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Micro Foundations of Earnings Differences

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ABSTRACT

Micro Foundations of Earnings Differences

This paper examines how human capital based approaches explain the distribution of earnings. It assesses traditional, quasi-experimental, and new micro-based structural models, the latter of which gets at population heterogeneity by estimating individual-specific earnings function parameters. The paper finds one's ability to learn and one's ability to retain knowledge are most influential in explaining earnings variations. Marketable skills actually acquired in school depend on these two types of ability. However, schools may also implement ability enhancing interventions which can play a role in improving learning outcomes. Policy initiatives that improve these abilities would be a possible strategy to increase earnings and lower earnings disparity.

JEL Classification: I3, J3, J7

Keywords: earnings distribution, human capital, heterogeneity, ability

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I. Introduction

Modern labor economics considers workers as a conglomeration of heterogeneous units each differing in productivity. As such, most labor economists now focus on how skills differ between individuals, and as a result, how dissimilar capabilities give rise to each worker commanding a different earnings. Thus, rather than concentrating on the functional distribution of income between labor and capital, as had been the case in the past, economists now focus more on pay differences across various segments of the population. Indeed some of these differences have vastly widened in the last 35 years.[1] This chapter examines the microeconomic basis of such variations in earnings, why they occur, and why they have changed over time.

We begin by examining patterns in current data. Repeatedly and overwhelmingly one finds earnings are significantly correlated with one's years of school and one's age. Indeed education appears to be the surest path to success, as all data indicate an individual's earnings to be higher the greater the years of schooling completed. With regard to age, one typically observes earnings to rise as one gets older, but at a diminishing rate. Earnings also vary by occupation, industry, size of firm, location and a myriad of other factors. But there are other patterns too: Males earn more than females, whites earn more than blacks, but the gender gap within race is smaller for blacks than white. Single childless women earn almost as much as single men, but married women lag far behind married men. Children exacerbate the gender wage gap. Immigrants earn less than natives, but over time in the country, immigrant earnings converge to natives' earnings.

Many theories have been used to explain *some* but not all these patterns. These include stochastic models entailing sheer luck, whereby circumstances largely outside one's control determine success; agency models whereby wage structures perhaps instigated by institutional forces such as tax policy or unions determine well-being; efficiency wage models that link wages to unemployment; matching models which account for why job turnover declines with tenure;

[1] One reason for the increased attention, at least in the United States, stems from the rising share going to labor until the 1970s (Krueger, 1999 and Armenter, 2015). However, of late, there has been a reversal of this trend and a renewed interest in the functional distribution of income, only now dealing with the rising share to capital especially since the 2000s (Mike Elsby, et al., 2013 and Karabarbounis and Neiman, 2013). One new theory attributes this change to firm heterogeneity. In particular, Autor et al. (2017) describe "superstar firms" where labor's share fell relatively more.

crowding models that elucidate why women earn less than men; screening models which describe why education enhances earnings; occupational segregation models that portray why women are in different occupations than men; and productivity enhancement contract models that provide an explanation for upward sloping age-earnings profiles. Whereas each of these theories has some predictive power, they individually deal with a single narrow aspect of earnings. In our opinion, only the life-cycle human capital model appears to explain the preponderance of all patterns simultaneously. Thus this chapter focuses on human capital theory and the empirical work emanating from it. The theory postulates a person's earnings capacity to be directly proportional to his or her labor market skills and knowledge, collectively known as human capital. Each year a person augments human capital stock by the amount of new human capital he or she creates, and diminishes it by the amount he or she depreciates.

Creating new human capital entails combining time and existing human capital. The greater one's ability, the more human capital one can produce, and the more rapidly one's earnings rise. Of course, measuring ability is tricky. Most studies use IQ or achievement tests, but these standardized tests have been criticized because they get at analytic academic capabilities that lead to success in school, but not necessarily a proficiency that translates into real-world accomplishments (Sternberg, 1985). The human capital model contains five measures related to the production of human capital. Of these, three correspond directly to one's ability to create human capital, one to skill depreciation, and one to a person's time discount rate.

These human capital parameters are important in various branches of economics. For example, they are used in earnings dynamics models (Blundell, 2014; Meghir and Pistaferri, 2011), dynamic general equilibrium models (King and Rebelo, 1999), but more importantly they are used to interpret skill formation (Cunha et al., 2006) in understanding earnings distributions. Typically, due to the lack of panel data and cumbersome computation, past studies estimate these parameters population-wide in a more or less representative agent framework. However, representative agent models are limited and can yield misleading inferences (Browning, Hansen and Heckman, 1999). Polachek, Das, and Thamma-Apiroam (2015) estimate these parameters person-by-person. Getting at these individual-specific human capital parameters enable them to test predictions of the human capital model. It allows us in this chapter to evaluate the importance of ability and other factors in shaping the earnings distribution. Our results suggest these five measures to be the most important explanatory factors that predict labor market success.

Much current research adopts a log-linear specification of the human capital model. Many implications emerge. These include how earnings rise with age at a diminishing rate over the lifecycle, how earnings differ by demographic group, but most important how school relates to earnings. Early studies viewed education as an exogenous variable and obtained estimates of rates of return to schooling. However, because many recognized the endogeneity of schooling, subsequent researchers utilized quasi-experimental analyses to assess the value of education.

Quasi-experimental methods are not the panacea for identification. For example, instrumental variable results estimating the rate of return to schooling widely vary between 3.6% and 94.0% (Card, 2001). Many question the validity of the exclusion restriction requirement for these instruments. But independent of this criticism, employing linear models, as they typically do, necessarily yields erroneous parameter estimates even with a valid instrument. This is because the omitted nonlinear portion of the earnings-schooling relationship constitutes a part of the error term, inevitably correlating the IV with the error. Moreover ignoring heterogeneity further exacerbates the endogeneity problem.

We begin this chapter by describing inherent earnings patterns. We argue these patterns can be explained using the lifecycle human capital model. We utilize a simplified Mincer formulation and its extensions to explore observed demographic earnings differences and their trends. We then utilize five person-specific structural parameters obtained from a complex nonlinear earnings function and discuss its implications regarding predictions obtained from theory. From here, we exploit interpersonal differences in these five parameters to explain earnings inequality. We concentrate on the importance of ability compared to schooling. We review studies that evaluate the impact of schooling using OLS and quasi-experimental approaches, then we explain their pitfalls. We conclude by showing that the ability parameters we obtain are the most important determinants of earnings distribution. From a policy perspective, we claim treatments that enhance ability such as through early childhood interventions are the most effective in reducing earnings inequality.

II. Earnings Patterns

Earnings differ by age, schooling level, gender, race, and many more demographic factors. Understanding why these differences arise is important because the answers can help improve individual and societal well-being. Policy makers can use the answers to devise strategies to help ease poverty and eventually to help put countries on a path of increased growth and prosperity. To set the stage, we examine a number of these demographic earnings differences. We do so in six tables and one figure.[2] Each explores aspects of earnings inequality.

Table 1 depicts average US weekly wages in 2000 dollars by race, gender age, and education. As can be seen, women earn less than men, and blacks earn less than whites. Men's earnings both rise with age, but at a diminishing rate, even turning down at older ages between 1980 and 2000. For women, earnings also rise with age, but not as quickly. Conspicuously, earnings rise with years of school both for men and women.

Of these patterns, a number of outcomes are particularly surprising. First, the gender gap (in percent terms) for whites is almost twice as great as that of blacks. In 1980 white women earned 58% as much as white males, but black women earned 76% as much as black men yielding gender gaps of 42% and 24% respectively. In 2016 these figures were 75% for whites and 86% for blacks, yielding gender gaps 25% and 14%. Clearly during this 36 year period women's earnings rose relative to males, such that the gender gap diminished equally by about 40% for both whites and blacks. Second, as also seen in Figure 1, the gender wage gap starts out relative small for younger workers 16-24 (24% in 1980 and only 13% in 2016), but more than doubles by the time employees reach the 54-65 age bracket. Thus older women fair far worse relative to men than younger women. Third, level of education has no effect on the gender wage gap. In 1980 women high school graduates and below earned about 60 percent of male earnings (a 40% gap) which was similar to college educated women. In 2016 the pay ratio was about 70%, which again was similar at each level of education. So on average, women don't fare any worse with little education compared to women with college degrees. Fourth, the black-white earnings gap for men remain relatively constant, being 27% in 1980 and 25% in 2016.

[2] These tables update data previously presented in Polachek (2008).

Table 2 gives US results based on age and marital status. Again, earnings rise with age at a diminishing rate. However, here, the gender wage gap is far smaller for singles than marrieds. As before, the gender wage gap rises with age for marrieds, but not so much for singles. When accounting for children the results are more stark. Table 3 indicates only a 5% gender gap in 2012 for single childless women, but a 28% gap for married men and women with children 6-17 years of age. Finally, spacing children more widely exacerbates the gender gap further (Polachek, 1975b).

Taken together, we find earnings rise with education and age, differ by gender but more so for whites than blacks, and that being married and having children widely spaced apart intensifies gender earnings differences. In short, earnings disparities abound throughout the US.

Patterns observed in the US also hold true in other countries. The Luxemburg Income Study (LIS) contains harmonized survey microdata from over 47 upper- and middle-income countries. Tabulations in Tables 4 and 5 contain earnings data (2011 PPP US dollars) by age, education and gender for 23 countries contained in the LIS. As in the US, earnings rise with age and schooling level. Men's age-earnings profiles are steeper than women's. The gender earnings gap is smaller for the young (indeed women have the advantage in at least four countries), but rises as employees get older. Also, as in the US, the gender earnings gap appears independent of one's years of school. Finally, Table 6 examines LIS data by gender and marital status (again in 2011 PPP US dollars). For most countries wage parity is observed for unmarried men and women. (Exceptions are France, Israel, Japan, and surprisingly Norway and Sweden with the biggest gaps for the unmarried.) As in the US, the gap varies from 13-50% for married men and women, with the largest gaps being in France, Norway, and Sweden.

In summary, earnings are not uniform across demographic groups. Instead, they differ by race, gender, age, education. Some patterns are expected, such as how earnings rise with schooling, but other patterns are not, such as how the gender earnings gap rises with age, but not years of school. Also less obvious, the gender gap is almost non-existent between single childless men and women, but large between married men and women with children.

III. Why do earnings differ?

The predominant explanation entails human capital theory. This theory postulates earnings power results when individuals produce human capital through inputs as parental time, schooling, on-the-job training, and perhaps a bit of luck. Its roots go back at least to early 1691 when economists began to consider the value of wealth embodied in individuals (Kiker, 1966). Sir William Petty's essay "On the Value of People" written around 1655 (Hull, 1899: 108-112) computed the worth of people based on deducting property rent from national income. Later economists who considered human value include Adam Smith (1723-1790), Gasper Melchor de Jovellanos (1744–1811), Jean Baptiste Say (1767-1832), Nassau William Senior (1790-1864), Friedrich List (1789-1846), Johann Heinrich von Thünen 1783-1850), Ernst Engel (1821-1896), Léon Walras (1834-1910), and Irving Fisher (1867-1947) who formally used of the term "human capital" in 1897. These economists tended to consider aggregate labor which they applied to measuring national wealth and its changes resulting from war, migration, and disease. Not until 1935 did John Walsh, and later in 1945 did Friedman and Kuznets, consider specific occupations. Although human capital theory evolved over a long period of time, it did not really takeoff until 1958 when Jacob Mincer embedded schooling into a cogent parsimonious investment framework showing precisely how years of education translate into earnings power. Slightly later, Becker and Chiswick (1966), Ben-Porath (1967), and then Mincer (1974) extended the human capital model to incorporate work experience obtained over the life cycle.

Of course, many other factors besides human capital can influence individual earnings. These comprise institutional factors including unions, market structure, government legislation, discrimination, corporate payment schemes to enhance productivity, as well as individual factors such as non-cognitive personality traits. Before the human capital approach became popular, the predominant theory of earnings distribution attributed success mostly to luck. Obviously, such a theory offers no economic rationale into the earnings generation process. Since the development of human capital theory, other models evolved to consider various factors that affect earnings. These include occupational segregation models, crowding models, efficiency wage models, matching models, and models depicting productivity enhancing contracts. Occupational segregation and crowding models describe why women's outcomes differ from men's, but they don't explain why the gender wage gap widens with age or why family characteristics such as marital status and children are related to earnings in the opposite way for men and women. Efficiency wage models argue that some individuals earn more than competitive market wages thus justifying unemployment, but they don't explain why efficiency wages vary over the life cycle or why earnings vary by race and gender. Matching models sort out why turnover declines with tenure but don't explain gender differences in earnings. Productivity enhancing contract models give insight why earnings profiles slope upward, but they don't explain the concavity. As such, each of these theories offers some insight for particular aspects of earnings. However, they do not give a unified framework that explains each of the observed patterns illustrated above. We believe only the life-cycle human capital model appears to account for the preponderance of all patterns simultaneously. Thus we focus on this theory and empirical work emanating from it.

IV. The Human Capital Model

The backbone behind formal structural human capital models originates with Adam Smith (1776). He argued job characteristics shape labor market equilibria because workers need to be compensated for taking "unpleasant" jobs. Though going to school and investing in on-the-job training need not be unpleasant, these activities typically take time away from paying work and for this reason yield a wage premium. [3] As such, the extra money needed to forgo pay while undertaking human capital purchases is a "compensating wage differential." Couched in an investment framework, this means the present value of earnings an individual need obtain must exceed the costs of such expenditures, of course including direct and indirect opportunity outlays.

At first, only schooling investments were considered (Mincer, 1958 and Becker, 1964), but rigorous lifetime models (Ben-Porath, 1967) imply something more. Assuming a finite working life and opportunities for post-school investments, such as through on-the-job training, individuals have an incentive to invest throughout their lives, but at a diminishing rate. Large human capital investments during school, followed by gradually diminishing investments throughout the lifecycle, lead to the typically observed concave earnings profile. Ben-Porath derived this result

[3] Human capital investment comprises of general and specific training. Specific training enhances productivity in the firm and nowhere else. Firms provide such training because of its limited applicability. However, to reduce turnover incentive compatible contracts can arise in which firms equally share the costs and benefits of such training with its employees (Kuratani, 1973). This survey deals mainly with general training which enhances productivity throughout the economy. This type training is usually borne by the individual, though because of its social value, much of schooling is subsidized by the government. Bishop (1997) presents evidence that employers can pay for general (as opposed to specific) training, as well. Acemoglu and Pischke (1999) argue firms do so because even general training can have a specific component. We concentrate on the costs and benefits of that part of human capital an individual purchases either in school or on the job.

by assuming individuals invest in themselves to maximize lifetime earnings subject to the production technology associated with human capital creation:

$$\underset{K_t}{Max} \quad J = \int_0^N e^{-rt} Y_t dt$$

where J is the total discounted disposable earnings over the working life-cycle, r is the personal time discount rate and N is the number of years after which one retires (assumed known with certainly). Disposable earnings are $Y_t = R[E_t - K_t]$ where R is the rental rate for human capital E_t and K_t is the fraction of human capital stock reinvested. Individuals create human capital using various inputs. This activity can be modeled using a very general production function, but for simplicity most employ a Cobb-Douglas model combining own time and existing human capital. We denote the human capital accumulation process as $Q_t = \beta K_t^b$ where $b \in [0,1]$ and β are production function parameters.[4] The parameter b indicates the rate at which current human capital stock is transformed to new human capital. It reflects how one acquires new knowledge from old, and as such exhibits how quickly one learns. The β parameter depicts the "scale" at which one learns and as such represents total factor productivity. Both β and b reflect an individual's ability to learn. An individual's initial human capital stock is E_0. This endowment becomes relevant to the individual when he or she determines K_t during the process of lifetime earnings maximization. One can interpret E_0 to be a person's initial ability to earn. The rate of change in human capital stock E_t is expressed as the amount of human capital produced Q_t minus depreciation so that $\dot{E}_t = Q_t - \delta E_t$, where δ is the constant rate of human capital stock depreciation. This depreciation parameter is symbolic of one's ability to retain (or not retain) knowledge.[5]

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[4] Ben-Porath (1967) assumed a more general production function employing "goods" inputs such as teachers and books $q_t = \beta K_t^{b_1} D_t^{b_2}$ where D_t equals other inputs. Because goods inputs are difficult to measure, most analyses subsequent to Ben-Porath omit this factor. These include Haley (1976), Johnson (1978), and Wallace and Ihnen (19758).

