Returns to Education in Germany

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Abstract

Administrative data can serve many useful purposes. This paper uses such data, specifically German Social Security Administrative data, to evaluate the expected wage returns to various levels of education in Germany. Through multiple regression analyses using a ordinary least squares fixed effect model and regular ordinary least squares estimation, this paper quantifies these returns. Furthermore, rather than quantifying returns to years in school, it evaluates gains associated with attainment of levels of education. Based on estimates attained through fixed effects regression, students acquiring college degrees had returns in the order of 99 to 136 percent higher than those of the minimum level of secondary education.

Introduction

There are many reasons people seek to achieve higher levels of education. Some seek it for prestige while others seek it to broaden their horizons. Many seek it to truly learn something new and expand upon their worldview. What all these people have in common is that they expect to earn higher wages from their hard work in school. This common denominator gives rise to the questions this paper seeks to evaluate and answer. What are the returns in wages to increasing levels of education? If I go to college, how much more should I expect to earn than someone who only has a high school diploma? Are wage returns consistent through levels of education or are there bigger jumps at different levels than others? What about vocational schooling rather than strictly high school or traditional college?

In order to answer questions like these, I use German Social Security administrative data to analyze the wage returns to various levels of education in Germany. I focus on both the levels Americans would be familiar with such as high school and college as well as less conventional levels like vocational school and universities of applied sciences. Through regression analysis, I seek to quantify the wage returns to each of these specific levels.

Knowing estimates of expected wage increases for rising levels of education has numerous useful applications. First, individuals who are debating between increasing their education and continuing to work at their current job or a similar position could better evaluate whether or not it is worth it for them to go to school. Second, these statistics could be helpful in government policy decisions. With knowledge of expected earning potential, a government could make better decisions regarding forms of education to subsidize for certain demographic groups in an attempt to drive higher wages and push a countries' economy forward. Third, universities or vocational schools could use these statistics to advertise their value and attempt to boost applicant rates.

While on the surface exploring returns to schooling seems relatively straightforward, there are some important complications that need to be addressed. The standout issues are ability as an unobserved variable and the endogeneity of education. Of course, one way to manage this issue is to use a proxy or some observable measure of ability and include it in the regression. In *Returns to Schooling,* Griliches suggests the possibility of employing some test score as this proxy but goes on to explain many of the potential problems associated with this. These scores are subject to problems of testing inaccuracies as well as the bigger question of whether or not they are even a proper proxy for ability. Education as an endogenous variable appears as an issue naturally, since choice of level of education is based on expected earnings and costs, functions that vary person to person (Griliches). I use a model that includes fixed effects to manage these two issues.

Theory

My theoretical approach to modeling the increases in earnings from levels of education in Germany closely mirrors the standard Mincer Earnings Function, as specified in his book, *Schooling, Experience, and Earnings* (Mincer). His model relates gains in earnings to years of schooling and experience in the labor market. While my model is similar, it includes some important modifications. Mincer's earnings function, specifically, appears as follows:

$$\ln(y) = \ln(y_0) + rS + \beta_1 X - \beta_2 X^2 + u \tag{1}$$

The natural logarithm of earnings, ln (y), equals the natural logarithm of earnings of an individual without any schooling or experience, ln (y_0), plus *r* rate of return on S years of schooling, rS, plus the negative quadratic function of experience, $\beta_1 X - \beta_2 X^2$, plus some disturbance term, u.

Intuitively, each piece is relatively straightforward. An individual without schooling or experience would yield

$$\ln(y) = \ln(y_0) \tag{2}$$

where $S = X = X^2 = 0$ reflecting the absence of schooling and experience. This intercept provides the baseline for comparison when individuals gain experience or schooling. As an individual gains years of schooling, S, one would expect that these result in an increase in their stock of human capital. This increase in human capital should translate to wage gains at some rate, r. Finally, the negative quadratic experience portion of Mincer's Human Capital Earnings Function represents the concave nature of experience. As an individual accumulates more and more experience, these incremental years of experience add less and less to their stock of human capital. Consider, in a person's first few years out of college they are acquiring large amounts of on the job training and their productivity rises greatly. However, after many years on the job, this same individual has very little additional on the job training yearly and gains little human capital from their most recent years of experience. Thus, it is reasonable to believe that a parabolic function aptly reflects diminishing marginal returns to experience. Finally, Mincer's use of a log-level model has the convenient quality that coefficients reported are easily transformed into percentage gains or losses. For example, if r reported as 0.30, a brief mathematical transformation of

$$(e^{r=0.30} - 1)\times 100 = \%\Delta y = 34.9\% \tag{3}$$

yields the proper percent change in y given an additional unit of schooling, S.

