BACHELOR THESIS IN ECONOMICS

Factors Affecting Earnings
A Research on American Data

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ABSTRACT

During a lifetime an individual is faced with the decision whether or not to pursue additional years of education, and one may ask if this will generate some sort of payoff, for example, if higher earnings is to be received later in life. The aim of this paper is to investigate how an individual’s earnings is affected by the amount of years one spends in school and also to see if gender and experience are contributing factors. We will investigate these relationships by first introducing the two theories “Human Capital” and “The Mincer Equation”. These build upon each other and are connected. Thereafter, modifications of the Standard Mincer equation will develop our four different regression equations. These regressions will be run on an American cross-sectional data set, by use of the Ordinary Least Squares (OLS).

Our chosen explanatory variables do affect earnings and the specific data set shows that additional years of schooling do increase earnings. We also found a distinct difference in hourly earnings between men and women.

Keywords: earnings, schooling, experience, human capital, the Mincer Equation
ACKNOWLEDGEMENTS

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1. Introduction

Our own educational journey began as six-year olds at preschool and then continued to primary school. Thereafter, we had to make a choice whether or not to pursue our journey by attending high school and there spend an additional three years of learning. However, having a high school degree does not usually open up many job opportunities, unless you have gone to a vocational-oriented programme such as hairdresser, electrician or carpenter. Yet, another decision had to be made, namely, to continue on to college or to start working right then and there. Questions like these have been arising since our high school graduation, we decided to continue and started at Mälardalens University in the fall of 2015. So close to the end, the decision process starts over again, whether to be satisfied with a bachelor’s degree or to continue even further with a master’s degree. Every few years you face a decision whether to continue going to school or to start your career and work. It can be seen as a choice between schooling and experience, but how do we know what to choose?

1.1 Problem formulation

The reason behind this thesis is simply in our own interest because the future decision to invest in further education is close in time. It is a way to see if pursuing an education is “worth” the time and money from a financial point of view and if it will generate greater earnings in the future. This will hopefully not only help us, but also anyone who is considering whether or not to attain a college degree of any form or to start working right after high school. It is easy to compare different amounts of years and use the equations for your own personal needs.

The payoff of education in higher earning is something that is frequently discussed. As more and more people choose to pursue a higher degree of education, we find it interesting to explore this subject, since we are in the same position.
1.2 Literature Review

Schultz (1961) and Becker (1964) were among the first to carry out seminal research on human capital. They both agreed that investing in education was investing in human capital and that there was value in that.

Today, human capital is a broad, commonly used subject with many different interpretations. The word capital means ‘head’, originates from Latin, and could have many different meanings. Today, human capital is more referred to the “population as a source of national wealth”, according to Merriam-Webster (2018). This is simply saying that investing in human capital is like investing, not only in the labor force, but in actual people and their abilities which could very much contribute to the well-being of the country.

When reviewing the subject, we find that concepts like education, experience and competence are frequently associated with human capital and the conclusion is that these are connected. Investing in human capital requires investments in the population and that includes education and experience (Investopedia, 2018). Thus, that is what is needed for us to be useful in professional settings and to contribute as employees.

Cahuc, Carcillo and Zylberberg’s book Labour Economics (2014) has a thorough summary of the most well-known research on human capital and return on education. Because of this, their fourth chapter is frequently used for references in this thesis. They have used more recent data compared to ours, from the Organisation for Economic Co-operation and Development (OECD) and analyzed it and compared with Becker and Mincer’s results.

Different results, arising from using different equations, different data and from different periods in time have given an interval of return. All sources present a positive return on education, some have found lower and some higher returns. The difference is actually up to nine percent. Despite that, it seems that schooling and
experience have the predicted positive effects on earnings, but there is something missing from the equation. Human capital research has found that gender as well affects this percentage return, and that there is a significant difference between men and women.

However, most empirical findings also show a lack of explanatory variables. There are other factors that would help to explain the effect of earnings but knowing what or how to measure these components has not shown to be easy. Things such as individual inherited abilities could be nearly impossible to actually get applicable data on.

Schultz, Becker, Mincer, Card, Psacharopoulos and Patrinos are only a few names that have contribute to this field of research. Their findings are both the same but different, which shows the tremendous amount of work that can still be done on this topic and how difficult and complex it actually is. Having consistent measurements and knowing exactly what the effects are and therefore hard to conclude.

One person who used the human capital theory and developed a specific formula to estimate the relationship between earnings and education, was Jacob A. Mincer. He published a book in 1974, where he suggests that there is a positive relationship between the amount of years that an individual spends in school, on education and his/her later earnings in life. However, the effects of schooling and education may not be the only forces affecting earnings and therefore the correlation is rather weak. To investigate how and what causes differentiation in earnings among age groups, Mincer adjusts the original human capital model by relating earnings to on-the-job training and to other human capital investments that follow the schooling stage of the life cycle. The main objective of his research is to examine the observed distribution and structure of earnings. In order to do so, he derives the human capital earnings function.
The number of researches based on and questioning the work of Jacob A. Mincer is enormous, and to track each one of them would be almost impossible. As Lemieux (2006) states, “the Mincer equation is one of the most widely used models in empirical economics”. Even though Schooling, Experience and Earnings (Mincer, 1974a) was published over 40 years ago, a great part of researchers still tend to evaluate earnings regression based on the standard Mincer equation. The articles represented in our paper have all modified the standard Mincer equation, which is also what we will do in an attempt to examine the aim of our thesis.

Björklund and Kjellström (2002) investigates how well the schooling variable in the standard Mincer equation approximates the marginal internal rate of return to education. Their results imply some weaknesses in the specification regarding the Mincer equation. Therefore, they develop two alternative models, which will be presented in the theory section.

Another person, Suqin Ge (2013), wishes to analyze the appropriateness of a dynamic discrete choice model of schooling and employment in account for the observed OLS and IV estimates of returns to schooling in a log earnings function.

In addition, Lemieux (2006) wishes to examine how well the standard Mincer equation performs in this developed world of labor economics. Hence, he finds that it is crucial to adjust the standard Mincer equation.

1.3 Aim of the thesis

The purpose of this thesis is to examine how the chosen independent variables affect earnings based on the two theories, Human Capital and the Mincer Equation. The theoretical part is of great use when developing the empirical one. We will also explore if there is a possibility of differentiated earnings between men and women.
This paper will examine how the amount of years in schooling affects an individual's earnings later in life and thereby make some conclusions regarding the return on education and try to answer if it is worth investing additional years spent in school.

1.4 Limitations

Like with all research, there are factors that could affect the outcome that is harder to predict and measure. There are a few things to consider regarding limitations for this thesis.

The lack of Swedish data and access to it have made us come to the decision to investigate U.S data instead. Although the data from the United States of America is available, it is still not as recent as we would like it to be. This gives us an estimation that possibly have changed a bit during the last couple of decades. With a gap of almost 40 years, it is safe to say that our predictions will be somewhat ‘out of date’. However, this is not a reason not to go through with the research. Previous results from different research show an interval of returns to education from different time periods. It will still provide relevant information on the subject.

In the Mincer equation, ability is not a contributing factor. This can also affect earnings in an individual’s future, education does not determine all factor regarding the payoff. Since ability is so hard to measure, it is usually excluded from this type of regression equations. It is still important to be aware of other contributing factors that can impact our results.

Also, as suggested by Human Capital Theory, the choice of pursuing higher education may not only be because of economic benefits. An individual’s decision could be affected by their expectations, perceptions and beliefs. These factors are difficult to know beforehand, making them hard to predict. (van der Merwe, 2010)
1.5 Outline

The paper will consist of six sections. The 1st section is the introduction where we discuss the problem definition, a review of the literature, our aim and limitations. Under the 2nd one, the method and data collection will be presented. This is followed by the theoretical part, the 3rd section, that contains “Human Capital” and “The Mincer Equation”. These theories are used to establish our empirical part, which is the 4th section. Here we will develop and estimate four regression equations based on American data that will lead to our results. From our findings we will analyze the outcomes, this can be found in section 5. Finally, a conclusion will summarize this thesis in section 6.
2. Method

We will begin this paper with a theoretical approach to explain the different concepts and models that will enable us to run four regressions based on the standard Mincer Equation:
\[ \ln Y_s = \ln Y_0 + rs \]

Where \( Y \) denotes earnings, \( r \) denotes the discount rate and \( s \) years of schooling.

The theoretical part of this study will discuss the two concepts, “Human Capital” and “Mincer”, and they are based on information gathered from scientific articles and previous researches. These theories are discussed in order to make it easier for the readers to follow through the paper. The next step was to find relevant data to use in the regression equations. We have used a cross-sectional data set, “National Longitudinal Survey of Youth 1979” (NLSY79). Our choice of the subset was randomly chosen out of a given group of datasets (Data set, 2016).

Thereafter, four regression equations based on the standard Mincer equation were constructed and then the Ordinary Least Squares (OLS) method was used. The natural logarithm of earnings (left-hand side) was not transformed, since we wished to investigate how the dependent variable, earnings, adjusts in percentage terms to a unit change in an independent variable. On the right-hand side, we have included the independent variables schooling, experience and an intercept dummy for gender. Schooling and experience are expressed in different forms for each equation depending on what each specific equation attempts to examine. These choices were based on our theoretical part. Before any regressions were run, we formed hypotheses about the signs of the coefficients for the included variables in each regression function. In Excel, the analysis tool was used to run each of these four regressions. Also, we constructed a presentation of a correlation matrix to investigate if any form of multicollinearity between the variables existed. It was then time to evaluate and compare these analysis results. To picture our findings in the simplest way, two tables
were constructed, one including measures of coefficients for each independent variable, measure of fit, standard error and p-values, and the other showing values of correlations between the independent variables. The tables are presented under Results and Multicollinearity, respectively. The results for each regression function are discussed. Under the section Analysis, we have chosen one specific value for years of schooling (S) and another for years of experience (EXP) to examine how these particular values contributes to the changes in the dependent variable, the natural logarithm of earnings. Further, using our chosen data set from NLSY79, we calculated the mean of years of schooling and years of experience, and thereafter used their respective values in each regression function to find the average effect on the dependent variable. Since cross-sectional data have been used, it could imply that the measure of fit might be lower than if it was a time series data (Studenmund, 2017). We have kept this in mind when analyzing our results. A summary of our findings is discussed under “Conclusion”.

