Returns to Education in Asian Americans

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Abstract

For more than two decades now, Asian Americans have had the highest median wages of any race group in the United States. Past research has also long documented Asian Americans' high educational attainments. Yet, there is no clear consensus on the distribution and magnitude of discrepancies in returns to education among Asian Americans. That is, analyses have yielded varying conclusions as to which Asian subgroups experience different returns to education relative to that of whites; both the magnitude and direction of these discrepancies are of interest. The following research aims to investigate the returns to education of Asian Americans and, by disaggregating ethnic subgroups and sex, uncover potential heterogeneity within the Asian American aggregate. Using public data from the American Community Survey, my analysis provides evidence that 1) Asian Americans have slightly lower average returns than whites, with the difference more pronounced in females; 2) Asian American subgroups have significantly differing returns to education with varying gender effects: from 0.117 for Indian males to less than 0.05 for Bhutanese females; and 3) while the Asian aggregate does not exhibit greater heterogeneity of returns than whites, a number of subgroups have a wider spread in returns than do whites. Additionally, I found that these conclusions may vary depending on model specification, which suggests the need to properly account for immigration status and for nonconstant returns to education in future studies. Results from this study could serve as a reference in the construction of social programs to include historically overlooked subsets of the population; it also advises future research to assess the accuracy and usefulness of "Asian Americans" as a monolithic category.

Introduction

In discrimination research, the literature has rightfully paid increasing attention to the socioeconomic status of Black and Hispanic Americans. This is in large part due to the historical and present disparities that these groups have disproportionately endured. And indeed much progress has been made. From these studies, researchers have found evidence suggesting persistent labor market obstacles for Black and Hispanic Americans with respect to whites (Hirschman and Wong 1984; Daly, Hobjin, and Pedtke 2017; Chetty et al. 2020). Especially concerning is that after controlling for observable factors such as age and education, the wage gap appears to be increasing over time for some of these groups.

For Asian Americans, the picture and the resulting literature has been mixed. Asian Americans are a recently immigrated and rapidly growing population in the United States, such that the ethnic grouping itself is a new but already outdated categorization. The term "Asian Americans" was coined around the height of the U.S. Civil Rights movement by the late historian and activist Yuji Ichioka (Zhou 2016). Yet, to speak on the socioeconomic conditions of the population, the umbrella term masks potential heterogeneity between and within Asian subgroups. On the one hand, Asian American populations were impacted by discriminatory legislation such as the Chinese Exclusion Act of 1882 and the forced relocation and internment of Japanese American during World War II. The idea of the "Yellow Peril" represented a dramatically negative image of Asian immigrants. In popular culture and media, the tragic history is at times juxtaposed with the apparent socioeconomic gains in recent years by some Asian American groups. This has led to generalizations such as the model minority stereotype; from media coverage in the 1960s praising Chinese and Japanese immigrants for having achieved socioeconomic success in the U.S., the concept of the model minority was eventually imposed onto the entire Asian American population as explicit legal discrimination waned. Furthermore, even in light of these supposed gains, racially motivated crimes against Asian Americans have been on the rise in recent years, perhaps in relation to the COVID-19 pandemic (James and Hanson 2021). As a result of these complications, scholars continue to research and debate whether model minority perceptions are supported by statistics.

As with other demographic minorities, economists have taken interest in and begun exploring the socioeconomic conditions of Asian America. This effort has gathered steam in recent years, as prior efforts had been largely limited due to data constraints. Still, as the literature expands in this area, data limitations remain both a cause for concern and motivation for further research. For instance, Chiswick (1983) examined the earnings of Chinese, Filipino, and Japanese Americans using public-use data from the U.S. Census. Some main conclusions include that Chinese and

Japanese Americans are more educated and earn more than their white counterparts; on the other hand, Filipino Americans tend to be disadvantaged in these regards compared to whites. Relatedly, Hirschman and Wong (1984) describes that these Asian American groups achieve socioeconomic parity with whites due to the former's overeducation. These two studies uncover significant and important results, but the implications remain limited: the samples are restricted to a few subgroups of Asian Americans, and in particular only males. Hurh and Kim (1989) add to the two studies by examining additional Asian groups such as Indians, Koreans, and Vietnamese; Barringer, Takeuchi, and Xenos (1990) examined similar groups and reached the conclusion of a lack of income parity for Asian Americans compared to whites. Most recently, Zeng and Xie (2004) attributes some of the white-Asian income disparity to the place of education as opposed to race. Yet again, these studies focus on male workers from a subset of Asian American groups; Zeng and Xie (2004) also acknowledges heterogeneity among Asian subgroups and calls for a "more nuanced interpretation" of their analysis on the aggregate groups.

Due to various limitations beyond these researchers' control, these approaches can lead to incomplete conclusions. By examining only the largest Asian subgroups (or only Asians as a homogeneous aggregate), we omit between- and within-group heterogeneity. Additionally, the omitted subset might then be comparable in size to or larger than the specified subgroups. As a result, the literature is mixed on whether Asian Americans face differential returns to education. Most propose a nuanced image that particular subgroups experience discounted returns to education while certain others receive premiums; yet, the literature is in much disagreement on which particular subgroups are advantaged, such as the studies mentioned above.

Here, I summarize some observations and theories, which will motivate my hypotheses. The existence or the size of the white-Asian wage gap aside, research has repeatedly found Asians to be overeducated for their earnings or occupation (Hirschman and Wong 1984; Barringer, Takeuchi, and Xenos 1990; Friedman and Krackhardt 1997; Takei, Sakamoto, and Kuo 2014). Recent literature in sociology further describes Asian Americans as a hyperselected immigrant group, which characterizes Asian immigrants as highly credentialed compared to peers in their countries of origin *and* to their American counterparts (Zhou and Lee 2017; Model 2018). In addition to whether Asian Americans' high average educational attainments are properly rewarded, the high degree of heterogeneity complicates the picture. As noted previously, it remains up to debate which particular subgroups of

Asian American (if any at all) have achieved earnings parity with whites conditional on education and other factors (consider Chiswick 1983; Hurh and Kim 1989; Barringer, Takeuchi, and Xenos 1990; Zeng and Xie 2004; Takei, Sakamoto, and Kim 2013). Still, researchers seem to agree that various subgroups have drastically different outcomes. Some prominent dynamics include lower returns for foreign-born or foreign-educated immigrants; particularly for Asian Americans, those from certain Southeast Asian countries are also documented with lower educational attainments and returns. Lastly, there seems to also be significant heterogeneity even within Asian American subgroups compared to within the white population. A driver could be differences between U.S. nationals and recent immigrants, given the immigration history of Asian Americans. Qian, Lichter, and Crowley (2010) highlight differences in child poverty rates among Chinese Americans by country of origin (since individuals of multiple nationalities may report as being ethnically Chinese), immigrant status, and family structure. The research shows that, even within a group that is well-off on average, socioeconomic condition can still vary widely.

Using data from the Census Bureau, my analysis and results provide support for my hypotheses on the aggregate and on between-variation in Asians' returns to education; my hypothesis on within-variation in Asian subgroups finds partial support although the underlying assumption is challenged. On average, I found that Asian Americans have lower returns to education to whites. In particular, since white females have higher returns than white males, and Asian females have lower returns than Asian males, the white-Asian difference in returns is more pronounced among females. Secondly, across Asian subgroups, returns to education vary dramatically. Subgroups' returns to education appear to be somewhat lower as population shrinks, but exceptions exist where relatively small subgroups have comparable returns to the Asian average. Lastly, heterogeneity of returns to education within Asian subgroups is smaller in magnitude than within the white aggregate. However, the relationship between earnings percentile and returns to education appears to be reversed in Asians compared to whites, creating nuance and challenges to the comparison of heterogeneity. These results are in line with prior research demonstrating lower average returns in Asian Americans and significant heterogeneity between Asian subgroups. The analysis also contributes to the literature by adding nuance in considering many Asian subgroups and accounting for gender effects.

The paper will proceed as follows. I describe my data source, derive my empirical strategy, and list my hypotheses. Then, I present the results from my primary analysis in greater detail. The next section checks for robustness using alternative specifications. Lastly, I conclude with a discussion of the results, potential policy implications, and suggestions for future research.

Data

This study employs public-use microdata from the U.S. Census Bureau's American Community Survey (ACS) from the years 2005 to 2019. The time frame is selected in the interest of the ACS becoming standardized in 2005. Indeed, the panel data would also allow me to explore temporal effects. The particular data sets come from IPUMS.org ("Integrated Public Use Microdata Series"), which is maintained by the Minnesota Population Center at the University of Minnesota (Ruggles et al. 2021). The survey is a 1% nationally representative sample of the U.S. population, with sampling weights that allow adjustments for representativeness. These weights will be applied in the regressions (where applicable) throughout this paper to ensure accurate results. The research will focus on whites and Americans of several Asian origins; for the interest of this paper, and as suggested by the U.S. Bureau of the Census, Asian American groups include Chinese, Indian, Filipino, Vietnamese, Korean, Japanese, Pakistani, Cambodian, Thai, Laotian, Hmong, Bangladeshi, Taiwanese, Indonesian, Nepalese, Burmese, Sri Lankan, Malaysian, Bhutanese, and Mongolian Americans, and omitted categories. So then, the analysis in this research does not account for Western Asian Americans; the data also does not allow for effective analysis of polyethnic or multiracial individuals.

I restricted the age of the observations to between 18 and 65 years old; that is, from adulthood to retirement. In particular, I do not omit observation working less than full time (whereas some previous studies do). Additionally, I omit observations identifying as both white and Asian. From the data set, using variables on hours worked per week and weeks worked per years, I transformed annual earned income into the natural logarithm of hourly wage (log-wage). I also generate a variable for potential labor market, *exper*, from years of education and age. I also include demographic variables such as sex, years spent in the U.S., years of education, and dummy variables for various Asian racial subgroups.

