills among graduating students, and market outcomes can refine skill attributions. Slightly more formally, hedonic attribution is based on labor market matching. In a frictionless hedonic equilibrium, markets assign a worker with skill level s to activity a through the mapping $a = g(s)$. If the mapping is invertible, then a worker carrying out job a has skill $s = g^{-1}(a)$. In the notation of the previous section, in research on agglomeration, when there is an invertible skill assignment mapping, we have $q(s) = q(g^{-1}(a))$. This allows estimation of a well-specified model if the econometrician can identify activities and can map activities to skills. It is worth noting that in this situation, it is sufficient to use only the skill attribution information. An econometrician in possession of noisy data on characteristics, education/investments, skills, and activities would employ the least noisy data.

In the next section, we will implement a hedonic attribution using data from the NLSY79 and the DOT. The NLSY79 reports worker occupations. The DOT characterizes the skill requirements of occupations. Matching the DOT with the NLSY79 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.[13] 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. There are 44 different job characteristics available in the DOT. Using the textual definitions of the variables, we identify three broad skill categories in the DOT data for our analysis. We

[12] It is worth noting that these measures assess either late adolescence (AFQT, Rotter, Pearlin) or childhood (Sociability). None of them is calculated more than once for the NLSY79 sample. Thus, despite its richness compared to the Census, we are unable to say much about the impact of urbanization on multiple stages of the process of skill formation.

[13] 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. This is why we do not use O-NET.

will work primarily with indices for cognitive, motor, and people skills created using principal component (factor) analysis. The indices are also re-scaled to have a mean of 1 and a standard deviation of 0.1.

The cognitive index is constructed through factor analysis of seven DOT cognitive skills. The skills capture the 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. A high value on this cognitive index indicates that substantive complexity is involved in carrying out the job. Similarly, we construct a motor skills index from nine DOT variables. These variables capture the complexity of the job in relation to things; aptitudes for manual dexterity, finger dexterity, motor coordination, eye-hand-foot coordination, spatial and form perception, and color discrimination; and adaptability to situations requiring attainment of standards. A higher value on the motor skills index indicates a job with greater manual demands. Finally, we construct a people skills index based on four DOT measures that relate to the people skills involved in an occupation. These variables capture an occupation's requirements of "adaptability to dealing with people beyond giving and receiving instructions," if an occupation requires direction, control, and planning , and if an occupation requires exerting influence.

This hedonic imputation of skill is based on occupation level evaluations of the skill content of work and the maintained hypothesis of a hedonic equilibrium that matches workers' bundles of skills to the skill requirements of occupations. The ideal, of course, would be to observe skills at the individual worker level. In applications such as measuring an urban skill premium, the potential problem is that errors in the attribution of skills could be correlated with regressors such as city size. Bacolod et al (2009a) address this through estimating worker fixed effects in a panel and by including additional controls to attempt to eliminate as much unobserved heterogeneity as possible. The specific controls included are based on the selectiveness of the college or university attended and abilities and traits that could potentially be associated with wage.

What alternatives might be possible? One approach would be to ask workers to assess their skills. Another would be to for some sort of skill auditor to evaluate worker skills. The question that arises for both would be: are these evaluations more accurate than the evaluations of the market? It seems to us that it is not certain that they are. In any case, neither Census nor NLSY nor the Panel Study of Income Dynamics have such direct evaluations of skills. This means that any possible advantage of the evaluation of skills at the individual worker level (which would be costly) must be weighed against the disadvantage of losing the precise estimation that is made possible by the relatively large sample sizes of these standard data sources.

Appendix Table A-1 details the sample in our data. Our NLSY79 worker sample includes respondents who worked in the last year, with non-missing hours, and whose occupational codes were merged with DOT information using the crosswalk from the National Crosswalk Service Center. For reasons that will become more evident below, we include only worker-years when workers are aged 25+.

IV. Estimating models of skill development

A. Overview

Section II lays out the case for constructing measures of worker skills as being distinct from education. Section III lays out how the measures have been constructed. This section will discuss the results of estimating models of urban skills. This section will address the left half of Figure 3, skill development. This will involve looking at the spatial allocation of traits and intelligences. It will also involve estimating models of the roles of education and cities in skill development.

Before considering this, we will briefly discuss related prior work, research that has considered the right half of Figure 3 relating skills to outcomes. Bacolod-Blum-Strange (2009a, 2009b) model and measure the spatial allocation of skills. These papers show that workers have higher levels of cognitive skills on average in larger cities. However, the differences are not especially pronounced, with magnitudes somewhat smaller than, for instance, the not especially large difference in the percent of workers with college education. Bacolod-Blum-Strange (2009b) shows that there are also more social skills on average in larger cities, with a more pronounced effect at the top of the distribution. In some situations, there is a negative effect at the bottom of the skill distribution. Bacolod-Blum-Strange (2009a) show that city size increases the value of cognitive and social skills, not physical skills. Urban wage models are not the only possible outcome model that one might estimate using Figure 3's framework. One could also make the case that estimates of human capital externalities should be based on local skill levels rather than on local education levels. Likewise, models of agglomeration and innovation should also depend at least in part on local skills and not just on local education or the local presence of universities. We discuss these issues further in the conclusion.

B. The spatial allocation of traits and intelligences

As mentioned in the Introduction, the spatial distribution of skills is important for a number of reasons. First, it is associated with urban growth. Cities whose populations are more skilled are likely to experience more rapid population growth. Second, it is associated with innovation. Cities with more skilled workforces are likely to develop more new products. Third, skill is associated with productivity. Cities with more skilled populations have higher wages and rents, an external effect that is consistent with agglomeration economies. The framework laid out in Section II shows that skills are related to education and to traits and intelligences. Prior work has characterized the spatial patterns of skills and education. We will now characterize the parallel pattern for traits and intelligences.

Table 1a describes the spatial pattern of AFQT, Rotter, Pearlin, Rosenberg, and Sociability. It is worth re-iterating that Sociability is constructed quite differently by means of a simple survey rather than psychometric test and reference to age 6 rather than to adolescence. We adjust all four of these measures so that they are positively oriented (more is better) and range from 0 to 1.[14] The table computes the various measures for MSAs with fewer than 500,000 inhabitants (small cities) and for those with more (large cities). The table reports both totals and values for selected individual occupations.

The key pattern that the table illustrates is that there is relatively little difference in these measures between large and small cities. Beginning at the bottom of the table, the overall average level of AFQT is slightly larger (less than 2%) in the smaller cities. For Rotter, the means are almost identical in small and large cities. For Pearlin and Rosenberg, we have slightly larger values in larger cities at the mean and at the 90th percentile. For Sociability, the mean value is on the order of 10% larger in large cities than in small.[15] The pattern for individual occupations exhibits is similar. Mean values are insignificantly different between small and large cities.

Table 1b looks at how migration between small and large cities impacts the spatial allocation of traits and intelligences. Specifically, it looks at the values of AFQT, Rotter, Pearlin, Rosenberg, and Sociability for two sorts of "stayers" (small-always and large-always) and two sorts of "movers" (small-to-large and large-to-small). Looking at the totals, an interesting pattern emerges. For AFQT, the movers, both small-to-large and large-to-small, tend to have higher values, although the differences are not statistically significant. The value is smallest for those who remain in small cities, but the difference is again insignificant. For Rotter, Pearlin, and Rosenberg, the differences are small and are statistically insignificant. For Sociability, the pattern is as for the AFQT, with higher values for movers of both kinds and the lowest value for stayers. Taken with Table 1a, Table 1b's results are only weakly supportive of selection of intelligences and traits into larger cities.

