# **Impact of Education on Wages**

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**Author Note**

I have slightly digressed from the classic APA structure in order to provide a better overview for the given assignment and to align with the given instructions regarding formatting.

# **Introduction**

Human capital theory in a broad sense encompasses the central idea that human capital and thus labor output varies across individuals due to some underlying characteristics. These intangible characteristics include skills, training, ability, formal education, and other that impact economic productivity and with that the earnings of an individual. Some of the mentioned characteristics fall into the internal locus of control for an individual which then implies the possibility, along with the implied incentive, of both the individual and the environment (state, employer) to treat the controllable factors as a form of long-term investments. In that regard, the focal point of this research is going to be a relationship between *education* and the returns on it in the form of future *wages*.

This relationship is among the “most robust findings in social science” ([[1]](#footnote-1)). This is not surprising when we take into account the explosive expansion of the field of human capital since the nineties of the past century ([[2]](#footnote-2)). Consequently, the expansion of research itself on this topic is hardly surprising, when the observed increase in education of the world population has skyrocketed since the 1950s; the proportion of those with secondary education went from 13% to 51%, and for those with tertiary 2.2% to 14.6% ([[3]](#footnote-3)). In the same manner public spending on education around the world has increased with a slightly steeper upsurge in developed countries ([[4]](#footnote-4)).

With this in mind, it is only natural ask why is this so? Well, it is nothing but a sensible response of both individuals and states to the underlying incentives empirically revealed by the studies. The studies emphasize education and its ability to explain the wage variance both within and between countries, accounting for up to one-third and one-half of variance respectively ([[5]](#footnote-5)).

The field of human capital has come a long way since its early inception with the work of Becker ([[6]](#footnote-6)). This was not without the criticisms on numerous grounds. From the very terminology that might insinuate workers as assets of the capital owner, or the failure to address inequality and the socio-economic obstacles that come with it, to the overemphasis on formal education and the economic returns, while ignoring the quality as an important aspect of said education, non-economic benefits of learning, and the possible effects of social capital factors on wages. These critiques are all sound and some have compelled research to new and uncharted areas, but they all fall out of scope for this work.

This work zeroes in on the wages regressed on the education, along with other controls and instrumental variables to account for possible endogeneity. To that end further structure will consist of the main body, discussion, and conclusion. The main body will introduce relevant literature as well as the assumptions, methods, and the dataset, with the variables within it in parallel to the research pertinent to them. The part on discussion will wrap up the findings, review possible gaps that might sprout further research, and rationalize the policy relevance of the findings before the final conclusion.

**Impact of Education on Wages**

The “Mincer equation” will form the basic structure of our models ([[7]](#footnote-7)). It formalizes the relationship between log earnings, linear years of education, and quadratic experience in the model below:

There were some unknowns with regard to the dataset provided. Among them, was the exact point in time at which the data was collected (‘recent years’ was given) which forces an assumption of data collection at the point of analysis in order to calculate age and experience. This might create a problem with how experience relates to wages. If the data was collected at an earlier point in time, the quadratic effect might ‘stretch’ to a longer interval based on my faulty assumption, and thus provide an inadequate estimate of quadratic experience. This is delved upon further in the section of analysis.

Lemieux ([[8]](#footnote-8)) has proposed some additions to the formal model mentioned above. First, he proposes quartic function for experience to better capture the understatement of the initial experience returns in the first 15 years of the career. This does make sense, but using higher order polynomials here would output an error, possibly due to limits in floating-point computations, which would require data manipulation in such a way that would obfuscate interpretations. Here, the data fits the quadratic form of experience, and possibly even the linear. Second, he proposes quadratic term for years of education to account for the convexity, but this convexity was not captured by this dataset. Similar proposals are made by David Card ([[9]](#footnote-9)), however this paper will rely on Mincer equation as a foundation.