[5] Parameters *b, β, r, δ,* and $E_0$are assumed constant throughout one's life. Obviously, this need not be the case, but is consistent with the notion that IQ remains constant (Tucker-Drob, 2009). Of the parameters, skill depreciation seems most likely to increase as one ages, but to our knowledge, no one has estimated this in the context of a lifecycle model human capital model.

Maximization of lifetime earnings requires producing human capital to equate its marginal costs and marginal benefits in each time period. This yields a nonlinear (in the parameters) earnings function[6]

$$Y_t = W^{\frac{1}{(1-b)}}\left[\left\{\left(\frac{1}{\delta}+\left(E^{1-b}-\frac{1}{\delta}\right)e^{\delta(b-1)t^*}\right)^{\frac{1}{(1-b)}}-\left(\frac{1}{\delta}\left[\frac{b}{r+\delta}\right]^{\frac{b}{(1-b)}}\right)e^{\delta(t^*-t)}\right\}+\right.$$

$$\left\{\frac{1}{\delta\left[\left[\frac{b}{r+\delta}\right]\right]^{\frac{b}{(1-b)}}\left(1-\frac{b\delta}{r+\delta}\right)}\right\}+\left\{\left[\frac{b}{r+\delta}\right]^{\frac{1}{(1-b)}}\frac{1}{(1-b)}e^{(r+\delta)(t-N)}\right\}-$$

$$\left.\left\{0.5\left[\frac{b}{r+\delta}\right]^{\frac{1}{(1-b)}}\left(\frac{1}{(1-b)}\right)\left(\frac{b}{(1-b)}\right)e^{2(r+\delta)(t-N)}\right\}\right]+\epsilon_t. \qquad (1)$$

where $W=\beta R^{1-b}$; $E=\frac{E_0}{\beta^{\left(\frac{1}{1-b}\right)}}$; t^* is the age at which the individual graduates from school; N is the anticipated retirement age which we take as 65, a reasonable assumption for this cohort; and E_0 is the human capital stock when training begins. In reality parents begin training their children at (or prior to) birth, but for our purposes now we consider period 0 to begin when the child starts formal schooling because this is the point we know children begin learning full-time.[7]

Three issues underlie equation (1). First, the derivation assumes a continuous employment history. However, not all individuals work continuously throughout their career. This is particularly the case with women. According to Polachek (1975a) and later Weis and Gronau (1981) discontinuous work implies a non-monotonic decline in human capital investment. To date no one to our knowledge has derived the resulting earnings function for such a discontinuous worker. Second, at the time it was initially derived, the model proved difficult to estimate given its complex nonlinear structure. As such, most analyses adopted a quadratic approximation derived by Mincer (1974). Third, because its derivation is based on an individual's optimization of lifetime earnings,

[6] A derivation of (1) is contained in Polachek, Das and Thamma-Apiroam (2015) Appendix A. This specification differs slightly from Haley (1976). The above assumes a two-term Taylor expansion for the third term in Haley's earnings function.
[7] Later we examine parental investments in children.

one should estimate (1) using lifetime data for a given person. Instead, at least until recently, all analyses used cross-sectional or panel data to obtain aggregate population-wide estimates.

V. Simplification of the Earnings Function

Estimation of nonlinear functions such as (1) derived from a lifecycle model is difficult because its complex nonlinear specification impedes convergence. Indeed Polachek, Das and Thamma-Apiroam (2015), hereafter PDT, utilize the Genetic Algorithm to optimize numeric strings using genetic reproduction, crossover, and mutation concepts (Goldberg, 1989).[8] These techniques globally search the parameter space leading to convergence more efficiently than traditional Newton-Raphson hill-climbing algorithms which rely on a point-to-point gradient-based search (Dorsey and Mayer, 1995). Even so, the technique uses lots of computer time, especially when estimating the earnings function person by person.

The complexity of estimating these nonlinear equations is probably why early analyses used a simplified formulation based on Mincer (1958, 1974). Further, because long enough panel data were not available, all prior analyses estimated aggregate population-wide earnings functions. Thus we now examine Mincer's formulation as well as various extensions of it. This entails describing his specification and interpreting its implications. Following this, we use Mincer's results as a benchmark to evaluate what can be learned from obtaining individual-specific parameters. Then finally, we deal with techniques current researchers use to get at exogeneity issues regarding returns to human capital investment.

1. The Mincer Model

By equating the present value of benefits to costs, Mincer (1958) derived his original earnings function

$$\ln Y_i = \alpha_0 + r_s S_i + \epsilon_i \qquad (2)$$

where Y is earnings and S is schooling, which he estimated using cross-sectional census data. Of prime interest was the r_s coefficient that depicts the rate of return to school. Of less interest is α_0,

[8] The algorithm was originally developed by Holland (1975).We use a version of GA written by Czarnitzki and Doherr (2009).

that represents the logarithm of earnings assuming no school. Even in the 1960s when Mincer first estimated this equation, he realized the equation had shortcomings. Most obvious was an omitted experience variable which is necessary in order to introduce lifecycle considerations into the model. This omission causes r_s to underestimate the true rate of return because both schooling and labor market experience are positively related to earnings, but schooling and labor market experience are inversely correlated.[9] Becker and Chiswick (1966) as well as Mincer (1974)[10] incorporate Ben-Porath's (1967) theorem that human capital investments decline monotonically with age assuming a finite (and continuous) work horizon. This yields a concave earnings function. Although Mincer experimented with several specifications,[11] the following log-linear model is the one that prevailed, probably because of its simplicity[12]

$$\ln Y_i = \alpha_0 + r_s S_i + \beta_1 t_i + \beta_2 t_i^2 + \epsilon_i \qquad (3)$$

where all variables are the same as before, except now t represents work experience. The coefficient α_0 is related to initial earnings capacity, β_1 and β_2 are a combination of the amount and the return to human capital investments.[13] Numerous examples of this equation appear in the literature. All yield positive returns to schooling (in the 3-20% range) and all yield concave earnings profiles (exhibited by negative β_2 coefficients), but here too, there are biases.

Mincer estimated (3) using the 1960 Public Use U.S. Census data to obtain:

$$\ln Y = 6.20 + .107S + .081t - .0012t^2 \qquad (4)$$

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[9] Of course there were other biases but these were considered later.

[10] Also Tom Johnson (1970).

[11] These include a Gompertz specification as well as various interaction terms.

[12] Heckman and Polachek (1975) use Box-Cox and Box-Tidwell transformations to show the log-linear fit works best when compared to a set of other common functional forms. Heckman, Lochner and Todd (2003) modify the Mincer model to incorporate individuals choosing their education levels to maximize their present value of lifetime earnings. They also relax other restrictions such as the constraint that log earnings increase linearly with schooling and the constraint that log earnings-experience profiles are parallel across schooling classes, but Mincer also relaxes these latter constraints in a number of his specifications which contain an interaction term between experience and schooling. Indeed he finds (1974:92-3) nonparallel profile shifts, as well.

[13] These five aspects are related to, but not exactly the same as, PDT's five parameters. The coefficients $\alpha_0 = \ln E_0 - k_0[1+\frac{k_0}{2}]$, $\beta_1 = r_t k_0 + \frac{k_0}{T}(1+k_0)$ and $\beta_2 = -[\frac{r_t k_0}{2T} + \frac{(k_0)^2}{2T}]$ assuming a linearly declining post-school investment function $k_t = k_0 - \frac{k_0}{T}t$ where k_0 is initial and k_t concurrent "time-equivalent" investment and T is the total period of positive investments. Mincer also considered three other specifications for k_t. These entail (1) a linear declining dollar specification, (2) an exponentially declining dollar specification, and (3) an exponentially declining time-equivalent investment specification. These yielded nonlinear in the parameters less popular earnings functions that by and large have been ignored in the literature.

Given there are four coefficients representing five aspects of human capital, one must make an identifying restriction.[14] Assuming equal rates of return for schooling and post-school investment (r_s=r_t) yields an E_0 of $1185.59 in 1960 dollars, or $9778 2016 dollars, which reflects the earnings power of an individual with no human capital. The initial time-equivalent investment just upon completing school k_0 would equal 0.492 meaning that one initially spends about 50% of the time on one's first job investing in on-the-job training. Finally, T equals 25.82, implying that earnings peaks just after 25 years in the labor force.[15]

According to the Ben-Porath optimization model, human capital investment declines continuously over one's lifetime. If going to school entails 100% use of one's time, then time investment just after completing school should be slightly below 1.0, but not as low as the 0.5 observed above. One explanation centers on governmental and familial subsidies to those attending school (Johnson, 1978). According to this argument, school enrollees receive subsidies if and only if they remain in school. To obtain the maximum subsidy, individuals stay in school longer than otherwise, but revert back to regular investment patterns when the subsidy disappears. Given possible social benefits from an educated population, this does not necessarily imply distortions in the amount of school individuals purchase.[16]

VI. Direct Applications of the Mincer Earnings Function

At least three important empirical implications emerge directly from the Mincer earnings function. First, earnings rise with human capital investments. This means the coefficient on

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[14] The parameters are the initial human capital stock (E_0), the rate of return to schooling (r_s), the rate of return to post-school human capital investment (r_t), and the time when gross human capital investment just equals depreciation which is the experience level at which net human capital investment goes to zero (T).

[15] The computation results from solving the following equation:

$$\ln Y - k(1+\frac{k}{2}) = 6.2; r_s = .107; r_t k + \frac{k}{T}(1+k) = .081; -r_t \frac{k}{2T} + \frac{k^2}{2T^2} = -.0012; r_s = r_t \text{ for } T, k, r_s, r_t,$$

and Y .s:

[16] See Psacharopoulos and Patrinos (2004) and Psacharopoulos (2006) for an analysis of social rates of return to education.

schooling should be positive, and bigger the better the quality of education. Second, the coefficient on experience-squared should be negative indicating less earnings growth mid-career. Third, earnings distribution should be related both to levels and variations in human capital accumulation. This means the variance of earnings widens as schooling levels increase and as a population ages. However, interestingly, holding schooling level constant, relative earnings differences (as measured by the variance of the logarithm of earnings) should narrow with experience then widen, exhibiting a U-shaped log variance of earnings (Polachek, 2003).

Each of these is widely observed. Literally dozens of studies estimate schooling rates of return. These entail multiple countries and cover numerous years. One survey (Patrinos and Psacharopoulos, 2010) contains rate of return estimates for over 70 countries spanning more than 25 years. A second (Trostel, Walker and Woolley, 2002) contains estimates for 28 countries. A third (Montenegro and Patrinos, 2014) utilizes the World Bank International Income Distribution Database to estimate rates of return for 139 economies mostly since 2000. Philip Oreopoulos and Uros Petronijevic (2013) in a survey on the returns to college education by claim that "the earnings premium associated with a college education has risen substantially" and that college is still a "sound investment" (p. 1).

Although more school is associated with higher earnings, it is not obvious schooling actually raises productivity. A number of theories claim not. For example, signaling models argue that better workers "signal" their prowess by going to school, but school itself doesn't affect productivity. Similarly screening models claim that firms screen on certain characteristics such as completing a degree because "finishing" signals stick-to-itiveness a characteristic defining potentially "better" workers, but again schooling by itself doesn't affect productivity. Finally, long-term contract models yield escalating lifecycle earnings. However, these pay schemes reflect techniques firms use to hire the best workers, decrease turnover and minimize on the job shirking, but do not necessarily increase worker productivity. Although actual employee productivity is hard to measure, and few data sets actually have such quantities, some studies exist linking educational investments to actual productivity. For example, utilizing productivity data on 296 household farms in West Bengal, India, Kumbhakar (1996:188) showed "that education increases [actual] productivity" and that this enhanced productivity increased farmers' wages. Generalizing these results to economic growth, Barro and Sala-i-Martin (1999) find that the higher a population's education, the higher its GDP and GDP growth per capita. With regard to sheepskin effects, Clark and Martorell (2014) find little evidence of signaling when comparing the earnings of workers who barely passed and barely failed exams leading to a high school diploma. With respect to social effects of school, Lochner and Moretti (2004) show that schooling reduces the probability of incarceration and arrest. In another realm, Benmelech and Berrebi (2006), based on a unique data detailing the biographies of Palestinian suicide bombers, find that more educated suicide bombers are more likely to succeed in their mission and are more likely to induce casualties when they attack. In addition, education positively affects non-labor market activities. For example, Michael (1973) shows that education improves one's efficiency in consuming everyday commodities. Polachek and Polachek (1989) illustrate "reverse intergenerational transfers" by showing that even one's children's education positively affects the way one consumes. In summary, schools appear to increase cognitive and non- cognitive skills. However, not obvious is whether these acquisitions primarily come about because of school or simply because of students' innate abilities. More on this later.

Also universal is earnings function concavity exhibited by a negative β_2 coefficient found when estimating equation (3). Early studies (Mincer, 1974) tested this proposition using OLS regression with cross-sectional data.[17] This result is universal across countries and years (Polachek, 2008). These results also hold when one adjusts for selectivity biases (Hartog, et al., 1989; Kiker and Mendes de Oliveira, 1992; or Baldwin, Zeager, and Flacco, 1994, and Gibson and Fatai, 2006) and for individual specific heterogeneity using standard and not so standard fixed-effects techniques (Mincer and Polachek, 1978; Licht and Steiner, 1991; Kim and Polachek, 1994; Light and Ureta, 1995; and Bhuller et al., 2014).

Finally, as Mincer predicts, the distribution of earnings varies over the lifecycle. According to Mincer, $\sigma^2(\ln Y_{it})$ where i denotes an individual and t denotes an experience level is likely U-shaped over t, with the trough occurring at Mincer's "overtaking" point" ${}^{1}/_{r_s}$ years after graduating school. Predicting this trough is unique to the human capital model. Mincer verified this with US data, Brown (1980) found some evidence, and Polachek (2003) corroborated this with Luxemburg Income Study (LIS) data from nine countries.

[17] Some use panel data, but one can question how these adjust for price changes. Another exception is in executive pay late in some individuals' career paths.

