Statistical Discrimination, Productivity and the Height of Immigrants*

Shing-Yi Wang

New York University

May 2, 2011

Abstract

Building on the economic research that demonstrates a positive relationship between height and worker ability, this paper considers whether employers use height as a tool for statistical discrimination. The analysis focuses on immigrants and native-born individuals because employers are likely to have less reliable signals of productivity for an immigrant than a native-born individual. Using multiple data sets, the paper presents a robust empirical finding that the wage gains associated with height are almost twice as large for immigrants than for native-born individuals. This result is consistent with two hypotheses. First, in the relative absence of other sources of information about immigrants, employers place more weight on height for immigrants than for native-born individuals. Second, height is more correlated with productivity for immigrants than for native-born individuals. The empirical results provide support for the hypothesis that the productivity gap between tall and short immigrants is greater than the productivity gap between tall and short native-born workers. The evidence does not support the hypothesis of statistical discrimination based on height.

*Email: shingyi.wang@nyu.edu.

This paper has benefited from conversations with Santosh Anagol and Nicola Persico and comments from various seminar participants. A previous version has benefited from comments from Joe Altonji, Hanming Fang, Fabian Lange, T. Paul Schultz and Chris Udry. April Collaku provided excellent research assistance. All errors are my own.

1 Introduction

In models of statistical discrimination in labor markets, employers use a characteristic that is both easy to observe and correlated with unobservable ability to make decisions on hiring, task assignment and promotion of workers. The existing empirical literature on statistical discrimination has focused on employers use of race and gender (Altonji and Pierret 2001, Coate and Loury 1993, Farber and Gibbons 1996). My paper is the first to consider the possibility of statistical discrimination on the basis of height in the labor market.[1] The statistical use of the information associated with height by employers is plausible given that height, like race and gender, is easy to observe and strongly correlated with unobservable components of worker productivity.

A large amount of empirical evidence demonstrates a positive correlation between height and earnings throughout the world. In the context of developing countries, the focus of this analysis has been on the relationship between health and nutrition inputs and height (Bozzoli, Deaton and Quintana-Domeque 2009, Deaton 2008, Steckel 1995, Strauss and Thomas 1998). The positive relationship between height and earnings is not surprising given that physical size and health are likely to be important for manual labor in developing countries (Glick and Sahn 1998). However, sizable wage gains associated with height persist in rich countries such as the United States and Britain where the importance of physical strength is likely to play a smaller role in the labor market. Taste-based discrimination against short people is a possible explanation (Kuhn and Shen 2009).[2] More convincing explanations are that the returns to height in developed countries are explained by the relationship between height and cognitive ability (Case and Paxson 2008, Beauchamp et al 2010, Schick and Steckel 2010), and non-cognitive ability such as social skills (Persico, Postlewaite and Silverman 2004, Schick and Steckel 2010).

Given the correlations between height and ability, employers may use height to infer differences in productivity across workers. I examine this question by comparing immigrants and native-born individuals in the United States and in the United Kingdom. The comparison of immigrants and native-born individuals is particularly useful for this exercise because it is plausible that employers face substantial differences in the quality of information signals as they are comparing the expected productivity of immigrants and native-born individuals. Employers may have uncertainty about the academic degree system, the curriculum or the quality of schools in other countries. Furthermore,

[1] The statistical use of height has been considered by Mankiw and Weinzierl (2009). Their theoretical paper argues that government taxation of height, which is correlated with productivity but not affected by effort, would maximize welfare in a model where worker effort is not observable by the government.

[2] This hypothesis is consistent with the findings on the returns to beauty (Hamermesh and Biddle 1994) and weight (Averett and Korenman 1996).

language barriers may generate or exacerbate noise in employers' assessment of productivity signals from immigrants. This paper considers the idea that employers rely on the information associated with height more for immigrants than for native-born individuals given the relative absence of other information about worker productivity for immigrants.

There are two approaches to modeling statistical discrimination. One approach focuses on employers use of (or beliefs about) differences in the average outcomes of groups (Altonji and Pierret 2001, Coate and Loury 1993, Farber and Gibbons 1996, Fryer 2007). A different strand of theoretical literature on statistical discrimination focuses on the amount of *uncertainty* around the information available to employers rather than any differences in productivity across groups (Aigner and Cain 1977, Phelps 1972, Lundberg and Startz 1983, Oettinger 1996). In these models, employers have an observable, continuous signal of productivity, but the quality of this information is different across groups. Phelps (1972) and Aigner and Cain (1977) show that expected productivity (and hence wages) will be flatter for the group for which there is greater uncertainty in the signal. Lundberg and Startz (1983) demonstrate that this type of statistical discrimination can lead to an equilibrium in which there is lower investment in skills in the group that has more noise in the signal of productivity even in the absence of differences in underlying ability.

The main framework used in this paper builds on these latter models of statistical discrimination. My paper emphasizes differences in the precision of information that employers have about immigrants as compared with native-born individuals. To my knowledge, this is the first paper that empirically tests the theoretical predictions of this class of models of statistical discrimination. I extend the model to a context where there are two signals of productivity, height and education, and there is more uncertainty regarding the signal of education for immigrants than for native-born individuals. A key prediction of the model is that the wage returns to height will be higher for the group for which the quality of other signals is worse. In other words, a model of statistical discrimination suggests that employers will place more weight on height and less weight on education for immigrants relative to native-born individuals. Using several data sets, I present a robust empirical finding that the wage gains associated with height are almost twice as large for immigrants than for native-born individuals. In addition, the returns to education are slightly lower for immigrants.

While this empirical result is consistent with the model of statistical discrimination, it is also consistent with an alternative explanation in which there is no statistical discrimination by employers but the underlying mapping of height and education into productivity is different for immigrants than for native-born individuals. To disentangle these two hypotheses, I use additional predictions of the model. To analyze the first hypothesis of statistical discrimination, I examine the idea that as uncertainty about immigrant signals is reduced, the returns to height and education of immigrants should move to be more similar to those of native-born individuals. Furthremore, I take advantage of newly available data that offers information about an immigrant's labor market experiences in his country of origin prior to migration as well as in the United States. Assuming that the noise of signals is lower for employers in the the country of origin than in the U.S., I can use this new data to test the model of statistical discrimination as well as evaluate other measures of information quality. Finally, to analyze the alternative hypothesis, I use measures of worker productivity that are available in the data but not observed by employers to test whether height is more correlated with these measures of productivity for immigrants than for native-born individuals.

In addition to the literature on statistical discrimination, this paper contributes to the existing literature on the migration decision of individuals as well as the literature on the process of economic assimilation. The impact of asymmetric information problems on decisions to migrate to another country have been analyzed in the context of theoretical models of brain drain where it is assumed that host country employers have less information than employers in the originating country (Chau and Stark 1999, Kwok and Leland 1982). Rather than analyzing the impact of asymmetric information on labor market opportunities across countries, this paper focuses on the effects of information asymmetries between immigrants and native-born individuals within a country.

The results of this paper also contribute to our understanding of the process of economic assimilation of immigrants and the individual decision regarding whether to stay in the host country. Borjas (1994), Borjas (1999) and Card (2005) provide overviews of the literature on the process economic assimilation of the immigrants in the U.S. One area of this literature examines the performance of immigrants in the host country and the speed at which they converge towards the labor market outcomes of natives over time. To my knowledge, my paper is the first that attempts to empirically examine the role of statistical discrimination on immigrant outcomes.

The results of the paper do not support the hypothesis that employers use height to statistically discriminate against immigrants in the relative absence of other good signals about their productivity. Instead, the results suggest that the productivity gap between tall and short immigrants is greater than the productivity gap between tall and short native-born workers. The differences in the mapping between height and productivity is consistent with the idea that health and nutrition inputs vary considerably in developing countries and have long-run consequences for both adult height and productivity. The evidence suggests that taller immigrants have higher levels of work productivity and are rewarded accordingly in the labor market.

2 Conceptual Framework

The classic model of statistical discrimination is based on an observable, continuous measure of skill (Aigner and Cain 1977, Phelps 1972). This skill measure has been conceptualized as a test score such as on a college entrance exam or an employer administered exam. The economic literature on statistical discrimination of groups in the labor market and the uncertainty in the information provided by a continuous test score has been almost entirely theoretical. This may reflect the reality that very few employers administer exams as part of their hiring practices or ask about standardized test scores. The framework presented in this section builds on these existing theoretical models with height representing the continuous measure of skill. One of the advantage of the focus on height rather than test scores is that it is plausibly observed by employers.

2.1 Statistical Discrimination

In the classical model of statistical discrimination, employers use a measure, H, that is correlated with the worker's true marginal productivity, P, to make decisions regarding hiring and assignment of workers. The relationship is given by:

$$H_i = P_i + \epsilon_i \tag{1}$$

where ϵ is a normally distribution error term with mean zero and a constant variance that is independent of P. While H is observable to employers, P is not. Thus, employers want to estimate marginal productivity which is given by:

$$\widehat{P_i} = (1 - \gamma)\alpha + \gamma H_i \tag{2}$$

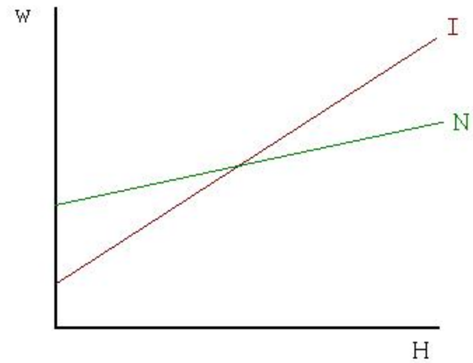
where $\widehat{P_i}$ denotes predicted marginal productivity, α is the group mean of H and

$$\gamma = \frac{Var(P)}{Var(P) + Var(\epsilon)}. \tag{3}$$

Assuming that workers are paid their marginal product, an individual's equilibrium wage will be a weighted average of mean productivity and the individual signal of productivity, H_i.

Consider two groups, immigrants and native-born individuals, denoted by I and N, respectively, where H is a more reliable indicator for members of group I than for members of group N. In other

Figure 1: Relationship Between Wages and H



words,

$$H_i^I = P_i + \epsilon_i^I; \quad H_j^N = P_j + \epsilon_j^N \tag{4}$$

and $Var(\epsilon^N) > Var(\epsilon^I)$. In this case, employer statistical discrimination will lead to the slopes γ differing for the two groups with $\gamma^I > \gamma^N$, as shown in Figure 1. All else equal, tall immigrants will be paid more than tall native-born individuals but the reverse is true for short immigrants and short natives.

There are a few possible reasons that height may be a more reliable signal of ability and productivity for immigrants than for native-born individuals. One possible explanation is that there is more variance (perhaps genetic) in the height of Americans and Britons than in other groups that is not reflective of ability. Another potential (and more likely) explanation is that height is a more reliable signal of productivity for immigrants than native-born individuals *conditional* on other worker characteristics that are observable to the employer. In this case, height is correlated with something, such as educational attainment, that is observed with less noise for native-born individuals than for immigrants. Thus, employers place less weight on educational attainment for immigrants than native-born individuals because the signal of human capital has more noise for immigrants, and relatively more weight on height which is observed with less noise.

To see this formally, consider the case where the true relationship determining marginal productivity, P^*, is given by

$$P_i^* = \alpha + H_i^* \beta + X_i^* \delta + \epsilon_i \tag{5}$$

where H^* is perfectly observable by employers. True human capital, denoted by X^*, is observed with error:

$$X_i = X_i^* + \zeta_i. \tag{6}$$

I assume that ζ_i is uncorrelated with X_i^* and H_i^*.

The estimated returns to H, $\hat{\beta}$, is given by

$$\hat{\beta} = \frac{Cov(H_i^*\beta + X_i^*\delta, H_i^* - X_i\hat{\pi}_{xh})}{Var(H_i^* - X_i\hat{\pi}_{xh})} \tag{7}$$

where $\hat{\pi}_{xh} = \frac{Cov(X_i, H_i^*)}{Var(X_i)}$.