**Dataset, Variables, and Methods** The dataset in question contains fifty thousand observations, and is assumed to be randomly sampled so we assume data points to be independent and identically distributed. Assumed year of data collection is 2024. It contains seven variables out of which we can extract additional information. Additionally, the dataset contains no missing values.

***Wage and logwage***– is the sole dependent variable of interest here. Following the Mincer model, regressand will be in the logarithmic form. The literature does point out possibilities of better fits with different transformations in different cases of observed form on wages; hourly, monthly, etc. However, this dataset provides weekly earnings of an individual and the plain log function is easier to interpret.

***Edu*** – refers to years of education an individual has acquired and the dataset does not provide level of educational attainment in such a way in which we could create distinct categories. Having this would possibly allow to examine significant jumps after completed different levels, or perhaps varying slopes across different levels. Examining these categories would be important especially important if we were to place weight on the assumptions of Signaling Theory; which claims that employers use education to raise wages since it signals a higher level of ability ([[10]](#footnote-10)). Nonetheless, we must not discount the effects years of education have in and of themselves. Numerous studies have shown that additional years of study result in higher wages even when no degree is earned and thus no signal is present ([[11]](#footnote-11)).  
 Yet before continuing, we have to address the problems that arise around it. First, we have a specification bias, which points to omitted variable in the model related to both the dependent variable and included independent variable, thus forcing the double burden on the included one. With this context we have to assume any rational agent will seek to maximize education given that he is aware of the returns on it. With that we have to assume some measure of individual’s ability to include it to control for this ([[12]](#footnote-12)). In this case, we do risk measurement error, when assuming the test validity of IQ as a measure of ability, but psychometric discussions are beyond the scope of this work. Second, endogeneity of education in the presence of omitted ability could be corrected for through the use of instruments such as distance to nearest university, family background, or extended years of education due to peculiarity of state laws. These will be discussed in further paragraphs.

***Edu\_par*** – refers to years of education attained by parents. The literature shows a long-standing tradition of using family background, and in particular parental education, to either directly control for unobserved ability or to instrumentalize education ([[13]](#footnote-13)). This is due to high correlation between education and parental education, so much so that twin studies would show up to sixty percent of explained variation in education using observed and unobserved family background factors, while thirty percent of the variation in education in the US adults is explain by education of the parents. However, Card ([[14]](#footnote-14)) emphasizes that unless all of the unobserved ability is absorbed by the family background controls, there is of it being an illegitimate instrument in a way in which it might reduce bias, but still lead to upward-biased returns to education.

***IQ*** – refers to the results of a recently taken IQ test. Among the potential sources of heterogeneity across the individual’s education we have already reviewed family background, and we are left with school quality, and the aforementioned ability ([[15]](#footnote-15)). School quality is an interesting avenue to observe and account for, especially since we know that majority of the educational expansion in the US, in the previous decades, has occurred in the less prestigious institutions ([[16]](#footnote-16)). Further, some argue for much higher estimates of returns to education if we were to control for quality of the institution ([[17]](#footnote-17)). Regardless, with no data on which institutions were attended, this route of investigation falls out of scope. Finally, we are left with an IQ score that acts as a proxy for ability in our case. Altonji and Dunn ([[18]](#footnote-18)) produced a number of papers where they fit log earnings onto education along with controls and their interactions, among which they used IQ which yielded likely imprecise estimates. Additionally, harsher criticisms claim IQ has negligible effects on wages, and thus should not be used as a measure of ability ([[19]](#footnote-19)). This data-set has shown some correlation of wages and IQ and will be investigated further.

