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Risk and Returns to Educational Fields

A Financial Asset Approach to Vocational and Academic Education

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Risks and Returns to Educational Fields - A Financial Asset Approach to Vocational and Academic Education

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Abstract: Applying a financial assets approach, we analyze the returns and earnings risk of investments into different types of human capital. Even though the returns from investing in human capital are extensively studied, little is known about the properties of the returns to different types of human capital within a given educational path. Using information from the German Micro Census, we estimate the risk and returns to around 70 fields of education and differentiate between vocational and academic education. We identify fields of education that are efficient investment goods, i.e. high returns at a given level of risk, and fields that are chosen for other (non-monetary) reasons. Furthermore, we rank fields of education by their return per unit of risk and find that university education is not always superior to other educational paths.

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1 Introduction

The positive effects of investments in human capital on the level and evolution of earnings, employment, and other aspects of well-being is one of the most robust and important empirical findings in labor economics (see e.g. Blundell, Dearden, Meghir, and Sianesi, 1999; Oreopoulos and Salvanes, 2011; Psacharopoulos and Patrinos, 2004). In developed countries, education is an important resource for the economy and assumed to be one of the key determinants in technological development, production and, thus, economic growth. Therefore, politicians aim at increasing the population's educational level (see e.g. EUROPE 2020 - indicators (European Comission, 2010)). As increasing the countries overall educational level requires individuals to invest in their education, researchers focus on the individual's (economic) benefits of education, mainly the increase in earnings due to investments into more education.

Even though the returns from investing in human capital in general are widely studied, little is known about the properties at a more disaggregated level, i.e. field specific returns to education. Standard economic models of schooling decisions (Becker, 1964; Mincer, 1974) model the average returns to years of schooling by comparing future income streams to the costs associated with an additional year of schooling but do not differentiate between different fields. To overcome the assumption of homogeneity of human capital investments, we differentiate between fields of education within and across levels of education. Borrowing from financial economics models (see e.g. Cochrane, 2001), we contribute to the literature on human capital investment by differentiating between a large variety of educational fields and by incorporating the unexplained variance of the returns, the earnings risk, into the evaluation of the benefits from education.

To learn more about the properties of returns to different types of human capital and how they compare across fields is important from both a theoretical and a political perspective. From a theoretical perspective variations in returns to educations across fields and the earnings variation within a field have important consequences for models on educational choice that usually only consider aggregated earnings streams at different levels of education as explanatory variable. By aggregating over different fields of education one might, for example, overstate the additional value of a further year of education if the additional year of education is spent in an educational program with low labor market returns.

From a political perspective it is important to know the financial attractiveness of an educational field for various reasons. First, our results can serve as an instrument to evaluate the demand for graduates on the labor market. In Germany, for example, it is controversially discussed as to whether there is a lack of graduates from engineering fields or more broadly from MINT-fields[1]. While some experts claim that there is a lack of skilled engineers and demand that politicians take action (see e.g. Anger, Koppel, and Plünnecke, 2011), others do not share

[1]MINT-fields include fields in mathematic, computer science, engineering, natural science and other technical fields.

this opinion (see e.g. Brenke, 2010). Identifying the field specific returns and associated risks could serve as a tool to evaluate the demand for graduates of a certain field of education on the labor market, with high earnings and low levels of earnings variance indicating a high demand for skilled labor in a specific field.

Second, the main impact politicians have on individual investment can be assumed to be through the costs of the investment or by providing information on the benefits of the investment in education. One factor through which politics influence educational investments are tuition fees. Discussions about tuition fees are usually charged with the argument that the main beneficiary of education is the individual (in addition to some positive externalities), so the investment does not have to be free of charge as the individual will capture the returns to his/her investment later in life. Thus, fields with high labor market returns might be charged higher fees, while there could be an interest to keep tuition fees of subjects with smaller labor market returns but high non-pecuniary returns (for example, arts) or high social returns (for example, education) low. It could further be assumed that there is an information deficit among prospective students or incorrect perceptions about returns to fields and levels of education, which lead to inefficient sorting into the fields. In that case politicians could rely on the estimates when informing about the financial attractiveness of the various fields of education.

Altering the expected returns to different fields of education in order to navigating educational investments of prospective students, can be assumed to be an effective political instrument. Existing models estimating the effect of expected earnings streams in different fields of education on the college major choice suggest that this choice is partly guided by expected earnings and further by non-pecuniary factors as preferences or ability (see e.g. Arcidiacono, Hotz, and Kang, 2011; Arcidiacono, 2004; Berger, 1988; Beffy, Fougre, and Arnaud, 2012; Boudarbat and Montmarquette, 2009).

The risk associated with different types of education should not be neglected. The question of whether, empirically, human capital investments are risky is addressed by Becker (1964), who notes that there is more earnings variation among college graduates than among high school graduates. Literature on the decision to pursue higher education, incorporating risk, originates with Levhari and Weiss (1974). They find that increasing risk, i.e. the variance in the payoff for education, reduces investment to education. Subsequent studies similarly find that reducing uncertainty in returns increases educational participation (see e.g. Hartog and Vijverberg, 2007; Carneiro, Hansen, and Heckman, 2003; Fossen and Glocker, 2011).

The highest expected earnings are usually found for fields in social science (mainly business and law) and medical subjects, while humanities and arts are rather unattractive investments in terms of monetary returns (Walker and Zhu, 2011).[2] The authors estimate the returns to groups of subjects but the variance of the returns within the group of fields is not considered.

[2] Other studies are Ammermüller and Weber (2005) and Wahrenburg and Weldi (2007) for Germany, Arcidiacono (2004) for the US, Boudarbat and Montmarquette (2009) for Canada, Kelly, O'Connell, and Smyth (2010) for Ireland and Chevalier (2011) for the UK.

