Gender Based Occupational Segregation and Sex Differences in Sensory, Motor and Spatial Aptitudes

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Abstract— Research on sex differences in humans documents gender differences in sensory, motor and spatial aptitudes. These aptitudes, as captured by Dictionary of Occupational Titles (DOT) codes, predict the occupational choices of men and women in the directions indicated by this research. We simulate that eliminating selection on these skills reduces the Duncan index of gender based occupational segregation by 20-23 percent in 1970 and 2012. Eliminating selection on DOT variables capturing other accounts of this segregation has a smaller impact.

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Introduction

The male/female gap in labor market compensation has declined significantly over the past three decades in many developed countries. In the U.S., the female/male ratio of median annual earnings for full time workers has increased from 0.62 in 1979 to 0.83 in 2014 (Bureau of Labor Statistics 2015), while in countries that measure the gender gap in hourly earnings the female/male ratio is even higher (e.g., 0.88 (2014) in Canada (CANSIM) and 0.91 (2015) in the UK (Office for National Statistics 2015). In comparison, the pace of change in the gender segregation of employment in recent decades has been glacial. Gross (1968) reported that the Duncan index[1] of segregation was steady at roughly 0.67 from 1900-1960. In the five decades since then, it has fallen by just 25%, to just over 0.50 in 2012 (e.g., Blau et al. 2013). At 0.50, the index tells us that the segregation of males and females remains substantial—over half of men (or women) would need to change occupations for the occupational distributions of male and female employment to be the same.

It is important to understand why gender occupational segregation persists. It accounts for part of the remaining gap between male and female compensation—the within-occupation wage gap fell by nearly 50% from 1970 to 2012, while the between-occupation component of the wage gap rose slightly. Persistent segregation of the genders across occupations implies that sectoral change that accompanies economic growth is likely to have important effects on the relative compensation of men and women. Finally, if occupational segregation is of intrinsic policy interest, an effective response must be rooted in an understanding of its sources.

In this paper, we extend this literature by examining the potential importance of sex differences in sensory, motor and spatial aptitudes—for example, the sense of touch, fingering

[1] The Duncan index, defined below, ranges between 0 and 1 and is interpreted to indicate the proportion of women or men who would need to change occupations to produce a similar occupational distribution of men and women.

abilities and depth perception—to this segregation, which, to our knowledge, have not been systematically investigated previously. There is extensive research documenting sex differences in these skills, many starting at very young ages, and they are clearly relevant to job skills in many occupations.

We map the evidence of sex differences in these aptitudes into occupational aptitudes, as captured by the Dictionary of Occupational Titles (DOT, e.g., U.S. Department of Labor Employment and Training Administration 1991), which we in turn relate to occupational selection by men and women. With few exceptions, females and males select into occupations on the DOT attributes in accordance with the predictions of the research. These relationships largely remain once we control for other explanations of gender occupational segregation, including measures of cognitive demands, physical strength, people/things orientation, "occupational risk" (death, competition and prestige), and time flexibility.

The estimated relationships are quantitatively important. We simulate that eliminating the observed correlation between these skill demands and male/female selection would reduce occupational segregation by about 20% in 1970 and 23% in 2012—relatively more than the combined effect of variables representing more traditional explanations of gender segregation.

A qualification to these conclusions is the difficulty of identifying the effect of specific job characteristics on an outcome because they may be correlated with other important unobserved characteristics. Gender differences in these unobserved characteristics, or unobserved demand side employer discrimination, could potentially be driving the differential male and female occupational selection. For example, to use a better known gender difference, it may be that males are found disproportionately in jobs requiring physical strength, not because they are stronger on average, but because employers in these occupations are more discriminatory towards females.

To some extent, these concerns are mitigated by the facts that we are jointly testing for the effect of multiple skills—it is unlikely we would observe the precise pattern of selection predicted by previous research if it were not related to these skills—and we control for variables capturing many of the competing explanations. We attempt to push further on this issue for the female advantage in the sense of touch, which as explained below, has been attributed, in part, to their smaller average finger/hand size. This suggests that males with smaller fingers should select into "touch jobs", which we identify with the DOT measure of feeling, as females do. Using height as a proxy for finger size, we cannot reject the hypothesis that this is true. This suggests that a unobserved demand or supply side variable confounding these results must be correlated with height (hand size) rather than gender.

II Previous Literature on Occupational Segregation

There is a large literature documenting the existence of, and trends in, gender based occupational segregation (e.g., Blau Weiskoff 1972, Blau et al 2013). Explanations generally fall into three classes. The first highlights the role of differences in human capital or skills. A recent emphasis is females' hypothesized advantage in social skills (e.g., Bacolod and Blum 2010, Black and Spitz-Oener 2010,Borghans et al. 2014 and Levanon and Grusky 2016).[2] More comparable to our focus is Bielby and Baron's (1986) investigation of the relationship between occupational segregation in California in the 1960s and 70s and DOT skill measures.

The second class of explanations relates occupational segregation to gender differences in preferences for job attributes. For example, because women are more likely to experience job disruptions related to family responsibilities, they may prefer to select into jobs that minimize the

[2] Levanon and Grusky (2016) examine a number of the occupational characteristics examined here aggregated into composite measures.

penalty for family leaves (for work documenting the penalty for career disruptions, see Light and Ureta, 1995 or O'Neill and O'Neill, 2006; for work discussing the influence of this penalty on occupation selection, see Polachek 1981, Kosteas, 2010, or Goldin 2014.) Another focus is gender differences in preferences for risk, competition and prestige (e.g., Akerlof and Kranton 2000, Buser et al. 2014, Goldin 2013, Pan 2015).[3]

A third class of explanations of occupational segregation explores the role of discrimination. Several papers using matched pairs of applicants or randomized resumes have found discrimination against female applicants in male-dominated jobs and against male applicants in female-dominated jobs (e.g., Riach and Reich, 2006 and reviews in Riach and Reich, 2002)

In this paper, we first extend research examining the role of gender differences in skills to sensory, motor and spatial skills. Second, we simultaneously examine the contributions of other explanations of occupational segregation. Of course, the distinction between "skills", "preferences" and "discrimination" is somewhat artificial. If discrimination or social norms affect skill and preference formation, our results will also pick up the effect of these processes. We consider this less likely for some of the sensory, motor and spatial skills that have stronger biological origins or are evident at very young ages.

III Gender Differences in the Skills and Abilities

We briefly summarize the findings of research for the specific gender differences we investigate here. A fuller discussion of the underlying research is available in Baker and Cornelson (2015a). We note that explanations of these differences include 1) biological, 2) evolutionary and 3) environmental factors. To be clear, our analysis does not shed light on the

[3] See also Croson and Gneezy (2009) and Eckel and Grossman (2008) on risk aversion, Gneezy et al. (2003), Niederle and Vesterlund (2007) and Cotton, McIntyre and Price (2013) on competition Deleire and Levy (2004) Leeth and Ruser (2006), Bonin et al. (2007) and Grazier and Sloane (2008) on earnings and mortality risk.

source of the differences.

Gender Differences in Sensory Functions

Gender differences in some sensory functions have long been reported (Velle 1987; see also Halpern 2012, 105-107 for an overview).

Vision—Males have a higher incidence of color blindness because the most prevalent forms (red/green) are a result of gene deletion or damage on the X chromosome and color blindness is a recessive trait. Recent research suggests that, within a sample of college students, females exhibit greater sensitivity to colour than males in populations with normal vision (Handa and McGivern 2015; Abramov et al. 2012b, Murray et al. 2012), while in a sample of 16-23 month old infants a higher proportion of females could distinguish colors (Mercer et al. 2014).

There is also research reporting that adult males exhibit better visual acuity—sensitivity to fine detail and rapidly moving stimuli (Velle 1987, Abramov et al. 2012a), and that females have better accuracy in near space, and males in far space, in a sample of young adults (Stancy and Turner 2010).

Hearing—Females have been observed to have a higher degree of auditory sensitivity than males (detecting weak sounds in quiet), especially at higher frequencies, starting in childhood (Halpern 2012, McFadden 1998, Velle 1987). Conversely, males have been observed to have a higher tolerance of noise, again starting in childhood (Velle 1987). Roughly speaking females have been found to experience a given noise level twice as strongly as males.