VII. Extending the Human Capital model

Adding categorical dummy variables to the basic Mincer earnings function yields estimates of earnings differences across population subgroups. In this vein, numerous studies proliferated beginning with analyses of the union/nonunion wage gap (Lewis, 1963, 19863), race (Welch, 1974), gender (Fuchs; Suter and Miller, 1973) migration and ethnicity (Chiswick, JPE, 1978; Borjas, 1982, 1985, 1993), and health status (Grossman, 1972). Nowadays a host of other factors related to earnings are considered. For example. beauty (Hamermesh and Biddle, 1994; Scholz and Sicinski, 2015), height (Lundborg, Nystedt, Rooth, 2014), dress (Hamermesh, Meng, Zhang, 2002), hair color (Dechter, 2015), grooming (Robins, Homer, and French, 2011), sexual orientation (Sabia, 2015; Klawitter, 2015), college major (Webber,2014), bilingualism (Saiz and Zoido, 2005), social skills (Weinberger, 2014), personality (Groves, 2005), mental state (Cseh, 2008), childhood disorders (Fletcher, 2014), teenage drug use (Burgess, Propper, 1998), veteran status (Gabriel, 2016), religion (Steen, 2004), and more.

Interpreting these earnings differences is tricky as many of these variables might not be truly exogenous. This is certainly the case for schooling. If higher ability student go to school longer, then part of the often measured return to school may be a return to student ability, and not school per se. A long literature spells out and attempts to correct for this endogeneity bias arising from omitted ability. We will discuss this later. But it is also the case that other seemingly more likely exogenous variables are not truly exogenous.

Take the case of gender. Many define gender wage differences holding education, experience (though most studies use potential rather than actual experience) and other variables constant to constitute discrimination. Such regression models indicate women earn less than men. In the US the gap is approximately 22%. Among OECD countries the gap averages 15%. One might argue this indicates rampant discrimination, namely that firms pay women lower wages despite seemingly equal qualifications. But the story is far more complicated.

An exogenous variable must be randomly assigned independent of other variables. Certainly in the US and OECD countries where there is no apparent child preference, gender is typically thought to be randomly assigned at birth. True, gender does not appear to affect or be affected by other variables in the human capital model. However, there still are a number of endogeneity issues. For one, gender is not independent of other omitted variables, but instead it is correlated with other factors that may affect earnings. Expected lifetime labor force participation is the most notable. For example, marriage and motherhood are often cited as the prime reasons for intermittent participation. Women who do not get married or have children have comparable lifetime work histories and wages relative to non-married childless single women. But women and married women with children have wildly different lifetime labor force participation than their men counterparts.

To see the effects of these omitted variables, we modify the Mincer earnings function to include marital status and number of children, along with a set of interaction terms between these and gender. One such specification is:

$$\ln Y_i(t) = a_0 + a_1 S_i + a_2 t_i + a_3 t_i^2 + \alpha_5 F_i + \alpha_6 M_i + \alpha_7 F * M_i + \alpha_8 C_i + \alpha_9 F * C_i + \alpha_{10} F * M * C_i + \alpha_{11} X_i + \varepsilon_i \tag{5}$$

where ln(Y) is the logarithm of earnings, S represents years of schooling, t and t^2 depict years of experience and its square, as have already been defined; and F is a categorical gender dummy variable for being female, M a categorical dummy variable for marital status, F*M an interaction term between gender and marital status, C the number of children, F*C and interaction term between gender and number of children, F*M*C a three-way interaction term, X other relevant exogenous variables, and ε_i a random error term for each individual observation. This specification yields estimates of the gender wage gap for married men and women separately from single men and women. It also estimates the effect of children on the gender wage gap. The interesting result is a "family wage gap" in which the gender difference in earnings is relatively small for single men and single women, yet large for married men and married women, and especially large for those married men and women with children. Polachek (2008) presents results of the marital status differential for 14 countries using the Luxembourg Income Study data. Independent of country or year, the gender gap for singles varies between 20% in favor of men to 4% in favor of women (the unweighted average is about 8% in favor of single men over single women) to between 3 and 56% (with an unweighted average of about 30%) for married men and over married women. This means the gender wage gap is not uniform. It is small for childless single men and women, but relatively large for married men and women with children. Why?

The reason is an omitted variable. To see this note that marriage and children are related to lifetime labor force participation, but both marriage and children influence lifetime work differently for men and women. For men, being married having children is associated with higher lifetime work, but for women marriage and children decrease lifetime work. These work patterns are illustrated in both cross-sectional data as well as retrospective work histories. Figure 2 depicts gender-marital status labor force participation patterns for the United States in 1970 and 2010. Married men in 1970 have the highest lifetime labor force participation. Married women have the lowest, peaking at about 47% between the ages of 20 and 24. The drop between ages 25-35 reflects intermittent labor force participation related to childbearing. The gap between single males and females is the narrowest. By 2010, the gender differences are appreciably smaller, but still remain. Figure 3 shows how female labor force participation decreases with children. It indicates younger children have a larger negative effect on work.

The same lifetime work patterns emerge from retrospective data. Using the 1980 Panel Study of Income Dynamics Data (PSID) Miller (1993) finds that married women average 10.04 years out of the labor force. Similarly, using a panel of 2659 individuals from the 1976-1987 PSID data, Kim and Polachek (1994) find that women averaged 9.62 years out of the labor force relative to men's 2.22 years. Current data for foreign countries are comparable. Using Canadian data, Simpson (2000) finds that in 1993 married women with children averaged 7.6 years (or 36.4% of their work years) out of the labor force, whereas single women spent 1.5 (or 12.9%) of their work years out of the labor force. For men, this figure is 0.9 years (or 8.1%). Data within narrow professions yield similar results. Catalyst (2003) finds that only 29% of women MBA graduates work full time continuously since graduation compared to 69% for men, and similarly only 35% of women law graduates worked continuously since graduation compared to 61% for men.

1. The Segmented Earnings Function

Mincer and Polachek (1974) modified earnings function (3) to incorporate discontinuous labor force participation.[18] The empirical specification is derived assuming linearly declining human capital investments in each work/non-work segment to obtain

$$\ln Y_t = a_0 + r_s S + \alpha_1 e_1 + \delta_h h + \alpha_2 e_3 + \varepsilon \qquad (6)$$

where e_1, h, and e_3 are the work and non-work segments.[19]

The α_1 and α_2 coefficients range from 1.2% to 4.0%, depending on the population subgroup studied and on one's level of education. The δ coefficient ranges from -4.5% to -0.5% depending on the respondent's amount and type education. In general, the higher one's education and the more skilled one's job, the greater the magnitude of these coefficients. Also, α_2 often exceeds α_1 because upon reentering the labor one has a greater commitment to working more continuously (Polachek, 1975a). By now, numerous studies adopted this approach to assess the effect of work interruptions. Examples include Albrecht et al., 1999; Baum, 2002; Corcoran and Duncan, 1979; Corcoran et al., 1983; Hotchkiss and Pitts, 2003, 2005; Jacobsen and Levin, 1995; Kim and Polachek, 1994; Light and Ureta, 1990, 1995; Mincer and Ofek, 1982; Mincer and Polachek, 1974; Phipps, Burton and Lethbridge, 2001; Rummery, 1992; Sandell and Shapiro, 1980; Sen, 2001; Stafford and Sundstrom, 1996; Stratton, 1995 and Spivey (2005).

2. Intermittent Labor force Participation and Human Capital Investment

[18] In empirical work Mincer and Polachek (1978) adjust for endogenous lifetime work using two-stage least-squares estimation. Also see Gronau (1988).

[19] Assuming a linear human capital investment function $k(t) = a_i + b_i t$ where a$_i$ is the initial "time-equivalent" investment and b$_i$ is the rate of change in investment taking place in of the n work/non-work segments i yields $\ln E_t = \ln E_0 + r_s S + r_p \sum_{i=1}^{n} \int_0^{e_i} (a_i + b_i t)dt$ .For the three period case (n=3), the earnings function is a quadratic in each work/non-work segment:

$$\ln E_t = \ln E_0 + r_s S + r_p (a_1 e_1 + \frac{1}{2} b_1 e_1^2 + a_2 e_2 + \frac{1}{2} b_2 e_2^2 + a_3 e_3 + \frac{1}{2} b_3 e_3^2)$$

Taking a linear approximation of the quadratic in each segment and denoting segment e2 as h (since it represents time at home out of the labor force) yields (6).

As already illustrated, the lower the expected lifetime work, the smaller the gains from human capital investment, and the lower the amount invested. For this reason a worker who anticipates discontinuous labor force participation procures less on-the-job training than the continuously employed worker. As a result, women's earnings need not exhibit the typical concave age-earnings profile characteristic of men. Instead, they are flatter and often exhibit a non-monotonic pattern depending on the degree of intermittent work behavior.

To see this analytically modify the lifecycle optimization model spelled out in equations (1) to (3) above by introducing the possibility that labor force participation can vary year-by-year over the lifecycle (Polachek, 1975a). As such, modify (1) so that

$$Y(t) = R[N(t)E(t) - K(t)]$$

where N(t) is the proportion of time available spent working in the labor force and investing in human capital. Assume N(t) is exogenous to the investment process, but dependent on gender, marital status and the number of children. Allowing for such intermittent labor force participation implies N(t) is not constant in each period. This yields the following marginal gain from investment:[20]

$$\dot{\psi} = -w_0 N(t) e^{r(t-T)} + w_0 r e^{rt} \int_t^T [N(\tau) - N(t)] e^{-r\tau} d\tau$$

The first term represent the marginal revenue if labor force participation were constant each time period. It is negative and identical to Ben-Porath's declining marginal gain from investment over the lifecycle. The second term represents the incremental change to marginal revenue when labor force participation is *not* constant over the lifecycle. This term is positive if future labor force participation is expected to rise, as in the case when a woman anticipates reentering the labor force after raising her children. A sufficiently large second term implies an increasing present value of human capital investment. This means that intermittent labor force participation can cause human capital investment to rise during and after one's childrearing years instead of falling monotonically as Ben-Porath predicted. As such, post-school human capital investment (on-the-job training) crucially depends on expected lifetime labor force participation.

[20] See Polachek (1975a) for a derivation.

Most current studies of the gender wage gap do not take account of expected future labor force participation. As such, most overestimate the amount of the unexplained wage gap. The one set of studies accounts for these biases. Polachek (1975a), Golden and Polachek (1987) and Kao *et. al.* (1994) analyze wage differences for the US and for Taiwan. In contrast to traditional decomposition studies which explain 30-50% of the gender wage gap, these results explain up to 93%. To illustrate the robustness of the procedure, these studies also explain 82% of the marital status wage gap within genders. Thus lifetime work, governed by gender, marital status, and children, affect human capital acquisition which explains why there is a gender wage gap. Whereas the human capital model emphasizes expected lifetime labor force participation, other studies also look at willingness to work long hours (Goldin 2014; Cortés and Pan, 2016), workplace preferences (Wiswall, Matthew and Zafar, Basit. 2016) as well as psychological and motivational differences. These include payment scheme preferences (Dohmen and Falk, 2001), time preference (Brown and van der Pol, 2015), mortality risk (Hammitt, and Tuncel, 2015), risk preference (Booth and Katic, 2013; Rai and Kimmel, 2015). A survey of such articles[risk] are contained in Croson and Gneezy, 2009. Non-cognitive skills (Cobb-Clark and Tan, 2011).

3. Gender Wage Gap: Whites Vs. Blacks

Related to lifetime work is the gender pay gap between whites and blacks. As indicated in Table 1, the gender earnings gap for blacks is smaller than for whites. One reason is lifetime labor force participation. At least in the past, black women worked slightly more over their lifetimes than white women, but black men compared to white men worked less. Figure 4 indicates racial differences in labor force participation. Although the data constitutes annual rates, the figure is indicative of lifetime trends. The gender earnings gap for whites in 2015 is 0.78, but for blacks it is 0.90.[21]

4. Changes in Lifetime Labor Force Participation and the Gender Wage Gap

Changes in lifetime labor force participation can answer the second question, why the gender wage gap narrowed. At least since the time data has been collected, women's, especially married women's, labor force participation has risen. In 1890, only 4.9% of US married women participated. In 1948 this figure was approximately 33% and in 2015 it was 57%. Figure 5

[21] Based on data from: https://www.dol.gov/wb/resources/Womens_Earnings_and_the_Wage_Gap_17.pdf

illustrates these labor force participation rates from 1948-2015. Higher labor force participation raises expected lifetime work and as a result increases human capital investments and wages. At the same time male labor force participation declined moderately from 86% in 1948 to 70% in 2015. As such, female human capital investments most likely rose relative to males' human capital investments, thereby resulting in a higher female-to-male wage ratio. This is precisely what is observed in Figure 6. However, there are exceptions, such as between 1960 and 1975. Polachek and Robst (2001:869) found that the rapid rise in "new female labor force entrants in the 1970s brought down mean female wages, thereby driving down female wage growth." This is probably the case for the 1940s, as well, which witnessed an unprecedented influx of women workers during World War II.

Whereas the Mincer earnings function can be used to explain these demographic patterns of the earnings data, this formulation is insufficient with regard to other theoretical implications. These entail estimating person by person the five structural parameters discussed earlier, as well as their implications. Nowadays sufficiently long panel data are available to follow each person for a long enough time period to obtain person-specific estimates. We do so now.

VIII. Human Capital Parameter Values

Among the first to estimate nonlinear earnings functions was Haley (1976). He used CPS (Series P-60, No. 56) schooling and earnings (unfortunately earned and unearned income) data for individuals 18-64 in 1956, 1958, 1961, 1963, 1964, and 1966, thus implying the pooling of 6 cross-sections. However, his slightly more complex formulation had identification problems precluding his ability to estimate E_0, β, and R. Nevertheless, the crucial parameters $b, r,$ and δ were obtained for seven schooling levels, along with parameters defining earnings growth across cohorts. Most of Haley's estimates are as expected. For example, discount rate estimates are between 5 and 7%, and the b ability coefficient is about 0.6. These estimates compare favorably to other studies that estimate aggregate Ben-Porath based models, though understandably there are differences due to alternative methodologies and data. For example, Heckman's (1975) 0.67, Heckman's (1976) 0.51-0.54, Heckman et al.'s (1998) 0.80, Song and Jones's (2006) 0.5, and Liu's (2009) 0.52 compare favorably Haley's 0.54-0.59. Haley's 0.17-0.43 for δ compares favorably to Johnson and Hebein's (1974) 0.022 and Heckman's (1976) 0.04-0.07. Further, as already mentioned, each uses slightly different human capital production functions, and some incorporate life-cycle labor supply. On the other hand, not all the human capital theory's predictions are observed in Haley's estimates. For one, a higher b should imply more schooling, but Haley does not find this. Also the relationship between skill depreciation and schooling level should be negative, but this is not the case in Haley's empirical work.

1. Heterogeneity

With the advent of speedier computers, better optimization routines, and longer panels than in the past, one can retrieve individual-specific parameters of the human capital life-cycle model by estimating appropriate earnings functions individual-by-individual. This allows one to account for heterogeneity because ability-type parameters can be estimated for each person. The first to do this is PDT (2015). They obtain the five parameters $b, r, \delta,\ E_0,$ and $\beta,$ for individuals contained in the National Longitudinal Survey of Youth, as well as a population-wide value for the rental rate of human capital R. They plot kernel density functions and find significant heterogeneity. Important to macroeconomists, accounting for this heterogeneity dramatically reduces estimates of population-wide persistence of permanent and transitory shocks in earnings dynamics models by over 50 percent.[22]

Their technique also yields a number of additional new findings. For example, on the micro level, they find that blacks have higher rates of skill depreciation than whites. Here, we extend PDT's work to include Hispanics, and present average coefficient estimates for them as well as for blacks and whites in Table 7. More interestingly, whereas typical ability measures obtained from Armed Forces Qualification Test (AFQT) test scores[23] differs widely between Hispanics, blacks, and whites, there are far smaller differences in the human capital ability parameters $b, \beta,$ and E_0 indicating possible racial biases in typical psychology-based aptitude, achievement and intelligence test scores. This is consistent with Fryer and Levitt (2004, 2013) who find small racial differences in IQ once adjusting for a number of demographic factors.