Relatively little research, thus, tries to understand how the risk-return trade-off for different human capital investments compare at the margin. Palacios-Huerta (2003) is the first to empirically analyze risk properties of various human capital returns. He presents an empirical comparison of risk adjusted human capital investments to financial investments. Christiansen, Joensen, and Nielsen (2007) take up his approach and analyze the risk-return trade-off in human capital investments with Danish labor market data. In both studies, the authors compare the risk properties of human capital assets by applying a framework that is standard for the analysis of financial assets.

We contribute to this stream of literature by comparing the risk and returns to a large number of educational fields in Germany. Germany provides a good framework for studying returns and risk properties to different types of education for various reasons: In Germany upper secondary high school graduates can choose between vocational education, education at a university of applied science or at a university. These educational paths have different characteristics, for example, different lengths of study, qualification levels or levels of specialization. Despite the different characteristics, they offer, in a lot of cases, similar fields of education. For example, a person interested in business or manufacturing can choose between all three paths. Hence, for a decision maker it is not only interesting to know how earnings and earnings risk vary across the paths on average but also how earnings vary between the paths for one specific field. This variation in educational choices also allows us to restrict our sample to upper secondary school graduates who obtained a university entrance certificate. Due to this sample selection, a bias stemming from sorting into the fields based on ability can be assumed to be relatively small. The group can be assumed to have a rather homogenous level of general ability. Beyond the educational framework, it is interesting to evaluate the financial performance of fields of education in Germany because of the controversially discussed lack of skilled graduates in some fields of education.

Using a large German data set, the German Micro Census, we are able to estimate the returns and earnings variances for about 70 fields of education. We estimate the returns to different fields of education by extending the standard Mincer wage equation to allow for different fields of study. By analyzing the risk-return trade-off for a large number of fields, we identify fields that are efficient in terms of investment goods and fields that are likely to be chosen for other reasons (consumption purposes). Because students have different preferences and abilities, we also look at the efficiency of different levels of educations within a certain group of fields (e.g. engineering fields). For instance, for someone interested in engineering, we find that a university degree in manufacturing engineering is an efficient investment as there is no other engineering field that earns a higher rate of return with the same level of earnings variation. Similarly an applied science degree in precision engineering should be chosen over a university degree in electrical engineering because it yields about the same returns but at a lower variation level.[3] We find that fields in all educational paths can be efficient investments. Hence, the decision about the

[3]This is true only under the standard assumption that individuals are risk averse.

level of education as well as the field of education is important when deciding about investments in education.

The paper is structured as follows: The following section explains the methodology for estimating the performance measures. Section 3 describes our dataset. Section 4 provides the results of our analysis, followed by the conclusion in Section 5.

2 Empirical model and methodology

2.1 Performance measure

As we analyze different fields of education in terms of their investment value, we need to find an adequate measure for the efficiency of each field. The literature analyzing the returns to educational subjects focuses on the returns themselves and tends to neglect the risk associated with the different investments (see e.g. Wahrenburg and Weldi, 2007). However, this might bias the evaluation of the investment value, as the risk of an investment largely influences the investment decision (see Hartog and Vijverberg, 2007; Carneiro, Hansen, and Heckman, 2003; Fossen and Glocker, 2011). With respect to the educational decision, one might think of unemployment risk associated with different educational qualifications that add some uncertainty with regard to the expected returns. The variation of unemployment risk across educational qualification is well documented, (see e.g. Mincer, 1991; Riddell and Song, 2011; Reinberg and Hummel, 2007). The unemployment risk may not only vary between different educational paths, but also between the field of education majored in.

Interpreting the different fields of education as different investment strategies, we use a standard financial economics approach: The mean-variance model of Markowitz (1952). In the model, assuming that the returns are normally distributed, investors only consider the expected returns and their variances in their decision making process. Graphing the expected returns and their standard deviation in a so-called mean-variance plot exhibits all feasible investments. Depending on the individual's utility function (increasing with returns and risk-avoidance), the optimal investment strategy lies on the efficient frontier, i.e. the investment which exhibits the highest returns for a given risk. We assume investment in education to be a discrete choice. Portfolios of educations are not considered in this study. For that reason, the mean-variance plot for human capital investments is a scatter-plot whereas the empirical efficient frontier for financial assets is a continuous line.

Following Christiansen, Joensen, and Nielsen (2007) we use a modified version of the Sharpe-ratio (Sharpe, 1966) to formally describe those plots and to rank the different educational investments. The Sharpe-ratio is a return to variability measure that also uses the expected (excess) returns compared to a risk free alternative, standardized with its standard deviation. Since a risk free return in the context of educational choices is not straight forward, we compare the returns of a certain educational field with the (risk free) sample average returns $\overline{R}$ over all fields as a proxy for the true population average returns:

$$S_j = \frac{E[R_j - \overline{R}]}{\sqrt{VAR[R_j - \overline{R}]}}. \quad (1)$$

The Sharpe-ratio S_j then indicates the efficiency gain or loss from investing into educational field j compared to the average. Thus, a higher value of the Sharpe-ratio relates to a better performance of the investment.

2.2 Measuring the returns

To derive our performance measure, we need the returns associated with a certain field of education. Thus, we calculate the individual hourly wages in each educational field and use this information to estimate field average returns.

To obtain the returns, we use a modified version of the standard Mincer wage regression (Mincer, 1974). We allow the log hourly wage ($\log(W)$) of individual i to non-linearly increase with age. We prefer age over experience, as we do not observe the true work experience. A constructed measure of potential experience as a linear combination of age, years of education and the general school starting age could bias our results since possible unemployment spells are not accounted for. However, our constructed measure also neglects the information on unemployment experience, which is potentially correlated to the fields of study and may effect wages due to human capital depreciation. We try to attenuate this omitted variable bias by including information on tenure in the recent job in our model.