After a little additional algebra, we get

$$\begin{aligned}
\hat{\beta} &= \frac{\beta Var(H_i^*)[1 - \frac{Cov(X_i,H_i^*)^2}{Var(X_i)Var(H_i^*)}] + \delta\frac{Cov(X_i^*,H_i^*)Var(\zeta_i)}{Var(X_i^*)+Var(\zeta_i)}}{Var(H_i^*) - \frac{Cov(X_i,H_i^*)}{Var(X_i)}} && (8)\\
&= \beta + \frac{\frac{Cov(X_i^*,H_i^*)Var(\zeta_i)}{Var(X_i^*)+Var(\zeta_i)}}{Var(H_i^*)(1 - R_{xh}^2)}\delta && (9)
\end{aligned}$$

where R_{xh}^2 is the R-squared of a regression of X on H^*. The sign of the fraction preceding δ in equation 9 is determined by the direction of the correlation between H^* and X^*. If H^* and X^* are positively correlated and educational attainment increases productivity ($\delta > 0$), then error in the employers' observations of X^*, denoted by $Var(\zeta_i)$, leads to an overestimate of the returns to H. Furthermore, if the differences across the two groups are such that $Var(\zeta_i^I) > Var(\zeta_i^N)$, then all else equal, statistical discrimination by employers implies that $\hat{\beta}^I > \hat{\beta}_N$.

The estimated returns to X are given by

$$\hat{\delta} = \delta\left[1 - \frac{Var(\zeta_i)}{(1 - R_{xh}^2)(Var(X_i^*) + Var(\zeta_i))}\right]. \tag{10}$$

Thus, under statistical discrimination, the returns paid by employers for human capital are attenuated by the noise associated with the signal. Greater noise in the signal of human capital leads to a lower estimate of the relationship between wages and observed human capital.

In the data, this hypothesis suggests that the wage gains associated with height to be greater for immigrants than for native-born individuals and the wage gains associated with education to be greater for native-born individuals than for immigrants. Furthermore, if uncertainty in immigrants' signals of productivity is reduced, the model of statistical discrimination implies that the gaps between the two groups in wage returns to height and education should close. To test the implications of statistical discrimination, I consider three measures of information quality. Two of the measures, years since immigration and any education in the host country, are available in cross-sectional data on immigrants. While the quality of the signal of human capital is likely to increase with immigrants' time in the host country or human capital acquisition in the host country, these measures may also be correlated with unobservable characteristics. To address this issue, I consider an alternative approach that relies on variation in signal reliability before and after immigration. Assuming that employers in the U.S. observe signals of productivity with more noise than employers in the country of origin, I can use pre-immigration labor market experiences to evaluate the hypothesis of statistical discrimination using height. This time-series variation also allows for an examination of the validity of the other two measures of signal quality.

2.2 Differences in the Relationships between Height, Education and Productivity

The pattern of larger returns to height for immigrants than for native-born individuals is consistent with a model of statistical discrimination but it is also consistent with a model where the relationship between individual productivity and height is different across groups. In other words, it may be the case that employers do not use height to statistically discriminate among workers but the mapping between height and productivity differs for the two groups:

$$H_i^I = b_I P_i + \epsilon_i^I; \quad H_j^N = b_N P_j + \epsilon_j^N \tag{11}$$

and $b_I < b_N$ and $\epsilon_i^I = \epsilon_i^N$. In this case, we also get $\gamma_N < \gamma_I$.

There are three possible explanations that height and productivity may have a different relationship for immigrants than for native-born individuals. First, there may be variation in returns to height across types of jobs, and immigrants sort into jobs where height has greater returns. For example, it may be the case that height increases productivity for certain types of physical labor such as fruit picking or construction, and immigrants tend to work in these types of jobs.[3] If this is true, the gap in the returns to height should disappear with the inclusion of controls for industry and occupation. Second, a different relationship between height and productivity may be explained by the selection of the types of individuals who choose to immigrate to the U.S. and the U.K. If selection explains the

[3] Using U.S. Census data, Peri and Sparber (2009) find that foreign-born workers are more likely to work in jobs that use physical labor while native-born workers occupy jobs that use communication skills.

differences in the returns to height and education, the gap in the returns should disappear with the inclusion of controls for country of origin and cohort of arrival.

Finally, there may be a stronger relationship between height and ability for immigrants due to the mapping of height and nutrition, cognitive ability or non-cognitive skills. If Americans and Britons experience less variation in nutrition and health inputs during the key stages of their development than individuals from poor countries, then immigrant height may reflect more information about health and cognitive development than native-born height. If either of the last two explanations is correct, we expect that the empirical relationship between height and health or ability to be very similar to the relationship between height and wages.

While the model of statistical discrimination predicts that immigrants will receive lower returns to education than native-born individuals, differences in the returns to education for immigrants and for native-born individuals is also consistent with this alternative story about the mapping into productivity. If education acquired in a foreign country is lower quality or has less relevance in the host country than in the source country, then each additional year of education may map into smaller increases in productivity for immigrants than for those who are native-born.

3 Data

This section provides a short overview of the data sets used in the paper. Additional details on the data sets and the construction of variables are provided in Appendix A. The four main data sets used in this analysis are the National Health Interview Survey (NHIS), the Health Survey of England (HSE), the Health and Retirement Survey (HRS) and the New Immigrant Survey (NIS). These four household-level data sets contain the necessary information on height, immigrant status and labor market outcomes, and include a substantial number of immigrants.

The NHIS is a repeated cross-sectional survey conducted by the U.S. National Center for Health Statistics and the Centers for Disease Control Prevention. It is the principal source of data on the health of the civilian population in the U.S. In this paper, I pool together data from the waves from 2000 to 2007. While the annual survey began in 1989, only the waves starting after 2000 contain information on the area of birth of survey respondents who were born outside of the U.S.

The HSE is the only British data set used in this analysis. This data set allows us to examine whether the relationship between height and labor market outcomes depends host country-specific circumstances. It is a representative sample of adults in private households in Britain conducted by the Social Survey Division of the ONS National Statistics. The repeated cross-sectional data was collected beginning in 1991. I use the waves from 1999 and 2004 because these rounds contain information about country of birth and year of immigration. Immigrants were over-sampled in these two rounds and comprise over 30% of survey respondents in those two years.

Conducted by the University of Michigan, the HRS is a panel of Americans that occurs every two years beginning in 1992. The HRS sampled individuals born between 1931 and 1941, and their spouses or partners. Given that the focus of this paper is on labor market experiences rather than the transition into retirement, I use only the 1992 wave. In addition to their current labor market experiences, the HRS also asks retrospective questions about past labor market experiences.[4] These retrospective questions allow for a construction of a pseudo-panel for the analyses using wage information.

The 2003 wave of the NIS is a nationally representative sample of legal immigrants drawn from U.S. government records on admission to legal permanent residence in 2003. This includes new arrivals to the U.S. as well as immigrants who are adjusting their visas.[5] In this paper, I use the adult and spouse samples of the 2003 wave. While the NIS does not allow for a comparison of immigrants with native-born Americans because the sample almost entirely excludes native-born Americans, the data set offers the advantage of rich retrospective information about the pre-immigration characteristics and experiences of survey respondents. Some native-born Americans enter the sample through marriage with an immigrant but I exclude these observations from the analysis. The sample size of individuals born in the U.S. in the NIS is not large and the American-born individuals that marry immigrants are likely to be different from the general population. This data set differs from the NHIS and HRS in that the immigrants are relatively recent arrivals and legally admitted into the U.S.

In all data sets, I restrict the sample to adults between the ages of 20 and 60. The samples are further limited to the set of observations that provide all of the information needed for the various analyses. Immigrant status is defined by country of birth. Thus, individuals born in the U.S. who lived in another country before returning to the U.S. would not be classified as an immigrant. Specific country of birth is only available in the HSE and NIS; the NHIS has information on region of birth while the HRS only identifies whether the individual was born in the U.S. or not.

Table 1 displays summary statistics for the four data sets, broken down by whether the individual was an immigrant or native-born. On average, native-born individuals are taller than immigrants by about two inches for men and one inch for women. The average age of the individuals in the sample range from the late thirties to the early forties. The exception is the HRS sample where the average

[4]The survey covers job information immediately before retirement for retired respondents and work prior to the most recent job for all respondents. For each of these jobs, the survey asks for both the starting and ending (or most recent) wage information.

[5]Complete details about the NIS can be found in Jasso et al (forthcoming).

age of individuals is about five years older; given the age frame that is sampled, the age distribution between 20 and 60 associated with the HRS data is skewed towards an older population than the other data sets.

The table presents real yearly earnings for all data sets and real hourly earnings for the NHIS, HRS and the NIS. For the regression results that use individual real earnings, the hourly earnings measures are used for the NHIS, HRS and the NIS, and annual earnings is used for the HSE.[6] With the exception of HRS men, immigrants tend to earn less than native-born individuals and this gap varies across samples. Immigrants are also less likely than native-born individuals to be employed in a white collar job.

Conditional on employment, American immigrants in the NHIS are quite similar to American immigrants in the NIS along most observable characteristics. For both men and women, NIS immigrants earn slightly less than NHIS immigrants. This pattern is reversed for women with female NIS immigrants earning slightly less than female NHIS immigrants. HRS immigrants have substantially lower earnings than immigrants in the NIS and NHIS. This is likely explained by the older cohorts from which the HRS samples.

Panel A of Table 2 shows characteristics of immigrants in the four main data sets. The average NHIS immigrant in my analysis entered the U.S. at age 19 and has lived in the U.S. for over 18 years.[7] The numbers are fairly similar for HSE immigrants; on average, they entered after age 18 and have lived in the U.K. for over 21 years. The average characteristics for NIS and HRS immigrants are quite different from the NHIS and the HSE. This reflects the unique sampling approaches of the NIS, which includes recent, legal immigrants, and the HRS, which includes older adults. The average NIS immigrant entered in their late twenties and has resided in the U.S. for 6 to 7 years. The average HRS immigrant entered in their late twenties and has resided in the the U.S. for about 19 years. Host country education refers to whether the individual completed any education in the host country.[8] This is constructed from direct information on post-immigration education in the NIS. However, the other data sets lack specific information about the location of a respondent's schooling; the variable is constructed to equal one if the number of years of schooling plus five is greater than the age of immigration. The share of immigrants that have any schooling in the host country varies substantially across the samples. This variation corresponds with differences in the average age of immigration.

[6]More details about the earnings variables are available in Appendix A.

[7]The NHIS does not collect information on the precise time of arrival of the immigrant. The averages are constructed from the categories for time of arrival which are less than 1 year ago, from 1 to less than 5 years, 5 to less than 10 years, 10 to less than 15 years and over 15 years.

[8]The host country is the U.K. for the HSE sample and the U.S. for the other samples.

The distribution of region of birth of immigrants is in Panel B of Table 2. The majority of immigrants in the NHIS are from Mexico or other areas of Central or South America (67% of male immigrants and 65% of female immigrants). In contrast, in the NIS sample of recent legal immigrants, more immigrants are from Asia than from Central and South America. The majority of immigrants in the U.K. were born in South Asia. Specific country or area of origin is not available for immigrants in the HRS.

4 Immigrant and Native-Born Returns to Height

4.1 Baseline Results

The basic framework to examine the relationship between height and earnings is estimated using the following equation:

$$\log w_i = \alpha_0 + \alpha_1 H_i + \beta X_i + \epsilon_i \tag{12}$$

where w_i is the wage of individual i, H is height, X is a vector of covariates and ϵ is an error term. The errors are clustered at the household level.[9] The covariates included in X vary by specifications. In the most parsimonious specification, X includes a quadratic in age, indicators for region of residence in the U.S. or the U.K. and for year. The parsimonious specification provides a benchmark of comparison with parsimonious estimates of the returns to height presented in other papers.

The parsimonious results for the sample of native-born individuals are presented in column 1 of Table 3. The corresponding results over a sample of immigrants are in column 4. Among native-born men, the coefficients suggest that an additional inch of height translates to a 1.7 to 2.6% increase in wages. The corresponding estimates for immigrant men range between 4.0 to 4.3%. The coefficient estimates on height for men are significant at the 1% level. The returns to height for native-born women range from 2 to 2.5% and are similar in magnitude and significance as the estimates for men. Female immigrants in the NHIS and the HSE earn substantially higher returns to height than their native-born counterparts and these estimates are significant at the 1% level. However, the returns to height for immigrant women in the HRS are smaller in magnitude than the estimates for native-born women and not statistically different from zero.

