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Why do women have a higher rate of return to schooling than men?

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Abstract

The rate of return to schooling is estimated higher for women than for men in most studies. Our explanation is the greater increase in expected lifetime work hours for women compared to men due to increased education. We compute the expected lifetime annual work hours, EXPHRS, by using a deterministic approach and include it in the wage equation. We find that EXPHRS positively affects hourly wages, and the effects are greater for women than for men. By controlling for the effects of EXPHRS, women have a slightly lower rate of return to schooling. It suggests the female-male differential in the rate of return to schooling can be explained by the gender difference in EXPHRS.

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Why Do Women Have a Higher Rate of Return to Schooling than Men?

1. Introduction

The rate of return to schooling is a measure of the returns that individuals gain from investing in human capital. An individual can determine the effectiveness of investing in education by estimating the relationship between the schooling years and the income he or she earns. The rate of return to schooling is also an important indicator of the productivity of education. Research on the rate of return to schooling can be used by governments as policy guidelines to make decisions about educational programs and educational reforms.

The early economic models on the returns to schooling concentrate on the quantifiable economic costs and benefits of schooling investments (Renshaw, 1960; Hansen, 1963; Becker, 1964). In these studies, the returns to schooling are measured in different ways. Renshaw (1960) estimates the median income in different age groups as the returns to schooling. Hansen (1963) and Becker (1964) take the present value of the individual's earnings as the returns to schooling.

Mincer (1974) was the first to develop an econometric technique to measure the rate of return to schooling, which is now commonly known as the Mincer earnings equation. It is expressed as:

$$lnY_{it} = \alpha_0 + r_s S + \alpha_1 t + \alpha_2 t^2 + \varepsilon_i \quad (1)$$

where lnY_{it} is the logarithm term of an individual i's earnings at year t. S is the individual's total years of schooling. t is the individual's potential work experience which is usually measured as age minus schooling minus 6, assuming the person attends school starting at age 6 and starts working right after school. ε_{it} is the error term. The estimated coefficient associated with the total years of schooling, r_s, represents the average marginal effect of one additional year of schooling on an individual's logarithm of earnings. In other words, r_s is the average return of an additional year of schooling.

Numerous studies use the Mincer earnings function to analyze the U.S. labor market. Most studies find a higher estimated schooling coefficient for women, which suggests that women receive a higher rate of return to schooling than men (e.g. Angle and Wissmann, 1981; Blau and Kahn, 1997; Card, 1999; Dougherty, 2005). Higher returns to schooling for women are also found in studies on data from other countries (e.g. Trostel, Walker and Woolley, 2002; Psacharopoulos and Patrinos, 2002; and Schultz, 2003).

Existing explanations on why women earn a higher rate of return to schooling include sample selection bias, top-coding bias, discrimination, endogeneity of schooling, and occupational choice. In the Mincer earnings equation, the dependent variable is the logarithm term of individuals' earnings. Observations are dropped from the regression process if earnings are zero. If the person is temporally out of the labor force, he or she will be excluded from the sample. Since many women experience an interruption in their life working pattern due to household activities, their labor force participation rates tend to be lower compared to men. This could lead to an overestimation in the rate of return to schooling for women. However, the effects of selection bias are found to be small in most studies (Blau and Beller; 1988; Wellington, 1993; and Dougherty, 2005).

Hubbard (2011) uses CPS data to study top-coding bias. He finds no gender difference in the college premium after correcting the top-coding bias. However, he finds no evidence that top-coding bias has effects on the gender difference in the returns to schooling.

The impact of discrimination, tastes, and circumstances (DTC) is another explanation provided by Dougherty (2005). The results suggest DTC accounts for about half of the male-female differential in the returns to schooling, and another half of the gender difference in the returns to schooling remains unexplained. The study also examines the endogeneity of schooling, work experience and occupational effects in the gender gap in the returns to schooling. However, by controlling schooling and work experience as endogenous, the gender differential in the returns to schooling does not decrease as expected.