As with the standard Mincer returns to schooling approach, estimating field specific returns might result in several problems (see Altonji, Blom, and Meghir, 2012, for a detailed overview). A major concern, first described by Willis and Rosen (1979), and frequently discussed in the context of estimating returns to education, addresses the problem of unobserved variables that might be correlated with the educational variable, i.e. motivation or ability. Unfortunately, our dataset neither includes ability measures nor retrospective information that would allow us to model the selection process into educational fields. To keep a possible ability bias small, we constrain our sample to students that passed the university entrance examination (*Abitur*) such that variation due to unobserved ability is reduced. Studies analyzing the effect of educational qualifications[4] on wages, tend to find a significant effect due to ability sorting (see e.g. Carneiro, Hansen, and Heckman, 2003). In contrast to these findings, studies focusing on college majors including measures for ability conclude, that such a bias due to omitted ability variables is rather small (Berger, 1988; Arcidiacono, 2004).

[4]Educational qualification referring to the standard Mincerian approach of an additional year of schooling, but also to studies estimating the returns of different education qualification like university or college degrees.

The second problem we face is possible endogeneity of educational fields. We may observe the individuals in the respective fields, because they chose that field according to their expectations about the associated returns. Arcidiacono, Hotz, and Kang (2011) show, that an increase in the expected earnings in a certain field of education has a significant positive effect on choosing this major. A possible solution for this problem would be to instrument the educational field variables, but with our dataset we are not able to construct such instrumental variables to account for this possible endogeneity. When interpreting our finding, we should keep the literature findings in mind, which indicate that our return estimates might be biased upwards.

We estimate the earnings by applying a OLS model for the working population:[5]

$$
\begin{aligned}
\log(W_i) \quad = \quad & \sum_{j=1}^{J} \alpha_{0j} F_i L_i + \sum_{l=1}^{L} \alpha_{1l} \text{age}_i L_i + \sum_{l=1}^{L} \alpha_{2l} \text{age}_i^2 L_i + \beta X_i + \epsilon_i, \qquad (2) \\
& \text{with} \\
& j = 1, ..., J \quad \text{and} \quad l = 1, ..., L \\
& \text{where} \\
& \epsilon_i \sim N(0, \sigma_\epsilon^2).
\end{aligned}
$$

The logarithm of the observed hourly wage of individual i is denoted by $\log(W_i)$. F_i is a field specific dummy which indicates whether the individual graduated in the respective field j. L_i is a dummy for the educational level, i.e. if the individual graduated from university, university of applied science or finished vocational training. To get our field specific returns for each educational level, we include the interaction of F_i and L_i. As described above, we use age, both in levels and squares, interacted with the dummies indicating the educational path. Thus, we allow for a flexible age-earnings-profile across, but homogeneous within the educational path. We do not interact the fields of education with the elements of the matrix X_i, i.e. person specific and demographic characteristics like tenure in the current job, nationality, regional- and year-dummies, since we assume that those have a unique effect on the wages unrelated to the field of education. Due to well-known differences in the age-earnings-profiles between men and women, we estimate the model separately rather than including gender dummies. Furthermore, we assume that the error terms follow a normal distribution.

After estimating the individual log wages, we can calculate the log hourly wages for the working population for each educational field. Since we allowed the earnings profile to vary with age in each educational path, we take this information into account by calculating the (discounted) capital value for each investment at the time of decision. Comparing the field

[5]There might be a bias resulting from non-random sample selection into work participation varying by field of education. We controlled for this possible selection using a standard Heckman estimation model (see Heckman, 1979). While we find that the selection term is significant, it does not affect our coefficient-estimates for the returns to educational fields. This finding is in line with Lauer and Steiner (2000). The Heckman estimation results are available upon request from the authors.

specific returns at an arbitrary age might bias our measure, i.e. in younger ages the vocational educations tend to have a higher return, whereas university education pays off at a later age. Therefore, we calculate the (discounted) capital value[6] at the time of high-school graduation, the time when decisions of further educations are made. This procedure allows us a more accurate comparison between the different fields of education as different durations of educational programs are adequately taken into account. To picture the problem, Figure B1 and Figure B2 in the appendix show the age-earnings profiles for the different educational levels for men and women.

For our efficiency analysis, we are interested in the average of the estimated field specific returns net of the effect of individual characteristics. Thus, we calculate the log hourly earnings as function of field specific characteristics, taking into account the age profile for the respective educational path:

$$\begin{aligned}\hat{R}_j \;=\; & \sum_{t=0}^{T_R} \frac{1}{\gamma^t}\left(\sum_{j=1}^{J}\hat{\alpha}_{0j}F_j + \sum_{l=1}^{L}\hat{\alpha}_{1l}(19{+}\mathrm{t})L_j + \sum_{l=1}^{L}\hat{\alpha}_{2l}(19{+}\mathrm{t})^2 L_j\right) \\ & - \left(\sum_{t=0}^{T_{edu_j}} \frac{1}{\gamma^t}\left(\sum_{j=1}^{J}\hat{\alpha}_{0j}F_j + \sum_{l=1}^{L}\hat{\alpha}_{1l}(19{+}\mathrm{t})L_j + \sum_{l=1}^{L}\hat{\alpha}_{2l}(19{+}\mathrm{t})^2 L_j\right)\right) \qquad (3)\end{aligned}$$

with

γ : Discount factor, and

T_R : Retirement age, and

T_{edu_j} : Years of education for field j.

The fact that some fields of education require more years to graduate than others is denoted by the substraction term. This way periods with no labor income (because the individual is still in education) are accounted with zero income.[7]

As we want to compare the returns of a specific field to the average returns, we calculate the average capital value of the sample returns $\bar{R}$ over all fields:

$$\overline{\hat{R}} \;=\; \frac{1}{N}\sum_{j=1}^{J} N_j \hat{R}_j. \qquad (4)$$

N_j denotes the number of all working persons in field j, whereas N reflects the number of all working individuals in the sample.