Taste and Smell—Females have been observed to have a better sense of smell and taste (see Brand and Millot 2001 for a survey). Sex differences have not been observed for all smells, but where detected they always favor females. Halpern (2012, p.106) reports that the advantage "extends across the entire lifespan". The evidence on sex differences in taste recognition and perception are more mixed suggesting females perceive some tastes better, but others not as well (Halpern 2012 107).

Touch—Females have been observed to have a better sense of touch, a finding for both blind and sighted subjects and so distinct from sex differences in visual acuity (Halpern 2012). In one dimension this difference appears to be biological, as the perception of textures is hypothesized to be related to the density of sense perceptors—Merkel cells—in the hand. Smaller fingers have a higher density of these cells, so female's smaller stature and finger size, on average, provides them an advantage (Peters et al. 2009). Touch sensitivity has been found to be similar between men and women with similar finger size.

Gender Differences in Perceptual Motor Tasks

Motor Abilities—Tests of abilities for aiming at moving or stationary targets appear to favour males by a relatively large margin (Hall and Kimura 1995, Watson and Kimura 1991, but also see Auyeung et al 2011), while females demonstrate an advantage in fine motor dexterity (Nicholson and Kimura 1996). Tests of both these abilities find similar sex differences among young children (Sanders and Kadam 2001).

Common tests of these abilities have been criticised for conflating any sex differences in perceptions of near and far space (see above) with any sex differences in specific motor skills. Controlling for sex differences in space, Sanders et al. (2007) present evidence that females perform better in finger tasks while males perform better in arm tasks.

Recent research takes up this distinction between a gross motor movement advantage for males and a fine motor movement advantage for females (see Sanders 2013 for an overview). For example, females have an advantage in movements of the wrist and fingers (Sanders and Walsh 2007, Sanders and Perez 2007).

Perceptual Motor Tasks—Sex differences in some perceptual motor tasks, especially those involving digits and alphabets, appear to favour females (e.g., Roivainen 2011). These include perceptual speed, fine motor manipulations and tactile skills. For example, females have an advantage in the "Digit Symbol" task (formerly part of the Wechsler Scales) but not the "Inspection Time" task (Halpern 2012, Burns and Nettelbeck 2005). A female advantage in the Processing Speed Index of the Wechsler scales has been reliably found in a sample of primary and secondary school aged children (Longman et al. 2007).

Some of these differences are again attributed to females' smaller stature, on average—females' smaller hand size on average might contribute to their advantage in fine motor tasks (Peters et al. 1990 and Peters and Compagnaro 1996).

Gender Differences in Visiospatial Abilities

Sex differences in visiospatial abilities have been widely documented and in general favour males. Halpern (2012) reports a male advantage in spatial perception, mental rotation, spatiotemporal ability, and to a lesser extent, spatial visualization. Females have an advantage in remembering the spatial location of objects in an array (Sanders 2013). There is evidence that the gender difference in some of these abilities emerges at very young ages (e.g., Moore and Johnson 2008, Quinn and Liben 2008). Among high school seniors, Baker and Cornelson (2016b) report a gender gap favouring males in a test of three dimensional mental rotation of 0.388 of standard deviation in 1960 and 0.253 of a standard deviation in 1980.[4]

IV Data and Empirical Framework

Occupational Characteristics Data

We link the sex differences documented in the last section to occupational segregation,

[4] For 1960 they report a gender gap, controlling for age, of 0.275 standard deviations for high school freshman and 0.415 for high school seniors.

using information on occupational skill requirements from the 1977 and 1991 DOT. The DOT, rates several thousand occupations for aptitudes, temperaments, interests and physical demands. In Table AI of the appendix, we describe the DOT measures that we believe are most closely linked to sex differences outlined in the previous section.[5]

To assess the importance of sensory, motor and spatial skills relative to other explanations of occupational gender segregation, we also attempt to capture an occupation's i) overall physical demands, ii) math and verbal skill requirements, iii) people/things orientation, iv) degree of risk and competitiveness, v) social stature, and vi) time flexibility. As outlined in the appendix we capture these alternative explanations with additional DOT variables, occupational mortality rates derived from the Bureau of Labor Statistic's Census of Fatal Occupational Injuries,[6] measures of occupational competition and time flexibility from the O*NET database[7] and occupational status using the occupational prestige score proposed by Nakao and Treas (1994).[8]

Occupations

We link the DOT measures and the other occupational characteristics to occupations to decennial Census data and the 2012 3-year American Community Survey (denoted as 2012).

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[5] We do not make use of the DOT physical demand codes kneeling, climbing, balancing, stooping, crouching, crawling, talking and reaching. We also exclude the aptitude form perception (the ability to perceive pertinent detail in pictures and graphs) and the physical demands accommodation (the adjustment of the eye to bring things into focus), and field of vision. A fuller discussion of our "expected" signs is presented in Baker and Cornelson (2016a).
[6] We use information on the number of fatalities for each occupation in 2012, and convert this to a mortality rate using employment information. The earliest fatalities data are from 1992. Because these data are provided for different occupational codes, however, we can only match them to 431 Census 2000 occupations (as opposed to the 468 used in our main analysis.) The results are similar if we use the 1992 fatalities information for our 1970 analysis.
[7] O*NET, produced by the U.S. Department of Labor, has supplanted the DOT in recent years, and provides many similar measures of occupational requirements as well as some additional characteristics. For time flexibility we use Goldin's (2014) proposed measures. Note that the "structure" variable is reverse-coded in the O*NET, with higher values indicating more freedom for the worker to determine tasks, priorities and goals.
.[8] This is based on data from the 1989 General Social Survey, in which respondents were asked to rank occupations on scale of social standing from 1 to 9. The initial scores were based on the 1990 Census occupational coding, we obtain the measures for the 2000 Census occupational coding using data from IPUMS (Ruggles et al., 2010).

Our main analysis focuses on the 1970 and 2012 data sets linked to the DOT files. We use the intervening 1980, 1990 and 2000 Census data to replicate basic statistics from earlier work. We use the crosswalk developed by Blau et al. (2013) to convert occupations in the earlier Census years and the ACS to the 2000 Census occupational coding. We are able to match DOT ratings to 476 of the 505 Census occupational codes. Because the DOT occupations are more detailed than Census occupations, we average the ratings across all DOT occupations within a Census code, with weights corresponding to that occupation's share of employment. As a result while the DOT measures are categorical, they are continuous in our data. Where possible, we use 1977 DOT measures for the 1970 and 1980 Censuses, and the 1991 DOT measures thereafter. We use the 1991 measures for all years for physical demands[9] and certain environmental conditions that are only available in 1991. We use a crosswalk provided by the U.S. Census Bureau to link the O*NET measures and the fatality information from the Census of Fatal Injuries to Census 2000 occupational codes. We were able to link O*NET measures to 468 Census occupations (all of which also have fatalities information), which provide the final sample of occupations for our analysis. These occupations account for 98.4% of the U.S. workforce in 2012, and have a Duncan index that is nearly identical to the Duncan index for the U.S. workforce as a whole. Other details of the data construction are provided in the appendix.

Empirical Framework

Our objective is to estimate Duncan indices of gender occupational segregation net of any gender occupational selection on occupational differences in the DOT sensory, motor and spatial attributes. The Duncan index is defined as

$$D = (0.5) \bullet \sum_j \left| m_j - f_j \right|$$

[9] Excepting physical strength, which is available in both years.

where f_j is the fraction of all employed women who work in occupation *j* and m_j is the fraction of all employed men who work in occupation *j*. The index, which ranges between 0 and 1, is commonly interpreted to indicate the proportion of women or men who would need to change occupations if the occupational distribution of men and women were to be the same.

We start by estimating the relationship between our occupational attribute measures and the relative probability that men and women select into an occupation. Specifically, we regress the log odds of male to female employment in an occupation

(1) $$l_j = \ln\left(\frac{\frac{m_j}{(1-m_j)}}{\frac{f_j}{(1-f_j)}}\right)$$

on our measures of occupational characteristics. The term $f_j/(1-f_j)$ represents the odds that a randomly selected, employed female works in occupation *j*. The ratio of these odds for men and women tells us about the relative likelihood that men and women select into occupation *j*.

Our main regression equation is:

(2) $$l_j = \alpha + \beta S_j + \varepsilon_j$$

where S_j are measures of the characteristics of occupation *j*.