C. Reduced form relationship between traits, intelligences, and skills

Figure 3 depicts a relationship between traits, intelligences, and skills that has both a direct channel and indirect channels that operate through education and urbanization. To estimate the total direct plus indirect relationship in a reduced form model requires the estimation of

$$S_{it} = a_1 T_i + a_2 X_{it} + e_{it}. \qquad (1)$$

[14] This means that in all discussion to follow and in all tables, we are using an inverse of the standard Rotter measure of the locus on control.

[15] We have also computed the 10th and 90th percentile values of the five measures. The extremes of the distribution are also not much different between small and large cities.

S_{it} is the skill level of the ith worker at time t.[16] As described above, we work with indices of cognitive, people, and motor skills constructed from factor analysis, with mean 1 and standard deviation 0.1. T_i is the vector of traits and intelligences (AFQT, Rotter, Pearlin, Rosenberg, Sociability; hereafter just "traits") for the ith worker. X_{it} is a vector of other covariates for worker i at time t, including an intercept term, age, age squared, gender, race, a marital status dummy (worker is married or remarried), and the number of children at year t. Some of the measures are not reported for some workers; we therefore include "missing variable" indicators for AFQT, Rosenberg, and Sociability. Both Rotter and Pearlin are reported for all the workers in our sample. In this specification, we pool together all worker-years to estimate the reduced form manifestation of cognitive, motor, and people skills from traits. We estimate the skills equations jointly via FGLS to take into account correlation in errors across the skills. We also include controls for urban status in 1979 to condition on early urbanization (a dummy variable for a worker who resided in 1979 in an MSA with population of 500,000 or greater). In addition to estimating a pooled model, we also estimate equation (1) separately for large and small cities and separately by educational attainment in order to get at the impact of urbanization and education on the manifestation of worker skills.

The results are presented in Tables 2a and 2b. Table 2a presents the total and small/large MSA models. It is immediately apparent that traits are positively related to skills. This is not at all surprising. Beginning with the full sample estimates at the left of Table 2a, measures of personality, self-esteem and social abilities are all highly predictive of people skills. Higher levels of these traits also translate to greater cognitive skills. Cognitive ability as captured by the AFQT is also positively predictive of people and cognitive skills. In contrast, it is negatively predictive of motor skills.[17]

The relationships of skills to other controls are standard and expected. Cognitive and people skills are increasing in age at a diminishing rate, while physical skills are declining in age. Women have more cognitive and people skills and lower levels of motor skills. Blacks have higher levels of cognitive skills (if we did not condition on AFQT and other abilities, this would be negative) and less motor skills. Married workers have higher levels of cognitive and people skills, but they are not significantly different from singles in motor skills. Cognitive and people skills are diminishing in number of children, while the level of motor skills is increasing. These magnitudes are not large, however. Having one child is related to a decline of less than one standard deviation.

The relationship to the urban variables is consistent with various ideas in the agglomeration literature regarding skills and cities. Urbanization is included in two ways. The first is the control for

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[16] It is worth noting that in this model and in others to follow below, error in skill attribution does not introduce bias.

[17] A similar relationship emerges in a model where we do not control for urbanization in 1979.

early exposure to urbanization in 1979. This is included in the pooled model, and in all the models that follow. Being in a large MSA at the beginning of the period is significantly and positively related to high cognitive skills. It is insignificant in its relationship to motor and people skills. The result that a worker's urban status in 1979 exerts a continuing effect on the worker's cognitive skills is worth considering in some detail. Learning is a crucial source of agglomeration economies, and it has been considered in numerous papers, only a small subset of which are listed in the Introduction. Learning is more than crucial in developmental psychology; it is the whole field. And the field is clear that a substantial amount of learning takes place at early ages. As discussed above, traits are stable, and are not much changed beyond early childhood. Abilities continue to develop through adolescence, but they do become relatively set in early adulthood. There is certainly continued learning through life, but a lot of really important learning takes place early in life, a fact that has become increasingly apparent to labor economists (i.e., Heckman and Cunha (2007) among others).

It is somewhat striking that although learning is a first-order issue in urban economics, there has been relatively little attention paid to the impact of cities on learning. The attention that has been paid is mostly in the form of indictments of central city schools, an issue that conflates the selection of families into locations and big-city political economy issues with the possibility of an influence of agglomeration on learning. An interesting paper by Gibbons and Silva (2008) is an exception. It shows a positive effect of density on pupil attainment in a panel estimates, using compulsory transitions between primary and secondary schools to achieve identification. Our paper's estimates the effects of urban status in 1979 are related in showing a positive impact of early agglomeration.

The second way that we consider urbanization is to separately estimate skill manifestation models for small and large cities. The results of this estimation are reported in the two panels on the right side of Table 2a. The relationship between traits and skills clearly varies between the large and small cities, particularly for the deployment of personality traits and social abilities into cognitive, people, and even motor skills. Personality traits and social abilities (except for Rotter) are significantly negatively related to the deployment of motor skills in large cities, but are essentially zero (except for Rotter) in small cities. Having a personality with a better sense of control over one’s environment (as measured by Rotter) leads to a significantly higher development of motor skills in a small city but not in a large city. This suggests that small cities enhance the development of motor and manual skills particularly for individuals with better social abilities and well-adjusted personalities. One possibility is that there are more opportunities for youth in the development of their manual coordination in small-town settings. Meanwhile, personality and social abilities are associated with a higher level of cognitive skills in large cities than in small cities. With respect to people skills, a personality with a better sense of control over one’s environment (Rotter) leads to a significantly higher development of people skills in a large city but not in a small city. Higher self-esteem (Rosenberg) also gets deployed to better people skills in a large city greater in magnitude than in a small city. The other two personality traits (Pearlin and Sociability) are significantly related with people skills in both large and small cities, but are greater in small than in large cities. These results are all conditional on where one was living before age 25 (respondents were aged 14-21 in 1979), so we are comparing skill manifestation in large versus small cities conditioning out early exposure to urbanization. Finally, the relationships between skills and the other controls (for example, age and married) are substantially different in small versus large cities. This suggests that workers in small and large cities are different, and that taking into account worker selection into small versus large cities may change the relationship between traits and skills. To summarize somewhat roughly, Table 2a suggests traits are more developed in urban areas towards better cognitive and people skills. Motor skills seem to be better enhanced in small cities.

Table 2b considers the impact of a worker's education on skill manifestation. As noted above, the relationship between abilities and skills also varies by education even conditional on urban status in 1979. For instance, higher levels of cognitive ability as measured by AFQT translate to higher cognitive skills across all education levels. However, while higher AFQT is deployed as better people skills for workers with less than high school and for high school graduates, higher AFQT translates to less people skills for workers with college-plus education. Rotter for college-plus workers is insignificant across all skills. The deployment of social ability and personality traits into skills is most pronounced and significant for high school graduates. This finding is perhaps consistent with the GED puzzle in the labor economics literature. Heckman and Rubinstein (2001) show that high school dropouts who earn their high school degrees via passing the General Educational Development (GED) exam have the same achievement test scores as high school graduates, but earn on average the wages of dropouts. Heckman, Stixrud and Urzua (2006) then show that the poor labor market performance of GED recipients is due to their low levels of non-cognitive skills, lower even than dropouts. Our finding that the deployment of interactive traits into skills is most significant for high school graduates is consistent with this GED literature, since the high school graduates in our data include those who earned their high school degrees through formal schooling and those who pass by taking the GED exam. The labor literature has established that it is for this particular group that differentiation in non-cognitive traits matters.