Furthermore, we assume that an individual takes into account possible unemployment risk

[6]Note that this is the capital value of the logarithm of the hourly wages and not of the actual hourly wages.

[7]Actually, students in vocational training receive a small wage and university students are eligible for student support. We view this income as a subsistence income and do not include it in the calculation of lifetime income. Further, we neglect from any moonlighting during the course of education.

when he/she forms his/her expectations about the field specific returns. We thus weight the returns with the unemployment probability in each field calculated as ratio of unemployed individuals on individuals in labor force. Thus, with the probability $r_{ue,j} = P(\text{unemployed} = 1|F_j)$ a graduate in field j will only receive a minimum payment UBR. In Germany, unemployed persons are entitled for unemployment benefit rate, i.e. *Arbeitslosengeld 1*, which is 63 percent (67 percent for parents) of the previous net wage in the first year of unemployment. As we only have cross-sectional data, we have no information on the duration of unemployment, but since individuals with a university entrance exam have a relative small unemployment probability it is a reasonable assumption that unemployment only occurs temporarily.

$$E[\hat{R}_j] \quad = \quad (r_{ue,j} * UBR + (1 - r_{ue,j}))\hat{R}_j \tag{5}$$

2.3 Measuring the variability

The second part of the Sharpe-ratio is an indicator for the variability of the returns. The straight forward measure is the standard deviation. With our estimation approach, we are able to split the variation in the returns into an explainable part, as well as an unexplainable part, which is the residual variation between individuals. The latter one is of interest when accounting for the variability in the returns of a specific field and will be referred to as earnings risk.[8] Our variance within a specific field j is thus defined as:

$$\begin{aligned} VAR[R_j] \quad = \quad & \sigma^2_{R_j} = \sum_{t=0}^{T_R} \frac{1}{\gamma^t} VAR[\epsilon_i] - \sum_{t=0}^{T_{edu_j}} \frac{1}{\gamma^t} VAR[\epsilon_i] \qquad \forall i \in j \\ & \text{with} \\ & \epsilon_i = \log(w_i) - \widehat{\log(w_i)} \\ & \text{and} \\ & \gamma : \text{Discount factor, and} \\ & T_R : \text{Retirement age, and} \\ & T_{edu_j} : \text{Years of education for field j.} \end{aligned} \tag{6}$$

As we calculated the earnings as (discounted) capital value over the lifetime, we do the same with the variances. While more education leads to a shorter working period over the lifetime, the (non-existent) income while being in education is risk free. To account for different unemployment incidents across the fields, we explicitly include the unemployed individuals in our calculation of ϵ_i by setting their hourly wage to 63 percent of the field specific average log-wage. Thus, the higher the share of unemployed persons in a specific field, the higher the

[8]Strictly speaking, the error term also includes factors that are not directly interpretable as earnings risk since they might be known to the individual but unobservable for the researcher.

variance in the respective field will be.[9]

We now have all relevant measures: The returns and their variability which allow us to evaluate the fields of education in terms of their efficiency by calculating the modified Sharpe-ratio as:

$$\hat{S}_j = \frac{E[\hat{R}_j] - \overline{\hat{R}}}{\hat{\sigma}_{R_j}}. \tag{7}$$

3 Data and descriptives

Our empirical analysis is based on data from the German Micro Census for the years 2005 to 2009. The Micro Census is the main German labor force survey, a 1 percent representative sample of the German population. Thus, the Micro Census has the advantage of a large sample size. Starting in 2005, the survey asked each participant about his/her subject of degree as a compulsory question.[10]

Our sample is restricted to individuals who passed the university entrance exam, the *Abitur*, and finished a professional degree in either a vocational program, at a university of applied science or a university. In Germany, individuals can choose between these three options after secondary schooling. While vocational programs are open to students from all levels of secondary schooling, the university educations are open only to those who passed the university entrance examination after 13 years of schooling.[11] Depending on the field of education the academic educations usually last between 4 to 6 years. Educational programs at a university of applied science are usually shorter than programs at a university. To account for different lengths of educational programs, we assign the median number of semesters needed to graduate to each field of study.[12] Three years of training are usually required to obtain a vocational training certificate. Hence, we assign three years to all vocational training fields.[13] Because we only

[9] This assumption holds as long as unemployed persons do not dominate, then the effect would reverse, e.g. with everyone being unemployed, the variance would be eliminated since everyone would get the same "wage". But the occurrence of unemployment in our sample is overall rather low since we are only observing graduates with a university entrance diploma (see Table A3 and A4).

[10] To answer the questions is compulsory by law. Before 2005 participants were asked about their subject of degree, but the answer was voluntary, which leads to a large share of missing values and might result in a selection bias. Before 2002 only graduates from an academic institution were asked about their subject of degree in every fourth wave of the survey.

[11] During the period the individuals of our sample are observed students had to attend school for 13 years (with the exception of some eastern federal states with only 12 years) and pass the university entrance examination after the 13th year of schooling to be able to choose between all three types of education. Our sample also includes students who left school after 12 years of education and are only eligible for university of applied science and vocational education but not for university education.

[12] The median number of semesters refer to the median number in 2003 and are taken from Wissenschaftsrat (2005b) and Wissenschaftsrat (2005a). We convert the median number of semesters to years of education by dividing by two (two terms per year).

[13] It is possible to shorten the vocational training time to 2 or 2,5 years for students with a university entrance certificate. Still, many students need at least 2,5 years.

have individuals in our sample who finished a professional education, the youngest person in our sample is 21 years old.[14]

The sample is further restricted to individuals younger than the official retirement age of 65 years. There is no direct question on earnings in the German Micro Census. However, the survey asks for respondent's monthly net income. For the analysis of earnings, we restrict our sample to those who report income from own labor to be their main source of income. Because only net income is available in the data set, our measure of earnings is not free of effects the tax system has on earnings. To proximate a measure for earnings which is free of effects from the tax system, we use information on family status and employment status (part-time or full-time).