The regressions in columns 2 and 5 also control for years of education. For men, while the returns to height decreases slightly with the inclusion of the additional control, the height premium for male

[9] The results for immigrants are robust to clustering the errors by area of origin or by arrival cohort.

immigrants relative to male natives is not eliminated. The gap remains such that each additional inch of height yields about twice more wage gains for immigrants than for native-born individuals. In contrast, the returns to height for immigrant and native-born women converge to be quite similar in the NHIS data set. The premium in the returns to height for immigrants remains only for women in the HSE sample. The returns to height for women in the HRS sample is small and negative in magnitude and not statistically different from zero. This is consistent with some previous evidence that the returns to height are not as robust for women as for men. Glick and Sahn (1998) find a positive relationship between height and earnings for men in Guinea but no relationship for women. Using the youth cohort of the National Longitudinal Survey, Loh (1993) finds the magnitude and significance of the relationship between height and wages to be lower for American women than for American men. These differences may be explained by selection issues where a large share of women do not participate in the labor force. Another possible explanation is that women sort into jobs where height and physical strength do not matter.

Furthermore, the returns to education are consistently lower for immigrants than for native-born individuals. These results are consistent with the prediction of the model of statistical discrimination where immigrant height is given more weight by employers because the signals of human capital for immigrants is observed by employers with error. The education signal for immigrants may be observed with less reliability for many reasons. The mapping between a foreign degree and the American or British system may be unclear to employers. The quality of the schools may be difficult to determine for immigrants than for native-born individuals. However, these results may be also be consistent with an alternative story in which the mapping between years of education and productivity in other countries is less steep due to lower quality schools.

Finally, columns 3 and 6 of Table 3 include industry and occupation fixed effects. The precision of these fixed effects range from the one-digit level in the HRS to the two and three-digit levels in the other data sets.[10] By looking within job categories, we can evaluate the hypothesis that the height premium for immigrants is due to sorting into specific types of jobs where physical strength has stronger effects on worker output. While the coefficient estimates of height decline, the estimates for immigrant men remain much larger than the corresponding estimates for native-born men. Thus, the results indicate that occupational sorting does not explain the higher returns to height for immigrant men over native-born men.

Table 4 displays the estimates for immigrant men and women in the NIS sample. The results for NIS women are similar to HRS immigrant women; the magnitude of the wage returns to height

[10] See Appendix A for more details.

for women are small and not statistically different from zero in any of the specifications that include years of education. The returns to height for NIS men are slightly lower than the other immigrant samples in the parsimonious specifications, and the estimates in the full specification with industry and occupation fixed effects are similar to the American immigrant men in the NHIS.

Overall, the results provide strong evidence that the wage returns to height are substantially larger for immigrant men than for native-born men. The similarity in the results for men across the four samples suggests that the results are quite general and not driven by a particular cohort or country. The results for immigrant and native-born women are much less consistent across the samples. Given that the returns to height for women do not change much with the inclusion of industry and occupation fixed effects, it seems unlikely that occupational sorting explains the lack of a gap between immigrant and native-born women.

4.2 Occupational Sorting and Physical Labor

To further investigate the possibility that the patterns in the returns to height are driven by sorting into different types of jobs, this section examines whether the returns to height vary by the physical demands of the work. I divide jobs coarsely by how physically demanding they are. Non-physical jobs include professionals, managers, sales and administrative support. The remaining categories of physical jobs include technicians, protective service, service, farming, precision production, operators, transportation, laborers and military. If the greater returns to height for male immigrants are driven by their sorting into jobs that require physical strength, then we would expect that the returns to height are larger for workers in physically demanding jobs.

Table 5 presents the results that include interactions of height with the indicator that equals one if the individual's occupation is not physically demanding. The estimates of the interaction term is positive for men in all cases except NHIS natives. This suggests that the returns to height is actually larger for jobs that are not physically strenuous. However, the returns to height for non-physical jobs in not statistically different from the returns for physical jobs except for HRS natives. The sign of the interaction term in the estimates for women in Panel B is less consistent but confirm that the returns to height for women are not statistically different for physical versus non-physical jobs. The results of Table 5 confirm that the patterns in the relationship between height and wages among immigrants and natives are not driven by sorting of immigrants into physically strenuous jobs.

4.3 Labor Force Selection of Women

The results indicate that the relationship between height and earnings is quite different by gender, and occupational sorting is unlikely to explain these gender differences. Another possible explanation is selection of women out of the labor force for the gender differences in the results. The ideal method of examining whether the returns to height for women are affected by selection is to use the Heckman two-stage correction for selection bias (Heckman 1979). However, the method requires a variable that predicts selection into employment by women but does not directly affect wages, and it is difficult to think of a variable that would plausibly meet that criteria. As the next best option, I examine whether the empirical relationship between height and employment status provides suggestive evidence that selection bias is dampening the height premium among women.

The relationship between height and employment is presented in Table 6.[11] The probability of employment is estimated using a linear probability model, but the results are very similar if I estimate the relationship with a probit. For men aged 20 to 60, the probability of working ranges from 71 to 88% across the three samples. The corresponding probabilities for women are lower, ranging from 46 to 73%. The evidence in Table 6 shows that the impact of height on employment is much stronger for immigrant women than for native-born women. An additional 10 inches increases the probability of employment for immigrant women in the U.S. by 3% and has no effect on the probability of employment among native-born women. In the United Kingdom, an additional 10 inches increases the probability of employment by 21% for immigrant women and by 11% for native-born women. The relationship between height and employment is less consistent among men but this is not surprising given that the vast majority of men are working. The positive impact of education on employment is also not very strong among men but quite strong among women. The evidence indicates that height plays a role in the selection of women into the labor force, and that each unit of height maps into a higher probability of employment for immigrant women and for native-born women. This provides suggestive support for the idea that the gender differences in the wage returns to height are explained by selection bias.

[11]The HRS sample is excluded because panel information on past employment status is not asked. Note that the sample sizes are larger than the wage regressions because the estimates include individuals that do not report earnings information.

5 Specification and Robustness Checks

5.1 Nonlinearities in the Returns to Height

The results presented in Section 4 assume that the relationship between height and the logarithm of wages is linear. This specification follows the standard in the bulk of the literature on the wage returns to height. Nonparametric estimates of the returns to height provide support for the linearity assumption (Strauss and Thomas 1998). However, given that immigrants are on average several inches shorter than native-born individuals, this assumption could be problematic for the analysis of this paper if the actual relationship between height and earnings is concave. This section demonstrates that the estimated differences in the relationship between height and wages for immigrants and for natives is not driven by the functional form of the estimating equation.

I examine two alternative specifications of the relationship between height and wages. First, I estimate the relationship with a quadratic in the height of the individual. Second, I include the logarithm of height rather than the level of height in inches. The results are presented in Table 7 and are comparable to the results in columns 3 and 6 of Table 3. Columns 1-6 of Table 7 demonstrate that the returns to height are still approximately twice as large for immigrant men than for native-born men. This is true both under the quadratic specification (Panel A) and under the logarithmic specification (Panel B). This holds in both the NHIS and the HRS data for Americans as well as in the HSE data for Britons. For women, the gap in the nonlinear estimates of the returns to height for immigrants and native-born individuals are similar to the linear estimates. Overall, the significance of the relationship between height and wages remains weaker for women.

5.2 Selection of Immigrants

This section considers the idea that the observed relationship between height and wages of immigrants is explained by heterogeneity in the selection process across immigrants. It is possible that only tall individuals succeed in immigrating to the U.S. or the U.K., but this would not introduce a bias in the estimated returns to height among immigrants given the assumption of linearity in the relationship between height and wages. The kind of selection that is necessary to generate an upward bias in the returns to height for immigrants is more complicated. One possibility is negative selection of illegal immigrants from Central America, where the average height is relatively low, combined with positive selection of immigrants from areas where people are taller due to immigration policies.[12] Given that

[12] For analysis on the determinants of negative or positive selection of immigrants, see Borjas (1987) and Jasso and Rosenzweig (1990).

the returns to height are similar in samples where the distribution of originating countries and the time of arrival are very different (as shown in Tables 3 and 4), this concern is unlikely to be driving the results. For additional confidence, I implement two other specifications, one that includes country fixed effects and one that includes fixed effects for country interacted with arrival cohort. Under the assumption that selection effects vary across countries rather than within countries, the specification with country fixed effects removes the effects of selection. Furthermore, this specification will also address other possible explanations that depend on differences in characteristics across countries of origin. Under the assumption that selection effects vary across time as well as across countries, the specification that includes fixed effects for country interacted with arrival cohort will provide the within country-cohort returns to height for immigrants.

The NIS and HSE include information on country or region of birth of immigrants, but the NHIS only has region of birth of immigrants.[13] The HRS does not share any information about place of origin of immigrants, and is excluded from the analysis in this section. Immigrants' arrival cohorts are defined by the decade of arrival into the United States or the United Kingdom.

The results are presented in Table 8. The results correspond with the specification presented in column 6 in Table 3 and columns 3 and 6 of Table 4 with the addition of country or region fixed effects or country-cohort fixed effects. The odd columns include country or region fixed effects. The even columns include fixed effects for the interaction of country or region with cohort of arrival. For America immigrants in the NHIS and NIS, the inclusion of country fixed effects and country-cohort fixed effects does not have much effect on the estimates of the returns to height and to education. For British immigrants, the inclusion of country fixed effects in column 3 and of country-cohort fixed effects in column 4 slightly decreases the returns to height for men and women. Overall though, the returns to height for men remain substantially higher than those of native-born male Britons. Thus, the results suggest that the returns to height are not solely driven by differences in selection across countries or time, but also hold when comparing tall and short immigrants from the same country and from the same country and cohort.

5.3 Measurement Error in Height

Another potential concern is that systematic differences in reporting error for height between immigrants and native born individuals could bias the coefficient estimates and generate the observed, larger returns to height for immigrants. While height in the NHIS and NIS are self-reported, height is measured by trained interviewers in the HSE. Given that the ratio of the returns to height for immi-

[13] More details about the regions and countries of origin are provided in Appendix A.4.

grants and native-born individuals are similar for the HSE and the NHIS, it is unlikely that the larger returns to height for immigrants are explained by measurement error in height. Height is self-reported in the 1992 wave of the HRS used in this analysis. Height is also self-reported in all subsequent waves of the HRS, but in 2006 height was also measured by trained staff and the average reporting error was very low at around 1-2% with no significant differences by racial or ethnic subgroups (Meng, He and Dixon 2010).

A method for addressing systematic reporting error in height was suggested by Lee and Sepanski (1995) and Bound, Brown and Mathiowetz (1999). They use an independent source of data that contains both the true and the reported values of the variable. By estimating the true value of the variable as a function of its noisy reported value and other observable characteristics, one can derive a relationship between the reported and the true values. Assuming that the relationship between the reported and the measured values are the same in both data sets, the estimated relationship from the validation data can be used to calculate the true value of height from the reported value in the primary data set.

Respondents in the Third National Health and Nutrition Examination Survey (NHANES III) from the U.S. Department of Health and Human Services reported their own estimates of height and were professionally measured four weeks later. Using this data set to implement the correction for reporting error in height separately for immigrants and native-born individuals does not remove the large gap in the returns to height for immigrants and for native-born individuals in the NHIS and NIS.[14]

6 Testing for Statistical Discrimination

The following sections examine whether there is evidence that employers use height as a tool of statistical discrimination by testing whether changes in signal reliability alter the returns to height and to education in ways predicted by the model of statistical discrimination. If employers statistically discriminate based on immigrant height in the absence of high quality information on other characteristics that are available for native-born individuals, then the returns to the perfectly observable characteristic for immigrants should decline with improvements in other sources of information. Furthermore, assuming that employers in the immigrant's country of origin have better signals of quality than host country employers, the effects of statistical discrimination on the returns to height and

[14] I use the NHANES III rather than the HRS for this exercise because the age distribution of the NHANES III sample is more similar to the age distributions of the NHIS and NIS data. These results are available from the author upon request.

education should not be observed in pre-immigration wage data.

6.1 Cross-Sectional Variation in Signal Reliability

Over a sample of immigrants, I estimate the following equation:

$$logw_i = \beta_0 + \beta_1 H_i + \beta_2 H_i * Q_i + \beta_3 S_i + \beta_4 S_i * Q_i + \beta_5 Q_i + \beta_5 X_i + \epsilon_i \tag{13}$$

where S is total years of schooling and Q is a measure of signal quality. If signal quality is increasing in Q and $\beta_1 > 0$ and $\beta_3 > 0$, the model of statistical discrimination predicts that the wage returns to height are decreasing in signal quality ($\beta_2 < 0$) and the wage returns to education are increasing in signal quality ($\beta_4 > 0$). In other words, as the reliability of the signal of S improves, employers place more weight on S and less weight on the perfectly observable characteristic, H. This relies on plausible assumptions that height is observed perfectly by employers for both immigrants and natives but S is observed with more error for immigrants than for native-born individuals.