2.1 Data collection

Swedish data regarding this subject were not easily accessible to us. Because of that, the chosen data comes from the United States and is accessed through Oxford University Press’ website (Dougherty, 2016). As mentioned under limitations, creating our own data would have been too time consuming and also a little risky. The data presented by OUP is a cross-sectional data set called Educational Attainment and Earnings Functions (EAEF). The data is from a panel survey that started in 1979. The information was gathered through interviews with both male and females when the participants were 14-21 years old. After 1979, the interviews have continued yearly until 1994, when they started with two-year intervals. From the start, there were 3003 males and 3108 females included in the datasets in total. Since the data is so detailed and includes much variety, “it is regarded as one of the most important databases available to social scientists working with U.S data”, as mentioned by Dougherty (2016). We are providing a direct link to the data set for this thesis in the reference list. It contains 500 observations with 250 observations of each gender.
This survey contains many different variables, but they are not all relevant for our purpose. The elected variables that suit this paper’s needs would be earnings, schooling (S), experience (EXP) and a female dummy variable. These variables are extremely common when trying to find effects on earnings and explain the concept of human capital. With some modifications and a more recent set of data than commonly used, these variables, in different forms, will help us reach some sort of understanding and realization of the connections they may possess. The variables chosen are originally communicated by Dougherty (2016), as follows:

*Earnings is expressed originally as current hourly earnings in $ reported as of 2002.*
*Schooling is expressed as years of schooling with highest grade completed as of 2002.*
*Experience is expressed as total out-of-school work-experience in years as of 2002.*
*Female takes the form of 1 if female and 0 if male.*

To run the regressions, Excel has been used because of familiarity and accessibility. With the tool pack, correlations and a summary of the statistics have also been produced. Below you can see Table 1 with summary statistics from the variables used in our regressions.

<table>
<thead>
<tr>
<th></th>
<th>In earnings</th>
<th>S</th>
<th>EXP</th>
<th>$^2$</th>
<th>$EXP^2$</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.778</td>
<td>14.712</td>
<td>6.737</td>
<td>224.16</td>
<td>53.933</td>
<td>0.5</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.026</td>
<td>0.124</td>
<td>0.131</td>
<td>3.636</td>
<td>1.880</td>
<td>0.022</td>
</tr>
<tr>
<td>Median</td>
<td>2.773</td>
<td>15</td>
<td>6.692</td>
<td>225</td>
<td>44.787</td>
<td>0.5</td>
</tr>
<tr>
<td>Mode</td>
<td>2.303</td>
<td>16</td>
<td>6.231</td>
<td>256</td>
<td>38.822</td>
<td>0</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>0.576</td>
<td>2.781</td>
<td>2.927</td>
<td>81.300</td>
<td>42.046</td>
<td>0.501</td>
</tr>
<tr>
<td>Sample Variance</td>
<td>0.332</td>
<td>7.733</td>
<td>8.569</td>
<td>6609.73</td>
<td>1767.832</td>
<td>0.251</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1.072</td>
<td>-0.697</td>
<td>-0.489</td>
<td>-0.789</td>
<td>0.635</td>
<td>-2.008</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.230</td>
<td>-0.129</td>
<td>0.152</td>
<td>0.224</td>
<td>1.039</td>
<td>0</td>
</tr>
<tr>
<td>Range</td>
<td>4.057</td>
<td>13</td>
<td>14.269</td>
<td>351</td>
<td>203.611</td>
<td>1</td>
</tr>
</tbody>
</table>
This is to help get an overview of the elements of the data set and summarizing the most common measures.

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>Sum</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.756</td>
<td>4.813</td>
<td>1388.993</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>20</td>
<td>7356</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>14.269</td>
<td>3368.269</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>49</td>
<td>400</td>
<td>112080</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>203.611</td>
<td>16966.599</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>250</td>
<td>500</td>
</tr>
</tbody>
</table>
3. Theory

3.1 Human Capital

There have been many similar definitions of the term human capital throughout the years. At first, Schultz (1961) and Becker (1964) defined it as “a means of production and the product of investment in education”, and “the economic value of education”, respectively. In 1988, Coleman developed a definition that includes more than just education, saying “knowledge, abilities and skills acquired by individuals through education, experience or training”. This later definition is what is mostly used today, since competence and potential can be developed through more than schooling. The definition has been specifically combined with employees and their contribution to a company. Armstrong (2001) describes human capital as “knowledge, skills and abilities of employees in an organization”. Meaning that an individual’s attributes is used for a company’s benefits and helping them generate growth and value.

The definition of human capital would be all the attributes and skills that a person possess that can be beneficial for a company or even the country’s economy (Cambridge English Dictionary, 2018). Investing in human capital is like investing in a person and all that they are. Their knowledge, skills and talents bring value and enhances growth and productivity (Olaniyan and Okemakinde, 2008). Through education and training you are investing in human capital, whether it is for yourself, the company or the country. Becker (1994) also mentioned that “education and training are the most important investments in human capital”.

Economic effects of education seem to be something that interests many different people (Becker, 1975). Especially nowadays when it is more common to pursue a higher degree. When it comes to education and human capital, there are many researchers who have argued for positive effects between the two and there is also a lot of research on the subject (Mincer, 1974a; Becker, 1964; Card, 1999; Cahuc, Carcillo and Zylberberg, 2014). Even if the relationship between the variables is not the whole story, one of the reasons that education and schooling is such a huge part of human
capital theory is because of its accessibility. It is easy to both observe and measure (Acemoglu and Autor, n.d.)

Investing in education is like investing in the future income you could supposedly earn, because of the competence that you will acquire from schooling. It is confirmed that people with higher education do have a higher income, less risk of unemployment and what can be seen as a higher status job (Card, 1999). Behind the efficiency and knowledge of a worker in this case, there are several years invested in education, which then leads to an income increase (Becker, 1964). Because of the higher earnings, one might suggest that productivity increases more, and it becomes a motivational factor for always getting the job done (Becker, 1994).

The years in school, and therefore the level of education is increasing among some of the countries that are a part of the OECD. When comparing the level of secondary schooling on 25-35-year old’s and 55-64-year old’s, the years of the level of schooling had increased. Even if secondary schooling is increasing more than post-secondary, there are still significant changes in both levels. (Cahuc and Zylberberg, 2004)

The correlation between education and employment is clearly positive and the wages differ depending on the level of degree you have. Essentially, a person that has not finished high school earns about 77% of a worker that has. If you have an even higher degree, you can earn up to 54% more than a high school graduate. The difference in earnings tend to increase with age and around the ages 45-60, the difference is the largest since both groups maximize their earnings. So, no matter what degree or number of years of education you have, the wage still follows the same curve, but the difference is the wage differential between the education levels at different ages along the curve. For both groups, you reach an earnings peak between ages 45 and 60. College graduates with 16 years of schooling can earn up to $30,000 more per year (on average) than high school graduates at their peaks. (Cahuc, Carcillo and Zylberberg, 2014)
Cahuc, Carcillo and Zylberberg (2014) shows the return on education for below upper secondary education and tertiary education for different countries included in the OECD. From OECD data we can see that these countries have an average return on 13% for upper secondary and 12% for tertiary education. There are also other conclusions to be drawn: the gains of retrieving higher education increases and the opportunity costs decrease when unemployment increases. There will always be (high) demand for high-skilled, high-educated workers, and since a tertiary education level is less common than the secondary level, the return tends to be higher where there are fewer workers with this education level. Therefore, workers with tertiary education can be seen as more valuable, since there is a limited amount. (Cahuc, Carcillo and Zylberberg, 2014).

Cost of schooling is usually not included in the calculation because of convenience, but such costs can include tuitions, books and materials and housing. There is also an opportunity cost involved, and that is the loss of potential wages during the time you are in school or studying instead of actually working a normal job, usually mentioned as forgone earnings. Another cost that is not usually mentioned is the psychological distress like stress and anxiety that can appear from the pressure and stress of intense and higher-level studies, which can in turn appear as physical symptoms. The financial reward of education should be higher than the direct, psychological and physical costs and the foregone earnings combined (Cahuc and Zylberberg, 2004). This is of course if the only reason for pursuing a higher level of education is to ‘make money’. However, different people go to college for different reasons, the financial return can just be one of those reasons, among things like personal ambition and development, and less risk of unemployment. These are also benefits from the years of schooling (Card, 1999). Becker (1994) believes that the wage you lose for pursuing education is the most crucial aspects when it comes to costs. It seems to be a better investment to get your degree at an earlier stage, keeping the forgone earnings at a minimum (Bae and Patterson, 2014). Since the wage curve peaks around 50-55 years of age, the forgone earnings would be at a minimum at the beginning of one's career.
It seems that the characteristics of a person influence the years of schooling and if you are efficient, you study longer (Cahuc, Carcillo and Zylberberg, 2014). It is argued that education is selective in the manner of filtering and bringing out the people that have certain characteristics to begin with, such as efficiency and therefore it works a signal tool to employers. It is hard to say if higher wages are caused by their education level or if their education level is caused by individual characteristics, in the sense that they have more earning potential and are more disposed to be effective people by inheritance (Card, 1999). So, higher education can be a signal to employers that the individual is a ‘good’, hardworking employee and he or she has good attributes because he or she managed to get a higher education. He or she has the patience and has acquired much knowledge. If you are efficient to begin with, you tend to gravitate towards getting that degree (Cahuc, Carcillo and Zylberberg, 2014).

This correlation between education and attributes discussed above can also be seen as: the longer a person studies, the higher ability the person has, and education is a way of enhancing the knowledge and that characteristic. If the level of education you decide to pursue is caused by the fact that you are born with a certain type of personality, it is seen as ability bias. This bias is frequently discussed in human capital theory because it would overestimate the rate of return of education. The other bias usually associated with this theory is selection bias. It basically means that if an individual is motivated enough to become a certain profession that requires many years of studying he or she will spend more time on education. This can lead to both under- and over estimations for the different kinds of individuals, which in turn leads to wrong estimates in the rate of return. (Cahuc and Zylberberg, 2004)

Even though higher-educated people have a higher income, there is more than one reason for this: hourly wages are higher (as we have mentioned before) but the workload is larger as well. The conditions and benefits on the workplace tend to be better, despite the hefty schedules (Cahuc and Zylberberg, 2004). Other factors such as quality (Hanushek and Rivkin, 2012), how many students/teachers (Card and
Krueger, 1994) and at what time in life you choose to pursue a higher degree (Cahuc, Carcillo and Zylberberg, 2014), can also affect the return.

It is not only wages that have a positive private effect for individuals. A person’s characteristics and abilities can also become more patient, goal-oriented and making them “less likely to engage in risky behavior”, as mentioned by Cahuc, Carcillo and Zylberberg (2014). A minimum age of leaving school seems to make students more prone to engage and care about politics and other similar activities. Cahuc, Carcillo and Zylberberg (2014) also find that “better-educated nations are more likely to preserve democracy and to protect it from coups”. A reduction of 14%-26% in criminality is what you get with a more educated population. This applies to a high school degree at least. It is also more likely that the next generation will pursue education if their parents have, so the benefits will continue for generations. There are also clear signs that higher educated people have a smaller chance of unemployment. The difference between a high school degree and a high school dropout is 4.7% and 12.5%, respectively (Cahuc, Carcillo and Zylberberg, 2014). It has also been argued that an educated population is something to strive for since it is a source of economic growth (Fagerlind and Saha, 1983).