We use the results of estimating (2) to simulate the effect of removing any differential selection on skills across occupations. We first predict the log odds for each occupation that would occur if a particular set of occupational characteristics did not differentially affect the occupation choices of men and women. Let S_k denote a subset of occupational characteristics, and S_{-k} denote all of the remaining occupational characteristics. The predicted log odds for occupation *j*, eliminating differential gender selection on the characteristic set *k* are:

(3) $$\hat{l}_j = \hat{\alpha} + \hat{\beta}_{-k} S_{-k} + \hat{\varepsilon}_j$$

Next, we find the unique occupational shares, $\hat{f}_j$ and $\hat{m}_j$, that solve these log odds and also keep each occupation's total share of employment at its actual level (this yields 936 equations in 936 unknowns).[10] Finally, we construct Duncan indices from these predicted shares.

In order to evaluate whether these predicted indices are significantly different from the actual Duncan index in each year, we compare them to a distribution of Duncan indices constructed from 500 rounds of resampling from the actual data. Because the sample size is large, this procedure produces bounds that are quite narrow. As a result, all of our estimated Duncan indices are significantly different from the actual Duncan index at the 1 percent level, and therefore we therefore omit the standard indications of significance from the tables 5 and 6.

V Regression Results

An Overview of Gender Occupational Segregation

In Table 1 we report estimates of the Duncan index of occupational gender segregation by census year and for 2012 based on ACS data. While the estimates differ slightly in magnitude, they tell the same story as Blau et al. (2013). The Duncan index falls more than 10 percentage points between 1970 and 1990, and less than 4 percentage points in the next 22 years. In 2012 just over half of men or women would need to change occupations for the occupational distribution of males and females to be the same.

The five occupations that make the largest contributions to the Duncan index in each year are in the next five next rows. They are very stable over time—for example, secretaries and administrative assistants make the largest contribution in every year. The proportion of the Duncan index contributed by these top five occupations (seventh row) declines gradually from

[10] This procedure produces occupation shares m_j and f_j that do not add up to one.. We solve this problem by rescaling so that the shares do add up to one, by allowing the total number of men and women in the labor market to change. In practice, the changes in the total size of the labor force are fairly small – about 3% for men and 1% for women.

around 21 percent to around 17 percent over the period.[11]

A recent focus of economic research on occupational segregation is STEM occupations. While there are many reasons to focus on these occupations, their contribution to overall gender employment segregation is not one of them. The proportion of the Duncan index represented by segregation in these occupations (eighth row) ranges from about 4% at the beginning of the sample to 5% in 2012.[12] Similarly, many discussions of occupational segregation focus on women's disadvantage in high-earning management and leadership occupations (e.g. Kosteas, 2010.) However, the final row in the table shows that management occupations account for just 6% of occupational segregation in all years.

In the final rows, we report the total number of occupational categories with positive employment in each year, and indicators of the importance of the occupations making the largest contributions to the Duncan index to overall gender segregation. For example, just 25-30 occupations in each year, or just 6 percent of the total number, can account for 50 percent of the Duncan index. The disproportionate contribution of these occupations arises partially because of their relatively large size: in 2012 they represented around 35% of total employment. However, these occupations are also substantially more segregated than a typical occupation. The odds of the dominant gender's employment in a typical occupation (compared to the non-dominant) are around 3:1; in the smaller set of observations that contribute most to the Duncan index, these odds are 5:1. Similarly, the last row of Table 1 shows that, in each year, roughly 170 of 505 occupations can account for 90 percent of the Duncan. These results amplify the message that gender occupational segregation is concentrated in a relatively small number of occupations.

[11] In Table 1, we report results for all 505 Census occupation categories. In the analysis of skills we use the 468 occupations that can be matched to DOT codes. This makes very little difference: the Duncan index for our 468 occupations is 0.644 in 1970 (the same as for the full set of occupations) and 0.508 in 2012 (versus 0.506 for all occupations.)

[12] Our definition of STEM jobs is from the U.S. Department of Commerce (2011).

Gender occupational selection on aptitudes

In Table 2 are the results of estimating equation (2). For both 1970 and 2012 we present both "univariate" estimates, from specifications in which the indicated skill is the only regressor, and "multivariate" estimates from a single regression in which all aptitudes and skills are regressors. These latter estimates account for the fact that occupational characteristics are not necessarily independent of one another. For example, men may be more (rather than less) likely to work in jobs that demand color vision because these jobs also demand aptitudes for which they are relatively advantaged, or because these jobs have other characteristics that men tend to value more than women.

In the first row is the result for the DOT variable for physical strength, which is a familiar attribute of male advantage and can be used to baseline the estimates for the other attributes. All occupational attributes are normalized to have mean 0 and standard deviation one, so the estimates are interpreted as the change in the log odds associated with a one standard deviation increase in a skill. As expected, occupations with higher demands for physical strength have higher log odds, indicating that there are more men in these occupations. This effect is substantial: the univariate estimates indicate that in 1970 a one standard deviation increase in the physical strength measure is associated with a 0.728 increase in the log odds of male employment in 1970 and a 0.996 increase in 2012. In 2012 the odds ratio is just over 2.7 in an occupation one standard deviation above the mean in physical strength. In the multivariate results this association is attenuated, the estimates just over half the univariate values.

In the next panel are the results for the sensory attributes. In the univariate results the estimates for color vision and color discrimination are not of the expected sign, while those for the remaining skills are. Larger estimates are observed for far acuity and the two measures of auditory sensitivity—the estimates for noise are larger than the estimates for physical strength. In the multivariate estimates the “wrong signs” of the colour variables are mostly rectified. Statistically significant relationships approaching the magnitude of the results for strength are observed for the noise and feeling variables.

The next panel contains the results for the motor skills. In the univariate results most of the estimates are of the expected sign, with the exception of motor coordination and handling in 2012. The manual dexterity attribute involves both arms and hands and we do not have a prediction for the sign of the effect. The result here indicates a positive association with male employment. In the multivariate results, the estimates for many of the individual skills are now statistically insignificant and, of note, wrong signed for eye-hand-foot.

The spatial skills are in the next panel. While in the univariate results the estimated relationships are mostly larger than for physical strength, they are attenuated conditional on the other aptitudes. Nevertheless, the multivariate estimates are right signed and comparable to the estimates for noise, feeling, and some of the strength estimates.

In the final panel are the estimates for the variables capturing alternative accounts of gender based occupational segregation. Amongst the cognitive—GED—variables, it is math that is a significant predictor, of relative male employment, in the multivariate results. There are relatively more females in occupations requiring a temperament for dealing with people, although this relationship is statistically insignificant and small conditional on the other attributes. Relatively more males are in occupations requiring an interest in working with things, a result that is statistically significant in both specifications. The estimates for the remaining variables are of the expected signs, but only statistically significant in the multivariate specification for competition, freedom to make decisions and to a lesser extent mortality risk.

The associations, however, are generally smaller than for attributes such as physical strength, noise, the spatial skills and math.

In unreported results (available upon request), we examine which variables appear to matter most for the differences in the estimates between the univariate and multivariate specifications, and in particular instances of "wrong signs" in the univariate results—for example for math, prestige, work structure, color discrimination and vision, handling and motor coordination. In all cases, these anomalies appear to be mainly accounted for by men's tendency to select into more physical jobs (and women's tendency to select into more social/cognitive jobs.) Including any of the variables "physical strength", "interest – things", "temperament – people", or "GED – language" alone typically results in a change in the coefficients in the expected direction, in both years. None of the other control variables has a significant impact on the univariate coefficients for these variables.

In the appendix we report how the results change in a series of robustness checks. These include adding the ratio of male to female wages and average weekly hours[13] at the occupational level as additional occupational attributes, omitting nominally duplicate skill measures (e.g., color vision and color discrimination) and investigating alternative DOT measures of people skills. Each of these modifications has little impact on the inference. We also estimate models that use either only the 1970 or 1991 DOT definitions for both the 1970 and 2012 data, which lead to minor changes in inference for one or two attributes.[14]

[13] Weekly hours are provided in intervals in the 1970 Census data; we use the midpoint of each interval to impute weekly hours.