***Dist*** – refers to distance to the nearest university city. Data description provided with the dataset phrases this as “distance to the next city/town that offers higher education”. This might mean that for some individuals which reside in the university city, the data would point to a distance to the nearest next/other university city. This would greatly confound the data, so it is assumed here that the data shows distance to the first/nearest university city. Using distance to university as an instrument to education is logical since proximity will certainly affect decision making directly by providing opportunity, or indirectly by observing others taking up those opportunities, but we should keep in mind the risk with this data; potentially residence at the time of data collection was used to calculate distance, and is thus not the same as the residence at the time the participants were making the decision to go to university ([[20]](#footnote-20)). It is assumed here that the distance refers to the one at the time of making the decision (18-20 years old). Additionally, dummies could be constructed in to create categorically segment the sample (e.g. very near, near, far, very far), there was no need for it in this case and the variable will be treated solely as continuous.

***State*** – refers to the state of residence. It ranges from 1 to 56, and the mapping to which states it refers to was not provided. Some literature did show the use segments as dummy such as states of the south or similar, but here, since it is not possible to map exact states, we can factorize the state variable and use it as a set of dummies to observe how the intercept might change; i.e. we can see the wage difference across different states and control for it.

***Born*** – provides us with the date of birth (DOB). This can be further used to extract age and experience, under the assumption data was collected in 2024. A notable use of the exact dates was in the work of Angrist and Krueger ([[21]](#footnote-21)) where they noticed a peculiarity with state mandated schooling where individuals born in the first quarter of the year would start at an older age and can therefore drop out after less completed years overall. This can be observed by using a dummy for all observations born in the first quarter. This is not as relevant in this sample since these effects diminish with further education. The next two variables are constructed on the basis of this one.

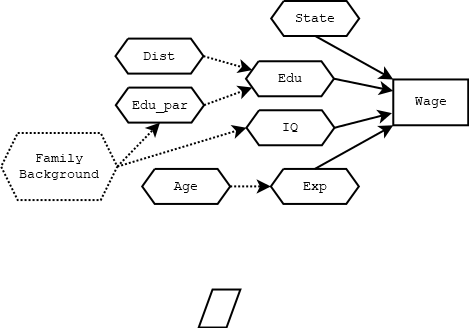
***Age*** – is calculated by taking the day at which the analysis is done and subtracting the given DOB, and it should be kept in mind that age is floored in these calculations.

***Exp*** ***and Exp2*** – refers to the experience of the individual and is calculated by subtracting years of education from the age, and then subtracting addition six years, to satisfy the assumption that primary education starts at the age of seven. Mincers model suggests using the quadratic form which will be ‘Exp2’, but when modelling linear form will be considered too. Age will be used as a natural instrument to experience.

The methods used here will rely on linear regressions with the use of instrumental variables. Although, there could be a place and time for regression discontinuity (RDD) if there was a number of distinct categories made out of a running variable (e.g. with distance), and those categories had visible shifts, or perhaps it might be possible to find a more adequate fit using varied slopes RDD. That is not considered here.

There are more general limitations to be considered before moving on. We should not lose sight of the possibility that returns on education might fluctuate over time. Furthermore, same could be said for all other variables mentioned and possible interactions among them. This paper assumes constant effects across time. Additionally, fine grained geographical observation (along with their ethnic and class composition) could be better at revealing more appropriate shapes of the relationships. This cannot be done here. Bearing this in mind, the goal here is to find a simple model that would correspond to the previous findings that estimate returns on education for each additional year in the range of 6-18%, with the median in the range 10-12% ([[22]](#footnote-22)). Before proceeding with the analysis and modeling the graphical representation of the relationships mentioned is laid out below in Figure 1.

**Figure 1**  
*Diagram of Assumed Underlying Relations*



*Note*. The diagram shows how concept of family background can be accounted for through the use IQ as a proxy for ability. In addition, it shows how distance and parental education satisfy relevance criteria, but also exclusion since their effects are only through education and they do not affect ability.

**Analysis, Results, and Discussion**

With the diagram above to guide the reasoning, the following paragraphs will present the models that result from these assumptions. It should be noted that full code can be reviewed in the Appendix B (R Quarto document). First of all, we observe the correlational matrix below.

