Height, Skills, and Labor Market Outcomes in Mexico

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Abstract

Researchers have used the positive relationship between height and earnings to shed light on the productivity of health as well as the effect of health on economic growth. A prominent explanation for this relationship is that physical growth and cognitive development share inputs, inducing a correlation between height and two productive skills, strength and intelligence. This paper uses data from Mexico to examine the skill returns underlying the labor market height premium in poorer countries. Consistent with the shared inputs hypothesis, parental socioeconomic status and childhood living conditions are positively associated with height, cognitive skill, and educational attainment in adulthood. Cognitive test scores account for a limited portion of the earnings premium to taller workers, but roughly half of the premium can be attributed to these workers' higher educational attainment or to their more lucrative occupations, which have greater intelligence requirements and lower strength requirements. These patterns suggest that the height premium partly reflects a return to cognitive skill, even in an economy reliant on manual labor.

Keywords: Health, Development, Height, Labor Productivity

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1 Introduction

In a wide range of settings, taller people earn more than their shorter counterparts. Studies have documented this relationship in contemporary settings ranging from the United States and Britain, where an extra inch of height receives a 1 to 2 percent wage premium (Persico et al. 2004; Case and Paxson 2008); to urban Brazil, where that inch earns a worker 10 percent higher wages (Strauss and Thomas 1998); to the rural Philippines, where it leads to a 2 percent wage boost (Haddad and Bouis 1991).[1] The return to height was also high historically, for example in the antebellum American South, where an inch of height raised a slave's market value by 1.5 to 3 percent (Margo and Steckel 1982).

Given the ubiquity of this relationship in such diverse settings, researchers have devoted considerable effort to determining its origins, setting forth numerous hypotheses. In developing countries, the predominant view is that the returns to stature derive from the superior physical robustness of taller individuals, which leads to a productivity advantage in economies that rely heavily on manual labor (Haddad and Bouis 1991; Thomas and Strauss 1997).[2] Traditional explanations for industrialized countries are more varied, involving pathways such as self esteem (Freedman 1979), social dominance (Hensley 1993), discrimination (Loh 1993; Hamermesh and Biddle 1994), and the social consequences of being short in adolescence (Persico et al. 2004).

However, more recent research provides evidence that the height premium in wealthy countries has much to do with the correlation of height with biologically-determined productive characteristics. Case and Paxson (2008) argue that the labor market height premium in industrialized countries stems largely from the correlation of height and cognitive ability. They posit that physical growth and cognitive development share many inputs—such as health, nutrition, and care in early life (including in utero)—so that for a given genetic height potential, people who achieve greater

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[1] The figure for Brazil is based on an analysis that does not include covariates (Strauss and Thomas 1998). In separate work on the same sample, Thomas and Strauss (1997) show that the height-earnings elasticity falls substantially upon the addition of covariates (although it remains highly statistically significant). However, that work supplies no information on the average height in the sample, so it does not permit calculation of a per-inch earnings premium.

[2] The strength-based explanations have largely grown out of interest in nutrition-based efficiency wage models (Liebenstein 1957; Dasgupta and Ray 1986). In these models, productivity is an increasing function of nutritional status, with the function convex over low levels of nutrition (for example, due to nutrition thresholds below which one cannot work). Sufficiently poor individuals may fall into poverty traps in which low income begets malnutrition, which in turn begets low income. In practice, it turns out that calories are typically too cheap for the model to be taken seriously, at least as a description of short-run nutrition (Subramanian and Deaton 1996; Swamy 1997). But with a longer time horizon, the literature continues to take seriously the possibility that ill health and malnutrition constrain individuals in the labor market.

stature also tend to be more intelligent. Using data from Britain, they show that childhood cognitive test scores explain much of the correlation between height and earnings in adulthood. In an earlier working paper (Case and Paxson 2006), they also find that taller workers in the United States select into occupations requiring more cognitive skill and less physical strength. Building on this evidence, Lundberg et al. (2009) study the population of Swedish men, finding that cognitive test scores account for a meaningful share of the height premium but that measures of physical capacity account for much more. This result implies, somewhat surprisingly for a wealthy country like Sweden, that both cognitive and physical skill lie behind the height premium.

The extent to which cognitive skill (and human capital more generally) explains the height premium in contemporary developing economies is an open question. The reliance of these economies on manual labor does not necessarily bias them towards a solely strength-based height premium. Cognitive capacity improves entrepreneurship, the capacity to adapt to shocks, and general problem-solving skills, which may be valuable even entirely agrarian economies. For example, the literature on technology adoption in developing countries has emphasized the abilities of farmers to learn about the optimal uses of new seed varieties and fertilizers (Foster and Rosenzweig 1995; Duflo et al. forthcoming).

This paper examines the link between linking height and labor market outcomes in Mexico, a country that straddles the line traditionally dividing economies intensive in manual labor from their skilled-labor-intensive counterparts. My analysis takes advantage of rich data from the the Mexican Family Life Survey (MxFLS), which includes modules on health, anthropometry, cognitive skill, parental characteristics, and labor market outcomes. The MxFLS is the first nationally representative survey from a developing country to administer cognitive tests to working-age adults, providing a unique opportunity to unpack the height premium in a less industrialized setting.

After setting up a simple empirical model of height, wages, and occupational choice, the paper presents an empirical analysis of three parts. The first examines the early-life determinants of adult height, cognitive ability, and educational attainment, paying particular attention to parental socioeconomic status and household health conditions, such as access to clean water and sanitation. Consistent with the previous literature, the results suggest that children who experience healthier living conditions or greater household socioeconomic resources grow up to become taller, smarter, and better educated adults.

The analysis then moves on to the correlation that motivates this work, that between height and earnings. It appraises the roles of health and cognitive ability in mediating the correlation, in addition to considering the share of the returns to height and cognition attributable to observable conditions in early life. The results suggest that childhood health conditions and parental socioeconomic status explain a substantial share of the height premium, but the premium remains statistically and economically significant even after adjustment for these background characteristics. The cognitive test score accounts for only a limited part of the height premium. The test instrument is relatively crude, so this result is not surprising. At the same time, because survey respondents took the test in adulthood, their scores may in part reflect job-related opportunities to practice cognitive tasks, which would tend to (spuriously) inflate the role of cognitive skill. Physical health, at least as measured in the survey, plays an even smaller role in the height premium. The findings do indicate, however, that roughly half of the premium can be attributed to the sorting of workers across skill groups or occupations.

The third and final section of the analysis examines this last result more carefully, exploring the relationship between height and occupational choice. In line with the evidence from industrialized countries, taller men and women select into occupations with higher intelligence reruirements and lower strength requirements. This result is consistent with a Roy (1951) model in which taller workers have a comparative advantage in intelligence-intensive tasks. Importantly, education mediates nearly all of the relationship between height and occupational choice; taller workers tend to have more education, and educated workers tend to work in skill-intensive occupations. The role of education has two natural interpretations. First, parents' propensities to invest in child health and education may be correlated, a hypothesis raised by both Haddad and Bouis (1991) and Strauss and Thomas (1997) as a caveat to their argument that the height premium reflects a return to strength. Second, the early-life conditions that promote growth in childhood also promote cognitive development, which may raise the productivity of educational investments. Either way, the data suggest a strong role for cognitive skill—or human capital more broadly—in explaining the earnings premium paid to taller workers.

These findings inform recent research on the effect of health on economic growth. In a widely cited paper, Weil (2007) uses microeconomic estimates of the height premium to calibrate the effect of health on economic growth. By viewing height as a broad measure of health, he treats the height premium as essentially a sufficient statistic for the effect of health on productivity. But specific knowledge of the skill returns underlying the height premium affects the interpretation of his results. For example, if the skills reflected in height are complementary to schooling, then the height premium relevant for calibration must take into account the productivity associated with health-induced investments in schooling. This complementarity is especially likely when cognitive skill underlies much of the height premium.