2. Implications of Individual-Specific Human Capital Parameters

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[22] Other studies concentrate on heterogeneity by allowing ARMA processes to vary across individuals (e.g., Browning and Ejrnæs, 2013). Some present decile ranges of key parameters illustrating that heterogeneity affects the speed individuals respond to shocks (e.g., Browning, Ejrnæs, and Alvarez, 2010; and Browning and Ejrnæs, 2013). In other realms, Greene (2004, 2005) examines heterogeneity by using fixed and random effects models.

[23] AFQT scores are computed using the Standard Scores from four ASVAB subtests: Arithmetic Reasoning (AR), Mathematics Knowledge (MK), Paragraph Comprehension (PC), and Word Knowledge (WK).

Schooling Levels and Human Capital Parameters

Obtaining individual specific parameters enables PDT to verify a number of previously untested theorems based on the life cycle human capital model. More specifically, human capital theory predicts a positive correlation between ability measures b and β and one's years of schooling, a negative relation between initial stock of human capital E_0 and schooling level, and negative correlations between a person's years of school and his/her discount (r) and skill depreciation (δ) rates. Greater ability to learn raises the amount of human capital one can produce per unit of time, thus lowering the cost of human capital acquisition, and increasing the amount of school obtained On the other hand, more initial human capital E_0 is a substitute for schooling and thus leads one to stop school earlier. Higher depreciation rates lower the amount of human capital retained, thus making school relatively more costly and decreasing the amount purchased. Finally, schooling levels decrease with time discount (r) because individuals with high discount rates are more reluctant to put off the gratification of current market earnings.

Personality and Human Capital Parameters

Similarly PDT find human capital parameters to be related to personality. They observe greater ability as well as lower skill depreciation and time discount rates for those individuals with a high internal locus of control and for those individuals who demonstrate high levels of self-esteem. Individuals inclined towards mental depression have a higher time discount. At the same time, family background, such as higher parental education, is associated with a greater ability to learn, lower skill depreciation, and a smaller rate of time discount. Educational stimuli, such as growing up in a household that subscribed to newspapers and magazines, are associated with a higher ability. Conversely, growing up poor is associated with lower levels of ability. These correlations which are now broken down by race and ethnicity are given in Table 8.

3. Homogeneity vs Heterogeneity of Human Capital

Strictly speaking, the human capital model assumes potential earnings are directly related to the amount of human capital one purchases throughout one's life ($Y_t^P = RE_t$) and observed earnings equals potential earnings minus current investments ($Y_t = R[E_t - K_t]$). Earnings rise with age as one accumulates more human capital, but eventually falls when skill depreciation outweighs appreciation. Underlying this approach is an assumption that all human capital is homogeneous because everyone faces the same rental rate per unit of human capital. One earns more because one has more human capital, but not because one has a different *type* human capital. But it is not obvious that human capital is homogeneous and that all earnings variations come about because amounts and not types of human capital differ across the population. For example, holding years of school constant, do newly graduating engineers earn more than new humanities majors because engineers have more human capital, or do new engineers earn more because they bought a different type human capital? In other words, is human capital homogeneous or is it heterogeneous?

A number of papers claim the latter. For example, Polachek (1979, 1981) argues in favor of heterogeneity. He devises a matching model in which the production function for human capital varies by occupation. Although many human capital production function parameters can vary, he concentrates in his case simply on skill depreciation due to non-use (atrophy) when dropping out of the labor force because he is interested in gender occupational segregation. As such, he assumes $\dot{E} = f(K_t) - [\dot{\delta} + (1 - N_t)\xi]E_t$ where ξ is an occupation specific atrophy rate and N_t is the proportion of time working in year t.[24] Given that compensating market differentials likely rewards high-depreciation occupations more generously, the human capital rental rate (R) should increase with atrophy, implying $R = R(\xi)$ such that $R'(\xi) > 0$. He shows that those individuals more likely to drop out will plausibly choose occupations with low atrophy rates. Based on this, he explains a large amount of gender-based occupational differences.[25]

One aspect of the PDT identification strategy is their approach to measure R, the population-wide human capital rental rate.[26] PDT can do this because the human capital model assumes R is a

[24] Atrophy is zero when N_t is 1, but is ξE_t when N_t is 0.
[25] Heckman Layne-Farrar, and Todd (1996) also claim heterogeneity in human capital. They do so by exploiting three interactions: (1) between school quality and education, (2) between regional labor shocks and education, and (3) between place of birth and place of residence.
[26] Heckman, Lochner and Taber (1998) adopt an alternative identification strategy to determine R. Their approach exploits the fact that all observed earnings changes (adjusted for hours) between two time periods must be attributed to rental rates changes when in "flat periods" human capital stock (Et) remains constant. Typically, flat spots occur late in life, usually around the mid-fifties, an age greater than any current respondent in the NLSY. As will be shown in Section 5.2, Bowlus and Robinson (2012), who apply the flat spot identification approach with CPS data, obtain similar results to ours.

constant determined by market forces, whereas the human capital parameters vary by individual. But one can go farther by checking whether other factors alter this relationship. This gets at a direct test of human capital homogeneity. Homogeneity implies that each basic human capital unit rents for the common price determined in the market. Under homogeneity this rental rate should be the same independent of any factor since human capital in all endeavors is the same. However, heterogeneity implies rental rates can differ if the market rewards various types of human capital differently. In short, human capital is homogeneous if rental rates remain constant, but is heterogeneous if rental rates vary by type of human capital. Obviously, nonmarket considerations such as discrimination, regional variations, or time varying macroeconomic conditions can tweak the rental rate, since supply and demand fluctuations can alter spot market prices.

PDT test for homogeneity. They find very little variation in rental rates across industries, across occupations, or by schooling level. Only unemployment is negatively correlated, but they also find slight race differences. On the other hand, preliminary research by Andrew Verdon (2017) corroborates this for the UK (using the British Household Panel Survey) and Korea (using the Korean Labor and Income Panel Study), but finds rental rate differs by industry in Germany (using German Socio-Economic Panel) and by occupation in the US using PSID data, though more research on this is needed.

One limitation of PDT is they perform the analysis only for men. As stated earlier, a structural earnings equation for potentially discontinuous workers is far more complex and less tractable empirically.

IX. Inequality

Past studies explain earnings differences based on schooling and experience. However PDT show that abilities to learn and earn, time preference and skill depreciation previously not measured are also important in explaining earnings differences. To illustrate we can examine the effect of these attributes on earnings, earnings profile slopes, and on the distribution of earnings.

Both the complex nonlinear earnings function as well as the aggregate log-linear simplification estimated population-wide have implications regarding the earnings distribution. Unlike the log-linear aggregate approach in which earnings variations arise because observables, in particular schooling and labor market experience, vary across the population, the individually estimated complex model allows for differences in both observables as well as previously unobserved b_i, β_i, r_i, δ_i, *and* E_{0i}. As discussed, the nonlinear specification first identifies five basic human capital parameters b, β, r, δ, and E_0; second yields individual by individual estimates of b_i, β_i, r_i, δ_i, and E_{0i}; and third teases out a market-wide rental rate per unit of human capital enabling one to test for human capital heterogeneity. To get at the relevance and relative contributions of these new individual-specific parameters, we examine their influence on both earnings levels as well as earnings disparities (variance). We do this in three ways. First, we compare the impact of the previous *unobserved* parameters to the impact of the previous *observables* on earnings levels. Second, we compare the added explanatory power (R^2) of the previously unobservable parameters to the previous observables. Then third, we compare the relative importance of the previous unobservables to the observables in explaining a measure of earnings distribution (σ_y^2).

1. Comparing the Impact of Observables and Unobservables on Earnings Levels

The relative importance of the previous unobservable attributes can be determined by comparing their elasticities computed from eq. (1). As expected, elasticities for $b, \beta,$ and E_0 are positive because ability enhances human capital production and hence earnings (Table 9). The elasticities are negative for δ and r because both make investment less valuable.

More specifically, the table shows that, on average, a 10% rise in b and β lead to a 12.7% and 19.7% rise in earnings, whereas a 10% rise in δ leads to an 8.1% decline in earnings. A 10% increase in experience (t) yields a 13.8% rise in earnings, but interestingly only a 10% increase in years of school only augments earnings 3.3%. Also, relatively of small importance is E_0 and r. The elasticity of earnings with respect to E_0 is 0.19 and with respect to r it is -.04. In summary, b, β, t, and δ, are relatively important, whereas schooling, E_0, and r are not.

The earnings elasticities with respect to b and schooling are slightly higher for whites, whereby the earnings elasticities with respect to β and E_0 is slightly higher for blacks. Earnings elasticities for Hispanics are lower than blacks and whites.

Table 9 presents average elasticities indicating the impact observable and previously unobservable attributes have on earnings levels. However, these effects are nonlinear. We use individual specific parameters based on PDT to get at this nonlinearity. We plot these nonlinear elasticities over the range of parameter values. Figure 7 plots these relationships.

The elasticity with respect to b rises as the value of b rises. This means that an intervention that raises b will increase earnings by a greater percent for those already with a high b. In short, the more able will benefit more.

The pattern for β is the opposite. These elasticities decrease with β. This means that an intervention that increases β will increase earnings proportionally more for those individuals with lower β.

The earnings elasticities with respect to E_0 and schooling have a similar pattern to each other. They first rise as the level of E_0 and schooling rise, and then decline. These similar patterns are expected as both schooling and E_0 represent stocks of human capital. The inverted U shapes indicate that either a rise in schooling or in E_0 raise earnings at an increasing rate when these attributes are low. But after a certain schooling level (at college), earnings rise at a decreasing rate.

The effect of the skill depreciation rate (δ) and time discount rate (r) on elasticities are somewhat similar. As δ and r rise, the elasticities decline at an increasing rate. Except, at a very high level of δ there is a slight upward trend, but in terms of the magnitude the elasticities remain negative. The next graph indicates that incremental earnings decline as one ages.

2. On Comparative R^2

The benefit of the PDT model is its capability of identifying five person specific human capital parameters. Thus, in addition to schooling and experience, we can assess the extent each of these attributes explain earnings. To assess these, we compute the explanatory power of each of these factors by calculating their contribution to R^2 while holding the others constant. For instance, to assess the contribution of schooling, we allow years of schooling to vary while holding b_i, β_i, r_i, δ_i, E_{0i} and t constant at their mean levels. By holding all these factors constant, the R^2 from this exercise can be interpreted as the variance of observed earnings explained by the variance in schooling alone.

The results of these exercises are presented in Table 10. First, the explanatory power of each of the attributes are fairly stable across the life-cycle. Second, the parameter β has the highest explanatory power. Third, the explanatory power of the abilities to learn and human capital depreciation rate are substantially higher than the explanatory power of E_0 and schooling. Fourth, time preference plays almost a negligible role in explaining the earnings variance. And, fifth, in absolute terms, schooling and E_0 have very little explanatory power.

Noteworthy is the observed weak explanatory power of schooling. In a sense this is paradoxical, especially since most past studies argue that school is the most important determinant of earnings. Yet we find schooling to play a more minor role compared to b, β, and δ. These three parameters respectively reflect the ability generate and retain earnings power. Thus the results imply that ability is more important in determining earnings than school level per se. Not only does one's ability dictate one's schooling level, but also a higher ability enables one to produce more human capital while in school. Further, skill depreciation (δ) measures the degree one retains knowledge. Thus the ability to learn and retain knowledge seem to be the important determinants of earnings. In a sense this finding is consistent with work to be discussed shortly on how past studies overestimate schooling rates of return by neglecting to appropriately account for ability.

Another way to look at this is to compare the explanatory power of individual-specific parameters to observables. Table 11 reports adjusted R^2 measures for various specifications of the earnings function. AFQT increases the adjusted R^2 by only 0.04 over schooling and experience in a linear fit, whereas b, β and E_0 increase adjusted R^2 by 0.19. Incorporating AFQT adds virtually nothing (0.01) when including PDT's other three ability measures b, β, and E_0. Adding schooling (Column 2) raises the explanatory power only when ability is not included. AFQT essentially does nothing when b_i, β_i, r_i, δ_i, and E_{0i} are already in the regression. Thus the five human capital parameters jointly explain earnings more than schooling and traditionally measured ability (AFQT).

3. Variance Decomposition

Our third approach is to decompose the earnings variance into that part attributable to observable schooling and experience, and that part attributable to b, β, r, δ, and E_0. Chiswick and Mincer (1972) devise a framework to identify sources of earnings inequality. Their approach concentrates on schooling and work experience which they find to explain a substantial portion of the earnings inequality. However, they cannot evaluate the role differences in individual abilities, time discount and skill depreciation rates (b_i, β_i, r_i, δ_i, and E_{0_i}) play because they do not estimate individual specific parameters.

Based on PDT's individual-specific estimates and the structure of the human capital framework, we assess the relative importance of these parameters. We examine how sensitive earnings variance is to changes in the variation in these factors.

To answer this question, we conduct a variance decomposition exercise. Unlike in Chiswick and Mincer (1972), the earnings function we use is the nonlinear function given in PDT. The complex nonlinearity makes variance decomposition difficult. To circumvent this difficulty, we first linearize it with a first order Taylor series expansion and then conduct the variance decomposition on the linearized version:

$$\begin{aligned} f(b,\beta,E_0,\delta,r) & \\ &\approx f(b_a,\beta_a,E_{0a},\delta_a,r_a,t,TSTAR) + f_b^a(.)(b-b_a) + f_\beta^a(.)(\beta-\beta_a) \\ &+ f_{E_0}^a(.)(E_0-E_{0a}) + f_\delta^a(.)(\delta-\delta_a) + f_r^a(.)(r-r_a) + \; + f_t^a(.)(t-t_a) \\ &+ f_{TSTAR}^a(.)(TSTAR - TSTAR_a) \end{aligned}$$

where $b_a, \beta_a, E_{0a}, \; \delta_a, r_a, t_a, TSTAR_a$ are the average of $b, \beta, E_0, \delta, r, t, TSTAR$, $f^a(.)$s are the corresponding partial derivatives of earnings function with respect to each of the factors respectively and evaluated at the mean values of $b, \beta, E_0, \delta, r, t, TSTAR$. Collecting terms and adding an error ϵ yields

$$Y \approx A + \; f_b^a(.)b + f_\beta^a(.)\beta + f_{E0}^a(.)E_0 + f_\delta^a(.)\delta + \; f_r^a(.)r + \; f_t^a(.)t + f_{TSTAR}^a(.)TSTAR + \epsilon.$$

Assuming $b, \beta, E_0, \delta, r, t, TSTAR$ are uncorrelated with ϵ, the variance of Y (that is σ_Y^2) in terms of the right hand side variables is

$$\sigma_Y^2 = \sum_m f_m^2(.)\sigma_m^2 + \sum_{m \neq l} Cov(m,l) + \sigma_\epsilon^2 = \sum_m f_m^2(.)\sigma_m^2 + \sum_{m \neq l} f_m(.)f_l(.)\sigma_m\sigma_l R_{ml} + \sigma_\epsilon^2 \; \#(7)$$

where $m, l = b, \; \beta, \; E_0, \; \delta, \; r, \; t, \; TSTAR, \sigma_m$ are the standard deviations, and R_{ml} are the pairwise correlation coefficients between m, l. Table 12 presents the values of each of these σ_Y^2 components:

Expression (7) enables one to assess the effect of a change in the standard deviation of a right-hand side variable on the variance of earnings. By taking partial derivatives with respect to each of the factors we obtain the following:

$$\frac{\partial \sigma_Y^2}{\partial \sigma_m} = 2f_m^2(.)\sigma_m + 2f_m(.)\sum_{m \neq l} f_l(.)\sigma_l R_{ml} \qquad (8)$$

Multiplying both sides of (8) by (σ_m/σ_Y^2) yields the elasticity of σ_Y^2 with respect to σ_m. These elasticities for each of the factors are in Table 13.