D. The relationship between traits and abilities and urban status and education

As discussed above, there are two indirect channels by which traits can impact skills. Denote the education of worker i at time t by E_{it}. As above, continue to denote the urban status (large or small) by U_{it} and the traits by T_i. If the vectors X^E_{it} and X^U_{it} denote the covariates that impact, respectively, education and urbanization, then we estimate these indirect channels by estimating the following equations. The previously introduced X includes everything in X^E and X^U.

$$E_{it} = \gamma T_i + \Psi X^E_{it} + v_{it}\ , \tag{2}$$

$$U_{it} = \beta T_i + \Phi X^U_{it} + \omega_{it}\ . \tag{3}$$

We could estimate equations (2) and (3) separately as ordered discrete choice models, with E_{it} denoting the highest completed education level and U_{it} denoting progressively larger SMSA size categories. Given our small sample and the later joint estimation with skills, we prefer a more parsimonious estimation strategy. To show that our results are similar across a linear versus discrete choice model, Equation (2) is estimated in two ways, by OLS with E_{it} denoting highest grade completed (years of completed schooling) and by multinomial logit where E_{it} denotes completing an education level (less than high school, high school and college). Equation (3) is also estimated in two ways, by OLS and by simple logit (large or small city).

The results are presented in Table 3.[18] First, higher AFQT workers choose to live in large cities. Second, workers with better personality and social ability are also more likely to live in large cities. These coefficients are very similar in both significance and magnitude across the nonlinear logit estimation and OLS. Third, married workers are 2.6% significantly less likely to live in large cities than in a small city. Having one more child is also associated with 3% less likelihood of living in a large vs. small city. In our later estimation, we will use marital status and number of children as exclusion restrictions.

With respect to the relationship between traits and schooling, as is well known, AFQT is positively associated with educational attainment. Our OLS estimates show that a one percentile improvement in AFQT is associated with five more years of schooling.[19] Second, better personality, social ability (self-esteem, control) and sociability traits (is outgoing) are also associated with more years of schooling. Third, the multinomial logit results indicate that individuals with higher AFQT and better social traits are less likely to graduate from high school relative to dropping out. Since high school graduates are confounded with GED recipients, this result is not inconsistent (see above discussion of the

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[18] The results are the same in models that do not control for urban status in 1979.
[19] Cascio and Lewis (2006) estimate that an additional year of schooling raises AFQT of minorities in the NLSY79 by 0.31 to 0.32 standard deviations. Although this estimate is in the opposite causal direction (the effect of schooling on AFQT identified using a regression discontinuity design based on birth dates and schooling start dates), our estimate of the relationship between schooling and AFQT is consistent with this literature (for instance, Heckman and Vytlacil 2000 that estimate the impact of cognitive ability on educational attainment).

GED puzzle). In addition, note that the constant is positive (workers are on average more likely to graduate from high school than drop out). Finally, we find that early exposure to urbanization makes it less likely for one to graduate from college relative to dropping out of high school.

Overall these results show us that traits and abilities are potentially endogenous to location choices and to human capital investment decisions. All measures of cognitive and social traits are significant determinants of schooling and the choice of living in a large vs. small city.

E. Structural direct and indirect effects

An alternative approach to estimating the direct and indirect channels of the relationship between traits and skills is to estimate the three channels jointly. This framework is similar to other estimation strategies in labor economics that endogenize schooling choices (i.e., Heckman, Stixrud and Urzua 2006), although the outcomes of interest in those papers are labor market outcomes such as wages and employment instead of skills. This approach involves estimating the system:

$$S_{it} = \alpha_0 E_{it} + \alpha_1 T_i + \alpha_2 U_{it} + \Gamma X^S_{it} + u_{it} , \quad (4)$$

$$E_{it} = \gamma T_i + \Psi X^E_{it} + v_{it} , \quad (5)$$

$$U_{it} = \beta T_i + \Phi X^U_{it} + \omega_{it} . \quad (6)$$

X^S includes covariates relevant to the skill equation. The direct effect of traits on skills are captured by the parameter α_1. The indirect effect of traits that works through education is captured by $\alpha_0 * \gamma$, while the indirect effect that works through urbanization are captured by $\alpha_2 * \beta$. In order to identify γ from β, X^U cannot overlap perfectly with X^E. Thus, exclusion restrictions are necessary in order to estimate equations (4)-(6) jointly—either factors that determine schooling but not urbanization, or factors that determine the location decision but not schooling. We use marital status and the number of children affecting the urban decision but not the education decision. Conceptually this is reasonable as workers in our sample are all over age 25. Most workers have completed their schooling by age 25, and thus, marital status and number of children at age 25 and older are excludable as determinants of schooling. Meanwhile a single worker is more likely to be in an urban environment for a larger access to the marriage market or other types of amenities that singles consume. A worker's number of children is also a potential determinant of the urban decision, as workers with more children are possibly more likely to live in smaller cities with lower cost-of-living and cheaper access to good public schools. We estimate the entire system above via feasible generalized least squares (FGLS).

The estimates are reported in Table 4. As expected, urbanization has a significantly positive direct impact on cognitive and people skills and negative on motor skills. The same holds true with education. Table 5 presents the calculations of the direct and indirect estimates. Interestingly, the indirect effects via education of traits on skills is greater than the direct effects. In other words, schooling magnifies both cognitive and social traits in the deployment of cognitive and people skills, once we condition on urban status in 1979. Furthermore, urbanization also has an indirect effect on the deployment of skills but not as substantial as education. It is worth recalling that we also condition on urban status in 1979, so these estimates do not imply no relationship at all of urbanization on skills.

Overall, these estimates confirm the framework we laid out above. There is a significant relationship between traits and skills. Some of this works directly through the direct impact of traits on skills. However, there is also a substantial indirect effect that works through urbanization and education.

F Movers and Stayers

The final reported results (Table 6) are computed using the mover – stayer breakdown discussed above. The table reports the marginal effects from a multinomial logit model of moving between small and large cities. AFQT is positively associated with both kinds of move, small-to-large and large-to-small. The effect is significantly larger for the small-to-large move. This has two implications. First, the net effect is towards higher AFQT in large cities, the sort of selection effect that has been noticed previously (i.e., Combes et al, 2008). Second, both types of movers have higher levels of AFQT. This result, new to the literature, suggests that the way that sorting might work in a dynamic framework is not simply for the most able to move to the biggest cities.

Taken as a group, the results for the four measures of social traits have a somewhat similar pattern, but not an identical one. The pattern for Rosenberg (self-esteem) and Sociability are exactly the same as for AFQT: a net selection effect towards big cities, with more able workers making both types of moves. The pattern for Rotter exhibits the same net selection effect, but the pattern for ability levels of movers is different. There is a positive marginal effect associated with Rotter for small-to-large moves, but the effect is insignificant. There is a significant negative effect associated with Rotter for large-to-small moves. The only exception to the basic pattern is for Pearlin (self-mastery), where the small-to-large marginal effect is positive but insignificant, while the large-to-small marginal effect is positive, large, and significant. These coefficients are consistent with more able workers moving, but not with net selection towards large cities.

V. Conclusion

This paper begins with the observation that skill does not equal education. The paper is devoted to clarifying the relationship of skill to education and what this means for the urban and regional economic analysis of skills. The bottom line is that education is a part of the process that determines skills, a crucial part. However, a worker's prior abilities and traits matter too. With contributions from education and also from agglomeration, traits and intelligences determine skills.