Mincer's model is not without its limitations, but it closely fits with what I seek to evaluate and therefore fits as a theoretical base from which to build. While my modifications are few in number, they are important and change the interpretation significantly. In my model, I add a variable to control for time worked, utilize education categorically rather than continuously, and add a fixed effects intercept adjustment that is dependent on the individual. Specifically,

$$\ln(y) = \beta_i + \sum_{n=1}^{5} \alpha_n E_n + \sum_{n=6}^{7} \alpha_n T_n + \beta_1 X - \beta_2 X^2 + u \tag{4}$$

In my specification, β_i represents the individual specific intercept term, differing across individuals to reflect the fixed effect nature of the model; $\sum_{n=1}^{5} \alpha_n E_n$ represents the various levels of education, E_n, and their corresponding coefficients; α_n; $\sum_{n=6}^{7} \alpha_n T_n$ represents the time-worked dummy variables, T_n, and their respective coefficients, α_n; and $\beta_1 X - \beta_2 X^2$ represents the concave returns to experience portion of the function.

An important departure for my model from Mincer's original is the use of fixed effects. In a standard ordinary least squares model, one of the key assumptions is that the error terms must be uncorrelated with the regressors. If the error terms are correlated with the regressors, the regression coefficients are not accurately depicting the effect of that particular regressor alone, but are potentially swallowing other effects, leading to estimation bias. However, in a fixed effects model the intercept term is allowed to vary such that individual specific components are accounted for by the intercept term rather than by the regression coefficients. Thus, the fixed effects model removes the source of endogeneity and gives better estimates of the regression coefficients.

The importance of using a fixed effects model rather than an ordinary least squares model is clear when one considers two perennial issues when estimating the returns to education: ability as an unobserved variable and endogeneity of education. An individual's ability would likely have an impact on their wages and ought to be included in any regression attempting to estimate this. However, there are numerous issues in measuring ability for several reasons. First, how do we properly measure ability or even find a proxy for it? Second, how do we justify our proxy as truly encompassing "ability"? For example, one could argue that IQ scores are a viable proxy. However, one could just as easily argue they are poor indicators of actual ability to be productive in the workplace. Or, if one wanted to incorporate motivation or energy into their view on ability, how is this possible to quantify? Clearly, it is a major challenge to reasonably include one measure of ability in a model, but cannot be unaccounted for as that would lead to misspecification bias. As stated above, the fixed effects model accounts for this ability on a person-by-person basis through the varying intercept term and removes this source of bias.

The fixed effects model also takes care of the endogeneity of education through this variable intercept term. The source of endogeneity of education comes from the fact that schooling is partially based on individual's and families' optimizing choices (Griliches). Individuals and families make schooling decisions based on what they expect to earn, which again leads to potential correlation with the disturbances. Again, rather than leaving this correlation present, the fixed effects model pulls it into the intercept term and removes this potential for bias.

My other major departure from Mincer's model lies in the treatment of education. In Mincer's model, gaining a year of education has the same coefficient whether it is a second year of college or a graduating year of college. This treatment stems both from use of education as a continuous variable and the approach to it as a year of human capital accumulation for the individual. This provides the benefit of seeing what each year of education adds in quantifiable human capital appearing in earnings gains for the individual, but potentially loses the major jumps resulting from completion of a level of education rather than strictly a year. By using education categorically, I gain the ability to see what each level of education adds to ones earnings potential. Furthermore, these categories can clearly be interpreted as percent increases per level and easily show the gains to levels such as college or vocational training rather than merely years of human capital accumulation.

Data

The data set used for this research and analysis is from the Sample of Integrated Labor Market Biographies (SIAB) campus file. This particular file is a selected portion of an SIAB Scientific use file, which contains German Social Security administrative data along with other administrative data from the federal employment agency. The scientific use file contains 1,515,463 individuals' employment history data. From this, the campus file records 48,795 German individuals aged 25-50 in 2005.

In particular, I use a partition of the SIAB campus file with complete education history data, which comes from the Beschaftigten Historik (BeH). This portion of the data contains 35,842 observations and accounts for 6,572 people. The reason I use only a partition of the campus file is because this portion of the data set contains complete educational data across entries and this is a variable that is central to my analysis. The BeH acquires its data nationally through an integrated notification procedure for health, pension, and unemployment insurance. Under this, employers are obligated to report to the applicable government agencies for all employees covered by social security. As a result, this data set covers white and blue collar workers and apprentices but does not include civil servants and the self-employed.