[14] We have calculated the log odds ratio separately for the age groups 18-24, 25-34 and 35-64 and estimated the pooled regression testing for interaction effects between dummy variables for the younger age groups and the DOT aptitude measures. The estimates of these interactions are uniformly statistically insignificant. We have also pooled the 1970 and 2012 data and estimated a pseudo panel model, with occupation fixed effects for the limited number of aptitudes that are coded separately in the 1977 and 1991 data. Just over half of the estimates from this specification are right signed, but less than half are statistically significant as the standard errors a generally much larger (one statistically significant estimate is wrong signed. We note that the temporal variation of the DOT codes in this

The message of this analysis is that estimated relationships between the male to female log odds ratio and the DOT measures of sensory, motor and spatial aptitudes are largely the sign predicted by the cited research on sex differences, although multicollinearity is a challenge to isolating the relationships for individual skills.[15] The estimates for the attributes/skills of noise, feeling, spatial and depth perception stand out as making an empirically unique contribution to the log odds employment ratio. The analogues of these DOT skills in the research literature—hearing, touch and spatial perception—are among the least controversial and widely acknowledged sex differences, and ones that have been documented at young ages.

VI Omitted Variables: The Case of Feeling

As noted in the introduction, omitted variables potentially confound our inference. Of concern would be gender specific demand side factors such as employer discrimination, or unobserved supply side factors correlated with our DOT measures. We note similar challenges are faced in the growing literature on the hypothesized social skills of females (and things orientation of males) and are ultimately not resolved absent some random variation in the aptitude of interest. Furthermore, even with random design it is uncertain whether the resulting variation has external validity for the empirical difference in a given aptitude across the sexes.

Because some dimensions of the gender difference in the sense of touch are thought to be a function of finger size (which in turn is correlated with gender) rather than a function of gender per se, this aptitude provides an opportunity to make some progress on this issue. If the sense of touch is a function of finger size and not gender, then finger size should predict the occupational

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analysis could be due to sub occupational compositional changes, and since only 9 of the 28 aptitudes/skills in table 2 are included.

[15] We have estimated the models reported in table 4 using the shrinkage estimator Least Absolute Shrinkage and Selection Operator (LASSO). For 1970, the estimates from this method are zero for color vision, manual dexterity and motor coordination. For 2012 the estimates are zero for color vision, near acuity, hearing, manual dexterity, motor coordination and eye-hand-foot coordination. For both years, the estimates for noise, feeling, handling and the spatial measures are mostly modestly smaller that in table 4. These results are available from the authors on request.

choices of males as it does females. This "test" helps us rule out a hypothesis that a measure of touch is a proxy for some gender specific demand side factor.[16]

Our measure of touch is the DOT variable "feeling". As documented in table 2 this aptitude is a significant correlate of relative female employment. We are not aware of a representative data set that provides measures of finger or hand size. However, the National Health Interview Survey (NHIS) provides measures of respondents' heights and of their occupational choices. A number of studies document that finger size and hand size and height are positively correlated (e.g., Garrett 1971, Guerra et al. 2014, Suseelamma 2014).

We next show that i) individuals select into jobs with feeling demands on the basis of height, and that ii) this selection is similar for men and women. Using the 1990-1994 NHIS surveys[17], we run a logit regression of the probability that individual *i* is observed in occupation *j* on the height of individual *i*, the skill demands of job *j*, the interaction between height and all skill demands, and a set of individual-level controls (age, race and education.) An observation in this regression is an individual by job interaction, with the dependent variable equal to 1 for the job that the individual actually occupies, and 0 for all other occupations. In principle, this requires approximately 472 x 250,000 observations (472 occupations times the number of individuals in the NHIS.) For computational ease, we instead take a random sample of 5 occupations that the individual does not work in, and add them to the occupation that the individual does work in, for a total of 6 observations per person. McFadden (1978) outlines the

[16] As another test we have investigated whether simply adding a control for height diminishes the correlation of the log odds of employment and the DOT feeling variable. To do this we calculate the average *male* height by occupation using the 1990-1994 NHIS, and enter this as an additional control in regressions specification reported in table 2. The results, reported in Baker and Cornelson (2015a) indicate that adding this measure of height diminishes somewhat the correlation between the log odds ratio and the feeling variable, but also does not have a substantive effect on the correlation between the log odds and our measures of cognitive and non cognitive skills.

[17] The NHIS does not provide detailed occupational coding after 1994..

conditions in which this sampling of the “option set” results in consistent estimates.[18] The coefficient on the interaction between “height” and “feeling” in this regression tells us whether taller individuals are more or less likely to select into jobs with a higher feeling rating. We estimate this regression separately for men and women.

In table 3 we report the estimates of the interactions between height and our various aptitudes, for males and females separately. As hypothesized both males and females select into feeling occupations on height and in a very similar way—taller individuals are less likely to work in jobs with high feeling scores. We cannot reject the hypothesis that the male and female estimates are the same (column 3). Note also that height is generally negatively correlated with fine motor skills, including finger dexterity, handling and manual dexterity.

Many of the other statistically significant estimates in table 3 are consistent with research on the correlates of height. For example, there is evidence that hearing is positively correlated with height (Berranas et al. 2005, Welch and Dawes 2007), as are spatial skills (Zhou et al. 2016). One could connect the positive relationship between height and occupational prestige, competition and freedom to make decisions to research linking height to non cognitive skills (e.g., Persico et al. 2004, Lundborg et al. 2014, Schick and Steckel 2015). Perhaps surprisingly (Case and Paxson 2008), height has little relationship with the primary measures of cognitive skills (GED math and language) except with language for males. However, there is a positive and very similar association for males and females of height with clerical cognition.[19] .

[18] The “uniform conditioning property” implies that every alternative randomly sampled from the choice set has some positive probability of being observed. McFadden gives several examples of selection procedures that satisfy this property; our selection procedure corresponds to his example C-1 on page 544.

[19] Importantly, the correlation of height with an attribute does not necessarily imply that the average height difference between males and females rationalizes the sex selection we see in the data. On one hand a dimension of the sense of touch is hypothesized to be mechanically related to finger size, and males and females of similar finger size have been found to have similar senses of touch. On the other, while taller men and women select into jobs that require better hearing, and research indicates stature is positively related to hearing for each sex, as noted above females are found to have more acute hearing in some dimensions despite their smaller stature.

We next demonstrate that the relative propensity of females to select into jobs demanding feeling is attenuated once we limit males' height advantage. To do this we construct a predicted log odds of employment in each occupation. This is based on the actual occupational choices of the females in our NHIS sample, but a prediction of the male occupational distribution that would occur if males selected on the basis of height and job skill demands as per the logit regression estimates reported in table 3 but had the same height distribution as females. Specifically, we adjust the number of men in each occupation by the amount:

$$\begin{aligned}(4)\qquad \Delta^m = &\sum\nolimits_H \Pr^m(job = j \mid h = H, x = X)\cdot \Pr^m(x = X \mid h = H)\cdot \Pr^m(h = H) - \\ &\sum\nolimits_H \Pr^m(job = j \mid h = H, x = X)\cdot \Pr^m(x = X \mid h = H)\cdot \Pr^f(h = H)\end{aligned}$$

where h represents an individual's height and x represents the vector of individual covariates, and the summation sign is over all observed values of height. The first term represents the predicted number of men in each occupation, based on the logit model's results; the second term represents the number of men that would be predicted to be in each occupation if men selected on the basis of height the way they currently do, but had the female height distribution. The difference between the two represents the change that would occur if we shifted men to the same height distribution as women. We use the predicted number of men (the actual number plus Δ^m from (4)) and the actual number of women to calculate predicted log odds, and then substitute them as the dependent variable in (2).

In the first column of table 4 are estimates of the multivariate version of (2) using the 1990 census.[20] This is the census that temporally matches our NHIS data. The estimates are largely consistent with the multivariate estimates for 2012 in table 2. In the second column are the results of estimating a similar regression using the 1990-94 NHIS data. These results are

[20] For these regressions, we switch to the 1990 Census occupational codes, which is the coding available in the NHIS. There are 472 occupations with non missing log odds in the NHIS data; as a result, we limit analysis to these occupations

largely consistent with those in the first column demonstrating that our inference is not affected by using the NHIS.   In the third column we present estimates for a restricted set of occupations using the NHIS. This is because our predicted log odds procedure results in negative predicted values of men in some occupations, and we drop these occupations from our analysis. As can be seen, there are no major changes in the estimates from focusing on this smaller set of occupations.

Finally in the last column of the table are the estimates using the predicted log odds. For DOT feeling variable the result is a substantively diminished correlation with relative female employment. This suggests that the estimates for feeling in columns 1 through 3 are substantially picking up an effect of being shorter rather than an effect of some other attribute of being female.

The estimates for most of the other attributes with statistically significant relationships with the log odds, change in expected ways given the results in table 3. For example, the spatial measures are less related 0 to relative male employment once males' height advantage is diminished. Similar changes are observed for occupational prestige, competition and freedom to make decisions.