Fortunately, it is possible to characterize worker skills using occupation level data on the skill requirements of jobs such as the DOT and O-NET. If markets for skill clear in a hedonic sense, then workers are matched to jobs that require the skills that they possess. This approach allows one to consider the spatial distribution of skills (Bacolod-Blum-Strange, 2009a and 2009b) and to consider the impact of agglomeration on the hedonic prices of skills (Bacolod-Blum-Strange, 2009a).

This is an approach that has the potential to contribute to the solution of other important questions in urban and regional economics. For instance: what is the effect of the local level of human capital on growth and productivity? Since Rauch's (1993) seminal paper establishing a strong relationship between wages and rents and the percentage of an MSA's workers with college educations, there has been considerable attention focused on the endogeneity of education. This concern is well-placed. Another concern -- one that has largely escaped attention -- is that education is not synonymous with skills. Theories of agglomeration based on matching do not simply focus on matching workers differentiated by their education (i.e., college or not). They focus on matching workers with different skills (i.e., ability to manage). Theories of agglomeration based on learning certainly do not focus on an increase in the ease of acquiring a college degree. They focus on learning job skills from nearby workers. It is therefore worth considering whether it is the presence of multi-dimensional skills that contributes to productivity and growth. Similarly, local innovation has been shown to be related to the presence of educated workers and to universities themselves. In this case, as well, a largely unasked question is whether it is local skill that impacts innovation.

This discussion has focused on the implications of the measurement of worker skill for the various outcomes that are believed to be impacted by agglomeration. A second contribution of the traits-abilities-skills framework is that it suggests a way of thinking about the role of agglomeration in skill determination. It is already understood by researchers in education that intelligences and traits are associated with skills, and that education contributes to this relationship. It is also understood by researchers in urban and regional economics that agglomeration can contribute to skill development as well.

The construction of skill measures by hedonic attribution allows the formal analysis of this relationship. This paper shows that agglomeration is related to the manifestation of skills from traits and intelligences for both cognitive and people skills. We do not find evidence of such a relationship for motor skills. In addition, for both cognitive and people skills, there is evidence of sorting, where more skilled workers disproportionately choose large cities.

Table 1a. Traits and Abilities in Large and Small Cities

	AFQT %ILE/100			Rotter Locus of Control			Pearlin Control Mastery			Rosenberg Self-Esteem			Sociability Trait 'not shy' (%)		
	MSA Size			MSA Size			MSA Size			MSA Size			MSA Size		
Occupation	Small(<.5M)	Large(.5+M)	Total	Small(<.5M)	Large(.5+M)	Total	Small(<.5M)	Large(.5+M)	Total	Small(<.5M)	Large(.5+M)	Total	Small(<.5M)	Large(.5+M)	Total
Managers	0.63	0.65	0.64	0.48	0.49	0.48	0.75	0.76	0.76	0.81	0.83	0.82	0.51	0.45	0.48
	(0.26)	(0.25)	(0.26)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.1)	(0.1)	(0.1)	(0.5)	(0.5)	(0.5)
Engineers	0.79	0.78	0.79	0.50	0.49	0.49	0.78	0.76	0.77	0.83	0.82	0.83	0.42	0.43	0.43
	(0.21)	(0.21)	(0.21)	(0.1)	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.1)	(0.1)	(0.1)	(0.5)	(0.5)	(0.5)
Therapists	0.60	0.63	0.62	0.49	0.47	0.48	0.72	0.75	0.74	0.82	0.86	0.84	0.29	0.46	0.37
	(0.24)	(0.26)	(0.25)	(0.17)	(0.13)	(0.15)	(0.1)	(0.11)	(0.11)	(0.06)	(0.1)	(0.08)	(0.46)	(0.5)	(0.48)
College Profs	0.81	0.75	0.78	0.51	0.51	0.51	0.74	0.75	0.74	0.86	0.86	0.86	0.34	0.46	0.40
	(0.17)	(0.25)	(0.21)	(0.11)	(0.11)	(0.11)	(0.14)	(0.13)	(0.13)	(0.1)	(0.1)	(0.1)	(0.48)	(0.5)	(0.49)
Teachers	0.68	0.66	0.67	0.49	0.49	0.49	0.76	0.74	0.75	0.82	0.83	0.83	0.41	0.51	0.46
	(0.24)	(0.23)	(0.23)	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.1)	(0.09)	(0.1)	(0.49)	(0.5)	(0.5)
Lawyers	0.92	0.88	0.90	0.49	0.53	0.51	0.73	0.81	0.77	0.85	0.87	0.86	0.62	0.41	0.51
	(0.13)	(0.16)	(0.14)	(0.07)	(0.11)	(0.09)	(0.12)	(0.12)	(0.12)	(0.09)	(0.09)	(0.09)	(0.5)	(0.49)	(0.5)
Sales Person	0.87	0.85	0.86	0.53	0.50	0.51	0.75	0.72	0.74	0.84	0.84	0.84	0.43	0.43	0.43
	(0.2)	(0.19)	(0.19)	(0.09)	(0.11)	(0.1)	(0.07)	(0.12)	(0.1)	(0.11)	(0.08)	(0.1)	(0.5)	(0.5)	(0.5)
Food Services	0.40	0.43	0.42	0.45	0.46	0.45	0.71	0.71	0.71	0.77	0.79	0.78	0.38	0.41	0.40
	(0.28)	(0.27)	(0.27)	(0.14)	(0.13)	(0.14)	(0.12)	(0.12)	(0.12)	(0.09)	(0.1)	(0.09)	(0.49)	(0.49)	(0.49)
Mechanics	0.49	0.44	0.47	0.51	0.48	0.49	0.73	0.73	0.73	0.80	0.78	0.79	0.34	0.44	0.39
	(0.28)	(0.26)	(0.27)	(0.14)	(0.14)	(0.14)	(0.12)	(0.11)	(0.12)	(0.09)	(0.1)	(0.1)	(0.47)	(0.5)	(0.49)
Construction	0.42	0.41	0.42	0.47	0.47	0.47	0.71	0.73	0.72	0.79	0.79	0.79	0.37	0.45	0.41
Workers	(0.27)	(0.26)	(0.26)	(0.14)	(0.14)	(0.14)	(0.11)	(0.12)	(0.11)	(0.09)	(0.1)	(0.1)	(0.48)	(0.5)	(0.49)
Janitors	0.26	0.30	0.28	0.41	0.44	0.43	0.68	0.71	0.69	0.73	0.77	0.75	0.31	0.38	0.35
	(0.24)	(0.26)	(0.25)	(0.15)	(0.15)	(0.15)	(0.11)	(0.12)	(0.11)	(0.1)	(0.1)	(0.1)	(0.46)	(0.49)	(0.47)
Natural	0.74	0.82	0.78	0.50	0.49	0.49	0.79	0.76	0.78	0.77	0.80	0.79	0.41	0.42	0.42
Scientists	(0.24)	(0.21)	(0.22)	(0.13)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)	(0.08)	(0.09)	(0.08)	(0.5)	(0.5)	(0.5)
Nurses	0.71	0.67	0.69	0.50	0.51	0.50	0.73	0.75	0.74	0.83	0.84	0.83	0.44	0.46	0.45
	(0.22)	(0.21)	(0.22)	(0.15)	(0.13)	(0.14)	(0.1)	(0.11)	(0.1)	(0.1)	(0.09)	(0.09)	(0.5)	(0.5)	(0.5)
Social Workers	0.61	0.55	0.58	0.47	0.49	0.48	0.78	0.79	0.79	0.83	0.84	0.83	0.20	0.45	0.32
	(0.23)	(0.26)	(0.24)	(0.12)	(0.13)	(0.12)	(0.12)	(0.11)	(0.12)	(0.09)	(0.09)	(0.09)	(0.4)	(0.5)	(0.45)
Technicians	0.69	0.69	0.69	0.50	0.48	0.49	0.75	0.75	0.75	0.80	0.82	0.81	0.44	0.39	0.42
	(0.25)	(0.26)	(0.26)	(0.13)	(0.13)	(0.13)	(0.11)	(0.12)	(0.11)	(0.1)	(0.1)	(0.1)	(0.5)	(0.49)	(0.49)
Admin Support	0.53	0.51	0.52	0.47	0.46	0.47	0.72	0.73	0.73	0.79	0.80	0.80	0.36	0.38	0.37
	(0.25)	(0.25)	(0.25)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.1)	(0.1)	(0.1)	(0.48)	(0.49)	(0.48)
Personal	0.45	0.43	0.44	0.45	0.48	0.47	0.70	0.72	0.71	0.78	0.79	0.78	0.41	0.42	0.42
Services	(0.27)	(0.26)	(0.26)	(0.12)	(0.14)	(0.13)	(0.12)	(0.12)	(0.12)	(0.1)	(0.1)	(0.1)	(0.49)	(0.49)	(0.49)
Total	0.62	0.61	0.62	0.48	0.48	0.48	0.74	0.75	0.74	0.81	0.82	0.81	0.39	0.43	0.41
	(0.23)	(0.24)	(0.23)	(0.13)	(0.13)	(0.13)	(0.11)	(0.12)	(0.12)	(0.1)	(0.1)	(0.1)	(0.48)	(0.5)	(0.49)