There is a difference between men and women that is worth mentioning. According to Mincer’s equation using data from 1994 and 1995, one extra year of schooling increases wages by 7.9% for women and by 7.2% for men, on average. Even if women’s returns are slightly higher than men’s, it does not change the fact that men a higher salary on average, for the same amount of work and similar job. So, the wages are not higher for women, the marginal gain from education is (Cahuc, Carcillo and Zylberberg, 2004). This was not always the case, earlier data shows that the financial return was much lower for women (Becker, 1975). There has been a shift in recent years turning this trend around.

The result of return is different in different countries. Looking at wage structures of the countries, we see that some Nordic countries (Sweden, Denmark, Norway),
known for having a compressed wage structure, achieve lower returns of education in general. This could be due to the strong influence that unions have on the wage structure. However, education is basically free or costs very little up to a high level, and this might be a reason as well. In countries were costs are substantial, returns will be higher. There is also a large interval between the average span of education between countries. We see that developing countries have a higher return, probably due to the fact that higher levels of education are uncommon and finding workers with those skill sets can be more challenging. (Cahuc, Carcillo and Zylberberg, 2014)

Different countries also spend different amounts on their education systems and on average, 6.3% of the nation’s GDP goes to educational institutions. All kinds of different services are included in these institutions, such as maintenance, administrative services regarding admission, counseling, research and transportation. (Cahuc, Carcillo and Zylberberg, 2014)

It is hard to compare different results in all these research that exist. Since the information rarely comes from the households, but the firms, it can be selective to large firms that have many employees. Even at these firms, they employees themselves do not fill in the surveys, that is usually handled by the payroll department. The private and public sector are very different, and in the public sector it is more common that wages does not follow the markets. (Psacharopoulos and Patrinos, 2004)

Mincer came to a conclusion running regressions on his data, namely that “time spent in school has a significant positive effect on income. The rate of return of an extra year of schooling is 7%”, quoted by Cahuc, Carcillo and Zylberberg (2014). Although, the problem was that the years spent on education only explained a small percentage of the wage (about 7%). It was suggested that qualified experience was lacking and might be a huge impactor. Even if you are educated and possess a ton of knowledge, you are still learning as you go about your work every day. You are using your skills and also develop them during the course of your career. Adding on experience to the
function really increases the explanation of the variables. (Cahuc and Zylberberg, 2004)

Mincer’s model has good fundamentals, but it also has flaws, for example, that every year of schooling would yield the same ‘amount’ of return. It seems very possible to have different percentage returns over the education years. Recalling the hypothesis he had, it is more likely that it is not as valid anymore. After making some modifications to the original equation, it is seen that return to education is not constant, especially not for 12 years and above, where the return is much higher. There are more factors than what he mentioned in his equation that need to be taken into account and some restrictions do not apply. Some factors elements that weaken the return for college students, are tuitions and taxes. The impact on lower levels are not that significant though. (Cahuc, Carcillo and Zylberberg, 2014)

So, despite all factors, the perception is that the return is between 6.4% and 8.1%, depending on measurements and other factors according to Card (1999) and about 10% according to Psacharopoulos and Patrinos (2004). We will get different amounts of return depending on our equation, variables and dataset. Cahuc, Carcillo and Zylberberg (2014) conclude that the returns on one extra year of education is between 6-15% taking factors previously mentioned in to account.

3.2 Mincer and His Equation

According to Jacob A. Mincer, there is a positive relationship between individual’s schooling and their later earnings, which may indicate the productivity-augmenting effects of education. However, this relationship is not straightforward since schooling and education are not synonymous, due to the differentiations in quality of education. In addition, the ability to absorb and acquire knowledge and education may differ between individuals, locations and times.

Differentiation among individuals’ earnings may thus be caused by other factors than education and schooling. Such forces could be deviations from the equilibrium wages
rate and differences in the amount of years spent in employment in the labor market, especially when these variations are observed over shorter time periods. Therefore, Mincer argues that in spite of the positive correlation between educational attainment, measured in years spent in school, and earnings of individuals, the correlations are rather weak. Nevertheless, clear and strong diversities arise when earnings are averaged over groups of individuals differing in schooling.

Mincer uses the initial and simplest form of the human capital model when examining the schooling group differentials in earnings. He then modifies the model in order to handle the earnings deviations among age groups within the separate schooling groups. This is achieved by relating earnings to on-the-job training and to other human capital investments that follow the schooling stage of the life cycle, which is an idea that originates in Becker’s *Human Capital* (1964). By introducing individual differences in investments and productivity within schooling groups and after completion of schooling into the model, one can find some insights regarding the distribution of earnings within age-education groups and in the aggregate as well.

His study is based on the concept of the human capital earnings function, where the two distributions, earnings and net investments in human capital, are related. He combines this concept with information on the distribution of accumulated net investments in human capital among workers, to grasp some knowledge regarding the main and fundamental objective of his research, which is the observed distributions and structures of earnings. He clearly states that his work is an attempt to analyze personal income distribution at an early and primitive stage, suggesting that future research in human capital and income distribution can be built upon his examination.

Mincer addresses some limitations regarding his research and brings them to discussion. He first mentions the lack of appropriate data on individual investments in human capital. Individuals gain fundamental capacities in and by their home
surroundings, which are excluded when estimating their total capital stock and therefore the aggregate net investment.

The second limitation discussed, is the differences in the rates of return that individuals receive. Data on the specific rates that each individual receive is not accessible. Considering the importance of differentiated rates of return in the earning distribution, which to some extent is captured, Mincer adopts it as a part of the residual variation in his analysis, which depicts earnings to volumes of investment. However, the differences in rates of return do not stand for the residual variation alone. Rather, some variation is due to unmeasured quantities of human capital as well. Thus, it is not appropriate to define residual variation as a variation in rates of return, nor as a measure of risk in human capital investment.

The third limitation, with the same uncertainty applies to one of the causes of variation in rates of return, namely ability. There is no statement to what degree, if at all, diverse ability measures serve any unobserved factors of the human capital stock. Other limitations are discussed and suggestions for further investigation are provided.

He suggests that the use of the human capital approach does not work as a substitute for alternative models of earnings distribution. Rather, the numerous approaches are complementary and not mutually exclusive in many ways.

Each additional period spent in schooling or on the job training defers the time of one's receipt of earnings and also diminishes the span of the individuals working life, assuming retirement occurs at a fixed age. Therefore, deferred earnings and the possibility of reduced periods of earning life are time costly. Thus, the total cost of investment consists of two components, the time costs and the direct money outlays. Individuals do only undertake these costs associated with investments if they increase the deferred flow of earnings. Thereby, the present value of real earnings flows, including or excluding the investment costs, are equal only at a positive discount rate. This rate is the internal rate of return to investment and is often served as a parameter
for the individual. There is an assumption that a change in an individual’s investment does not change that person’s marginal, and also therefore the average, rate of return. Also, costs of investments are assumed to be time costs, which is a more realistic assumption in such forms of human capital investments as on-the-job training, however less realistic in others, such as schooling, migration, or investments in health. Mincer also addresses an assumption regarding the student’s direct private costs. One can interpret detailed data on direct costs to the model in order to gain a more explicit empirical analysis. He argues that this component is not necessary for his research since he wants to achieve an analysis as simple as possible.

The analysis begins by examining the effects of investments in schooling on lifetime earnings. A few assumptions are made in this research. First of all, it is assumed that individuals do not undertake any investment in human capital after completion of schooling. Also, the flow of earnings is assumed to be constant during an individual’s working life. Hence, one crucial and adequate condition is the cessation of net investment. The analysis does not account for economy wide changes that may have an impact on individual productivity and earnings. Net concept is used in most parts of his analysis because changes in earning are formed by net investments in the human capital stock. Depreciation is assumed to be at zero during the individual’s years in school and zero net investment during their working lives. Modification of these assumptions are made in a later phase of Mincer’s investigation. By defining the amount of years in individuals earning lives, it is assumed that each additional year spent in school reduces the persons earning life by an equal amount of years. Mincer gives an alternative, and mathematically simpler, formulation in which the length of earnings life persists the same in all cases, with a greater part of educated people retiring at later ages. From an analytical point of view, he suggests that this assumption is more or less the proper one. If the earning life is long, it means that the described assumption above does not make much of a difference. Instead, postponed earnings are one component that contribute to the differences. Hence, Mincer suggests that the cost of currently postponing earnings by one-year results in greater
differences compared to the differences resulting from reducing the present cost of earnings by one year or four to five decades.

3.2.1 A Technical Presentation of Mincer’s Model

The following part will get in to the technical presentation of the Mincer Equation. It will be close in line with the original presentation from his book, *Schooling, Experience and Earnings* (1974a).

When one measures the effects of schooling on earnings, it is assumed that earnings are postponed because pursuing schooling decreases the amount of years one could be working and earning money.

Let
\[ n = \text{length of working life plus length of schooling} \]
\[ = \text{length of working life for persons without schooling} \]
\[ Y_s = \text{annual earnings of an individual with } s \text{ years of schooling} \]
\[ V_s = \text{present value of an individual’s lifetime earnings at start of schooling} \]
\[ r = \text{discount rate} \]
\[ t = 0, 1, 2, \ldots, n \text{ time, in years} \]
\[ d = \text{difference in the amount of schooling, in years} \]
\[ e = \text{base of natural logarithms} \]

Then the present value of earnings is
\[ V_s = Y_s \sum_{t=s+1}^{n} \left( \frac{1}{1+r} \right)^t \]

when the discounting process is discrete. And, more conveniently, when the process is continuous:
\[ V_s = Y_s \int_{s}^{n} e^{-rt} \, dt = \frac{Y_s(e^{-rs} - e^{-rn})}{r} \]
Also, for an individual who pursues $s - d$ years of schooling, the present value of lifetime earnings become:

$$V_{s - d} = \frac{Y_{s - d}}{r}(e^{-r(s - d)} - e^{-rn})$$

By letting $V_s = V_{s - d}$, the ratio, $k_{s,s-d}$, of annual earnings after $s$ years to $s - d$ years of schooling can be found:

$$k_{s,s-d} = \frac{Y_s}{Y_{s - d}} = \frac{e^{-r(s-d)} - e^{-rn}}{e^{-rs} - e^{-rn}} = \frac{e^{r(n-s)-1}}{e^{r(n-s)-1}}$$

(1.1)

This equation shows that $k_{s,s-d}$ is 1) greater than unity, 2) a positive function of $r$, 3) a negative function of $n$. Specifically, 1) individuals with more schooling get higher annual wages, 2) because of the difference in investment of $d$ years of schooling is greater, the higher the rate of return on schooling. There is a differentiation between individual’s earnings, 3) the shorter the general length of working life, the larger the difference since the cost of going to school must be recovered over a shorter period of time.

While the three conclusions above are rather obvious, the result that $k_{s,s-d}$ is a positive function of $s$ (holding $d$ fixed) is less obvious. It means, for example, that the relative income differentiation between individuals with 10 years and eight years of schooling is greater than for those individuals with four and two years of schooling.