I consider two measures of Q. The first measure of Q is years since immigration. As an immigrant spends more time in the host country, the quality of productivity signals is likely to improve. This may occur because communication becomes easier either through improved language ability or cultural assimilation, or because immigrants accumulate labor market experience in the host country that demonstrates their true level of human capital. The second measure of Q is an indicator for whether the immigrant completed any education in the host country. The quality of the signal of human capital is plausibly improved when an immigrant attends school in the host country. For example, if an individual has a graduate degree from an American university in addition to a foreign degree, the noise in the signal for employers is plausibly lower than if the individual had a similar graduate degree from an unfamiliar foreign university.

An alternative possibility to the model of statistical discrimination is that the measures of Q capture unobserved ability rather than signal quality. The predictions associated with this alternative interpretation of Q would be different. If we assume that education and ability are complements in worker productivity and there are also complementarities between different types of ability, then this alternative model would suggest that $\beta_2 > 0$ and $\beta_4 > 0$.[15] It is possible that the measures of Q may capture variation in worker ability. The cultural assimilation or improved English language abilities associated with years in the host country may increase worker productivity directly in addition to

[15] The assumption that education and ability are complementary inputs into worker productivity is common (Lang and Manove forthcoming, Mwabu and Schultz 1996). Evidence suggests strong complementarities types of ability such as cognitive ability and social skills (Cunha and Heckman 2007, Weinberger 2011).

reducing the noise in the signal of productivity. Furthermore, over time some immigrants chose to leave the host country and this selection may generate a correlation between ability and years in the host country. If high ability immigrants remain in the U.S. or if productivity increases directly with the amount of time in the host country due to assimilation, then we would expect $\beta_2 > 0$ and $\beta_4 > 0$. If selection is such that low ability immigrants are more likely to remain in the U.S., then we would expect $\beta_2 < 0$ and $\beta_4 < 0$. As with the other measure of Q, host country education may be correlated with individual ability. If immigrants with host country education tend to have higher ability due to admissions policies and immigration rules, or if productivity directly improves as the result of any education in the host country, then we expect $\beta_2 > 0$ and $\beta_4 > 0$.

The results are presented in Table 9 for male immigrants. For men, the evidence on how the returns to education vary with the amount of time spent in the U.S. or the U.K. is fairly mixed. It is positive and significant in the NHIS data, negative and significant in the NIS data, and statistically and economically not different from zero in the HSE and HRS. Years since immigration generally has a positive effect on the returns to height rather than the negative effect predicted by the model of statistical discrimination. In fact, the effect for each additional decade in the host country is extremely small in magnitude and not statistically different from zero. The results in the even columns where Q is an indicator for education in the host country also are not consistent with the predictions of statistical discrimination. The magnitude and significance of the estimates of the interaction between height and education in the host country suggest that there is no impact of host country education on the returns to height. Overall, the evidence does not support the hypothesis of statistical discrimination by employers against immigrants. The results also do not support the alternative possibility that Q captures unobserved ability rather than signal quality.

The results for female immigrants displayed in Table 10 are somewhat different from the results for men. The coefficients on β_2 and β_4 are mostly consistent with the model of statistical discrimination when Q is years since immigration. However, in the results in which Q is host country education, the sign of the coefficients are more mixed. However, the coefficients are rarely significant at standard levels.

6.2 Variation in Signal Reliability and Panel Data

The NIS asks retrospective information on the labor market experiences of immigrants in the year that they immigrated to the U.S. Assuming that the reliability of the signal of human capital is lower for employers in the host country than for employers in the country of origin, pre-immigration labor market information offers another test of the model of statistical discrimination.

Over a sample that pools pre- and post-immigration labor market experiences of individuals in the NIS, I estimate the following equation:

$$logw_{it} = \gamma_0 + \gamma_1 H_i + \gamma_2 H_i * PreImmig_{it} + \gamma_3 S_{it} + \gamma_4 S_{it} * PreImmig_{it} + \gamma_5 X_{it} + \upsilon_{it} \tag{14}$$

where $PreImmig$ is an indicator that equals one if the data refer to a period prior to immigration to the U.S., and X includes a quadratic in age, and indicators for country of origin and year. The panel data set includes two observations for every individual, one observation prior to immigration and one observation after immigration.[16] Age and years of education are adjusted appropriately in the pre-immigration data. I include country fixed effects to address the issue that the returns to height and education may vary in different countries. The key coefficients of interest, γ_2 and γ_4, yield the difference between the pre- and post-immigration wage returns to height and education among individuals originating from the same country.

The key assumption of equation 14 is that employers in the immigrants' country of origin observe signals of productivity that are less noisy than the signals observed by American employers. Statistical discrimination based on height by American employers would yield $\gamma_2 < 0$ and $\gamma_4 > 0$. If employer statistical discrimination on height occurs in the absence of other reliable sources of information, then we expect that employers' reliance on height to be less strong for immigrants in their country of origin than in the U.S. In other words, the wage returns to education are higher prior to immigration when the signal is clearer. The weight placed on height is lower given the availability of other information on productivity.

The NIS pseudo-panel data offers additional predictions in combination with the measures of signal quality, Q, discussed in the previous section. I estimate the following regression:

$$\begin{aligned} logw_{it} = {} & \gamma_0 + \gamma_1 H_i + \gamma_2 PreImmig_{it} * H_i + \gamma_3 S_{it} + \gamma_4 PreImmig_{it} * S_{it} + \\ & \gamma_5 PreImmig + \gamma_6 H_i * Q_i + \gamma_7 S_{it} * Q_i + \gamma_8 PreImmig_{it} * Q_i + \\ & \gamma_9 H_i * PreImmig_{it} * Q_i + \gamma_{10} S_{it} * PreImmig_{it} * Q_i + \gamma_{11} Q_i + \gamma_{12} X_{it} + \upsilon_{it} \end{aligned} \tag{15}$$

where Q is years since immigration to the U.S. divided by ten or whether the individual has any education in the U.S. The measures of Q are time-invariant in this equation to allow us to determine

[16] One of the key limitations of the panel results is that the sample in this section only includes a selected group of individuals that worked both before and after immigration. For example, individuals that immigrate to the U.S. for education and never worked in their origin country would not be included in this analysis.

whether Q is measuring post-immigration signal reliability or whether Q reflects time-invariant unobservable ability. Under statistical discrimination, the post-immigration interactions of height and Q would be as previously discussed ($\gamma_6 < 0$ and $\gamma_7 > 0$) because as the signal of education improves less weight is placed on height and more on education. Furthermore, the model of statistical discrimination also implies that the net effect of the pre-immigration interactions should be zero ($\gamma_6 + \gamma_9 = 0$ and $\gamma_7 + \gamma_{10} = 0$) because subsequent American education or tenure in the U.S. should not affect signal reliability *before* immigration. In contrast, if the effect of Q is driven by a correlation with unobserved ability rather than capturing signal quality, we should see positive returns to Q both before and after immigration as well as positive estimates of the interactions of Q with height and education both before and after immigration ($\gamma_6 > 0$, $\gamma_7 > 0$, $\gamma_6 + \gamma_9 > 0$ and $\gamma_7 + \gamma_{10} > 0$).

The results of equations 14 and 15 are presented in Table 11. Columns 1 and 4 corresponds to equation 14 for men and women, respectively. The signs on the interactions are opposite to the predictions of statistical discrimination for men, and they are both positive for women. The estimated signs are not consistent with statistical discrimination for either men or women. However, we cannot statistically reject the hypothesis because none of the estimated interactions are significantly different from zero at the 10% level on their own or jointly.

Columns 2 and 5 present the results where Q is the amount of time that the immigrant has spent in the U.S. (divided by 10). For men, $\gamma_6 > 0$ and $\gamma_7 < 0$ which is not consistent with either statistical discrimination or Q reflecting ability, but these estimates are not significantly at the standard levels. However, we can reject the prediction of the model of statistical discrimination that $\gamma_6 + \gamma_9 = 0$ at the 1% level. For women, the results indicate that the post-immigration returns to height is decreasing in years in the U.S. ($\gamma_6 < 0$) while the post-immigration returns to education are increasing in years after immigration ($\gamma_7 > 0$). While the signs are consistent with the predictions of the model of statistical discrimination, the standard errors are very large and the pre-immigration interaction of height and education with years since immigration (γ_9 and $\gamma_1 0$, respectively) are both negative. Finally, the results where Q is a dummy variable for American education is displayed in columns 3 and 6 of Table 11. The key predictions of the model of statistical discrimination regarding education are rejected for men. First, the post-immigration returns to education are decreasing with U.S. education (γ_7) rather than increasing as predicted by statistical discrimination and this estimate is statistically significant. Second, the total pre-immigration interaction between American education and the returns to years of education ($\gamma_7 + \gamma_1 0$) are statistically different from zero at the 5% level. For women, the estimates are too noisy to be conclusive but the signs of the coefficients are not supportive of either the hypothesis of statistical discrimination or Q reflecting unobserved ability.

Overall, the results do not support the model of statistical discrimination using height given variation in signal reliability across groups for men. The evidence is weaker for immigrant women in that the predictions cannot be rejected statistically at standard levels. The pre-immigration effects of both measures of Q are not statistically different from zero. The evidence against the model of statistical discrimination depends on the assumption that the measures of Q are good measures of signal quality. The lack of significance of the pre-immigration and post-immigration effects of Q suggests that the estimates of Q do not reflect unobserved ability.

7 Productivity Differences in the Height Signal

The evidence in the previous sections suggests that statistical discrimination cannot explain why immigrants experience higher wage returns to height than native-born individuals. The following sections consider the alternative hypothesis that the slope of the relationship between height and productivity differs between immigrants and native born individuals. The previous literature has demonstrated evidence for the linkage between height and health (Strauss and Thomas 1998, Steckel 1995), cognitive skills (Case and Paxson 2008) and non-cognitive skills (Persico, Postelwaite and Silverman 2004). It is possible that the larger impact that each additional unit of height has on immigrant wages over native-born wages results from non-linearities in the mapping between nutritional inputs and health and cognitive development. For example, the returns to increasing investment in health and nutrition can have higher returns in both height and productivity at low levels of investment. I test this hypothesis in two ways. First, I examine whether the higher returns to height for immigrants are driven by immigrants from poorer regions of the world. Second, I directly test whether height is more correlated with measures of productivity for immigrants than for native-born individuals.

7.1 Returns to Height by Income of Country of Origin

First, I examine whether the returns to height for immigrants vary by the average income of their country of origin. The following wage regression is implemented over a sample of immigrants:

$$\log w_{ij} = \alpha_0 + \alpha_1 H_{ij} + \sum_{k=2}^{4} \alpha_k GDPN_{j \in k} * H_{ij} + \beta X_{ij} + \gamma_j + \epsilon_{ij} \tag{16}$$

where $GDPN_{k \in j}$ is an indicator variable for whether the real per capita GDP of the individual's country of origin j is in quartile k in the year of immigration across all immigrants in the sample.[17]

[17] Data on real GDP per capita in the country of origin across years is the Laspeyres series from the Penn World Tables with a reference year of 1996.

The specification includes country fixed effects, γ_j. The estimate of α_1 yields the within-country returns to height for immigrants from countries in poorest quartile of the immigrant sample. The estimate of α_k indicates whether the within-country returns to height for immigrants from countries in the kth poorest quartile are different from those in the poorest quartile.

If the difference in the relationship between height and productivity for immigrants and native-born Americans and Britons is driven by higher productivity returns to nutritional and health inputs at low levels of investment, then we expect the wage returns to height to be largest for immigrants from poor countries relative to others from the same country. In other words, the productivity hypothesis suggests that the coefficient estimate of α_1 to be positive and large, and the coefficient estimates of α_k to be negative and decreasing in k. This is a weak test of the productivity hypothesis. If the described pattern in the coefficients is not observed, then the this is evidence against the productivity hypothesis; however, if the pattern in the coefficients is observed, the results are consistent with the productivity story but also consistent with a model of statistical discrimination if the reliability of the signal of height is decreasing in the per capita GDP of the immigrants' country of origin.[18]

These equations are estimated using the NIS and HSE samples which contain information on the specific country of origin of immigrants. The distribution of the immigrants' origins are quite different across these samples (see Panel C of Table 2); thus, it is not surprising that the distribution of GDP per capita is very different across the samples. The quartiles are constructed within the NIS and HSE so the categories refer to different levels of GDP per capita for the samples.[19] The sample for this analysis is further limited to immigrants for which there is a specific country of origin; immigrant observations that are only provide a region of origin are not included.[20]

Table 12 displays the results. For male immigrants, the estimated coefficient on height is positive and statistically different from zero at the 5% level. The coefficient estimates on the interactions are all negative in the sample of male immigrants. The returns to height decrease with the quartile of the GDP per capita of the country of origin. Furthermore, the magnitude of the coefficients on the interactions for both NIS and HSE males are consistent with the hypothesis that immigrant returns to height reflect productivity. The gap in wages associated with a ten-inch difference in height for two male immigrants in the U.S. who are from a poor country like Ethiopia will be 12% but the corresponding gap would only be around 5% for two male immigrants from a rich country like the

[18]A pattern of an inverse relationship between the magnitude of the returns to height and the level of development of the country of origin is necessary but not sufficient support for the productivity hypothesis. While the pattern is consistent with a particular type of statistical discrimination, it is neither necessary nor sufficient.