Note: Average traits and abilities are calculated by occupation and MSA size at *t* using sampling weights. Entries in parentheses are standard errors. The last three columns report percentage of workers in that occupation-MSA who are outgoing.

Table 1b. Traits and Abilities: Movers and Stayers

Occupation	AFQT %ILE/100				Rotter Locus of Control				Pearlin Control Mastery				Rosenberg Self-Esteem				Sociability Trait 'not shy' (%)			
	Small Always	Move Small to Large	Move Large to Small	Large Always	Small Always	Move Small to Large	Move Large to Small	Large Always	Small Always	Move Small to Large	Move Large to Small	Large Always	Small Always	Move Small to Large	Move Large to Small	Large Always	Small Always	Move Small to Large	Move Large to Small	Large Always
Managers	0.61	0.74	0.68	0.64	0.49	0.51	0.48	0.49	0.73	0.77	0.77	0.76	0.82	0.85	0.83	0.83	0.42	0.47	0.53	0.45
	(0.29)	(0.22)	(0.24)	(0.25)	(0.15)	(0.12)	(0.11)	(0.13)	(0.11)	(0.11)	(0.14)	(0.12)	(0.1)	(0.09)	(0.09)	(0.1)	(0.49)	(0.5)	(0.5)	(0.5)
Engineers	0.65	0.82	0.93	0.78	0.48	0.51	0.47	0.49	0.74	0.76	0.80	0.76	0.80	0.81	0.87	0.82	0.54	0.42	0.52	0.44
	(0.25)	(0.17)	(0.08)	(0.21)	(0.13)	(0.09)	(0.09)	(0.12)	(0.09)	(0.1)	(0.15)	(0.11)	(0.11)	(0.09)	(0.08)	(0.1)	(0.51)	(0.5)	(0.51)	(0.5)
Therapists	0.24	0.79	0.55	0.63	0.55	0.55	0.51	0.49	0.68	0.71	0.80	0.76	0.79	0.90	0.92	0.85	0.10	0.91	0.20	0.37
	(0.15)	(0.23)	(0.18)	(0.25)	(0.06)	(0.03)	(0.1)	(0.15)	(0.06)	(0.12)	(0.21)	(0.11)	(0.05)	(0.1)	(0.08)	(0.09)	(0.31)	(0.3)	(0.44)	(0.48)
College Profs	0.80	0.60	0.76	0.76	0.48	0.57	0.48	0.51	0.76	0.79	0.79	0.75	0.87	0.82	0.81	0.86	0.34	0.85	0.46	0.44
	(0.16)	(0.21)	(0.16)	(0.24)	(0.14)	(0.1)	(0.05)	(0.11)	(0.14)	(0.15)	(0.12)	(0.12)	(0.1)	(0.11)	(0.07)	(0.09)	(0.49)	(0.38)	(0.51)	(0.5)
Teachers	0.72	0.68	0.65	0.66	0.48	0.53	0.49	0.49	0.76	0.77	0.80	0.74	0.78	0.85	0.87	0.83	0.21	0.74	0.44	0.50
	(0.25)	(0.25)	(0.14)	(0.23)	(0.16)	(0.11)	(0.09)	(0.12)	(0.14)	(0.11)	(0.13)	(0.12)	(0.1)	(0.07)	(0.1)	(0.09)	(0.41)	(0.44)	(0.5)	(0.5)
Lawyers	0.73	0.89	n.a.	0.88	0.45	0.44	n.a.	0.54	0.77	0.70	n.a.	0.82	0.73	0.81	n.a.	0.88	0.06	0.61	n.a.	0.39
	(0.15)	(0.08)		(0.17)	(0.11)	(0.1)		(0.1)	(0.05)	(0.09)		(0.12)	(0.01)	(0.09)		(0.08)	(0.27)	(0.5)		(0.49)
Sales Person	0.83	0.95	0.92	0.81	0.56	0.51	0.60	0.49	0.75	0.72	0.71	0.72	0.84	0.84	0.88	0.84	0.77	0.29	0.25	0.48
	(0.26)	(0.09)	(0.14)	(0.2)	(0.1)	(0.07)	(0.06)	(0.12)	(0.06)	(0.13)	(0.04)	(0.12)	(0.13)	(0.05)	(0.05)	(0.09)	(0.44)	(0.46)	(0.49)	(0.5)
Food Services	0.31	0.56	0.39	0.43	0.44	0.44	0.41	0.46	0.68	0.71	0.68	0.71	0.76	0.77	0.78	0.79	0.29	0.54	0.27	0.41
	(0.27)	(0.31)	(0.24)	(0.26)	(0.14)	(0.16)	(0.1)	(0.13)	(0.12)	(0.12)	(0.1)	(0.12)	(0.09)	(0.09)	(0.09)	(0.1)	(0.45)	(0.5)	(0.45)	(0.49)
Mechanics	0.51	0.34	0.42	0.44	0.52	0.51	0.51	0.48	0.71	0.70	0.83	0.73	0.80	0.72	0.81	0.78	0.28	0.31	0.32	0.44
	(0.29)	(0.29)	(0.34)	(0.25)	(0.14)	(0.1)	(0.15)	(0.14)	(0.11)	(0.09)	(0.15)	(0.11)	(0.09)	(0.1)	(0.06)	(0.1)	(0.45)	(0.46)	(0.48)	(0.5)
Construction Workers	0.44	0.37	0.59	0.41	0.46	0.43	0.44	0.47	0.71	0.73	0.76	0.73	0.79	0.74	0.80	0.80	0.30	0.40	0.71	0.45
	(0.26)	(0.28)	(0.26)	(0.26)	(0.13)	(0.12)	(0.16)	(0.14)	(0.11)	(0.1)	(0.1)	(0.12)	(0.09)	(0.12)	(0.08)	(0.1)	(0.46)	(0.49)	(0.46)	(0.5)
Janitors	0.19	0.29	0.46	0.30	0.40	0.45	0.37	0.44	0.68	0.73	0.64	0.71	0.72	0.79	0.82	0.77	0.25	0.55	0.52	0.37
	(0.2)	(0.27)	(0.3)	(0.26)	(0.15)	(0.12)	(0.14)	(0.15)	(0.11)	(0.13)	(0.11)	(0.12)	(0.1)	(0.12)	(0.1)	(0.1)	(0.43)	(0.5)	(0.52)	(0.48)
Natural Scientists	0.71	0.69	0.89	0.82	0.53	0.40	0.39	0.49	0.82	0.63	0.82	0.77	0.77	0.63	0.76	0.81	0.60	0.14	0.21	0.43
	(0.26)	(0.3)	(0.17)	(0.2)	(0.13)	(0.07)	(0.12)	(0.11)	(0.12)	(0.05)	(0.08)	(0.12)	(0.08)	(0.05)	(0.11)	(0.09)	(0.5)	(0.39)	(0.44)	(0.5)
Nurses	0.71	0.58	0.51	0.68	0.52	0.45	0.50	0.51	0.72	0.71	0.69	0.75	0.84	0.82	0.89	0.83	0.41	0.34	0.23	0.44
	(0.22)	(0.29)	(0.3)	(0.21)	(0.13)	(0.12)	(0.16)	(0.12)	(0.07)	(0.08)	(0.11)	(0.11)	(0.1)	(0.06)	(0.06)	(0.09)	(0.5)	(0.48)	(0.45)	(0.5)
Social Workers	0.66	0.48	0.46	0.55	0.50	0.52	0.46	0.49	0.71	0.82	0.77	0.79	0.88	0.86	0.77	0.84	0.30	0.47	0.20	0.45
	(0.28)	(0.22)	(0.19)	(0.26)	(0.07)	(0.1)	(0.17)	(0.13)	(0.08)	(0.08)	(0.14)	(0.11)	(0.07)	(0.07)	(0.06)	(0.09)	(0.47)	(0.51)	(0.41)	(0.5)
Technicians	0.66	0.75	0.74	0.68	0.54	0.50	0.45	0.48	0.75	0.72	0.76	0.75	0.81	0.80	0.82	0.82	0.44	0.39	0.46	0.39
	(0.27)	(0.24)	(0.25)	(0.26)	(0.13)	(0.12)	(0.11)	(0.13)	(0.11)	(0.1)	(0.15)	(0.12)	(0.11)	(0.1)	(0.08)	(0.1)	(0.5)	(0.49)	(0.5)	(0.49)
Admin Support	0.53	0.50	0.69	0.51	0.47	0.48	0.49	0.46	0.72	0.73	0.72	0.73	0.78	0.82	0.83	0.80	0.29	0.44	0.54	0.38
	(0.25)	(0.27)	(0.23)	(0.25)	(0.14)	(0.13)	(0.11)	(0.13)	(0.11)	(0.1)	(0.15)	(0.12)	(0.1)	(0.1)	(0.1)	(0.1)	(0.46)	(0.5)	(0.5)	(0.49)
Personal Services	0.42	0.46	0.55	0.43	0.43	0.51	0.50	0.48	0.71	0.78	0.76	0.72	0.78	0.82	0.88	0.79	0.36	0.59	0.65	0.42
	(0.25)	(0.24)	(0.24)	(0.26)	(0.13)	(0.12)	(0.09)	(0.14)	(0.12)	(0.12)	(0.12)	(0.12)	(0.1)	(0.09)	(0.1)	(0.1)	(0.48)	(0.5)	(0.49)	(0.49)
Total	0.57	0.62	0.64	0.61	0.49	0.49	0.47	0.49	0.73	0.73	0.76	0.75	0.80	0.80	0.83	0.82	0.35	0.50	0.41	0.43
	(0.24)	(0.23)	(0.22)	(0.24)	(0.13)	(0.1)	(0.11)	(0.13)	(0.1)	(0.11)	(0.12)	(0.12)	(0.09)	(0.09)	(0.08)	(0.1)	(0.45)	(0.47)	(0.48)	(0.49)