Empirical Strategy

I begin with the the human capital earnings function (Mincer, 1974) of the form

$$\ln(wage_i) = \beta_0 + \beta_1 educ_i + \beta_2 exper_i + \beta_3 exper_i^2 + \epsilon_i \tag{1}$$

where *wage* is hourly wage, *educ* is years of education, and *exper* is potential labor market experience (measured as current age less the years spent in and before school). Each observation is for some individual in year t; respondents are randomized across years, which reduces autocorrelation but does not rule out time-dependent covariates. The choice of the model is motivated by the abundance of literature in human capital theory (Becker 1962; Mincer 1974). In particular, log-wage is used given the strong positive skew often found in income distributions. Then, I turn to the literature to motivate the specific functional forms and relevant demographic covariates. Sex will be included as a covariate. This is motivated by discrimination research examining Black-white wage differences – the Black-white wage gap is largely driven by wage discounts in Black males (Daly et al., 2017). It would be of interest to explore whether such patterns are found across subgroups of Asian Americans. The literature also motivates controlling for immigration particularly due to differential returns to foreign education (Zeng and Xie, 2004; Wiers-Jenssen and Try, 2005; Argue and Velema, 2021) Similarly, assimilation theory would predict that the time spent in the U.S. to accumulate or transfer human capital post-immigration may also correlate with earnings. While Barringer, Takeuchi, and Xenos (1990) found the assimilation hypothesis unsupported given the lack of earning parity between Asians and whites, other research have found limited parity for some subgroups of Asian Americans (Chiswick, 1984; Zeng and Xie, 2004; Takei, Sakamoto, and Kuo 2014). This suggests that years spent in the U.S. remains a variable of interest. In terms of occupations and industries, Sakamoto, Goyette, and Kim (2009) raise concerns about overspecification as well as endogeneity. As an additional specification, and as motivated by literature in the screening theory of education, it could be of interest to examine nonlinear or non-constant returns to education (Layard and Psacharopoulos 1974; Stiglitz 1975).

For the primary analysis, I elect to use the estimating equation:

$$\begin{aligned}\ln(wage_i) = \beta_0 + \beta_1 educ_i + \beta_2 exper_i + \beta_3 exper_i^2 + \beta_4 female_i \\ + \beta_5 female_i \times educ_i + \beta_6 female_i \times exper_i + \beta_7 female_i \times exper_i^2 + \epsilon_i\end{aligned} \tag{2}$$

to account for the gender wage differential within subsamples. Furthermore, to control for time effects, the regression to run will be on the equation:

$$\begin{aligned}\ln(wage_i) = \beta_0 + \beta_1 educ_i + \beta_2 exper_i + \beta_3 exper_i^2 + \beta_4 female_i \\ + \beta_5 female_i \times educ_i + \beta_6 female_i \times exper_i + \beta_7 female_i \times exper_i^2 + \delta year_i + \epsilon_i\end{aligned} \tag{3}$$

where *year* is a categorical variable for Census year (or equivalently indicators for each year). And for robustness checks, I first test *yearsInUS*, which records the number of years that a foreign-born individual has spent in the United States. To expand on the previous description, Zeng and Xie (2004) for instance concluded that among Asian Americans, only the foreign-educated experience an earning disadvantage. However, this conclusion is impacted due to the data restriction to male workers. On the other hand, Kim and Zhao (2014) provide evidence that Asian American women are not advantaged compared to whites, though heterogeneity exists based on immigration status. So, I include *yearsInUS* as a useful control for immigration status, and it also provides insight into the change in wages associated with assimilation. Then, I test for nonconstant returns to education. I allow the returns to schooling to vary across different ranges of education (i.e., for 0-6 years, 7-12 years, 13-16 years, etc.) represented by indicator variables. The screening theory of education would imply discrete effects at each stage where a certificate or degree is conferred. This method is motivated by the short paper Hungerford and Solon (1987) demonstrating the potential importance to consider sheepskin effects, or at least nonconstant returns to education.

Hypotheses

My hypotheses are the following:

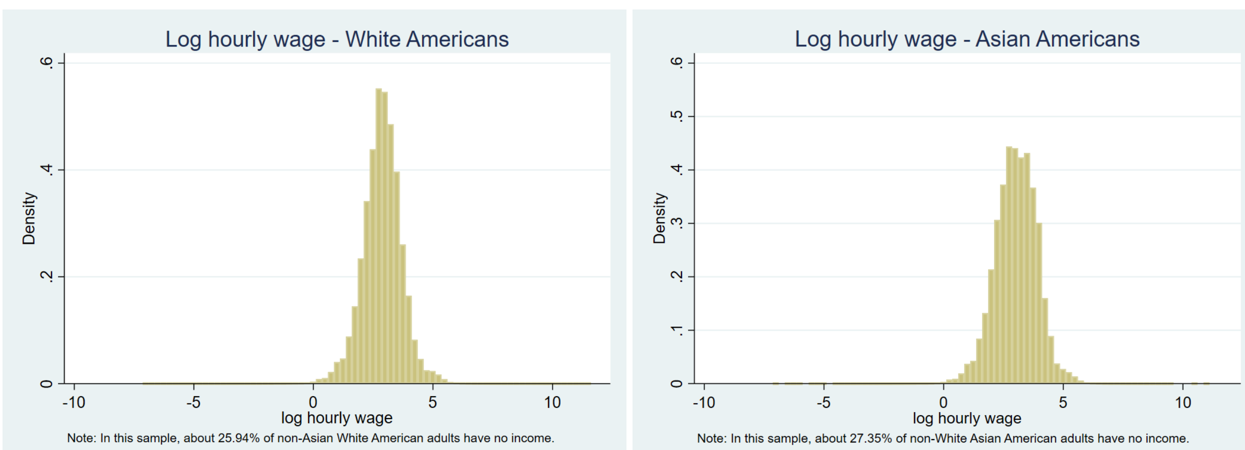
1. *Asian Americans have lower returns to education than whites.*

2. *There are statistically and economically significant differences between the returns to education of Asian subgroups.*

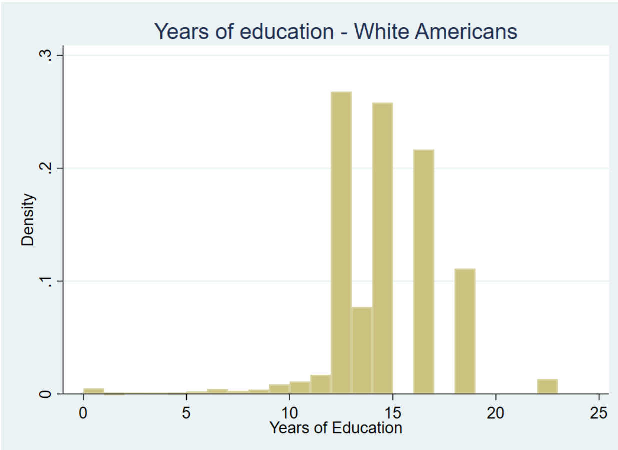
3. *There is more within-group heterogeneity of returns to education in Asian subgroups than in whites.*

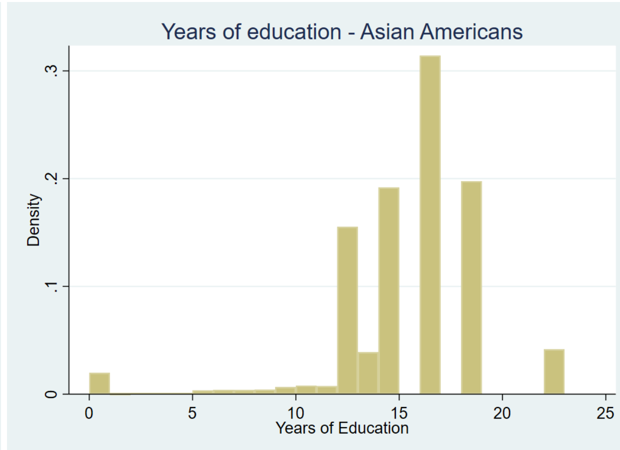
Results

Below, I plot the log hourly wage for white Americans ($n = 16,670,311$) and Asian Americans ($n = 1,128,748$). In terms of spread, the Asian American distribution has a slightly higher standard deviation ($s \approx 0.879$) in contrast to white American's tighter curve ($s \approx 0.817$). In terms of center, the Asian American mean log wage ($\overline{lnwage}_A \approx 3.03$) is about 0.16 higher than that of whites ($\overline{lnwage}_A \approx 2.87$); the p-value of this difference is 0. That is, on average, Asian Americans appear to earn higher (log) wages than their white counterparts, but there is also modestly greater heterogeneity among Asian American's earnings. This motivates the research into potentially higher heterogeneity of returns among Asian Americans.



Next, I repeat the above exercise with the years of education; I restrict to the observations with nonzero wage (i.e. non-missing log wage). Now, the image is more complicated. In this sample, about 55.3% of Asian Americans obtain at least a bachelor's degree (or equivalent) compared to about 34.0% of white Americans. However, the difference narrowly reverses when comparing high school completion: about 94.0% of Asians complete at least high school compared to about 94.3% of whites. Additionally, about 2.0% of Asians have no education on record compared to 0.5% of whites.





To formalize some of these observations, I regress the Mincer model with gender interactions on the full sample, the white subsample, and the Asian subsample of the data. Equivalently to the latter two regressions, I also run a full interacted model with white and Asian indicators. At this point, the only demographic controls I have included are an indicator *female* to control for sex and indicators *year* to address time fixed effects.