Our sample is restricted to those for whom we observe income from labor and to individuals who are unemployed. The second group, the unemployed, is included in the sample to calculate the field-specific unemployment rate and to account for the risk of unemployment when estimating the field-specific earnings risk. The Micro Census provides the information on income in 24 brackets. We calculate the mean for each bracket with data from the German-Socio-Economic Panel. Table A1 shows that the calculated means are very close to the bracket mean in all cases. In our analysis we use hourly earnings by dividing the monthly earnings by the individuals hours usually worked.

Table A2 shows the descriptives of our sample, which consists of 215,810 individuals, 126,314 men and 89,496 women. The average hourly net earnings for men are 16 Euros and 12 Euros for women. This wage differential is in line with estimates for the gender wage gap (Machin and Puhani, 2003). Men and women spent on average 17 years in education. Men have tenure at their current workplace of about 10 years and women of about 9 years. The level of unemployment in our sample is 5 percent for men and 6 percent for women. The table further describes the means of the additional control variables.

The large number of observations guarantees that we have sufficient observations even in educational fields that are less frequently chosen.[15] To achieve a strong validity of our results, we restrict our analysis to fields of education in which we observe the earnings of at least 300 individuals. When restricting our sample to fields with a sufficient number of observations we have 74 fields left for our analysis. For men we observe more fields with more than 300 individuals (63 educational fields) than for women (56 educational fields).

For presentation purposes we focus on 25 fields out of the 74 fields of education when discussing our results. We selected these fields from vocational and academic education with

[14] School entrance age of 6 years + 12 years of schooling (includes elementary and secondary education)+ 3 years of vocational education.

[15] Another potential data source would be the German Socio Economic Panel (SOEP), which recently added information on subject of graduation additionally to the already available information on higher educational degrees. The disadvantage of this data set is the smaller sample size, which would only allow us to analyze the most popular fields of education.

varying program length in order to represent the characteristics of the full range of fields in the sample. The chosen fields and their characteristics are shown in Table A3 and A4. The first column of the tables depicts the hourly earnings for men (Table A3) and women (Table A4). The average hourly earnings by field are not corrected for varying distribution of characteristics over the fields as for example different age structures and different magnitudes of forgone earnings due to more years spent in education. For this uncorrected measure of earnings the fields of dentistry (uni), medicine (uni), industrial engineering (appsc.), management science (appsc.) and finance and insurance (appsc.) rank highest for men. For women the medical fields are followed by university educations in teaching, law and business. As we will see later on, the ranking of fields changes when field specific characteristics as the length of the educational program, the unemployment probability and personal characteristics of the graduates are controlled for.

4 Results

The results of the field specific returns are derived from estimating a modified version of the standard Mincer wage regression as described in Section 2. Table A5 gives the coefficients of the regression. The first and third column give the estimation results for men and women. Column 5 shows the estimation results for men who graduated from an engineering field. As expected, for all fields, the hourly earnings increase with age at a diminishing rate. The effect of tenure in the current firm is significantly positive for men and women. Furthermore, German nationals tend to have higher hourly earnings and earnings tend to be lower in the eastern part of Germany. Our dependent variable is net earnings because gross earnings are not reported in the dataset. For that reason, the return and risk measure is not free of effects the tax system and social insurance has on net earnings. We include a dummy variable for being married and for working part-time (and the interaction between both) in the wage equation to catch the major tax effects. Married taxpayers in Germany can file a joint tax return which reduces the tax burden and, thus, increases net earnings. The monetary benefit of this joint tax return increases, the higher the income difference of the married couple is. As expected, being married has a positive effect on net earnings for men. For women the effect of being married is not statistically significant. Part-time work can also lead to a lower tax-rate and therefore increased net earnings. The effect of part-time on earnings is positive and significant for both sexes. For women, though, the interaction of being married and working part-time has a strong negative effect on earnings.

The excess returns $(E[\hat{R}_j]-\overline{\hat{R}})$[16] for the selected fields are shown in Table A6 and Table A7.[17] Columns 1 to 3 give the excess returns when the capital value of each field is not discounted ($\gamma = 1$). Columns 4 to 5 show the values when earnings are discounted with a rate of $\gamma = 1.03$.

[16]Note that the excess returns for men and women are calculated with respect to the sample average for men and women respectively. The sample average for men is $\overline{\hat{R}} = 45.85$, and for women $\overline{\hat{R}} = 43.41$.

[17]Table A12 and A13 show the returns for the full set of fields.

For men, the university fields of dentistry and medicine yield the highest returns over the life-cycle if earnings are not discounted. The medical fields are followed by an education in industrial engineering (appsc.), business (uni) and computer science (uni). Other than for men, teaching belongs to the "top 5" performing fields for women. The "top 5" fields for women are: Dentistry (uni), medicine (uni), management science (appsc.), teaching (uni) and finance and insurance (appsc.). Dentistry and medicine are clear outliers with an hourly wage that is almost 50 percent higher than the sample average. This result is comparable to the results of Chevalier (2011) who finds a similar pattern for the UK. At the lower end of the distribution of returns are vocational educations, both for men and women. Although graduates from a vocational program forgo fewer earnings early in their life, academic graduates catch up through higher earnings and a steeper wage increase over the life-cycle. The academic education with the lowest returns is social work (uni) for men and construction engineering for women. However, even if most of the academic fields yield comparably high returns, a university education is not in all cases preferable to vocational education in terms of returns. For example, for men an education in vocational training in business yields higher returns as a university education in political science.

