Impact of education, experience and other factors on wages earned by women

This report will look at the factors affecting women's wages and the significance of these factors. Wages for women historically have always been lower when compared against men. In the past discrimination in the workplace was very evident, not only in terms of sex but in terms of race too. This created a large gender wage gap between men and women, men earning considerably more across the same jobs. This was improved significantly however, once the Equal pay act was introduced in 1963 by Kennedy, which meant employers could not discriminate against any sex by paying different wages for the same job. This marked an improvement for women's earnings and reduced the gender pay gap significantly.

Literature

According to O'Neill (2000) the cause of this is due to productivity differences between men and women. Women suffer due to having to commit more time to home responsibilities, e.g. childcare, housekeeping. Even though this has reduced significantly over the last 50 years it is still a determining factor. As a result of this women tend not to stay in prolonged periods of work, thus meaning they lose out on much experience which would have been gained by working on job. Thus, meaning lower average hourly rates, and a higher gender pay gap. Looking at the data, in March 2001, at ages 25–44, the prime period for career development, 34 percent of women with children under the age of six were out of the labor force, compared to 16 percent of women without children. Thirty percent of employed mothers worked part-time, compared to 11 percent of women with no children. Among men, however, the presence of children is associated with an increase in work involvement. Only 4 percent of men with children under the age of six are out of the labor force, and among employed fathers only 2 percent work part-time. (O'Neill 2000)

According to ONS Annual Survey of Earnings and Hours in 2017, The Gender Pay gap was at its lowest since the survey was introduced in 1977, of 9.1% down from 9.4% in 2016. Looking at averages for pay across both full time and part time, men were better off. This was because more part time jobs were occupied by women, in 2017 42% of women were in part time jobs whereas only 12% of men were in part time occupations. This means, due to average working hourly rates being lower for part time jobs, women's hourly rates are lower than men's.

When we compare the gender pay gap between part-time and full-time employees by looking at the number of paid hours worked we can see that typically, more men are employed in jobs that involve working a higher number of hours, and for these jobs, it gives the portrayal that the gender pay gap is therefore in favour of men. However, for jobs where the number of paid hours worked by an employee is around 10 and 30, more women work in these types of jobs and in this case the gender pay gap is actually in favour of women. (ONS 2017)

Polachek (2004) believed that human capital investment was a key factor in wage determination, and a pivotal in reducing the gender wage gap between men and women. According to human capital theory, the time one expects to work across their life is dircetly proportional to the incentive to invest in one’s training. It shows the relation of expected lifetime labour commitment to one’s incentive to acquire market oriented training. Therefore, expected work history across one’s lifetime is the most significant factor towards an individuals achieving high wage earnings. During early life individuals have many years to work, where investments reap large effects, and are received for a long time, however later down the line the “present value” of training is greatly reduced as there are less years remaining for the returns to be accumulated. Also once older individuals are less incentive driven to invest in human capital.

Marital status and Division of Labour has shown to be intersting determinants impacting the wages of women. THis is illustrated by looking at the labour force participation patterns for males and females, both who are single or married. THis diagram shows that from 1970-20011, married women have the lowest lifetime labour force participation at 48%, married men have the highest. The drop for married women between ages 25 and 34 reflect the leaving and joining of the labour force due to childbearing. The participation gap is lowest between single men and women.

According to this division of labour, families have biased gender work patterns,most commonly meaning smaller wage gains from investment for women. This is one of the reasons why male human capital investment is higher than women’s, and thus their wages are also higher.

“Since, on average, women work fewer hours throughout their lives, one expects women to purchase less human capital investments than men. Lower human capital investments relative to men, translate to lower per hour relative women’s wages. Hence the malefemale wage gap widens. On the other hand, as women’s lifetime labor force participation rises, and as men’s lifetime labor force participation falls, one should expect the male-female wage gap to narrow” Polachek (2004)

Econometric Model

One of the first models to look at is Mincers Earnings Function. Mincers model is defined as:

ln[w(s, x)] = ?0 + ?ss + ?0x + ?1x2 + ?

Where w(s,x) is defined as wage at schooling level of s and work experience. ?s is the rate of return to schooling and ? is an error term with E(?|s, x)=0

Polachek (2007) explained that the Mincer earnings function pointed out three important empirical implications. First, it explains how earnings levels are related to the level of human capital investments. This explains how the more human capital investments an individual makes the higher his or her earnings will be. Further, the coefficient on the schooling variable reflects the rate of return to schooling. As such, assuming that markets are relatively competitive, empirical analysis should yield coefficients of schooling in the range of common interest rates. Additionally, earnings are related to the quality of schooling. Those attending higher quality schools should earn more. Assuming the market rewards productivity, higher productivity should result in higher earnings.