The results suggest that for every 10 percent decline in standard deviation of b, the variance of earnings declines by 2.1 percent. The effect of a change in the standard deviation of β on the variance of earnings is slightly larger. The elasticities with respect to the standard deviation of other parameters, t, and S are relatively small. This result again implies that one's ability to create new human capital form old is the most important factor determining earnings distribution. In short, ability matters.

X. Endogeneity Issues: Causal effect estimation

Over the past few decades, researchers have identified a number of factors and estimated their impact on earnings and the earnings distribution. A large number of identification strategies were proposed to establish the causal effects. The basic idea underlying these methods is to generate exogenous variation in the explanatory variables so that the causal impacts are identified without other potential confounding factors. The earlier studies on this topic assume that independent variables are exogenous and apply OLS. However, as the potential biases originating from omission of relevant variables and non-representative sample selection were recognized, researchers adopted a variety of alternative identification strategies. These include instrumental variables, twin comparisons, and natural or quasi natural experiments.

The most widely studied topic is the effect of years of schooling on earnings. A larger number of papers appeared since the early 1990s that apply the instrumental variable method to estimate the return to schooling (Angrist and Krueger, 1991; Ashenfelter and Rouse, 1998; Kane and Rouse

1993; Card 1995; Harmon and Walker 1995; Staiger and Stock 1997; Conneley and Uusitalo 1997; Ichino and Winte-Ebmer 2004; Lemieux and Card 1998; Meghir and Palme 1999; Maluccio 1997; Duflo 2001). The estimates from these studies vary widely, ranging from 3.6 percent to 94.7 percent.

Despite the volume of the previous work, the validity of many of the IVs used so far remain unclear. Specifically, the exclusion restriction condition imposed on these IVs became the main point of concern. For instance, Card (1995) uses geographic proximity to college as an instrument in an earnings regression. Presumably being near a college reduces the cost of attendance, for example, by allowing students to live at home. Thus living nearby increases college attendance but by itself is not correlated with other unobserved factors influencing earnings. However, this assertion received a mixed reaction. Carneiro and Heckman (2002) show that distance to college in the NLSY79 is correlated with ability thereby violating the exclusion restriction. Slichter (2015) also concludes that geographic propinquity to college is an invalid instrument and likely results in an overestimate of the returns to college education. On the other hand, Kitagawa (2015) finds no evidence of its invalidity as an instrument when also adjusting for race, region, job experience, parental education, and whether living in an urban area.

Another well cited instrument is the quarter of birth used by Angrist and Krueger (1991). Students born at the beginning of the academic year are older. A good number of these leave school upon reaching the minimum compulsory drop out age, thus having one less year of school than their counterparts born slightly later. In essence they use an estimate of the earnings impact of this extra year of school as an unbiased estimate of the return under the assumption birth quarter is random. Despite its appeal, Bound and Jaeger (1996) criticize this approach. They present a number of studies that show that quarter of birth may be an invalid instrument because it is correlated with other determinants of earnings. These include studies showing quarter of birth to be correlated with mental illness, retardation, personality, and family income. Further, a placebo test using data predating the compulsory school laws yields the same result that birth quarter affects earnings.

Another substantive concern with the IV based estimation is the use of weak instruments (Staiger and Stock 1997; Kleibergen 2002; Moreira 2003). For instance, Angrist and Krueger (1991) use many weak instruments. Many of their first-stage F-statistics are less than 5 (Staiger and Stock, 1997). Bound, Jaeger and Baker (1995) argue that the use of a large number of weak instruments make the IV estimates move closer to OLS. Using the same data as in Angrist and Krueger (1991), Bound et. al. (1995) replace the quarter of birth IV by irrelevant random numbers and estimate 6% returns to schooling with an estimated standard error of ± 1.5 % (See Imbens and Rosenbaum 2005).

Due to these limitations, an alternative literature emerged that uses a partial identification strategy. The attractive feature of this approach is that it relies on weaker yet more credible assumptions than the ones necessary for standard IV-based regressions. However, the approach leads to a bounded estimate of the causal effect rather than a point estimate. Manski and Pepper (2000, 2009) develop a framework used by many to bound estimates of the return to education (Manski and Pepper 2000; Okumura and Usui 2014; Marrioti and Meinecke 2015). For instance, employing a monotone instrumental variable method, they find that the lowest upper bound of the return to schooling is 15.9% for 13 to 14 years of education and 16.5% for 15 to 16 years of education.

The partial identification literature also addresses concerns with invalid instruments. For instance, Flores and Flores-Lagunes (2013) derive nonparametric bounds for the local average treatment effect (LATE) without imposing the exclusion restriction assumption. Slichter (2015) bounds estimates of the returns to college using Card's (1995) data. His lower bound is based on the returns of those individuals whose college attendance is unaffected by living close four-year colleges (always takers). His upper bound is computed based on those individuals whose college attendance depends on distance (compliers). Slichter's bounded estimates are between 6.9% and 18.9%.

A significant body of research also examined the impact of school quality on earnings. Card and Krueger (1992) find that higher school quality measured by a lower student teacher ratio, a longer average term length, and higher teacher pay yield significantly larger returns to schooling for people born between 1920 to 1949. However, in a later paper, Heckman, Layne-Farrar, and Todd (1995) find that the relationship between school quality and earnings is weak and sensitive to the specification used. Thus results regarding the impact of school quality are not robust and also are prone to specification biases.

The partial identification bounds estimation approach is also implemented for policy evaluation. For instance, Flores and Flores-Lagunes (2013) and Blanco, Flores and Flores-Lagunes (2013) estimate bounds for the effect of GED, high school vocational degree, and Job Corps program on earnings. Lee (2009) examines the effect of the Job Corps program on earnings in the presence of sample selection. All these findings suggest that these programs raise earnings for those who participated. Flores and Flores-Lagunes (2013) get a schooling rate of return upper bound of 28% for Job Corps participants.

Partial identification and bounded estimates are nevertheless fallible. They are primarily used to identify causal effects, but can get erroneous parameter estimates if the underlying model is nonlinear. In the human capital model, schooling is nonlinearly related to earnings. A linearized version necessarily omits higher order schooling terms which are no doubt contained in the error. This linearization is a classic misspecification. As a result, even otherwise valid IVs of schooling yield biased and inconsistent estimates.

XI. Early Childhood Development

Our work finds ability to be an important, if not most important, determinant of earnings. If ability is innate and cannot be changed, then altering the earnings distribution would be impossible. On the other hand, if one can find an intervention to alter ability, then the earnings distribution can be transformed perhaps making it more equal. As Heckman (2008) indicates, one such intervention is investment in early childhood development. These developmental skills, in turn could boost future earnings. For example, Boisierre, Knight and Sabbot (1985), Murnane et. al.(1995), Cawley, Heckman and Vytlacil (2001) have demonstrated a positive relationship between cognitive abilities and earnings. Research also shows that a substantial portion of earnings inequality is explained by cognitive abilities (Blau and Kahn, 2005).

Studies that focus on non-cognitive abilities also arrive at the same conclusion. Goldsmith et. al. (1997) shows that self-esteem and locus of control positively influence wages. Kuhn and Weinberger (2004) shows that leadership skills positively influence earnings. Muller and Plug (2006) show that the big-five (agreeableness, conscientiousness, extraversion, openness, neuroticism) traits influence earnings, with agreeableness having the strongest effect. Finally, Muller and Plug's (2006) paper also finds non-cognitive abilities are as important as cognitive abilities in determining earnings.

Because cognitive and non-cognitive abilities influence the level and distribution of earnings, these type abilities are important for policy consideration. Some studies argue schooling enhances cognitive skills (Hansen, Heckman and Mullen, 2004). But a number of other studies emphasize the role of the family. For example, in an early and controversial study, Coleman and his colleagues (1966) highlighted the importance of social capital, namely attributes inherent in the community and family that are useful to the social development of children. Improving resources in the home might be one such initiative. Of course the other extreme is Hernstein and Murray (1994) who imply few, if any, interventional benefits.

Recent research links early childhood interventions to boost cognitive and non-cognitive type skills. Bowles and Gintis (2002) argue skills can be transferred from previous generations to the next, making the new generation more valuable in the labor market. Based on a randomized experimental setting, Heckman et. al. (2006, 2010) show that family level intervention during childhood leads to significant improvement in non-cognitive abilities. A number of other studies (Fletcher and Wolf, 2016; Anger and Schnitclein, 2016) also find that family plays an important role in shaping one's cognitive and non-cognitive skills.

Two important issues should be considered to evaluate potential interventions. First is defining the underlying mechanism how family and other factors influence abilities. Second is assessing their economic viability, namely that the benefits outweigh the associated costs. A number of recent studies address both aspects. Regarding the first, Cunha and Heckman (2007) and Cunha, Heckman and Schennach (2010) offer a dynamic structure of skill formation to demonstrate the mechanism through which family and other factors influence children's cognitive and non-cognitive skills. Using Project STAR data on 11,571 kindergarten to third grade students in Tennessee, Chetty, Friedman, Hilger, Saez, Schanzenbach, and Yagan (2011) find small classes increase the likelihood of college attendance many years later. Also, high scoring classmates lead to higher future earnings, as do more experienced teachers. Further, gains in non-cognitive compared to cognitive skills last longer. Chetty, Friedman and Rockoff find that teacher inputs matter. Employing 1989-2009 data on students and teachers in grades 3-8 from a large urban school district, they find they students assigned to a high "value-added" teacher are more likely to attend college, achieve a higher salary, and less likely to have out of wedlock children. Regarding the second issue, Heckman et. al. (2006, 2010) show that every dollar spent on such childhood interventions yield a 5.7 dollar increase in observed earnings and a projected 8.7 dollar increase in lifetime earnings. These findings reemphasize that appropriate family level interventions not only enhance abilities and raises earnings, but does so in an economically viable way.

XII. Conclusion

Earnings are not uniform across the population. They vary by age, gender, race, and other individual and market characteristics. Many theories evolved to explain earnings. However, in our opinion, the lifecycle human capital approach does best in accounting for the preponderance of these variations. This paper begins by exploring how human capital can explain demographic differences in earnings. In the human capital model earnings are related to the net stock of human capital an individual accumulates over his or her lifetime. At young ages, when one just enters the labor market and accumulates little human capital, wages are relatively low. At that point men and women earn comparable wages, but not blacks and whites, most likely because of school quality differences. Over the lifecycle earnings rise at a diminishing rate, with men's earnings growing more quickly than women's, most likely because of expected differences in lifetime work patterns.

Theory yields a complex nonlinear specification of the earnings function. In the past this function was too complicated for most researchers to estimate, and still is for intermittent workers. However, the structural model's beauty is its parameterization of previously unmeasured human attributes, specifically three ability measures (two constituting the ability to learn and one constituting the ability to earn), a skill depreciation rate, and a rate of time preference. Unlike IQ and achievement test scores, which have been criticized because they merely assess potential academic accomplishments, these parameters reflect the ability to achieve real world economic success. Because this structural model directly yields parameters defining rates of time preference, it thereby eliminates the need to perform experimental studies that rely on hypothetical rather than a real-world situations. However, this model's complex nature, the lack of long enough panel data, algorithmic inefficiencies, and slow computers, earnings functions emanating from this model have only been estimated population-wide in the aggregate, thus precluding individual specific values. Nowadays with new computational technologies and long enough panel data, such functions have finally been estimated person-by-person.

Our paper makes use of these estimates which vary significantly across the population. A few interesting results emerge when we compare these ability measures with standard IQ values.

Whereas these ability measures correlate with IQ-type scores, the correlation between the two is not perfect. Also, the variance of these ability measures is much smaller than the variance in standardized tests. Most of all, racial differences are not as wide. Further, the ability to learn measures are positively related to years of schooling, as is IQ (actually AFQT), but the ability to earn is not -- a prediction we verify, but that cannot be verified with IQ-type data. In addition, we assess the importance of these new ability measures in explaining earnings variation.

Past analyses estimate a log-linear simplification. This specification, known as the Mincer earnings function, became the workhorse in empirical analysis of earnings determination. Estimated population-wide, and not individual-by-individual, this line of research emphasized schooling as a main determinant of earnings. As a result, numerous studies concentrate on education as a causal function. Although these studies show a positive relationship between schooling and earnings, the magnitudes of the estimates differ significantly. Initial OLS analyses yield rates of return that typically range between 5-15%, but these estimates are often criticized because schooling is not exogenous, in part because of latent factors such as unobserved ability. Newer studies rely on instrumental variable techniques to alleviate these biases. However, as Card (2001) reports, the estimates obtained from instrumental variable methods range from 3.6% to 94%.

Such a staggeringly wide range of estimates is not helpful for policy makers. Even if one recognizes that studies examining schooling and earnings use datasets from different countries, years and age cohorts, and rely on different instrumental variables, it is unlikely that the differences in data alone explain such a large variation in the estimates. Rather, it is plausible that the instrumental variables chosen for the estimation may not be fully valid. Many studies show that the IVs used to identify returns to schooling often violate the exclusion restriction, the relevance condition, or both. Of course, the various violations of the assorted IVs can lead to diverse estimates. To unravel these discrepancies one must understand the underlying structural mechanisms by which the exogenous variations influence the human capital investment process.

Human capital theory postulates that earnings power is determined by accumulated human capital. Schooling emerges as an optimal outcome determined by the relative marginal cost and benefits. The IV-based studies typically identify exogenous variation that influences this decision. But it is perfectly possible that the IVs used, intended solely to measure variation in school, actually influence other aspects of the investment process, as well. The following example illustrates this point. Consider two interventions that cause exogenous variations in years of school: (a) tax credit financial support for education, and (b) skill enhancements such as the Perry Preschool Project or Job Corps interventions leading to more education. Each of these interventions can independently serve as an instrument for years of school. Tax credits lower the cost of school attendance, whereas improvements in skill lower the cost of learning leading to more investment in human capital. From a statistical point of view both would be valid instruments if the interventions are exogenous. As such, they should be able to identify and consistently estimate the causal impact of schooling on earnings. However, these interventions can have other implications for investments in human capital. A tax credit helps lower the cost of enrolment, and hence only increases the amount of school one obtains, and nothing else. On the other hand, an improvement in skills lowers learning costs, thereby increasing years of school, but may also affect post-school investment via the job one gets. In short, the latter instrument affects a moderating variable, as well.

Instrumental variables may also generate erroneous estimates for another reason. The human capital model yields a nonlinear earnings-schooling relationship. Instrumenting the schooling variable in a linear earnings function framework necessarily omits higher order schooling terms. This omission is a classic misspecification that results in biased and inconsistent estimates. In such a scenario, it is impossible to generate a consistent estimate of the returns to schooling even with an instrument that is uncorrelated with other omitted determinants of earnings. It is therefore not possible to fully assess the impact of schooling on earnings without considering the formal structure.