As the change in $k_{s,s-d}$ with a change in $s$ and $n$ is significant (Mincer, 1974b), when $n$ is large, it can be considered as a constant, $k$. This consideration of $k$ as a constant is valid when the length of earnings life is assumed to be fixed, regardless of schooling. To illustrate this, Mincer reformulated $n$ as the fixed length of earning life:

$$V_s = Y_s \int_s^{n+s} e^{-rt} \, dt = \frac{Y_s}{r} e^{-rs} (1 - e^{-rn});$$

$$V_{s - d} = Y_{s - d} \int_{s - d}^{n+s-d} e^{-rt} \, dt = \frac{Y_{s - d}}{r} (1 - e^{-rn}) e^{-r(s-d)};$$

by solving $k_{s,s-d}$ from the equalization of present values, this results in:
\[ k_{s,s-d} = \frac{Y_s}{Y_{s-d}} = \frac{e^{-r(s-d)}}{e^{-rs}} = e^{rd} \]  

(1.2)

Compared to equation (1.1), (1.2) implies that the earnings ratio, \( k \), of income, deviating by \( d \) years of schooling does not depend on the level of schooling, \( s \). Neither does it depend on the length of earning life, \( n \), when \( n \) is fixed even though it might be short.

Mincer then defines \( k_{s,0} = Y_s/Y_0 = k_s \). By (1.2), \( k_s = e^{rs} \). Using the natural logarithms, the equation develops into:

\[ \ln Y_s = \ln Y_0 + rs \]  

(1.3)

Equation (1.3) shows the fundamental conclusion that the percentage increase in earnings are strictly proportional to the absolute variation in the amount of years spent in school, with the coefficient of proportionality being the rate of return. In other words, this equation presents a relationship between the logarithm of earnings and time spent in school that is perfectly linear.

The main objective of Mincer’s study was to model and estimate the relationship between accumulated investments in human capital for laborers and their earnings. He then used this derived human capital earnings function to work towards his aim.

3.2.2 Modifications of the Standard Mincer Equation

One duo that has modified and done research on the standard Mincer Equation is Björklund and Kjellström (2002). In their article they investigate how well the schooling variable in the standard Mincer equation approximates the marginal internal rate of return to education. In other words, the authors examine some of the assumptions that form equality between the coefficient of the schooling variable and the internal rate of return. This is done by estimating data from the Swedish Level of Living Surveys for the years 1968, 1981 and 1991. The estimated data set is the most commonly used one in previous studies of the return to education in Sweden; see, e.g.,

In the introduction section, Björklund and Kjellström (2002) explain that the Mincer equation relates the logarithm of hourly earnings to years of schooling, years of work experience and years of work experience squared, and that this estimated relationship is one of the most commonly used ones in labor economics.

A general conclusion regarding the relationship between a statistical earnings function and the marginal internal rate of return to education is shown by Willis (1986). The authors then let the earnings function be

\[ y = f(s, x) \]  

(1)

where \( y \) denotes earnings, \( s \) years of schooling and \( x \) years of work experience. This function depicts the earnings path across individuals’ working life with various schooling levels. Under a set of assumptions, the marginal internal rate of return to additional schooling equals the derivative of log earnings with respect to years of schooling, or

\[ \frac{\delta \ln y}{\delta s} \]  

(2)

These are short descriptions of the underlying assumptions, as mentioned by Björklund & Kjellström (2002):

**Assumption 1.** The earnings measure captures the full benefits of investments.

**Assumption 2.** The only costs of schooling are foregone earnings.

**Assumption 3.** The earnings function is separable in \( s \) and \( x \) so that \( \delta \ln y/\delta s \) is independent of years of work experience

**Assumption 4.** The length of working life is the same independent of the length of schooling.

**Assumption 5.** Schooling precedes work.

**Assumption 6.** The economy is in a steady state without any wage and productivity growth.
Björklund & Kjellström (2002), argue that these assumptions are quite unlikely to be satisfied in the real world. Some assumptions might be more reasonable for some specific purposes and for some countries, than for others. Therefore, by relaxing some of these assumptions, the authors wish to investigate the effect of doing so. Assumption A1 and A2 are ignored, A3 to A6 are the ones emphasized. Hence, the main question to be addressed is, how well does the standard Mincer equation approximate the social return to schooling, if direct schooling costs are small? To answer this question, they start by focusing on the most suitable functional form, implied by A3. The analysis gives them a preferred functional form. It is then investigated how sensitive the outcomes are to assumption A4. The next step is to examine the consequence of deferring schooling, A5. As a final step, the implications of A6 are examined.

The next section presents the data set used for their research. As mentioned previously, they use data from the Swedish Level of Living Surveys for the years 1968, 1981 and 1991. Only observations on employed individuals are included because of scarce detailed data of hourly earnings of self-employed. Also, the research only observes men because the labor market of women, during the particular period for which they have data, does not agree to the assumptions that the Mincer equation is based on: many women made interruptions in their work careers and often worked part-time.

Now to the section where the authors establish a functional form to examine the purpose of their study, how deviations from the standard Mincer model affect the interpretation of the schooling coefficient. It is argued that the standard Mincer equation can be modified in various ways. The authors apply a so-called Box-Cox transformation to some of the variables in the equation. This modification makes the model more adjustable without introducing new parameters. The Box-Cox method transforms the dependent variable (earnings) and the independent variable schooling as follows:
\[
\frac{y_i^{\lambda_1} - 1}{\lambda_1} = \beta_0 + \beta_1 \frac{s_i^{\lambda_2} - 1}{\lambda_2} + \beta_2 x_i + \beta_3 x_i^2 + \varepsilon_i
\]

which is a non-linear regression model with the semi-log functional form (the standard Mincer equation) as the special case when \( \lambda_1 \) approaches 0 and \( \lambda_2 \) approaches 1, as quoted by Björklund & Kjellström (2002).

In order to examine the purpose of their study (how deviations from the standard Mincer model affect the interpretation of the schooling coefficient), they follow two regression strategies and then interpret their consequences for estimated internal rates of return. The Box-Cox transformation is the first regression strategy and is used to save parameters by avoiding the use of dummies for years of schooling. This strategy also allows them to refrain interactions between schooling and experience since it already entails such interactions. The second strategy of use, is to build on a general model that includes dummies for years of schooling, interactions between schooling and experience, and one that also converts the earnings variable by means of the Box-Cox transformation. It is then investigated whether the simplification of the assumptions can be rejected or not. Then, results of the two strategies are shown in tables.

Their results show some weaknesses regarding the specification of the Mincer equation. Therefore, Björklund and Kjellström (2002) find it appropriate to use two alternative models. One model is developed from the first regression strategy, the Box-Cox transformation to earnings and schooling, and is called B-C-1. The second model is built on the second regression strategy, the Box-Cox transformation to earnings, but now with a dummy variable on each year of schooling instead of years of schooling as a regressor, and this second model is called B-C-2. These two models, B-C-1 and B-C-2, are then used to estimate the internal rate of return to schooling and make comparisons with the standard Mincer model.
The authors conclude three results from their analysis of the usefulness of the schooling coefficient in the standard Mincer equation that they believe are valuable findings for understanding the Swedish labor market and are also suggested for future researchers to investigate.

First, it turns out that the semi-log functional form is misleading in one way. Data from 1968 to 1981 shows a substantial decrease in the return to schooling and is due to reduction in the return to college education, while the return to high school education is fairly steady. This finding was revealed by using a functional form allowing greater flexibility for years of schooling rather than the semi-log one. However, there might be differences between countries since a research on data from the United States of America resulted in strong support for the semi-log functional form (Card, 1999).

One assumption was made regarding the length of working life, or the retirement age for individuals with different length of schooling, and the internal rates of return to schooling turns out to be somewhat sensitive to this specific assumption. According to Swedish data, people with more education tend to retire at higher ages, hence the implied assumption behind using the Mincer schooling variable as a measurement of the internal rate of return to schooling is not considerably at variance with the data. Even so, their estimates are sensitive, and they therefore suggest that the effect of education on the length of working life is a crucial subject to investigate for future research.

Finally, the schooling coefficient or an estimate of the internal rate of return based on a schooling coefficient does not generally explain the advantage of taking education at a young age, rather than an older age. According to the authors, by using the present value of lifetime earnings, one can show the advantage of taking education at an earlier stage in life. When making these estimates, they exercise the same earnings functions on all educational levels. It is questioned if this application of the earnings function is appropriate or not and to answer this requires further empirical
A deeper investigation of all assumptions that are involved when estimating the rate of return to education highlights many crucial questions regarding schooling and the labor market and is suggested to future research. It is also stressed that the authors did not examine the concerns involved in assumption A1, that hourly earnings are a complete measure of the output of schooling and assumption A2, the direct costs of education. If one would attempt to analyze these parts even further, severe but perhaps not the most crucial questions would arise.

Even though the authors emphasize that the interpretation of the schooling coefficient in a standard Mincer equation as returns to investment in education can be misleading, they argue that if one reaches for simplicity in an analysis of the impact of schooling and work experience on wages, the Mincer equation is hard to beat.

A great part of previous researches has the main focus to investigate the (average) rate of returns to schooling. The understanding of how the amount of years spent in school affects labor markets rewards plays a crucial role to policymakers, as Ge (2013) writes about in her article. To analyze this relationship, one useful estimation is the standard OLS estimates of variants of the human capital earnings function, the Mincer equation (Mincer, 1974a):

\[
\ln y = \beta_0 + \beta_1 S + \beta_2 X + \beta_3 X^2 + \varepsilon
\]

where \(y\) denotes earnings, \(S\) years of schooling, \(X\) years of work experience, and \(\varepsilon\) is the wage residual. The coefficient on schooling measures the percentage effect of incremental increases in schooling on earnings and is described as the rate of return to schooling. Yet, the author argues that the OLS estimates of returns to schooling may be biased since they do not include unobserved personal traits, such as ability or innate skills, correlated with schooling that affect education on earnings. The OLS estimated of the schooling coefficient are upward-biased estimates of the true returns.
to schooling since people with higher skills are more likely to spend additional years in school.

For this study, Ge (2013) formulates a standard dynamic discrete choice model of endogenous education and employment, following Keane and Wolpin (1997), to analyze whether observed ordinary least squares (OLS) and instrumental variable (IV) estimates of schooling returns in the Mincer equation can be reproduced in such models. A stylized two-period model of schooling and employment choices and its analytical result is conducted to emphasize this analysis. Under some alternative assumptions, OLS and IV estimators are created for individual endowment, behavior and preferences. A comparison between these estimates and the population average returns to schooling gives a possibility to examine the sources of biases. The author argues that the dynamic choice model allows adequate flexibility to account for the observed estimates of returns to schooling.

The research consists of a dynamic choice model of human capital accumulation both in school and on the job, in order to appraise quantitatively the model performance in accounting for observed schooling returns. To account for heterogeneous individuals, the model recognizes such characteristics by different returns to schooling and utilities of attending school. The behavior model is able to monitor self-selection by allowing for unobserved types, and the dynamic model decision process is solved for each type. Therefore, the model carries out a solution for selection biases. A panel of white females taken from the National Longitudinal Survey of Youth 1979 (NLSY79) is used for these estimations.