[19]The cutoffs for the quartiles for the HSE are USD$1386, $1641 and $2505. In the NIS, they are $2741, $4707 and $8256.

[20]Detailed information on country and region of origin is available in Appendix A.4.

U.K. Thus, the returns to height for American immigrants from wealthy countries is very similar to the estimated height premium for native-born Americans. The results for female immigrants are more mixed and are not statistically different from zero in the HSE data.

These results demonstrate that the within-country slope of the relationship between height and productivity is decreasing in the level of development of immigrants' country of origin. Thus, the empirical results are consistent with the hypothesis that the larger wage returns to height for immigrants are explained by a different relationship between height and productivity for immigrants than for native-born individuals. However, as previously mentioned, these results are necessary but not sufficient evidence for the productivity hypothesis because they can also be explained by the mechanism of statistical discrimination under some assumptions. The next section presents a stronger test of the productivity hypothesis.

7.2 Height and Direct Measures of Ability

In the second test, I directly examine whether height is more correlated with measures of productivity for immigrants than for native-born individuals. This hypothesis is reflected in equation 4 of the theoretical framework and tested with the following regression over a sample that includes both immigrants and native-born individuals :

$$P_i = \beta_0 + \beta_1 H_i + \beta_2 H_i * I_i + \beta_3 I_i + \beta_4 X_i + \epsilon_i \tag{17}$$

where I_i is an indicator that equals 1 if individual i is an immigrant. The dependent variable, P, is health status or cognitive ability.[21] If the gap in the returns to height reflect differences in the relationship between height and productivity for immigrants and for native-born individuals, then we expect the coefficients β_1 and β_2 to have the same sign and the magnitude of β_2 relative to β_1 to be similar to the gap in the returns to height for immigrants relative to native-born individuals displayed in Table 3.

The OLS results are presented in Table 13. In the first three columns, the dependent variable is individuals' self-reported health status where 1 refers to excellent health and 5 poor health.[22] For both men (in Panel A) and women (in Panel B) in all three samples, taller individuals are also healthier, and these estimates are significant at the 1% level. Furthermore, the evidence in the NIS

[21]Ideally, the analysis would also have measures of non-cognitive ability as a dependent variable, but such measures are not available in the four data sets used in the paper.

[22]The results in Table 13 assume that the measure of health status can be treated as an interval variable. The results are robust to relaxing this assumption by allowing the dependent variable to be ordinal in an ordered probit specification. These results are available from the author upon request.

and HSE suggests that each additional inch of height corresponds to a larger improvement in health for immigrants than for native-born individuals. The effects are strongest in the HSE sample where a ten inch change in height corresponds with one-quarter of a standard deviation of better health for native-born men and women and with one-half of a standard deviation of better health for immigrant men and women. In contrast, the results of the HRS show the opposite result; the impact of height on health is smaller for immigrants than for natives but this is not statistically significant.[23] For women, the sign of coefficient indicates that height is more strongly correlated with health for immigrants than for native-born individuals.

The last three columns of Table 13 correspond to equation 17 with the dependent variable as a measure of cognitive ability. Of the main data sets used in this analysis, only the HRS has a direct measure of cognitive ability of adults. HRS adults are administered the Wechsler Adult Intelligence Scale (WAIS) test, which is the primary instrument used to measure the intelligence quotient (IQ) of adults and adolescents.[24] A higher score of the test corresponds to higher IQ. I supplement the analysis with data from the Third National Health and Nutrition Examination Survey (NHANES III), which contains information on immigration status, height and several measures of cognitive ability.[25] The symbol-digit substitution test (SDST) is one of the tests included in the WAIS and measures coding speed. Individuals are presented with pairings of digits and symbols and are asked to enter the corresponding digit for a series of the symbols as quickly as possible. Five trials were conducted and the score used is the error-corrected speed. A lower value corresponds to faster responses and higher cognition. In addition, the NHANES includes a serial digit learning test (SDLT), which measures learning and recall. Individuals are presented with a sequence of digits. Afterwards, the individual is asked to enter the entire sequence of numbers in the order presented. A smaller number represents fewer mistakes and higher cognition.

The results demonstrate that for all three measures, taller men and women also have higher cognitive ability. This is consistent with the results of Case and Paxson (2008). This analysis also indicates that the correlation between height and cognition is stronger for immigrants than for native-born individuals. This holds for both men and women and for the three measures of cognitive ability. The difference is statistically large in magnitude and significant for the NHANES sample and the HRS sample of women but not statistically significant at the 10% level for the HRS male sample.

[23]The HRS does not ask about past health status, so the HRS sample for Table 13 is limited in 1992.

[24]The WAIS covers verbal comprehension, memory, perceptual organization and processing speed.

[25]The NHANES III spans 1988-1994 and was designed to obtain nationally representative information on health and nutrition of individuals in the U.S. This data isn't used in the other analyses of the paper because it lacks information on the income of respondents.

The NHANES results suggest that each additional inch of height corresponds to more than twice as large an increase in cognition for immigrants than for native-born individuals. Overall, the results provide evidence in support of the hypothesis that the greater wage returns to height experienced by immigrants reflects a higher slope in the mapping between height and productivity.

Table 14 examines whether the inclusion of measures of health and cognitive ability reduce the gap in the wage returns to height for immigrants and natives. The regressions include the interaction of health status and immigrant status for the NHIS and HSE and the interaction of immigrant status with both health status and cognitive ability in the HRS.[26] The returns to height for male immigrants remain substantially higher than for male natives, though this difference is not statistically significant. It is important to note that the height variable contains much more variation than self-reported health status which is divided coarsely into five categories. Similarly, the WAIS score available in the HRS is also fairly coarse with only 15 values. While the relationship between height and the measures of health and cognitive ability is stronger for immigrants than for natives, it is likely that there is residual variation in height that reflects differences in non-cognitive skills, cognitive ability or health beyond the coarse measures available in the data. Thus, the results of Table 14 are consistent with the conclusion that the gap in the wage returns to height for male immigrants and natives is explained by differences in the mapping between height and health or height and cognitive and non-cognitive ability.

8 Conclusion

Using several different data sets, this paper presents a very robust empirical finding that the returns to height are much larger for immigrant men in the U.S. and the U.K. than they are for native-born men in those countries. The theoretical framework demonstrates that this finding is consistent with two hypotheses. First, it is consistent with a model of statistical discrimination whereby employers weigh a characteristic that is perfectly observable, height, more for immigrants than for native-born individuals because other signals of productivity are not reliable for immigrants. Second, the baseline results are also consistent with a model in which the mapping between productivity and height is different for immigrants.

The empirical evidence suggests that there is a stronger relationship between height and unobserved components of productivity, including health and cognitive ability, for immigrants than for

[26]The impact on the returns to height for natives and for immigrants is quite similar if indicators for health status and cognitive ability are included instead of as interval variables.

native-born Americans or Britons. This suggests a concave relationship between health and nutritional inputs during early life and long-run outcomes such as adult height and productivity. This research contributes to two strands of the large and growing economic literature on height. One strand of the literature uses height as an outcome to compare individuals within countries as well as across countries. Another strand of the literature examines height as an input into an individual-level production function.

In addition, this paper contributes to the literature that tests for employer statistical discrimination. The paper is the first to present an empirical analysis that focuses on height. Given how it is as easy to observe as race and gender, this physical characteristic is simple for employers to use. The distinction between immigrants and native-born individuals presents plausible groups for whom there is a discrepancy in the reliability of other signals of productivity, such as education. While the results suggest that height offers information about productivity that is otherwise not directly observed, the empirical evidence indicates that employers do not use height as a tool of statistical discrimination. This finding is similar to previous results that suggest that employers do not use race to statistically discriminate among workers despite the differences in average outcomes by race (Altonji and Pierret 2001).

These results have important implications for our understanding of the immigration decisions of individuals as well as the process of assimilation of immigrants. The empirical findings of this paper do not support previous theoretical hypothesis that the anticipation of statistical discrimination may influence migration and human capital decisions of individuals in developing countries. Furthermore, improvements in signal quality over time and statistical discrimination on the basis of height does not play a role in the convergence over time wages among immigrants in the U.S. or U.K.

A Data Appendix

This appendix provides detailed information on the data used in the analysis. In particular, sections A.1 to A.4 clarify how variables used in the analysis were constructed, and highlight any differences across the data sets.

A.1 Earnings

The NHIS provides information on total earnings in the last year divided into 11 categories.[27] Taking the midpoint of the range to get a continuous measure of earnings, I then convert the continuous

[27] The first range is 0 to $4999, and the second to last range is $65,000-$74,999.

measure into hourly earnings using the reported number of hours that the individual worked in the past week.[28] Because the NHIS and HRS data span several years, I use a BLS consumer price index to convert these earnings data into real 2004 dollars.

The measure of earnings constructed from the NIS is the individual's self-reported current salary or wage. Individuals can choose to report their salaries or wages in various units including hourly, monthly and yearly. I convert the salaries into hourly salaries using information on hours usually worked per week. For the NIS results in Table 11 that add pre-immigration wage information of the last job abroad, the pre-immigration data are converted into real 2004 local currency using the Penn World Tables, and then converted in the 2004 U.S. dollars using OANDA exchange rate data. One extreme outlier where annual earnings of over \$1 million is dropped. Information on the industry and occupation associated with the last job abroad is not provided.

Respondents in the HRS can report their current salary in various units including hourly, bi-weekly, monthly and yearly. Given that many of the respondents are retired, I construct a pseudo-panel in this data using salary information in the most recent job if the individual is retired. The pseudo panel also includes information on the starting and ending salary in one additional long-term job prior to the current or most recent job for all respondents. I convert information on salaries reported per two weeks, per month and per year into hourly earnings using the corresponding hours per week worked in each of the jobs. Two extreme outliers of hourly earnings of over \$3000 are dropped. Information about the industries and occupations associated with these previous jobs is asked, and the respondent's age is adjusted appropriately for past labor market experiences. In the HRS pseudo-panel, the median year of employment data is 1986 and the earliest year of data is 1938.[29]

In contrast to the other data sets, the key disadvantage of the HSE data is that income is not reported at the individual level. For the HSE data, I construct an individual level measure using joint annual income reported at the couple level. First, I convert 31 categories of joint annual income into a continuous measure that is based on the midpoint of the range of the category.[30] After that, I transform the continuous measure of the couple's income into an individual measure. In the majority of cases, the assignment is simple for the households where an individual is not married or is the only person in the household working. In other cases, the individuals' share of joint income is weighted by

[28] This assumes that the number of hours worked in the past week is a good approximation of the number of hours the individual worked in the past year. However, the assumption is supported by the robustness of the results to the use of annual earnings rather than hourly earnings. These results are available on request.

[29] To address concern regarding recall bias in past wages, I examined all of the results with only recent information on current job and the most recent job for retirees. The results are robust to this truncation and available upon request.

[30] These category divisions are quite fine. The first category is under £520, the second category is from £520 to under £2600 pounds, and the second to last category is £140,000 to under £150,000.

whether they work full-time or part-time. For example, if both members are working full-time, the individual measure of income evenly divides their joint income. If one member works full-time and the other part-time, the member who works full-time is assigned three-quarters of the joint income and the remaining one-quarter is assigned to the part-time worker.[31] The measure of income in the HSE is converted into 2004 pounds using a GDP deflator from the U.K. Office of National Statistics. No information about hours worked at the individual level is provided so the measure of real earnings used in the analysis for the HSE sample is the real annual earnings.

