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STATURE AND STATUS: HEIGHT, ABILITY, AND LABOR MARKET OUTCOMES

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ABSTRACT

It has long been recognized that taller adults hold jobs of higher status and, on average, earn more than other workers. A large number of hypotheses have been put forward to explain the association between height and earnings. In developed countries, researchers have emphasized factors such as self esteem, social dominance, and discrimination. In this paper, we offer a simpler explanation: On average, taller people earn more because they are smarter. As early as age 3 — before schooling has had a chance to play a role — and throughout childhood, taller children perform significantly better on cognitive tests. The correlation between height in childhood and adulthood is approximately 0.7 for both men and women, so that tall children are much more likely to become tall adults. As adults, taller individuals are more likely to select into higher paying occupations that require more advanced verbal and numerical skills and greater intelligence, for which they earn handsome returns. Using four data sets from the US and the UK, we find that the height premium in adult earnings can be explained by childhood scores on cognitive tests. Furthermore, we show that taller adults select into occupations that have higher cognitive skill requirements and lower physical skill demands.

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I. Introduction

It has long been recognized that taller adults hold jobs of higher status and, on average, earn more than other workers. Empirical research on height and success in the U.S. labor market dates back at least a century. Gowin (1915), for example, presents survey evidence documenting the difference in the distributions of heights of executives and of “average men.” Gowin also compares the heights of persons of differing status in the same profession, finding that bishops are taller on average than preachers in small towns, and sales managers are taller than salesmen, with similar results for lawyers, teachers, and railroad employees (p. 32).

Height continues to be highly correlated with labor market success in developed countries. Figures 1 and 2 provide evidence from the US and the UK that more highly-skilled jobs attract taller workers.[1] On average, American men in white collar occupations are an inch taller than men in blue collar occupations. Among 30-year-old men in the UK, those working in professional and managerial occupations are six-tenths of an inch taller on average than those in manual occupations. Results for women are quite similar: in the UK, women working as professionals and managers are an inch taller than those in manual unskilled occupations.

Taller people also have higher average incomes and earnings. Table 1 presents results on the relationship between the logarithm of income and height for men and women observed in the US National Health Interview Survey (column 1), and between log earnings and height for men and women in a 1958 British birth cohort study (columns 2 and 3), and in a 1970 British cohort study (column 4). For both men and women, the relationship is striking: a one-inch increase in

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[1]The US evidence is based on data from the National Health Interview Survey, and the British evidence is based on data from the 1970 British Cohort Study. These data sets will be discussed in more detail below.

height is associated with a 2 to 2.5 percent increase in income or earnings. An increase in US men's heights from the 25th to the 75th percentile of the height distribution — an increase of four inches — is associated with an increase in earnings of 10 percent on average.

A large number of hypotheses have been put forward to explain the association between height and earnings. In developing countries, the height premium in earnings is often attributed to the greater strength and better health that accompany height (Haddad and Bouis 1991, Steckel 1995, Strauss and Thomas 1998). In developed countries, researchers have emphasized factors such as self esteem (Freedman 1979, Lechelt 1975, Wilson 1968, Young and French 1996); social dominance (Hensley 1993, Klein et al. 1972) and discrimination (Loh 1993, Magnusson, Rasmussen, and Gyllensten. 2006). In a recent paper, Persico, Postlewaite and Silverman (2004) suggest that boys who are taller during adolescence are more likely to participate in social activities that build productive human capital. They postulate that adolescent experiences are responsible for the higher earnings observed for taller men in adulthood, so that those who are short as teenagers have lower earnings, even if their heights "catch up" by adulthood.

In this paper, we offer a simpler explanation: On average, taller people earn more because they are smarter. As early as age 3 — before schooling has had a chance to play a role — and throughout childhood, taller children perform significantly better on cognitive tests. The correlation between height in childhood and adulthood is approximately 0.7 for both men and women, so that tall children are much more likely to become tall adults. As adults, taller individuals are more likely to select into higher paying occupations that require more advanced verbal and numerical skills and greater intelligence, for which they earn handsome returns.

In Section II, we review the literature on environmental and genetic determinants of growth and cognition and discuss the reasons why height and cognitive ability are likely to be correlated. The timing of physical growth and cognitive development is important for our empirical work, and we highlight the patterns that exist for each. Section III contains a theoretical framework that motivates our empirical research, and Section IV discusses the data sets we use. Section V presents evidence. We first show how the heights of children and adults are related to the childhood environment, and make the case that common factors influence both height and cognitive ability. We present evidence from three data sets — two from Britain and one from the US — that taller children score better on a variety of cognitive tests administered at different ages. We then examine how heights are related to earnings and occupational choice. We find that the height premium in adult earnings can be explained by childhood scores on cognitive tests. Furthermore, we show that taller adults select into occupations that have higher cognitive skill requirements and lower physical skill demands.

II. A Primer on the Determinants of Growth and Cognition

Adult height reflects cumulative growth up to maturity. Figure 3 depicts the usual pattern of growth observed in wealthy countries. After a period of intense growth from ages 0 to 3, growth becomes relatively stable at approximately 6 cm a year until adolescence, at which point an adolescent growth spurt (AGS) accelerates growth to an (adolescent) *peak height velocity* of approximately 10 cm a year. In current European cohorts, girls tend to reach peak height velocity at age 12, and boys at age 14. Final adult height is attained when growth ceases, which depends on the timing and duration of the AGS. (See Beard and Blaser, 2002, for a thorough discussion and references.)

Age-specific growth patterns and final adult height depend on a combination of factors, including genes, environmental conditions (particularly nutrition and illness) and gene-environment interactions. Although genes are key determinants of individual height, many studies suggest that differences in average height across populations are due largely to environmental factors (Steckel 1995). The marked increase in heights observed throughout the developed world during the 20th Century occurred too rapidly to be due to selection and genetic variation (Beard and Blaser 2002). Silventoinen (2003) argues that a full 20 percent of variation in body height between individuals in developed countries today is due to environmental factors.

Adult height depends in part on a child's uterine environment. Mother smoking during pregnancy is a critical risk factor for intrauterine growth retardation (Institute of Medicine 2001). In addition, low birth weight is a significant predictor of lower stature in adulthood (Hack et al. 2003, Ericson and Kallen 1998).

Adult height is also sensitive to environmental conditions experienced in childhood. The period from birth to age three is generally identified as the postnatal period most critical to adult height. The speed of growth is more rapid during this period than at any other during the life course, and nutritional needs are greatest at this point. Infections (especially gastrointestinal and respiratory) can be frequent and severe in early childhood, and these can impair growth. In addition, children are at special risk from poor care-giving at youngest ages; once children are more autonomous, they may be better equipped to protect themselves. (See Martorell, Kettel Khan and Schroeder 1994 for discussion.)

Environmental conditions in childhood also affect the timing of the growth patterns described above. The age of onset of the adolescent growth spurt (AGS) has fallen over the past two centuries, in step with a fall in age at maturation. In late 19th Century Europe, adult height was attained at age 26 – substantially different from today's estimates of age 18 for boys, and age 16 for girls (Beard and Blaser, 2002). The timing of the AGS and age at maturation also vary cross-sectionally. Through a combination of better nutrition and improved disease environments, children of higher socioeconomic status experience an earlier AGS and attain their adult heights at earlier ages. Conversely, children who experience deprivation may experience an extension of the growth period that can last several years (Steckel 1995). An extended AGS can help shorter children gain a similar amount of height as other children do during adolescence, but on average this does not erase height deficits that developed in early childhood (Martorell et al 1994, Martorell et al 1990, Satyanarayana et al 1989, Hack et al 2003).

Differences in the timing of pubertal growth spurts act to temporarily magnify differences in heights between economic classes during adolescence. This has long been true: data collected at a boarding school in Germany in the 18th Century, for example, suggests that upper class boys reached their peak height velocity a full year earlier than lower class boys, exaggerating the height difference between them during their teen years. Controlling for year and region of birth, height differences between low aristocrats and middle class boys grew from 2.4 cm at age 10, to 5.8 cm at age 15, before returning to a mean height difference of 2.1 cm at age 19 (Komlos et al 1992).

Height and cognitive ability

While a positive correlation between body height and intelligence has been documented in studies stretching back at least a century (Tanner 1979), the precise links between height and cognition are still not well understood. Research on the determinants of cognitive ability suggests an important role for nutrition, which may well prove to be a significant link between height and intelligence (Lynn 1989, Kretchmer, Beard and Carlson 1996). Randomized control trials of supplemental feeding have shown that growth-retarded children's cognitive development benefits significantly from better nutrition (Grantham-McGregor 2002).

There may be chemical channels that influence both height and cognition. Work on insulin-like growth factors suggests that these may affect body growth while also influencing areas of the brain in which cognition occurs (Berger 2001). Similarly, thyroid hormone is known to stimulate growth and at the same time influence neural development (Richards et al 2002).

Features of the uterine environment may influence height and cognitive development. Both prenatal smoking and low birth weight predict poorer cognitive ability. Maternal smoking during pregnancy is associated with lower cognitive test scores, behavioral problems, and Attention Deficit Hyperactivity Disorder (Weitzman, Gortmaker and Sobol 1992; Romano et al. 2006). While these outcomes may be the result of factors correlated with mother smoking while pregnant rather than the direct effect of smoking, animal studies have documented the role of prenatal nicotine exposure on neural development (Slotkin 1998). Being born at low weight also predicts poorer cognition (Ericson and Kallen 1998). Richards et al. (2002) examine data collected on height and cognition at several points in childhood and adulthood for the 1946 British birth cohort study. They find that low birth weight is associated with lower cognitive test scores through age 26.

Height and cognitive ability may also be linked by genes, although recent research on the genetic ties between height and intelligence shows mixed results. One Norwegian twin study suggests that approximately a third of the correlation between height and intelligence may be due to overlapping genetic factors (Sunder et al 2005). However, other work on Finnish twins finds no evidence that the correlation between height and educational attainment is due to genetic overlap (Silventoinen et al 2000). Magnusson et al. (2006), comparing first and second born biological brothers in Sweden, find that the taller brother is significantly more likely to attend higher education. The height effect estimated across brothers is almost identical to that estimated across all men, suggesting that the correlation between height and intelligence is not driven solely by genetic or environmental factors common to brothers.

Nutrition and health affect cognitive development throughout childhood (Walter 1993, Pollitt and Mathews 1998). There is limited evidence on whether individuals with low levels of cognitive development in early childhood can catch up to others. However, recent work suggests that catch up, if physically possible, is generally not complete. Using a large cohort of individuals observed from birth to age 53, Richards and Wadsworth (2004) find that children who experience early adverse circumstances have lower cognitive test scores at all ages. Abbott et al (1998) document a significant correlation between height of men in mid-life and their cognitive performance after age 70. Even after adjustment for education and father's occupation, they find a strong and significant association between height and cognitive function.

III. Framework

Our hypothesis is that the associations between height and labor market outcomes are primarily due to the correlation of height with intelligence. In this view, returns to height in the labor market are not due to pure discrimination against shorter individuals, nor are they due to the greater strength or physical ability of taller people. Rather, the height premium is due to omitted variables bias, with estimates of the height premium reflecting returns to unmeasured cognitive ability.[2]

The following framework formalizes this idea and motivates our empirical work. Following the earnings equations shown in Table 1, we start with a linear model of the form:

(1) $$w_i = \theta h_i + \varepsilon_i$$

for an individual i with log earnings w who stands at height h. All other determinants of earnings are grouped in the unobservable, ε. Our interest is in determinants of earnings that are correlated with height and that could bias our estimate of a true height premium, should one exist. In particular, we focus on ability, η, an unmeasured determinant of earnings that may also be correlated with height. Ignoring momentarily other determinants of earnings, we write

(2) $$\varepsilon_i = b\eta_i + e_i$$

where e_i is the idiosyncratic component of earnings assumed to be orthogonal to height. If ability is correlated with height, then part of the estimated height premium is a reflection of that correlation. Specifically, the probability limit of the OLS estimate of the height premium can be expressed

(3) $$p\lim\hat{\theta} = \theta + p\lim(h'h)^{-1}h'\varepsilon = \theta + b\sigma_{\eta h} / \sigma_h^2,$$

where $\sigma_{\eta h}$ is the covariance of height and ability and σ_h^2 is the variance in height. The OLS estimate is then a combination of a genuine height premium θ (due perhaps to height-based

[2] If our hypothesis is correct, it is possible that employers with incomplete information about the cognitive ability of their workers practice height-based statistical discrimination.

discrimination in the labor market, or a genuine efficiency gain directly attributable to height), and the projection of ability onto height.