The author states that, even though the individual skill type is known and monitored, individuals vary in valuation of school and leisure, which will influence their decisions regarding schooling and work in a systematic manner and therefore create biases in the estimates of returns to schooling.
The structural model yields fairly low returns, while the OLS and IV estimates can be appreciable higher. Throughout the research, it is shown that the dynamic model can recreate the observed estimates of returns to school, both in theoretical and empirical forms. By examining simulated data, one can demonstrate that the greatest source of bias in the OLS estimates of returns to schooling, is the ability selection. It is argued that, even though a properly designed IV estimator lies between the maximum and minimum schooling returns in the population, the estimates are sensitive when it comes to the correlation between instrument and wage errors, and to employment selection, which commonly appears in non-experimental data.

Apart from instrument exogeneity, Ge (2013) finds that when estimating returns to schooling, the outcomes of dynamic employment decision and instrument importance are far from harmless. Ge (2013) suggests development of a dynamic framework and the consideration of weak identification as important areas for future researchers to investigate.

Lemieux (2006) states that the Mincer equation is one of the most widely used models in empirical economics. Even thirty years after publishing *Schooling, Experience and Earnings* (Mincer, 1974a), a great part of researchers still tend to estimate earnings regression based on the standard Mincer equation. While these earnings equations usually add a number of other regressors, the logarithm specification for earnings is still used in most cases.

Since Mincer released his work “*Schooling, Experience and Earnings*” in 1974, there has been a remarkable development in the number of microeconomic data sets and estimation techniques available to labor economists. Hence, Lemieux (2006) is interested to investigate how well the standard Mincer earnings equation is able to perform in light of all these improvements in empirical labor economics. He also asks if it is time to reexamine this benchmark. Based on the existing literature and some
new empirical estimates, the author believes that the Mincer equation is still a proper benchmark to use when estimating wage determination equations. However, in order to serve accuracy, the Mincer equation must be adjusted in three ways according to Lemieux (2006): 1) include a quartic function in potential experience instead of only a quadratic one, 2) allow for a quadratic term in years of schooling to capture the growing convexity in the relationship between schooling and wages, and 3) allow for cohort effects to grasp the dramatic growth in returns to schooling among cohorts born after 1950.

The author emphasizes the limitations regarding his attempt to answer these questions. He states that no attempt is made to cover the broad literature on earnings determination. Existing researches with some new empirical findings based on the Current Population Survey (CPS) for the years 1979 to 2001 are added as supplements to this research’s main results.

He looks at whether the natural logarithm is the appropriate transformation for earnings, whether education should enter linearly, and experience should enter as a quadratic function in a separable earnings function. He also raises the issue of separability between schooling and experience and examines whether the earnings function should include the cohort effects.

This study results in two broad conclusions. First, the standard Mincer equation is a simple estimation and can be of good use in many cases. However, it may understate or overstate the consequences of experience and schooling on earnings for some groups. One particular case when the model understates, is when estimating the effect of experience on the earnings of young laborers. Yet, by the addition of higher order polynomials (up to a quartic) of potential experience to the basic model, this problem can be solved. The model tends to overstate the effect of skills (either schooling or experience) on earnings at the very low end of the skill distribution. This overstatement could be due to, for example, the compression effect associated with minimum wages.
Also, the study shows that the standard Mincer human capital earnings function appears to have a greater fit to the data in the 1960s and 1970s than the data in the 1980s and 1990s. Lemieux (2006) suggests two underlying reasons for this cause. The first problem being the fact that wages are a convex function of years of schooling at an increasing rate. The second problem is that experience-wage profiles are no longer parallel for different education groups. However, existing studies suggest that the increase in today’s relative supply of educated labor does not grow at the same phase as the increase in relative demand, and therefore result in these departures from the standard Mincer model.

Moreover, in a steady society where educational accomplishment expands evenly over ensuing cohorts of laborers, the findings from this study shows that the Mincer equation is still an appropriate benchmark to use. Yet, today’s environment is not stable, and the educational accomplishment does not grow evenly over ensuing cohorts of laborers. From an econometric point of view, the outcomes of this research emphasize the crucial part to establish the robustness of the standard Mincer equation to the formation of a quadratic term in years of schooling and cohort effects. Finally, Lemieux points out that, despite previous discussion, the Mincer human capital earnings function remains a fairly accurate estimate when analyzing the relationship between earnings, schooling and experience.
4. Empirical Section

4.1 Estimations

Our estimates include relevant variables, although there are also other factors that can correlate with schooling and effect the return, such as ability and inherent characteristics, as mentioned earlier. These things are not easily measured so we will not include them in the regressions. From previous research, we can see that this is worth mentioning but is also referred to as a further research area and not taken into the actual regression equations.

We will start off with a simple, basic equation with only two independent variables and these will later on be expressed in different functional forms. Also, we will add an intercept dummy for gender. These modifications might unfold different results.

\[ \ln \text{Earnings} = \beta_0 + \beta_1 \ast S + \beta_2 \ast EXP \]

The reason for using the natural log function of earnings would be to see the earnings effect in percentage term if the independent variables increase with one unit (as was seen in section 3). This makes it somewhat easier to interpret the results. For schooling and experience to be measured in years and not take the form of a currency, in this case dollars, while calculating for earnings, the dependent variable should be expressed logarithmic (Mincer, 1974a). This gives us the possibility to measure the changes in years and get the effects in percentages.

The more years spent in school reflects positively on the earnings (Becker, 1975; Mincer, 1974a). Our estimation for schooling, even though it has a low measure of fit when added alone as Jacob A. Mincer showed, is positive. This variable is important because it is one of the main purposes of this thesis, to see how education affects the wage (or how much). Even if schooling cannot explain the whole variation of earnings, it is still a key source for development of skills and knowledge (Becker, 1975). The connection between schooling and earnings has been made by numerous other researchers, and there are mainly positive correlations between them (Mincer, 1974a;
Becker, 1975; Card, 1999; Psacharopoulos and Patrinos, 2004). It is because of this we expect the connection between earnings and schooling to be positive.

Since the degree of explanation of schooling is low, we are of course interested in what else can lead to higher earnings and experience is something that is frequently brought up in the same research. Experience would be the amount of years you have been working and gained professional experience in one or more areas from one or more employments. You usually have some sort of training or introduction when you start a new employment and it is very common that you continue to learn throughout your working life (Becker, 1975). Even if this is not learning from education, it is still a part of human capital and there is a positive effect on earnings here as well (Becker, 1975). Our conclusion is therefore that, just as schooling, experience is another way of increasing productivity and investing in human capital and it should have a positive correlation with earnings.

Earlier empirical studies mention that schooling alone does not give that much of an explanation to earnings (low $R^2$) (Becker, 1975; Mincer, 1974a). That does not mean that it is not relevant, mainly because that is a relationship worth looking into for us. Adding the other independent variables, we would expect a somewhat higher $R^2$ due to what previous researches have showed. However, we are also aware that it is hard to estimate something as complicated as earnings and have the right data to all contributing factors. We do expect all the variables to be significant and have an impact on earnings. We expand the regression equation the following way:

\[
\ln Earnings = \beta_0 + \beta_1 * S + \beta_2 * EXP + \beta_3 * D
\]

Using the same independent variables and just adding the intercept dummy, we would still expect schooling and experience to have positive effect on earnings. The previous research support that.

Many researchers have found a difference in return when it comes to gender. In 1975, Becker presented research from Mincer (1962) and Renshaw (1960) that showed a
lower money return of education for females. The reason being that women who graduated from college married wealthier men right after graduation providing them with the possibility not to work and therefore not get an actual return, real moneywise, on their education. Although, there is a difference between nonwhite and white women, where nonwhite women had a higher return of education since they actually participated in the labor force after graduation. Back then, women supposedly attended college to attract wealthier and higher educated men. However, after a more recent research on OECD countries using Mincer’s equation, the return for women were actually higher than for men (Cahuc, Carcillo and Zylberberg, 2014). Considering that the data we have used is from 1979, we would expect the results to be similar to Mincer’s and Renshaw’s estimations rather than Cahuc, Carcillo and Zylberberg’s. Therefore, the estimation of the coefficient would be negative at that point in time.

Continuing with the next equation that take a nonlinear curve into account:

\[
\ln(Earnings) = \beta_0 + \beta_1 \times S + \beta_2 \times EXP + \beta_3 \times S^2 + \beta_4 \times EXP^2
\]

Just as for the previous equations, the independent variables schooling, and experience are expected to be positive.

The reasoning behind choosing the squared variables together with the linear ones is to get quadratic relationship between the independent and dependent variable. The function itself is thus not linear. The motivation is that previous research has found that the earnings increase up to a certain age, no matter your background and then decrease after reaching its peak around 50 years of age. To take this relationship in to consideration, we added the polynomial variables too. Evidence from OECD countries that Cahuc, Carcillo and Zylberberg (2014) have analyzed shows that there is a distinct difference in the change of earnings depending on the level of education, but they follow the same pattern. Therefore, it is hard to say where the turning points in our data lies, and because of this, the coefficients, \(S^2\) and \(EXP^2\) might as well be negative or positive.
We are also aware that a polynomial function can affect the results since it makes it harder to interpret individual coefficients (Studenmund, 2017). However, as mentioned, reason speaks for a positive total effect from the two terms. Therefore, drastic extreme changes would be somewhat surprising, but we do not know exactly how the regression is going to act.

We can also mention that we expect some correlation between schooling and squared schooling and experience and squared experience since they basically measure the same thing but in different ways. This can lead to imperfect multicollinearity.

Lastly, our final regression includes all of the previous variables:

\[ \ln(Earnings) = \beta_0 + \beta_1 \times S + \beta_2 \times EXP + \beta_3 \times S^2 + \beta_4 \times EXP^2 + \beta_5 \times D \]

The same interpretation applies for regression 4 as for the rest of the equations. We would not expect any drastic changes in the coefficients between the last two regressions by adding the intercept dummy variable. The expectations are still that the dummy is negative.

4.2 Functional Form

In order to examine how earnings are affected by the three components, schooling, experience and gender, we have computed four regression equations. Each of these has the natural logarithm of earnings on the left-hand side, while the right-hand side includes different forms of schooling and experience depending on what the equation attempts to investigate. In addition, some equations include a dummy variable. Next, we will discuss the meaning and reasoning of each functional form used in this study.