This study provides a new explanation for the higher rate of return schooling found for women. Our explanation is based on the difference in the expected lifetime work patterns between men and women. We argue that an increase in schooling years may increase one's earnings through two different ways. First, more schooling increases a person's human capital stock, which enhances one's productivity and thus increases one's earnings. The theoretical model and empirical works on this link between education and earnings can be found in various studies (e.g., Mincer 1974; Polachek, 2008; Hanushek, Wiederhold, and Woessmann, 2015; Psacharopoulos and Patrinos, 2018). Second, more schooling leads to a higher labor market participation rate over a person's life cycle, which increases the person's lifetime work hours and lifetime earnings. High-educated people tend to participate more in the labor market compared to low-educated individuals (e.g. Fernandez and Wong, 2014). Most previous studies focus on the first part of the education returns (higher earnings due to the increased human capital stock) but ignore the latter part of the education returns (higher earnings due to increased lifetime work hours). If the increased lifetime work hours due to more schooling years are greater for women than for men, the effects of the increased lifetime work hours on earnings will be greater for women, and thus women would receive a higher rate of return to schooling.

The rest of the paper is organized as follows. Section 2 proposes our hypothesis and describes the methodology we use to compute one's expected lifetime work hours. Section 3 presents the data we use to compute the expected lifetime work hours and discusses our measurement strategy. Section 4 interprets the main empirical findings. Section 5 offers conclusions.

2. The Computation of Expected Lifetime Labor Force Participation

More years of schooling affects a person's earnings through two different channels: greater human capital stock and more hours worked over the life cycle. Education enhances personal earnings due to the increased human capital stock, as discussed in many previous studies. Furthermore, more education encourages people to work longer and more continuously in the labor market. We hypothesize that the effects of the expected lifetime labor force participation on earnings are greater for women than for men. That is, by adding one more year of schooling, if the increased the lifetime work hours are greater for women than for men, the effects of the labor force participation from schooling on earnings would be greater for women as well. This can explain why women receive a higher rate of return to schooling than men. Failure to account for the effects of the expected lifetime labor force participation on earnings in the wage equation may cause biased estimates in the schooling coefficient.

We define the expected lifetime labor force participation, *EXPLFP*, as the total hours that an individual expects to work over his or her lifetime. Our work follows Polachek (1975) and uses a deterministic approach to compute *EXPLFP*. We consider several factors that may determine *EXPLFP*. The first one is the schooling years. More education leads to a higher wage rate, which increases the opportunity cost of leisure, leading to an increase in one's lifetime work hours. The positive relationship between education and work hours is discussed in many studies. Second, work hours vary by cohort, especially for women. The past several decades saw a significant increase in women's labor force participation, while male labor force participation has remained roughly the same (e.g., Olivetti, 2006; Fernandez and Wong, 2014). Location is another determinant of work hours. We use state of residency as the location variable in our study. State economic conditions and public policies, such as employment laws, unemployment insurance and compensation benefits may impact a person's expectations to work. Finally, the expected work hours differ between men and women. Men tend to work more than women, regardless of education level, cohort, and location (e.g., Gayle and Golan, 2010; Knowles, 2007)[1].

As discussed above, for person *i*, the expected lifetime work hours, *EXPLFP*, between the first working year *t* and the last year working year *T*, can be computed as:

$$EXPLFP_{igjsk} = \sum_{t=1}^{T} HRS_{gjskt} \tag{2}$$

where *i* is the individual index, g denotes the gender of the person, *j* is the state of residency, *s* is the person's total years of schooling, and k is the cohort. *HRS* represents the person's expected annual work hours between year *t* and *T*. We define *HRS* as the average annual work hours of people in the same state who have the same gender, age, cohort, and schooling years. We assume that when a person decides how much to work in the future, he or she refers to people with a similar background. For example, if a 25-year-old woman wants to find out how many hours she expects to work in the current year, she will refer to all 25-year-old women who have the same schooling years as her in her current state.

We compute the expected lifetime work hours in equation (2) by separating the entire population into subgroups by gender, schooling years, survey year and state of residency. In each subgroup, we calculate the average annual work hours by age. We then add the computed average annual work hours up to the highest age by using a different starting age in each subgroup. Since the computed *EXPLFP* decreases by age, we divide it by the total working years, $T - t + 1$, and get the expected lifetime annual work hours, *EXPHRS,* which eliminates the age effects on one's expectation to work.

$$EXPHRS_{igjsk} = \frac{1}{T-t+1} \sum_{t=1}^{T} HRS_{gjskt} \tag{3}$$

$EXPHRS$ is assumed to be exogenous in our study. Although a person's $EXPHRS$ is determined by his or her gender, age, education level and location as we discussed above, other personal characteristic (for example, family background, work experience and occupation) does not have any effect on one's $EXPHRS$.