**Table 1***Correlation Matrix of used Variables*

| X | wage | logwage | edu | edu\_par | age | age2 | exp | exp2 | iq | dist |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| wage | 1.00 | 0.79 | 0.56 | 0.05 | 0.01 | 0.01 | -0.43 | -0.40 | 0.15 | 0.03 |
| logwage | 0.79 | 1.00 | 0.68 | 0.06 | -0.00 | -0.00 | -0.53 | -0.52 | 0.20 | 0.04 |
| edu | 0.56 | 0.68 | 1.00 | 0.12 | -0.04 | -0.04 | -0.80 | -0.79 | 0.06 | 0.08 |
| edu\_par | 0.05 | 0.06 | 0.12 | 1.00 | 0.00 | 0.00 | -0.09 | -0.09 | -0.00 | 0.00 |
| age | 0.01 | -0.00 | -0.04 | 0.00 | 1.00 | 1.00 | 0.63 | 0.64 | 0.00 | -0.00 |
| age2 | 0.01 | -0.00 | -0.04 | 0.00 | 1.00 | 1.00 | 0.63 | 0.64 | 0.00 | -0.00 |
| exp | -0.43 | -0.53 | -0.80 | -0.09 | 0.63 | 0.63 | 1.00 | 0.99 | -0.04 | -0.07 |
| exp2 | -0.40 | -0.52 | -0.79 | -0.09 | 0.64 | 0.64 | 0.99 | 1.00 | -0.04 | -0.07 |
| iq | 0.15 | 0.20 | 0.06 | -0.00 | 0.00 | 0.00 | -0.04 | -0.04 | 1.00 | -0.00 |
| dist | 0.03 | 0.04 | 0.08 | 0.00 | -0.00 | -0.00 | -0.07 | -0.07 | -0.00 | 1.00 |

*Note*: state and born variables are left out. Continuity was assumed with the use of Pearson.

It is important to note any multicollinearity, along with checks for possible exclusion and relevance criteria, which will both be checked for in the first stage of 2SLS. The table shows correlation of ‘edu’ with both the ‘wage/logwage’, while it is low for ‘edu\_par’ and ‘dist’. The instruments do not correlate with ‘iq’ and thus show promise as instruments. Same can be observed for ‘exp’ and ‘age’ and their correlation with wage/logwage. ‘Exp’ and ‘edu’ show possibly concerning negative relationship for multicollinearity, but it is only logical to expect someone who spent longer in education has less experience.

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# CORMATRIX

# The exogenous variables he refers to are what you call instruments/exclusion restrictions.

# Correlation among instruments is not a problem per se. However, the more correlated they are,

# the less powerful they become as the extra information provided by the second instrument decreases.

## Discussion

FINDINGS AND FUTURE RESEARCH The discussion should be the largest part of your paper and include your argument, research, and experiences (for example, through Service-Learning). Each main point of your paper should start its own paragraph with a strong first sentence. Again, limit the use of “I” and “you” in academic writing.

POLICY RELEVANCE Remember to introduce quotations with who said it and/or why it’s important. Make sure quotes fit seamlessly in your paper. Include short quotations (40 words or less) in-text with quotation marks. Use ellipsis (...) when omitting sections from a quote and use four periods (....) (i.e., an ellipsis plus the period) if omitting the end section of a quote.

This is a longer quote, which is 40 or more words. Indent the quote a half-inch from the left margin and double-space it with no quotation marks. To get the right format, just click on “Quote” in the Styles area on the Word frame above. In parentheses, include the author’s last name, year, and page number at the end, but no period (Smith, 2017, p. 45)

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## Conclusion

The conclusion restates the thesis and summarizes the main arguments or points of the article, so that your reader could just read the conclusion to generally understand the paper. What is important to learn from reading your paper? If you know of areas in this topic that need further study, mention them. After this paragraph, there is a page break that forces References onto its own page: You will want to keep it there.

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## [[More References examples for your assistance here](http://libguides.uww.edu/apa/examples)]

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