Note: Weighted average traits and abilities are calculated by occupation and mover/stayer status between 1979 and year *t*. Entries in parentheses are standard errors. The last four columns report percentage of workers in that category who are outgoing.

Table 2a. Skill Manifestation in Cities

	OVERALL SKILLS			SMALL (<.5M) SKILLS			LARGE (.5M+) SKILLS		
	Cognitive	Motor	People	Cognitive	Motor	People	Cognitive	Motor	People
AFQT %ILE/100	0.134	-0.008	0.085	0.136	0	0.09	0.133	-0.01	0.083
	[0.002]***	[0.002]***	[0.002]***	[0.005]***	[0.005]	[0.005]***	[0.003]***	[0.003]***	[0.003]***
Missing AFQT	0.051	-0.009	0.027	0.058	-0.008	0.034	0.048	-0.01	0.024
	[0.003]***	[0.003]***	[0.003]***	[0.009]***	[0.009]	[0.009]***	[0.004]***	[0.004]***	[0.004]***
Rotter Locus of Control	0.008	0.012	0.011	0.017	0.065	0.005	0.006	-0.003	0.013
	[0.004]*	[0.004]***	[0.004]**	[0.010]*	[0.010]***	[0.010]	[0.005]	[0.005]	[0.005]***
Pearlin Control Mastery	0.07	-0.022	0.057	0.07	-0.013	0.072	0.068	-0.022	0.052
	[0.005]***	[0.005]***	[0.005]***	[0.012]***	[0.012]	[0.012]***	[0.006]***	[0.006]***	[0.006]***
Rosenberg Self-Esteem	0.027	-0.034	0.055	-0.001	-0.027	0.022	0.03	-0.036	0.061
	[0.006]***	[0.006]***	[0.006]***	[0.014]	[0.014]*	[0.014]	[0.007]***	[0.007]***	[0.007]***
Missing Rosenberg	0.021	-0.03	0.05	0.006	-0.041	0.036	0.021	-0.028	0.052
	[0.006]***	[0.006]***	[0.006]***	[0.015]	[0.015]***	[0.016]**	[0.007]***	[0.007]***	[0.007]***
Sociability Trait 'not shy'	0.005	-0.003	0.01	0.021	-0.001	0.022	0.001	-0.003	0.007
	[0.001]***	[0.001]***	[0.001]***	[0.003]***	[0.003]	[0.003]***	[0.001]	[0.001]***	[0.001]***
Missing Sociability	0.012	0	0.009	0.034	0.013	0.028	0.006	-0.004	0.003
	[0.004]***	[0.004]	[0.004]**	[0.009]***	[0.009]	[0.009]***	[0.004]	[0.004]	[0.004]
Age	0.009	-0.005	0.008	0.007	-0.005	0.003	0.009	-0.006	0.008
	[0.002]***	[0.002]**	[0.002]***	[0.005]	[0.005]	[0.005]	[0.002]***	[0.002]**	[0.002]***
Age-squared	0	0	0	0	0	0	0	0	0
	[0.000]***	[0.000]*	[0.000]***	[0.000]	[0.000]	[0.000]	[0.000]***	[0.000]*	[0.000]***
Female	0.029	-0.013	0.041	0.031	-0.014	0.044	0.029	-0.013	0.04
	[0.001]***	[0.001]***	[0.001]***	[0.003]***	[0.003]***	[0.003]***	[0.001]***	[0.001]***	[0.001]***
Black	0.004	-0.009	0.004	0.004	-0.009	0.008	0.004	-0.009	0.003
	[0.002]**	[0.002]***	[0.002]**	[0.004]	[0.004]**	[0.004]*	[0.002]*	[0.002]***	[0.002]
Married	0.009	0	0.006	0.008	0.006	0.004	0.01	-0.001	0.007
	[0.001]***	[0.001]	[0.001]***	[0.003]***	[0.003]**	[0.003]	[0.001]***	[0.001]	[0.001]***
No. of Children	-0.01	0.002	-0.007	-0.007	0.005	-0.004	-0.01	0	-0.008
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]	[0.001]***
MSA,1979=Large(.5+M)	0.003	0.001	0.001	-0.003	-0.005	-0.01	0	0.002	-0.001
	[0.001]**	[0.001]	[0.001]	[0.005]	[0.005]	[0.005]*	[0.001]	[0.001]	[0.001]
Constant	0.727	1.122	0.736	0.762	1.074	0.805	0.731	1.134	0.728
	[0.034]***	[0.034]***	[0.034]***	[0.077]***	[0.077]***	[0.078]***	[0.038]***	[0.038]***	[0.038]***
Observations	58487	58487	58487	13230	13230	13230	45257	45257	45257

Notes: Standard errors are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Each panel of skills is estimated jointly via FGLS.