So far, we have not distinguished between different types of ability. Height may be correlated with intelligence, as discussed above. However, height may also be positively correlated with other productive characteristics, such as physical strength or coordination. Indeed, the literature on developing countries typically assumes that the height premium in earnings reflects better physical health and productivity. The framework can easily be extended to include multiple kinds of ability, all of which may have different correlations with height. Suppose, for example, that there are two types of productive ability–cognitive ability, η^C, and physical ability or "strength", η^S, so that:

(4) $$\varepsilon_i = b^c \eta_i^c + b^s \eta_i^s + e_i .$$

In this case, the estimated height premium, assuming that both cognitive ability and strength are unobserved, will have a probability limit of:

(5) $$p\lim \hat{\theta} = \theta + \left[\frac{b^c \sigma_{ch} + b^s \sigma_{sh}}{\sigma_h^2} \right].$$

Estimates of the return to height may be biased upwards due to its correlation with either strength or cognitive ability. Note, however, that if the height premium is driven solely by the correlation between height and cognitive ability, then estimates of earnings equations that control for cognitive ability will show a height premium of zero. We examine this implication in the following empirical work.

This framework can also be extended to examine occupational choice. As above, we assume that height is correlated with a number of productive abilities. Following previous literature on occupational choice, we assume that the returns to these different abilities vary across occupations (Heckman and Scheinkman 1987; Gibbons et al 2005). Workers sort into the occupations that yield the highest returns. If height is more strongly associated with cognitive ability than physical ability—in a sense that we define more precisely below—then taller workers will sort into jobs that require greater cognitive skill relative to physical skill.

To fix ideas, we assume there are two occupations, 1 and 2. We assume that the productive abilities η^C and η^S are known by both workers and potential employers. (This model could be extended to include learning about productive characteristics, as in Gibbons et al 2005.) The wage equation has the same form used above, but with returns to productive abilities that vary across the two occupations. Suppressing the individual subscripts, the logarithm of the wage that a worker receives in occupation j is:

(6) $$w_j = \theta_j h + b_j^c \eta^c + b_j^s \eta^s + e_j \text{, for j=1, 2.}$$

Assume, with no loss of generality, that occupation 1 places a higher premium on cognitive skills and occupation 2 places a higher premium on physical skills, so that $b_1^c > b_2^c$ and $b_1^s < b_2^s$. We are agnostic about whether the pure height premium, θ_j, is larger in occupation 1 or 2. To simplify notation, define $\lambda^c = b_1^c - b_2^c$, $\lambda^s = b_2^s - b_1^s$, $\lambda^h = \theta_2 - \theta_1$, and $e = e_1 - e_2$. The worker chooses the highest-paying occupation given his or her characteristics, so that occupation 1 is chosen if:

(7) $$u = \lambda^c \eta^c - \lambda^s \eta^s + e > \lambda^h h \cdot$$

This equation indicates that, all else equal, an increase in λ^c, the excess return to cognitive ability in occupation 1, relative to λ^s, the excess return to strength in occupation 2, will shift workers from occupation 2 into occupation 1.

With assumptions about the joint distribution of height, productive abilities and e, it is possible to derive the probability that occupation 1 is chosen conditional on height, and examine how changes in height affect this probability. Assume that these variables have a multivariate normal distribution, the measure of height (h) has been standardized to have a mean of zero and a variance of 1, and the two productive abilities have means of zero. Using standard formulae for multivariate normals, the probability of choosing occupation 1 conditional on height is:

$$(8) \qquad P(u > \lambda^h h \mid h) = \Phi\left[\frac{(\lambda^c \sigma_{ch} - \lambda^s \sigma_{sh})h - \lambda^h h}{\sigma_u}\right]$$

where σ_{ch} and σ_{sh} are the covariances of height with cognitive skill and strength, respectively; σ_u is the standard error of u as defined in (7) ; and $\Phi(\cdot)$ is the standard normal distribution. The change in the probability of selecting occupation 1 with respect to height will be positive provided that $\lambda^c \sigma_{ch} > \lambda^s \sigma_{sh} + \lambda^h$. In words, if the covariance between height and cognitive ability, weighted by the excess return to cognitive skill in occupation 1, exceeds the covariance between height and physical ability, weighted by the excess return to physical skill in occupation 2, plus any pure excess height premium in occupation 2, then taller workers will sort into occupation 1.

In the empirical work that follows, we examine a number of the implications of the theory developed above. We first provide evidence that environmental factors thought to influence cognitive ability—including parents' educations and socioeconomic status, low birth weight and prenatal maternal smoking—are also correlated with heights and the timing of growth patterns, even controlling for parental heights. We then provide direct evidence that σ_{ch}, the covariance between cognitive ability and height, is positive. We present estimates of earnings equations that indicate that the height premium in earnings is generally eliminated when measures of cognitive ability in childhood are included in the models. Finally, we examine the implication that taller workers sort into occupations that place a premium on the skills highly correlated with height. We estimate multinomial logit models that relate height to occupational choice, and then use information on the skill requirements of different occupations to show that occupations that attract taller workers are those that require greater levels of cognitive skills.

IV. Data

We use four well known data sets that bring different strengths to the analysis. Documenting the chain from height and ability in childhood to earnings and occupational status in adulthood requires panel data that includes measures of heights from childhood to adulthood, childhood cognitive ability, and adult labor market outcomes. For these reasons, we use data from two British birth cohort studies — the 1958 National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS). The NCDS has followed all children born in England, Scotland and Wales in the week of March 3, 1958 from birth to age 42. Follow-up surveys on health and economic well being were conducted at ages 7, 11, 16, 23, 33 and 42. In similar fashion, the BCS has followed all individuals living in Great Britain born in the week of April 5, 1970. Full follow-up surveys were conducted at ages 5, 10, 16, 26 and 30. Both the NCDS and the BCS administered tests to cohort members at early ages (7 and 11 in the NCDS, 5 and 10 in the BCS), and both surveys report earnings in adulthood (at ages 33 and 42 in the NCDS, age 30 in the BCS). We use adult height measured at age 33 (for the NCDS) and self-reported at age 30 (for the BCS).

Summary statistics for these data sets are presented in the first two columns of Table 2, where we restrict our attention to cohort members who were measured in childhood, and again in adulthood (ages 7 and 33 for the NCDS, ages 5 and 30 for the BCS). Men in both surveys stand 5 foot 10 inches tall on average in adulthood, and women 5 foot four inches. Thirty percent of cohort members were born to fathers in higher social classes (executives, managers, skilled non-manual workers). Approximately 90 percent of men in both cohorts report working full or part time, true for 80 percent of women in the NCDS at age 42, and 74 percent of women in the BCS at age 30.

To examine the relationship between height and occupational choice, we use data from 9 years of the US National Health Interview Survey. In these large nationally representative cross-sectional data sets, over the period 1986 to 1994, the NHIS reported detailed information on occupations as well as on heights.[3] The strength of the NHIS is largely its size — we work with a sample of 435,514 men and women ages 18 to 65 who report an occupation — but it contains little information on factors other than height that might influence occupational choice. For this reason, we also examine height and occupational choice in the Panel Study of Income Dynamics (PSID), which covers fewer individuals than the NHIS but has the advantage of containing a richer set of controls, in particular information on parents' educations and a measure of whether respondents were poor in childhood. The sample for the PSID consists of observations on men between the ages of 25 and 65, from the 1988 to 1997 waves of the PSID. (The lower age cutoff

[3]For uniformity, we limit our analysis to the period prior to the NHIS sample redesign of 1995.

of 25 is used because heights are recorded only for heads of households and their spouses, whereas the NHIS records heights of all individuals over the age of 17.) The final sample consists of 4,517 men observed an average of 6.8 years each, for a total of 30,575 observations.

Summary statistics for these data sets are presented in columns 3 and 4 of Table 2. The heights of the men and women from the American data sets are similar to those in the British samples. In the NHIS, a large fraction (90 percent of men, 84 percent of women) who reported an occupation also reported that they worked in the week prior to the survey. The fraction of the PSID sample that reported childhood poverty is high — nearly 33 percent. To maintain a large sample size, we include the "Survey of Economic Opportunity" (SEO) sub-sample in our analyses. The SEO sub-sample, which comprised roughly 40% of the original PSID families enrolled in the study in 1968, were poor. The high fraction of this sample that were poor in childhood is therefore to be expected.

V. Results

Height and Growth in the NCDS Cohort

The growth literature suggests that children raised in healthier environments are taller in childhood and experience earlier adolescent growth spurts. We observe these patterns in the 1958 NCDS cohort. The top panel of Table 3 presents information on heights of male cohort members at ages 7, 11, 16 and 33, from regressions that control for ethnicity and for the month in which measurements were taken. We regress height on indicators for father's social class at the time of the cohort member's birth, with the omitted category being the highest social class (professional). Throughout life, children whose fathers were of lower social class are shorter. At age 7, boys born into the highest social class are 0.4 inches taller on average than those born into social class 2 (managers), and 1.4 inches taller than those born into social class 5 (unskilled manual laborers). Differences in average heights between classes remain constant between ages 7 and 11. Cohort members are growing between these ages, but at approximately the same growth velocity in each social class. But by age 16, boys in higher social classes have grown more rapidly than those in the lowest three classes, temporarily magnifying the gap in heights between them. Boys in the higher classes appear to reach their adolescent growth spurts earlier than those in the lower classes. That young men in the lower three classes experience some catch up, during their own later AGS, can be seen by comparing the differences in heights between the social classes at ages 16 and 33. Although men from lower social classes are on average a full inch shorter than are men from social class 1 when fully grown, they gained more height from 16 to 33 than did men from higher social classes. Girls from higher social classes in the NCDS are taller on average at every age. The timing of girls' AGS is earlier than that for boys, so that by age 16 the height differentials by social class for young women are nearly identical to what they had been at age 7.[4]

The timing of adolescent growth spurts — with young adults from healthier backgrounds with better nutrition reaching their AGS earlier — calls into question a key assumption of Persico et al (2004). These authors assume that "conditional on other observables, an individual's heights at various ages are exogenously given" (page 1030). Indeed, the timing of growth spurts leads us to a new interpretation of Persico et al's statement that "It's all in teen height." Boys' heights at

[4]That children in the NCDS from poorer backgrounds have "a delayed pattern of growth before the pubertal spurt, followed by catch-up growth" has earlier been noted by Li, Manor and Power (2004, p. 185).

age 16 may convey more information about childhood nutrition and health than do adult heights. If better nutrition and health in childhood lead to greater cognitive ability, then teen height may be a good marker for unobserved ability — perhaps a better marker than final adult height. We return to this below when we examine the relationship between height and earnings..