On balance we interpret the results in tables 3 and 4 as casting doubt that some gender specific demand side factor, such as employer discrimination, lies behind the relationship between feeling and the log odds of employment. They also suggest that any unobserved supply side variable that accounts for a significant part of the feeling impact must be correlated with a worker's height rather than their gender.

VII The Association of Gender Occupational Selection on Aptitudes with Gender Occupational Segregation

In tables 5 and 6, we provide estimates of adjusted Duncan indices following equation

(3). These estimates remove the impact of any sex difference in occupational selection on the indicated attribute, all else equal. Table 5 shows the Duncan indices constructed in this way from univariate regressions, while Table 6 shows the effect of eliminating different groups of occupational attributes based on the multivariate regressions. Because of the possibility of omitted variables bias in the underlying regressions we view the results as telling us more about the relative importance of various attributes than their absolute importance.

From an economic standpoint, the changes induced by individually removing the influence of many of the skills is quite small. For 1970 over the sensory and motor attributes the predicted Duncan indices range from 0.610 to 0.651, representing changes of no more than 5.5% from the actual Duncan index in that year. In 2012, some of these attributes have a larger effect: eliminating selection on hearing, noise, eye-hand-foot coordination or clerical perception would reduce the Duncan index by 7-12%.

The spatial attributes have more traction. The predicted Duncan removing the gender differential in selection on depth perception (which has the more significant effect) is 10.4% lower than the actual Duncan in 1970, and 16.1% lower than the actual in 2012.

Among variables capturing the competing accounts, physical strength and competition have the largest effect on the Duncan index in 1970, each reducing the index by around 5%. In 2012, physical strength, the temperament for dealing with people and mortality risk have the largest effect, in the 4-6% range.

Table 6 shows the results eliminating the impact of selection on different groups of skills based on the multivariate regressions in table 2. The impact of eliminating skill selection in groups is much larger than in the univariate results. In 1970, the effect of eliminating selection on sensory and motor skills is to reduce the Duncan by 4.2% and 5.1% respectively; the effect of eliminating selection on spatial skills is higher, at 10.9%. In 2012, eliminating selection on sensory skills would reduce the Duncan by 7.1%, while eliminating selection on motor skills is 3.3%. Again, spatial skills are quantitatively more important, with a predicted reduction of around 10.4%. In total, eliminating selection on sensory, motor and spatial skills would reduce the Duncan by 20.8% in 1970, and 22.6% in 2012.

The effect of eliminating selection on the variables representing the alternative hypotheses is generally smaller in 1970, ranging from 1.9-3.4%. In total, eliminating selection on these variables controls would reduce the Duncan index by 14.4%. In 2012, the impacts of the different groups ranges from 0-6.3%, with a combined effect of 18.3%.

Eliminating selection on all of the occupational attribute measures reduces the Duncan index to 0.420 in 1970 (a 34.8% reduction) and 0.299 in 2012 (a 41.1% reduction.) Selection on observable occupation attributes therefore accounts for a large portion of occupational segregation, although the majority of the Duncan index remains “unexplained”.[21]

VIII Conclusions

We bring research on sex differences in a number of sensory, motor and spatial aptitudes to the puzzle of persistent gender based occupational segregation in the US labor market. Our results suggest that males and females select into occupations in ways predicted by this research. For example, males have been found to have a higher tolerance of noise and are found

[21] We have also examined the implications of selection on these skills for the gender wage gap. Holding wages and overall employment in an occupation fixed, we examine the effect on male and female average wages of eliminating differential gender selection on observable occupational attributes. In many cases, skill-based occupational segregation favors women in terms of compensation. Eliminating selection on physical strength or people/things orientation substantially increases the gender wage gap in both years, while eliminating selection on sensory or motor skills increases the wage gap in 2012 (but decreases it in 1970). In contrast, eliminating selection on cognitive skills (particularly math), spatial skills and measures of occupational risk leads to a lower gender wage gap in both years, but particularly in 2012. These results underline that the significance of the segregation of males and females in employment for the gender gap in pay is dependent on the relative prices of these skills at a particular time and place. These results are available from the authors on request.

disproportionately in noisy occupations. We simulate that, conditional on our mapping of these sex differences into DOT occupational attributes, absent this selection the Duncan index of occupational segregation would be, all else equal, 20-23 percent lower than its observed level in both 1970 and 2012.

We also compare the quantitative importance of these variables to a set of variables intended to capture competing hypotheses of the sources of gender segregation. While we find that some of these alternative hypotheses do account for gender segregation, they are generally less important quantitatively than our measures of sensory, motor and spatial skills. Gender differences in spatial skills in particular appear to have an important relative impact on gender segregation.

We note that these comparisons are contingent on the ability of the DOT data to capture the different explanations of gender based occupational segregation, and any bias from important factors omitted from our regressions. We argue that the first message of the analysis is the relative importance of gender differences in sensory, motor and especially spatial aptitudes for occupational segregation.

The findings also highlight a lesson from the literature on these sex differences for research on the task content of jobs. The choice of specific DOT or O*NET skills to represent specific tasks may not be innocuous, particularly if differences across genders are to be compared or contrasted.[22]

[22] For example the DOT aptitudes Finger Dexterity (a fine motor skill) and Eye-Hand-Foot coordination (a gross motor skill) are used to represent routine and non routine manual skills respectively in the Autor et al. (2003) taxonomy of tasks. These skills are shown in tables 2-4 to have strong relationships with the log odds of male employment, particularly when used in isolation.

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Appendix

Table A1 – DOT and O*NET measures of sensory, motor and spatial skills and aptitudes

DOT measure(s) (type)	Scale	Expected coefficient on "male"	Description**	Occupations with highest/lowest rating
Color discrimination (aptitude)	1 to 5*	-	"The ability to match or discriminate between colors in terms of hue, saturation, and brilliance. Ability to identify a particular color combination from memory and to perceive contrasting color combinations."	Misc. personal appearance workers/ boilermakers
Color vision (physical demand)	0 to 3	-	"Ability to identify and distinguish colors"	Motion picture projectionists/ mathematicians
Near visual acuity (physical demand)	0 to 3	-	"Clarity of vision at 20 inches or less."	Tellers/ dancers and choreographers
Far visual acuity (physical demand)	0 to 3	+	"Clarity of vision at 20 feet or more"	Bus drivers/ lawyers
Hearing (physical demand)	0 to 3	-	"Perceiving the nature of sounds by ear."	Lawyers/ dancers and choreographers
Noise (environmental condition)	1 to 5	+	"The noise intensity level to which the worker is exposed in the job environment"	Misc. construction operators/ chiropractors
Taste/smell (physical demand)	0 to 3	-	"Distinguishing, with a degree of accuracy, differences or similarities in intensity or quality of flavors or odors, or recognizing particular flavors or odors, using tongue or nose."	Meter readers, utilities/ plasterers and stucco masons
Feeling (physical demand)	0 to 3	-	"Perceiving attributes of objects, such as size, shape, temperature, or texture, by touching with skin, particularly that of fingertips."	Chiropractors/ actuaries

Finger dexterity (aptitude)	1 to 5*	-	"The ability to move the fingers and manipulate small objects with the fingers rapidly or accurately."	Dentists/ clergy
Fingering (physical demand)	0 to 3	-	"Picking, pinching, or otherwise working primarily with fingers rather than with the whole hand or arm as in handling."	Tellers/ dancers and choreographers
Motor coordination (aptitude)	1 to 5*	_	"The ability to coordinate eyes and hands or fingers rapidly and accurately in making precise movements with speed. Ability to make a movement response accurately and swiftly"	Dancers and choreographers/ meter readers, utilities
Eye-hand-foot coordination (aptitude)	1 to 5*	+	"The ability to move the hand and foot coordinately with each other in accordance with visual stimuli."	Dancers and choreographers/ boilermakers
Clerical perception (aptitude)	1 to 5*	-	"The ability to perceive pertinent detail in verbal or tabular material. Ability to observe differences in copy, to proofread words and numbers, and to avoid perceptual errors in arithmetic computation. A measure of speed of perception is required in many industrial jobs even when the job does not have verbal or numerical content."	Computer programmers/ pressers, textile, garment and related materials
Manual dexterity (aptitude)	1 to 5*	?	"The ability to move the hands easily and skillfully. Ability to work with the hands in placing and turning motions…manual dexterity involves working with the arms and hands…Finger movements may or may not accompany the exercise of manual dexterity."	Veterinarians/ meter readers, utilities
Handling (physical demand)	0 to 3	-	"Seizing, holding, grasping, turning, or otherwise working with hand or hands."	Optometrists/ dancers and choreographers