Second, earnings functions are concave. Earnings rise rapidly at younger ages, but after that the growth in earnings tend to taper off into the middle of of one's career.

Third, the model has implications regarding the distribution of earnings. For example, because human wealth is defined by the present value of ones earnings across their lifetime, the distribution of earnings should exceed the distribution of “human wealth.”(Polachek 2007) Thus the variation in earnings should exceed the variance in human wealth as measured by the present value of the earnings stream. Also holding schooling level constant relative earnings differences (for example measured as the variance of the logarithm of earnings across the population) should narrow with experience then widen. Thus experience profiles of the log variance of earnings should be U-shaped. This section is divided into three parts, each presenting evidence on these implications.

The Rate of Return to Education – The correlation between earnings and schooling is clear, rates of return for schooling has been researched in depth for many countries over countless years. The positive correlation shows that education is a powerful investment into one's future.

Earnings Function is Concave shaped – Looking at the earnings function we find that it is concave in shape, due to the negative ?3 coefficient that is derived when estimating Mincers function. What this portrays; is that for those that stay in the labour market, earnings increase at a diminishing rate throughout their life until the point where human capital accumulation is exceeded by depreciation.

Distribution of Earnings over the Lifecycle: The Overtaking Point – this is one of the more unique, but not often exlpored points from Mincers earnings fucntion, known as the overtaking point. THis is the point in one’s life when the observed earnings is equal to the earnings potential at the point of graduation, assuming no post-school investment. Looking at the diagram (left) we can see the concave curve (Y0 Yj Yp) shows observed earnings, which is equal to potential earnings (Ej) minus human capital investments (Cj). We can see at the point where observed earnings equals potential earnings upon graduation, this is the overtaking point (J

) thus that YJ = E0 =Ys. The overtaking point allows us to observe one’s potetnial earning after graduating at each level of schooling. Different percentage earnings reflect the significance of school and determines rate of returns, furhter implying it has a large impact on ones wages.

Issues Regarding Estimation of the Mincer Earnings Function

Omitted and Mis-measured Variables

When Mincer originally created his original earnings function in 1958, he used an abbreviated “schooling model”, mentioned by which omitted the experience and experience-squared terms. This can lead to biased results, especially if the omitted variable and the explanatory variable are correlated as well as the remaining independent variables. As a result of this, with some of the data, it was portraying that experience and schooling were negatively correlated. This implied that those with more schooling have less experience. But we know that both schooling and experience have a positive correlation with earnings. This means omitting experience (and experience-squared) leads to a downward biased schooling coefficient.

We can use a Ramsey Retest to check for misspecification or for omitted variable bias. As we can see the model for the males ”pass” however for the female model it doesn’t, showing signs of misspecification. This implies that the regression is in error or hasn’t accounted for all variables. Most likely it is due omitted variable bias, as with this regression there are some terms that are hard to measure, as mentioned earlier for example, unmeasurable ability.

Selectivity – sample selectivity can arise due to the data used being nonrandom. Using nonrandom data to estimate the gender gap may result in a bias towards men, as generally there are less women compared to men in the labour market. If the sampling method was random the previous mentioned statement wouldn’t be an issue, but having nonrandom sampling creates bias. This is another possibility of the gender gap between men and women not decreasing recently.

Unobserved Heterogeneity – Multivariate regression Analysis, is used to keep variables constant in order to find factors that affect wages. However, the issue with this method is that it can lead to important variables being omitted, due to a lack of or having no data on it. In the example of wages, looking at individuals who stay in school longer, due to the relation between education and wages being positiviely correlated, one would assume that this will boost earnings, but this is not solely down to education, if more gifted individuals stay in school longer would create an upward bias in earnings, due to unmeasured ability. Thus this omission leads to an overestimate in the rate of return.

Dataset

Shown below is an Ordinary Least Squares regression, of women’s wages. We can see the two explanatory variables being looked at are Experience and Education. Looking at experience first we can see it has a Coefficient of 0.0344, showing a weak positive correlation towards women's wages. This implies that for every year of experience gained in work, this results in a 3.44% increase in wages for women. With a standard error of 0.000524 which implies a low error variance of 0.05%. Next looking at the next explanatory variable Education, we can see it has a coefficient of 0.074164, implying a strong positive correlation. For every year of schooling then, this will lead to a 7.42% increase in women's wages. Education has a standard error of 0.001049, similarly low in value as was experience at 0.1%. Next looking at the R squared values we can see with a value of 0.299163, this portrays that both Education and Experience indicate around 30% of the variations in women’s wages. This suggests there are other significant variables which are determining factors. Below R squared is Adjusted R squared, which has a value of 0.299114, similar to R squared but adjusted for error in data. This result shows that the level of error is 0.005% which is essentially negligible.