3. Data and Methodology

3.1. U.S. Census Survey and American Community Survey

Our sample is drawn from the U.S. census data 1% sample of 1950, 1960 and 1970, 5% sample of 1980, 1990 and 2000, and American Community Survey (ACS) 2010. The U.S. census data and ACS data are collected and provided by Integrated Public Use Microdata Series (IPUMS). Conducted by the U.S. Census Bureau, the U.S. census survey is the nation's largest household survey that is taken every decade. The ACS is a short form of the census survey on a yearly basis. Both the datasets gather detailed information on U.S. households' and individuals' information such as education, income, employment, occupation, migration, and disability, which is valuable for our study. More importantly, each survey contains enough observations, which makes it possible for us to compute the expected lifetime work hours. Given the fact that most people in U.S. retire in their 60s, we set the last year of working age, *T*, as 69 and limit our sample to men

[1] Other factors may also affect one's expected work hours, such as marital status and occupation. However, to make the model simple, we do not include these possible factors in this study.

and women who are between 18 and 69 years old in each survey year. Our initial sample contains 15,774,164 observations including 8,644,879 men and 7,129,285 women.

We compute the expected lifetime annual work hours, $EXPHRS$, for men and women by schooling year and decade, as discussed in the last section. The computed $EXPHRS$ are reported in Table 1. Overall, men expect to work more than women regardless of schooling years and decade. The computed $EXPHRS$ and schooling years are positively related. As schooling years increase, both men and women expect to work more. In addition, as the schooling years increase, women's $EXPHRS$ relative to men's increases for all decades. That is, women's expectation to work increases greater than that of men for each additional year of schooling.

Table 1. Computed Expected Lifetime Annual Work Hours for Men and Women by Schooling Years and Decade

Schooling Years	Men							Women						
	1950	1960	1970	1980	1990	2000	2010	1950	1960	1970	1980	1990	2000	2010
0	851	799	734	710	796	799	741	151	160	243	293	369	381	430
1	746	818	659	660	-	-	491	115	174	195	262	-	-	247
2	934	926	769	730	-	-	696	171	254	241	287	-	-	328
3	1121	995	844	753	-	-	753	197	249	252	286	-	-	330
4	1160	1033	915	789	754	-	675	196	250	292	320	347	-	371
5	1243	1143	973	834	-	-	717	230	304	303	327	-	-	399
6	1307	1253	1074	918	-	973	984	253	323	334	367	-	492	502
7	1430	1341	1161	924	-	-	611	260	372	387	374	-	-	356
8	1556	1430	1253	987	855	825	735	295	402	421	395	394	417	418
9	1451	1572	1412	1144	1007	970	818	304	521	520	500	497	518	494
10	1491	1613	1486	1185	1065	1006	783	370	547	578	531	534	549	482
11	1457	1651	1534	1258	1138	1085	848	360	574	626	592	588	605	535
12	1710	1773	1681	1455	1362	1290	1084	488	633	699	717	777	816	763
13	1320	1725	1676	1571	1493	1417	1195	397	658	712	833	966	1005	913
14	1393	1685	1672	1571	1571	1468	1278	429	618	674	806	1049	1096	1027
15	979	1543	1591	1585	-	-	-	363	661	633	789	-	-	-
16	1678	1893	1812	1709	1626	1572	1430	585	861	864	882	1000	1079	1058
>16	-	-	-	-	1684	1590	1516	-	-	-	-	1184	1190	1185

Data source: U.S. census data 1% sample of 1950, 1960, 1970, 5% sample of 1980, 1990 and 2000 and American Community Survey 2010.

3.2. Estimation Strategy

We hypothesize that more schooling years increases people's lifetime work hours, which increases their earnings. Ignoring the effects of the work hours on earnings may cause biased estimates of the rate of return to schooling. If the effects are greater for women than for men, then women's earnings would increase greater than men's earnings, given the same magnitude change in their schooling years. This can explain why women have a higher rate of return to schooling than men.