Table 1 below shows OLS regression results for the Mincer model on the three groups. The dependent variable in each regression is the natural logarithm of hourly wage. Here, the white and Asian subsamples are exclusive. On the full sample, the estimated coefficients are of the expected magnitude and in the expected directions in line with existing literature. Each additional year of education is predicted with approximately a 10.3% increase in hourly wages; in females, the returns is marginally higher, despite the estimated coefficient on the interaction term being statistically significant. The estimated coefficient on experience is also positive, consistent with human capital theory that additional experience should translate into increased earnings. The negative estimate on the quadratic term of experience is also expected: as age increases, wages should not continue increase linearly; its growth should decline with age. The predicted coefficient on the female indicator underscores the gender wage gap. Controlling for years of education and age, females on average earn approximately 12.8% lower than males. A colloquial description would be "women earn 87 cents on the man's dollar." At this stage, all of the estimated coefficients are much larger than their standard errors, owing in part to the large sample size; each estimate is statistically significant at any of the conventional levels.

Table 1: Mincer model on the full sample and on broad subsamples

	Full Sample	White	Asian	Interacted
Years of education (Educ.)	0.103***	0.105***	0.103***	0.0700***
	(0.000101)	(0.000118)	(0.000409)	(0.000232)
Female × Educ.	0.00607***	0.00778***	-0.00778***	0.0194***
	(0.000155)	(0.000180)	(0.000593)	(0.000351)
White × Educ.				0.0351***
				(0.000259)
White × Female × Educ.				-0.0114***
				(0.000393)
Asian × Educ.				0.0330***
				(0.000461)
Asian × Female × Educ.				-0.0267***
				(0.000672)
Experience	0.0577***	0.0618***	0.0502***	0.0439***
	(0.0000808)	(0.0000892)	(0.000381)	(0.000201)
Female × Experience	-0.0150***	-0.0174***	-0.0140***	-0.00547***
	(0.000112)	(0.000124)	(0.000522)	(0.000277)
White × Experience				0.0180***
				(0.000219)
White × Female × Experience				-0.0118***
				(0.000302)
Asian × Experience				0.00713***
				(0.000408)
Asian × Female × Experience				-0.00704***
				(0.000557)
Experience^2	-0.000847***	-0.000931***	-0.000811***	-0.000591***
	(0.00000178)	(0.00000197)	(0.00000866)	(0.00000431)
Female × Experience^2	0.000219***	0.000265***	0.000260***	0.0000564***
	(0.00000249)	(0.00000276)	(0.0000117)	(0.00000603)
White × Experience^2				-0.000340***
				(0.00000473)
White × Female × Experience^2				0.000206***
				(0.00000661)
Asian × Experience^2				-0.000220***
				(0.00000931)
Asian × Female × Experience^2				0.000170***
				(0.0000126)
Female	-0.128***	-0.151***	0.0840***	-0.307***
	(0.00243)	(0.00281)	(0.0102)	(0.00545)
White				-0.460***
				(0.00407)
White × Female				0.154***
				(0.00611)
Asian				-0.256***
				(0.00767)
Asian × Female				0.382***
				(0.0111)
constant	0.698***	0.650***	0.860***	1.112***
	(0.00176)	(0.00201)	(0.00807)	(0.00371)
R^2	0.258	0.271	0.229	0.265
Root MSE	0.696	0.688	0.760	0.693
Observations	20,977,398	16,670,311	1,128,748	20,977,398

Models include time fixed-effects. The base-group for race is non-Asians and non-Whites. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Also in Table 1, we look at the broad subsamples. To address Hypothesis 1, I analyses the white and Asian subgroups as aggregates. I did so by running regression on split samples; the rightmost column is an equivalent analysis using a fully interacted model. Compared to the Asian males in the sample, white males see larger estimated returns to education. Yet while the difference is statistically significant at the 1% level, it is unclear from the small magnitude whether such a difference is economically meaningful. On the other hand, while for white females the estimated returns to education is slightly higher than white males, Asian females see an estimated returns to education that is slightly lower than Asian males. Both estimates are highly statistically significant, and they have economic meaning as the estimates are in different directions (coincidentally, the estimates have the same magnitude). To further complicate the picture, the estimated gender wage gap (that is, the estimated coefficient on the female indicator) is about -15.1% for white females. Meanwhile, Asian females on average earn about 8.4% higher than Asian males, controlling for education and experience. Though not the primary focus of this research, the difference is worth exploring seeing as historical research often focused on the earnings of men (e.g. Chiswick, 1978, 1983; Hurh and Kim, 1989; Zeng and Xie, 2004). Furthermore, studies that examine gender effects (at least in the binary conception) have identified smaller gender wage gaps in Asian Americans than in whites (Takei, Sakamoto, and Kuo 2014; Wang, Takei, and Sakamoto 2017). For the purpose of this research, these results affirm the importance of controlling for gender effects in returns and earnings.

Result 1: To sum, these results appear to provide support for Hypothesis 1: that statistically, Asian Americans experience lower returns to education than whites. In particular, Asian females experience lower returns compared to their white counterparts.

Next, I explore the potential heterogeneity of returns among Asian Americans by disaggregating the Asian observations into race subgroups. These include the twenty identified Asian countries of origin and an "other" group for the remaining observations. In tables 2 through 5 in the Appendix, I post the regression results for each subgroup in order of the number of observations. Qualitatively, the estimated returns to education vary quite widely across subgroups: Bhutanese, Laotian, Hmong, and Burmese Americans appear to have significantly lower returns to education – less than half that of the aggregate sample; on the other hand, returns also exceed 0.09 for many East Asian and some South Asian subgroups. It might be important to note that these latter groups also tend to be some of the largest demographic subgroups of Asian Americans, which has two implications. First is that, although white-Asian difference is smaller than one might expect under the majority/minority paradigm, Asian minorities indeed appear to see significantly lower returns compared to larger Asian groups. Also, since the subgroups with higher returns also more observations, they essentially inflate the aggregate estimate on the full Asian subsample.

To further explore this latter claim, I ran additional regressions on the full Asian subsample, excluding subgroups one at a time.[1] Then, comparing each Asian subgroups' returns to education with other Asian, the results are striking. Among all 21 categories, only Indian Americans have statistically significantly higher returns to education compared to remaining Asian Americans. Of the remainder, most groups have statistically significantly lower returns to education compared to other Asians. Chinese, Pakistani, Indonesian, Sri Lankan, and Malaysian Americans are exceptions and see higher returns than respective other Asians, although the differences are not statistically significant; Mongolian Americans have slightly lower returns to education than their other Asian counterparts, but the difference is also not statistically significant. So then, there is much nuance behind the estimated returns to education on the aggregate Asian subsample. While the white-Asian difference in returns appears negligible or even favorable for some Asian subgroups, the majority of subgroups experience significantly lower returns compared to the aggregate Asian estimate and thus to the white estimate.

Result 2: To sum, these results appear to provide support for Hypothesis 2: that Asian subgroups in American experience statistically and economically significantly different returns to education. Each group also see varying trends of gender gaps in returns – differing in direction and magnitude.

Finally, I explore the within-heterogeneity hypothesis that Asian subgroups, although orders of magnitude smaller than the white subsample, should have higher heterogeneity in returns to education than whites as an aggregate. To test this hypothesis, I ran quantile regressions for the white subsample, Asian subsample, and Asian subgroups. Specifically, I examined the 20th and 80th percentile or wages for each group, and then I performed t-test on the difference between the two estimates (the 80th percentile estimate less the 20th percentile estimate). I provide t-statistics here for the sake of evaluating statistical significance, but since the number of observations span orders of magnitude across subsamples, they cannot be meaningfully compared with one another;

1. The results are not tabulated but are available in my data analysis script.

I will evaluate economic significance by observing the direction and magnitude of the difference. For white male, the difference is 0.0152 with a t-statistic of 100.2. (As a statistical exercise, I bootstrapped the quantile regression on the white subsample and set the sample size to the same as the Asian subsample. The estimated difference is the same with a smaller t-statistic of 24.89.) This means that at the 20th percentile of log wage, whites earn about 1.5 percentage points lower for each additional year of education compared to at the 80th percentile. For white females, the difference in returns is 0.00051 with a t-statistic of 2.96. Although statistically significant, it is unclear whether returns of white females differ meaningfully between the 20th and the 80th percentiles. Asian males have a difference of -0.00924 with a t-statistic of -15.90. So, Asian males at the 80th percentile earn about 0.92 percentage point lower for each additional year of education compared to at the 20th percentile. This difference is statistically and somewhat economically significant. For Asian females, returns at the 80th percentile is also lower than at the 20th percentile, by 0.00562. The estimate is statistically significant and somewhat economically meaningful. It is notable that the estimated differences are in opposite directions for whites versus Asian Americans. To address hypothesis 3, I will describe within-group heterogeneity among Asian subgroups.

Due the large number of subgroups, I will describe the five largest groups in quantitative detail; I will also make note of any qualitative patterns in the smaller subgroups. The largest subgroup is Chinese Americans. For this group, male returns to education at the 80th percentile is 2.36 percentage points lower than at the 20th percentile. The t-statistic of this estimate is -24.04, so it is highly statistically significant. For Chinese American females, returns at the 80th percentile is 2.10 percentage points lower than at the 20th percentile. This estimate is also highly significant with a t-statistic of -19.33. Next, for Indian American males, returns to education at the 80th percentile is 2.54 percentage points lower than at the 20th percentile. The t-statistic of this estimate is -18.50, so it is highly statistically significant. For Indian American females, the estimated returns to education at the 80th percentile is 1.41 percentage points lower than at the 20th percentile. This estimate is also highly statistically significant with a t-statistic of -8.30. The results are contrasted by the following three groups. For Filipino Americans, male returns to education at the 80th percentile is 1.51 percentage points higher than at the 20th percentile. The t-statistic of this estimate is 7.55, so it is highly statistically significant. For Filipino American females, returns at the 80th percentile is higher than at the 20th percentile by 1.47 percentage points. The estimate has a t-statistic of 7.99.