2 Growth, Cognitive Development, and Later-Life Achievement

Adult height reflects the interaction of genetic and environmental factors from the womb to adulthood (Tanner 1979). During this period, an individual experiences two phases of intense growth, the first during gestation and infancy—from ages zero to three—and the second during adolescence. Good nutrition and freedom from infection during these periods, particularly the first, are critical to achieving optimal growth. Apart from its direct effects on growth, nutritional deprivation increases young children's susceptibility to infection. Infection, in turn, inhibits nutrient absorption and appetite, leading to a "synergism" between nutrition and infection (Scrimshaw et al. 1968).

The prenatal and very early postnatal periods appear to be of particular importance for adult height and health. Early-life adversity may alter tissue differentiation and development in ways that boost short-run survival at the expense of long-run health (Barker 2001). A growing body of research indicates that deprivation during this period—whether inside or outside the womb—has lasting effects on stature. Among identical twins in Norway, those born with a 10 percent birthweight advantage over their twins gain an extra 0.6 centimeters in height by age 18 (Black et al. 2007). Results of this type extend as far as rural Indonesia, where Maccini and Yang (2007) show that women exposed to above average rainfall in their birth years attain significantly greater heights.

Negative health and nutrition shocks, both in utero and in early childhood, have similarly detrimental effects on cognition. In industrialized countries, a large body of research has documented cognitive deficits among children born with low birth weight (Breslau 1995).[3] The specific effects of low birth weight are not well-documented in developing countries, but randomized trials

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[3] In Black et al.'s study of Norwegian twins, a 10 percent increase in birth weight increases age 18 IQ by roughly one third of a standard deviation. Richards et al. (2002) find similarly-sized associations among young British adults who were born with low birth weight.

have confirmed the effects of nutrition on cognition (Grantham-McGregor 1995).[4]

Combined, these results suggest that superior health and nutrition promote both physical growth and cognitive development.[5] Indeed, height is correlated with cognitive test scores in children from a range of settings.[6] This association carries well into adulthood (Abbott et al. 1998; Richards et al. 2002; Case and Paxson 2008), as does the association between height and physical strength (Tuvemo et al. 1999; Lundborg et al. 2009). Taller individuals' enhanced cognitive skills also increase the productivity of schooling, which may explain the correlation between height and educational attainment, observed in such diverse settings as Brazil (Strauss and Thomas 1998), India (Perkins et al. 2010), Sweden (Magnusson et al. 2006), and the U.S. and U.K. (Case and Paxson 2010).

3 An Empirical Model of Height and Labor Market Outcomes

The current knowledge on the co-evolution of body size, strength, and cognitive skill fits into an empirical model in the tradition of Roy (1951).[7] A worker i's height, physical ability, and cognitive ability in adulthood depend positively on access to health and nutritional inputs in childhood:

$$h_i = \alpha^h + \beta^h z_i + \xi_i \tag{1}$$

$$v_i^p = \alpha^p + \beta^p z_i + \eta_i \tag{2}$$

$$v_i^c = \alpha^c + \beta^c z_i + \omega_i \tag{3}$$

where h_i is height, v_i^p is physical skill, v_i^c is cognitive skill, and z_i is a composite (scalar) measure of inputs in childhood. The coefficients β^h, β^p, and β^c are positive; greater access to inputs increases height, which is observable, as well as physical and cognitive skills, which are productive characteristics that the researcher cannot observe directly. The mutually independent error terms ξ_i, η_i,

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[4] In one well-known trial in Jamaica (Grantham-McGregor et al. 1991), administration of milk-based formula to young stunted children led to substantial gains on developmental tests, especially when researchers coupled cognitive stimulation with nutritional supplementation.

[5] Height and intelligence may share common chemical antecedents, including insulin-like growth factor (Berger 2001) and thyroid hormone (Richards et al. 2002).

[6] Conditional on age, sex, and family background characteristics, the correlation of height and cognitive test scores is roughly 0.05-0.10 among both British children (Case and Paxson 2008) and Ecuadorian children (Paxson and Schady 2007). Similarly, in a cohort of Peruvian children, severe stunting at age two is associated with a one standard deviation deficit in cognitive test scores at age nine (Berkman et al. 2002).

[7] This model has similarities to that of Case and Paxson (2006).

and ω_i have mean zero and are independent of z_i. They represent both genetics and random noise, but for clarity of exposition I refer to them as the "genetic determinants" of height and ability, in contrast to z_i, which indexes the "environmental determinants" of outcomes in adulthood. I refer to the ratio of their variances, $\frac{\sigma_\xi^2}{\sigma_z^2}$, as the gene-environment ratio.

The worker participates in a labor market with J sectors, indexed j. The worker's potential log wage in each sector is given by:

$$w_{ij} = \psi_j + \rho_j^p v_i^p + \rho_j^c v_i^c + \varepsilon_{ij} \tag{4}$$

Each sector has its own time varying intercept and its own returns to physical and cognitive skill. Because v_i^p and v_i^c are unobservable, (4) is not directly estimable. Given that height is observable, however, we can solve equations (1)-(4) to obtain a regression specification of the form:

$$w_{ij} = \delta_j + \varphi_j h_i + u_{ij} \tag{5}$$

We refer to φ_j as the "return to height" in sector j, even if height itself is not productive. If the error terms ξ_i, η_i, and ω_i are normally distributed, then the return to height equals:

$$\varphi_j^{\mathcal{N}} = \left(\frac{\rho_j^p \beta^p + \rho_j^c \beta^c}{\beta^h}\right)\left(1 + \left(\frac{1}{\beta^h}\right)^2 \left(\frac{\sigma_\xi^2}{\sigma_z^2}\right)\right)^{-1} \tag{6}$$

Even if the errors are not normally distributed, ordinary least squares estimates of φ_j converge in probability to $\varphi_j^{\mathcal{N}}$, as long as one correctly controls for sectoral choice in estimating specification (5) (or if one has data on potential wages in every sector). The decomposition of the return to height in expression (6) is useful because it separates sector-specific parameters (the first term) from population parameters (the second term). In his paper on health and economic growth, Weil (2009) assumes that $\sigma_\xi^2 = 0$, which allows him to ignore the second term. In that case, the return to height reduces to the effect of z_i on skills divided by the effect of z_i on height. Many existing studies (including the current study) estimate the economy-wide return to height, which reflects both within-sector returns (φ_j) and the sorting of workers across occupations with different intercepts (δ_j). This return can be derived by removing the j subscripts from equation (4) to generate an economy-wide wage determination equation.

The return to height rises with the returns to physical and cognitive ability (ρ_j^p and ρ_j^c, respectively) and with the sensitivities of physical or cognitive ability to health inputs (β^p and β^c, respectively). It decreases as the gene-environment ratio ($\frac{\sigma_\xi^2}{\sigma_z^2}$) rises. Finally, the responsiveness of the return to height to β^h depends on the size of the gene-environment ratio. If the gene-environment ratio is sufficiently small, the return to height decreases as β^h increases.[8]

These properties of the return to height can be squared with the existing evidence. One striking fact, evident in previous work and in the empirical work below, is that the return to height in developing countries exceeds that in industrialized countries. The model suggests two explanations for this phenomenon. First, the variance of the environmental determinants of height is higher in developing countries. Assuming a constant genetic variance, this fact implies a lower gene-environment ratio in developing countries, thus raising the return to height. Another potential reason for the high return to height in developing countries relates to skill returns ρ_j^p and ρ_j^c. Borjas (1987) finds much low-skill emigration from developing countries and much high-skill emigration from developed countries, suggesting that the returns to skill are higher in developing countries than in developed countries. If skills have decreasing returns, then the average return to height may be higher in setting with shorter (and therefore less skilled) workers.