The BeH data provides an excellent fit for evaluating wage returns to education because it contains most of the variables that one could theoretically relate to earnings. The only notably missing variable that would be desirable is one that could proxy for ability. There is no such variable in the data set that evaluates something related to natural ability such as an IQ score, standardized test score, or something similar. While this presents a minor challenge, the use of fixed effects as discussed in the theory portion sufficiently manage this missing variable. In addition to this, since employers must report the data, it decreases the likelihood of misreported earnings or education levels that may appear in survey data.

A particularly beneficial characteristic of the BeH data is the clear educational categories. Each entry is encoded with one of six major educational categories: secondary school, secondary school and vocational school, upper secondary school, upper secondary school and vocational school, university, and applied sciences university. Since these categories may sound foreign to a non-German reader, they are worth explaining briefly.

In Germany, children are put on an educational track around the age of 10. There are generally three paths, Gymnasium, Realschule, and Hauptschule. Respectively, these correspond to students who are deemed bright enough to attend college, students who are still intelligent enough to warrant white-collar work, and finally students who are headed for blue-collar jobs. Hauptschule prepares students for blue-collar work, and often allows additional time out of school for vocational training. This is the kind of school that is categorized as “secondary” in my analysis and in the data. Realschule prepares students for better jobs than Hauptschule (and in many respects is considered better than most American high schools) and is thus referred to as "upper secondary school" in the data. Lastly, Gymnasium is the top-flight type of school and prepares students for university education. These students aren't noted in the data since it is assumed they attended either university of applied sciences university.

The other major difference pertains to the divide between university and applied sciences university. Traditional universities in Germany provide relatively broad teachings and are very theoretically focused. Students choose their pace with which to study and primarily organize themselves. Applied sciences universities are geared toward teaching industry ready skills in a more structured environment. Their goal is to prepare students to directly enter the industry of their choice after graduation and worry less about theory and more on application. This difference in style means that students graduating from each type have quite different qualifications upon graduation.

Finally, the data contains one or more entries per person across the 3-year span. Since the data is reported for each entry as a spell of unemployment, some individuals have multiple entries corresponding to multiple spells of unemployment. Each of these entries have complete data across the variables of interest and thus allow for the use of a fixed effects model with the variation originating in changes of wages, education, and experience within the individuals.

Results

The fixed effects regression model used on German Social security data shows returns to education with positive coefficients for each level of education. It also generally shows increasing magnitudes of coefficients for higher levels of education. This rule contains one exception, where applied sciences university routinely, through the iterative regressions, shows a larger coefficient than traditional German university. Although somewhat puzzling, there are a few possible explanations for this that I will address later.

In Table 1, column (7), the full fixed effect regression is shown. In this specification, each coefficient associated with education corresponds to a percentage of returns in wages after the simple transformation shown in the theory section equation (3). These translations appear in Table 2.

First, Table 2 shows that gains to vocational schooling are significant and valuable. A 21% increase in earnings for someone who went to a lower secondary school and a 12% rise for someone who attended upper secondary school are not trivial gains and suggest that vocational schooling plays an important role in increasing ones earnings in Germany. Based on these two percentages it also appears as though gains to vocational schooling are realized more for individuals of lower educational levels. This intuitively makes sense as someone of a lower educational level likely has more to gain through specialized training that vocational schooling can provide. Furthermore, per Table 1, the standard errors are small, showing that these estimates are very precise.

Second, Table 2 shows that there is a large wage gap between those who did not attend universities and those who did. The increase in estimate from upper secondary schooling with vocational training to university is 41% and the increase from upper secondary with vocational training to applied sciences university is every greater at 78%. These increases are very significant and to an extent follow expectations, although the applied sciences university percentage gain appears relatively high. One possible explanation for this follows with the general concept of labor market demand. It may be the case that applied degrees are in higher demand than more theoretical ones in the current era. This seems very reasonable when one considers the demand for Science, Technology, Engineering, and Math (STEM) degrees in the United States.

Experience appears to play a much smaller role in this analysis than type of education. The gains to experience are approximately 7% initially with decreases that grow as years accumulate. However, this process of decreasing gains to experience appears to happen very slowly as the coefficient of experience squared is -0.00023 in the full fixed effects regression. Additionally, this coefficient reports a standard error of 0.000142, suggesting it is statistically insignificantly different from 0.