Table 2b. Skill Manifestation and Education

	<HS SKILLS			HS GRAD SKILLS			COLLEGE+ SKILLS		
	Cognitive	Motor	People	Cognitive	Motor	People	Cognitive	Motor	People
AFQT %ILE/100	0.024	-0.017	0.02	0.085	0.024	0.049	0.069	0.026	-0.022
	[0.011]**	[0.011]	[0.011]*	[0.003]***	[0.003]***	[0.003]***	[0.008]***	[0.008]***	[0.008]***
Missing AFQT	-0.003	-0.002	-0.005	0.034	0.004	0.017	0.017	0.007	-0.055
	[0.008]	[0.008]	[0.008]	[0.004]***	[0.004]	[0.004]***	[0.011]	[0.011]	[0.011]***
Rotter Locus of Control	-0.037	0	-0.057	0.015	0.014	0.019	-0.021	0.019	-0.007
	[0.012]***	[0.012]	[0.012]***	[0.005]***	[0.005]***	[0.005]***	[0.012]*	[0.012]	[0.012]
Pearlin Control Mastery	-0.001	-0.029	-0.032	0.064	-0.004	0.055	0.056	-0.044	0.039
	[0.017]	[0.017]*	[0.017]*	[0.006]***	[0.006]	[0.006]***	[0.012]***	[0.012]***	[0.012]***
Rosenberg Self-Esteem	0.07	-0.011	0.076	0.035	-0.014	0.055	-0.042	-0.078	0.011
	[0.020]***	[0.020]	[0.020]***	[0.007]***	[0.007]**	[0.007]***	[0.015]***	[0.015]***	[0.015]
Missing Rosenberg	0.039	-0.034	0.05	0.038	-0.016	0.056	-0.036	-0.068	0.046
	[0.017]**	[0.018]*	[0.018]***	[0.007]***	[0.007]**	[0.007]***	[0.020]*	[0.020]***	[0.020]**
Sociability Trait 'not shy'	-0.004	-0.009	-0.001	0.006	-0.003	0.009	0.003	0.001	0.01
	[0.004]	[0.004]**	[0.004]	[0.001]***	[0.001]**	[0.001]***	[0.003]	[0.003]	[0.003]***
Missing Sociability	0.001	-0.006	0.005	0.014	0.006	0.006	0.026	-0.025	0.032
	[0.009]	[0.009]	[0.009]	[0.004]***	[0.004]	[0.004]	[0.010]***	[0.010]**	[0.010]***
Age	0.003	0.003	-0.001	0.003	-0.004	0.002	0.015	-0.004	0.015
	[0.007]	[0.007]	[0.007]	[0.002]	[0.002]*	[0.002]	[0.005]***	[0.005]	[0.005]***
Age-squared	0	0	0	0	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]**	[0.000]	[0.000]**
Female	0.015	-0.045	0.042	0.036	-0.011	0.044	0.008	-0.006	0.024
	[0.004]***	[0.004]***	[0.004]***	[0.001]***	[0.001]***	[0.001]***	[0.003]***	[0.003]**	[0.003]***
Black	-0.02	-0.021	-0.001	-0.007	-0.003	-0.004	0.005	0.001	-0.013
	[0.005]***	[0.005]***	[0.005]	[0.002]***	[0.002]	[0.002]**	[0.005]	[0.005]	[0.005]**
Married	-0.004	-0.001	-0.001	0.006	0.002	0.002	0.012	-0.002	0.01
	[0.004]	[0.004]	[0.004]	[0.001]***	[0.001]	[0.001]	[0.003]***	[0.003]	[0.003]***
No of Children	0.001	0.003	0.001	-0.007	-0.001	-0.004	-0.003	0.001	-0.002
	[0.001]	[0.001]*	[0.001]	[0.001]***	[0.001]**	[0.001]***	[0.002]	[0.002]	[0.002]
MSA,1979=Large(.5+M)	0.008	0.005	0.006	0.004	0.002	0.001	0.002	-0.005	0.002
	[0.004]**	[0.004]	[0.004]	[0.002]***	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]
Constant	0.897	1.013	0.976	0.827	1.067	0.844	0.804	1.093	0.775
	[0.108]***	[0.110]***	[0.109]***	[0.038]***	[0.039]***	[0.038]***	[0.082]***	[0.082]***	[0.083]***
Observations	6977	6977	6977	37711	37711	37711	13799	13799	13799

Notes: Standard errors are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Each panel of skills is estimated jointly via FGLS.

Table 3. Abilities, Traits, Education, and Cities

	MSA at *t* is Large(.5+M)=1		MLOGIT		
	Logit, Marginal Effects	OLS/LPM	Highest Grade Completed	HSGrad	College+
AFQT %ILE/100	0.016	0.017	5.345	-0.7	0.901
	[0.007]**	[0.007]**	[0.032]***	[0.009]***	[0.008]***
Missing AFQT	0.06	0.056	2.196	-0.454	0.519
	[0.010]***	[0.010]***	[0.047]***	[0.011]***	[0.011]***
Rotter Locus of Control	0.004	0	0.333	-0.091	0.099
	[0.013]	[0.013]	[0.061]***	[0.014]***	[0.014]***
Pearlin Control Mastery	0.092	0.094	1.245	-0.149	0.199
	[0.014]***	[0.015]***	[0.069]***	[0.015]***	[0.015]***
Rosenberg Self-Esteem	0.147	0.16	1.455	-0.139	0.18
	[0.017]***	[0.018]***	[0.085]***	[0.018]***	[0.018]***
Missing Rosenberg	0.204	0.203	0.61	0.065	-0.039
	[0.019]***	[0.018]***	[0.085]***	[0.021]***	[0.021]*
Sociability Trait 'not shy'	0.013	0.014	0.145	-0.029	0.035
	[0.003]***	[0.003]***	[0.016]***	[0.003]***	[0.003]***
Missing Sociability	0.014	0.012	-0.156	0.037	-0.046
	[0.011]	[0.011]	[0.050]***	[0.012]***	[0.012]***
Age	0.01	0.01	0.258	-0.035	0.037
	[0.006]	[0.006]	[0.030]***	[0.006]***	[0.006]***
Age-squared	0	0	-0.004	0.001	-0.001
	[0.000]	[0.000]	[0.000]***	[0.000]***	[0.000]***
Female	-0.011	-0.012	0.245	-0.013	0.031
	[0.003]***	[0.003]***	[0.016]***	[0.003]***	[0.003]***
Black	0.022	0.021	1.029	-0.106	0.137
	[0.005]***	[0.005]***	[0.025]***	[0.006]***	[0.006]***
Married	-0.026	-0.026			
	[0.004]***	[0.004]***			
No of Children	-0.028	-0.03			
	[0.002]***	[0.002]***			
MSA,1979=Large(.5+M)	0.267	0.206	-0.117	0.005	-0.012
	[0.005]***	[0.004]***	[0.019]***	[0.004]	[0.004]***
Constant	-0.177	0.38	3.983	1.48	-1.63
	[0.097]*	[0.100]***	[0.469]***	[0.101]***	[0.100]***
Observations	58487	58487	58487	58487	58487
R-squared		0.06	0.39		