Given an endowment $\{v_i^p, v_i^c\}$, the individual selects the occupation that maximizes her wage.[9] Optimization implies that taller workers will have higher probabilities of selecting sectors with higher returns to height. If cognitive ability is the main driver of the return to height, then taller workers will sort into sectors requiring greater cognitive skill, and vice versa if the return to height is strength-driven. To see this, assume joint normality of ξ_i, η_i, and ω_i, and consider two occupations, l and m. A worker's probability of selecting l over m is:

$$\Pr[w_l > w_m] = \Phi\left[\left((\delta_l - \delta_m) + (\varphi_l^{\mathcal{N}} - \varphi_m^{\mathcal{N}})h_i\right) / \sigma^2_{(u_l - u_m)}\right] \tag{7}$$

where $\Phi[\cdot]$ is the standard normal distribution function and $\sigma^2_{(u_l-u_m)}$ is the variance of the difference in error terms between occupations. Differentiation of equation (7) with respect to h_i shows that the worker's probability of selecting occupation l increases in her height if and only if $\varphi_l^{\mathcal{N}} > \varphi_l^{\mathcal{N}}$. Equation (6) then implies that the probability of selecting occupation l increases in height if and only

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[8] In particular, differentiation of (6) shows that the return to height decreases in β^h if and only if $\frac{\sigma_\xi}{\sigma_z} < \beta^h$.

[9] I do not explicitly model the education decision, which can be seen as part of sectoral choice.

if $(\rho^c_l - \rho^c_m)\beta^c > (\rho^p_m - \rho^p_l)\beta^p$. If occupation l's return to cognitive ability exceeds occupation m's by more than occupation m's return to physical ability exceeds occupation l's, subject to a scaling factor $\frac{\beta^p}{\beta^c}$, then taller workers have a higher probability of choosing occupation l. It is in this sense that taller workers will sort into intelligence-intensive occupations if cognitive ability is the main driver of the return to height.[10]

This section has treated z_i as an index of health and nutritional inputs, but research in behavioral genetics suggests that some part of the correlations between height and intelligence, schooling, or strength may be genetic (Silventoinen et al. 2000, 2006, 2008; Sundet et al. 2005). The literature is far from a consensus on this issue, but the results point to a substantial role for non-genetic factors, even in Scandanavian countries, where the variance of environmental height determinants is relatively small. To accommodate the possible role of genetic factors, one could call z_i a more general "endowment" as in Case and Paxson (2008). But because the variance of the environmental determinants of height is high in Mexico, and because research on economic growth has used height as a cumulative measure of access to health inputs (Weil 2007), the focus on health and nutritional inputs is appropriate.

4 Data

The analysis of the returns to height draws on data from the the Mexican Family Life Survey (MxFLS), a panel with two waves (so far) in 2002 and 2005. The MxFLS, a nationally representative household survey, included modules on household economic decisions and household demographic structure, as well as individual-level questions on labor market participation, self-reported health, schooling, and the living conditions that adults experienced while growing up. The survey administered a short cognitive test to children and working-age adults, and it also collected biomarker data—including height, weight, hemoglobin counts, and blood pressure measurements—from all household members.

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[10] One can study this prediction using data on workers' occupational choices, but it is difficult to verify that occupations greater shares of tall workers do indeed have higher returns to height. The researcher observes only one realized wage per worker, rather than potential wages in every occupation. As a result, estimates of φ_j based only on realized wages within occupation are inconsistent because sorting induces a negative correlation between h_i and u_{ij}, conditional on a worker choosing occupation j. With adequate panel data and structural assumptions, one can recover within-occupation skill returns (see, e.g., Gibbons et al. 2005). However, these methods require substantial movement of workers across occupations, and too few workers in the Mexican Family Life Survey change occupations between survey waves.

I employ data on working age individuals, ages 25-65.[11] I use standing height in centimeters, measured directly by trained interviewers. I trim the top and bottom 0.5 percent of the height distribution to reduce the influence of outliers.

The measure of cognitive ability is based on a short-form Raven's Progressive Matrices test, intended to measure abstract reasoning (Raven et al. 1983).[12] The Raven test presents the subject with a series of patterns (called matrices), each with a missing element. For each matrix, the subject selects the missing element from a bank of eight candidates. In theheigh MxFLS, the adult Raven test comprised 18 matrices. To obtain a composite measure of test performance, I sum the number of correct responses and then standardize them within sample to have a mean of zero and a standard deviation of one. In interpreting analyses of the Raven test score, two caveats are worthy of note. First, the test score measures accumulated cognitive skill over the lifecycle, reflecting early-life cognitive development, schooling, and cognitive reinforcement learning in adulthood. Second, with only 18 simple matrices on the Raven test, the test score is a noisy measure of cognitive skill.

I measure hourly earnings using an individually-administered survey module on labor market outcomes over the previous year. Wages are notoriously difficult to measure in developing countries, given the prevalence of informal contracting and self-employment. However, the MxFLS posed a detailed set of questions that enable the calculation of hourly earnings for a wide variety of individuals, including farmers and small business owners. Every respondent answered questions about the number of weeks worked in his or her main job, the number of hours worked per week, and post-tax labor earnings. Non-working individuals reported on their previous jobs if they worked in the previous year. I compute hourly earnings for individuals who reported working 20 or more hours per week regularly over the previous year. For wage earners, the survey collected data on earnings both over the previous month and over the previous year. The appendix describes the algorithm used to reconcile differences between the monthly and annual reports.[13]

For much of the analysis, I use the 19-category Mexican Classification of Occupations (MCO) to label each worker's sector. However, the last section of the paper focuses on measures of oc-

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[11] In Mexico, many begin working well before age 25, but to avoid sample selection issues stemming from schooling decisions, I discard data on working individuals below this age. 65 is an appropriate age ceiling for working adults, but it is also in part determined by the data; the MxFLS did not gather detailed data on individuals above this age.

[12] The Raven test exhibits high 'g-loading,' meaning that its score correlates strongly with general factor intelligence, a unidimensional variable that many cognitive psychologists hypothesize underlies cognitive skills (Carroll 1993).

[13] Self-employed individuals, business owners, and farmers who tilled their own land provided either monthly or annual earnings but not both, so no reconciliation is necessary for them.

cupational skill requirements from the Dictionary of Occupational Titles (DOT), which one cannot match to the MCO. As an alternative, I use the nine civilian occupations in the coarser International Standard Classification of Occupations (ISCO), which can be matched to both the Mexican and the U.S. job classification systems.[14] From England and Kilbourne's (1988) job characteristics file, which maps DOT measures to the three-digit detailed occupational classification of the 1980 U.S. Census, I assign measures of occupational skill requirements to workers in the 1980 U.S. Census (Ruggles et al. 2008). Then, using the 1980 U.S. distribution of occupations, I then aggregate the detailed occupation categories up to the nine-category ISCO. This procedure assumes that the distribution of detailed occupations and relative skill requirements within each broad ISCO category is the same in the 1980 U.S. and 2002 Mexico. Although these assumptions are unlikely to hold exactly, the aggregation procedure can nonetheless provide a useful guide to the skill content of height-based occupation sorting.

In the analysis of the DOT, I use the "intelligence aptitude" and "strength" intensities of each occupation as measures of cognitive and physical skill requirements. Alternative measures from the DOT (such as "numerical skills" and "physical demands") yield results similar to those reported below. Some of the results are more interpretable with a binary categorization of occupational skill requirements, so that workers select either the "brains" sector or the "brawn" sector. Appendix Figure 1 plots intelligence aptitude requirements against strength requirements for the civilian occupations in the ISCO, revealing that the occupations divide naturally into "brains" and "brawn" sectors. I define the two sectors as indicated in the figure.

Most of the remaining covariates are straightforward reconstructions of survey responses. The survey included questions on the level of schooling attainment and the number of years completed within that level, which I use to construct a single variable corresponding to the number of years of completed schooling.[15] All analyses control for age and membership to an indigenous

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[14] Most of the two-digit MCO categories map perfectly onto the ISCO, but three do not: worker in personal establishments; worker in domestic services; and protection, monitoring and armed forces. In the analysis of skill requirements, I omit these occupations. Due to the independence of irrelevant alternatives assumption implicit in the multinomial logit regressions I run, this omission does not bias the estimates for other occupations.