Spatial (aptitude)	1 to 5*	+	"The ability to think visually of geometric forms and to comprehend the two-dimensional representation of three-dimensional objects. The ability to recognize the relationships resulting from the movement of objects in space."	Optometrists/ insurance sales agents
Depth perception (physical demand)	0 to 3	+	"Three-dimensional vision. Ability to judge distances and spatial relationships so as to see objects where and as they actually are."	Bus drivers/ sociologists
Other Aptitudes and Attributes				
GED language	1 to 5		"…though language courses follow a…pattern of progression in primary and secondary school, particularly in learning and applying the principles of grammar, this pattern changes at the college level. The diversity of language courses offered at the college level precludes the establishment of distinct levels of language progression for these four years. Consequently, language development is limited to five defined levels of GED."	Clergy/ parking lot attendants
GED math	1 to 6		"The description of the various levels of language and mathematical development are based on the curricula taught in schools throughout the United States. An analysis of mathematics courses in school curricula reveals distinct levels of progression in the primary and secondary grades and in college. These levels of progression facilitated the selection and assignment of six levels of GED for the mathematical development scale."	Mathematicians/ parking lot attendants
Temperament – dealing with people	0 to 1		"…interpersonal relationships in job situations beyond receiving work instructions."	Recreational therapists/ dancers and choreographers

Interests - things	0 to 1	“Things Functions can be divided into relationships based upon the worker’s involvement with either machine and equipment (machine related) or with tools and work aids (non-machine related)...Things Functions also represent levels of complexity based on the worker’s decisions or judgements.”	Parking lot attendants/ audiologists
Physical strength	1 to 5	“This factor is expressed by one of five terms: Sedentary, Light, Medium, Heavy and Very Heavy"	Therapists, all other / statisticians
Level of competition	1 to 5	To what extent does this job require the worker to compete or to be aware of competitive pressures?	Photographers/Crossing Guards
Time pressure	1 to 5	How often does this job require the worker to meet strict deadlines?	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic/Bartenders
Structured vs. unstructured work	1 to 5	To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? (Note: higher values imply more freedom for the worker)	Chiropractors/Telephone operators
Freedom to make decisions	1 to 5	How much decision making freedom, without supervision, does the job offer?	Gaming managers/Graders and Sorters, Agricultural Products

* Reverse coded in original data; re-labelled to be in increasing order of skill. ** Source—US Department of Labor (1991).

Data Methods

Converting Census data into 2000 Census occupation codes

We use the 1% Census samples provided by the IPUMS website, as well as the 2012 three-year ACS. The samples are 18-64 year olds who are employed in the civilian labor force, with non-allocated occupation codes.

We use the 2000 Census occupation codes throughout our analysis. To convert the 1970 Census data to the year 2000 codes, we follow the procedure outlined in Blau et al. (2013). We convert the 1970 data to 1980 codes using the gender-specific crosswalk provided by the Census Bureau (available on IPUMS at https://usa.ipums.org/usa/resources/chapter4/occ_70-80.pdf). For 1980 occupations that were combined into a single 1990 occupation (six pairs), we simply add the number of men/women in each 1980 occupation to arrive at the 1990 total. For the 1980 occupations that were split in the 1990 coding system, we redistribute the number of 1980 incumbents into the 1990 codes based on the distribution of employment in 1990. Finally, we use the crosswalk developed by Blau et al. (2013) to convert the data into the 2000 Census codes.

The 2012 ACS occupation codes are similar to those used in the 2000 Census. For the occupations that did experience changes from the 2000 Census to the ACS, we follow a procedure that is similar to that used in converting the 1980 data to 1990 codes.

Converting DOT data to 2000 Census occupation codes

The DOT77 data was obtained from a 1971 CPS file, augmented with DOT ratings, available from ICPSR, which contains both the DOT coding and the 1970 census occupational codes. Because each 1970 occupation contains several DOT occupations, we calculate the DOT rating for each 1970 occupation using an employment-weighted mean with weights from the 1971 CPS. We use procedures similar to that described in the Census data to convert the ratings to the 2000 Census occupation coding, taking employment-weighted means (from the appropriate Census samples) at each step. The crosswalks used in this process are not gender specific; each 2000 Census occupation is given a single DOT rating, not a separate rating for men and women.

The DOT91 data was also obtained from ICPSR. DOT91 ratings are only available for the 1991 DOT occupational coding. Most occupations had the same coding in 1977 and 1991. A list of exceptions was available in the ICPSR documentation, which was used to convert the remaining occupations (do-files available upon request.) Once the data was consistent with the 1977 coding system, the 1991 data was merged onto the 1971 CPS file, and was then converted to the 2000 Census codes in the same way as the 1977 data.

There are 505 occupations in the 2000 occupation coding system. Of these, 478 had non-zero employment for both men and women, in both 1970 and 2012. Another 2 occupations could not be matched to the DOT data, resulting in a sample of 476 occupations that could be matched to the DOT data.

*Converting O*NET and fatalities data to 2000 Census occupation codes*

The O*NET and Census of Fatal Injuries data are provided at the SOC occupation level. To convert these to Census Occupational Coding, we use the crosswalk provided by IPUMS. 494 Census occupations could be linked to the O*NET data; of these, 468 overlap with the DOT data and have non-zero employment for both men and women in both years. These 468 occupations represent our final sample.

Table A2- Sensitivity Analysis- Changes in the specification occupational skills and attributes

Alternative specification	**Results (Based on the full specification with all variables.)**
Controlling for the ratio of wages and hours	The predicted Duncan indices (negating selection

worked	on all attributes) are 0.410 and 0.292, compared to 0.420 and 0.299 in our main analysis.
Using only one of color discrimination or color vision	The predicted Duncan index ranges from 0.418-0.424 in 1970 and from 0.297-0.299 in 2012, depending on the combination used.
Using only one of fingering or finger dexterity	The predicted Duncan index ranges from 0.419-0.422 in 1970 and from 0.299-0.304 in 2012, depending on the combination used
Using only one of finger dexterity or motor control	The predicted Duncan index ranges from 0.418-0.422 in 1970 and from 0.299-0.304 in 2012, depending on the combination used.
Using only one of manual dexterity or motor control.	The predicted Duncan index ranges from 0.418-0.422 in 1970 and from 0.298-0.299 in 2012, depending on the combination used.
Controlling for alternative measures of the social skill of employment—DOT interests "activities involving contact with people", and O*NET work context "contact with others"	Using the "interests – activities involving contact with people" measure results in a Duncan index of 0.420 in 1970 and 0.300 in 2012. Using the O*NET work context "contact with others" results in a Duncan index of 0.420 in 1970 and 0.300 in 2012.
Alternative specification	**Results (Based on the full specification with all variables.)**
Switching to 1991 DOT definitions for both years	The only variable that changes significance is tasting-smelling, which would not have been significant in 1970 if the 1991 definitions had been used. If 1991 definitions are used, the predicted Duncan index (negating selection on all occupational attributes) becomes 0.414 in 1970.
Switching to 1977 DOT definitions for both years	The coefficient on clerical perception becomes larger and significant at the 5% level in 2012 if the 1977 definitions are used; the coefficient on eye-hand-foot coordination becomes smaller and insignificant. All other coefficients remain of similar magnitudes. If 1977 definitions are used, the predicted Duncan index (negating selection on all occupational attributes) becomes 0.295 in 2012.