The bottom panel of Table 3 reports how much of the variation in height we can explain using the rich set of household and individual level background variables we have in the NCDS data. Again restricting attention to male cohort members for whom measurements were taken at all four ages, we regress height on ethnicity, the month of the cohort member's height measurement, and family background variables broken into three sets: parents' socioeconomic status; cohort members' health at birth; and parents' heights. Parents' socioeconomic status is represented here by indicators for mother's and father's school leaving ages, maternal grandfather's social class, father's social class at the time of the cohort member's birth, and the logarithm of family income at age 16. Cohort members' health at birth is measured using an indicator for whether he was born at low birth weight (less than 2500 grams), and whether his mother smoked while pregnant. Mother's height was measured at the time of the birth, and father's height was reported when the cohort member was age 11. All three sets of background variables are highly significant predictors of the cohort member's height, with *F*-tests of each set having *p*-values below 0.01 at every age. Taken together, these variables explain a quarter to a third of the variation in heights at any age, with regression R^2s between 0.25 and 0.33. Mother's and father's SES and health at birth contribute to the R^2s, as can be seen in the incremental contributions to the R^2 presented in the second panel of Table 3. However, their contributions are dwarfed by that made by mother's and father's heights, whose contribution is larger, the older the cohort member becomes.

Mother's and father's heights contain both a genetic tie to cohort members' heights and environmental ties. Parents are taller, in part, because they were raised in healthier environments. Mothers' heights, for example, are significantly related to their own fathers' social class in a manner quite similar to that presented above for NCDS cohort members and fathers' social class in Panel A of Table 3. We are not able to distinguish which part of the association between parents' and cohort members' heights is due to genetics, and which to environment. For our analysis, this is not essential. What is important is that environmental factors that are thought to influence cognitive development — parental education and SES, and aspects of the prenatal environment — are also correlated with children's heights.

Height and Childhood Cognitive Test Scores

We present direct evidence on the relationship between height and test scores in childhood in Table 4, using data from the NCDS and BCS.

The tests administered to children vary across ages and surveys. For the 5-year-olds in the BCS, we show results for a human figure drawing score, designed to test conceptual maturity, a copy design test that measures visual-motor coordination, and the English Picture Vocabulary Test (EPVT) score, which measures the size of the child's vocabulary. At age 10, we show results for the four subscales of the British Ability Scales (BAS) included in the BCS. We chose to report these rather than scores on the math, reading and vocabulary tests that were given at age 10, since the BAS subscales are meant to measure cognitive ability rather than academic achievement. For the NCDS, we show results for the human figure drawing test and math and reading scores at age 7, and scores from verbal language, non-verbal language, math, and copy-design tests at age 11. All cognitive tests are standardized within sample to have a mean of zero and a standard deviation of one, and the height measures are transformed into height-for-age z-scores using the 2000 Centers for Disease Control growth charts (CDC, 2002). This standardization makes it easier to compare estimates across ages and tests.

For both surveys, we first show results of regressions of test scores on height, controlling for only a few key variables — the child's sex, ethnicity, and the age in months at which the testing occurred. We then show results (in the last column) that include an extended set of family background controls. For the NCDS, these controls are identical to those included in the regressions in the lower panel of Table 3. For the BCS, we substitute the mother's social class at the time of the child's birth for her father's social class, and a set of indicators for categories of family income at age 10 for the log of income at age 16. The results in Table 3 indicate that these family background variables are associated with heights in childhood and adulthood. We expect the covariance between height and cognitive test scores will be smaller after conditioning on these variables, since better-off children are both taller and have higher test scores. However, as was shown in Table 3, a large share of the cross-sectional variation in heights is not explained by these variables, and it is of interest to know if the correlation between height and cognitive ability persists even after observable determinants of height are accounted for.

We find a large and significant association between height and test scores for children followed in the BCS for tests they took at ages 5 and 10 (top panel) and for children in the NCDS for tests at ages 7 and 11 (lower panel). Although the coefficients are somewhat larger for the NCDS, especially among 11-year-olds, we find similar patterns across the two surveys. In neither survey does it appear that the associations are systematically larger for older versus younger children. The magnitudes of these associations are quite large, even when the extended controls are included. For example, in the NCDS data using extended controls, a one standard deviation increase in height at age 7 is associated with 10 percent of a standard deviation increase in reading score at age 7, and in verbal language score at age 11. This effect is as large as that predicted by a two standard deviation increase in log household income for these children.[5]

One possible explanation for these results is that taller children are provided with greater levels of cognitive stimulation at school. Teachers may pay more attention to taller children, or taller children may be more likely to be enrolled in school earlier than shorter children of the same age. However, evidence from other surveys indicates that the association between height and cognitive outcomes begins too early for this hypothesis to be plausible. For example, Rose (1994) finds that the length of 5- to 12-month-old infants is associated with measures of information processing speed.[6]

Additional evidence is shown in the bottom panel of Table 4. The data are drawn from the *Fragile Families and Child Wellbeing Study*, a US birth cohort study of urban children (Reichman et al. 2001). The Fragile Families data contains an assessment of both the child's and mother's verbal ability, as measured by the Peabody Picture Vocabulary Test (PPVT). The PPVT, on which the EPVT is based, is a test of receptive vocabulary that can be administered to individuals from ages 30 months through adulthood, and has been used in numerous studies of

[5]For reading scores at age 7 and verbal scores at age 11, log family income takes a coefficient of 0.24. A one-standard deviation increase in log income is 0.234, so that a two standard deviation increase would be necessary to have an effect as large as a one-standard deviation in height at age 7.

[6]These effects could be magnified by the behavior of teachers later in life.

pre-school-aged children (Dunn and Dunn, 1997).[7] We find that taller children perform significantly better on this test. A one standard deviation in height is associated with a 5 to 10 percent of a standard deviation increase in PPVT scores at age 3 for both boy and girls. This is true even controlling for mother's score on the PPVT, which is included in the set of extended controls. The correlation between height and cognitive ability in these data cannot be explained by differential treatment of taller children in school.

Height, Cognitive Ability and Earnings

We use data from the British birth cohorts to reexamine the height premia presented in Table 1, drawing on the information we have on cognitive ability and family background. We present results of log earnings regression in Table 5. The top panel shows results for men and women in the 1970 BCS, and the bottom panel for the 1958 NCDS. We restrict our sample to individuals who took cognitive tests at two points in childhood — ages 5 and 10 for the BCS cohort, ages 7 and 11 for the NCDS. We present results separately by sex, and then combine the sexes, running regressions that include an indicator for whether the cohort member is a woman.

For both men and women in the BCS cohort, we find a positive and significant association between height and log earnings, with an additional inch of height associated with a one to two percent increase in earnings (columns 1 and 4). We first add test score variables to the model. These are jointly highly significant in the BCS earnings equations, with *F*-tests of 31.1 for men and 38.5 for women. Inclusion of these cognitive test scores reduces the size of the height coefficients by more than 50 percent, and renders them insignificant. Inclusion of personal and

[7] Information on reliability and validity of the PPVT and a research bibliography can be found at http://ags.pearsonassessments.com.

parental background characteristics further reduces the height coefficients for men and women.

On average women earn 17 percent less than men in this sample. However, the height difference between men and women does not explain women's lower earnings. In the combined sample of men and women, with controls for height, cognitive ability and family background, men's earnings premium stubbornly remains at 17 percent. With cognitive test scores and family background variables included, the height coefficient is negative and insignificant in the combined sample.

The bottom panel of Table 5 reexamines the Persico et al. results that adolescent height is a better predictor of adult earnings in the NCDS data than is adult height—and specifically that men's adult heights are no longer associated with their earnings after controlling for adolescent height.[8] Above, we suggested that this might be because boys of higher socioeconomic status reached their AGS earlier and were relatively taller at age 16 than at age 33. We make this more concrete by modeling how earnings in adulthood relate to height at two points in time: height at age 16, h_{16}, when some adolescents are well along in their pubertal growth spurts, and at age 33, when final adult height, h_a, has been attained by all.

We assume that earnings are an increasing function of cognitive ability, η, which depends on nutrition in infancy (ages 0 to 3), n_I, and nutrition in childhood (ages 3 to puberty), n_C.

(9) $\eta = \alpha + \beta n_I + \gamma n_C + u_\eta$

[8]We could not explore this with BCS data because, although a follow-up survey was undertaken for the BCS cohort at age 16, two-thirds of cohort members were not measured at that age.

The literature discussed in Section II indicates that adult height is particularly sensitive to early nutrition, n_I. Although nutrition in childhood, n_C, can change the timing of the adolescent growth spurt, it does not change the amount of height children gain during their AGS. Thus we describe adult height as:

$$(10) \quad h_a = a + \delta n_I + u_a .$$

Height at age 16 depends on the timing of the adolescent growth spurt, which depends on nutrition in infancy and childhood, so that children who were better nourished are taller when observed at age 16:

$$(11) \quad h_{16}^s = (h_a - c_{16}^s) + \psi^s (n_I + n_C) + u_{16} \qquad for\ s = f, m$$

where c_{16}^s denotes the average gain in height experienced by cohort members of sex *s* from age 16 to maturity. Girls reach their pubertal growth spurt earlier than boys, so that for girls we expect c_{16}^f and ψ^f to be small.

The relationship between ability and heights at age 16 and in adulthood can be obtained by rearranging terms in (10) and (11) and substituting into equation (9). Suppressing the sex superscripts, we find that:

$$(12) \quad \eta = \tilde{\alpha} + [\tfrac{(\beta-\gamma)}{\delta} - \tfrac{\gamma}{\psi}]\, h_a \; + [\tfrac{\gamma}{\psi}]\, h_{16} \; + u$$

where $\tilde{\alpha}$ is a constant. In (12), the coefficient on height at age 16 is unambiguously positive. Its size depends upon the extent to which nutrition in childhood affects cognitive ability (γ), and the impact of nutrition in infancy and childhood on the timing of the pubertal growth spurt (ψ).

In contrast, the coefficient on adult height can be positive or negative. Specifically, the greater the impact of childhood nutrition on intelligence (i.e., the larger is γ), the smaller will be the estimated relationship between final adult height and earnings, and the larger will be the estimated relationship between height at age 16 and earnings.

Equation (12) also has implications for the coefficients on heights at different ages in earnings equations for women and men. If ψ^{f} is smaller than ψ^{m} (because girls have nearly completed their AGS by age 16) and all other coefficients are the same for boys and girls, the coefficient on height at 16 in an earnings equation will be larger for girls than for boys, and the coefficient on adult height will be smaller. However, because height at 16 and adult height are more highly correlated for girls than boys (the correlation coefficient is 0.92 for girls in the NCDS relative to 0.77 for boys), coefficients for girls may be less precisely estimated when both height measures are included.

The bottom panel of Table 5 presents evidence that is consistent with this model. The results for men in the first column are similar to those of Persico et al, in that the coefficient on height at age 33 (0.009) is smaller than that on height at age 16 (0.016), and only the coefficient on height at 16 is statistically significant. The inclusion of test scores at ages 7 and 11 reduces the age 16 height premium by more than 50 percent, similar to results shown for the BCS cohort in the top panel. Moreover, their inclusion leaves the coefficients on height at ages 33 and 16 identical. That is, once controls for cognitive ability are included, the data have no reason to favor height at 16 over height at 33. Although neither coefficient is individually significant, an *F*-test reveals that these variables are jointly significant (*F*-test=7.07, *p*-value=0.001). The additional inclusion of family background variables reduces the joint significance of the height variables further, and leaves them just shy of significance at the 1 percent level.

Consistent with the model developed above, the results for women in the first column show that the coefficient on height at age 16 is larger than that for men, and the coefficient on adult height is smaller. Although the women's height variables are jointly significant (*F*-test=6.15, *p*-value=0.002), the point estimates are not precisely estimated, and the hypothesis that the women's coefficients are the same as the men's cannot be rejected. The inclusion of test scores at ages 7 and 11 renders the height variables jointly insignificant in women's earnings equations. Estimating results for men and women together, we continue to find a two-percent premium for each inch of height at age 16, in the absence of other controls. The premium disappears when cognitive test scores are added to these regressions.