To reiterate, these results contrast with that of the two previous groups; lower-earning Filipino Americans have lower returns to education than higher-earning Filipino Americans, whereas lower-earning Chinese and Indian Americans have higher returns than their higher-earning counterparts. Next, Vietnamese American males at the 80th and 20th percentiles of earnings have a difference in returns to education of only 0.06 percentage points, which has neither economic nor statistical significance, with a t-statistic of 0.27. Vietnamese American females at the 80th percentile have higher returns than at the 20th percentile by 1.60 percentage points; the estimate has a t-statistic of 7.34, so it is both statistically and economically significant. Lastly of the five subgroups, Korean Americans fare similarly to Filipino Americans: at the 80th percentile, they see 1.10 percentage points higher returns to education than at the 20th percentile of earnings. This estimated difference has a t-statistic of 4.60, so it is also highly statistically significant. The estimated difference for Korean American females is neither statistically nor economically significant. The majority of the remaining groups either have this positive relationship between earnings percentile and returns to education, or they have statistical nulls. (The only exception being Taiwanese Americans) So, I observe a familiar pattern as I did in result 2. Just as how the Asian average returns to education appeared to be driven by the high returns of Indian American, the direction of the heterogeneity in returns between Asian Americans appear to be driven by heterogeneity within the two largest Asian subgroups.

Result 3: To sum briefly, the results provide partial support for hypothesis 3 as stated. While Asian American subgroups experience statistically and economically significant within-heterogeneity, the variations are not all of the hypothesized magnitude nor all in the same direction. While whites at the 20th percentile of log wage see lower returns to education than at the 80th percentile, the direction is reversed for the Asian aggregate. Within Asian subgroups, many groups see positive differences, a few see negative differences, and the rest have statistically insignificant differences. For some subgroups, such as Chinese and Indian Americans, we do indeed see greater within-group heterogeneity than in whites as hypothesized.

I summarize again and review findings as follows: The first set of regressions I performed on the full sample, whites, and Asian Americans provide statistical evidence for Hypothesis 1. The average returns to education for Asian Americans is arguably not economically significantly lower than that of whites. Still, the analysis I performed for the Asian subgroups highlight differences in returns to education within Asian Americans and compared to whites. Together, these results provide some support for Hypothesis 1, since certain subgroups of Asian Americans appear to have significantly lower returns to education than whites. In addition, these results also support Hypothesis 2, as the intergroup difference in estimated returns to education is statistically and economically significant. And last, the results provide partial support for Hypothesis 3: some subgroups have larger within-group discrepancies in returns to education than whites, but the relationship between returns and earnings was unexpected.

Robustness Checks

Due to data and time constraints, I primarily focus my robustness checks on the largest subgroups. At the same time, the smallest groups are also not large enough for statistical analysis. Further, the robustness analysis for hypotheses 2 and 3 become unwieldy when using the categorical variable for education.

Immigration

An important control to examine is immigration. The data provides information on the number of years immigrants have spent in the U.S.; for U.S.-born individuals only (at least in this data set), the variable take value 0. In this sample, about 9.2% of whites are first-generation immigrants. This is compared to 75.9% of first-generation Asian immigrants. Among immigrants, the distributions are similar with white immigrants having spent on average some two years longer in the U.S. than Asians. Yet, the difference in proportions warrants careful treatment of immigrant effects on human capital accumulation. To capture the marginal effect of years spent in the U.S. on log wages, I would need to assign a value for U.S.-born individuals. The logical assignment would be their age or their potential experience; however, including this variable as an additional covariate would essentially double-count the experience for immigrants. Two viable means of implementation are as follows: 1) I could assign age to yearsInUS for U.S.-born individuals, and run regressions on

$$\begin{aligned}\ln(wage_i) = \beta_0 + \beta_1 educ_i + \beta_2 yearsInUS_i + \beta_3 yearsInUS_i^2 + \beta_4 female_i + \beta_5 female_i \times educ_i \\ + \beta_6 female_i \times yearsInUS_i + \beta_7 female_i \times yearsInUS_i^2 + \delta year_i + \epsilon_i \qquad (4)\end{aligned}$$

for subsamples of choice, or 2) I could forgo examining the marginal effects of domestic experience and instead repeat the analyses in this paper while further splitting each subsample into immigrant and non-immigrant groups. For the sake of statistical power, it might not be possible to perform such analysis for each Asian subgroup, as the non-immigrant group for the smaller subgroups would run too small and violate normality assumptions. For this section, I performed the former and compare results with the original analysis. Regression tables can be found in the appendix.

Notably, the white-Asian difference in returns to education reverses direction compared to the original Result 1. Now, Asian Americans have statistically significantly higher returns to education compared to their white counterparts. This difference of about 1.3 percentage points change in wages might also be considered somewhat economically significant. Interestingly, while the gender difference in returns to education maintains the same direction, Asian females now see a slight overall wage discount as opposed to the small wage premium prior.

On the subgroups, result 2 is not significantly changed. However, while many groups see a decline in estimated returns to education (as we would expect given the lower estimate on the aggregate Asian subsample), some groups see increases and some see significant declines. For instance, the estimated returns for Indian Americans is up slightly from 0.117 to 0.121, although the gender gap in return grows from -0.009 to -0.015 (that is, Indian females' returns are unchanged between these two specifications). On the flip side, in this specification, the estimated returns for Vietnamese Americans falls sharply from 0.0801 to 0.0577. The gender gap in return also grows slightly from -0.000432 to -0.000396. And whereas Vietnamese females appear to enjoy a small wage premium of 3.4% in the previous specification, they now appear to experience a moderate wage discount by about 11.6%.

Testing result 3, the conclusion still holds, although the trends deviate from the original analysis. For whites, heterogeneity is still higher than any of the Asian subgroups. In particular, higher earners still see higher returns than lower earners. And at both quantiles, white females see higher returns than white males. For Chinese and Indian Americans, higher earners still see similarly lower returns to education than lower earners. As before, these estimates are highly statistically significant. Filipino Americans at the 80th percentile of earnings see similarly higher returns to education than at the 20th percentile, but this estimated difference is now statistically insignificant with a t-statistic of 1.10. The estimated difference remains not particularly economically significant for Vietnamese Americans, at 0.008, even though the estimate is now statistically significant with a t-statistic of 4.83. Lastly, for Korean Americans, the estimated difference is now -0.010 with a t-statistic of -4.09. This is a reversal compared to the previously positive estimate of about 0.011. Of the remaining subgroups, there are additional groups with negative estimated differences. Returns to education for Taiwanese Americans at the 80th percentile is about 0.0332 lower than at the 20th percentile. This estimate is statistically significant with a t-statistic of -4.11. Returns to education for Malaysian Americans at the 80th percentile is about 0.0364 lower than at the 20th percentile. The magnitude is significant; the t-statistic of this estimate is -2.02, which is statistically significant at the 5% level. Other groups have either positive estimated differences or statistically insignificant estimates. Still, the additional groups with lower returns at a higher earnings percentile differs from result 3 in the original specification, where only the two largest groups have statistically significant negative differences.

However, this specification has a major flaw. By using only years spent in the U.S. to measure labor market experience, the estimating equation nullifies all experience gathered abroad. This is an extreme assumption: even as the quality of education and labor experience vary across countries, it would be naïve to claim that foreign accumulation of human capital does not contribute at all to earnings. So I proceed with the technique outlined in 2) on the broad subsamples of whites and Asian Americans.

The specification in Table 2 is similar to that of Zeng and Xie (2004). Here, the model labels FD, FI, WD, WI, AD, and AI correspond to, respectively, regressions on full domestic subsample, full immigrant subsample, white domestic subsample, white immigrant subsample, Asian domestic subsample, and Asian immigrant subsample. In their research, the authors divide the immigrant group further into those educated abroad and those educated in the U.S.; their research also examines nonconstant returns to education. In contrast, my analysis splits subsamples by immigration status as opposed to place of education; it contains the additional group of foreign-born whites (WI); and it examines gender effects. Overall, my results differ slightly from those of Zeng and Xie. By controlling for birthplace, U.S.-born Asians males have the highest estimated returns to education, followed by U.S.-born Asian females, U.S.-born white females, U.S.-born white males, immigrant Asian males, immigrant Asian females, immigrant white females, and lastly immigrant white males. So even broadly, the ordering is U.S.-born Asians, U.S.-born whites, immigrant