4.2.1 Natural Logarithm

A semi-log functional form is a variant of a double-log in which some but not all variables, both dependent and independent, are expressed in terms of their natural logs. This kind of model has neither a constant slope nor a constant elasticity.
However, it enables one to interpret the coefficient in a useful way: when the independent variable $X_1$ increases by one unit, the dependent variable $Y$ will change in percentage terms. More specifically, the $Y$ variable will change by $\beta_1 \times 100$ percent for every unit that $X_1$ increases, holding all other independent variables constant. Therefore, taking the natural logarithm of the dependent variable $Y$, is perfect for any model in which the dependent variable $Y$ (earnings, in our case) adjusts in percentage terms to a unit change in an independent variable. It also has the advantage of allowing the effect of an independent variable to tail off as that variable increases. Specifically, for our regression number 2, $ln\ Earnings = \beta_0 + \beta_1 * S + \beta_2 * EXP + \beta_3 * D$, this would mean that for each additional year of schooling, $\beta_1$, measures the percentage increase in earnings, holding the other independent variables, $\beta_2$ and $\beta_3$ constant. (Studenmund, 2017)

4.2.2 The intercept term

We have included an intercept term, $\beta_0$, in all four regressions. Suppressing the constant term violates Classical Assumption II (that the expected value of the error term is zero: $\beta_0$ absorbs any non-zero mean). If one would suppress this term, the impact of the constant is forced into the estimates of other coefficients, causing potential bias. However, $\beta_0$ is usually not interpreted due to the following two reasons: 1) Much that is collected in $\beta_0$ cannot be separated, and it is therefore meaningless to run a t-test on $\beta_0$. 2) An interpretation of $\beta_0$ would be the value of $Y$ when all independent variables are zero, which is far outside the sample. (Studenmund, 2017)

4.2.3 Linear forms of the independent variables

When an independent variable, $X$, is expressed in its simplest form, i.e. linear, one can find the changes in the dependent variable $Y$ resulting from changes in the independent variable by taking the derivative of $Y$ with respect to $X$, as illustrate in Studenmund (2017):

$\frac{\Delta Y}{\Delta X_k} = \beta_k$, where $k = 1, 2, ..., K$ (or $\frac{\delta Y}{\delta X_k} = \beta_k$). The slope is constant; for each unit that $X_k$ grows, $Y$ changes by $\beta_k$ units (ceteris paribus).
The elasticity,

\[ Y, X_k = \left( \frac{\Delta Y / Y}{\Delta X_k / X_k} \right) = (\Delta Y / \Delta X_k) \times (X_k / Y) = \beta_k \times (X_k / Y), \]

describes how many percent \( Y \) changes as \( X_k \) increases by one percent.

4.2.4 Polynomial form of the independent variables

The two independent variables \( S \), schooling and \( EXP \), experience, are expressed as polynomials with squared terms (quadratic functional forms) in regressions 3 and 4. Polynomial functions can take on U or inverted U shapes, depending on the values of the coefficients, holding all other independent variables constant. A polynomial function is appropriate to use when one wishes to investigate a more complex nonlinear relationship between the dependent variable and the independent variables. (Studenmund, 2017)

For example, in a second-degree polynomial (quadratic) equation when one independent variable is squared, exhibited in Studenmund (2017):

\[ Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{1i}^2 + \beta_3 X_{2i} + \epsilon_i \]

The slope of \( Y \) with respect to \( X_1 \) is:

\[ \frac{\Delta Y}{\Delta X_1} = \beta_1 + 2\beta_2 X_1 \]

so, the slope depends on the level of \( X_1 \).

If \( X_1 \) increases by one unit, \( Y \) will change by \((\beta_1 + 2\beta_2 X_1)\) units.

Taking this into consideration of our regression, as one spends an additional year of schooling, \( Y \) will change by \((\beta_1 + 2\beta_2 S)\) percent.

Thus, it is appropriate to use polynomial forms if the slopes of a relationship are expected to depend on the level of the variable itself. As the years of schooling increases, earnings will also increase. However, beyond some point, earnings increase by fewer percent. Hence, a negative sign of the quadratic term of Schooling, shows
that it is increasing but at a decreasing rate, and a positive sign of the quadratic term of schooling, shows that it is decreasing at an increasing rate.

Now, consider our regression equation where \( \ln Y \), denotes log of earnings and our independent variable is \( \text{EXP} \), years of experience. By introducing experience in quadratic terms \( (\text{EXP}^2) \), our equation tests the quadratic relationship between years of experience and earnings. One might assume that earnings increases simultaneously with each additional year of experience as people gain more knowledge through experience. As discussed above, an additional assumption may be that at the higher level of experience, earnings start to increase at decreasing rate, and at some point, the wage does not grow (reaches the optimal earnings level) and then starts to fall (they retire, and their earnings starts to decrease). Therefore, the relationship between experience and age is inverted U-shaped (life cycle effect) (Studenmund, 2017; Dougherty, 2016).

4.2.5 Intercept Dummy

We have decided to use an intercept dummy instead of a slope dummy to avoid any signs of multicollinearity. This variable changes the constant or intercept term and takes on the value of 0 (male) or 1 (female), depending on whether the qualitative condition (gender) is met. However, the slopes remain constant with respect to the qualitative condition. A positive value of \( \beta_i \) raises the intercept to \( \beta_0 + \beta_i \) for observations with \( D_i = 1 \). Even though there are two conditions, 0 or 1, only one dummy variable is needed. The omission of \( D_i \) being equal to 0, is captured by the intercept term, \( \beta_0 \). If one where to include two dummy variables, they would be the mirror image of each other, causing multicollinearity and thereby making the Ordinary Least Square, OLS, incapable of generating estimates of the regression coefficients. (Studenmund, 2017)

4.3 Results

The aim of this paper is to investigate if and how earnings are affected by the three components, schooling, experience and gender. In order to examine these
relationships, we have formulated four regression equations, which are reproduced here for convenience.

1. \( \ln \text{Earnings} = \beta_0 + \beta_1 \times S + \beta_2 \times \text{EXP} \)
2. \( \ln \text{Earnings} = \beta_0 + \beta_1 \times S + \beta_2 \times \text{EXP} + \beta_3 \times D \)
3. \( \ln \text{Earnings} = \beta_0 + \beta_1 \times S + \beta_2 \times \text{EXP} + \beta_3 \times S^2 + \beta_4 \times \text{EXP}^2 \)
4. \( \ln \text{Earnings} = \beta_0 + \beta_1 \times S + \beta_2 \times \text{EXP} + \beta_3 \times S^2 + \beta_4 \times \text{EXP}^2 + \beta_5 \times D \)

Presenting our result in Table 2, you can see the different equation values and a measure of fit. It presents the coefficients for each term and each equation, as well as the standard errors and significance from the p-values. After that follows a short presentation of each regression.

<table>
<thead>
<tr>
<th></th>
<th>Reg. 1</th>
<th>Reg. 2</th>
<th>Reg. 3</th>
<th>Reg. 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.985*</td>
<td>1.016*</td>
<td>1.68*</td>
<td>1.745*</td>
</tr>
<tr>
<td></td>
<td>(0.198)</td>
<td>(0.192)</td>
<td>(0.576)</td>
<td>(0.559)</td>
</tr>
<tr>
<td>Schooling</td>
<td>0.1*</td>
<td>0.108*</td>
<td>-0.0007</td>
<td>0.00038</td>
</tr>
<tr>
<td></td>
<td>(0.0103)</td>
<td>(0.0101)</td>
<td>(0.082)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Experience</td>
<td>0.048*</td>
<td>0.045*</td>
<td>0.047</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.0098)</td>
<td>(0.0095)</td>
<td>(0.0339)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td>-0.262*</td>
<td></td>
<td>-0.263*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.047)</td>
<td></td>
<td>(0.047)</td>
</tr>
<tr>
<td>(\text{Schooling}^2)</td>
<td></td>
<td></td>
<td>0.0035</td>
<td>0.0037</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0028)</td>
<td>(0.0027)</td>
</tr>
<tr>
<td>(\text{Experience}^2)</td>
<td></td>
<td></td>
<td>0.00017</td>
<td>-0.000264</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0024)</td>
<td>(0.0023)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.1603</td>
<td>0.20996</td>
<td>0.163</td>
<td>0.213</td>
</tr>
<tr>
<td>(\bar{R}^2)</td>
<td>0.157</td>
<td>0.205</td>
<td>0.156</td>
<td>0.2051</td>
</tr>
</tbody>
</table>
The F-value resulting from all regressions are extremely close to 0, which indicates that our regressions are of significance.

The intercept term ($\beta_0$)
As suggested by theory, one should not interpret the result of the intercept term. It is only necessary to make sure such a term exists in a regression equation.

4.3.1 Regression 1

$$\ln Earnings = \beta_0 + \beta_1 * S + \beta_2 * EXP$$

$R^2$
We found that the measure of fit, $R^2 = 0.1603$. This indicates that 16.03% of the variation in earnings is explained by the independent variables schooling and experience. The closer this measurement is to 1, the better the regression line fits the data. So, for our regression, this result shows a fairly poor fit. However, this does not indicate that we should exclude any of the included independent variables.

$\bar{R}^2$
Taking our sample size and degrees of freedom into consideration, the adjusted measure of fit decreases slightly. $\bar{R}^2 = 0.157$, saying that 15.7% of the variation in earnings is explained by the independent variables schooling and experience. Overall, the same interpretation applies for this result.

P-value
The p-value for each variable is well below 0.05, this means that all of them are significant and have an effect on earnings.

Coefficients
The schooling coefficient \((\beta_1)\) is equal to 0.1. In other words, for each additional year of schooling, earnings will increase by 0.1 percentage points (10%), holding all other independent variables constant.

The experience coefficient \((\beta_2)\) is equal to 0.048. In other words, for each additional year of experience, earnings will increase by 0.048 percentage points (4.8%), holding all other independent variables constant.

### 4.3.2 Regression 2

\[
\ln(Earnings) = \beta_0 + \beta_1 \times S + \beta_2 \times EXP + \beta_3 \times D
\]

\(R^2\)

We found that the measure of fit, \(R^2 = 0.20996\). This indicates that 20.996% of the variation in earnings is explained by the independent variables schooling, experience and gender. This result again shows a fairly poor fit. Yet, this does not indicate that any of the included independent variables should be excluded.

\(\bar{R^2}\)

Taking our sample size and degrees of freedom into consideration, there is a slight reduction in the adjusted measure of fit. The adjusted \(\bar{R^2} = 0.205\), implying that the independent variables schooling, experience and gender explains 20.5% of the variation in earnings. Overall, the same interpretation applies for this result.

**P-value**

The p-value for each variable is well below 0.05, this means that all of them are significant and have an effect on earnings.

**Coefficients**

The schooling coefficient \((\beta_1)\) is equal to 0.108. In other words, for each additional year of schooling, earnings will increase by 0.108 percentage points (10.8%), holding all other independent variables constant.
The experience coefficient ($\beta_2$) is equal to 0.045. In other words, for each additional year of experience, earnings will increase by 0.045 percentage points (4.5%), holding all other independent variables constant.

The gender coefficient ($\beta_3$) is equal to -0.262. In other words, when the observation is equal to 1 (female), earnings will decrease by -0.262 percentage points (26.2%), holding all other independent variables constant.

4.3.3 Regression 3

$$\ln \text{Earnings} = \beta_0 + \beta_1 \ast S + \beta_2 \ast EXP + \beta_3 \ast S^2 + \beta_4 \ast EXP^2$$

$R^2$

This regression results in a measure of fit equal to $R^2 = 0.163$. This finding implies that 16.3% of the variation in ln earnings is explained by the independent variables schooling, experience, squared schooling and squared experience. This shows that our regression is of a fairly poor fit. However, it does not imply that we should exclude any of the included independent variables.