Further evidence that the timing of growth spurts is related to cognition comes from examining the associations between cognitive ability and changes in height at different ages—from age 11 to 16, and from age 16 to adulthood. Because girls begin their adolescent growth spurts earlier than boys, the associations between growth at different ages and cognitive ability should vary by sex.

We first consider the relationship between changes in heights measured at ages 11 and 16 and cognitive ability, for girls and boys. At age 11, healthier girls will have begun their AGS. We write girls' heights at age 11:

$$h_{11}^{f} = (h_{a}^{f} - c_{11}^{f}) + \tau(n_I + n_C) + u_{11}$$

where c_{11}^{f} represents the average amount of height girls will gain between age 11 and maturity, and τ measures the extent to which healthier girls have grown by age 11. Most girls have completed their growth by age 16, so that c_{16}^{f} and ψ^{f} will be close to zero, and we can represent the difference between girls' heights at age16 and age 11 as:

$$(h_{16}^{f} - h_{11}^{f}) = c_{11}^{f} - \tau(n_I + n_C) + (u_{16} - u_{11}) .$$

A comparison of this equation with the expression for cognitive ability in equation (9) shows that, for girls, cognitive ability should be negatively associated with the gain in height from ages 11 and 16. In contrast, even healthy well-nourished boys would not have begun their AGS by age 11. Their heights at age 11 can be written as:

$$h_{11}^{m} = (h_{a}^{m} - c_{11}^{m}) + u_{11} .$$

We can then express the difference between boys' heights at age 16 and age 11:

$$(h_{16}^{m} - h_{11}^{m}) = (c_{11}^{m} - c_{16}^{m}) + \psi(n_I + n_C) + (u_{16} - u_{11}) .$$

This equation implies that measures of cognitive ability will be positively associated with boys' growth from 11 to 16.

The first four columns of Table 6 present evidence that is consistent with these predictions. Each cell shows the coefficient from a separate regression of an age 11 test score on the change in height from age 11 to 16, for girls and boys. Girls show negative associations between the change in height and each of the test scores, whereas these associations are positive for boys. The sizes and significance levels of these coefficients change little when extended family background controls are included, indicating that these observed variables do not capture the common factors that influence both growth and cognitive development.

Different patterns are expected for the association between changes in height from age 16 to adulthood and test scores. By age 16, both boys and girls from better environments would have completed most of their growth. The model implies that, for both boys and girls, those with greater height gain between 16 and 33 are those who had experienced poorer environments in childhood, and so should have lower age 11 test scores. Furthermore, larger height gains for girls over this period are a signal of more severe deprivation than is the case for boys. For this reason, lower cognitive ability at age 11 should predict larger height gains from 16 to 33 for girls than for boys . The results in Table 6 are consistent with these implications. For both boys and girls, there is a negative and significant association between height gain after age 16 and test scores at age 11, with the association for girls twice as large as that for boys.

Height and occupational choice

The framework developed in Section III indicates that, if the covariance between height and cognitive ability is large relative to the covariance between height and physical ability, taller workers should select occupations that require more cognitive relative to physical skills. This section presents evidence on this proposition. Our strategy is to estimate models that relate occupational choice to height using a large sample of adult workers, ages 18 to 65, from the National Health Interview Surveys from 1986 to 1994. We then examine the extent to which occupations that attract taller workers are those which require high levels of cognitive relative to physical skills, where the measures of skill requirements are drawn from the Dictionary of Occupational Titles (DOT), described in more detail below.

For men and women separately, we estimate multinomial logit models of occupational choice, where the log odds of being in occupation j relative to a baseline occupation *1* is:

(13) $$\ln(P_j/P_1) = X\beta_j + \gamma_j h + \upsilon_j, \quad j\text{=2..}J.$$

In (13), P_j is the probability of working in occupation *j*, *h* is height and *X* is a vector containing a set of controls for characteristics that may affect occupational choice independent of workers' non-time-varying productive abilities, including age, age squared, and indicators for race and city size. (Models that exclude these controls yield similar results.)

The second step, after estimating (13), is to examine how the estimates of γ_j—which measure the change in the log odds of being in occupation *j* relative to the baseline occupation with respect to height—are associated with the characteristics of occupations. Occupational characteristics are obtained from the *Occupational Measures from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations* (England and Kilbourne 1988). This data set contains ratings of specific job characteristics for the 503 occupations included in the 1980 Census detailed occupational categories—the same occupational categories used in the NHIS. Our analysis uses ratings of four physical skill requirements, including manual dexterity, motor control, physical demands, and strength, and four intellectual skill requirements, including spatial skills, numerical skills, verbal skills, and intelligence.[9] Each of these ratings were reverse coded if necessary, so that higher values correspond to higher skill requirements. The ratings range (in theory) from 0 to 5, although in practice few occupations require the minimum or

[9]The ratings provided in this data set are based on even more finely detailed information on 12,099 occupations collected by the Department of Labor through direct observation and written job descriptions, and published in 1977. England and Kilbourne aggregated these ratings so that they could be used with the 1980 Census detailed occupational codes. Further information on how the original data were collected, as well as caveats about their reliability, can be found in Cain and Treiman (1981).

maximum level of any skill.

DOT occupational ratings were matched to each person with an occupation in the NHIS. After matching, our sample consisted of 230,172 men distributed across 479 occupations, and 205,027 women distributed across 469 occupations. Estimating multinomial logits with such a large number of occupations is not feasible. Instead, we classified workers as being in one of 15 more broadly-defined occupations. Occupational characteristics for these 15 broad occupations were computed as the (weighted) sample average of the 3-digit level occupational characteristics. Thus, the characteristics of more common 3-digit occupations carry more weight when computing average characteristics within the 15 broad groups. The mean characteristics were computed separately for men and women.

The first 6 columns of Table 7 provide information on the occupational categories we use, the fraction of the sample in each, and the average values of two of the six DOT characteristics we use—the amounts of strength and intelligence required. There are substantial differences in the distributions of men and women across occupations. Women are more likely to be administrative/clerical workers, and to work in other service-sector positions. Men are more likely to be transport workers, farmers, and to work in construction. When estimating the multinomial logit models, we excluded any cell that had fewer than 500 observations—so that men in domestic service and women in construction/mining are excluded from the regressions. The table also shows unsurprising results for the patterns of scores for intelligence and strength required for each broad occupation. The intelligence score is highest for professionals and lowest for household service workers. Strength requirements are highest for farming and lowest for executives/managers. The average intelligence scores for men and women differ only because men and women have different distributions among the detailed occupations that make up each broad occupation. Although the intelligence scores are similar for men and women within broad occupations, the strength scores for women are typically lower, indicating that women tend to work in less strenuous jobs within the broad categories.

The last two columns of Table 7 show estimates of the multinomial logit models for men and women. We have converted coefficients to relative risk ratios by taking their exponents, i.e. $\exp(\gamma^j)$. The base occupation is "Laborers" so that the coefficients reported all show how a one-inch increase in height increases the chance of being in the indicated occupation group relative to being a laborer. An increase in height is, in general, associated with selection into white collar jobs relative to the base of "laborer." For example, the results for men, using the full sample and controlling for city size, indicate that an extra inch of height increases the odds of being an executive or manager or professional relative to those of being a laborer by 9.5 percent. The corresponding number for women is 4.6 percent. The relative risk ratios for blue collar jobs are typically close to or below 1.0. An exception is protective service workers: an extra inch of height increases the odds of being a protective service worker relative to a laborer by 10.4 percent for men and 7.0 percent for women. This may be an occupation for which height is valued in its own right.

Figure 4 (for men) and Figure 5 (for women) shows scatter plots of the estimates of the relative risk ratios against the eight DOT ratings we use. Results for physical skills are shown in the left side of the figure, and those for intellectual skills are shown on the right. Figure 4 indicates that, for men, occupations with higher relative risk ratios for height require lower levels of physical skills. For example, the raw correlation between strength and the relative risk ratio for height is –0.72. This correlation increases in absolute value to –0.81 when points are weighted by the number of men within the occupation group. In contrast, the raw correlation between intelligence and the relative risk ratio for height is 0.73, and the weighted correlation is 0.82. The correlations are not as large for all skill measures. For example, the weighted correlation of the relative risk ratio with motor control is –0.31, and that for spatial skills is 0.01. However, the general pattern is that the occupations into which taller individuals select have greater intellectual requirements and lesser physical requirements.

The results for women in Figure 5 are similar: the relative risk ratios for height are generally negatively correlated with physical skill requirements and positively correlated with intellectual requirements. However, the raw and weighted correlations differ more for women than they do for men. This divergence is primarily due to three occupation groups—protective service, mechanical repair, and transport—which have high relative risk ratios for height for women (1.070, 1.069 and 1.073, respectively), and also have high physical requirements relative to intellectual requirements. These are occupations in which very few women work. Combined, only 1.9 percent of women are in these three occupation groups, in contrast to 17.3 percent of men. It may be that women who are successful in these occupations must have physical skills that are comparable to those of the men with whom they work. These occupations aside, the results for women in Figure 4 are similar to those for men in Figure 5. The weighted correlations between relative risk ratios and the four physical skill measures are similar for men and women. The weighted correlations between the relative risk ratios and each of the intellectual skill measures are larger for women than for men.

Does the sorting of taller workers into occupations that require greater levels of cognitive skill reflect the better childhood socioeconomic status of taller workers? This question cannot be answered using data from the NHIS. However, the PSID contains measures of the education of the workers' parents, as well as a self-reported indicator for whether the worker was poor as a child. We use the PSID to examine whether the multinomial logit estimates of the relationship between occupational choice and height are altered when these variables are added as controls. We use the occupational data provided in the PSID to categorize workers as belonging to one of the 15 occupation groups used for the NHIS. (Note that the categorizations differ somewhat across the NHIS and the PSID, because the PSID uses detailed occupation codes from the 1970 Census whereas the NHIS uses those from the 1980 Census.) We first estimate multinomial logit models that control only for age and race, and then re-estimate these models adding a set of indicators for mother's education, father's education and childhood poverty.

The estimates of the relative risk ratios for height for these two specifications, plus the relative risk ratios from the NHIS, are graphed in Figure 6. The figure indicates that results for the two data sets, when no family background controls are included, are very similar. The largest differences are for precision production workers and machine operators. This may be due to fairly large changes in the coding schemes for the occupations in these groups between the 1970 and 1980 Censuses. The figure also shows that the selection of taller workers into occupations that require greater cognitive skill is not explained by parental education and childhood poverty. The relative risk ratios change very little when controls for these variables are included.

VI. Conclusion

There are substantial returns to height in the labor market in both the United States and Britain.

For both men and women, an increase in height of four inches is associated with an earnings premium of approximately 10 percent. The estimates shown in Table 7 imply that an American man who is 6 feet 2 inches tall is 3 percentage points more likely to be an executive and 2 percentage points more likely to be a professional than is a man who stands 5 feet 10.

The evidence we present is consistent with the hypothesis that economic returns to height are the result of correlation between height and cognitive ability — a correlation that is evident early in life and remains throughout. The return to height in earnings equations is generally eliminated when we control for measures of childhood cognitive ability. The higher return to adolescent height relative to adult height, in earnings equations that include both measures, is consistent with evidence that more advantaged children—with higher cognitive test scores—experience earlier adolescent growth spurts. Correlation between height and cognitive ability can also explain our findings that taller adults select into jobs that require greater levels of cognitive skills and lower levels of physical skills.