A.2 Height

Height is measured in centimeters by trained enumerators in the HSE. Height is self-reported in the NHIS, the NIS, and the 1992 wave of the HRS. The unit of measurement for height is inches in the NHIS and feet and inches in the HRS. Respondents of the NIS can choose whether to report their height in a combination of feet, inches, meters and centimeters. Without loss of information, I convert height in the HSE and NIS to inches for comparability across all data sets. I drop extreme outliers of height below 110 centimeters. This corresponds to a loss of three observations centimeters in the HSE and 24 observations in the NIS.[32] This has no effect on the samples in the HRS and the NHIS.

A.3 Industry and Occupation

Many of the regression results presented in the paper include controls for industry and occupation. The specificity of the controls varies across data sets and depends on the level of detail available in each data set. The NHIS offers two-digit industry and occupation information. The method of classification of industries and occupations changed between 2004 and 2005 such that the waves 2000 to 2004 use one set of codes and 2005 to 2007 use a different set of codes. No bridge is offered between the systems of classification, so I allow the estimation to provide separate coefficients on each industry and occupation code in the two systems. The HSE records industry at the two-digit level and occupation at the three-digit level. In the HRS, only one-digit industry and occupation codes are available in the data. Finally, the NIS contains four-digit industry and occupation information but there are not enough observations to estimate this many fixed effects so I aggregate the information to the next level.

[31] The results obtained from this method are generally similar to the estimates over a sample of individuals who are the sole earners in their marriage.

[32] The fact that there are more outliers in the NIS is not surprising given that respondents provide their height measurements and select the appropriate unit, and may have chosen the wrong unit to accompany the quantity.

A.4 Region

The regression results presented in the paper include controls for region of residence in the U.S. or the U.K. In the NHIS, region of residence is comprised of four categories: northeast, midwest, south and west. The HSE reports the government office region in which the respondent resides: North East, North West and Merseyside, Yorkshire and Humberside, West Midlands, East Midlands, Eastern, London, South East and South West. The observations in the HRS are divided into nine regions that are recoded from the state of residence, and information regarding the specific states included in each of the nine codes is not provided. The NIS provides information on the state of residence, aggregated into fifteen categories.

The NIS and HSE include information on country and region of birth of immigrants. The categories in the NIS are Canada, China, Colombia, Cuba, Dominican Republic, El Salvador, Ethiopia, Guatemala, Haiti, India, Jamaica, Korea, Mexico, Nigeria, Peru, Philippines, Poland, Russia, Ukraine, U.K., Vietnam, Europe and Central Asia, South Asia, Other North America, Latin America and the Caribbean, Sub-Saharan Africa, Middle East and North Africa, Oceania and the Artic Region. The categories of the HSE are Ireland, West Indies, India, Pakistan, Kenya, Uganda, Tanzania, Hong Kong, China, Malaysia, Vietname, Taiwan, Singapore, Other Africa, and other. The NHIS only has region of birth of immigrants; there are ten categories: Central America and the Caribbean, South America, Europe, Russia and former USSR areas, Africa, Middle East, Indian subcontinent, Asia, Southeast Asia, and elsewhere. The HRS does not provide any information about place of origin of immigrants.

A.5 Sample Weights

The NIS, NHIS and HRS all include sample weights. My analysis with the HSE sample pools the 1999 and 2004 waves but the HSE did not calculate sample weights for the 1999 wave. The results reported in the paper do not use sample weights, but the regression results for the NIS, NHIS and HRS are all robust to the use of sample weights.

References

[1] Aigner, Dennis and Glen Cain, "Statistical Theories of Discrimination in Labor Markets," *Industrial and Labor Relations Review*, 1977.

[2] Altonji, Joseph and Charles Pierret, "Employer Learning and Statistical Discrimination," *Quarterly Journal of Economics*, 2001.

[3] Averett, Susan and Sanders Korenman, "Economic Reality of the Beauty Myth," *Journal of Human Resources*, 1996.

[4] Beauchamp, Jonathan, David Cesarini, Magnus Johannesson, Erik Lindqvist and Coren Apicella, "On the sources of the height-intelligence correlation: New insights from a bivariate ACE model with assortative mating," *Behavior Genetics*, 2010.

[5] Bound, John, Charles Brown and Nancy Mathiowetz, "Measurement Error in Survey Data," *Handbook of Econometrics*, volume 5, eds. James Heckman and Ed Leamer. New York: Springer-Verlag, 2002.

[6] Borjas, George, "Self-Selection and the Earnings of Immigrants," *American Economic Review*, 1987.

[7] Borjas, George, "Economics of Immigration," *Journal of Economic Literature*, 1994.

[8] Borjas, George, "Economic Analysis of Immigration," *Handbook of Labor Economics*, volume 3, eds Orly Ashenfelter and David Card. North Holland, 1999.

[9] Bozzoli, Carlos, Angus Deaton and Climent Quintana-Domeque, "Adult Height and Childhood Disease," *Demongraphy*, 2009.

[10] Card, David, "Is the New Immigration Really So Bad?" *Economic Journal*, 2005.

[11] Case, Anne and Christine Paxson, "Stature and Status: Height, Ability, and Labor Makert Outcomes," *Journal of Political Economy*, 116(2008).

[12] Chau, Nancy and Oded Stark, "Human-Capital Formation, Asymmetric Information, and the Dynamics of International Migration," in *Economics of Globalization*, eds Assaf Razin and Efraim Sadka, 1999.

[13] Coate, Stephen and Glen Loury, "Will Affirmative Action Policies Eliminate Negative Stereotypes?" *American Economic Review*, 1993.

[14] Cunha, Flavio and James Heckman, "The Technology of Skill Formation," *American Economic Review*, 2007.

[15] Deaton, Angus, "Height, Health and Inequality: the Distribution of Adult Heights in India," *American Economic Review*, 2008.

[16] Farber, Henry and Robert Gibbons, "Learning and Wage Dynamics," *Quarterly Journal of Economics*, 1996.

[17] Foster, Andrew and Mark Rosenzweig, "Information, Learning and Wage Rates in Low-Income Rural Areas," *Journal of Human Resources*, 1993.

[18] Fryer, Roland, “Belief Flipping in a Dynamic Model of Statistical Discrimination,” *Journal of Public Economics*, 2007.

[19] Glick, Peter and David Sahn, “Health and Productivity in a Hetergeneous Urban Labor Market,” *Applied Economics*, 1998.

[20] Hamermesh, Daniel and Jeffrey Biddle, “Beauty and the Labor Market,” *American Economic Review*, 1994.

[21] Heckman, James. “Sample Selection Bias as a Specification Error,” *Econometrica*, 1979.

[22] Hersch, Joni, “Profiling the New Immigrant Worker: The Effects of Skin Color and Height,” *Journal of Labor Economics*, 2008.

[23] Jasso, Guillermina, Douglas S. Massey, Mark R. Rosenzweig, and James P. Smith. ”The U.S. New Immigrant Survey: Overview and Preliminary Results Based on the New-Immigrant Cohorts of 1996 and 2003.” In B. Morgan and B. Nicholson (eds.), *Immigration Research and Statistics Service Workshop on Longitudinal Surveys and Cross-Cultural Survey Design: Workshop Proceedings.* London, UK: Crown Publishing. Forthcoming.

[24] Jasso, Guillermina and Mark R. Rosenzweig, “Self-Selection and the Earnings of Immigrants: Comment,” *American Economic Review*, 1990.

[25] Kuhn, Peter and Kailing Shen, “Employers’ Preferences for Gender, Age, Height and Beauty: Direct Evidence,” NBER Working Paper 15564, 2009.

[26] Kwok, Viem and Hayne Leland, “An Economic Model of the Brain Drain,” *American Economic Review*, 1982.

[27] Lang, Kevin and Michael Manove, “Education and Labor Market Discrimination,” *American Economic Review*, forthcoming.

[28] Lee, Lung-Fei and J. Sepanski, “Estimation of Linear and Nonlinear Errors in Variables Models Using Validation Data,” *Journal of the American Statistical Association*, 1995.

[29] Loh, Eng Seng, “Economic Effects of Physical Appearance,” *Social Science Quarterly*, 1993.

[30] Lundberg, Shelley and Richard Startz, “Private Discrimination and Social Intervention in Competitive Labor Markets,” *American Economic Review*, 1983.

[31] Mankiw, Gregory and Mathew Weinzierl, “Optimal Taxation of Height: A Case Study of Utilitarian Income Redistribution,” NBER working paper 14976, 2009.

[32] Meng, Hondgao, Xiaoxing He, and Denise Dixon, “Self-Reported Versus Measured Height and Weight in the Health and Retirement Study,” *Journal of American Geriatrics Society*, 2010.

[33] Mwabu, Germano and T. Paul Schultz, “Education Returns Across Quantiles of the Wage Function: Alternative Explanations for Returns to Education by Race in South Africa,” *American Economic Review, Papers and Proceedings*, 1996.

[34] Oettinger, Gerald, “Statistical Discrimination and the Early Career Evolution of the Black-White Wage Gap,” *Journal of Labor Economics*, 1996.

[35] Persico, Nicola, Andrew Postlewaite and Daniel Silverman, “Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height,” *Journal of Political Economy*, 2004.

[36] Phelps, Edmund, "Statistical Theory of Racism and Sexism," *American Economic Review*, 1972.

[37] Schick, Andreas and Richard Steckel, "Height as a Proxy for Cognitive and Non-Cognitive Ability," NBER Working paper 16570, 2010.

[38] Peri, Giovanni and Chad Sparber, "Task Specialization, Immigration, and Wages," *American Economic Journal: Applied Economics*, 2009.

[39] Steckel, Richard, "Stature and the Standard of Living," *Journal of Economic Literature*, 1995.

[40] Strauss, John and Duncan Thomas, "Health, Nutrition and Economic Development," *Journal of Economic Literature*, 1998.

[41] Weinberger, Catherine, "Increasing Complementarity between Cognition and Social Skills," working paper, 2011.

Table 1: Summary Statistics

	NHIS		HSE		HRS		NIS
	Native	Immigrant	Native	Immigrant	Native	Immigrant	Immigrant
Panel A: Men							
Height (Inches)	70.35	68.13	69.22	67.50	70.04	67.96	68.12
	(2.65)	(2.83)	(2.68)	(2.66)	(2.77)	(3.26)	(3.39)
Age	39.52	37.87	40.14	40.13	45.18	46.90	37.02
	(10.72)	(9.99)	(10.11)	(9.51)	(11.26)	(9.63)	(8.91)
Yearly Earnings	44849	34669	27463	24010	24376	25593	33934
	(24836)	(23375)	(21979)	(22960)	(26626)	(56371)	(44793)
Hourly Earnings	21.95	16.52			22.67	23.88	15.81
	(39.58)	(23.56)			(32.19)	(74.28)	(20.05)
White Collar	0.34	0.25	0.44	0.38	0.32	0.27	0.30
	(0.48)	(0.43)	(0.49)	(0.50)	(0.47)	(0.45)	(0.46)
Education	13.81	12.45	12.13	12.90	12.32	10.59	13.72
	(2.23)	(3.21)	(2.26)	(2.96)	(3.12)	(5.07)	(4.62)
Health Status	1.94	2.00	1.79	1.93	2.58	2.54	1.87
	(0.89)	(0.92)	(0.79)	(0.83)	(1.19)	(1.20)	(0.91)
Observations	41537	9652	3519	1643	9200	904	2958
Panel B: Women							
Height (Inches)	64.62	63.46	63.98	62.79	64.45	63.15	63.50
	(2.54)	(2.42)	(2.45)	(2.72)	(2.56)	(2.94)	(3.01)
Age	39.59	38.91	39.60	40.69	45.23	45.86	36.01
	(10.88)	(9.92)	(9.99)	(9.76)	(9.95)	(9.24)	(9.03)
Yearly Earnings	32199	26907	20545	20455	14525	13691	22512
	(20702)	(19599)	(19093)	(21772)	(23976)	(12746)	(27309)
Hourly Earnings	17.76	14.72			14.91	13.07	11.84
	(27.83)	(27.01)			(27.85)	(13.13)	(12.99)
White Collar	0.44	0.32	0.35	0.37	0.31	0.18	0.28
	(0.50)	(0.47)	(0.48)	(0.48)	(0.46)	(0.39)	(0.45)
Education	13.96	12.86	12.16	12.87	12.51	10.79	13.66
	(2.11)	(2.98)	(2.07)	(2.68)	(2.50)	(4.35)	(4.29)
Health Status	2.00	2.08	1.84	2.02	2.45	2.71	2.05
	(0.91)	(0.96)	(0.82)	(0.83)	(1.16)	(1.24)	(0.94)
Observations	43803	7400	3892	1336	10168	1036	2018

Notes: Standard deviations in parentheses. Earnings are displayed in real 2004 US dollars for the NHIS and NIS samples and in real 2004 British sterling for the HSE sample. Health status ranges from 1 to 5 where 1 equals excellent health and 5 poor health.