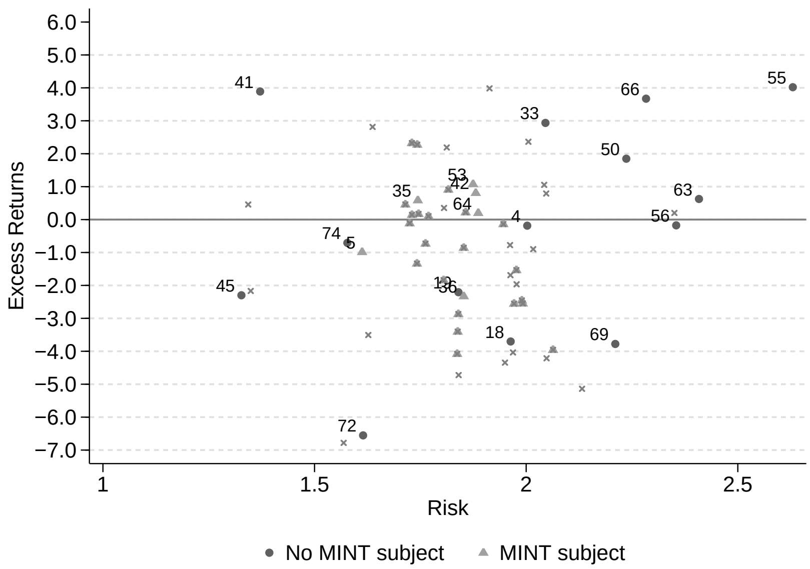
If the capital value of each field is discounted to consider that individuals prefer earnings at an earlier point in time, the ranking of fields changes. In particular fields with a shorter program length, e.g. programs at a university of applied science and in vocational training, become financially more attractive. Graduating in law or computer science from a university, for example, looses rank, while a degree from a university of applied science in management science or business becomes one of the five top-performing fields for men and women.

When calculating the returns to a field of education, we do not consider costs associated with the field except for forgone earnings while in education. Since there were no tuition fees for post-secondary education in Germany for the students observed in our sample, we do not have to account for this type of cost. Still, some fields of education yield high returns mainly for those who become self-employed. As shown in Table A3 and A4, dentists, medical doctors and legal scientists have the highest share of self-employed and earnings vary widely between the self-employed and employees. For medical doctors and dentists high investment costs are associated with becoming self-employed, i.e. starting their own doctor's office. Hence, it has to be kept in mind that some of the returns to these educations will be the returns to investment into financial capital that the individual had to make earlier. The high returns for management science, teaching and finance and insurance can be assumed to be connected to the civil servant status and the low risk of unemployment of a high proportion of the graduates from these fields. To account for the special status of civil servants and self-employed, we estimate a specification of the Mincer wage regression which adjusts the returns for the employment status. Table A8 and A9 show that, as expected, the returns to management science and teaching rank lower than in the baseline specification because the specification controls for the effect the civil servant status has on earnings.

4.1 Mean-variance plots

In order to evaluate the fields of education as investment goods, we depict our estimation results as mean variance plots in Figure 1 for men and Figure 2 for women. Returns and risk for each field are plotted against each other. The fields chosen for presentation are labeled. Further, fields belonging to the group of technical subjects (MINT-fields) are marked because they receive special attention in our analysis. As described above, our measures are the discounted capital values of the logarithm earnings over the life-cycle. The expected excess returns are thus defined as the deviation of the discounted capital value of log earnings for each field from the sample mean of the discounted capital value of log earnings over all fields. The sample means of the discounted capital values of log-earnings account to 45.85 Euros for men and 43.41 Euros for women. The risk measure is the standard deviation of capital value of the (log-) earnings within a field. As we conducted separate earnings regression, we also present all parameters separately for men and women.

Figure 1: Mean-Variance plot: Men

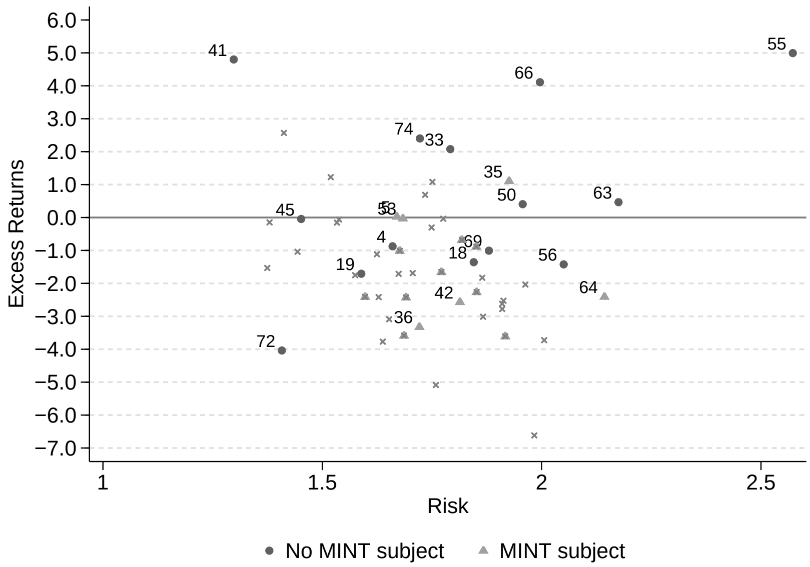


4	Voc:Business
5	Voc:Chemical Engineering
18	Voc:Media
19	Voc:Medical Services
33	AppSc:Business
35	AppSc:Computer Science
36	AppSc:Construction Engineering
41	AppSc:Management Science
42	AppSc:Manufacturing Engineering
45	AppSc:Social Work
50	Uni:Business
53	Uni:Computer Science
55	Uni:Dentistry
56	Uni:Economics
63	Uni:Law
64	Uni:Manufacturing Engineering
66	Uni:Medicine
69	Uni:Political Science
72	Uni:Social Work
74	Uni:Teaching

Notes: Only selected fields are labeled. The remaining fields are depicted as x.