Together, this evidence supplies a rationale for why economic returns to height continue to be observed, even in wealthy countries where increasingly small fractions of workers do physically demanding work. It also provides an alternative to explanations for the height premium that rely on pure discrimination or social stigma against shorter individuals.

The results of this paper suggest several areas for further research. One is the study of the long-run effects of improved prenatal and childhood nutrition. Evidence from the medical literature indicates that nutrition in childhood plays an important role in determining both height and cognitive ability. However, there are few studies that have tracked children over time to see how early nutritional interventions affect cognitive functioning and labor market outcomes in adulthood. For the design of effective interventions, it is also essential to know whether there are stages at which nutrition is most important for cognitive outcomes that are rewarded in the labor market.

Much of the research on nutrition, child growth and cognitive function that has been conducted to date provides evidence on very poor settings, where children may face large deficits in calories and protein and a heavy disease burden. The extent to which insults in utero and childhood illness and nutrition affect cognitive function in developed countries is not well understood. Research in wealthier settings is also clearly warranted.

References

Abbott, Robert D., Lon R. White, G. Webster Ross, Helen Petrovitch, Kamal H. Masaki, David A. Snowdon, and J. David Curb. 1998. "Height as a Marker of Childhood Development and Late-life Cognitive Function: The Honolulu-Asia Aging Study." *Pediatrics* 102(3): 602-9.

Beard, Albertine S. and Martin J. Blaser. 2002. "The Ecology of Height: The Effect of Microbial Transmission on Human Height." *Perspectives in Biology and Medicine* 45 (Autumn): 475-99.

Berger, Abi. 2001. "Insulin-Like Growth Factor and Cognitive Function." *BMJ* 322:203.

Cain, Pamela S. and Donald J. Treiman. 1981. "The Dictionary of Occupational Titles and Source of Occupational Data." *American Sociological Review* 46 (June): 253-78.

Centers for Disease Control. 1977. "Data from the National Health Survey. NCHS Growth Curves for Children, Birth-18 Years, United States." *Vital and Health Statistics*, Series 11, Number 165 (November).

Centers for Disease Control. 2002. "2000 CDC Growth Charts for the United States: Methods and Development." *Vital and Health Statistics*, Series 11, Number 246 (May).

Dunn, L. M. and L. M. Dunn. 1997. *The Peabody Picture Vocabulary Test - 3rd Edition.* Minnesota: American Guidance Service.

England, Paula, and Barbara Kilbourne. 1988. *Occupational Measures From the Dictionary of Occupational Titles for 1980 Census Detailed Occupations* [Computer file]. Richardson, TX: Paula England and Barbara Kilbourne [producers]. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor].

Ericson, Anders and Bengt Kallen. 1998. "Very low birthweight Boys at Age 19." *Archives of Disease in Childhood – Fetal and Neonatal Edition* 78 (May): F171-4.

Freedman, D. G. 1979. *Human Sociobiology*. New York: Free Press.

Gibbons, Robert, Lawrence F. Katz, Thomas Lemieux and Daniel Parent. 2005. "Comparative Advantage, Learning, and Sectoral Wage Determination." *Journal of Labor Economics* 23: 681-723.

Gowin, E. B. 1915. *The Executive and His Control of Men*. New York: Macmillan.

Grantham-McGregor, Sally. 2002. "Linear growth retardation and cognition." *Lancet* 359: 542.

Hack, M. M. Schluchter, L. Cartar, M. Rahman, L. Cuttler and E. Borawski. 2003. "Growth in Very Low Birth Weight Infants to Age 20 Years." *Pediatrics* 112 (July): e30-8.

Haddad, Lawrence J. and Howarth E. Bouis. 1991. “The Impact of Nutritional Status on Agricultural Productivity: Wage Evidence from the Philippines.” *Oxford Bulletin of Economics and Statistics* 53 (February): 45-68.

Heckman, James and Jose Scheinkman. 1987. “The Importance fo Bundling in a Gorman-Lancaster Model of Earnings.” *Review of Economic Studies* 54: 243-55.

Hensley, Wayne E. 1993. “Height as a Measure of Success in Academe.” *Psychology, A Journal of Human Behavior* 30: 40-46.

Institute of Medicine, 2001. “Reproductive and Developmental Effects,” Chapter 15 in *Clearing the Smoke: Assessing the Science Base for Tobacco Harm Reduction,* Washington: National Academy Press: 543-559.

Klein, R. E., H. E. Freeman, J. Kagan, C. Yarbrough, and J.P. Habicht. 1972. “Is big smart? The relation of growth to cognition.” *Journal of Health and Social Behavior* 13: 219-225.

Komlos, J., J. M. Tanner, P. S. W. Davies, and T. Cole. 1992. “The Growth of Boys in the Stuttgart Carlschule, 1771-93.” *Annals of Human Biology* 19(2): 139-52.

Kretchmer, Norman, John L. Beard and Susan Carlson. 1996. “The Role of Nutrition in the Development of Normal Cognition.” *American Journal of Clinical Nutrition* 63: 997S-1001S.

Lechelt, Eugene C. 1975. “Occupational Affiliation and Ratings of Physical Height and Personal Esteem.” *Psychological Reports* 36: 943-946.

Li, Leah, Orly Manor and Chris Power. 2004. “Early Environment and Child-to-Adult Growth Trajectories in the 1958 British Birth Cohort.” *American Journal of Clinical Nutrition* 80: 185-92.

Loh, Eng Seng. 1993. “The Economic Effects of Physical Appearance.” Social Science Quarterly 74(June): 420-438.

Lynn, R. 1989. “A nutrition theory of the secular increases in intelligence, positive correlation between height, head size and IQ.” *British Journal of Educational Psychology* 59: 372-77.

Magnusson, Patrik K.E., Finn Rasmussen, and Ulf B. Gyllensten. 2006. “Height at Age 18 Years is a Strong Predictor of Attained Education Later in Life: Cohort Study of Over 950000 Swedish Men.” *International Journal of Epidemiology* 35 (January): 658-63.

Martorell, R., L. Kettel Khan and D.G. Schroeder. 1994. “Reversibility of Stunting: Epidemiological Findings in Children from Developing Countries.” *European Journal of Clinical Nutrition* 48: S45-S57.

Martorell, R., J. Rivera, and H. Kaplowitz. 1990. "Consequences of Stunting in Early Childhood for Adult Body Size in Rural Guatemala." Annales Nestlé 48: 85-92.

Persico, Nicola, Andrew Postlewaite and Dan Silverman. 2004. "The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height." *Journal of Political Economy* 112 (October): 1019-1053.

Pollitt, Ernesto and Rebecca Matthews. 1998. "Breakfast and Cognition: An Integrative Summary." *American Journal of Clinical Nutrition* 67(4): 804S-813S.

Reichman, Nancy, Julien Teitler, Irwin Garfinkel and Sara McLanahan. 2001. "Fragile Families: Sample and Design." *Children and Youth Services Review* 23 (4/5): 303-26.

Richards, Marcus, Rebecca Hardy, Diana Kuh and Michael E.J. Wadsworth. 2002. "Birthweight, Postnatal Growth and Cognitive Function in a National U.K. Birth Cohort." *International Journal of Epidemiology* 31(April): 342-48.

Richards, M. And M.E.J. Wadsworth. 2004. "Long Term Effects of Early Adversity on Cognitive Function." *Archives of Disease in Childhood* 89: 922-27.

Romano, E., R.E. Tremblay, A. Farhat, and S. Cote. 2006. "Development and Prediction of Hyperactive Symptoms From 2 to 7 Years in a Population Based Sample." *Pediatrics*, 117(6): 2101-10.

Rose, S.A. 1994. "Relation Between Physical Growth and Information Processing in Infants Born in India." *Child Development* 65(3): 889-902.

Satyanarayana, K., G. Radhaiah, K. R. Murali Mohan, B. V.S. Thimmayamma, N. Pralhad Rao, B.S. Narasinga Rao, and S. Akella . 1989. "The Adolescent Growth Spurt of Height Among Rural Indian Boys in Relation to Childhood Nutritional Background: An 18 Year Longitudinal Study." *Annals of Human Biology* 16(4): 289-300.

Slotkin, T.A. 1998. "Fetal Nicotine or Cocaine Exposure: Which One is Worse?" *The Journal of Pharmacology and Experimental Therapeutics* 285(3), 931-934.

Silventoinen, Karri. 2003. "Determinants of Variation in Adult Body Height." *Journal of Biosocial Science* 35: 263-85.

Silventoinen, Karri, Jaakko Kaprio, and Eero Lahelma. 2000. "Genetic and Environmental Contributions to the Association Between Body Height and Educational Attainment: A Study of Adult Finnish Twins." *Behavior Genetics* 30(6): 477-85.

Steckel, Richard H. 1995. "Stature and the Standard of Living." *Journal of Economic Literature* 33 (December): 1903-40.

Strauss, John and Duncan Thomas. 1998. "Health, Nutrition and Economic Development." *Journal of Economic Literature* 36 (June): 766-817.

Sunder, J. M., K. Tambs, J. R. Harris, P. Magnus, and T. M. Torjussen. 2005. "Resolving the Genetic and Environmental Sources of the Correlation Between Height and Intelligence: A Study of Nearly 2600 Norwegian Male Twin Pairs." *Twin Research and Human Genetics* 8: 307-11.

Tanner, James M. 1979. "A Concise History of Growth Studies from Buffon to Boas." Chapter 17 in Frank Falkner and J.M. Tanner (eds.) *Human Growth, Volume 3, Neurobiology and Nutrition*, New York: 515-93.

Walter, T. 1993. "Impact of Iron Deficiency on Cognition in Infancy and Childhood." *European Journal of Clinical Nutrition* 47: 307-16.

Weitzman, M, S. Gortmaker and A. Sobol. 1992. "Maternal Smoking and Behavior Problems of Children." *Pediatrics* 90(3): 342-349.

Wilson, Paul R. 1968. "Perceptual Distortion of Height as a Function of Ascribed Academic Status." *Journal of Social Psychology* 74: 97-102.

Young, Thomas J. and Laurence A. French. 1996. "Height and Perceived Competence of U.S. Presidents." *Perceptual and Motor Skills* 82: 1002.

Table 1. Log earnings and height

	NHIS 1986-94	NCDS (1958 Birth Cohort)		BCS (1970 Cohort)
		MEN		
	1986-94	Age 33	Age 42	Age 30
Height in inches	0.024	0.024	0.023	0.015
	(0.001)	(0.003)	(0.005)	(0.002)
Number of observations	74501	3027	2447	4161
		WOMEN		
Height in inches	0.019	0.029	0.019	0.028
	(0.001)	(0.005)	(0.007)	(0.004)
Number of observations	88195	3195	2610	3868

Notes: OLS regression coefficients are reported, with standard errors in parentheses. The dependent variables are the log of family income (NHIS); log weekly net earnings at ages 33 and 42 (NCDS); and log annual net earnings at age 30 (BCS). All regressions include indicators for race (NHIS) or ethnicity (NCDS, BCS). The NHIS regressions also include a complete set of age and survey year indicators. NHIS regressions are weighted using person weights. The NHIS reports family income in brackets. We use data from the CPS to assign households the mean income in their bracket in the year surveyed. We restrict our NHIS sample to persons aged 18-60 who are not currently married, to best approximate earnings for these individuals.