Table 2: Summary Statistics of Immigrants

	NHIS		HSE		HRS		NIS	
	Male	Female	Male	Female	Male	Female	Male	Female
Panel A: Mean Characteristics								
Age of Immigration	18.8	19.2	19.1	18.1	29.4	27.3	28.0	28.0
	(9.04)	(9.35)	(10.0)	(9.72)	(11.8)	(11.8)	(10.5)	(10.8)
Years in U.S. or U.K.	18.0	19.7	21.0	22.6	18.7	19.6	8.9	8.0
	(11.0)	(10.6)	(13.0)	(12.6)	(12.3)	(12.2)	(8.2)	(8.0)
Host Country Education	0.43	0.49	0.41	0.42	0.14	0.13	0.22	0.25
	(0.49)	(0.50)	(0.49)	(0.49)	(0.35)	(0.34)	(0.42)	(0.43)
Panel B: Distribution of Region of Origin								
Central & South America	67.2	64.8					25.3	26.4
Europe & Central Asia	10.1	11.8	7.2	11.3			18.9	19.9
Africa & Middle East	5.7	4.3	20.8	21.6			11.3	7.7
Asia	14.5	16.1	56.1	44.4			30.2	32.4
Other	2.5	3.0	15.8	22.7			14.3	13.5
Panel C: Immigrant Height by Region of Origin								
Central & South America	67.7	63.3					67.2	63.1
	(2.69)	(2.34)					(3.29)	(3.16)
Europe & Central Asia	70.3	64.6	68.5	63.5			70.2	65.2
	(2.68)	(2.45)	(2.22)	(2.43)			(3.04)	(2.70)
Africa & Middle East	69.3	64.5	67.7	63.1			69.0	64.7
	(2.75)	(2.30)	(2.59)	(2.94)			(3.75)	(3.25)
Asia	67.8	62.9	67.1	62.4			67.4	62.6
	(2.57)	(2.27)	(2.59)	(2.63)			(2.87)	(2.54)
Other	70.3	64.7	68.0	63.0			67.7	63.2
	(2.76)	(2.69)	(2.87)	(2.68)			(3.42)	(3.58)

Notes: In panel A, standard deviations in parentheses. For the U.S. data, "Other" is comprised mainly of Canada and Oceania. For the British (HSE) data, "Other" is comprised mainly of North America. Host Country Education is an indicator that equals one if the individual completed at least one year of schooling in the host country.

Table 3: Baseline Returns to Height for Natives and Immigrants

	Native Born			Immigrant		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: U.S. Men (NHIS)						
Height	0.017	0.009	0.006	0.043	0.018	0.013
	[0.001]**	[0.001]**	[0.001]**	[0.002]**	[0.002]**	[0.002]**
Education		0.087	0.058		0.083	0.042
		[0.001]**	[0.002]**		[0.002]**	[0.003]**
Observations	41537	41537	41537	9652	9652	9652
Adjusted R^2	0.14	0.23	0.32	0.13	0.28	0.39
Panel B: U.K. Men (HSE)						
Height	0.026	0.022	0.010	0.043	0.039	0.023
	[0.005]**	[0.005]**	[0.004]*	[0.008]**	[0.008]**	[0.008]**
Education		0.069	0.01		0.048	0.001
		[0.008]**	[0.006]		[0.008]**	[0.008]
Observations	3519	3519	3519	1643	1643	1643
Adjusted R^2	0.09	0.13	0.31	0.05	0.07	0.33
Panel C: U.S. Men (HRS)						
Height	0.025	0.012	0.009	0.040	0.021	0.015
	[0.003]**	[0.003]**	[0.003]**	[0.010]**	[0.009]*	[0.008]+
Education		0.072	0.065		0.057	0.047
		[0.003]**	[0.003]**		[0.006]**	[0.007]**
Observations	9200	9200	9200	904	904	904
Adjusted R^2	0.05	0.13	0.16	0.17	0.26	0.33
Panel D: U.S. Women (NHIS)						
Height	0.020	0.009	0.007	0.028	0.008	0.005
	[0.001]**	[0.001]**	[0.001]**	[0.004]**	[0.003]*	[0.003]+
Education		0.114	0.075		0.108	0.054
		[0.002]**	[0.002]**		[0.003]**	[0.003]**
Observations	43803	43803	43803	7400	7400	7400
Adjusted R^2	0.09	0.22	0.31	0.05	0.26	0.37
Panel E: U.K. Women (HSE)						
Height	0.020	0.013	0.005	0.032	0.029	0.012
	[0.005]**	[0.005]**	[0.005]	[0.009]**	[0.009]**	[0.009]
Education		0.122	0.053		0.049	-0.001
		[0.008]**	[0.007]**		[0.010]**	[0.009]
Observations	3892	3892	3892	1336	1336	1336
Adjusted R^2	0.05	0.14	0.32	0.02	0.04	0.23
Panel F: U.S. Women (HRS)						
Height	0.025	0.012	0.011	0.013	-0.001	-0.001
	[0.003]**	[0.003]**	[0.003]**	[0.008]	[0.008]	[0.008]
Education		0.092	0.074		0.05	0.033
		[0.003]**	[0.004]**		[0.006]**	[0.007]**
Observations	10168	10168	10168	1036	1036	1036
Adjusted R^2	0.11	0.21	0.24	0.11	0.20	0.25
Ind & Occ FE	No	No	Yes	No	No	Yes

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real earnings. Height is in inches. All regressions include a quadratic in age, indicators for year and for region, and a constant term. Columns 3 and 6 include industry and occupation indicators.

Table 4: Returns to Height for Immigrants in the NIS

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Height	0.023	0.015	0.009	0.013	0.005	0.006
	[0.003]**	[0.003]**	[0.003]**	[0.004]**	[0.004]	[0.004]
Education		0.08	0.032		0.086	0.037
		[0.007]**	[0.007]**		[0.009]**	[0.010]**
Observations	2958	2958	2958	2018	2018	2018
Adjusted R^2	0.08	0.12	0.24	0.03	0.08	0.18
Ind & Occ FE	No	No	Yes	No	No	Yes

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real earnings. Height is measured in inches. All regressions include a quadratic in age, indicators for year and for region, and a constant term. Columns 3 and 6 include indicators for industry and occupation.

Table 5: Returns to Height by Physical Demands of the Occupation

	NHIS		HSE		HRS		NIS
	Native	Immigr	Native	Immigr	Native	Immigr	Immigr
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Men							
Height	0.008	0.011	0.007	0.016	0.003	0.009	0.015
	[0.002]**	[0.003]**	[0.006]	[0.011]	[0.004]	[0.009]	[0.012]
Height*Non-Physical Job	-0.003	0.003	0.004	0.015	0.014	0.012	0.017
	[0.002]	[0.004]	[0.008]	[0.017]	[0.006]*	[0.018]	[0.016]
Non-Physical Job	0.074	0.148	-0.146	-1.167	-0.916	-0.869	-0.967
	[0.210]	[0.336]	[0.590]	[1.182]	[0.418]*	[1.203]	[1.117]
Observations	41537	9652	3519	1643	9200	904	2958
Adjusted R^2	0.31	0.39	0.31	0.33	0.17	0.34	0.23
Panel B: Women							
Height	0.013	0.006	0.008	0.015	0.011	-0.005	0.001
	[0.003]**	[0.005]	[0.008]	[0.014]	[0.004]*	[0.008]	[0.015]
Height*Non-Physical Job	-0.007	0.000	-0.004	-0.005	-0.001	0.008	0.033
	[0.003]*	[0.006]	[0.010]	[0.019]	[0.005]	[0.016]	[0.021]
Non-Physical Job	0.593	-0.068	0.267	0.958	0.159	-0.276	-1.718
	[0.216]**	[0.447]	[0.629]	[1.238]	[0.345]	[0.998]	[1.364]
Observations	43803	7400	3892	1336	10168	1036	2018
Adjusted R^2	0.31	0.37	0.32	0.23	0.25	0.27	0.18

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real earnings. Height is measured in inches. Non-physical job is an indicator that equals one if the person's occupation is executive or managerial, professional, administrative including support or sales. All regressions include a quadratic in age, education, indicators for year, region, industry and occupation, and a constant term.

Table 6: Impact of Height on Employment

	U.S. (NHIS)		U.K. (HSE)		U.S. (NIS)
	Native-Born	Immigrant	Native-Born	Immigrant	Immigrant
	(1)	(2)	(3)	(4)	(5)
Panel A: Women					
Height	0.000	0.003*	0.011**	0.021**	0.003
	[0.001]	[0.002]	[0.002]	[0.003]	[0.002]
Education	0.039**	0.032**	0.025**	0.037**	0.033**
	[0.001]	[0.001]	[0.002]	[0.002]	[0.005]
Observations	82514	18386	11382	4061	5331
Adjusted R^2	0.054	0.060	0.044	0.148	0.028
Dep. Var. Mean	0.731	0.611	0.670	0.455	0.497
Panel B: Men					
Height	0.002**	-0.002	0.004	0.011**	0.003
	[0.001]	[0.001]	[0.002]	[0.003]	[0.002]
Education	0.026**	0.000	-0.000	0.013**	0.001
	[0.001]	[0.001]	[0.003]	[0.003]	[0.155]
Observations	66488	15925	4916	2813	5088
Adjusted R^2	0.068	0.024	0.066	0.067	0.035
Dep. Var. Mean	0.844	0.877	0.816	0.708	0.785

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is an indicator for whether the person is working. Height is measured in inches. All regressions include a quadratic in age, indicators for year and for region, and a constant term.

Table 7: Nonlinear Estimates of the Returns to Height

	Men						Women					
	NHIS Data		HSE Data		HRS Data		NHIS Data		HSE Data		HRS Data	
	Native	Immigr	Native	Immigr	Native	Immigr	Native	Immigr	Native	Immigr	Native	Immigr
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Quadratic Specification												
Height	0.097	0.209	0.121	0.352	0.000	0.115	0.146	-0.047	0.148	0.139	0.029	0.048
	[0.045]*	[0.085]*	[0.143]	[0.260]	[0.056]	[0.168]	[0.048]**	[0.123]	[0.150]	[0.172]	[0.099]	[0.097]
Height^2	-0.001	-0.001	-0.001	-0.002	0.000	-0.001	-0.001	0.000	-0.001	-0.001	0.000	0.000
	[0.000]*	[0.001]*	[0.001]	[0.002]	[0.000]	[0.001]	[0.000]**	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
F-stat	18.46**	19.95**	3.05*	4.69**	4.58**	1.45	23.55**	1.56	1.02	1.21	7.96**	0.12
Obs	41537	9652	3519	1643	9200	904	43803	7400	3892	1336	10168	1036
Adj R^2	0.32	0.39	0.31	0.33	0.15	0.3	0.31	0.37	0.32	0.23	0.25	0.24
Panel B: Logarithmic Specification												
Log(Height)	0.446	0.875	0.543	1.436	0.516	0.916	0.465	0.337	0.405	0.773	0.588	0.080
	[0.077]**	[0.151]**	[0.282]+	[0.562]*	[0.198]**	[0.555]+	[0.075]**	[0.195]+	[0.296]	[0.557]	[0.172]**	[0.468]
Obs	41537	9652	3519	1643	9200	904	43803	7400	3891	1333	10168	1036
Adj R^2	0.32	0.39	0.33	0.35	0.15	0.30	0.31	0.37	0.32	0.23	0.26	0.26

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real wages. Height is measured in inches. All regressions include a quadratic in age, education, indicators for year, region, industry and occupation indicators, and a constant term. The F-statistic refers to whether height and height squared are jointly significant.