There are efforts (partial identification) to address the potential invalidity of IVs. But most of these efforts make modifications and refinements either based on a given linear functional form or based on non-parametric methods. However, the underlying structural mechanisms still are missing from these analyses. Arguably these new methodological developments can provide some sense of the estimates by bounding them. But in the absence of an explicit theoretical structure, one cannot be sure the assumptions for bounds (e.g., monotonicity) are necessarily valid.

Another structural aspect that was largely ignored in current empirical work is interpersonal heterogeneity. Heterogeneity essentially means that the functional relationship between the schooling and earnings vary person by person. Estimations without recognizing these structural differences can lead to incomplete and in some cases misleading results. As our preliminary findings show, the results based on the structure and heterogeneity adjusted framework substantially differ from the existing method that does not rely on explicit structures. Contrary to many existing studies, our tentative findings suggest that formal years of schooling only plays a limited role in explaining earnings. In contrast, ability is far more influential in explaining earnings variations. Specifically, one's ability to learn and ability to retain knowledge play the most important roles. This however by no means suggests that formal schooling is unimportant. It rather suggests that what is actually learned in school depends on these abilities, so that learning is heterogeneous. Schools may implement ability enhancing measures which play a role in improving learning outcomes, but merely going to school is not sufficient to learn marketable skills. Thus, measures that improve these abilities would be a natural policy intervention to increase earnings and lower earnings disparity.

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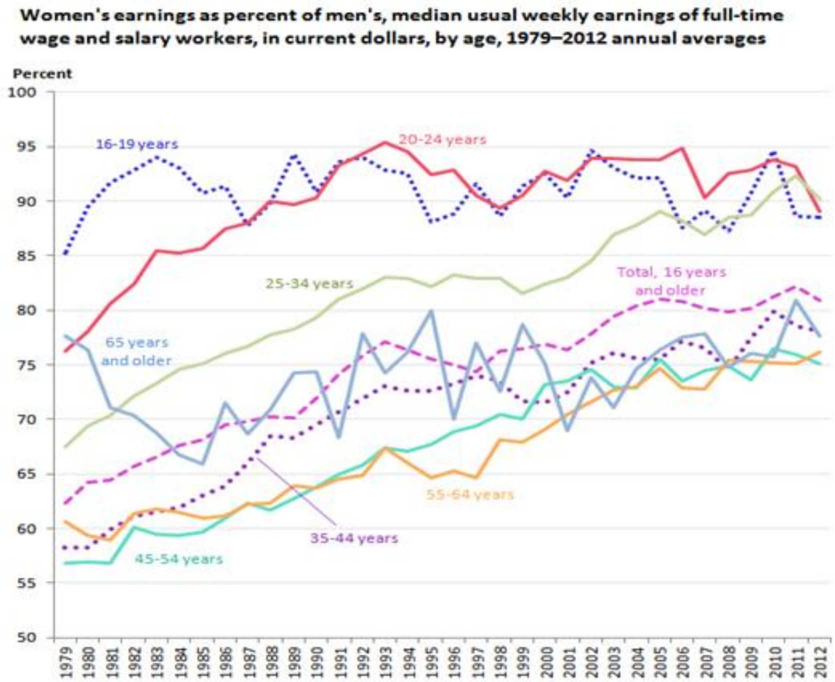
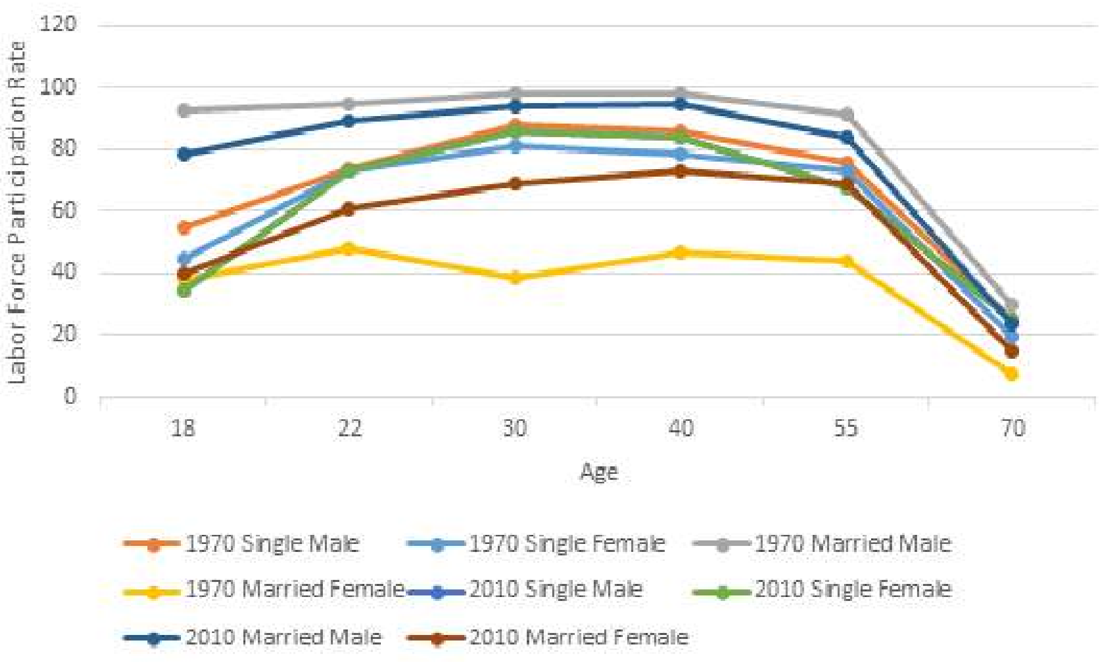
Figure 1: Gender wage differentials (by age group)



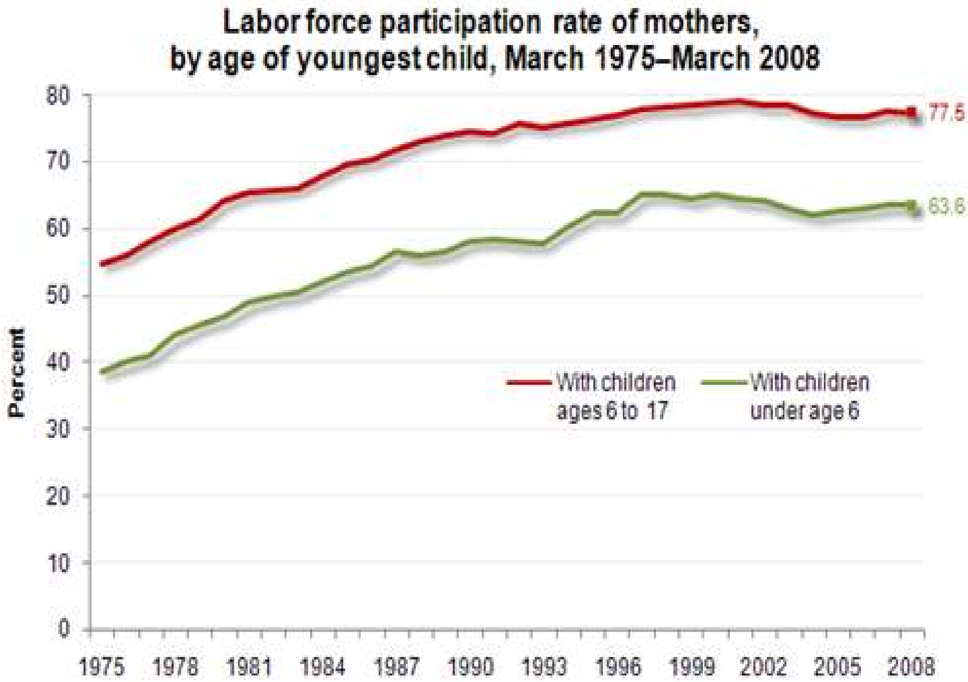
Source: U.S. Bureau of Labor Statistics.

Figure 2: U.S. labor force participation rate (by gender, marital status, age)



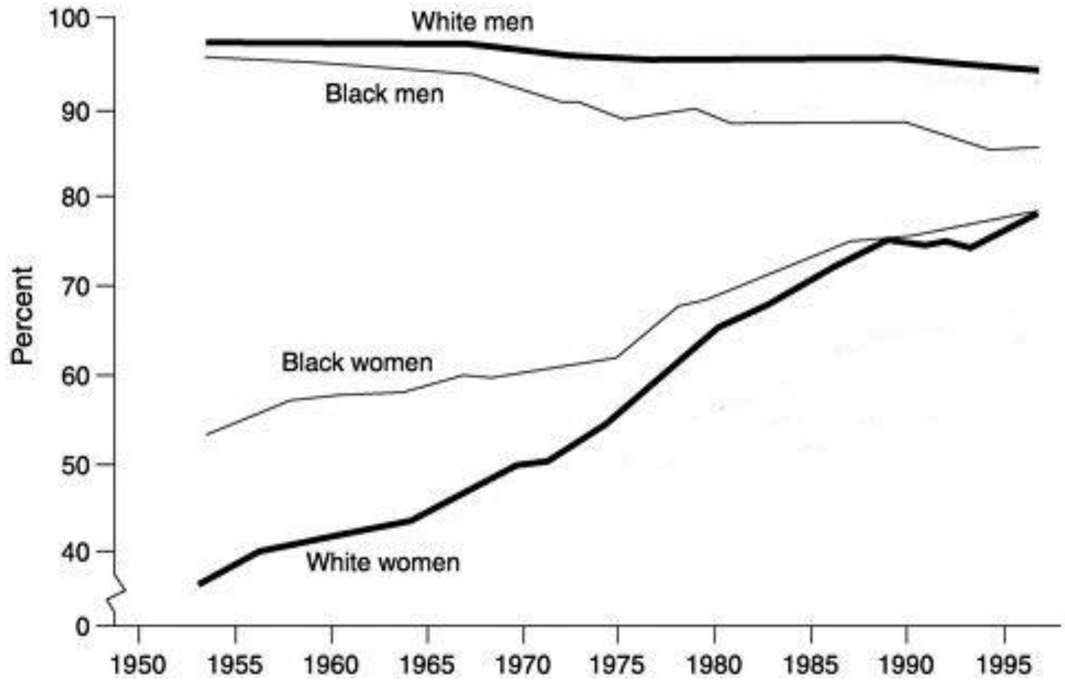
Source: U.S. Bureau of Labor Statistics.

Figure 3: Labor force participation rate of mothers.



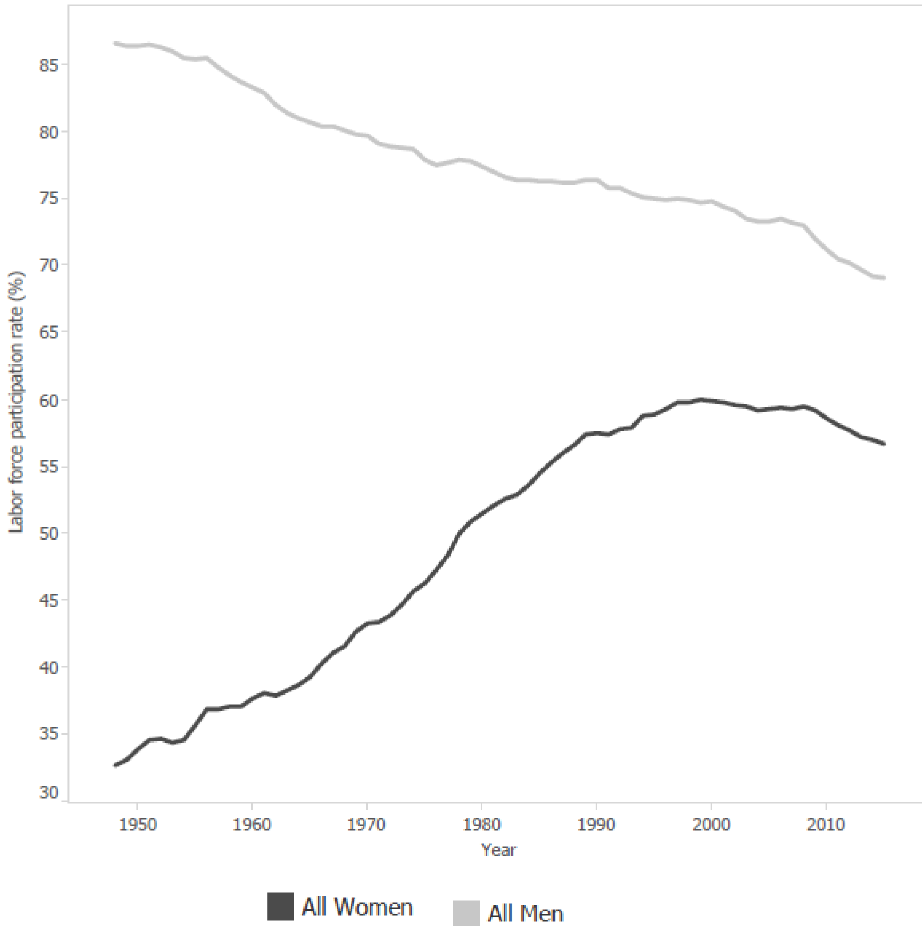
Source: U.S. Bureau of Labor Statistics.

Figure 4: Labor Force Participation by Gender and Race



Source: https://www.dol.gov/wb/stats/facts_over_time.htm#labor

Figure 5: Labor force participation rate by gender (1948-2015 annual averages)

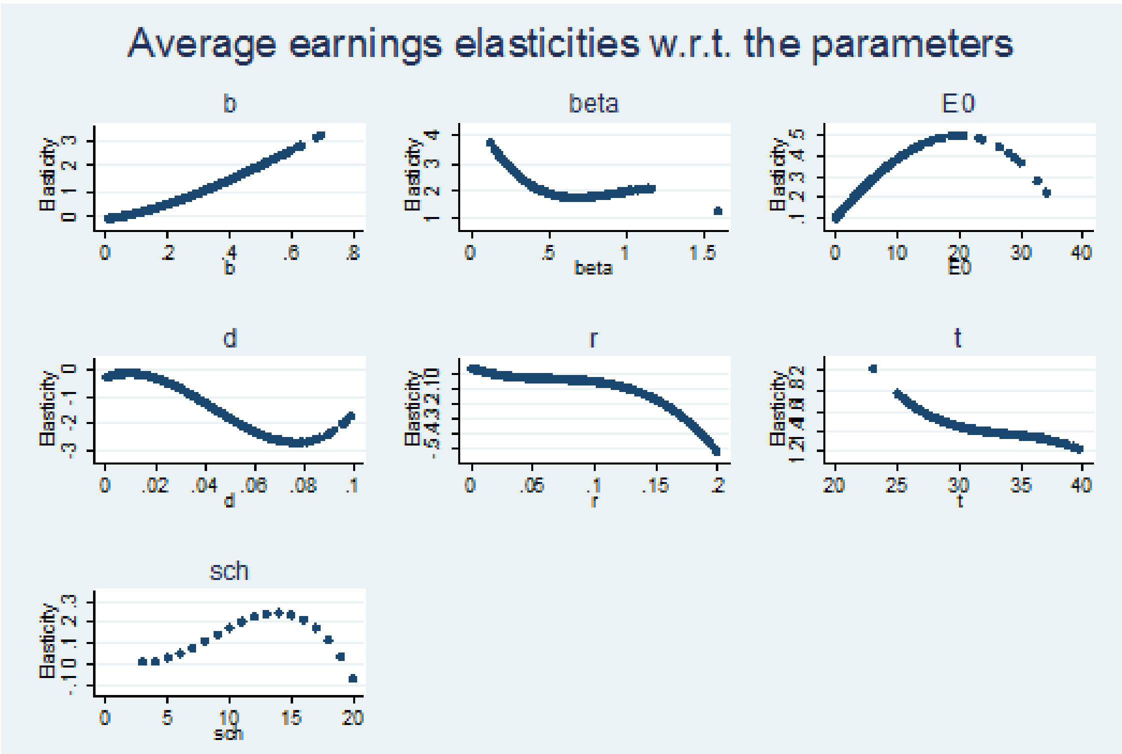


Source: 1948-2015 annual averages, Current Population Survey, U.S. Bureau of Labor Statistics.
Notes: Includes persons in the civilian noninstitutional population that are employed or actively looking for work. Based on persons 16 years of age and older.