$\bar{R}^2$

Considering our sample size and degrees of freedom, the adjusted measure of fit decreases slightly. The $\bar{R}^2 = 0.156$, saying that 15.6% of the variation in earnings is explained by the independent variables schooling, experience, squared schooling and squared experience. If we compare this result to the findings from regression 1, we can find a slight decrease. Overall, the same interpretation applies for this result.

**P-value**

For the independent variables the values are as follows:

Schooling = 0.994  
Experience = 0.169  
Squared schooling = 0.213
Squared experience = 0.942

They are all greater than 0.05, which indicates that none of them is statistically significant. Their respective p-value suggests that changes in the predictor are not associated with changes in the response. They also indicate that there is insufficient evidence in our sample to conclude that a non-zero correlation exists. However, since we got a low F-value, the equation as a whole is significant.

4.3.4 Regression 4

\[ \ln(Earnings) = \beta_0 + \beta_1 * S + \beta_2 * EXP + \beta_3 * S^2 + \beta_4 * EXP^2 + \beta_5 * D \]

\[ R^2 \]

We found that the measure of fit, \( R^2 = 0.213 \). This indicates that 21.3% of the variation in earnings is explained by the independent variables schooling, experience and gender. So, for our regression, this result shows a fairly poor fit. Yet, this result does not mean that any of our included independent variables should be excluded.

\[ \bar{R}^2 \]

Taking our sample size and degrees of freedom into consideration, the adjusted measure of fit decreases slightly. The \( \bar{R}^2 = 0.2051 \), saying that 20.51% of the variation in ln earnings is explained by the independent variables schooling, experience and gender. Overall, the same interpretation applies for this result.

\[ P-value \]

For the independent variables the values are as follows:

Schooling = 0.996
Experience = 0.129
Squared schooling = 0.171
Squared experience = 0.908
For the independent variables, the high value suggests that changes in the predictor are not associated with changes in the response. They also indicate that there is insufficient evidence in our sample to conclude that a non-zero correlation exists. As for regression 3, since we got a low F-value, equation 4 as a whole is significant. Then gender coefficient ($\beta_5$) is equal to -0.263. In other words, when the observation is equal to 1 (female), earnings will decrease by -0.263 percentage point (26.3%), holding all other independent variables constant.
5. Analysis

This examination lies in our own interest, as we will graduate this summer and will face the decision whether or not to pursue additional years of education. Both of us have 15 years of schooling which represents a bachelor’s degree in Sweden, and since we are using an American data set we had to adjust the amount of years to 16, that amplify a bachelor’s degree in the U.S.

The number of years of experience is based the fact that we have spent almost our entire adult life in school instead of gaining work experience.

Also, using our chosen data set, we calculated the mean of years of schooling and years of experience, and we will use their specific values in each regression equation to find the average effect on the dependent variable.

The result from the measure of fit shows that the two regressions without the intercept dummy has similar values. They explain less of the variation in ln earnings compared to the two regressions that include the intercept dummy. However, the measure of fit for all regressions are fairly low, even for cross-sectional data. This implies that there are more factors that could explain the changes in earnings. Even if there may be additional components affecting earnings, the coefficients of our included variables show that they do have an impact on the dependent variable in two of the equations, and with expected signs.

The p-values for most of the coefficients for regression 3 and 4 are not significant. In these two regressions, the p-value for schooling and squared experience are close to one, which of course is well above 0.05. One should in practice use the p-values to decide whether or not to include those variables, however, we have chosen to present these findings. This enables us to compare the regressions’ different results and explore their importance to our cause.
This is supported by the fact that in both regression 1 and 2, our estimate of the schooling coefficient, $\beta_1$, is 0.1 and 0.108 respectively, which are values close to our result from all regressions. In other words, earnings increase by approximately 10% for one extra year of schooling.

Our aim of this paper is to see if additional years of schooling will give some sort of payoff, in other words, an increase in earnings later in life. For this purpose, a comparison between the mean of $S$ (14.712) and our chosen value of $S$ (16) is of great use.

5.1 Regression 1

$$\ln Earnings = \beta_0 + \beta_1 \times S + \beta_2 \times EXP$$

We will now evaluate the estimated equation for $S$ and $EXP$ at two levels.

$S = 16$ and $EXP = 2$

$$\ln Earnings = 0.985 + 0.1 \times 16 + 0.048 \times 2 = 2.681$$

$$earnings = e^{2.681} = 14.5997$$

This result implies that when an individual has spent 16 years in schooling and additional two years of experience, one may expect an hourly wage of $14.5997.

Now, doing the same calculations using the mean of $S = 14.712$ and mean of $EXP = 6.737$.

$$\ln Earnings = 0.985 + 0.1 \times 14.712 + 0.048 \times 6.737 = 2.78$$

$$earnings = e^{2.78} = 16.113$$

This result implies that when an individual has spent 14.712 years in schooling and additional 6.737 years of experience, one may expect an hourly wage of $16.113.

Comparing these results, one can see that by having 16 years of schooling and 2 years of experience, the wage is $14.5997 per hour. Also, by having 14.712 years of schooling
and 6.737 years of experience give hourly earnings of $16.113. This shows that by having 1.288 less years of schooling and 4.737 more years of experience, one would expect to earn $1.513 more per hour.

5.2 Regression 2

\[ \ln(\text{Earnings}) = \beta_0 + \beta_1 \times S + \beta_2 \times EXP + \beta_3 \times D \]

We will now evaluate the estimated equation for S and EXP at two levels.

\( S = 16 \) and \( EXP = 2 \)

When female:  \( \ln(\text{Earnings}) = 1.016 + 0.108 \times 16 + 0.045 \times 2 - 0.262 \times 1 = 2.572 \)

\( earnings = e^{2.572} = 13.092 \)

When male:  \( \ln(\text{Earnings}) = 1.016 + 0.108 \times 16 + 0.045 \times 2 - 0.262 \times 0 = 2.834 \)

\( earnings = e^{2.834} = 17.013 \)

This result implies that when an individual has spent 16 years in schooling and additional two years of experience, one may expect an hourly wage of $13.092 for female and $17.013 for men.

Now, doing the same calculations using the mean of \( S = 14.712 \) and mean of \( EXP = 6.737. \)

When female:  \( \ln(\text{Earnings}) = 1.016 + 0.108 \times 14.712 + 0.045 \times 6.737 - 0.262 \times 1 = 2.645 \)

\( earnings = e^{2.645} = 14.083 \)

When male:  \( \ln(\text{Earnings}) = 1.016 + 0.108 \times 14.712 + 0.045 \times 6.737 - 0.262 \times 0 = 2.908 \)

\( earnings = e^{2.908} = 18.32 \)
This result implies that when an individual has spent 14.712 years in schooling and additional 6.737 years of experience, one may expect an hourly wage of $14.083 for female and $18.32 for men.

We will now compare for female and male:
For female, having 16 years of schooling and 2 years of experience, the wage is $13.092 per hour. Also, by having 14.712 years of schooling and 6.737 years of experience give hourly earnings of $14.083. This shows that by having 1.288 less years of schooling and 4.737 more years of experience, one would expect to earn $0.991 more per hour.

For male, having 16 years of schooling and 2 years of experience, the wage is $17.013 per hour. Also, by having 14.712 years of schooling and 6.737 years of experience give hourly earnings of $18.32. This shows that by having 1.288 less years of schooling and 4.737 more years of experience, one would expect to earn $1.307 more per hour.

It is also interesting to compare the different results for men and women. When having 16 years of schooling and 2 years of experience, men earn $3.921 more per hour than women. In addition, having 14.712 years of schooling and 6.737 years of experience, men get an hourly wage of $4.237 more than women. Our estimations of this relationship between men and women is supported by these findings.

Since we have an intercept dummy, our results imply that earnings for women are lower compared to earnings for men. This due to that $\beta_3$, a negative coefficient (-0.262), is multiplied by 1 when the gender is female, and multiplied by 0 when the gender is male and therefore disappears, removing the negative term. However, if $\beta_3$ would have been a positive coefficient, earnings for women would have been higher compared to earnings for men. Nevertheless, this applies for this specific data only and one might get different results if using more recent data.

The following calculation is a way of making the most direct comparison between the earnings for men and women:
\[ earnings = e^{-0.262} = 0.7695 \]

This means that men earn $0.7695 more per hour compared to women.

5.3 Regression 3

\[ ln\ Earnings = \beta_0 + \beta_1 \ast S + \beta_2 \ast EXP + \beta_3 \ast S^2 + \beta_4 \ast EXP^2 \]

Calculating with \( S = 16 \) and taking the derivative of \( Y \) wrt. \( S \)

\[ \frac{\delta Y}{\delta S} = \beta_1 + \beta_3 \ast 2 \ast S \]

With \( \beta_1 = -0.0007, \ \beta_3 = 0.0035 \) and \( S = 16 \)

\[ \frac{\delta Y}{\delta S} = -0.0007 + 0.0035 \ast (2 \ast 16) \rightarrow \frac{\delta Y}{\delta S} = -0.0007 + 0.112 \]

\[ \rightarrow \frac{\delta Y}{\delta S} = 0.1113 \]

This result implies that the additional year, when an individual has spent 16 years in schooling, yields an increase in earnings of 11.13\%, holding the other independent variables constant. This is not strikingly far from the estimated coefficients in the linear regression equations.

Calculating with \( EXP = 2 \) and taking the derivative of \( Y \) wrt. \( EXP \)

\[ \frac{\delta Y}{\delta EXP} = \beta_2 + \beta_4 \ast 2 \ast EXP \]

With \( \beta_2 = 0.047, \ \beta_4 = 0.00017 \) and \( EXP = 2 \)

\[ \frac{\delta Y}{\delta EXP} = 0.047 + 0.00017 \ast (2 \ast 2) \rightarrow \frac{\delta Y}{\delta EXP} = 0.047 + 0.00068 \]

\[ \rightarrow \frac{\delta Y}{\delta EXP} = 0.0477 \]

This finding implies that the additional year, when an individual has two years of experience, yields an increase in earnings of 4.77\%, holding the other independent variables constant. This result is close to the estimated coefficients of the linear regression equations.
Now, doing the same calculations for each regression using the mean of $S = 14.712$ and mean of $\text{EXP} = 6.737$

Taking the derivative of $Y$ wrt. $S$

$$\frac{\delta Y}{\delta S} = \beta_1 + \beta_3 \times 2 \times S$$

With $\beta_1 = -0.0007$, $\beta_3 = 0.0035$ and $S = 14.712$

$$\frac{\delta Y}{\delta S} = -0.0007 + 0.0035 \times (2 \times 14.712) \rightarrow \frac{\delta Y}{\delta S} = -0.0007 + 0.102984$$

$$\rightarrow \frac{\delta Y}{\delta S} = 0.1023$$

This result implies that the additional year, when an individual has spent 14.712 years in school, yields an increase in earnings of 10.23%, holding the other independent variables constant.