Table 1: Gender based occupational segregation in the US labor market

	1970	1980	1990	2000	2012
Duncan Index	0.644	0.586	0.540	0.519	0.506
Top 5 Occupations	Secretaries and administrative assistants	Secretaries and administrative assistants	Secretaries and administrative assistants	Secretaries and administrative assistants	Secretaries and administrative assistants
	Driver/sales workers and truck drivers	Driver/sales workers and truck drivers	Driver/sales workers and truck drivers	Driver/sales workers and truck drivers	Registered nurses
	Elementary and middle school teachers	Bookkeeping, accounting and auditing clerks	Elementary and middle school teachers	Registered nurses	Driver/sales workers and truck drivers
	Bookkeeping, accounting and auditing clerks	Elementary and middle school teachers	Registered nurses	Elementary and middle school teachers	Elementary and middle school teachers
	Maids and housekeeping cleaners	Registered nurses	Bookkeeping, accounting and auditing clerks	Bookkeeping, accounting and auditing clerks	Nursing, psychiatric and home health aids
% of Duncan Accounted by top 5 Occupations	20.7	21.3	21.3	17.9	17.4
% of Duncan Accounted by STEM Occupations	3.9	3.9	4.6	5.2	5.1
% of Duncan Accounted by Management Occupations	5.9	6.1	5.4	6.2	6.1
Total Number of Occupations	505	505	505	505	505
Number of Occupations that account for 50% of the Duncan	25	26	28	31	31
Number of Occupations that account for 90% of the Duncan	166	172	177	176	172

Notes: Authors' calculations from 1970-2000 censuses and 2012 American Community Survey.

Table 2: The relationship between the log odds ratio of male to female employment and occupational skills, aptitudes and attributes; multivariate regressions

			1970		2012	
		Sign	Univariate	Multivariate	Univariate	Multivariate
	Physical strength	+	0.728***	0.466***	0.996***	0.481***
			(0.084)	(0.115)	(0.067)	(0.108)
Sensory	Color discrimination	-	0.157*	-0.084	0.180**	-0.298***
			(0.091)	(0.095)	(0.081)	(0.102)
	Color vision	-	0.450***	-0.016	0.349***	0.015
			(0.089)	(0.112)	(0.080)	(0.103)
	Near Acuity	-	-0.173*	0.016	-0.230***	-0.075
			(0.091)	(0.088)	(0.082)	(0.070)
	Far Acuity	+	0.594***	0.290***	0.471***	0.140*
			(0.087)	(0.101)	(0.078)	(0.080)
	Hearing	-	-0.542***	0.091	-0.800***	-0.003
			(0.088)	(0.138)	(0.073)	(0.110)
	Noise	+	0.951***	0.316***	1.170***	0.367***
			(0.080)	(0.103)	(0.061)	(0.081)
	Tasting-smelling	-	-0.070	-0.135**	-0.037	-0.004
			(0.091)	(0.064)	(0.081)	(0.050)
	Feeling	-	-0.154*	-0.306***	-0.132	-0.319***
			(0.091)	(0.081)	(0.081)	(0.066)
Motor	Fingering	-	-0.404***	0.013	-0.244***	0.109
			(0.090)	(0.099)	(0.081)	(0.080)
	Finger Dexterity	-	-0.148	-0.316**	-0.064	-0.184*
			(0.091)	(0.128)	(0.081)	(0.101)
	Handling	-	-0.020	-0.183**	0.277***	-0.092
			(0.091)	(0.090)	(0.081)	(0.070)
	Manual dexterity	?	0.452***	0.033	0.672***	0.185
			(0.089)	(0.123)	(0.076)	(0.126)
	Motor Co-ordination	-	0.153*	0.024	0.336***	-0.078
			(0.091)	(0.108)	(0.080)	(0.096)
	Eye-Hand-Foot	+	0.659***	-0.221**	0.736***	-0.144*
			(0.086)	(0.088)	(0.074)	(0.077)
	Clerical Perception	-	-0.543***	-0.196*	-0.855***	-0.141
			(0.088)	(0.114)	(0.072)	(0.107)
Spatial	Spatial skills	+	0.908***	0.586***	0.685***	0.296***
			(0.081)	(0.107)	(0.075)	(0.100)
	Depth perception	+	1.052***	0.306**	1.138***	0.413***
			(0.077)	(0.123)	(0.062)	(0.099)
Other	GED – language	-	-0.091	-0.085	-0.505***	-0.243

Attributes			(0.091)	(0.178)	(0.078)	(0.174)
	GED – math	+	0.226** (0.090)	0.484*** (0.148)	-0.171** (0.081)	0.552*** (0.137)
	Temperament – people	-	-0.714*** (0.084)	-0.057 (0.143)	-0.946*** (0.069)	-0.114 (0.112)
	Interest - things	+	0.747*** (0.084)	0.458*** (0.087)	0.863*** (0.071)	0.239*** (0.068)
	Occupational prestige	+	0.127 (0.091)	0.184* (0.109)	-0.238*** (0.081)	0.132 (0.087)
	Mortality risk	+	0.560*** (0.087)	0.118* (0.064)	0.602*** (0.079)	0.110** (0.050)
	Competition	+	0.457*** (0.089)	0.217*** (0.067)	0.321*** (0.080)	0.285*** (0.053)
	Time pressure	+	0.253*** (0.090)	0.089 (0.070)	0.228*** (0.081)	0.056 (0.054)
	Structured/. unstructured work	+	0.044 (0.091)	0.033 (0.073)	-0.240*** (0.081)	-0.079 (0.057)
	Freedom to make decisions	+	0.213** (0.091)	0.209*** (0.074)	0.064 (0.082)	0.142** (0.058)
R^2			0.630		0.720	

Notes: Authors' calculations from 1970 census and 2012 American Community Survey. The estimates for each year are from a regression of the log odds ratio of male to female employment at the occupational level on the indicated measures of occupational skills or aptitudes in the indicated year. ***, ** and * indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 3: The interaction of height and job skill demands in predicting occupational selection (logit regressions)

	Dependent variable: indicator for "individual i in occupation j"		
Interaction with "height":	Men	Women	Difference
Sensory			
Color discrimination	0.007**	0.005	0.002
	(0.003)	(0.003)	(0.004)
Color vision	-0.001	-0.003	0.002
	(0.002)	(0.003)	(0.004)
Near acuity	0.003	0.003	-0.000
	(0.002)	(0.003)	(0.003)
Far acuity	0.002	0.008***	-0.007**
	(0.002)	(0.003)	(0.003)
Hearing	0.011***	0.007*	0.004
	(0.003)	(0.003)	(0.005)
Noise	0.001	0.000	0.000
	(0.002)	(0.003)	(0.003)
Tasting/smelling	-0.001	-0.004***	0.003
	(0.001)	(0.001)	(0.002)
Feeling	-0.005***	-0.008***	0.003
	(0.002)	(0.002)	(0.003)
Motor			
Fingering	-0.000	0.001	-0.002
	(0.002)	(0.003)	(0.004)
Finger dexterity	-0.001	-0.011**	0.009**
	(0.003)	(0.004)	(0.005)
Handling	-0.003**	-0.004	0.001
	(0.002)	(0.002)	(0.003)
Manual dexterity	-0.010***	0.006	-0.016***
	(0.003)	(0.004)	(0.005)
Motor coordination	-0.004	0.005	-0.009**
	(0.003)	(0.003)	(0.004)
Eye-hand-foot coordination	0.003	0.003	-0.001
	(0.003)	(0.004)	(0.004)
Clerical perception	0.011***	0.015***	-0.005
	(0.003)	(0.003)	(0.005)
Spatial			
Spatial aptitude	0.005*	0.014***	-0.009*
	(0.005)	(0.004)	(0.005)
Depth perception	0.012***	0.002	0.010**
	(0.003)	(0.004)	(0.004)
Other Attributes			
Physical strength	-0.007***	-0.001	-0.006
	(0.003)	(0.003)	(0.004)
GED – language	0.012**	0.001	0.012
	(0.005)	(0.005)	(0.007)
GED – math	-0.003	0.000	-0.004
	(0.004)	(0.005)	(0.007)

Temperament – people	0.000	0.007*	-0.007
	(0.003)	(0.004)	(0.005)
Interest – things	-0.002	-0.002	0.000
	(0.002)	(0.002)	(0.003)
Occupational prestige	0.007**	0.004	0.002
	(0.002)	(0.004)	(0.005)
Mortality risk	0.017**	-0.010	0.017
	(0.003)	(0.010)	(0.010)
Competition	0.008***	0.003*	0.005**
	(0.002)	(0.002)	(0.002)
Time pressure	-0.003**	0.005***	-0.008***
	(0.002)	(0.002)	(0.002)
Structured/. unstructured work	-0.001	0.000	-0.001
	(0.002)	(0.002)	(0.003)
Freedom to make decisions	0.016***	0.010***	0.006*
	(0.002)	(0.002)	(0.003)
N	773,862	704,766	1,478,628