Table 2: Mincer model on broad subsamples - split by immigrant status

	FD	FI	WD	WI	AD	AI
educ	0.117***	0.0834***	0.115***	0.0825***	0.127***	0.0985***
	(0.000138)	(0.000157)	(0.000145)	(0.000221)	(0.00124)	(0.000437)
female × educ	0.00478***	0.00302***	0.00655***	0.00195***	-0.00270	-0.00861***
	(0.000198)	(0.000257)	(0.000211)	(0.000364)	(0.00177)	(0.000632)
exper	0.0623***	0.0378***	0.0650***	0.0411***	0.0722***	0.0415***
	(0.0000880)	(0.000201)	(0.0000938)	(0.000271)	(0.000766)	(0.000457)
female × exper	-0.0165***	-0.0121***	-0.0185***	-0.0151***	-0.00498***	-0.0140***
	(0.000121)	(0.000291)	(0.000130)	(0.000404)	(0.00109)	(0.000625)
exper^2	-0.000954***	-0.000462***	-0.00101***	-0.000491***	-0.00122***	-0.000668***
	(0.00000197)	(0.00000397)	(0.00000209)	(0.00000535)	(0.0000197)	(0.00000986)
female × exper^2	0.000252***	0.000170***	0.000294***	0.000204***	0.00000639	0.000272***
	(0.00000271)	(0.00000583)	(0.00000289)	(0.00000810)	(0.0000281)	(0.0000133)
female	-0.107***	-0.0869***	-0.132***	-0.0646***	0.00848	0.0745***
	(0.00301)	(0.00487)	(0.00322)	(0.00674)	(0.0275)	(0.0118)
constant	0.474***	1.113***	0.493***	1.088***	0.368***	1.009***
	(0.00221)	(0.00372)	(0.00234)	(0.00515)	(0.0202)	(0.00934)
R^2	0.271	0.224	0.279	0.231	0.298	0.216
Root MSE	0.689	0.713	0.684	0.703	0.734	0.763
Observations	17,753,828	3,223,570	15,119,596	1,550,715	259,796	868,952

Models include time fixed-effects. The base-group for race is non-Asians and non-Whites. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Asians, and then immigrant whites; this differs from the ordering of the estimates from the analysis by Zeng and Xie using place of education. These results are interesting: separately, Asian U.S. nationals have higher returns than white U.S. nationals; Asian immigrants also have higher returns than white immigrants. However, as we saw earlier, on the aggregate level, given the proportion of Asian Americans being immigrants and white Americans being U.S.-born, the weighted average results in slightly lower returns to education for Asian Americans. Additionally, this robustness analysis also shows that both domestic and immigrant Asian females experience lower returns to education than corresponding Asian males, even as white females overall experience a premium in returns over white males. I only apply this specification to hypothesis 1, since the subgroups are potentially too small for further subdivisions.

Nonconstant Returns to Education

Next, I examine potential nonconstant returns to education by using indicators for highest degree completed in place of the continuous variable for years of education. On result 1, the new results are extremely significant. Whereas the original analysis found a statistically significant but small discount in Asians' returns to education, here the picture is much more nuanced. Compared to the reference group of males with less than high school completion, white male high school graduates experience higher returns to education on log wage by about 0.284. (Since the coefficient is larger, approximating the effect as a percent is less accurate; the effect of high school completion on wages, relative to less than high school, is slightly higher than 32%.) This is highly statistically significant and the estimate is slightly greater than but close to in the full sample. Asian American male high school graduates, on the other hand, have an estimated coefficient of 0.157. This effect considerably smaller than for males in the full sample or for white males. The estimate is also highly statistically significant. Female high school graduates appear to experience negligible discounts in returns to education. In the full sample, returns to education for females high school graduates is 0.00925 lower than males; the estimate for white females is statistically null. Both estimates are minuscule in magnitude. In the mean time, the returns for Asian American female high school graduates is 0.0240 lower than their male counterparts. The gender gap in returns for Asian female high school graduates is small in magnitude but much larger than in whites. To summarize the remainder of the coefficients, the completion of higher degrees are associated with (nonlinearly) higher returns. In particular, Asian males appear to "catch up" to and eventually exceed the returns of whites and the full sample for post-graduate degree completion. The gender gap in returns appears to grow at the same time. With the exception of the interaction term between female and two-year degree completion (whose estimated coefficient is statistically null), the gender gap in returns appears to widen as educational attainment increases. A similar trend is found in females in the full sample, although the gender gap in returns remains small. The same is not true for white females, for whom the gap is in fact slightly positive for two-year degree completion. Overall, the returns of white females appear comparable to white males.

On result 2, the robustness analysis with nonconstant returns to education also provide important nuance to previous conclusions. For instance, the effect of higher degree completion is greater for Chinese American males than white males. The exception is high school completion, for which the Chinese male estimate is statistically lower than the white male estimate, but the difference in magnitude is relatively small (0.074). On the other hand, Chinese American females experience larger penalties to their returns to education compared to Chinese American males than the gender gap in whites and in the Asian aggregate. Next, whereas Indian Americans had the highest returns to education using the constant returns specification, returns for males in the nonconstant specification are lower than average at every level of degree completion. In particular, each estimate is lower than that for Chinese males; for reference, the constant returns estimate was higher for Indian males. Each estimate is also lower than or comparable to estimates for the Asian aggregate. The gender gaps in returns vary from statistically null at lower levels to significant discounts for Indian American females at higher education attainments. Notably, the explained portions of the Indian gender gap in wages is not statistically significant in this specification compared to the moderately positive estimate in the original analysis. Next, estimates for Filipino male returns are significantly lower than the Chinese estimates; while the constant returns estimate for Filipino males is also lower than that of Chinese males, the magnitude of the difference is not as pronounced as the discrepancies at each level in the discrete estimates. The female estimates are in line with the constant returns estimates: each estimate on the interaction term between female and education degree is either statistically null or positive. Interestingly, the explained gender gap in wages for Filipinos is also statistically null whereas the original estimate was negative. The analysis for the remaining groups follow similarly. Notable is the nonconstant estimated returns: converting each education attainment indicator into its equivalent number of years, the differences in returns does not appear linear but rather exhibit initially increasing marginal returns and later decreasing marginal returns.

In light of the negative association between earnings percentile and average returns to education in Asian Americans, the robustness analysis for result 3 provides important nuance to the previous conclusion. For whites, lower degrees are associated with higher returns for lower earners; higher degrees are associated with higher returns for higher earners. At the 20th percentile of earnings, the gender gap in returns increases from slightly negative to a premium over males as education level rises. At the 80th percentile, however, the gender gap in returns positive for lower degrees but grows increasingly negative for higher degrees. For Chinese American males, the returns to education is slightly higher at the 80th percentile of earnings than at the 20th percentile at every category except post-graduate degree. Then, the negative estimate on the continuous education covariate in the previous analysis implies a large proportion of Chinese American males with professional or graduate degrees. At both quantiles, the gender gap in returns appears to increase with education level (penalizing females), although the gap is smaller on average at the 80th percentile of earnings. A similar phenomenon in observed in Indian American males. Returns to education is marginally higher for high school graduates at the 20th percentile than at the 80th percentile; it is significantly higher for post-graduate degree holders. For university degrees, returns are higher at the 80th percentile. At the 20th percentile, Indian American females experience increasing discrepancies in returns; at the 80th percentile, however, there is no distinct association between Indian Americans' gender gap in returns and level of education. For Filipino American males, returns is lower at the 20th percentile than at the 80th for lower levels of education attainment; for four-year degree completion and higher, returns is higher at the 80th percentile of earnings. Although less pronounced, this trend is similar to the one in whites. Filipino American females at the 20th percentile appear to experience a relatively consistent discount in returns across education levels; at the 80th percentile, on the other hand, Filipino American females appear to experience a mild premium in returns. Trends for the remaining groups vary, but the analysis again follows similarly. With regards to the original analysis, it is of note that the negative difference on the Asian aggregate is most likely driven by the estimated coefficient on post-graduate degrees for Chinese and Indian Americans.

Multiple Races or Ethnicity

One additional consideration is to examine the observations who identify as both white and Asian, since the previous analysis omitted such observations. I perform this check only for result 1, since the data set does not appear to count mixed individuals as belonging to any Asian subgroup. The returns to education for males this group is 0.107, and the estimate for females is higher by 0.006. Both of these estimates are statistically significant, although the gender gap in returns is minuscule in magnitude.

Discussion

The main findings of this research corroborate existing literature and provide important nuance to the labor market outcomes of Asian Americans. My primary analysis finds that Asian American males, on average, have statistically significantly lower but economically comparable returns to education compared to white males. On the other hand, the gap is significant for females: white females have slightly higher returns than white males, and Asian females slightly lower than Asian males, leading a significant difference in returns between white and Asian females. This latter result is important to include, since female returns frequently have not been documented alongside analyses of male returns. This result, however, is not robust controlling for immigration: either by using years spent in the U.S. as a proxy for domestic labor market experience, or via disaggregation over immigrant status, both native and immigrant Asian American males experience higher returns than their white male counterparts. The gender gap in returns persist and white females see higher returns than Asian females. These results could be reconciled given the fact that more than 75% of Asian Americans are first-generation immigrants compared to less than 10% of whites. Similarly, accounting for nonconstant returns to education, Asian American males have lower returns to degree completion than whites, except for post-graduate degrees. The gender gap is negative and larger in Asians except for two-year degree completion, for which the Asian estimate is statistically null and the white estimate is positive but small. Connecting the result with the main analysis, this would imply that Asians are concentrated in higher degrees, while whites' concentration in lower degrees yields a higher weighted average (since the white-Asian difference is greater for these education levels).

The research also highlights significant heterogeneity among Asian subgroups. Though the magnitude varies, a high degree of heterogeneity persists under various specifications. In particular, the analysis throughout the paper demonstrates that Asian subgroups differ dramatically in size and in socioeconomic conditions. As a result, average estimated effects often reflect the conditions of the largest groups but are not representative for most other subgroups. Despite the average returns being only marginally lower on average for Asian Americans, many Asian subgroups see returns to education that are a mere fraction of the average returns. These groups also tend to be smaller in size, which may raise concerns about a vicious cycle between inefficient allocation of resources and lower than average returns on wages. At the same time, the mechanism is not immediately clear. The majority/minority paradigm would suggest that smaller groups fare worse socioeconomically, which in this case would predict lower returns. I am not able to confidently reach this conclusion. Indonesian Americans are among the smallest subgroups, but they have some of the highest returns – both male and female. Among the five smallest subgroups, three also have returns comparable to the average. On the other hand, Cambodian and Laotian Americans are the 8th and 10th largest subgroups in this sample, yet their estimated returns to education are less than one-half and less than one-third of the average, respectively. As an alternative to the majority/minority paradigm, it could be that refugees and their posterity may experience lower returns. In such a case, Asian subgroups with significant refugee populations would see lower than expected returns given the subgroup's size. This would explain the lower returns for many subgroups, each having had influxes of refugees fleeing to the United States in the last century. However, this would not explain the higher than expected returns of other subgroups; nor does it explain other fluctuations in the returns of subgroups that do not have significant refugee populations.