[15] Respondents with post-secondary education did not reply to questions regarding years of schooling, so I impute years of schooling for them using data from the 2000 Mexican Census. I divide individuals with post-secondary education into sex-specific, five-year age groups, and I then calculate the average number of years of post-secondary schooling within each cell. I then merge these data with the MxFLS on the basis of sex and age group. The five-year age groups in the 2000 census tabulations run from 25 to 64, so they do not perfectly match the cohorts in the MxFLS, who were aged 25-65 in the year 2002. However, all of the cell means from the census are extremely close to four years, so this mismatch should not bias the results in any meaningful way.

group. Some also include childhood background characteristics, such as parental socioeconomic status and access to clean water and sanitation, all reported by the respondent during the interview. Still others add self-reported health status (on a scale of one to five), self-reports of specific symptoms, and hemoglobin counts, measured at the time of the interview.

Table 1 presents summary statistics for selected characteristics by sex, with one column for each of the three samples used in the study. The sample for the analysis of the childhood determinants of adult height, cognition, and education includes all individuals who have non-missing data on the outcomes and parental socioeconomic status, with one observation per individual. In contrast, the earnings and occupational choice analyses require labor market data to be non-missing but allow for missing childhood background data. These analyses allow up to two observations per individual. All three samples are on average about 40 years old, slightly more than a meter and a half tall, and ten to fifteen percent indigenous. The 'earnings' and 'occupation' samples are more educated than the 'determinants' sample, especially for women; indeed, the selection of highly educated women into the 'earnings' and 'occupation' samples is so strong that women have higher average earnings than men. However, a comparison of average height across samples shows no clear evidence of height-based selection into the labor force.[16]

All analyses use survey weights in order to estimate population regression parameters.[17] Additionally, by clustering at the primary sampling unit level, all variance estimates allow for error term correlations within PSUs over time (including within an individual).

5 The Returns to Height: Graphical Evidence

For four outcomes—log hourly earnings, educational attainment, cognitive test scores, and self-reported health—Figure 1 documents the returns to height graphically. Each panel shows a sex-specific local linear regression of an adult outcome on height. The solid curves correspond to the regression function estimates, while the dotted curves bound pointwise 95 percent confidence intervals.

The top left panel of Figure 1 shows a positive, monotonic relationship between height and

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[16] Sex-specific regressions of labor force participation on height and a set of demographic characteristics yield small, statistically insignificant coefficients on height.

[17] Because the paper aims to describe the relationship between height and labor market outcomes at the national level, the use of survey weights is appropriate (Deaton 1997).

earnings. For both men and women, an increase in height by 10 centimeters is associated with an increase in wages by roughly one quarter of a log point, implying a semi-elasticity of 2-3 percent per centimeter. Interestingly, women of a given height earn more than men of that height, which stands in contrast with Case and Paxson's (2008) findings for Britain. This pattern reflects the strong selection of highly educated women into the wage sample, discussed in Section 4.

Tall individuals enjoy other benefits, as the remaining panels of Figure 1 reveal. For every ten centimeters of height, educational attainment rises more than one year, cognitive test scores increase by 40 percent of a standard deviation, and self-reported health status improves by just short of 20 percent of a standard deviation (lower numbers correspond to better health status). For both men and women, all regression functions (including that for earnings) are precisely estimated, showing no evidence of nonlinearity. Height bestows advantages in cognitive skill, education, health, and earnings.

The non-parametric regressions in Figure 1 suggest several skill-based explanations for the covariance of height and earnings. One possibility, in the spirit of Case and Paxson (2008), is that the inputs to physical growth in childhood coincide with the inputs to cognitive development, so that height is merely a proxy for intelligence. This could also explain why educational attainment rises with height, if schooling and cognitive ability are complimentary. A competing account, one more in line with the previous literature on developing countries, would emphasize the negative association of short stature with health status and strength (Tuvemo et al. 1999; Lundberg et al. 2009). Here, height proxies not for cognitive skill but for physical robustness. Note, however, that the positive associations of height with cognitive skill, education, and health status may reflect unobserved heterogeneity—in parents' tendency to invest in all forms of child development, for example—which could just as easily explain the height-earnings gradient. The regression analyses below consider each of these explanations.

6 What Determines Height, Cognitive Skill, and Human Capital?

Before the analysis directly explores the correlations between height and labor market outcomes, Table 2 examines the extent to which conditions in early life can account for variation in adult height, cognitive ability, and educational attainment.[18] Apart from being interesting in their own right, these estimates can help shed light on the underlying correlates of height that drive the relationship between height and labor market outcomes. For instance, if parental socioeconomic status determines height, intelligence, and schooling but also influences unmeasured forms of human capital, then measures of parental socioeconomic status should play a central role in the analysis of the height premium.

The first column of Table 2 analyzes the early-life determinants of height, controlling for a vector of demographic variables. Parental socioeconomic characteristics strongly predict height in adulthood. In accordance with a large literature on the topic (e.g., Caldwell 1979), maternal education exerts a strong, positive influence on children's health. Compared to the children of mothers with no education, those who were born to women with tertiary education enjoy a height advantage of over three centimeters. Paternal characteristics appear to be somewhat less important, but a father's education level remains predictive of the height his child attains. Sanitation conditions in childhood also determine adult height. Children with access to toilets or latrines attain significantly taller stature—on the order of 1.5 centimeters—by the time they reach adulthood.

As shown in columns (2)-(5) of Table 2, conditions experienced in childhood also strongly predict cognitive skill (measured by the Raven score) and educational attainment. Collectively, observed parental socioeconomic characteristics and health conditions in childhood account for at least half of the correlations between height, on the one hand, and either cognitive ability or education, on the other. As in column (1), parental education is a strong determinant of adult outcomes. Relative to individuals with uneducated mothers or fathers, those whose mothers or fathers had post-secondary education have a 0.4 standard deviation advantage in cognitive test performance and nearly a four year advantage in schooling. Additionally, contrasting the height results, the first job of the respondent's father is significantly associated with both cognitive skill and schooling. Access to good sanitation also predicts cognitive test scores and schooling. A toilet in childhood is associated with a roughly 0.2 standard deviation gain on the Raven test and a 2 year gain in schooling.

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[18] For conciseness, Table 2 pools men and women. Unreported analyses by gender revealed no systematic differences between men and women. These analyses are available on request from the author.

7 Height and Earnings

Table 3 reports the basic results, regressions of the logarithm of hourly earnings on height. All regressions control for demographic characteristics including age, sex, and indigenous group membership. For comparison with the previous literature, I present both elasticities and semi-elasticities. Much of the literature on industrialized settings (e.g., Persico et al. 2004; Case and Paxson 2006) has analyzed height in levels, leading to semi-elasticities, whereas the literature on developing settings (e.g., Haddad and Bouis 1991; Thomas and Strauss 1997) has used the logarithm of height, leading to elasticities.

At 3-4, the height-earnings elasticities are large but comparable to the existing literature on developing countries. For comparison, Thomas and Strauss (1997) estimate an elasticity of 2.4 among Brazilian men, controlling for education. Because education is an endogenous variable, the baseline results in Table 3 do not control for it. However, the inclusion of education as a covariate in column (4) leads to a male elasticity of 1.9, close to that of Thomas and Strauss. Below, Table 4 examines the role of education in greater detail.

Meanwhile, the semi-elasticities in Table 3 imply that a one centimeter increase in height leads to wage gains of 2.1 percent and 2.9 percent for men and women, respectively. This result contrasts findings from the United States and Britain (e.g., Case and Paxson 2010), which estimate the semi-elasticity at roughly 2 percent per *inch* of height (or 0.8 percent per centimeter). As Section 3 mentioned, the difference has two interpretations. First, it may stem from differences in skill returns or the relationships linking child health with adult height, health, and cognition. Second, it may be the result of a higher variance of the non-genetic determinants of height in Mexico, which would bias upward the return to height, as shown in expression (6).

Table 4 looks more closely at the mechanisms mediating the returns to height. For ease of interpretation, the table focuses exclusively on semi-elasticities, but unreported results using elasticities show similar patterns. The top panel begins by repeating the baseline full-sample regression from column (2) of Table 3. The next column adds the cognitive test score, resulting in a 17 percent reduction in the height premium. A generalized Hausman test that allows for clustering indicates that the fall in the height premium is significant ($p < 0.01$). Although the inclusion of the Raven score induces only a moderate reduction in the coefficient on height, it should by no means be ignored.