We begin by estimating the rate of return to schooling for men and women, as well as the gender difference in the rate of return to schooling by using the basic Mincer function described in equation (1). To check the gender difference, we include a female dummy variable, *Fem*, in the regression. We then estimate the rate of return to schooling by adding the effects of the expected lifetime annual work hours, $EXPHRS$, on earnings in the regression. The equation takes the following form:

$$lnY_{it} = \alpha_0 + r_s S_{it} + \alpha_1 (S \cdot Fem)_{it} + \alpha_2 Fem_{it} + \beta_1 EXPHRS_{it} + \beta_2 (EXPHRS \cdot Fem)_{it} + \alpha_3 t_{it} + \alpha_4 {t^2}_{it} + \gamma X_{it} + \delta D_t + \varepsilon_{it} \quad (4)$$

where i is the individual index and t is the year index. Y is the CPI-adjusted hourly wage, which is calculated as one's wage and salary income divided by his/her total annual work hours[2]. S is the person's total years of schooling, which is adjusted by the highest degree of this person. Fem is the female dummy variable, taking on the value of 1 if the person is female and 0 if the person is male. $S \cdot Fem$ is an interaction term of the schooling variable and the female dummy. The estimated coefficient of S indicates the average rate of return to schooling for men. The estimated coefficient of $S \cdot Fem$ provides us the female-male difference in the rate of return to schooling. A positive estimated coefficient shows a higher rate of return to schooling for women. $EXPHRS$ is the expected lifetime annual work hours, which is measured in 1000s of hours. $EXPHRS \cdot Fem$ is an interaction term of $EXPHRS$ and the female dummy. t is the person's potential work experience years (computed as age-S-6) and t^2 is the work experience quadratic term. X_{it} denotes other explanatory variables that may affect the person's hourly wage. It includes a dummy variable indicating if the person is married, a dummy variable indicating if the person is black, number of children in the household, number of children under age 5 in the household, and the person's occupation. There are 10 categories of occupation based on the census data 1950 occupational code, including (1) professional and technical; (2) farmers and farm managers; (3) managers, officials and proprietors; (4) clerical and kindred workers; (5) sales workers; (6) craftsmen; (7) operatives; (8) service workers; (9) farm laborers; (10) laborers excluding farm. The definition and the summary statistics of the main explanatory variables are given in Table 2. For each explanatory variable, we test the equivalence of the mean for men and women samples. D_t denotes the year specific variable. ε_{it} is the error term with its normal properties. If our hypothesis is supported by the data, we expect to find the gender difference in the rate of return to schooling to decrease or disappear by controlling the effects $EXPHRS$ on earnings.

Table 2. Definition and Summary Statistics of the Main Explanatory Variables

Variables	Definition	Mean (Std.Dev)		Equivalence Test of the Mean	
		Men	Women	Difference	P-value
$EXPHRS$	Expected Annual Lifetime Work Hours; measured in 1000s of hours	1.363 (0.438)	0.778 (0.341)	0.586	0.000
S	Total years of schooling	12.018 (3.714)	11.950 (3.496)	0.069	0.000
t	Potential years of work experience; =age-s-6	26.369 (13.223)	26.930 (13.435)	-0.561	0.000
Married	=1 if respondent is married or permanently cohabiting; 0 otherwise	0.731 (0.443)	0.687 (0.464)	0.045	0.000

[2] For year 1980, 1990 and 2000, annual work hours are computed as weeks worked last year multiplied by the usual hours worked per week. For year 2010, the variable weeks worked last year is categorical. We use the median value of each category as the value for this variable.