Lastly, perhaps the most surprising result from the research, is the unexpected association between earnings percentile and returns to education that I stumbled upon in an attempt to examine heterogeneity. The wording of hypothesis 3 that there would be greater heterogeneity of returns within subgroups than within whites implicitly assumes that heterogeneity would occur in the same direction. And that it remained to compare the size of the effect of earnings percentile and returns to education. This was evidently not the case. The research finds that lower-earning whites have lower returns than higher earners. By contrast, lower-earning Asian Americans reflect higher returns than their higher-earning counterparts. The magnitude of the difference is greater in white males than Asian males, and it is greater in Asian females than in white females. While this would seem to not provide support for hypothesis 3, several subgroups exhibit comparable or greater heterogeneity than whites, albeit in differing directions. However, the interpretation for this supporting evidence is unclear; it might not be appropriate to simply conclude greater heterogeneity of returns if the directions are opposite. And even then, the t-statistic of the estimate difference between quantiles is much larger for white males than for males any Asian subgroup; the t-statistic for the white female estimated difference, however, is smaller than the majority of subgroups. With respect to the reference group, we could conclude that lower paying jobs reflect additional rewards for some Asian Americans given their education level (specifically Chinese, Indian, and Taiwanese Americans); on the other hand, higher paying jobs appear to discount the education credentials of these Asian Americans, male and female alike. For the remaining subgroups (that is, the overwhelming majority of groups as well as a moderate majority of the population), education tends to be rewarded in such a way where lower earnings correspond to lower returns to education.

Some limitations to the data and my analysis are as follows. For one, the analysis omits those with no income by nature of the logarithm function. A potential means to address the issue could be to add an arbitrary constant c to wages prior to the logarithmic transformation. However, this transformation would impact the interpretation of the estimate coefficient. Future studies may wish to examine this subpopulation using metrics besides earnings. Next, there is no available data to directly control for foreign versus U.S. education while simultaneously controlling for years spent in the U.S. labor market – it is not logistically possible. I will only control for years spent in the U.S. ($yearsInUS$). That is, it is not possible to correctly attribute immigration effect to place of education as opposed to place of labor market experience. My analysis also does not account for location and cost of living adjustments. Endogeneity of location is the concern that led to this omission (Wang, Takei, and Sakamoto 2017). That is, location selection might not be random but could in fact have economic incentives. Wang and collaborators address this issue both by estimating wages using two-stage least squares and by adjusting for cost of living. My models also do not directly account for inflation-induced wage increases (except with time fixed-effects).

The implications for this research are many. The findings from this project are not entirely novel: using recent data, I combined the approaches of previous studies to generate an analysis on the returns to education for Asian Americans. By analyzing the entire Asian American group and comparing important subgroups (i.e., by ethnic origins and by sex) side-by-side, my research puts into perspective discrepancies in returns to education between and within subgroups as well as compared to whites. Indeed on average, it appears that Asian Americans are quite well off, earning comparably to white Americans. However, the great heterogeneity, as demonstrated in this research, put into question the motivation and justification for describing Asian Americans as a self-similar, largely uniform group. In practical settings, focusing on the average outperformance overlooks the large number of underprivileged subgroups. As social programs and policy tend to target underperforming groups to efficiently allocate resources, Asian Americans as an aggregate may be omitted (Hurh and Kim 1989). So, while such targeting can quickly narrow down potential eligibility, it evidently would omit subgroups whose needs are masked by the well-being of their parent group. Future research examining the determinants of earnings and returns could benefit from focusing on a handful of subgroups, or even one. The consideration is that even for one subgroup, the importance of factors such as sex and immigration status demands large samples; practically, analysis of results can easily become unmanageable. On the other hand, studies on Asian Americans should exercise additional caution to specify the exact subset of interest. In light of my research, by omitting particular subgroups by sex, ethnicity, or immigration status, one cannot responsibly conclude that such results should describe the broader Asian American population. In general, future studies may wish to consider the effects of marriage and parents' education. These variables are known to correlate with earnings, and it would be interesting to observe how the conclusions of this research might vary conditional on additional factors.

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Appendix

Table 3: Mincer model on Asian subgroups

	Chinese	Indian	Filipino	Vietnamese	Korean
educ	0.104***	0.117***	0.0922***	0.0801***	0.0864***
	(0.000700)	(0.00110)	(0.00143)	(0.00129)	(0.00190)
female × educ	-0.00577***	-0.00904***	0.0103***	-0.000396	0.0102***
	(0.00105)	(0.00169)	(0.00196)	(0.00178)	(0.00272)
exper	0.0449***	0.0650***	0.0535***	0.0400***	0.0635***
	(0.000731)	(0.000933)	(0.000899)	(0.00109)	(0.00183)
female × exper	-0.00880***	-0.0225***	-0.0113***	-0.0187***	-0.0234***
	(0.000999)	(0.00139)	(0.00123)	(0.00148)	(0.00224)
$exper^2$	-0.000675***	-0.00124***	-0.000914***	-0.000566***	-0.00117***
	(0.0000165)	(0.0000229)	(0.0000198)	(0.0000226)	(0.0000453)
female × $exper^2$	0.000141***	0.000466***	0.000217***	0.000308***	0.000470***
	(0.0000225)	(0.0000334)	(0.0000267)	(0.0000307)	(0.0000539)
female	0.0664***	0.0767**	-0.119***	0.0336	-0.0925**
	(0.0191)	(0.0303)	(0.0308)	(0.0303)	(0.0459)
constant	0.857***	0.665***	0.949***	1.173***	0.982***
	(0.0149)	(0.0219)	(0.0236)	(0.0242)	(0.0374)
R^2	0.263	0.259	0.171	0.176	0.190
Root MSE	0.771	0.766	0.701	0.749	0.796
Observations	264,372	219,984	211,352	108,905	89,279

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Mincer model on Asian subgroups (continued)

	Japanese	Pakistani	Cambodian	Thai	Laotian
educ	0.0922***	0.106***	0.0524***	0.0744***	0.0314***
	(0.00240)	(0.00314)	(0.00313)	(0.00394)	(0.00337)
female × educ	0.0102***	-0.0141***	-0.0000823	-0.00838*	0.0155***
	(0.00334)	(0.00544)	(0.00426)	(0.00499)	(0.00471)
exper	0.0722***	0.0496***	0.0392***	0.0426***	0.0373***
	(0.00181)	(0.00256)	(0.00248)	(0.00383)	(0.00261)
female × exper	-0.0257***	-0.0130***	-0.0190***	-0.0225***	-0.0117***
	(0.00242)	(0.00407)	(0.00346)	(0.00472)	(0.00376)
exper^2	-0.00118***	-0.000847***	-0.000518***	-0.000712***	-0.000529***
	(0.0000387)	(0.0000596)	(0.0000522)	(0.0000832)	(0.0000528)
female × exper^2	0.000464***	0.000223**	0.000298***	0.000514***	0.000213***
	(0.0000514)	(0.0000974)	(0.0000729)	(0.0001000)	(0.0000766)
female	-0.131**	0.158*	0.0718	0.111	-0.201***
	(0.0566)	(0.0878)	(0.0655)	(0.0872)	(0.0731)
constant	0.857***	0.690***	1.518***	1.219***	1.769***
	(0.0431)	(0.0604)	(0.0532)	(0.0754)	(0.0550)
R^2	0.219	0.206	0.140	0.135	0.118
Root MSE	0.727	0.815	0.667	0.751	0.626
Observations	55,322	20,093	14,990	12,876	12,353

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Mincer model on Asian subgroups (continued)

	Hmong	Bangladeshi	Taiwanese	Indonesian	Nepalese
educ	0.0476***	0.0900***	0.0792***	0.114***	0.0743***
	(0.00349)	(0.00437)	(0.00702)	(0.00752)	(0.00437)
female × educ	0.00506	-0.00928	0.0105	-0.0265**	-0.0281***
	(0.00487)	(0.00737)	(0.00916)	(0.0107)	(0.00633)
exper	0.0495***	0.0271***	0.0762***	0.0338***	0.0271***
	(0.00261)	(0.00397)	(0.00777)	(0.00581)	(0.00477)
female × exper	-0.0114***	-0.00479	-0.0182**	-0.00942	-0.00717
	(0.00381)	(0.00668)	(0.00903)	(0.00778)	(0.00755)
exper^2	-0.000701***	-0.000404***	-0.00139***	-0.000355***	-0.000290***
	(0.0000582)	(0.0000921)	(0.000195)	(0.000132)	(0.000101)
female × exper^2	0.000221***	0.0000665	0.000332	0.0000322	0.0000704
	(0.0000824)	(0.000167)	(0.000223)	(0.000175)	(0.000171)
female	0.00733	0.0344	-0.198	0.386**	0.344***
	(0.0768)	(0.122)	(0.183)	(0.178)	(0.116)
constant	1.433***	0.878***	1.249***	0.607***	1.311***
	(0.0636)	(0.0970)	(0.151)	(0.136)	(0.0877)
R^2	0.157	0.166	0.232	0.191	0.173
Root MSE	0.649	0.771	0.776	0.727	0.719
Observations	11,976	7,449	7,297	5,039	4,562

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Mincer model on Asian subgroups (continued)