Notes: Authors' calculations from the 1990-1995 NHIS. The sample for this table is the set of respondents in the NHIS who are aged 18-64, are employed in one of the 472 occupations that contain both men and women, and have non-missing height information. The table shows the results from a logit regression of an indicator for individual "i" being in occupation "j" on characteristics of the individual (3 race, 5 education and 8 age categories), occupational skill demands, height, and height interacted with all of the other individual and occupation level controls. The reported estimates are for the interaction of height with the indicated aptitude. ***, ** and * indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 4: Actual and simulated log odds regressions, controlling for the interaction between height and skill demands in job selection

	Actual – 1990 Census	Actual – NHIS, all occupations	Actual – NHIS, restricted occupations	Predicted –NHIS, shifting men to female height distribution
Sensory				
Color discrimination	-0.040	-0.065	-0.020	-0.176
	(0.115)	(0.122)	(0.127)	(0.131)
Color vision	-0.120	-0.055	-0.128	0.006
	(0.114)	(0.121)	(0.123)	(0.128)
Near acuity	-0.015	0.004	-0.032	-0.045
	(0.072)	(0.076)	(0.078)	(0.081)
Far acuity	0.241***	0.185**	0.065	0.120
	(0.083)	(0.088)	(0.092)	(0.095)
Hearing	-0.006	0.011	-0.016	-0.095
	(0.117)	(0.125)	(0.132)	(0.137)
Noise	0.250***	0.239***	0.251***	0.197**
	(0.081)	(0.086)	(0.093)	(0.096)
Tasting/smelling	-0.070	-0.045	-0.046	0.072
	(0.054)	(0.057)	(0.056)	(0.058)
Feeling	-0.325***	-0.342***	-0.307***	-0.170**
	(0.068)	(0.073)	(0.074)	(0.077)
Motor				
Fingering	0.096	0.148	0.151	0.133
	(0.089)	(0.095)	(0.098)	(0.101)
Finger dexterity	-0.248**	-0.323**	-0.346***	-0.168
	(0.108)	(0.114)	(0.119)	(0.123)
Handling	-0.092	-0.123	-0.239**	-0.272**
	(0.081)	(0.086)	(0.096)	(0.099)
Manual dexterity	0.027	-0.041	-0.026	-0.022
	(0.131)	(0.140)	(0.141)	(0.147)
Motor coordination	0.002	0.051	0.127	0.038
	(0.105)	(0.112)	(0.118)	(0.123)
Eye-hand-foot	-0.206**	-0.218**	-0.075	-0.108
coordination	(0.081)	(0.086)	(0.096)	(0.100)
Clerical perception	-0.185	-0.208*	-0.129	-0.318**
	(0.113)	(0.120)	(0.129)	(0.134)
Spatial				
Spatial aptitude	0.481***	0.513***	0.610***	0.414***
	(0.104)	(0.110)	(0.121)	(0.125)
Depth perception	0.309***	0.351**	0.319***	0.283**
	(0.104)	(0.110)	(0.114)	(0.119)
Other Attributes				
Physical strength	0.502***	0.496***	0.504***	0.331***
	(0.105)	(0.111)	(0.114)	(0.118)
GED – language	-0.258	-0.322	-0.314	-0.381*

	(0.188)	(0.199)	(0.214)	(0.222)
GED – math	0.576***	0.600***	0.435**	0.440***
	(0.160)	(0.169)	(0.183)	(0.190)
Temperament – people	-0.153	-0.110	-0.027	-0.202
	(0.117)	(0.125)	(0.136)	(0.141)
Interest – things	0.259***	0.260***	0.254***	0.273***
	(0.072)	(0.076)	(0.075)	(0.078)
Occupational prestige	0.081	0.097	0.200	0.079
	(0.109)	(0.115)	(0.125)	(0.130)
Mortality risk	0.124**	0.114*	0.082	0.057
	(0.056)	(0.059)	(0.058)	(0.060)
Competition	0.275***	0.284***	0.303***	0.250***
	(0.061)	(0.065)	(0.067)	(0.070)
Time pressure	0.016	-0.014	-0.008	-0.067
	(0.061)	(0.065)	(0.065)	(0.068)
Structured/. unstructured work	-0.134*	-0.121	-0.172**	-0.206**
	(0.072)	(0.077)	(0.080)	(0.083)
Freedom to make decisions	0.336***	0.300***	0.288***	0.196**
	(0.062)	(0.066)	(0.069)	(0.072)
N	472	472	415	415
R^2	0.666	0.630	0.659	0.621

Notes: Authors' calculations from 1990 census and 1990-1994 NHIS. This table shows the results from regressions of the log odds of male to female employment on DOT and O*NET skill demand measures. The results in column (1) through (3) are from regressions using the actual log odds in the indicated surveys/samples. The results in column (4) are for the log odds that would be predicted if men had the same height distribution as women based on the regression results in Table 3. ***, ** and * indicate statistical significance at the 10, 5, and 1 percent levels respectively.

Table 5: Predicted Duncan indices negating occupational selection on occupational skills, aptitudes and attributes; univariate results

		1970		2012	
		Duncan	% Δ from Actual	Duncan	% Δ from Actual
Actual		0.644		0.508	
Sensory	Color discrimination	0.646	0.3	0.502	-1.2
	Color vision	0.648	0.6	0.500	-1.6
	Near Acuity	0.636	-1.2	0.489	-3.7
	Far Acuity	0.636	-1.2	0.498	-2.0
	Hearing	0.625	-3.0	0.473	-6.9
	Noise	0.619	-3.9	0.445	-12.4
	Tasting-smelling	0.643	-0.2	0.510	0.4
	Feeling	0.641	-0.5	0.504	-0.8
Motor	Fingering	0.610	-5.3	0.494	-2.8
	Finger Dexterity	0.633	-1.7	0.505	-0.6
	Handling	0.644	0.0	0.509	0.2
	Manual dexterity	0.648	0.6	0.518	2.0
	Motor Co-ordination	0.651	1.1	0.519	2.2
	Eye-Hand-Foot	0.627	-2.6	0.470	-7.5
	Clerical Perception	0.620	-3.7	0.454	-10.6
Spatial	Spatial skills	0.580	-9.9	0.475	-6.5
	Depth perception	0.577	-10.4	0.426	-16.1
Other	Physical strength	0.607	-5.7	0.476	-6.3
Attributes	GED - language	0.645	0.2	0.507	-0.2
	GED - math	0.635	-1.4	0.509	0.2
	Temperament – people	0.628	-2.5	0.481	-5.3
	Interest - things	0.623	-3.3	0.495	-2.6
	Occupational prestige	0.640	-0.6	0.511	0.6
	Mortality rate	0.627	-2.6	0.487	-4.1
	Competition	0.612	-5.0	0.497	-2.2
	Time pressure	0.629	-2.3	0.490	-3.5
	Structured/unstructured work	0.643	-0.2	0.508	0.0
	Freedom to make decisions	0.633	-1.7	0.507	-0.2

Notes: Authors' calculations from 1970 census and 2012 American Community Survey. The predicted Duncan indices are constructed as per equation (3) in the text based on the estimates in Table 2. All predicted indices are statistically significantly different from the actual Duncan index in the indicated year at the 1 percent level.

Table 6: Predicted Duncan indices negating occupational selection on occupational skills, aptitudes and attributes; multivariate results

	1970		2012	
	Duncan	% Δ from Actual	Duncan	% Δ from Actual
Actual	0.644		0.508	
Sensory	0.617	-4.2	0.472	-7.1
Motor	0.611	-5.1	0.491	-3.3
Spatial	0.574	-10.9	0.455	-10.4
Combined: sensory, motor and spatial	0.510	-20.8	0.393	-22.6
Physical strength	0.622	-3.4	0.476	-6.3
Cognitive	0.632	-1.9	0.508	0
People/things	0.627	-2.6	0.486	-4.3
Occupational risk	0.623	-3.3	0.498	-2.0
Flexibility	0.627	-2.6	0.502	-1.2
Combined – Other Attributes	0.551	-14.4	0.415	-18.3
All	0.420	-34.8	0.299	-41.1

Notes: Authors' calculations from 1970 census and 2012 American Community Survey. "Cognitive includes GED—language and GED—math. "People/Things" includes temperament—people and interest—things. "Occupational risk" includes occupational prestige, mortality risk and competition. "Flexibility" includes time pressure, structured/unstructured work and freedom to make decisions. The predicted Duncan indices are constructed as per equation (3) in the text based on the estimates in Table 2. All predicted indices are statistically significantly different from the actual Duncan index in the indicated year at the 1 percent level.