In addition to the fixed effects model, I tested regressions using ordinary least squares specifications. These results appear in Table 3 column 2. As is apparent, the coefficients in the ordinary least squares model are strikingly similar to the coefficients in the fixed effects model, with a few exceptions. The coefficients corresponding to secondary schooling with vocational training, upper secondary schooling, upper secondary with vocational training, and university schooling are all quite close to the coefficients for their respective regressors in the fixed effects model (Table 3). The educational category where coefficients differ greatly is applied sciences university. Strangely enough, the coefficient is much larger in the fixed effects model than the ordinary least squares model. This result suggests that unobserved ability is negatively correlated with returns to applied university. Since graduates from applied sciences universities are reaping greater returns to education when controlling for ability, the model suggests that these are actually "lower ability" individuals relative to the other categories. Thus, it is possible that applied sciences universities are taking marginal ability students and better preparing them for the current labor market situation.

Conclusion

Through analysis of German Social Security data, I have shown that education has a powerful effect on earning potential. When an individual acquires an additional level of education in Germany, they can expect their earnings to rise corresponding to the degree of that level. Students that attended universities, whether applied or traditional, saw the biggest gains to education. Both secondary and upper secondary educated students saw significant gains to vocational schooling. Additionally, in an ordinary least squares model that does not employ fixed effects, men saw a 20% increase in wages over women. Based on these findings, school, including vocational schooling, seems to be an effective way to increase earnings.

Due to the nature of this analysis, it is somewhat difficult to provide direct comparison to previous literature on returns to schooling. Most previous literature is searching for a coefficient reporting the gains to a year of human capital accumulation, regardless of the type of schooling. My model takes into account not only the number of years an individual attended school, but the type of school they attended. Thus, comparing the gains I have found to various levels of education to the gains to a general year of education among other studies could potentially lead to faulty conclusions.

Despite this mismatch, previous literature can be useful in confirming the puzzling issue of downward bias on the ordinary least squares estimates relative to the fixed effects estimates. In *Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems,* Card discusses using instrumental variables to manage endogeneity in education. He continues to provide a brief survey of 11 recent studies on returns to education that reported both ordinary least squares and instrumental variables estimates. Routinely, these studies reported ordinary least squares estimates that were downward biased relative to their instrumental variables estimates counterparts. Similarly, Trostel, Walker, and Woolley performed a study on returns to education across 28 countries using both ordinary least squares and instrumental variable techniques and found results consistent with this downward bias. While this doesn't necessarily explain the oddity of the downward bias, it suggests that this is a persistent happenstance and not an error in my model.

So, what can these findings tell us? First and foremost, maybe the prospect of everyone attending the same type of traditional college is not that great after all. In Germany, students have many acceptable avenues other than college. Vocational training offers an excellent alternative for students who don't find a traditional college setting to be a good fit for them. Furthermore, applied universities offer an alternative for students who want to focus on getting directly into their industry of choice and not pursuing deeper academic areas.

It is challenging to extrapolate if these results would hold in the United States and if there is necessarily carryover of the suggestions to which this model leads, but this presents an excellent opportunity for further research. Maybe some students should reconsider the college route and should instead be given time for vocational schools at a younger age so they miss out on fewer earning years after high school. Cultural norms are different and rather tough to change but this could be an avenue to boost the middle class in America from fast food jobs into better paying manufacturing jobs or service jobs, as every presidential candidate seems to wish. Maybe more technical schooling programs could help students who desire the benefits of a "higher class" college degree without some of the hassles associated with traditional college.

At the root of the German education system is a different set of cultural norms that make statements about the application of their system in another country challenging. In particular, putting students on a track at the age of ten and essentially deciding their future at that stage will never happen in the United States. However, it is easy to see that evaluation of different options to broaden our, and other nations, educational systems could benefit all involved greatly. Maybe the key to engaging a more robust and productive workforce is getting students who are bound to drop out after one year at a traditional university to spend that year in trade school. Maybe some college requirements ought to be reevaluated and changed to reflect the dynamics of our globalized, modern labor market. Maybe the key to maximizing the potential of our economy is not more absolute education for everyone, but more fitting education for everyone.

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Table 1: Fixed Effects Model- German Earning returns to Education

	(1)	(2)	(3)
Constant	3.26	2.10	2.87
	(0.02)	(0.01)	(0.10)
Secondary and Vocational	0.39		
	(0.02)		
Upper Secondary	0.25		
	(0.07)		
Upper Secondary with Vocational	0.52		
	(0.04)		
Applied University	0.73		
	(0.05)		
University	0.67		
	(0.06)		
Upper Part time		1.51	
		(0.01)	
Full time		1.84	
		(0.01)	
Experience (x10)			0.22
			(0.09)
Experience^2 (x1000)			0.53
			(0.20)
R^2			
Within	0.02	0.52	0.01
Between	0.05	0.50	0.00
Overall	0.04	0.53	0.00