In general, we find that higher levels of education are associated with higher expected returns but also with higher risk. Literature suggests that the variance of earnings is increasing with the level of schooling (see e.g. Levhari and Weiss, 1974; Hartog and Vijverberg, 2007), but this view is not straight forward (Belzil and Leonardi, 2007). Schooling may reduce earnings variation by reducing the unemployment risk or by raising the job offer probabilities but it may increase wage variation if more educated workers find jobs in sectors of occupations where wages are more volatile. Our estimates take into account the lower unemployment risk at higher education levels as explained in Section 2. Unemployment is rather low for our sample of individuals with a university entrance degree, hence the probability of unemployment does not contribute a lot

Figure 2: Mean-Variance plot: Women



4	Voc:Business
5	Voc:Chemical Engineering
18	Voc:Media
19	Voc:Medical Services
33	AppSc:Business
35	AppSc:Computer Science
36	AppSc:Construction Engineering
41	AppSc:Management Science
42	AppSc:Manufacturing Engineering
45	AppSc:Social Work
50	Uni:Business
53	Uni:Computer Science
55	Uni:Dentistry
56	Uni:Economics
63	Uni:Law
64	Uni:Manufacturing Engineering
66	Uni:Medicine
69	Uni:Political Science
72	Uni:Social Work
74	Uni:Teaching

Notes: Only selected fields are labeled. The remaining fields are depicted as x.

to the earnings variation. In addition to the higher risk at higher education levels, we find that the different fields also show a high heterogeneity with respect to risk and returns within an education level, which is disregarded, when only comparing different levels of education.

The graph also shows the importance of taking risk into account. Simply comparing the returns for men for e.g. management science (appsc.) with business (appsc.) would yield no difference because the monetary return over the life-cycle is relatively close. But the average returns for business exhibit a much higher risk level, such that this field is more unattractive than management science in terms of an investment good.

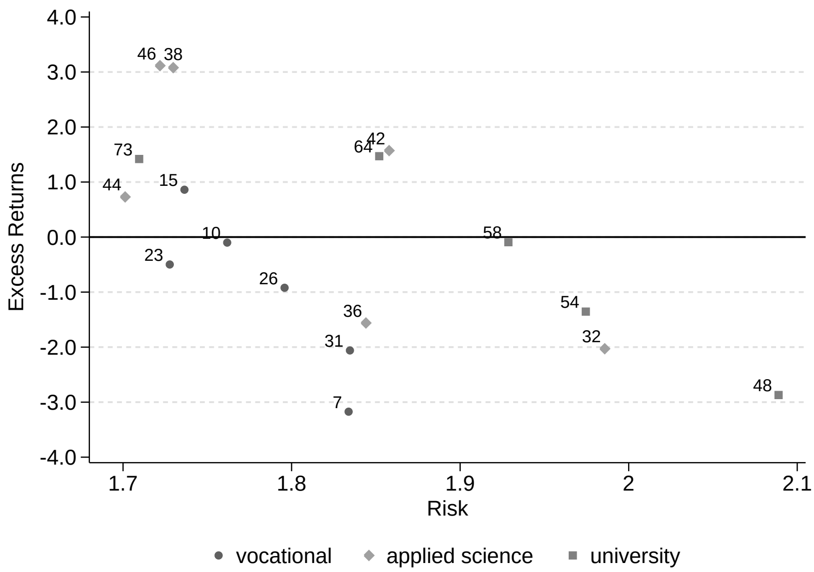
Fields belonging to the group of technical fields receive special attention because of the controversially discussed shortage of graduates from these fields of education in Germany. The mean-variance plots show the efficiency of one field compared to another. Following standard economic theory of demand and supply, prices for graduates from fields with a shortage of graduates should be high, i.e. we should observe high earnings and a low level of earnings risk. Our results do not suggest that there is a shortage of skilled labor in these subjects since we do not observe high prices for graduates from technical fields compared to other fields. Other fields, especially from the group of social science fields are still more attractive investments. However, our model is not suited to predict a possible shortage in the (near) future, as we are only able to use retrospective data.

4.2 Technical abilities

To reduce the role of potential ability bias, we compare the properties of human capital returns within a group of fields. Individuals who revealed a preference for a engineering field of education are likely to be similar with respect to their educational preferences and abilities. Figure 3 shows the mean-variance plot for all engineering educations for men.[18] The sample average mean of the discounted capital value of log-earnings for men who graduated from a technical field is 44.88 Euro. For the technical fields risk seems to decrease with returns. On the one hand, the highest paying fields supply engineering and electrical engineering (appsc.) have a very low risk level. On the other hand, students who graduate from architecture can expect only low returns at a high level of risk. When comparing earnings within a certain group of fields, we observe that the discounted life-time log-earnings with a vocational degree are often not much lower than with a university degree. Manufacturing engineering at a university yields about the same returns over the life-cycle as a vocational degree in the same field. Further, the earnings risk is to some extend lower when graduating from vocational training. In contrast, graduating from a university of applied science with a degree in electrical engineering is preferable to a vocational training degree in the same field. Hence, university education is not always the choice with the highest investment value.

The results show that the field of education is as interesting as the level of education when assessing human capital investments. A student interested in a university of applied science education in a technical field should, for example, prefer manufacturing engineering over construction engineering because it yields a higher return at the same level of risk.

Figure 3: Mean-Variance plot: Engineering fields, Men



7 Voc:Construction Engineering
10 Voc:Electrical Engineering
15 Voc:Manufacturing Engineering
23 Voc:Precision Engineering
26 Voc:Supply Engineering
31 Voc:Transport Engineering
32 AppSc:Architecture
36 AppSc:Construction Engineering
38 AppSc:Electrical Engineering
42 AppSc:Manufacturing Engineering
44 AppSc:Precision Engineering
46 AppSc:Supply Engineering
48 Uni:Architecture
54 Uni:Construction Engineering
58 Uni:Electrical Engineering
64 Uni:Manufacturing Engineering
73 Uni:Supply Engineering

[18] Returns and risk measures are estimated based on a sample of 37,385 male graduates from MINT-fields. Results for women are available from the authors upon request.