Despite past emphasis by (some) cognitive scientists on the existence of a unidimensional factor underlying intelligence, cognitive skill is in fact multifaceted, so one cannot expect an analysis to fully identify its effects with a single, 18-question matrices test. Nonetheless, insofar as skill-intensive work reinforces workers' cognitive skills, a cognitive test taken in adulthood may overstate the role of cognitive skill.

Columns (3) and (4) show that childhood conditions explain much of the height premium that remains after controlling for cognitive skill, while health does not. In column (3), the addition of childhood background characteristics (the same set used in Table 2), results in a larger reduction in the height premium. Part of the height premium is thus attributable to parental socioeconomic characteristics and childhood health conditions. Column (4) then adds three health variables: self-reported health status, the number of self-reported adverse symptoms (from a predetermined list), and a measure of anemia. This regression is less well-identified than the previous regressions, since earnings may affect health status. However, with this caveat in mind, these health variables may shed light on strength-based explanations for the height premium. The inclusion of health covariates has limited of no effect on the height premium.

Columns (5), (6), and (7) investigate whether the returns to height accrue within or between occupation and education groups. This is strictly an accounting exercise; occupation and education should be interpreted as choice variables. The inclusion of either occupation dummies or educational attainment cuts the estimated height premium approximately in half (compared with column [1]), implying that a large part of the height premium is attributable to the higher educational attainment of taller workers or to their sorting into higher-paying occupations.[19] As shown in the lower panel of Table 4, this occupational sorting seems to occur primarily among urban workers. The invariance of the rural height coefficient to the inclusion of occupation dummies is not surprising. Over 50 percent of rural workers concentrate in only two occupational categories, agriculture and crafts.

In the second panel of Table 4, the subgroup analyses reveal some interesting, albeit imprecise, heterogeneity. As in Table 3, the return to height among women exceeds that among men, although the difference in returns is not statistically significant. This result challenges strength-

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[19] A Mincer-style earnings regression that omits height yields a return to schooling of 8.2 percent. This is somewhat greater than typical OLS estimates of the returns to schooling in the United States, but it is on par with estimates from developing countries (e.g., Duflo 2001).

based explanations for the height premium, which would predict a low height premium among women, who are less likely than men to perform manual labor. The height premium is also slightly (insignificantly) higher in rural areas than in urban. Finally, as in Thomas and Strauss (1997), the height premium is larger among the self-employed than among wage laborers, although this difference is again not statistically significant. To intepret this result, one should take into account several caveats. First, the net earnings of self-employed workers may in part reflect rates of return to capital, rather than the marginal product of labor, so the results for self-employed and wage workers are not directly comparable. Second, self-selection into wage labor may bias within-sector estimates of the height premium.[20] Because self-employed workers are more likely to work in manual occupations, Thomas and Strauss (1997) interpret the stronger influence of height among the self-employed as evidence that the height premium is due to a return to strength. Unreported regression results from the MxFLS do not support this interpretation; the measured height premium is identical in the "brains" and "brawn" sectors.[21]

8 Height and Occupational Choice

The results of the previous section imply that sorting across occupations contributes to the returns to height. This finding is interesting, especially in light of Case and Paxson's (2006) evidence from the United States that taller individuals sort into occupations with greater cognitive demands. As discussed in Section 3, if the return to cognitive ability is sufficiently high relative to the return to strength, then the tallest workers will sort into the most cognitively demanding occupations. This section assess height-based occupational selection in two steps. First, it assesses whether "taller" occupation groups in the ISCO have higher intelligence aptitude or strength requirements. Second, it explores the roles of cognitive skill, childhood conditions, health, and educational choices in explaining height-based selection into "brains" or "brawn" occupations. Throughout, it uses a full sample of workers, rather than restricting the sample to workers with non-missing hourly earnings. The full sample exhibits occupational sorting that is similar to the earnings sample in Section 7. Appendix Table 1 assigns each worker the mean hourly earnings of her occupation-industry-education cell in the 2000 Mexican census, and then regresses the logarithm of this sectoral earnings

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[20] However, in unreported results, height did not significantly predict wage labor versus self-employment.

[21] Note that selection bias due to occupational sorting by height makes this result difficult to interpret.

score on height and demographic characteristics. The coefficients on height in the full sample and the earnings sample are virtually identical.

Following Case and Paxson (2006), for the first step, I estimate sex-specific multinomial logit regressions of occupation category (as classified by the ISCO) on height:

$$\ln\left[\frac{p_{ij}}{p_{i0}}\right] = \gamma_j height_i + X_i'\Gamma_j,\ j > 0 \tag{8}$$

where p_{ij} is the probability that worker i selects an occupation in category j, and $j = 0$ corresponds to the professional occupation category. To reduce the dimensionality of the likelihood maximization problem, I restrict X_i, the vector of control variables, to include only a constant term, ethnicity, age, and a squared term in age. Although the theoretical framework leads most naturally to a probit specification (because it assumed normal errors), multinomial logit estimation is attractive because its exponentiated coefficients are relative risk ratios, which are more interpretable than probit coefficients. After estimating the logit regressions, I plot occupational skill measures from the DOT against each occupation category's relative risk ratio on height (e^{γ_j}). An occupation category's relative risk ratio measures the association between height and the risk of selection into that occupation category, relative to the professional occupation category. By plotting each occupation category's cognitive and physical skill intensities against its relative risk ratio on height, one can infer whether physical or cognitive skill drives height-based occupational selection.

The results, which appear in Figure 2, indicate that taller men and women systematically select into occupations with larger intelligence aptitude demands and smaller strength demands. The plots are surprisingly similar to the occupational sorting patterns that arise in industrialized countries (Case and Paxson 2006). Combined with Table 4, we reach the conclusion that nearly half of Mexico's height premium can be attributed to the sorting of taller workers into occupations intensive in congnitive skill. Seen through the lens of the theoretical framework of Section 3, this result suggests that the return to cognitive ability (and human capital more broadly) drives a substantial part of the height premium.

To further understand these patterns, Table 5 performs an analysis of occupational choice that is analogous to Table 4's analysis of the height premium. The table reports marginal effects from logit regressions in which the dependent variable equals 0 for a "brains" occupation and 1 for a “brawn” occupation. The marginal effects are multiplied by 100, so that a marginal effect of 1 corresponds to a 1 percentage point incrase in the probability of working in a “brawn” occupation. Each column adds a different set of covariates to the basic specification.

The associations of height with cognitive skill, childhood conditions, and educational investments account for the lion’s share of the decreased likelihood of taller workers to select into manual occupations. Column (1) indicates that a centimeter of height decreases the probability of working in a “brawn” occupation by 0.7 percentage points. This association falls to 0.5 percentage points with inclusion of the Raven test (column [2]) as a covariate, and further to 0.2 percentage points with the addition of childhood conditions. Cognitive skill and childhood conditions play important roles for both genders, but they have greater explanatory power for women. For neither gender do health covariates explain occupational sorting by height (column [4]).

Strikingly, the roles of cognitive skill and childhood conditions pale in comparison to that of educational attainment. In column (5), the inclusion of educational attainment as covariate all but eliminates the negative relationship between height and manual labor. The educational investments of taller workers entirely explain their selection into more lucrative, more skilled occupations. Of course, these education investments have antecedents in cognitive ability and childhood conditions. Regardless, these results suggest that most of the relationship between height and occupational choice in adulthood is set before labor market entry.

9 Conclusion

Despite the universality of the association between height and labor market outcomes, conventional wisdom holds that its sources differ widely by setting. This paper shows that the origins of the height premium in developing and industrialized economies may be more similar than was previously thought. Much of the height premium accrues across broad occupation and schooling categories. As with Americans and Britons (Case and Paxson 2006), taller Mexicans sort into occupations with greater cognitive skill requirements and lower physical strength requirements, a pattern almost entirely explained by their greater educational attainment. Cognitive test scores and childhood conditions account for some of the higher wages and “brainier” occupations of taller workers.