Note: Data sourced from January 2005 to December 2008. Standard Errors are in parenthesis.
Dependent Variable: Natural Logarithm of Daily wage
Regressors: 5 levels of education past secondary school with secondary school acting as base category (ascending order), time worked (less than part time as base category, part time, full time), experience, and experience squared

Table 1 (continued)

	(4)	(5)	(6)	(7)
Constant	1.97	1.28	1.53	0.58
	(0.01)	(0.12)	(0.07)	(0.08)
Secondary with Vocational	0.14	0.46		0.19
	(0.01)	(0.02)		(0.01)
Upper Secondary	0.27	0.43		0.38
	(0.05)	(0.07)		(0.05)
Upper Secondary with Vocational	0.30	0.76		0.46
	(0.03)	(0.04)		(0.03)
Applied University	0.40	1.40		0.86
	(0.04)	(0.06)		(0.04)
University	0.37	1.15		0.69
	(0.04)	(0.06)		(0.04)
Upper Part time	1.50		1.50	1.48
	(0.01)		(0.01)	(0.01)
Full time	1.83		1.83	1.81
	(0.01)		(0.01)	(0.01)
Experience (x10)		0.89	0.23	0.68
		(0.10)	(0.06)	(0.07)
Experience^2 (x1000)		-0.05	0.17	-0.23
		(0.20)	(0.14)	(0.14)
R^2				
Within	0.52	0.04	0.52	0.53
Between	0.53	0.00	0.41	0.33
Overall	0.55	0.00	0.46	0.39

Note: Data sourced from January 2005 to December 2008. Standard Errors are in parenthesis.
Dependent Variable: Natural Logarithm of Daily wage
Regressors: 5 levels of education past secondary school with secondary school acting as base category (ascending order), time worked (less than part time as base category, part time, full time), experience, and experience squared

Table 2: Fixed effects translated to percentage gains

	Fixed Effects coefficient	Percentage wage gain
Secondary with Vocational	0.19	21%
Upper Secondary	0.38	46%
Upper Secondary with Vocational	0.46	58%
Applied Sciences	0.86	136%
University	0.69	99%

Note: Fixed effects coefficients taken from column (7) of Table 1. Conversions to percentage wage gain follow transformation outlined in equation (3) from theory section.

Table 3: Fixed effects (1) vs. OLS estimates (2)

	(1)	(2)
Constant	0.58	1.75
	(0.08)	(0.03)
Secondary with Vocational	0.19	0.15
	(0.01)	(0.01)
Upper Secondary	0.38	0.30
	(0.05)	(0.04)
Upper Secondary with Vocational	0.46	0.44
	(0.03)	(0.02)
Applied University	0.86	0.59
	(0.04)	(0.02)
University	0.69	0.72
	(0.04)	(0.02)
Male		0.20
		(0.01)
Upper Part time	1.48	1.46
	(0.01)	(0.01)
Full time	1.81	1.83
	(0.01)	(0.01)
Experience (x10)	0.68	0.07
	(0.07)	(0.03)
Experience^2 (x1000)	-0.23	-0.12
	(0.14)	(0.06)
R^2		0.56
Within	0.53	
Between	0.33	
Overall	0.38	

Note: Data sourced from January 2005 to December 2008. Standard Errors are in parenthesis.
Dependent Variable: Natural Logarithm of Daily wage
Regressors: 5 levels of education past secondary school with secondary school acting as base category (ascending order), time worked (less than part time as base category, part time, full time), experience, and experience squared

Table 4: Summary statistics

	Mean	Std. Dev.	Min	Max
Year of Birth	1968	7.44	1955	1980
Age	39	7.5	25	53
Wage (daily)	49.82	32.32	0	173
Log wage	3.6	.96	0	5.15
Experience	21.5	7.7	1	37

Note: Table reports general summary statistics for entirety of data used in regression analysis.

Table 5: Education level breakdown

	Observations	Percent
Secondary	6,312	17
Secondary + Vocational	26,214	72
Upper Secondary	251	1
Upper Secondary + Voc.	1,429	4
Applied University	816	2
University	1,312	4

Note: Overall breakdown of observations per grouping of schooling. 23 percent of individuals showed a change in schooling level during 2005-2008 (duration of data set).

Table 6: Wages by Time worked

	Observations	Mean	Std. Dev
Less than half time	5,654	9.92	11.30
Over half time	4,112	39.05	21.13
Full time	26,309	60.33	29.44

Note: Table reports daily wages in euros. Divisions are by whether employee worked less than half time, over half time, or full time.