Taking the derivative of $Y$ wrt. $\text{EXP}$

$$\frac{\delta Y}{\delta \text{EXP}} = \beta_2 + \beta_4 \times 2 \times \text{EXP}$$

With $\beta_2 = 0.047$, $\beta_4 = 0.00017$ and $\text{EXP} = 6.737$

$$\frac{\delta Y}{\delta \text{EXP}} = 0.047 + 0.00017 \times (2 \times 6.737) \rightarrow \frac{\delta Y}{\delta \text{EXP}} = 0.047 + 0.00229058$$

$$\rightarrow \frac{\delta Y}{\delta \text{EXP}} = 0.0493$$

This finding implies the additional year, that when an individual has 6.737 (mean) years of experience, yields an increase in earnings of 4.93%, holding the other independent variables constant.

We will now evaluate the derivative of the estimated equation wrt. to $S$ at two levels.

$S = 16$: $\frac{\delta Y}{\delta S} = 0.1113$

$S = 14.712$: $\frac{\delta Y}{\delta S} = 0.1023$

The wage increases by 11.13% for one extra year of schooling if you already have 16 years of schooling. The wage increases by 10.23% for one extra year of schooling if you
already have 14.712 years of schooling. So, the payoff is higher for those that already are at a higher level. By adding 1.288 years of schooling from the average 14.712 years, one may expect 0.9% more increase in earnings. This tells us that pursuing education will give a payoff in terms of higher salary.

We will now evaluate the derivative of the estimated equation wrt. to EXP at two levels.

\[
\frac{\delta Y}{\delta \text{EXP}} = 0.0477 \\
\frac{\delta Y}{\delta \text{EXP}} = 0.0493
\]

The wage increases by 4.77% for one extra year of experience if you already have 2 years of experience. The wage increases by 4.93% for one extra year of experience if you already have 6.737 years of experience. So, the payoff is higher for those that already are at a higher level. As seen above, by adding 4.737 years of schooling from the average 6.737 years, one may expect 0.16% more increase in earnings. This tells us that pursuing education will give a payoff in terms of higher salary.

5.4 Regression 4

\[
\ln \text{Earnings} = \beta_0 + \beta_1 * S + \beta_2 * \text{EXP} + \beta_3 * S^2 + \beta_4 * \text{EXP}^2 + \beta_5 * D
\]

Calculating with \(S = 16\) and taking the derivative of \(Y\) wrt. \(S\)

\[
\frac{\delta Y}{\delta S} = \beta_1 + \beta_3 * 2 * S
\]

With \(\beta_1 = 0.00038\), \(\beta_3 = 0.0037\) and \(S = 16\)

\[
\frac{\delta Y}{\delta S} = 0.00038 + 0.0037 * (2 * 16) \rightarrow \frac{\delta Y}{\delta S} = 0.00038 + 0.1184
\]

\[
\rightarrow \frac{\delta Y}{\delta S} = 0.1188
\]

This result implies that the additional year, when an individual has spent 16 years in schooling, yields an increase in earnings of 11.88%, holding the other independent variables constant. When comparing regression 4 to regression 3, there is a slight
increase in the effect on earnings, which may be the result from including a dummy variable.

Calculating with EXP = 2 and taking the derivative of Y wrt. EXP

\[
\frac{\delta Y}{\delta EXP} = \beta_2 + \beta_4 \times 2 \times EXP
\]

With \( \beta_2 = 0.05 \), \( \beta_4 = -0.000264 \) and EXP = 2

\[
\frac{\delta Y}{\delta EXP} = 0.05 - 0.000264 \times (2 \times 2) \rightarrow \frac{\delta Y}{\delta EXP} = 0.05 - 0.001056
\]

\[
\rightarrow \frac{\delta Y}{\delta EXP} = 0.0489
\]

This finding implies that the additional year, when an individual has two years of experience, yields an increase in earnings of 4.89%, holding the other independent variables constant. If we compare regression 4 and regression 3, there is a slight increase in earnings (0.12%), this may be due to the additional variable, a dummy for gender.

Now, doing the same calculations for each regression using the mean of S = 14.712 and mean of EXP = 6.737

Taking the derivative of Y wrt. S

\[
\frac{\delta Y}{\delta S} = \beta_1 + \beta_3 \times 2 \times S
\]

With \( \beta_1 = 0.00038 \), \( \beta_3 = 0.0037 \) and S = 14.712

\[
\frac{\delta Y}{\delta S} = 0.00038 + 0.0037 \times (2 \times 14.712) \rightarrow \frac{\delta Y}{\delta S} = 0.00038 + 0.1088688
\]

\[
\rightarrow \frac{\delta Y}{\delta S} = 0.10925
\]

This result implies that the additional year, when an individual has spent 14.712 years in schooling, yields an increase in earnings of 10.925%, holding the other independent variables constant.

Taking the derivative of Y wrt. EXP
Lindberg & Svensson, 2018

\[
\frac{\delta Y}{\delta EXP} = \beta_2 + \beta_4 \times 2 \times EXP
\]

With \( \beta_2 = 0.05 \), \( \beta_4 = -0.000264 \) and \( EXP = 6.737 \)

\[
\frac{\delta Y}{\delta EXP} = 0.05 - 0.000264 \times (2 \times 6.737) \rightarrow \frac{\delta Y}{\delta EXP} = 0.05 - 0.00355714
\]

\[
\frac{\delta Y}{\delta EXP} = 0.0464
\]

This finding implies that the additional year, when an individual has 6.737 (mean) years of experience, yields an increase in earnings of 4.644\%, holding the other independent variables constant.

We will now evaluate the derivative of the estimated equation wrt. to \( S \) at two levels.

\( S = 16: \frac{\delta Y}{\delta S} = 0.1113 \)

\( S = 14.712: \frac{\delta Y}{\delta S} = 0.1023 \)

The wage increases by 11.88\% for one extra year of schooling if you already have 16 years of schooling. The wage increases by 10.925\% for one extra year of schooling if you already have 14.712 years of schooling. So, the payoff is higher for those that already are at a higher level. This regression includes a dummy variable for gender. By having this additional independent variable, the difference between \( S = 16 \) and \( S = 14.712 \) is larger, a 0.96\% more increase in earnings. Compared to regression 3, the effect of years of schooling is 0.06\% higher.

Even though we are most interested of the effects of schooling, it is also necessary to evaluate the results for experience since it is a contributing factor. This will be examined in the same manner as schooling.

We will now evaluate the derivative of the estimated equation wrt. to \( EXP \) at two levels.

\( EXP = 2: \frac{\delta Y}{\delta EXP} = 0.0489 \)

\( EXP = 6.737: \frac{\delta Y}{\delta EXP} = 0.0464 \)
The wage increases by 4.89% for one extra year of experience if you already have 2 years of experience. The wage increases by 4.64% for one extra year of experience if you already have 6.737 years of experience. So, the payoff is lower for those that already are at a higher level. This regression includes a dummy variable for gender. By having this additional independent variable, the difference between EXP = 2 and EXP = 6.737 is less, a 0.25% less increase in earnings. Compared to regression 3, the effect of years of schooling is 0.09% higher. The decrease is due to that $\beta_4$ in regression 4 is negative and multiplied with $2 \times 6.737$, which makes the value even lower.

5.5 Multicollinearity

The following table shows the correlation between the different variables for all equations.

<table>
<thead>
<tr>
<th></th>
<th>ln earnings</th>
<th>S</th>
<th>EXP</th>
<th>$S^2$</th>
<th>$EXP^2$</th>
<th>Female</th>
</tr>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
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<td></td>
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<tr>
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<td>-0.561</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S^2$</td>
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<td>0.994</td>
<td>-0.568</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$EXP^2$</td>
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<td>-0.565</td>
<td>0.969</td>
<td>-0.565</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Female</td>
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<td>0.2045</td>
<td>-0.156</td>
<td>0.205</td>
<td>-0.1625</td>
<td>1</td>
</tr>
</tbody>
</table>

5.5.1 Imperfect

Imperfect multicollinearity can be described as a linear functional relationship between two or more independent variables that is strong enough to significantly affect the estimation of the coefficients of the variables. Perfect multicollinearity takes the value of 1 in absolute value, while imperfect multicollinearity can take any values from -1 to +1. Therefore, a correlation value close to 1 in absolute value illustrate an
imperfect relationship. The functional relationship is imperfectly linear, which indicates that one independent variable, $X_1$, is not completely explained by another independent variable, $X_2$. However, the degree of imperfect multicollinearity varies from sample to sample.

Studenmund (2017) mentions that “when severe multicollinearity exists, the major consequences is to increase the variances of the estimated regression coefficients and therefore decrease their calculated t-scores of those coefficients and extend the confidence intervals.” However, multicollinearity does not cause any bias in the estimated coefficients, and the effect on the overall significance of the regression or on the estimates of the coefficients of any non multicollinear independent variable is fairly small.

The table anticipate imperfect multicollinearity between several variables, $S^2$ and $EXP^2$, $S^2$ and $EXP$, $EXP^2$ and $S$, $S$ and $EXP$. These variables have correlations values that lies around -0.56 (approximately). If one looks at $S^2$ and $EXP^2$, they have a value of -0.565 which fairly close to 1.

As easily detected in our table, we have a few cases of strong imperfect multicollinearity. The explanatory variable $EXP$ and $EXP^2$ have a value of 0.969, which indicates severe imperfect multicollinearity since it is utterly close 1. This means that $EXP$ cannot be completely explained by $EXP^2$. One can see the same relationship between $S$ and $S^2$. However, the strong connections between these different variables are due to something called “Structural multicollinearity”. Also, this may explain why so few coefficients are insignificant in regression equations 3 and 4.
6. Conclusion

There is much to be said about education, earnings and all circulating factors. Much research has been done and much more will probably be done in the future. This was just one possible way to go about it.

The measure of fit for our four regressions are somewhat low. This implies that there are other forces influencing earnings. Still, the coefficients of our included explanatory variables in regression 1 and 2 are shown to be valuable and do affect earnings. Even though the p-value for regression 3 and 4 are shown to be statistically insignificant we have chosen to present these results. This enables to evaluate the different outcomes from the four regressions to get an idea of the contrasts. Also, an interesting notice is that regression 3 and 4 produce coefficients that have similar values as regression 1 and 2.

The aim of this thesis was to investigate whether additional years of schooling would impact earnings in a positive direction. Our results show that for our significant regression equations, there is a positive impact on earnings from both schooling and experience.

It is of great importance to keep in mind that these results originate from our specific value for the independent variable Schooling and Experience and also our chosen data set. One may get different findings by changing these variables and use other data.

6.1 Further research

We have focused on the individual (microeconomics) in this thesis. It would be interesting to look at this topic from a Macroeconomic perspective and how it could affect the society and individual country.
Lindberg & Svensson, 2018

Doing similar research on other countries and comparing would most certainly be fascinating. One could see if there are any differences in other parts of the world and why this may be.
List of References