	Burmese	Sri Lankan	Malaysian	Bhutanese	Mongolian	Other Asian
educ	0.0466***	0.104***	0.103***	0.0313***	0.0923***	0.0722***
	(0.00328)	(0.00727)	(0.0123)	(0.00972)	(0.0147)	(0.00458)
female × educ	0.00791	0.00930	-0.0150	0.0152	-0.0479*	-0.0106*
	(0.00514)	(0.0120)	(0.0176)	(0.0156)	(0.0249)	(0.00629)
exper	0.0347***	0.0588***	0.0734***	0.0358***	0.0345**	0.0437***
	(0.00459)	(0.00625)	(0.0121)	(0.00869)	(0.0152)	(0.00437)
female × exper	0.000505	-0.00966	0.00221	-0.0190	-0.0143	-0.00611
	(0.00767)	(0.00915)	(0.0165)	(0.0174)	(0.0238)	(0.00618)
exper^2	-0.000395***	-0.000993***	-0.00123***	-0.000574***	-0.000506	-0.000603***
	(0.0000938)	(0.000140)	(0.000298)	(0.000171)	(0.000368)	(0.0000979)
female × exper^2	0.0000107	0.000179	-0.000189	0.000566*	0.0000982	0.0000813
	(0.000161)	(0.000205)	(0.000406)	(0.000318)	(0.000560)	(0.000136)
female	-0.193*	-0.251	0.0837	-0.0880	0.829*	0.125
	(0.108)	(0.212)	(0.306)	(0.288)	(0.425)	(0.110)
constant	1.625***	0.690***	0.598**	1.720***	0.789***	1.086***
	(0.0771)	(0.157)	(0.260)	(0.184)	(0.271)	(0.136)
R^2	0.165	0.252	0.286	0.107	0.125	0.182
Root MSE	0.654	0.756	0.769	0.641	0.761	0.790
Observations	3,920	3,393	1,348	630	553	6,542

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Mincer model on the full sample and on broad subsamples - controlling for immigration

	Full Sample	White	Asian	Interacted
Years of education (Educ.)	0.0847***	0.0856***	0.0980***	0.0482***
	(0.000108)	(0.000127)	(0.000398)	(0.000239)
Female × Educ.	0.0101***	0.0129***	-0.0130***	0.0232***
	(0.000162)	(0.000189)	(0.000556)	(0.000358)
White × Educ.				0.0369***
				(0.000270)
White × Female × Educ.				-0.0101***
				(0.000403)
Asian × Educ.				0.0495***
				(0.000462)
Asian × Female × Educ.				-0.0358***
				(0.000653)
Years in U.S.	0.0121***	0.0241***	0.00591***	0.00631***
	(0.0000861)	(0.000116)	(0.000302)	(0.000184)
Female × Years in U.S.	0.00315***	0.00343***	0.00811***	0.00363***
	(0.000127)	(0.000171)	(0.000429)	(0.000271)
White × Years in U.S.				0.0179***
				(0.000216)
White × Female × Years in U.S.				-0.000182
				(0.000318)
Asian × Years in U.S.				-0.00295***
				(0.000341)
Asian × Female × Years in U.S.				0.00474***
				(0.000488)
Years in U.S.^{2}	0.0000274***	-0.000108***	0.0000600***	0.0000588***
	(0.00000115)	(0.00000148)	(0.00000555)	(0.00000270)
Female × Years in U.S.^{2}	-0.0000845***	-0.0000858***	-0.000130***	-0.0000613***
	(0.00000167)	(0.00000215)	(0.00000781)	(0.00000385)
White × Years in U.S.^{2}				-0.000166***
				(0.00000307)
White × Female × Years in U.S.^{2}				-0.0000249***
				(0.00000439)
Asian × Years in U.S.^{2}				0.0000296***
				(0.00000586)
Asian × Female × Years in U.S.^{2}				-0.0000669***
				(0.00000824)
Female	-0.363***	-0.430***	-0.0673***	-0.486***
	(0.00300)	(0.00388)	(0.00999)	(0.00579)
White				-0.741***
				(0.00445)
White × Female				0.0535***
				(0.00694)
Asian				-0.317***
				(0.00802)
Asian × Female				0.414***
				(0.0114)
constant	1.174***	0.933***	1.316***	1.677***
	(0.00211)	(0.00271)	(0.00819)	(0.00373)
R^2	0.205	0.225	0.195	0.219
Root MSE	0.721	0.710	0.777	0.714
Observations	20,977,398	16,670,311	1,128,748	20,977,398

Models include time fixed-effects. The base-group for race is non-Asians and non-Whites. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Mincer model with only domestic labor experience

	Chinese	Indian	Filipino	Vietnamese	Korean
educ	0.0933***	0.121***	0.0978***	0.0577***	0.0947***
	(0.000622)	(0.00108)	(0.00146)	(0.00110)	(0.00201)
female × educ	-0.00900***	-0.0154***	0.00856***	-0.000432	-0.00134
	(0.000899)	(0.00160)	(0.00197)	(0.00150)	(0.00262)
yearsInUS	0.0211***	0.00867***	0.0163***	0.0229***	0.000585
	(0.000629)	(0.000741)	(0.000778)	(0.00127)	(0.00141)
female × yearsInUS	0.00115	-0.00310**	0.00500***	-0.000295	0.0104***
	(0.000878)	(0.00122)	(0.00103)	(0.00175)	(0.00194)
yearsInUS^2	-0.000124***	-0.0000731***	-0.0000668***	-0.0000918***	0.000293***
	(0.0000113)	(0.0000176)	(0.0000144)	(0.0000259)	(0.0000285)
female × yearsInUS^2	-0.0000489***	0.0000974***	-0.000140***	-0.0000454	-0.000222***
	(0.0000158)	(0.0000280)	(0.0000193)	(0.0000359)	(0.0000388)
female	0.0321*	-0.0157	-0.182***	-0.116***	-0.226***
	(0.0176)	(0.0287)	(0.0317)	(0.0253)	(0.0481)
constant	1.174***	1.072***	1.115***	1.550***	1.287***
	(0.0144)	(0.0213)	(0.0249)	(0.0215)	(0.0418)
R^2	0.252	0.207	0.146	0.185	0.170
Root MSE	0.777	0.792	0.712	0.744	0.806
Observations	264,372	219,984	211,352	108,905	89,279

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Mincer model with only domestic labor experience (continued)

	Japanese	Pakistani	Cambodian	Thai	Laotian
educ	0.0894***	0.105***	0.0354***	0.0673***	0.0204***
	(0.00252)	(0.00307)	(0.00234)	(0.00400)	(0.00253)
female × educ	0.00773**	-0.0229***	-0.00123	-0.0120**	0.00892**
	(0.00337)	(0.00535)	(0.00312)	(0.00474)	(0.00351)
yearsInUS	-0.0150***	0.0183***	0.00702	0.0160***	-0.000780
	(0.00127)	(0.00273)	(0.00427)	(0.00401)	(0.00563)
female × yearsInUS	0.0299***	-0.00420	0.00372	0.00749	-0.00308
	(0.00177)	(0.00452)	(0.00541)	(0.00487)	(0.00790)
yearsInUS^2	0.000307***	-0.000112*	0.000132	-0.0000604	0.000270**
	(0.0000185)	(0.0000640)	(0.0000936)	(0.0000840)	(0.000108)
female × yearsInUS^2	-0.000379***	0.000105	-0.0000777	-0.000130	0.000132
	(0.0000255)	(0.000103)	(0.000119)	(0.000101)	(0.000153)
female	-0.812***	0.153*	-0.153**	-0.0237	-0.257**
	(0.0599)	(0.0926)	(0.0717)	(0.0859)	(0.106)
constant	1.808***	0.964***	1.972***	1.438***	2.227***
	(0.0474)	(0.0623)	(0.0653)	(0.0785)	(0.0807)
R^2	0.160	0.181	0.111	0.147	0.087
Root MSE	0.754	0.827	0.678	0.746	0.637
Observations	55,322	20,093	14,990	12,876	12,353

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Mincer model with only domestic labor experience (continued)

	Hmong	Bangladeshi	Taiwanese	Indonesian	Nepalese
educ	0.0189***	0.0858***	0.0969***	0.104***	0.0533***
	(0.00276)	(0.00424)	(0.00798)	(0.00823)	(0.00384)
female × educ	0.00287	-0.0148**	-0.00379	-0.0292***	-0.0259***
	(0.00355)	(0.00685)	(0.00983)	(0.0111)	(0.00531)
yearsInUS	-0.00569	0.0222***	0.0191**	0.0270***	0.0400***
	(0.00813)	(0.00590)	(0.00858)	(0.00460)	(0.00559)
female × yearsInUS	-0.00311	0.00800	-0.00392	-0.00132	-0.00162
	(0.0104)	(0.00796)	(0.00975)	(0.00634)	(0.00890)
yearsInUS^2	0.000545***	-0.000126	0.0000271	-0.000231***	-0.000676***
	(0.000159)	(0.000181)	(0.000157)	(0.0000826)	(0.000144)
female × yearsInUS^2	0.0000308	-0.000234	0.0000299	-0.0000200	-0.000115
	(0.000208)	(0.000223)	(0.000182)	(0.000113)	(0.000245)
female	-0.0268	-0.0129	-0.0394	0.323*	0.231***
	(0.124)	(0.114)	(0.222)	(0.169)	(0.0825)
constant	2.099***	1.009***	1.184***	0.866***	1.682***
	(0.104)	(0.0981)	(0.190)	(0.130)	(0.0707)
R^2	0.106	0.186	0.203	0.192	0.171
Root MSE	0.669	0.762	0.790	0.727	0.721
Observations	11,976	7,449	7,297	5,039	4,562