Whatever the explanation for the height premium, it lays bare the profound effects of early-life conditions on later-life outcomes in school and in the labor market. In Mexico as elsewhere, the children of better off parents attain experience superior physical growth and cognitive development. These dynamics may play an instrumental role in the intergenerational transmission of poverty, with parental poverty causing childhood deprivation, which in turn leads to lifelong poverty. Research that disentangles the mechanisms underlying these relationships—including the returns to height—will help guide policies aimed at improving health and expanding the capability sets of young individuals as they reach adulthood.

At a more macro level, research unpacking the height premium will also clarify height-based calibrations of the effect of health on economic growth. Rather than treating height as a black box measure of latent health, such research allows for a more nuanced understanding of the underlying productive skills represented in height. In this sense, the results of this paper are consistent with the argument of Hanushek and Woessman (2008) that cognitive skills, rather than schooling attainment alone, are vital to economic growth.

Appendix: Reconciliation of Annual and Monthly Earnings

As described in Section 4 of the text, the Mexican Family Life Survey (MxFLS) includes data on both monthly and annual earnings for wage earners. These data sometimes coincided, but in many cases they did not correspond perfectly. This short appendix describes the algorithm used to reconcile any differences and produce a measure of hourly earnings. First, some respondents simply reported annual income as twelve times their monthly income, without any adjustment for weeks worked. For individuals in this group who worked at least 48 weeks in their main occupations over the previous year, I used annual earnings, dividing by the product of weeks per year and hours per week. For individuals who worked less than 48 weeks, I used the monthly data, dividing by 4.35 times hours per week. I repeated this process for any individuals whose reported monthly earnings multiplied by twelve lay within 90 to 110 percent of their reported annual earnings. For remaining individuals, if the implied hourly wage from the monthly earnings report was within 20 percent of the implied hourly wage from the annual data, I averaged the two. From here, I settled any remaining discrepancies in individuals who worked less than 48 weeks by using the monthly data. Among discrepant individuals who worked more than 48 weeks, I discarded values that implied hourly earnings of greater than 200 pesos or less than 1 peso, which correspond to the top and bottom 0.5 percent of the wage distribution from census data. Finally, if remaining discrepant observations were professionals, technical workers, or directors, I used annual data. For the remaining occupations, I used monthly earnings.

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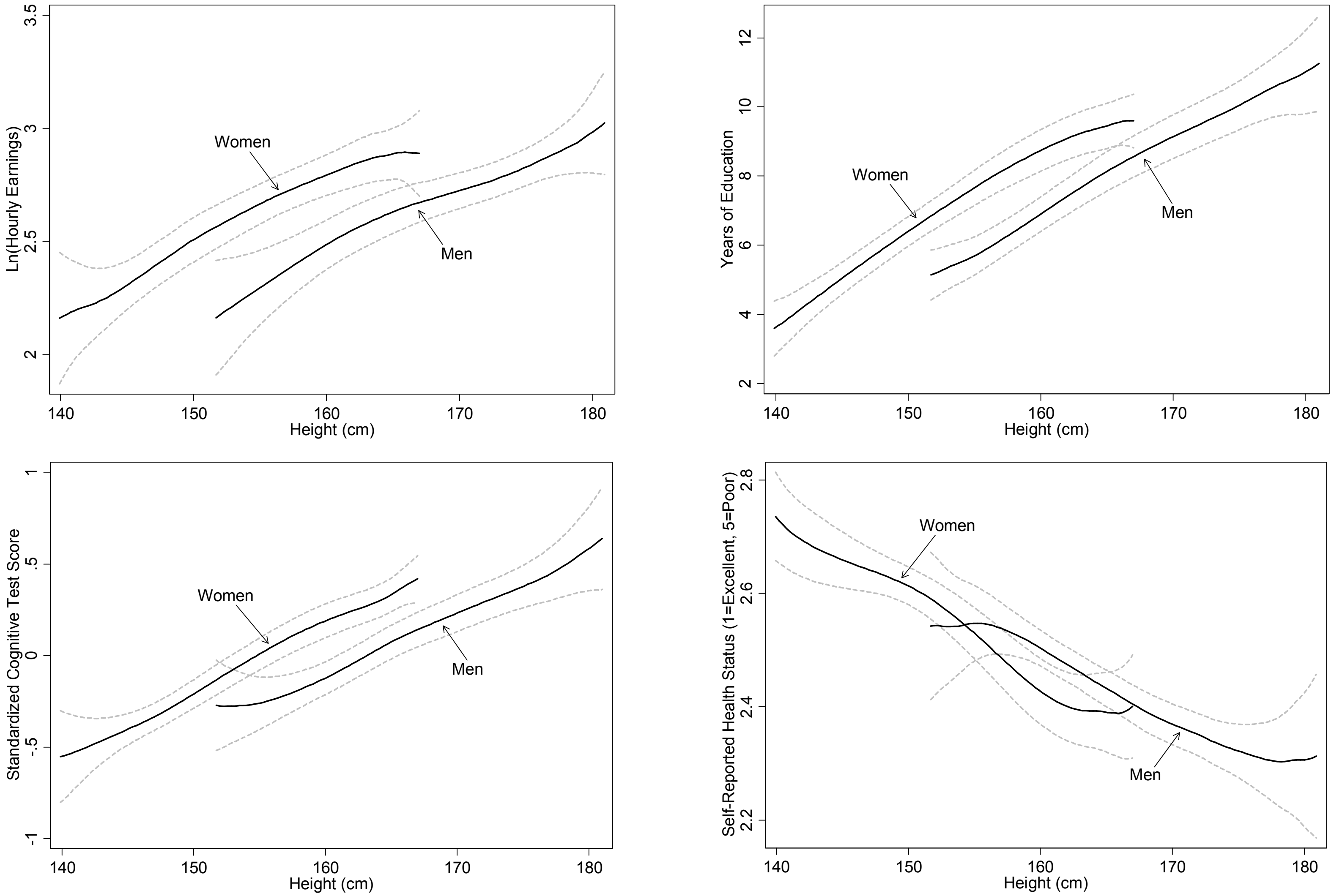
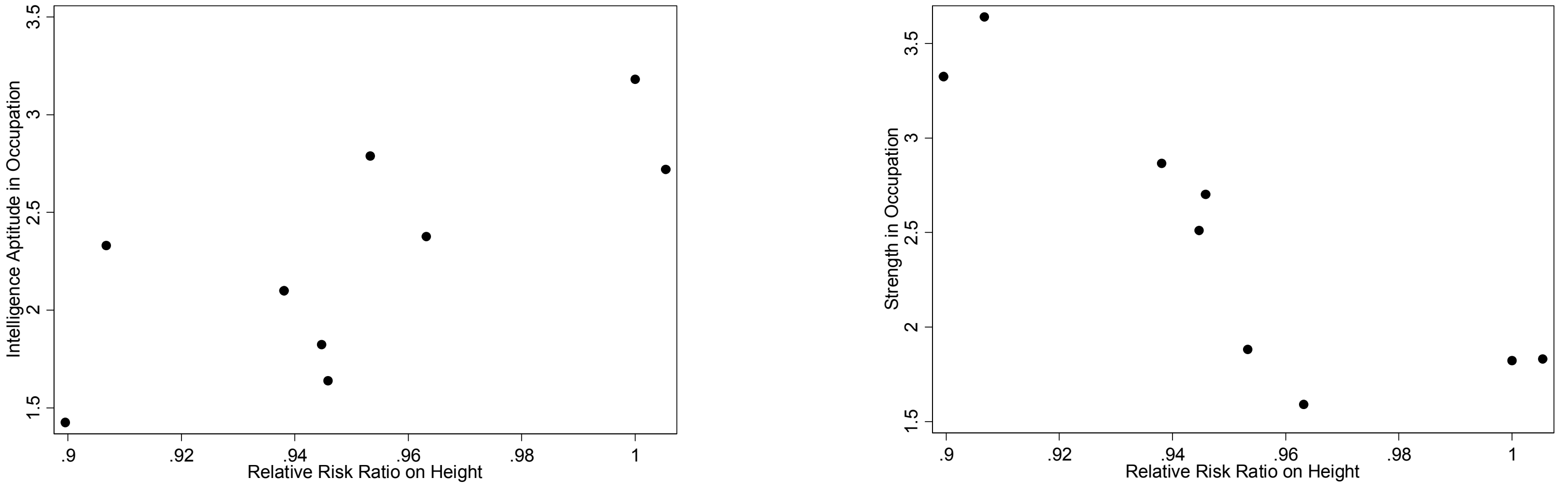
Figure 1: The Returns to Height, Various Adult Outcomes