Black	=1 if the respondent is black; 0 otherwise	0.092 (0.289)	0.104 (0.305)	-0.012	0.000
Child	Number of own children in the household	1.023 (1.303)	1.113 (1.315)	-0.090	0.000
Child5	Number of own children under age 5 in household	0.209 (0.531)	0.198 (0.514)	0.011	0.000
Occupation Variables					
PROF	=1 if respondent's occupation is professional and technical; 0 otherwise	0.153 (0.360)	0.165 (0.371)	-0.012	0.000
FARM	=1 if respondent's occupation is farmers and farm managers; 0 otherwise	0.022 (0.146)	0.003 (0.051)	0.019	0.000
MANG	=1 if respondent's occupation is managers, officials and proprietors; 0 otherwise	0.140 (0.347)	0.070 (0.255)	0.070	0.000
CLER	=1 if respondent's occupation is clerical and kindred; 0 otherwise	0.057 (0.231)	0.214 (0.410)	-0.157	0.000
SALE	=1 if respondent's occupation is sales workers; 0 otherwise	0.058 (0.233)	0.049 (0.216)	0.009	0.000
CRDF	=1 if respondent's occupation is craftsmen; 0 otherwise	0.193 (0.395)	0.150 (0.122)	0.043	0.000
OPER	=1 if respondent's occupation is operatives; 0 otherwise	0.152 (0.359)	0.076 (0.264)	0.076	0.000
SERV	=1 if respondent's occupation is service workers; 0 otherwise	0.074 (0.261)	0.131 (0.337)	-0.057	0.000
FLAB	=1 if respondent's occupation is farm laborers; 0 otherwise	0.011 (0.105)	0.005 (0.072)	0.006	0.000
LABO	=1 if respondent's occupation is laborers excluding farm; 0 otherwise	0.058 (0.233)	0.010 (0.098)	0.048	0.000

Data source: U.S. census data 1% sample of 1950, 1950, 1970, 5% sample of 1980, 1990 and 2000 and American Community Survey 2010.

4. Empirical results

4.1. Estimated Gender Difference in the Rate of Return to Schooling

We first run the regression without $EXPHRS$ and report the estimated results in Table 3 Columns 1 and 2. Column 1 in Table 3 presents the estimated coefficients on the basic Mincer earnings function as shown in equation (1). Leaving out the other control variables (i.e., Black, Married, Child, Child5 and occupations), the estimated rate of return to schooling for men is 0.0853 and it is statistically significant at the 1% level, given by the estimated coefficient of S. It shows that each additional year of schooling increases men's hourly wage by an average of 8.53%. The estimated coefficient of the interactive term, $S \cdot Fem$, is 0.0207 and it is statistically significant at the 1% level, suggesting women's rate of rate to schooling is 2.07 percentage points higher than that of men. This finding is consistent with most previous studies. Column 2 displays the results for the regression that include all the other explanatory variables. The estimated rate of return to schooling for men decreases to 0.0597, indicating each additional year of schooling increases men's hourly wage by an average of 5.97% after adjusting the effects of the other control variables. The estimated coefficient of $S \cdot Fem$ is 0.0132 and is significant at 1% level, suggesting women's rate of return to schooling is 1.32 percentage points higher than that of men.

Columns 3 and 4 in Table 3 display the regression results by introducing the variable $EXPHRS$, as well as the interactive term, $EXPHRS \cdot Fem$, in the wage equation. Column 3 shows the results of the regressions without the other control variables. The estimated coefficient on $EXPHRS$ is 0.2473 and it is statistically significant at the 1% level. It suggests on average, a 1000-hour increase in expected annual work hours increases men's hourly wage by an average of 24.73%. The effect of $EXPHRS$ on the hourly wage is greater for women than for men, given by the positive and significant estimated coefficient of the interactive term, $EXPHRS \cdot Fem$ (0.2784). A 1000-hour increase in $EXPHRS$ sees women's wages increase by 27.87 percentage points more than men's wages, on average. The estimated schooling coefficient is 0.0808 and statistically significant at the 1% level, indicating an additional year of schooling increases men's hourly wage by an average of 8.08%. The estimated coefficient of the interactive term, $S \cdot Fem$, is 0.0019 and it is statistically significant at the 1% level. It suggests the estimated rate of return to schooling is only 0.19 percentage points higher for women than for men after controlling for the effects of $EXPHRS$ on wages rates. In Column 4, by adding the effects of the other explanatory variables, the rate of return to schooling for men is estimated as 0.0569 and the female-male difference in the rate of return to schooling reduces to -0.0020. Both coefficients are statistically significant at the 1% level. Thus, by controlling for the effects of *EXPHRS*, women have a slightly lower rate of return to schooling.