Table 2. Summary statistics

	NCDS	BCS		NHIS	PSID
Number of observations	8912	8637	Number of observations	435,514	30,575
Female	0.508	0.515	Female	0.471	0
Adult height – women (inches)	64.16	64.15	Height – women	64.59	...
Adult height – men (inches)	69.65	69.73	Height – men	70.10	70.46
Indicator: Father executive, manager or skilled non-manual	0.288	0.301	Age	37.76	40.08
Weekly take-home pay at age 42 (in Year 2000 Pounds)	319.1	...	Major activity previous week was "working" – men	0.897	...
Annual net earnings at age 30 (in Year 2000 Pounds)	...	13994	Major activity previous week was "working" – women	0.837	...
Full/part-time employment, women	0.801	0.743	Reported poor when child	...	0.326
Full/part-time employment, men	0.920	0.899			

Notes: The NCDS cohort is restricted to individuals with height measured at ages 7 and 33. The BCS cohort is restricted to individuals with height measured at ages 5 and 30. Earnings are reported only for cohort members who report full- or part-time employment. Employment reported for NCDS at age 42 and for BCS at age 30. The NHIS sample is drawn from the 1986 to 1994 waves of data. The sample is restricted to men and women aged 18 to 65 who reported an occupation and had non-missing height data. The PSID is restricted to men aged 25 to 65 observed between 1988 to 1997. Height was only measured for heads of households and their wives, and only in selected years. The sample is restricted to men who were a head of household in at least one year that height was measured.

Table 3. Heights by social class and age, Men in the NCDS

	Age 7	Age 11	Age 16	Age 33
Panel A: Regressions of height on indicators of father's social class at birth				
SC 2: Managers	–0.419	–0.418	–0.480	–0.629
	(0.205)	(0.257)	(0.296)	(0.258)
SC 3.1: Skilled Non-manual	–0.580	–0.609	–0.774	–0.794
	(0.213)	(0.267)	(0.307)	(0.267)
SC 3.2: Non-skilled Non-manual	–0.953	–1.017	–1.202	–1.053
	(0.183)	(0.230)	(0.265)	(0.231)
SC 4: Partly skilled Manual	–1.121	–1.192	–1.356	–1.223
	(0.211)	(0.265)	(0.305)	(0.265)
SC 5: Unskilled Manual	–1.420	–1.530	–1.638	–1.144
	(0.233)	(0.292)	(0.336)	(0.293)
Panel B: Incremental contribution of variables to the R^2, as a fraction of R^2				
Mother's and father's education and SES	0.053	0.060	0.057	0.043
Low birth weight Prenatal smoking	0.042	0.030	0.030	0.030
Parents' heights	0.592	0.743	0.762	0.859
R^2	0.298	0.269	0.256	0.318

Notes. Dependent variable is height in inches (measured, not self-reported). The top panel reports OLS regressions with standard errors in parentheses. Reported are regression coefficients on indicators for father's social class at the time of the cohort member's birth. The omitted category is "Social Class 1: Professional." Number of observations = 2677. Included in all regressions are a complete set of ethnicity indicators, and for ages 7, 11, and 16, indicators for the month in which the cohort member was measured. The sample is restricted to men in the NCDS who were measured at all four ages. The bottom panel shows results of height regressions using the same samples. Reported are the incremental contribution to the regression R^2 of variables listed in the first column. All of these regressions include a complete set of ethnicity indicators, and for ages 7, 11, and 16, indicators for the month in which the cohort member was measured. The controls for education and SES include indicators for the parents' school leaving ages, the mother's father's social class, the father's social class at the time of the child's birth, and the logarithm of family income at age 16. Also included are indicators of low birth weight and maternal prenatal smoking, and mother's and father's heights.

Table 4. Test scores and height in childhood

	Controls for sex, ethnicity and age			Extended controls
	boys and girls	boys	girls	boys and girls
1970 BCS Coefficient on age 5 height-for-age z-score when dependent variable is:				
EPVT (receptive language) score at age 5	0.132 (0.008)	0.129 (0.012)	0.134 (0.012)	0.078 (0.009)
Human figure drawing score at age 5	0.070 (0.009)	0.057 (0.012)	0.083 (0.012)	0.041 (0.009)
Copy designs score at age 5	0.115 (0.008)	0.116 (0.012)	0.116 (0.012)	0.057 (0.009)
BAS Word score at age 10	0.131 (0.010)	0.125 (0.014)	0.133 (0.013)	0.064 (0.010)
BAS Similarities score at age 10	0.123 (0.010)	0.117 (0.014)	0.126 (0.013)	0.060 (0.010)
BAS Digit score at age 10	0.067 (0.010)	0.056 (0.014)	0.075 (0.014)	0.033 (0.011)
BAS Matrices at age 10	0.084 (0.010)	0.077 (0.014)	0.089 (0.014)	0.028 (0.010)
1958 NCDS Coefficient on age 7 height-for-age z-score when dependent variable is:				
Reading score at age 7	0.154 (0.008)	0.158 (0.012)	0.150 (0.011)	0.109 (0.009)
Math score at age 7	0.123 (0.008)	0.124 (0.012)	0.121 (0.012)	0.081 (0.009)
Drawing Score at age 7	0.112 (0.008)	0.111 (0.012)	0.111 (0.012)	0.077 (0.009)
Verbal language score at age 11	0.170 (0.009)	0.151 (0.127)	0.189 (0.012)	0.109 (0.009)
Nonverbal language score at age 11	0.179 (0.009)	0.175 (0.013)	0.184 (0.012)	0.117 (0.009)
Math score at age 11	0.184 (0.009)	0.182 (0.013)	0.185 (0.012)	0.120 (0.009)
Copy designs score at age 11	0.077 (0.009)	0.076 (0.012)	0.077 (0.012)	0.047 (0.010)
Fragile Families Coefficient on age 3 height-for-age z-score when dependent variable is:				
PPVT (receptive language) score at age 3	0.089 (0.020)	0.084 (0.029)	0.094 (0.029)	0.052 (0.020)

Notes: Samples sizes are 11,360 for the BCS at age 5 and 8,747 at age 10; 12,449 for the NCDS at age 7 and 11,232 at age 11; and 2,150 for the Fragile Families sample. All regressions control for the age of the child at measurement, a set of ethnicity indicators, and (for regressions in which boys and girls are pooled) an indicator for sex. For the

BCS, regressions with "extended controls" also include an indicator of low birthweight, the height of each of the child's parents, indicators for the parents' school leaving ages, the mother's and father's social class at the time of the child's birth, and indicators for family income category at age 10. The NCDS includes the same extended controls, except mother's social class at birth is replaced by her father's social class, and the logarithm of family income at age 16 is used in place of indicators for income at age 10. For Fragile Families results, the extended controls include an indicator for low birth weight, the heights of both parents, indicators for the education attainment of both parents, indicators for the maternal grandfather's education, the logarithm of family income at age 3, the mother's score on the PPVT, and an indicator of whether the mother took the Spanish-language version of the PPVT (i.e. the TVIP).

Table 5. Log earnings, test scores and the returns to height

	British Cohort Study (1970)								
	MEN Age 30			WOMEN Age 30			MEN and WOMEN		
Height at age 30	0.010 (0.003)	0.004 (0.003)	–0.004 (0.004)	0.015 (0.004)	0.006 (0.004)	0.002 (0.004)	0.012 (0.003)	0.005 (0.002)	–0.001 (0.003)
Tests scores ages 5 and 10 (F-test, p-value)	--	31.11 (0.0000)	15.20 (0.0000)	--	38.52 (0.0000)	19.75 (0.0000)	--	68.90 (0.0000)	35.02 (0.0000)
Extended controls?	No	No	Yes	No	No	Yes	No	No	Yes
Number of obs	2253	2253	2253	2127	2127	2127	4380	4380	4380
	National Child Development Study (1958)								
	MEN Age 33			WOMEN Age 33			MEN and WOMEN		
Height at age 33	0.009 (0.006)	0.007 (0.006)	0.009 (0.006)	0.003 (0.016)	0.010 (0.016)	0.007 (0.016)	0.006 (0.007)	0.007 (0.007)	0.006 (0.007)
Height at age 16	0.016 (0.005)	0.007 (0.005)	0.006 (0.005)	0.020 (0.016)	0.003 (0.016)	–0.003 (0.016)	0.018 (0.006)	0.006 (0.006)	0.004 (0.006)
Height variables F-test (p-value)	20.51 (0.0000)	7.07 (0.0009)	4.61 (0.0101)	6.15 (0.0022)	1.87 (0.1543)	0.24 (0.7902)	20.46 (0.0000)	6.05 (0.0024)	2.29 (0.1013)
Tests scores ages 7 and 11 (F-test, p-value)	--	33.93 (0.0000)	23.32 (0.0000)	--	26.03 (0.0000)	15.82 (0.0000)	--	50.78 (0.0000)	31.99 (0.0000)
Extended controls?	No	No	Yes	No	No	Yes	No	No	Yes
Number of obs	2116	2116	2116	2210	2210	2210	4326	4326	4326

Notes. OLS regression coefficients presented with standard errors in parentheses. The dependent variable for BCS regressions is log annual earnings at age 30, and for NCDS regressions is log weekly earnings at age 33. Included in all regressions are indicators for ethnicity. NCDS regressions all include indicators for region of residence at age 33. The regression with "extended controls" include indicators of mother and father school leaving ages, father's social class at the time of the cohort member's birth, mother's father's social class, low birth weight, prenatal smoking, and controls for mother's and father's heights, and log family income in childhood.

Table 6. The association between test scores in childhood and change in height from age 11 to 16, and from age 16 to 33 , NCDS

	Height gain from age 11 to 16				Height gain from age 16 to 33			
Each coefficient is from a different regression where the dependent variable is:	boys	girls	boys	girls	boys	girls	boys	girls
Verbal language score at age 11	0.020	–0.028	0.012	–0.026	–0.031	–0.053	–0.017	–0.050
	(0.010)	(0.008)	(0.009	(0.007)	(0.009)	(0.020)	(0.009)	(0.019)
Nonverbal language score at age 11	0.023	–0.022	0.014	–0.019	–0.038	–0.055	–0.023	–0.049
	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)	(0.020)	(0.009)	(0.019)
Math score at age 11	0.030	–0.030	0.021	–0.028	–0.038	–0.061	–0.022	–0.054
	(0.010)	(0.008)	(0.009)	(0.007)	(0.010)	(0.020)	(0.009)	(0.019)
Number of observations	3644	3478	3644	3478	2864	2877	2864	2877
Extended controls?	No	No	Yes	Yes	No	No	Yes	Yes

Note: Each coefficient comes from a separate regression where change in height from 11 to 16 is used as a control in columns 1 through 4, and change in height from 16 to 33 is used as a control in columns 5 through 8. Regressions with extended controls include indicators of mother's and father's school leaving ages, father's social class at the time of the cohort member's birth, mother's father's social class, low birth weight, prenatal smoking, and controls for mother's and father's heights, and log family income in childhood. Samples are restricted to children who did not lose more than an inch of height between the ages of measurement.

Table 7. Occupational characteristics and multinomial logit results

Occupation	% in occupation		Strength		Intelligence		Coefficient on height	
	men	women	men	women	men	women	men	women
Executives/ Managers	12.9	11.1	1.67	1.57	2.80	2.85	1.095 (0.004)	1.046 (0.007)
Professionals	11.1	15.0	1.76	2.09	3.38	3.10	1.086 (0.004)	1.050 (0.007)
Technicians	3.6	3.9	1.78	2.11	2.76	2.55	1.055 (0.005)	1.030 (0.008)
Sales	11.1	12.9	1.97	2.01	2.43	2.28	1.076 (0.004)	1.016 (0.007)
Administrative/ Clerical	5.8	27.0	2.05	1.40	2.13	2.48	1.035 (0.004)	1.015 (0.007)
Household Service	0.1	1.3	2.22	2.19	1.10	1.07	...	0.977 (0.009)
Protective Service	2.8	0.6	2.62	2.34	2.08	2.05	1.104 (0.006)	1.070 (0.013)
Other Service	6.9	15.7	2.91	2.62	1.67	1.68	0.980 (0.004)	0.986 (0.006)
Farming	4.3	1.1	3.60	3.57	2.01	2.04	0.996 (0.005)	1.021 (0.010)
Mechanics	6.9	0.3	3.01	2.82	2.06	2.09	1.021 (0.004)	1.069 (0.016)
Construction/ Mining	8.6	0.2	3.01	2.83	2.14	2.11	1.026 (0.004)	...
Precision Production	4.5	1.7	2.71	2.49	2.02	1.86	1.010 (0.005)	0.987 (0.009)
Machine Operators	8.3	6.5	2.75	2.49	1.68	1.51	0.985 (0.004)	0.976 (0.007)
Transport	7.5	0.9	2.73	2.88	1.87	1.92	1.044 (0.004)	1.073 (0.011)
Laborers	5.7	1.7	3.58	3.27	1.44	1.35	1.000	1.000

Notes: 230,034 men and 204,539 women. The percentages of workers in each occupation are calculated using sample weights. Multnimonal logit results are in the last two columns. The base occupation is “Laborers”. All regressions are weighted using sample weights provided by the NHIS. Other controls include age, age squared, race indicators and 8 indicators for population density interacted with MSA status.