Notes: Standard errors are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4. Structural Estimates of Skill Manifestation

	SKILLS Cognitive	Motor	People	Highest Grade Completed	Large MSA at *t*
Highest Grade Completed	0.013	-0.005	0.012		
	[0.000]***	[0.000]***	[0.000]***		
Large(.5+M)	0.016	-0.003	0.013		
	[0.001]***	[0.001]**	[0.001]***		
AFQT %ILE/100	0.071	0.018	0.026	5.345	0.019
	[0.003]***	[0.003]***	[0.003]***	[0.032]***	[0.007]***
Missing AFQT	0.025	0.001	0.002	2.196	0.057
	[0.003]***	[0.003]	[0.003]	[0.047]***	[0.010]***
Rotter Locus of Control	0.004	0.014	0.007	0.333	0
	[0.004]	[0.004]***	[0.004]	[0.061]***	[0.013]
Pearlin Control Mastery	0.055	-0.016	0.043	1.245	0.095
	[0.005]***	[0.005]***	[0.005]***	[0.069]***	[0.015]***
Rosenberg Self-Esteem	0.006	-0.026	0.036	1.455	0.16
	[0.006]	[0.006]***	[0.006]***	[0.085]***	[0.018]***
Missing Rosenberg	0.009	-0.026	0.04	0.61	0.203
	[0.006]	[0.006]***	[0.006]***	[0.085]***	[0.018]***
Sociability Trait 'not shy'	0.004	-0.003	0.009	0.145	0.014
	[0.001]***	[0.001]**	[0.001]***	[0.016]***	[0.003]***
Missing Sociability	0.014	-0.001	0.011	-0.156	0.012
	[0.004]***	[0.004]	[0.004]***	[0.050]***	[0.011]
Age	0.004	-0.004	0.004	0.258	0.01
	[0.002]*	[0.002]*	[0.002]	[0.030]***	[0.006]
Age-squared	0	0	0	-0.004	0
	[0.000]	[0.000]	[0.000]	[0.000]***	[0.000]
Female	0.025	-0.012	0.038	0.245	-0.012
	[0.001]***	[0.001]***	[0.001]***	[0.016]***	[0.003]***
Black	-0.014	-0.004	-0.011	1.029	0.02
	[0.002]***	[0.002]**	[0.002]***	[0.025]***	[0.005]***
MSA,1979=Large(.5+M)	0.001	0.001	0	-0.117	0.206
	[0.001]	[0.001]	[0.001]	[0.019]***	[0.004]***
Married					-0.027
					[0.004]***
No. of Children					-0.027
					[0.002]***
Constant	0.692	1.136	0.701	3.983	0.391
	[0.034]***	[0.034]***	[0.034]***	[0.469]***	[0.100]***
Observations	58487	58487	58487	58487	58487

Notes: Standard errors are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All equations are estimated jointly via FGLS.

Table 5. Direct and Indirect Effects of Traits and Abilities

	DIRECT EFFECT			INDIRECT EFFECT VIA EDUCATION			INDIRECT EFFECT VIA URBANIZATION		
	Cognitive	Motor	People	Cognitive	Motor	People	Cognitive	Motor	People
AFQT %ILE/100	0.0710	0.0180	0.0260	0.3795	0.0962	0.1390	0.0013	0.0003	0.0005
Rotter Locus of Control	0.0040	0.0140	0.0070	0.0013	0.0047	0.0023	0.0000	0.0000	0.0000
Pearlin Control Mastery	0.0550	-0.0160	0.0430	0.0685	-0.0199	0.0535	0.0052	-0.0015	0.0041
Rosenberg Self-Esteem	0.0060	-0.0260	0.0360	0.0087	-0.0378	0.0524	0.0010	-0.0042	0.0058
Sociability Trait 'not shy'	0.0040	-0.0030	0.0090	0.0006	-0.0004	0.0013	0.0001	0.0000	0.0001

See text for details on decomposition.

Table 6. Selection: Abilities, Traits, and Cities Using Mover/Stayer Sample

	Multinomial Logit Marginal Effects	
	Move Small to Large MSA	Move Large to Small MSA
AFQT %ILE/100	0.233	0.096
	[0.018]***	[0.012]***
Missing AFQT	0.051	0.14
	[0.032]	[0.014]***
Rotter Locus of Control	0.054	-0.083
	[0.035]	[0.022]***
Pearlin Control Mastery	0.022	0.123
	[0.040]	[0.024]***
Rosenberg Self-Esteem	0.191	0.094
	[0.047]***	[0.029]***
Missing Rosenberg	0.284	0.093
	[0.051]***	[0.030]***
Sociability Trait 'not shy'	0.077	0.051
	[0.009]***	[0.005]***
Missing Sociability	0.054	0.07
	[0.033]*	[0.016]***
Age	0.041	-0.009
	[0.017]**	[0.010]
Age-squared	-0.001	0
	[0.000]**	[0.000]
Female	-0.011	0.007
	[0.009]	[0.005]
Black	0.066	0.018
	[0.014]***	[0.009]**
Married	-0.017	0.041
	[0.010]*	[0.006]***
No of Children	-0.059	0.004
	[0.005]***	[0.003]*
Constant	-1.15	-0.257
	[0.263]***	[0.156]*
Observations	10031	10031

Notes: Move is defined anytime between 1979 and current year *t*. Standard errors are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample excludes respondent-years when respondent was in a Large MSA at current year *t* and was also in a Large MSA at *t*=1979. Baseline category: Small MSA at *t* and *t*=1979.

Appendix Table A1. Descriptive Statistics of NLSY79 Sample

Variables	Mean	Std Dev	Min	Max
Skills (from DOT) and Individual Abilities:				
Cognitive Skills Index	1.04	0.15	0	1.31
Motor Skills Index	0.97	0.14	0	1.35
People Skills Index	1.04	0.14	0	1.29
AFQT %ILE/100	0.45	0.29	0.01	0.99
Missing AFQT	4.03%			
Rotter Locus of Control	0.46	0.14	0	1
Missing Rotter	0.00%			
Pearlin Control Mastery	0.72	0.13	0.23	1
Missing Pearlin	0.00%			
Rosenberg Self-Esteem	0.80	0.10	0.24	1
Missing Rosenberg	2.80%			
Sociability Trait 'not shy'	0.40	0.49	0	1
Missing Sociability	2.82%			
Other Characteristics:				
Age	29.92	3.77	25	41
Percent Female	49.35%			
Percent Black	26.93%			
Percent Married	51.41%			
Number of Children	1.12	1.21	0	10
Mobility from t=1979 to current t:				
Small Always	6,471	12.11%		
Moved Small to Large	2,669	4.99%		
Moved Large to Small	891	1.67%		
Large Always	43,418	81.23%		
No of Respondents	8,733			
No of Respondent-Years	58,487			
Year	1990.52		1982	1998

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