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Mincer model with only domestic labor experience (continued)

	Burmese	Sri Lankan	Malaysian	Bhutanese	Mongolian	Other Asian
educ	0.0211***	0.0959***	0.0869***	0.0230***	0.0829***	0.0592***
	(0.00299)	(0.00650)	(0.0127)	(0.00689)	(0.0145)	(0.00426)
female × educ	0.00486	0.00163	0.000235	-0.00661	-0.0260	-0.0112*
	(0.00486)	(0.0106)	(0.0172)	(0.0116)	(0.0246)	(0.00594)
yearsInUS	0.0329***	0.0467***	0.0266**	0.00200	0.0232*	0.00702*
	(0.00608)	(0.00644)	(0.0109)	(0.0164)	(0.0140)	(0.00378)
female × yearsInUS	-0.00237	-0.0131	0.00594	0.00929	-0.0151	0.0120**
	(0.00864)	(0.00944)	(0.0150)	(0.0233)	(0.0185)	(0.00513)
yearsInUS^2	-0.000385**	-0.000726***	-0.000208	-0.000189	-0.000116	0.00000398
	(0.000160)	(0.000161)	(0.000292)	(0.000399)	(0.000232)	(0.0000662)
female × yearsInUS^2	0.0000513	0.000305	-0.000407	-0.000278	0.000194	-0.000176*
	(0.000207)	(0.000224)	(0.000368)	(0.000562)	(0.000305)	(0.0000905)
female	-0.147**	-0.178	-0.126	-0.00111	0.443	-0.0957
	(0.0721)	(0.186)	(0.296)	(0.162)	(0.428)	(0.0899)
constant	2.132***	0.977***	1.360***	2.183***	1.086***	1.721***
	(0.0557)	(0.142)	(0.247)	(0.180)	(0.233)	(0.123)
R^2	0.142	0.238	0.190	0.075	0.134	0.136
Root MSE	0.662	0.763	0.819	0.652	0.757	0.812
Observations	3,920	3,393	1,348	630	553	6,542

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Mincer model with discrete education

	Full Sample	White	Asian
High school	0.279***	0.284***	0.157***
	(0.000997)	(0.00120)	(0.00565)
female × HS	-0.00925***	-0.000414	-0.0240***
	(0.00158)	(0.00194)	(0.00782)
2-Yr degree	0.475***	0.475***	0.378***
	(0.00105)	(0.00125)	(0.00577)
female × 2-Yr	-0.00325**	0.00873***	0.00201
	(0.00164)	(0.00200)	(0.00805)
4-Yr degree	0.872***	0.863***	0.823***
	(0.00110)	(0.00129)	(0.00570)
female × 4-Yr	-0.0333***	-0.0219***	-0.0536***
	(0.00170)	(0.00205)	(0.00788)
Post-graduate	1.164***	1.132***	1.216***
	(0.00125)	(0.00145)	(0.00581)
female × Post-grad	-0.0436***	-0.0196***	-0.0956***
	(0.00186)	(0.00222)	(0.00820)
female	-0.0404***	-0.0481***	-0.00584
	(0.00176)	(0.00211)	(0.00830)
constant	1.639***	1.633***	1.780***
	(0.00137)	(0.00157)	(0.00704)
R^2	0.285	0.292	0.289
Root MSE	0.683	0.678	0.730
Observations	20,977,398	16,670,311	1,128,748

Models include time fixed-effects. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Mincer model with discrete education

	Chinese	Indian	Filipino	Vietnamese	Korean
High school	0.213***	0.0383**	0.0672***	0.131***	-0.0391
	(0.0106)	(0.0180)	(0.0178)	(0.0130)	(0.0387)
female × HS	-0.0599***	0.0165	-0.0443*	-0.0249	-0.0143
	(0.0147)	(0.0261)	(0.0238)	(0.0176)	(0.0497)
2-Yr degree	0.547***	0.246***	0.248***	0.381***	0.0919**
	(0.0116)	(0.0183)	(0.0177)	(0.0137)	(0.0386)
female × 2-Yr	-0.0981***	0.0335	0.00558	0.00965	0.0518
	(0.0159)	(0.0268)	(0.0236)	(0.0192)	(0.0507)
4-Yr degree	1.027***	0.822***	0.530***	0.834***	0.485***
	(0.0109)	(0.0173)	(0.0177)	(0.0144)	(0.0378)
female × 4-Yr	-0.142***	-0.142***	0.0794***	0.0331*	0.00296
	(0.0150)	(0.0254)	(0.0235)	(0.0199)	(0.0501)
Post-graduate	1.391***	1.166***	0.885***	1.199***	0.770***
	(0.0104)	(0.0171)	(0.0204)	(0.0181)	(0.0384)
female × Post-grad	-0.162***	-0.127***	-0.00650	0.0825***	0.0736
	(0.0148)	(0.0255)	(0.0266)	(0.0253)	(0.0513)
female	0.0759***	0.0203	-0.00987	-0.0419*	-0.0181
	(0.0156)	(0.0260)	(0.0245)	(0.0223)	(0.0512)
constant	1.606***	1.805***	1.966***	1.806***	2.010***
	(0.0134)	(0.0197)	(0.0202)	(0.0194)	(0.0440)
R^2	0.328	0.310	0.202	0.266	0.224
Root MSE	0.736	0.739	0.688	0.707	0.779
Observations	264,372	219,984	211,352	108,905	89,279

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Quantile regressions of the Mincer Model with discrete education

	White	Chinese	Indian	Filipino	Vietnamese	Korean
20th						
High school	0.302***	0.160***	0.0665***	0.107***	0.128***	-0.0751**
	(0.00129)	(0.0112)	(0.0170)	(0.0177)	(0.0144)	(0.0381)
female × HS	-0.0212***	-0.0398**	-0.0636***	-0.0916***	-0.0416**	0.0228
	(0.00205)	(0.0157)	(0.0242)	(0.0229)	(0.0184)	(0.0479)
2-Yr degree	0.479***	0.516***	0.268***	0.287***	0.404***	0.0590
	(0.00135)	(0.0125)	(0.0180)	(0.0175)	(0.0156)	(0.0380)
female × 2-Yr	-0.0182***	-0.117***	-0.0977***	-0.0839***	-0.0650***	0.0205
	(0.00212)	(0.0174)	(0.0255)	(0.0228)	(0.0207)	(0.0484)
4-Yr degree	0.815***	1.014***	0.835***	0.513***	0.829***	0.399***
	(0.00140)	(0.0116)	(0.0164)	(0.0175)	(0.0170)	(0.0373)
female × 4-Yr	-0.00951***	-0.165***	-0.343***	-0.0150	-0.0336	0.0316
	(0.00218)	(0.0162)	(0.0230)	(0.0226)	(0.0229)	(0.0475)
Post-graduate	1.046***	1.429***	1.305***	0.830***	1.141***	0.615***
	(0.00157)	(0.0109)	(0.0156)	(0.0218)	(0.0234)	(0.0381)
female × Post-grad	0.0698***	-0.190***	-0.357***	-0.0199	0.0700**	0.182***
	(0.00235)	(0.0157)	(0.0227)	(0.0279)	(0.0314)	(0.0492)
female	-0.0188***	0.136***	0.202***	0.0824***	0.00880	-0.0174
	(0.00230)	(0.0177)	(0.0254)	(0.0248)	(0.0246)	(0.0492)
constant	1.143***	1.018***	1.171***	1.430***	1.242***	1.508***
	(0.00173)	(0.0151)	(0.0213)	(0.0208)	(0.0223)	(0.0422)
80th						
High school	0.261***	0.244***	0.0659***	0.0699***	0.131***	-0.0194
	(0.00119)	(0.0134)	(0.0212)	(0.0235)	(0.0140)	(0.0488)
female × HS	0.0151***	-0.0534***	0.0421	0.0181	0.0331	0.0690
	(0.00201)	(0.0189)	(0.0336)	(0.0292)	(0.0202)	(0.0591)
2-Yr degree	0.465***	0.558***	0.324***	0.272***	0.371***	0.145***
	(0.00124)	(0.0142)	(0.0218)	(0.0235)	(0.0148)	(0.0493)
female × 2-Yr	0.0469***	-0.0652***	0.0991***	0.105***	0.129***	0.196***
	(0.00206)	(0.0199)	(0.0343)	(0.0293)	(0.0215)	(0.0603)
4-Yr degree	0.888***	1.033***	0.864***	0.604***	0.845***	0.575***
	(0.00129)	(0.0134)	(0.0212)	(0.0235)	(0.0147)	(0.0493)
female × 4-Yr	-0.0103***	-0.0975***	-0.0351	0.189***	0.159***	0.124**
	(0.00210)	(0.0191)	(0.0338)	(0.0291)	(0.0212)	(0.0601)
Post-graduate	1.198***	1.337***	1.140***	0.956***	1.215***	0.898***
	(0.00156)	(0.0135)	(0.0211)	(0.0256)	(0.0179)	(0.0501)
female × Post-grad	-0.0731***	-0.112***	-0.00584	0.0513	0.215***	0.156**
	(0.00235)	(0.0194)	(0.0338)	(0.0314)	(0.0252)	(0.0615)
female	-0.0853***	0.0163	-0.00594	-0.0867***	-0.146***	-0.127**
	(0.00213)	(0.0189)	(0.0324)	(0.0292)	(0.0235)	(0.0578)
constant	2.109***	2.187***	2.305***	2.428***	2.353***	2.475***
	(0.00149)	(0.0145)	(0.0215)	(0.0246)	(0.0190)	(0.0494)
Observations	16,670,311	264,372	219,984	211,352	108,905	89,279

Models include time fixed-effects. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$