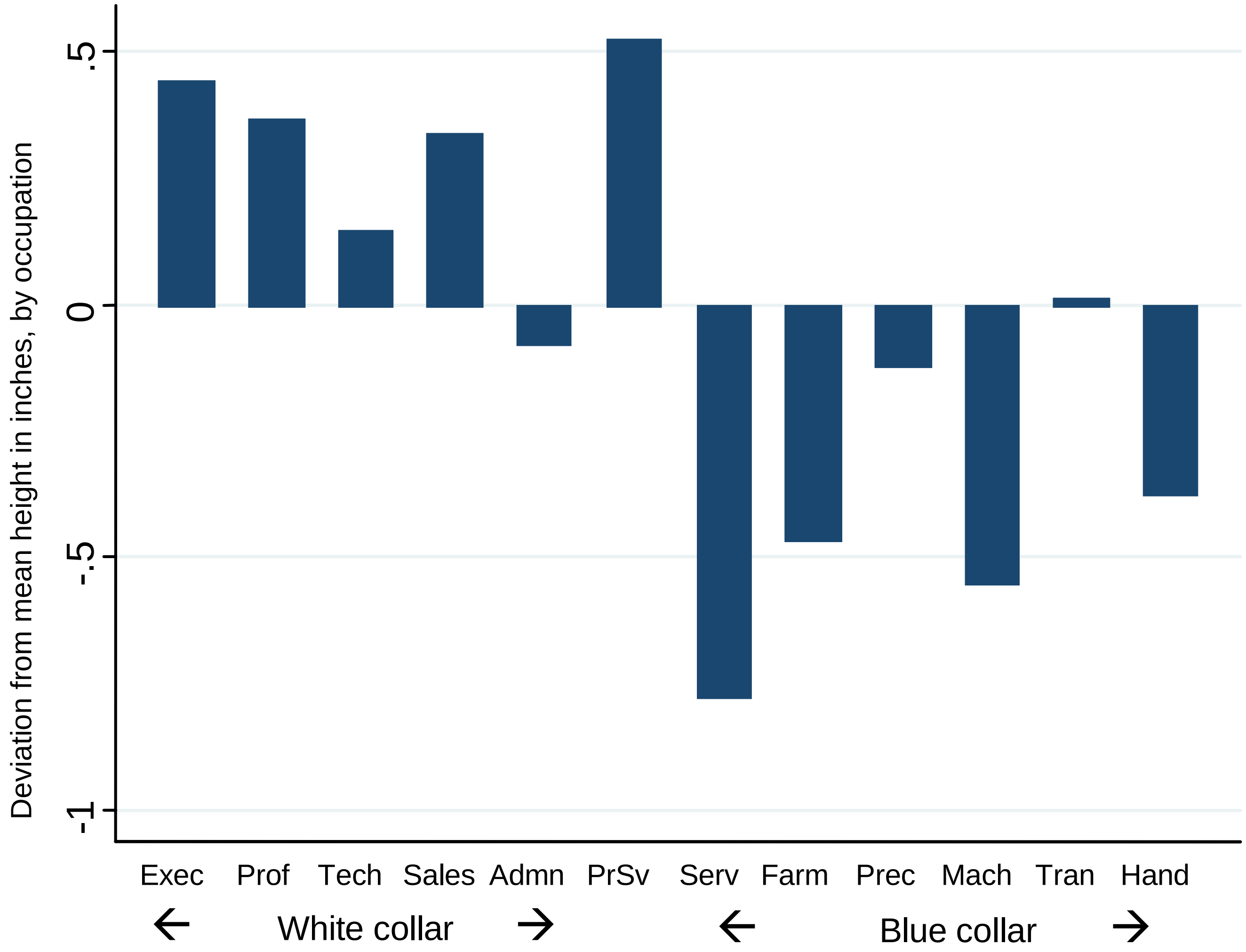

Figure 1: Heights by occupation, Men in the NHIS 1997-2001

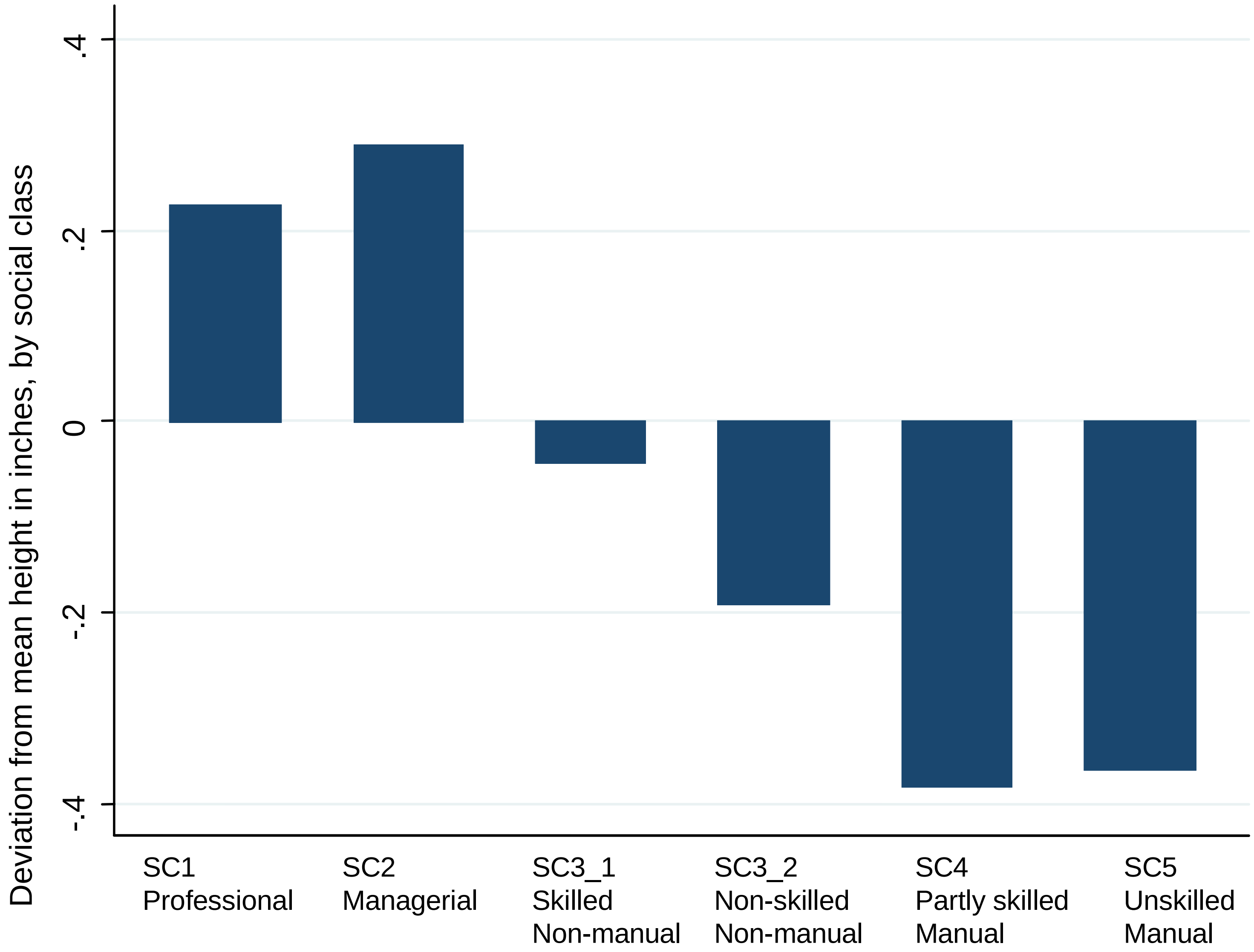

Figure 2: Heights and occupational class, Men at age 30, British Cohort Study (1970 cohort)

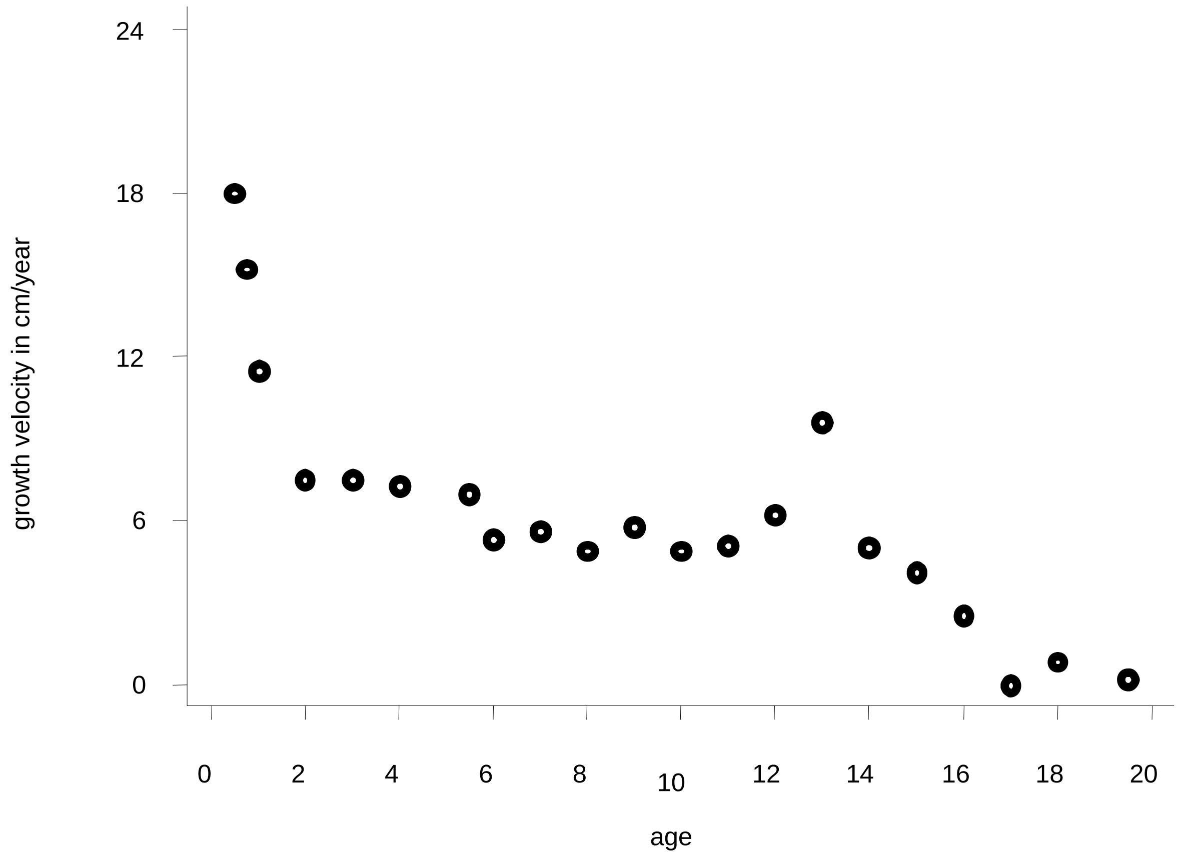

Figure 3: Growth velocity for boys in the US, centimeters per year

SOURCE: Center for Disease Control (1977)