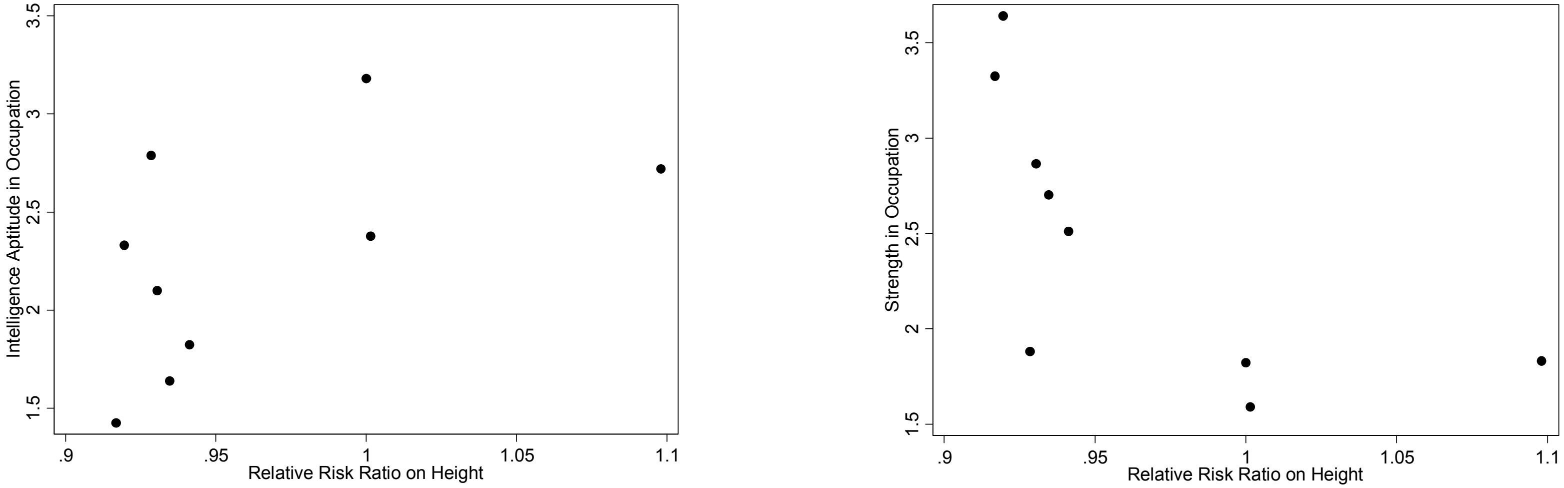
Notes: The panels show local linear regressions with bandwidths of 4 cm; the dashed curves correspond to pointwise 95 percent confidence intervals, block-bootstrapped at the PSU level. All regressions are weighted using sampling weights. The sample includes all adults aged 25-65.

Figure 2: Height and Occupation Skill Requirements

Men



Women



Notes: The panels plot occupational skill requirement measures from the Dictionary of Occupational Titles against relative risk ratios (RRRs) from multinomial logit regressions of occupation on height, controlling for survey year, age, and ethnicity. Each data point is an occupation from the International Standard Classification of Occupations.

Table 1: Summary Statistics

	Determinants of Height & Human Capital Analysis (1)		Earnings Analysis (2)		Occupational Choice Analysis (3)	
A. Men						
Height (cm)	165.2	[7.0]	165.6	[6.9]	165.4	[7.0]
Raven score	0.1	[1.0]	0.1	[1.0]	0.1	[1.0]
Years of education	8.0	[4.9]	8.4	[4.6]	8.1	[4.8]
Hourly earnings (2002 Mex$)			19.4	[17.2]		
Brawn occupation					0.89	
Age	42.7	[11.0]	40.1	[10.3]	41.0	[10.5]
Indigenous	0.14		0.12		0.15	
Rural residence	0.22		0.19		0.23	
# of observations	3,900		5,163		7,400	
# of individuals	3,900		3,786		4,714	
B. Women						
Height (cm)	152.7	[6.4]	153.6	[6.1]	154.6	[6.2]
Raven score	-0.1	[1.0]	0.1	[1.0]	0.2	[1.0]
Years of education	6.7	[4.5]	9.0	[4.7]	8.9	[4.8]
Hourly earnings (2002 Mex$)			20.2	[19.7]		
Brawn occupation					0.84	
Age	41.7	[11.0]	38.6	[9.4]	39.3	[9.7]
Indigenous	0.14		0.08		0.12	
Rural residence	0.22		0.11		0.17	
# of observations	5,543		2,658		3,855	
# of individuals	5,543		2,093		2,855	

Notes: Weighted sample means, with standard deviations in brackets. The sample in column (1) includes all individuals who have non-missing data on height, the Raven score, years of education, and parental socioeconomic status, with one observation per individual. The sample in column (2) only includes observations with non-missing wages, and the sample in column (3) only includes observations with occupations that can be matched to the Dictionary of Occupational Titles. The samples in columns (2) and (3) include observations with missing childhood background data.

Table 2: Childhood Determinants of Adult Height and Human Capital

OLS Estimates

Dependent Variable:	Height	Raven Score		Years of Education	
	(1)	(2)	(3)	(4)	(5)
Height (cm)		0.026	0.013	0.164	0.057
		[0.003]**	[0.002]**	[0.015]**	[0.008]**
Father's 1st Job (Ref. Agricultural Worker)					
Non-agric. worker	0.163		0.072		0.498
	[0.218]		[0.030]*		[0.194]*
Self-emp./landlord/ business owner	-0.191 [0.257]		0.077 [0.057]		0.733 [0.242]**
Father's Education Level (Ref. None)					
Elementary	-0.145		0.125		1.349
	[0.265]		[0.036]**		[0.149]**
Secondary	1.213		0.241		2.239
	[0.540]*		[0.058]**		[0.253]**
College/graduate	2.139		0.441		4.035
	[0.693]**		[0.110]**		[0.314]**
Mother's Education Level (Ref. None)					
Elementary	1.643		0.206		1.686
	[0.233]**		[0.035]**		[0.146]**
Secondary	2.728		0.304		2.844
	[0.463]**		[0.061]**		[0.277]**
College/graduate	3.211		0.459		3.705
	[0.889]**		[0.119]**		[0.376]**
Water and Sanitation at Age 12					
Piped water	0.314		0.074		0.407
	[0.312]		[0.041]		[0.150]**
Toilet	1.794		0.181		2.037
	[0.359]**		[0.044]**		[0.182]**
Latrine	1.626		0.073		1.342
	[0.334]**		[0.045]		[0.174]**
Urban birthplace	0.638		0.168		0.654
	[0.370]		[0.040]**		[0.159]**
F-tests (p-values):					
Parental SES	<0.0001		<0.0001		<0.0001
Water/sanitation	<0.0001		<0.0001		<0.0001
# of observations	9,443	9,443	9,443	9,443	9,443
# of individuals	9,443	9,443	9,443	9,443	9,443

Notes: Brackets contain standard errors clustered at the PSU level. Height is measured in centimeters; the Raven score has standard deviation 1. Regressions are weighted using sample weights and include indicators for gender, ethnicity, and age. The regressions with parental SES also include dummies corresponding to the father never working or to the respondent not knowing his/her father's first job.