Figure 6: Gender earnings ratio by race and Hispanic ethnicity (March 1960-2014)

Source: U.S. Bureau of Labor Statistics.

Figure 7: Earnings elasticities w.r.t personal attributes.



Source: PDT (2015); our computations.

Notes: Graphs represent predicted elasticities obtained from cubic regressions.

Table 1: Average weekly earnings by gender, age and educational groups (2000 USD)

	1980		1990		2000		2010		2016	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
White	847	494	841	559	917	628	973	702	973	726
Black	617	467	603	510	674	555	716	586	725	625
Age										
16-24	502	383	426	377	410	374	443	372	435	377
25-34	771	514	699	547	745	594	760	621	768	644
35-44	944	520	932	610	953	652	1017	737	1040	778
45-54	953	522	994	597	1077	683	1093	752	1083	792
55-64	912	506	961	545	1075	645	1109	759	1112	773
Education										
<=8	602	353	488	336	443	334	425	319	460	313
1-3 yrs HS	661	391	547	367	489	357	492	345	511	347
4 yrs HS	763	453	688	466	670	462	654	489	669	479
1-3 yrs Col	841	508	814	553	829	582	823	591	782	592
4 yrs Col	1095	668	1152	780	1338	891	1419	963	1396	972

Source: IPUMS-CPS (March rounds).

Note: The numbers represent the average weekly earnings in 2000 USD.

Table 2: Average weekly earnings by gender and marital status (2000 USD)

	1980		1990		2000		2010		2016	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Married, spouse present										
16-24	572	388	475	381	456	391	552	436	509	409
25-34	809	504	749	540	799	611	850	656	878	702
35-44	974	506	985	605	1040	664	1117	790	1138	853
45-54	987	502	1030	586	1139	696	1182	772	1177	830
55-64	933	492	989	541	1126	642	1176	770	1193	812
Never married/single										
16-24	459	377	407	375	399	372	423	362	422	372
25-34	658	547	628	583	687	600	674	612	688	608
35-44	693	631	746	682	732	670	775	698	818	669
45-54	696	635	798	684	777	712	841	741	813	721
55-64	711	618	745	595	778	687	899	758	893	742

Source: IPUMS-CPS (March round).

Note: The numbers represent the average weekly earnings in 2000 USD

Table 3

Median usual weekly earnings of full-time wage and salary workers, by sex, marital status, and presence and age of own children under 18 years old, 2012 annual averages			
	Men	Women	Ratio
Total, married, spouse present	$981	$751	77%
With children 6 to 17 years, none younger	1035	746	72%
Total, other marital statuses(1)			
With no children under 18 years	687	654	95%
With children 6 to 17 years, none younger	790	614	78%

Footnotes:
(1) Includes never-married, divorced, separated, and widowed persons

Source: https://www.bls.gov/opub/ted/2013/ted_20131203.htm

Table 4: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						Education			
		16-24	**25-34**	**35-44**	**45-54**	**55-64**	**All**	**Low**	**Medium**	**High**	**All**
Australia	Male	29550	45253	54382	56128	53832	49040	36013	42234	66043	49040
Australia	Female	27037	40183	40896	40113	39282	38328	29686	31749	45984	38328
Belgium	Male	21215	28899	31405	51641	33873	35882	25450	41544	39571	35982
Belgium	Female	16991	21862	23327	27424	24015	23328	17713	21234	26426	23341
Brazil	Male	7156	11761	14350	15751	15972	12988	8252	12902	37971	13108
Brazil	Female	6572	10247	11733	12198	12243	10535	5937	8193	23468	10722
Canada	Male	25387	42942	53201	56991	60429	51869	32578	41961	58972	51877
Canada	Female	24045	34684	40833	44263	38070	39054	23841	30883	43214	39100
China	Male	8101	12065	13366	14123	14098	13148	10697	12265	16682	13151
China	Female	7500	10042	10981	11855	8636	10661	7718	10745	13960	10660
Denmark	Male	28689	47169	58254	59995	56576	54882	41493	49814	68620	54921
Denmark	Female	26208	39919	44281	45349	43864	43260	35801	39659	49484	43280
Finland	Male	29032	40178	50584	52729	52103	48152	37263	40046	58976	48152
Finland	Female	26075	33688	38887	39548	39073	37838	29724	30885	43126	37838
France	Male	5664	22006	28250	29863	16107	13606	7344	16273	32576	16719
France	Female	3676	16084	17802	18411	8821	8497	3802	10353	21293	10229
Germany	Male	30658	44662	56521	59520	61856	56629	37558	45866	76708	56719
Germany	Female	25563	38978	43900	45907	50298	44458	32888	38295	55690	44505

Table 4: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						Education			
		16-24	**25-34**	**35-44**	**45-54**	**55-64**	**All**	**Low**	**Medium**	**High**	**All**
India	Male	3286	4636	5013	6471	6864	5080	3657	6257	10474	5081
India	Female	3315	3990	3378	3983	4180	3642	1982	6341	9813	3643
Israel	Male	9123	25763	37273	39320	40999	31232	18132	22065	44267	31281
Israel	Female	7963	20402	27759	28107	33570	23807	14711	15329	31580	23830
Italy	Male	16701	21069	26772	29335	30415	26655	22266	26603	38923	26655
Italy	Female	14245	18880	24203	24094	27324	23081	17692	22007	30624	23081
Japan	Male	28236	30808	42148	50411	46794	41707	25980	36548	48491	41739
Japan	Female	15171	21728	24315	24831	20923	22019	13560	18084	27361	21986
Luxembourg	Male	32004	47287	63538	66530	76510	60581	38933	52998	90885	60788
Luxembourg	Female	34784	51239	54456	59217	56088	53645	32827	45776	72875	53859
Mexico	Male	4861	7944	9966	9988	9276	8184	5402	9136	21768	8184
Mexico	Female	4086	7115	8408	7751	7812	6876	4112	7172	14984	6876
Netherland	Male	28009	43847	61002	64935	68314	58559	41437	48616	76043	58754
Netherland	Female	28273	43464	58108	55782	50329	49940	32334	42621	57899	50332
Norway	Male	12111	37851	51396	54152	45658	28186	17731	35584	54512	35836
Norway	Female	8717	24294	33225	35275	26673	17199	9243	19273	34767	21724
Poland	Male	2210	11746	13902	10080	5934	6035	1401	7324	16279	7356
Poland	Female	1342	6778	8287	7061	2919	3525	411	3441	10444	4142
Russia	Male	12287	16410	17282	14860	12337	15169	12208	13335	18064	15171
Russia	Female	9400	10928	11783	11520	9801	10972	8440	9338	11988	10972

Table 4: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						Education			
		16-24	**25-34**	**35-44**	**45-54**	**55-64**	**All**	**Low**	**Medium**	**High**	**All**
Spain	Male	15498	24626	32559	36750	38481	33037	24104	30456	42500	33038
Spain	Female	12758	23489	27429	30984	31532	28145	17915	22444	34480	28153
Sweden	Male	7951	26409	35275	35130	28926	18109	13088	26048	36915	25016
Sweden	Female	5941	16624	22262	24818	19359	11632	7102	16329	24228	16461
UK	Male	22111	36946	45892	47164	42491	41008	26629	33709	53678	41119
UK	Female	22189	32079	39989	37357	34305	34184	22191	26572	41203	34206
USA	Male	30904	50043	68448	73839	76422	65118	34671	47260	88022	65118
USA	Female	25807	42998	49132	50593	51197	47156	25643	35742	57719	47156

Source: LIS datasets.
Note:The calculations are based on LIS person level survey data for different countries in different years. All average are at constant prices (2011) and expressed in 2011 PPP US dollars. For Australia, Canada, Denmark, France, Italy, the averages are for 2010; for Belgium the averages are for 2000; for Brazil, Finland, Germany, Luxembourg, Netherland, Norway, Poland, Russia, Spain, UK, USA, the averages are for 2013; for Israel, Mexico, the averages are for 2012; for Sweden the averages are for 2005; for China the averages are for 2002; for India averages are for 2011; for Japan averages are for 2008. For Australia, Brazil, China, Israel, Japan, Mexico, Russia, UK, the calculations are based on workers who worked at least 35 hours per week; for Belgium, Canada,Finland, Germany, Italy, Luxembourg, Netherland, Spain, USA, the calculations are based on full time workers who worked at least 35 hours per week; for Denmark, India, the calculations are based on workers who identify themselves as full time workers; for France, Norway, Poland, Sweden, the calculations are based on all workers as no information on work intensity is available.

Education categories: Low: no education, pre-primary, primary, lower secondary education, compulsory education, initial vocational education; Medium: upper secondary general education, basic vocational education, secondary vocational education, post-secondary education; High: specialized vocational education, university/college education, (post)-doctorate and equivalent degrees.

Table 5: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						% Peak to Trough	Education			
		16-24	25-34	35-44	45-54	55-64	All		Low	Medium	High	All
Australia	Male	29550	45253	54382	56128	53832	49040	47%	36013	42234	66043	49040
Australia	Female	27037	40183	40896	40113	39282	38328	33%	29686	31749	45984	38328
	% difference	9%	11%	25%	29%	27%	22%		18%	25%	30%	22%
Belgium	Male	21215	28899	31405	51641	33873	35882	59%	25450	41544	39571	35982
Belgium	Female	16991	21862	23327	27424	24015	23328	38%	17713	21234	26426	23341
	% difference	20%	24%	26%	47%	29%	35%		30%	49%	33%	35%
Brazil	Male	7156	11761	14350	15751	15972	12988	55%	8252	12902	37971	13108
Brazil	Female	6572	10247	11733	12198	12243	10535	46%	5937	8193	23468	10722
	% difference	8%	13%	18%	23%	23%	19%		28%	36%	38%	18%
Canada	Male	25387	42942	53201	56991	60429	51869	55%	32578	41961	58972	51877
Canada	Female	24045	34684	40833	44263	38070	39054	46%	23841	30883	43214	39100
	% difference	5%	19%	23%	22%	37%	25%		27%	26%	27%	25%
China	Male	8101	12065	13366	14123	14098	13148	43%	10697	12265	16682	13151
China	Female	7500	10042	10981	11855	8636	10661	37%	7718	10745	13960	10660
	% difference	7%	17%	18%	16%	39%	19%		28%	12%	16%	19%
Denmark	Male	28689	47169	58254	59995	56576	54882	52%	41493	49814	68620	54921
Denmark	Female	26208	39919	44281	45349	43864	43260	42%	35801	39659	49484	43280
	% difference	9%	15%	24%	24%	22%	21%		14%	20%	28%	21%
Finland	Male	29032	40178	50584	52729	52103	48152	45%	37263	40046	58976	48152
Finland	Female	26075	33688	38887	39548	39073	37838	34%	29724	30885	43126	37838
	% difference	10%	16%	23%	25%	25%	21%		20%	23%	27%	21%

Table 5: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						% Peak to	Education			
		16-24	25-34	35-44	45-54	55-64	All	Trough	Low	Medium	High	All
France	Male	5664	22006	28250	29863	16107	13606	81%	7344	16273	32576	16719
France	Female	3676	16084	17802	18411	8821	8497	80%	3802	10353	21293	10229
	% difference	35%	27%	37%	38%	45%	38%		48%	36%	35%	39%
Germany	Male	30658	44662	56521	59520	61856	56629	48%	37558	45866	76708	56719
Germany	Female	25563	38978	43900	45907	50298	44458	44%	32888	38295	55690	44505
	% difference	17%	13%	22%	23%	19%	21%		12%	17%	27%	22%
India	Male	3286	4636	5013	6471	6864	5080	49%	3657	6257	10474	5081
India	Female	3315	3990	3378	3983	4180	3642	17%	1982	6341	9813	3643
	% difference	-1%	14%	33%	38%	39%	28%		46%	-1%	6%	28%
Israel	Male	9123	25763	37273	39320	40999	31232	77%	18132	22065	44267	31281
Israel	Female	7963	20402	27759	28107	33570	23807	72%	14711	15329	31580	23830
	% difference	13%	21%	26%	29%	18%	24%		19%	31%	29%	24%
Italy	Male	16701	21069	26772	29335	30415	26655	43%	22266	26603	38923	26655
Italy	Female	14245	18880	24203	24094	27324	23081	41%	17692	22007	30624	23081
	% difference	15%	10%	10%	18%	10%	13%		21%	17%	21%	13%
Japan	Male	28236	30808	42148	50411	46794	41707	44%	25980	36548	48491	41739
Japan	Female	15171	21728	24315	24831	20923	22019	39%	13560	18084	27361	21986
	% difference	46%	29%	42%	51%	55%	47%		48%	51%	44%	47%
Luxembourg	Male	32004	47287	63538	66530	76510	60581	52%	38933	52998	90885	60788
Luxembourg	Female	34784	51239	54456	59217	56088	53645	41%	32827	45776	72875	53859
	% difference	-9%	-8%	14%	11%	27%	11%		16%	14%	20%	11%

Table 5: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						% Peak to Trough	Education			
		16-24	25-34	35-44	45-54	55-64	All		Low	Medium	High	All
Mexico	Male	4861	7944	9966	9988	9276	8184	51%	5402	9136	21768	8184
Mexico	Female	4086	7115	8408	7751	7812	6876	47%	4112	7172	14984	6876
	% difference	16%	10%	16%	22%	16%	16%		24%	21%	31%	16%
Netherland	Male	28009	43847	61002	64935	68314	58559	57%	41437	48616	76043	58754
Netherland	Female	28273	43464	58108	55782	50329	49940	49%	32334	42621	57899	50332
	% difference	-1%	1%	5%	14%	26%	15%		22%	12%	24%	14%
Norway	Male	12111	37851	51396	54152	45658	28186	78%	17731	35584	54512	35836
Norway	Female	8717	24294	33225	35275	26673	17199	75%	9243	19273	34767	21724
	% difference	28%	36%	35%	35%	42%	39%		48%	46%	36%	39%
Poland	Male	2210	11746	13902	10080	5934	6035	78%	1401	7324	16279	7356
Poland	Female	1342	6778	8287	7061	2919	3525	81%	411	3441	10444	4142
	% difference	39%	42%	40%	30%	51%	42%		71%	53%	36%	44%
Russia	Male	12287	16410	17282	14860	12337	15169	17%	12208	13335	18064	15171
Russia	Female	9400	10928	11783	11520	9801	10972	18%	8440	9338	11988	10972
	% difference	23%	33%	32%	22%	21%	28%		31%	30%	34%	28%
Spain	Male	15498	24626	32559	36750	38481	33037	58%	24104	30456	42500	33038
Spain	Female	12758	23489	27429	30984	31532	28145	59%	17915	22444	34480	28153
	% difference	18%	5%	16%	16%	18%	15%		26%	26%	19%	15%
Sweden	Male	7951	26409	35275	35130	28926	18109	77%	13088	26048	36915	25016
Sweden	Female	5941	16624	22262	24818	19359	11632	76%	7102	16329	24228	16461
	% difference	25%	37%	37%	29%	33%	36%		46%	37%	34%	34%

Table 5: Average labor earnings, by countries (in 2011 PPP US dollars)

		Age group						% Peak to Trough	Education			
		16-24	**25-34**	**35-44**	**45-54**	**55-64**	**All**		**Low**	**Medium**	**High**	**All**
UK	Male	22111	36946	45892	47164	42491	41008	53%	26629	33709	53678	41119
UK	Female	22189	32079	39989	37357	34305	34184	41%	22191	26572	41203	34206
	% difference	0%	13%	13%	21%	19%	17%		17%	21%	23%	17%
USA	Male	30904	50043	68448	73839	76422	65118	58%	34671	47260	88022	65118
USA	Female	25807	42998	49132	50593	51197	47156	49%	25643	35742	57719	47156
	% difference	16%	14%	28%	31%	33%	28%		26%	24%	34%	28%

Source: LIS datasets.