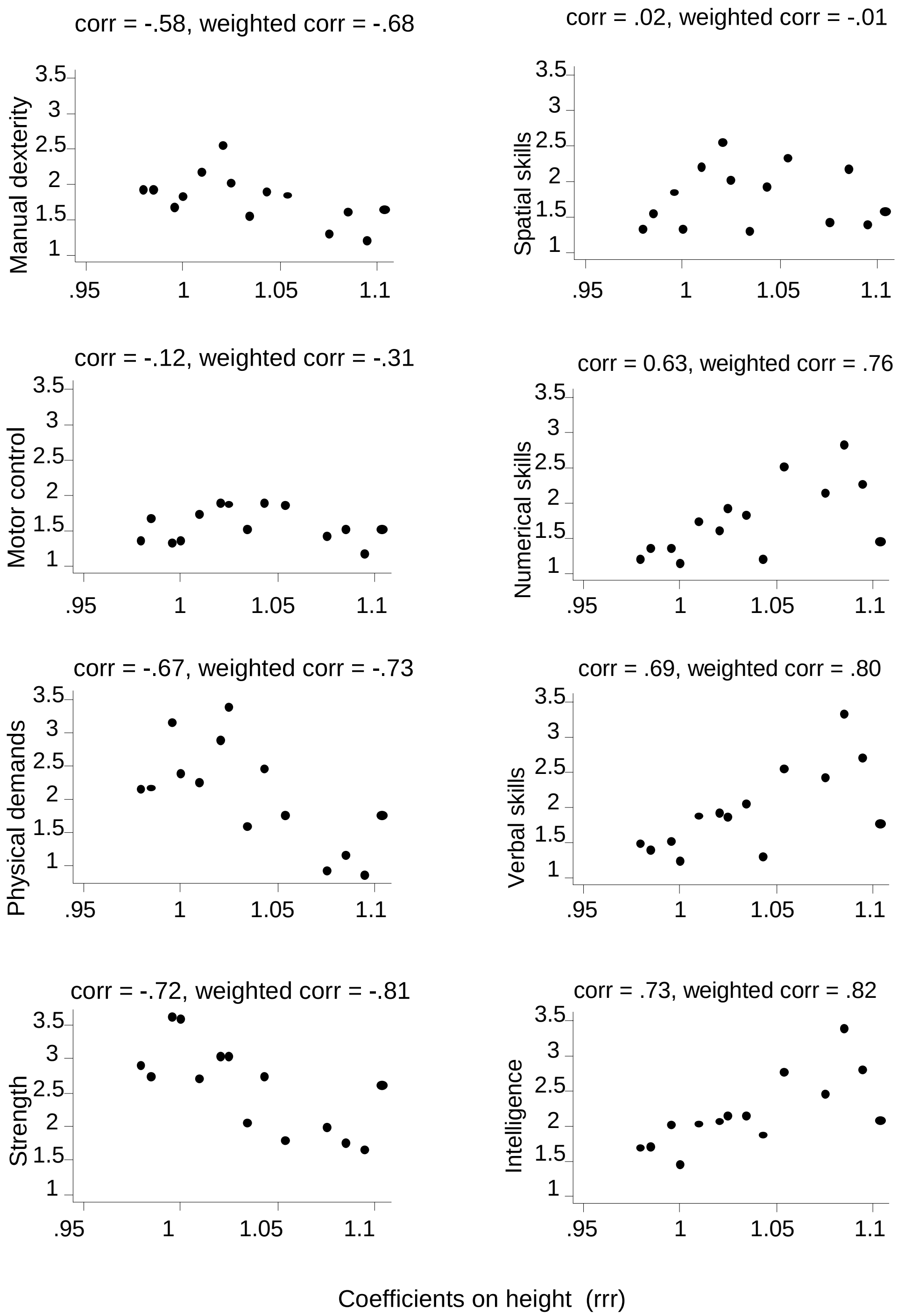

Figure 4: Height selection and occupational characteristics, Men

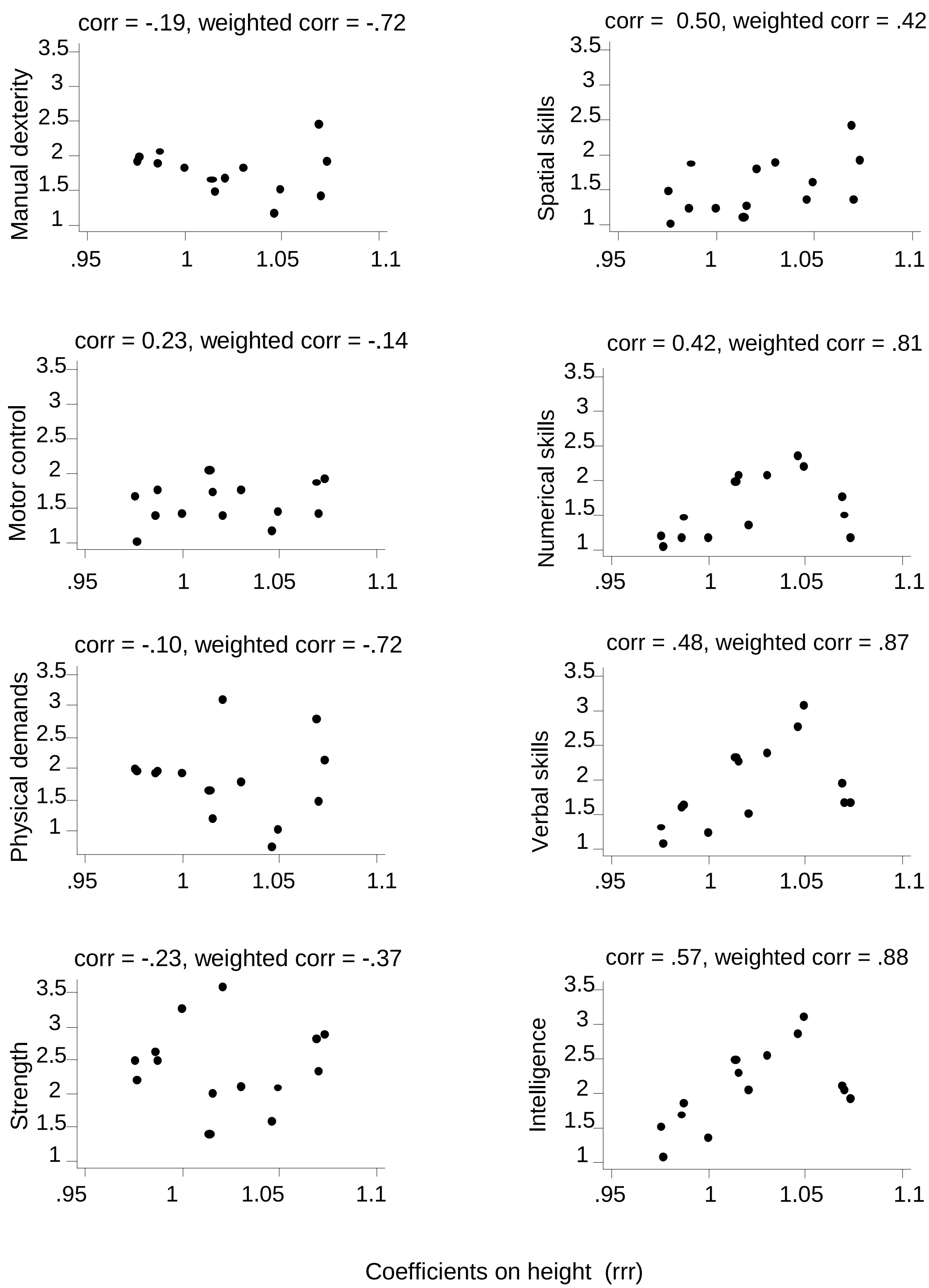

Figure 5: Height selection and occupational characteristics, women

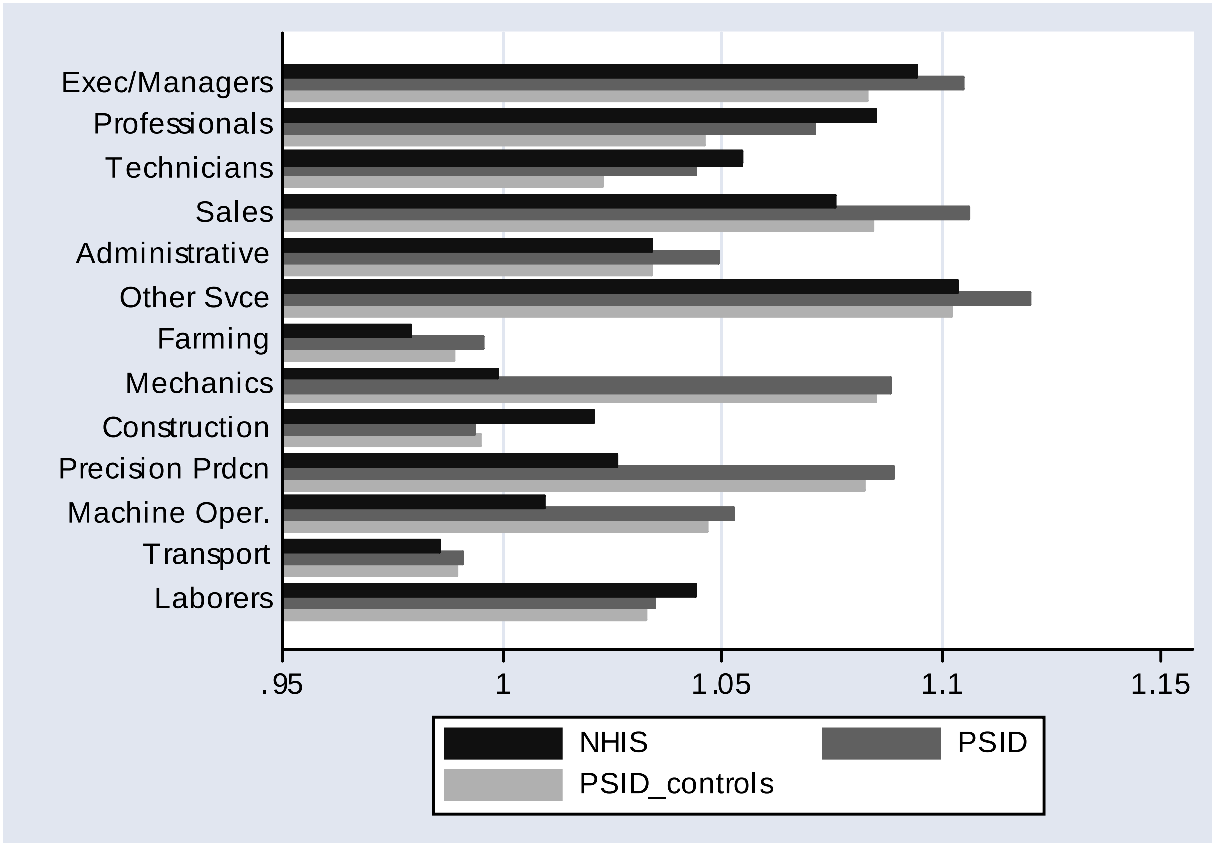

Figure 6: Relative risk ratios for height, NHIS and PSID