Table 3: The Wage Return to Height

OLS Estimates, Dependent Variable: Ln(Hourly Earnings)

	Both Sexes		Men		Women	
Height measured in:	Logs	Levels	Logs	Levels	Logs	Levels
	(1)	(2)	(3)	(4)	(5)	(6)
Height (cm)	3.804	0.023	3.455	0.021	4.453	0.029
	[0.458]	[0.003]	[0.569]	[0.003]	[0.694]	[0.004]
R^2	0.06	0.06	0.06	0.06	0.07	0.07
Dep. Var. Mean [S.D.]	2.62 [0.87]		2.62 [0.90]		2.62 [0.86]	
# of observations	7,821	7,821	5,163	5,163	2,658	2,658
# of individuals	5,876	5,876	3,786	3,786	2,093	2,093

Notes: Brackets contain standard errors clustered at the PSU-level. Regressions are weighted using sample weights and control for survey year, ethnicity, age, age squared, and (if applicable) gender.

Table 4: Explaining the Wage Return to Height

OLS Estimates, Dependent Variable: Ln(Hourly Earnings)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Full* Sample *(7,821 observations, 5,876 individuals)							
Height (cm)	0.023	0.019	0.012	0.018	0.013	0.011	0.010
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Raven score		0.188	0.128	0.178	0.069	0.034	0.020
		[0.017]	[0.015]	[0.017]	[0.012]	[0.011]	[0.011]
Years of education						0.082	0.051
						[0.004]	[0.005]
F-tests (p-values):							
Occupation dummies					<0.001		<0.001
Health covariates				<0.001			
Childhood covariates			<0.001				
B. By Gender and Sector							
Men	0.021	0.018	0.012	0.017	0.012	0.011	0.01
(5,163 obs., 3,786 inds.)	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Women	0.029	0.022	0.011	0.019	0.014	0.009	0.009
(2,658 obs., 2,093 inds.)	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]
Rural	0.024	0.021	0.017	0.020	0.019	0.015	0.018
(2,046 obs., 2,615 inds.)	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]
Urban	0.020	0.017	0.011	0.015	0.011	0.009	0.009
(3,906 obs., 5,206 inds.)	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Wage earners	0.021	0.017	0.01	0.015	0.010	0.008	0.008
(4,855 obs., 6,453 inds.)	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Self-employed	0.033	0.028	0.022	0.026	0.025	0.021	0.021
(1,253 obs., 1,368 inds.)	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Raven score		X	X	X	X	X	X
Education						X	X
Occupation dummies					X		X
Health covariates				X			
Childhood covariates			X				

Notes: Brackets contain standard errors clustered at the PSU-level. Regressions are weighted using sample weights and control for year, ethnicity, age, and age squared. The Raven score has standard deviation 1. The health covariates include self-reported health status, the number of reported symptoms (out of 15), and an indicator for anemia. The childhood covariates are the same as those listed in Table 2. To keep the sample sizes adequate, specifications that control for parental SES, health, or occupation also include indicators for whether these variables are non-missing. The *F*-tests in the top panel only test the coefficients on the actual variables, not the non-missing indicators.

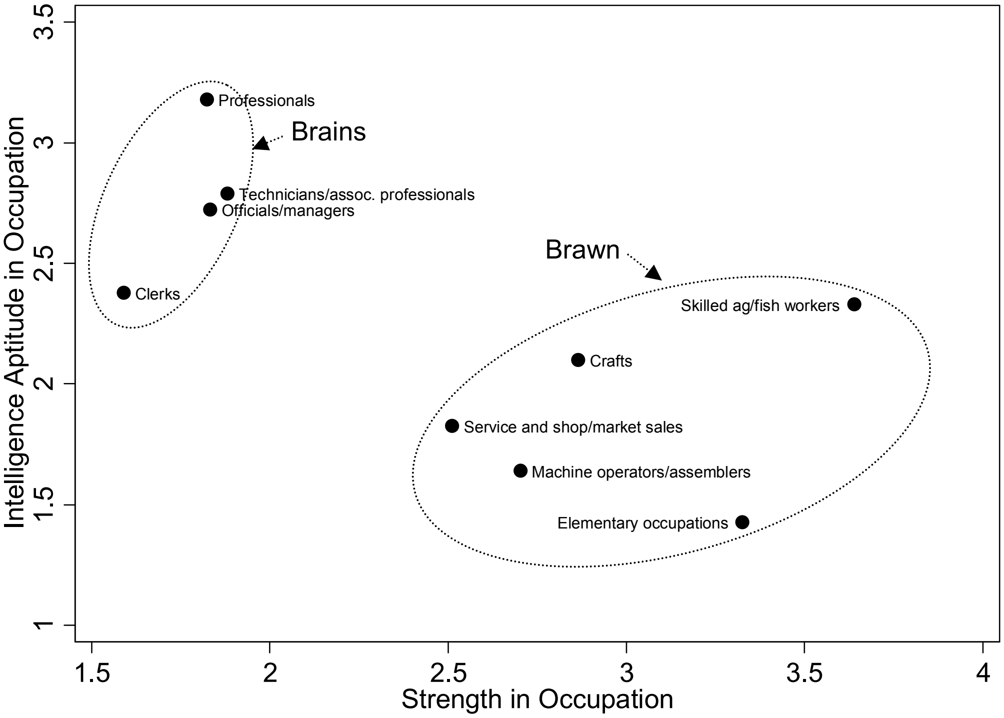
Table 5: Explaining Occupational Sorting by Height

Logit Marginal Effects, Dependent Variable: Pr(Brawn Occupation), 1 unit = 1 % point

	(1)	(2)	(3)	(4)	(5)
A. Full Sample (11,255 observations, 7,563 individuals)					
Height (cm)	-0.68	-0.46	-0.24	-0.42	-0.044
	[0.10]	[0.07]	[0.06]	[0.07]	[0.020]
Raven score		-6.66	-4.56	-6.22	-0.23
		[0.66]	[0.53]	[0.66]	[0.14]
Years of education					-1.22
					[0.11]
F-tests (p-values):					
Health covariates				<0.001	
Childhood covariates			<0.001		
B. By Demographic Group					
Men	-0.63	-0.42	-0.26	-0.40	-0.051
(7,400 obs., 4,714 inds.)	[0.10]	[0.08]	[0.07]	[0.08]	[0.022]
Women	-0.75	-0.40	-0.15	-0.41	-0.033
(3,855 obs., 2,855 inds.)	[0.14]	[0.12]	[0.11]	[0.12]	[0.041]
Raven score		X	X	X	X
Education					X
Health covariates				X	
Childhood covariates			X		

Notes: Marginal effects from logit estimations, evaluated at the means of all independent variables. Marginal effects are multiplied by 100, so that 1 unit equals 1 percentage point. Brackets contain standard errors clustered at the PSU-level. Regressions are weighted using sample weights and control for year, ethnicity, age, and age squared. The Raven score has standard deviation 1. The health covariates include self-reported health status, the number of reported symptoms (out of 15), and an indicator for anemia. The childhood covariates are the same as those listed in Table 2. To keep the sample sizes adequate, specifications that control for parental SES or health also include indicators for whether these variables are non-missing. The *F*-tests in the top panel only test the coefficients on the actual variables, not the non-missing indicators.

Appendix Figure 1: Intelligence Aptitude and Strength Requirements in the ISCO



Notes: The figure displays average Dictionary of Occupational Titles intelligence aptitude and strength requirement scores in occupation categories from the International Standard Classification of Occupations (ISCO). The brains/brawn categorization is the author's creation.

Appendix Table 1: Imputed Earnings Regressions

OLS Estimates, Dependent Variable: Ln(Sectoral Earnings Score)

	All Workers	Workers with Non-Missing Earnings
	(1)	(2)
Height (cm)	0.018	0.017
	[0.002]	[0.002]
Male	-0.219	-0.253
	[0.035]	[0.039]
Age	0.021	0.027
	[0.006]	[0.009]
Age Squared	-0.0003	-0.0004
	[0.0001]	[0.0001]
Indigenous	-0.187	-0.122
	[0.046]	[0.052]
# of observations	12,463	7,443
#of individuals	8,339	5,674

Notes: Brackets contain standard errors clustered at the PSU level. The sectoral earnings score is the average hourly earnings in the worker's occupation-industry-education cell in the 2000 Mexican census.