Table 3. Estimated Gender Difference in the Rate of Return to Schooling

	(1)	(2)	(3)	(4)
S	0.0853***	0.0597***	0.0808***	0.0569***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
S**Fem*	0.0207***	0.0132***	0.0019***	-0.0020***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Fem	-0.6254***	-0.5041***	-0.4916***	-0.3966***
	(0.0017)	(0.0017)	(0.0018)	(0.0018)
t	0.0242***	0.0223***	0.0231***	0.0218***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
t^2	-0.0003***	-0.0002***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EXPHRS			0.2473***	0.1996***
			(0.0011)	(0.0011)
*EXPHRS*Fem*			0.2784***	0.2256***
			(0.0014)	(0.0014)
Black		-0.0437***		-0.0463***
		(0.0006)		(0.0006)
Married		0.0626***		0.0570***
		(0.0004)		(0.0004)
Child		0.0048***		0.0024***
		(0.0002)		(0.0002)

Child5		0.0245***		0.0284***
		(0.0004)		(0.0004)
Occupation Dummies			Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Constant	0.5041***	0.7312***	0.1283***	0.4189***
	(0.0024)	(0.0054)	(0.0028)	(0.0056)
Observations	15,774,164	15,774,164	15,774,164	15,774,164
R-squared	0.170	0.213	0.176	0.217

Data source: U.S. census data 1% sample of 1950, 1950, 1970, 5% sample of 1980, 1990 and 2000 and American Community Survey 2010.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2. The Effect of $EXPHRS$ on Returns to Schooling: A Further Explanation

Our results suggest that no gender difference in the rate of return to schooling exists once we account for the expected lifetime annual work hours. We explain the effect of $EXPHRS$ on the returns to schooling by using the wage differential between and high-educated and low-educated workers caused by work hours.

Given the total schooling years, the rate of return to schooling depends on the wage differential between and high-educated and low-educated workers. For low-educated workers, the labor force participation rate is much lower for women than for men. For example, in 2000, for individuals with less than a high school diploma, the labor force participation rate for men and for women was 86.7 and 53.3, respectively (Hipple, 2016). In addition, low-educated women work fewer hours than men due to limited occupational choices and non-regular employment (OECD, 2017). Thus, for low-educated workers, women's work hours and average wage are much lower than that for men. For high-educated workers, women's labor force participation rate is comparable to men. For example, in 2000, among those with bachelor's degrees and higher, the labor force participation rate for men and for women is 95.6 and 90.1, respectively (Hipple, 2016). The average work hours for high-educated men and women are also comparable due to the change in factors such as discrimination in the labor market, which makes the male-female wage differential smaller at higher schooling years (Dougherty, 2005). Therefore, for women, the wage differential between low- and high-educated workers is greater than for men, and thus makes their rate of return to schooling higher. If women and men expect to work the same number of hours, the low-high educated wage differential and rate of return to schooling would be the same.

5. Conclusion

Our main explanation on why women have a higher rate of return to schooling than men is the greater increase in female expected work hours compared to male due to increased education. More years of schooling affects wages through two different channels: increase one's human capital stock, which directly increases one's earnings, and increase one's lifetime work hours, which indirectly increase in one's earnings. As schooling years increase, if women's lifetime work hours increase greater than that of men, the effects of increased lifetime work hours on earnings will be greater for women than for men, and thus women will see a higher rate of return to schooling.

To test our hypothesis, we compute the expected lifetime annual work hours, $EXPHRS$, by gender, cohort, education level, location and survey year and test the effects of $EXPHRS$ on hourly wage. We find that $EXPHRS$ positively affects hourly wage for both men and women, and the effects are greater for women than for men. After adjusting the effects of $EXPHRS$, the difference in the rate of return to schooling between women and men declines from 0.0207 to 0.0019. By adding the effects of the other explanatory variables, such as race, marital status, number of children, age of youngest child and occupational categories, the female-male difference in the rate of return to schooling decreases further to -0.0020, suggesting a slight lower rate of return to schooling for women.

Our results suggest that the female-male differential in returns to schooling can be explained by the female-male difference in $EXPHRS$. As schooling increases, women's $EXPHRS$ increases greater than men. In addition, the effect of $EXPHRS$ on hourly wage is higher for women than for men. Therefore, women receive greater returns to schooling than men. We also explain the effect of $EXPHRS$ on the rate of return to schooling by exploring the wage differential between and high-educated and low-educated workers caused by work hours. Due to the gender difference in labor force participation and occupational choices, the wage differential between high- and low-educated workers is greater for women. This leads to a higher rate of return to schooling for women.

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