Table 8: Within-Country and Cohort Estimates of Immigrants' Returns to Height

	U.S. (NHIS)		U.K. (HSE)		U.S. (NIS)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
Height	0.012	0.012	0.017+	0.017*	0.007	0.008
	[0.002]**	[0.002]**	[0.009]	[0.008]	[0.003]*	[0.003]*
Education	0.038	0.039	0.004	0.008	0.036	0.037
	[0.003]**	[0.003]**	[0.009]	[0.009]	[0.008]**	[0.008]**
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country*Arrival Cohort FE	No	Yes	No	Yes	No	Yes
Observations	9652	9652	1643	1643	2958	2958
Adjusted R^2	0.40	0.42	0.34	0.35	0.25	0.26
Panel B: Women						
Height	0.005	0.007	0.004	0.001	0.003	0.003
	[0.003]+	[0.003]*	[0.009]	[0.009]	[0.005]	[0.005]
Education	0.050	0.052	0.001	-0.001	0.046	0.046
	[0.004]**	[0.004]**	[0.009]	[0.009]	[0.011]**	[0.011]**
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country*Arrival Cohort FE	No	Yes	No	Yes	No	Yes
Observations	7400	7400	1336	1336	2018	2018
Adjusted R^2	0.38	0.39	0.24	0.25	0.20	0.20

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real earnings. Height is measured in inches. All regressions include a quadratic in age, indicators for year and for region of residence in the U.S. or U.K., and a constant term. The additional controls in the even columns are indicators for industry and occupation. The NIS and HSE both have country of birth of immigrants, but the NHIS only provides information on region of birth.

Table 9: Information Quality and the Returns to Height and Education of Male Immigrants

	NHIS Data		HSE Data		HRS Data		NIS Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Height	0.012	0.012	0.012	0.028	0.018	0.011	0.008	0.009
	[0.004]**	[0.003]**	[0.016]	[0.011]*	[0.013]	[0.008]	[0.005]+	[0.004]**
Height*Years Since Immigration/10	0.001		0.005		-0.006		0.001	
	[0.002]		[0.006]		[0.006]		[0.004]	
Education	0.039	0.035	-0.006	-0.002	0.039	0.034	0.056	0.030
	[0.004]**	[0.003]**	[0.015]	[0.009]	[0.009]**	[0.007]**	[0.011]**	[0.008]**
Education*Years Since Immigration/10	0.003		0.008		-0.001		-0.016	
	[0.002]+		[0.006]		[0.004]		[0.007]**	
Years Since Immigration/10	0.031		-0.311		0.551		0.276	
	[0.132]		[0.399]		[0.372]		[0.636]	
I(Educated in Host Country)		0.014		1.024		1.658		1.017
		[0.288]		[1.021]		[1.510]		[1.182]
Height*I(Educated in Host Country)		0.002		-0.013		-0.026		-0.005
		[0.004]		[0.015]		[0.020]		[0.007]
Education*I(Educated in Host Country)		0		0.005		0.021		0.000
		[0.004]		[0.017]		[0.024]		[0.014]
Observations	9652	9652	1643	1643	844	844	2958	2958
Adjusted R^2	0.41	0.4	0.35	0.34	0.37	0.36	0.25	0.24
P-value of F-test:								
$\beta_1 = 0$ & $\beta_2 = 0$	0.16	0.89	0.25	0.67	0.45	0.22	0.05	0.76

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real wages. Height is measured in inches. All regressions include a quadratic in age, indicators for year, region, industry and occupation indicators, and a constant term.

Table 10: Information Quality and the Returns to Height and Education of Female Immigrants

	NHIS Data		HSE Data		HRS Data		NIS Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Height	0.006	0.003	0.043	0.015	0.007	-0.002	0.009	0.007
	[0.006]	[0.004]	[0.020]*	[0.012]	[0.012]	[0.008]	[0.006]	[0.005]
Height*Years Since Immigration / 10	0.000		-0.014		-0.005		-0.003	
	[0.003]		[0.008]+		[0.005]		[0.005]	
Education	0.031	0.044	-0.021	-0.004	0.013	0.029	0.038	0.031
	[0.006]**	[0.004]**	[0.018]	[0.010]	[0.008]	[0.007]**	[0.014]**	[0.011]**
Education*Years Since Immigration / 10	0.014		0.008		0.010		0.005	
	[0.002]**		[0.007]		[0.005]*		[0.011]	
Years Since Immigration/ 10	-0.099		0.726		0.258		0.594	
	[0.180]		[0.501]		[0.323]		[0.847]	
I(Educated in Host Country)		-0.420		0.244		-0.79		0.969
		[0.383]		[1.132]		[1.441]		[1.718]
Height*I(Educated in Host Country)		0.006		-0.005		0.006		-0.005
		[0.006]		[0.018]		[0.023]		[0.011]
Education*I(Educated in Host Country)		0.015		0.009		0.035		0.010
		[0.005]**		[0.019]		[0.020]+		[0.021]
Observations	7400	7400	1336	1336	966	966	2018	2018
Adjusted R^2	0.39	0.38	0.23	0.23	0.30	0.29	0.19	0.18
P-value of F-test:								
$\beta_1 = 0$ & $\beta_2 = 0$	0.00	0.01	0.09	0.86	0.10	0.20	0.82	0.81

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real wages. Height is measured in inches. All regressions include a quadratic in age, indicators for year, region, industry and occupation indicators, and a constant term.

Table 11: Comparison of Pre- and Post-Immigration Wages of NIS Immigrants

	Male Immigrants			Female Immigrants		
Q=		Yrs in US	US Edu		Yrs in US	US Edu
	(1)	(2)	(3)	(4)	(5)	(6)
Height	0.018+	0.009	0.020+	0.008	0.010	0.016
	[0.010]	[0.014]	[0.011]	[0.017]	[0.025]	[0.019]
Pre-Immig*Height (γ_2)	0.010	-0.015	0.007	0.033	0.052+	0.032
	[0.013]	[0.019]	[0.014]	[0.020]	[0.030]	[0.023]
Education	0.101**	0.107**	0.127**	0.090**	0.079+	0.099*
	[0.021]	[0.030]	[0.024]	[0.028]	[0.048]	[0.042]
Pre-Immig*Education (γ_4)	-0.034	-0.012	-0.023	0.017	0.028	-0.008
	[0.031]	[0.039]	[0.031]	[0.045]	[0.066]	[0.053]
Pre-Immig	-2.339	1.662	-1.872	-6.415*	-9.556*	-5.936+
	[2.131]	[3.153]	[2.318]	[3.181]	[4.584]	[3.416]
Height*Q (γ_6)		0.011	-0.022		-0.004	-0.067
		[0.013]	[0.020]		[0.017]	[0.043]
Education*Q (γ_7)		-0.008	-0.110*		0.011	-0.039
		[0.019]	[0.050]		[0.035]	[0.053]
Pre-Immig*Q		-4.996	-1.511		4.477	-5.703
		[3.227]	[6.127]		[3.683]	[10.225]
Pre-Immig*Height*Q (γ_9)		0.033+	0.016		-0.026	0.027
		[0.020]	[0.034]		[0.023]	[0.062]
Pre-Immig*Education*Q (γ_{10})		-0.035	-0.106		-0.010	0.088
		[0.035]	[0.110]		[0.050]	[0.103]
Q		-1.799	5.652		0.597	11.489
		[2.221]	[3.571]		[2.664]	[6.989]
Observations	1053	1053	1053	618	618	618
Adjusted R^2	0.204	0.217	0.218	0.179	0.181	0.176
P-values of F-test:						
$\gamma_2 = 0$ & $\gamma_4 = 0$	0.487			0.192		
$\gamma_6 = 0$ & $\gamma_7 = 0$		0.594	0.729		0.132	0.323
$\gamma_6 + \gamma_9 = 0$		0.003	0.807		0.134	0.391
$\gamma_7 + \gamma_{10} = 0$		0.160	0.023		0.979	0.634

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of pre-immigration real wages at the time of immigration (in real U.S. dollars). Height is measured in inches. Years since immigration and education in host country refer to the individual's post-immigration status. All regressions include a quadratic in age, indicators for country and year of immigration, and a constant term.

Table 12: Immigrants' Returns to Height and Per Capita GDP of Country of Origin

	Male Immigrants		Female Immigrants	
	NIS Data	HSE Data	NIS Data	HSE Data
	(1)	(2)	(3)	(4)
Height	0.012	0.040	0.022	-0.006
	[0.005]*	[0.016]*	[0.012]+	[0.021]
Height* $\frac{GDP}{N}$ quartile 2	-0.004	-0.017	-0.028	0.053
	[0.011]	[0.024]	[0.017]	[0.045]
Height* $\frac{GDP}{N}$ quartile 3	-0.004	-0.027	-0.025	0.008
	[0.001]**	[0.031]	[0.017]	[0.034]
Height* $\frac{GDP}{N}$ quartile 4	-0.007	-0.039	-0.029	-0.018
	[0.002]**	[0.027]	[0.015]+	[0.035]
Observations	1914	1101	1323	721
Adjusted R^2	0.26	0.38	0.24	0.28

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. The dependent variable is the logarithm of real wages. Height is measured in inches. All regressions include a quadratic in age, indicators for year, for region, for GDP quartiles and for country of origin, education, industry and occupation controls, and a constant term.

Table 13: Relationship between Height, Health and Cognition

	Health Status			Cognitive Ability		
	NHIS	HSE	HRS	NHANES		HRS
				SDST	SDLT	WAIS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
Height	-0.023	-0.016	-0.039	-0.014	-0.091	0.124
	[0.002]**	[0.005]**	[0.008]**	[0.004]**	[0.017]**	[0.025]**
Immigrant*Height	-0.009	-0.033	0.013	-0.031	-0.161	0.027
	[0.004]*	[0.009]**	[0.021]	[0.007]**	[0.035]**	[0.077]
Immigrant	0.623	2.374	-1.018	5.778	30.103	-2.640
	[0.246]*	[0.430]**	[1.426]	[1.269]**	[5.950]**	[5.204]
Observations	51189	7462	2554	2300	2250	2195
Adjusted R^2	0.03	0.06	0.01	0.12	0.13	0.02
Panel B: Women						
Height	-0.019	-0.012	-0.014	-0.020	-0.104	0.099
	[0.002]**	[0.005]**	[0.007]+	[0.004]**	[0.016]**	[0.022]**
Immigrant*Height	-0.010	-0.004	-0.030	-0.033	-0.144	0.124
	[0.005]*	[0.009]	[0.024]	[0.009]**	[0.035]**	[0.062]*
Immigrant	0.688	0.409	0.392	5.993	25.653	-8.676
	[0.297]*	[0.573]	[1.067]	[1.381]**	[5.543]**	[4.006]*
Observations	51203	5651	3255	2761	2697	3019
Adjusted R^2	0.03	0.02	0.02	0.12	0.12	0.02

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. Height is measured in inches. All regressions include a quadratic in age, indicators for year and a constant term. In columns 1-3, the dependent variable, health, is a self-reported measure where 1 equals excellent health and 5 equals poor health. The measure of cognition is the error-corrected speed for the symbol digit substitution test (SDST), total score in the serial digit learning test (SDLT) in column 5, and the standardized Wechsler Adult Intelligence Scale (WAIS) score in column 6. Cognitive ability is increasing in the WAIS score, but decreasing in the other measures.

Table 14: The Relationship between Height and Log Earnings Controlling for Health and Cognition

	Male Sample			Female Sample		
	NHIS	HSE	HRS	NHIS	HSE	HRS
	(1)	(2)	(3)	(4)	(5)	(6)
Height	0.005	0.007	0.008	0.007	0.006	0.011
	[0.001]**	[0.004]+	[0.003]*	[0.001]**	[0.005]	[0.003]**
Height*Immigrant	0.007	0.020	0.011	-0.003	0.009	-0.025
	[0.002]**	[0.008]*	[0.009]	[0.003]	[0.009]	[0.009]**
Immigrant	-0.617	-1.587	-0.581	0.131	-0.595	1.651
	[0.167]**	[0.573]**	[0.612]	[0.205]	[0.604]	[0.556]**
Health Status	-0.061	-0.125	-0.035	-0.058	-0.092	-0.029
	[0.004]**	[0.015]**	[0.008]**	[0.003]**	[0.013]**	[0.007]**
Health Status*Immigrant	0.010	0.047	-0.070	0.010	-0.007	-0.015
	[0.007]	[0.028]	[0.034]*	[0.008]	[0.029]	[0.020]
Cognition			0.011			0.013
			[0.003]**			[0.003]**
Cognition*Immigrant			-0.004			0.000
			[0.011]			[0.009]
Observations	51189	5162	8820	51203	5224	10451
Adjusted R^2	0.35	0.36	0.18	0.33	0.30	0.25

Notes: Robust standard errors clustered by household in brackets. **, *, + denotes significance at the 1%, 5% and 10% level, respectively. Height is measured in inches. All regressions include a quadratic in age, years of education, indicators for year, region, industry and occupation indicators, and a constant term.