Note:The calculations are based on LIS person level survey data for different countries in different years. All average are at constant prices (2011) and expressed in 2011 PPP US dollars. For Australia, Canada, Denmark, France, Italy, the averages are for 2010; for Belgium the averages are for 2000; for Brazil, Finland, Germany, Luxembourg, Netherland, Norway, Poland, Russia, Spain, UK, USA, the averages are for 2013; for Israel, Mexico, the averages are for 2012; for Sweden the averages are for 2005; for China the averages are for 2002; for India averages are for 2011; for Japan averages are for 2008. For Australia, Brazil, China, Israel, Japan, Mexico, Russia, UK, the calculations are based on workers who worked at least 35 hours per week; for Belgium, Canada,Finland, Germany, Italy, Luxembourg, Netherland, Spain, USA, the calculations are based on full time workers who worked at least 35 hours per week; for Denmark, India, the calculations are based on workers who identify themselves as full time workers; for France, Norway, Poland, Sweden, the calculations are based on all workers as no information on work intensity is available.

Education categories: Low: no education, pre-primary, primary, lower secondary education, compulsory education, initial vocational education; Medium: upper secondary general education, basic vocational education, secondary vocational education, post-secondary education; High: specialized vocational education, university/college education, (post)-doctorate and equivalent degrees.

Table 6: Average labor earnings, by countries (in 2011 PPP US dollars)

Country		Unmarried*	Married
Australia	Male	39150	53317
Australia	Female	36584	39391
		0.93	0.74
Belgium	Male	26006	39847
Belgium	Female	22551	23008
		0.87	0.58
Brazil	Male	9538	16314
Brazil	Female	8866	12281
		0.93	0.75
Canada	Male	37965	55504
Canada	Female	37214	39481
		0.98	0.71
China	Male	9513	13563
China	Female	8646	10900
		0.91	0.80
Denmark	Male	44992	60304
Denmark	Female	40626	44111
		0.90	0.73
Finland	Male	40098	53305
Finland	Female	35188	39316
		0.88	0.74
France	Male	8893	19815
France	Female	7059	11229
		0.79	0.57

Table 6: Average labor earnings, by countries (in 2011 PPP US dollars)

Country		Unmarried*	Married
Germany	Male	47753	60477
Germany	Female	42542	46145
		0.89	0.76
India	Male	4271	5293
India	Female	5000	3391
		1.17	0.64
Israel	Male	17452	36809
Israel	Female	14735	27239
		0.84	0.74
Italy	Male	21763	28483
Italy	Female	22022	23496
		1.01	0.82
Japan	Male	30352	43727
Japan	Female	22229	21940
		0.73	0.50
Luxembourg	Male	50986	62921
Luxembourg	Female	52562	54068
		1.03	0.86
Mexico	Male	6416	8701
Mexico	Female	6655	6980
		1.04	0.80
Netherland	Male	48355	63600
Netherland	Female	46096	55547
		0.95	0.87

Table 6: Average labor earnings, by countries (in 2011 PPP US dollars)

Country		Unmarried*	Married
Norway	Male	18481	42371
Norway	Female	12358	24595
		0.67	0.58
Poland	Male	4131	9640
Poland	Female	3451	5287
		0.84	0.55
Russia	Male	13265	16161
Russia	Female	11994	10284
		0.90	0.64
Spain	Male	25974	34959
Spain	Female	24950	29035
		0.96	0.83
Sweden	Male	22016	26713
Sweden	Female	15793	16562
		0.72	0.62
UK	Male	30974	43954
UK	Female	31371	35331
		1.01	0.80
USA	Male	45385	73602
USA	Female	41191	50473
		0.91	0.69

Source: LIS datasets.

* Never Married

Table 7: Mean and standard deviation of the parameter estimate (by race).

	Mean	SD
Hispanic (436 persons)		
b	0.33	0.09
β	0.61	0.18
E_0	2.95	3.42
δ	0.028	0.017
r	0.044	0.041
Average weekly earnings (1982-84 $)	354	258
t	31.58	8.48
t^*	17.07	2.39
AFQT	30.61	26.10
Black (596 persons)		
b	0.32	0.12
β	0.57	0.16
E_0	2.73	3.41
δ	0.029	0.016
r	0.043	0.042
Average weekly earnings (1982-84 $)	309	243
t	31.94	8.48
t^*	17.71	1.87
AFQT	20.41	19.49
White (1230 persons)		
b	0.36	0.09
β	0.65	0.17
E_0	2.76	2.69
δ	0.026	0.014
r	0.041	0.038
Average weekly earnings (1982-84 $)	443	358
t	32.05	8.48
t^*	18.18	2.22
AFQT	52.35	27.78

Source: Based on the data in Polachek, Das, Thamma-Apiroam (2015).

Table 8: Correlation among estimated parameters and standardized test scored (by race).

	All					Hispanics					Black					Whites				
	b	β	E_0	δ	r	b	β	E_0	δ	r	b	β	E_0	δ	r	b	β	E_0	δ	r
Cognitive																				
Gen Sc.	0.19	0.18	0.05	-0.12	-0.03	0.17	0.24	0.04	-0.01	0.00	0.09	0.26	-0.01	-0.05	-0.06	0.17	0.10	0.07	-0.12	-0.02
Arithmetic	0.22	0.20	0.04	-0.13	-0.05	0.22	0.21	0.01	-0.03	-0.07	0.07	0.22	0.01	-0.08	-0.07	0.22	0.15	0.06	-0.13	-0.04
Word know	0.19	0.19	0.02	-0.14	-0.05	0.12	0.21	0.05	-0.04	0.03	0.08	0.20	-0.07	-0.09	-0.10	0.17	0.12	0.04	-0.13	-0.04
Para Comp	0.16	0.17	0.03	-0.14	-0.03	0.11	0.20	0.00	-0.07	0.01	0.07	0.18	-0.08	-0.13	-0.14	0.14	0.11	0.06	-0.14	-0.01
Numeric	0.21	0.26	0.05	-0.11	-0.04	0.19	0.26	0.07	-0.05	-0.02	0.08	0.25	-0.02	-0.06	-0.05	0.21	0.22	0.07	-0.11	-0.04
Coding	0.19	0.20	0.04	-0.12	-0.06	0.18	0.25	0.07	-0.02	-0.02	0.04	0.24	-0.03	-0.06	-0.07	0.18	0.15	0.05	-0.12	-0.06
Auto	0.07	0.19	0.06	-0.09	0.04	0.10	0.21	0.00	-0.02	0.10	0.03	0.18	0.02	-0.06	0.01	0.01	0.12	0.09	-0.07	0.05
Math know	0.23	0.21	0.02	-0.13	-0.10	0.21	0.14	-0.01	-0.09	-0.11	0.10	0.25	-0.04	-0.06	-0.12	0.23	0.17	0.03	-0.13	-0.10
Mechanical	0.15	0.17	0.04	-0.12	-0.01	0.13	0.21	0.02	0.02	0.00	0.06	0.16	-0.03	-0.07	-0.08	0.12	0.11	0.06	-0.12	0.01
Electronics	0.14	0.20	0.07	-0.11	0.02	0.12	0.21	0.05	-0.02	0.04	0.05	0.23	0.03	-0.05	-0.03	0.11	0.14	0.10	-0.11	0.04
AFQT (raw)	0.22	0.21	0.03	-0.15	-0.06	0.17	0.22	0.03	-0.06	-0.02	0.09	0.23	-0.07	-0.11	-0.12	0.21	0.15	0.05	-0.15	-0.05
Non-cognitive																				
Rotter	-0.12	-0.08	0.00	0.11	0.04	-0.02	-0.08	-0.10	-0.02	-0.05	-0.16	-0.06	-0.02	0.05	0.05	-0.11	-0.07	0.01	0.13	0.05
Self estm80	0.08	0.13	0.08	-0.08	0.06	0.13	0.25	0.12	0.03	0.03	0.05	0.14	0.06	-0.08	-0.02	0.07	0.11	0.09	-0.08	0.08
Pearlin	0.13	0.13	0.00	-0.10	-0.11	0.16	0.18	0.07	0.01	-0.08	0.11	0.14	-0.07	-0.06	-0.09	0.13	0.11	0.01	-0.11	-0.11
Trust	-0.11	-0.08	0.00	0.08	0.04	-0.11	-0.02	-0.03	0.06	0.04	-0.04	-0.09	0.04	0.01	0.13	-0.09	-0.06	0.00	0.08	0.02
CESD20	-0.10	-0.08	0.03	0.10	0.05	-0.07	-0.17	0.06	0.01	0.04	-0.17	-0.03	0.06	0.11	0.07	-0.07	-0.05	0.02	0.10	0.04
Family background																				
Mother edu	0.16	0.08	-0.04	-0.11	-0.07	0.17	0.10	-0.03	-0.10	-0.06	0.03	0.20	0.10	0.00	0.02	0.17	0.02	-0.07	-0.13	-0.09
Father edu	0.16	0.13	-0.04	-0.09	-0.10	0.22	0.07	0.00	-0.08	-0.08	0.02	0.12	0.06	0.01	-0.05	0.15	0.10	-0.06	-0.10	-0.11
Urban	-0.02	-0.07	-0.02	-0.02	-0.01	-0.11	-0.05	0.03	0.02	0.02	0.05	-0.04	-0.08	0.01	-0.02	-0.04	-0.09	-0.02	-0.02	-0.01
Magazine	0.15	0.11	0.01	-0.12	-0.06	0.11	0.13	0.02	0.01	-0.02	0.07	0.10	-0.01	-0.13	-0.04	0.14	0.06	0.02	-0.12	-0.06
Newspaper	0.08	0.11	0.04	-0.04	0.00	0.07	0.09	0.03	-0.04	-0.03	-0.04	0.13	0.05	-0.05	0.03	0.08	0.06	0.04	-0.02	0.01
Library	0.10	0.06	-0.02	-0.05	-0.05	0.06	0.21	0.01	0.03	0.04	0.06	0.05	0.11	-0.02	-0.03	0.10	0.03	-0.05	-0.05	-0.06
Poverty	-0.09	-0.15	-0.04	0.04	-0.03	-0.13	-0.13	-0.01	0.07	-0.05	-0.05	-0.19	-0.16	-0.05	-0.08	-0.05	-0.08	-0.01	0.04	-0.04

Source: Polachek,Das and Thamma-Apiroam (2015).

Note: AFQT represents Armed Force Qualification Test; CESD represents 20 question depression index.

Table 9: Earnings elasticities w.r.t. structural parameters, age and schooling (t^{*})

	b	β	E_0	δ	r	t	Sch
Hispanics	1.00	1.60	0.16	-0.60	-0.03	1.17	0.19
Blacks	1.00	2.06	0.20	-0.86	-0.03	1.42	0.23
Whites	1.33	1.98	0.19	-0.82	-0.04	1.39	0.24
All	1.27	1.97	0.19	-0.81	-0.04	1.38	0.24

Note: Computations are based on the earnings function and data given in Polachek, Das, Thamma-Apiroam (2015).

Table 10:							
Age group	$\boldsymbol{b}$	$\boldsymbol{\beta}$	$\boldsymbol{E_0}$	$\boldsymbol{\delta}$	$\boldsymbol{r}$	$\boldsymbol{t}$	**Sch**
20-24							
Obs	8408	8408	8408	8408	8408	8408	8408
R-squared	0.148	0.288	0.018	0.167	0.003	0.002	0.002
25-29							
Obs	10728	10728	10728	10728	10728	10728	10728
R-squared	0.155	0.282	0.018	0.160	0.003	0.001	0.003
30-34							
Obs	8640	8640	8640	8640	8640	8640	8640
R-squared	0.157	0.281	0.019	0.162	0.003	0.001	0.004
35-39							
Obs	5465	5465	5465	5465	5465	5465	5465
R-squared	0.155	0.282	0.018	0.158	0.003	0.001	0.004
40-44							
Obs	4879	4879	4879	4879	4879	4879	4879
R-squared	0.161	0.280	0.019	0.160	0.003	0.001	0.004
45-49							
Obs	3853	3853	3853	3853	3853	3853	3853
R-squared	0.155	0.288	0.019	0.152	0.003	0.001	0.004
50-54							
Obs	897	897	897	897	897	897	897
R-squared	0.218	0.299	0.023	0.156	0.003	0.000	0.005

Source: Computed based on the data and earnings function from Polachek, Das, Thamma-Apiroam (2015).
Note: R-squared are computed as the ratio of variance of the predicted earnings based on each factor to the variance of the actual earnings. Predicted earnings for each factor is calculated by allowing that factor to vary, while holding all other factors constant.

Table 11: Linear regression with level of y as dependent variable

	Adjusted R-squared	
Specification	**Without Sch in reg**	**With Sch in reg**
exp, exp2	0.100	0.268
exp, exp2, AFQT	0.219	0.287
exp, exp2, b, beta, E0, d ,r	0.460	0.500
exp, exp2, b, beta, E0, d ,r, AFQT	0.469	0.499

Source: NLSY79; Polachek, Das and Thamma-Apiroam (2015).
Note: Data obtained from NLSY79 and PDT(2015).

Table 12:

	$f^a(.)$	$SD(\sigma)$	**Correlation coefficients** b	β	E_0	D	R	t	Sch
b	948.8	0.103	1	0.011	-0.152	-0.024	-0.247	0.025	0.217
β	735.2	0.172	0.011	1	0.363	0.475	0.047	0.016	0.145
E_0	14.7	3.040	-0.152	0.363	1	0.474	0.409	0.016	-0.041
δ	-6824.5	0.015	-0.024	0.475	0.474	1	0.134	-0.034	-0.169
r	-307.3	0.040	-0.247	0.047	0.409	0.134	1	0.005	-0.145
t	5.8	8.458	0.025	0.016	0.016	-0.034	0.005	1	0.131
$TSTAR$	6.7	2.208	0.217	0.145	-0.041	-0.169	-0.145	0.131	1

Source: Polachek, Das and Thamma-Apiroam (2015); Our computations.
Note: Computations based on the data and earnings function given in Polachek, Das, Thamma-Apiroam(2015).

Table 13: Earnings variance elasticities (σ_Y^2)

b	β	E_0	δ	r	t	S
0.21	0.26	0.02	0.07	0.01	0.06	0.02

Source: Polachek, Das and Thamma-Apiroam (2015); Our computations.
Note: Coefficients are the percent impact on the variance of earnings of an increase in the variance of the indicated parameters.