4.3 Standardized return measure

In order to further assess the risk-return trade-off, we apply the standardized return measure. The standardized return measure gives us the returns per standard deviation of the unexplained part of the returns. Table A10 for men and Table A11 for women rank the educations from the highest standardized return to the lowest. As for the unstandardized returns the top-performing fields consist of programs at the university and university of applied science level. The ranking of the fields, thus, changes. Fields with a low earnings risk move up in the ranking. It is not surprising that management science performs better when earnings risk is taken into account. Around 80 percent of graduates from the field of management science are employed as civil servants. A career as a civil servant traditionally is connected to low earnings risk and low risk of unemployment. For men, social work at university and university of applied science belong to the low performing fields while for women construction engineering belongs to the worst 5 educations. Also, teaching ranks only 35^{th} for men, while it is one of the top-performing fields for women. Similarly, medical services is at the very bottom of the ranking for men, while it is one of the top performing vocational educations for women.[19]

The differences in the performance of fields between men and women might explain some of the wide differences of educational choices for men and women. As it is often discussed (see e.g. Machin and Puhani, 2003; Zafar, 2009) women are assumed to choose fields in humanities, language, education and creative arts etc., because it relates to the "traditional" female work environments. Our findings suggest that their choices can also be linked to "rational" investment choices.

5 Conclusion

In our paper, we analyze the risk and return properties of approximately 70 different educational fields. While there is a broad literature analyzing the returns to different educational levels, little research examines the returns to education at a more disaggregated level. Results suggest that the financial performance of different educations does not only vary across qualification levels but does also vary strongly within a qualification level. Further, the financial attractiveness of fields varies by gender.

We use the German Micro Census for the years 2005 to 2009 to estimate field specific returns by extending the Mincer wage equation controlling for different fields of education. We then use our estimation results to calculate an average measure of log hourly income over the life-cycle, as well as field specific earnings risk. Applying general models from the financial asset theory to our estimation results allows us to evaluate the fields of education in terms of their efficiency as investment goods.

[19] Table A12 and A13 show the standardized returns for the full set of fields.

In general, higher educational levels yield higher expected returns, but are also associated with greater variance. In addition, we show that beyond the general tendency across educational levels, there is heterogeneity within educational levels that should not be neglected. In this regard, graduating in business from a university yields higher expected returns than majoring in business at a university of applied science (between educational levels), it also yields higher returns than majoring in maths at a university (within educational level). Furthermore, we show that risk is a source that should not be neglected. Even though graduates in management science (university of applied science) earn on average the same as graduates in business (university level), the latter is associated with a higher risk which makes it an inefficient investment choice over management science.

The findings are in particular helpful in terms of analyzing shortages of skilled labor in certain fields of education, as well as finding instruments to solve this possible problem. A shortage of skilled labor should be reflected in high returns and a relatively low risk associated with the education that exhibits the shortage. In Germany, a controversially-discussed topic is the shortage of skilled labor in the MINT-subjects. Our results however do not suggest that there is a shortage of skilled labor in these subjects, at least not in the time of our analysis. However, our model is not suited to predict a possible shortage in the (near) future, as we are only able to use retrospective data.

Even though we are using a rich dataset, there are several problems we could not address in our study. Thus, it remains for future studies to determine possible biases resulting from ability sorting or endogeneity of educational fields when estimating field specific returns. Another extension of our study would be to incorporate our findings into an educational decision process. But so far, there is no extensive dataset available (for Germany) that would allow us to model the field an individual chooses while controlling for the individuals socio-economic background as well as the expected returns and the associated risk.

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Table A1: Income groups: Mean

Income group Micro Census	Mean SOEP
(1)	(2)
<150	52
150 - 300	231
300 - 500	404
500 - 700	620
700 - 900	818
900 - 1100	1023
1100 - 1300	1227
1300 - 1500	1437
1500 - 1700	1627
1700 - 2000	1884
2000 - 2300	2171
2300 - 2600	2475
2600 - 2900	2777
2900 - 3200	3065
3200 - 3600	3438
3600 - 4000	3865
4000 - 4500	4284
4500 - 5000	4836
5000 - 5500	5280
5500 - 6000	5864
6000 - 7500	6764
7500 - 10000	9005
10000- 18000	12886
>18000	21778
Number of observations	15,887

Notes: The means of each income group from the Micro Census are calculated based on a sample of 15,887 individuals from the German Socio-Economic Panel.

Table A2: Sample descriptives

	Men		Women	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Net hourly earnings (Euro)	16.43	11.20	12.29	7.53
Age (years)	43.41	10.12	40.38	10.17
Education (years)	17.33	1.52	17.10	1.50
Tenure (years)	10.49	9.67	8.99	8.95
Unemployment (percent)	4.54%		5.72%	
German (percent)	89.21%		88.30%	
Married (percent)	62.06%		49.73%	
Region (percent)				
North	24.71%		23.65%	
Middle	35.67%		37.20%	
East	22.51%		19.61%	
South	17.11%		19.54%	
Year (percent)				
2005	18.87%		17.82%	
2006	19.93%		19.47%	
2007	19.93%		19.64%	
2008	20.43%		20.92%	
2009	20.84%		22.15%	
Number of observations	126,314		89,496	

Source: Numbers based on German Micro Census, years 2005-2009.

Table A3: Characteristics: Selected fields of education, Men

	Hourly earnings (Euro)	Share of unempl. (%)	Length of education (years)	Share of students within degree (%)	Share of self-employed (%)	Share of civil servants (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Uni:Dentistry	26.56	2.24%	6	1.12%	88.00%	1.04%
Uni:Medicine	23.64	1.30%	6	5.73%	40.42%	3.36%
Uni:Business	21.16	3.68%	6	7.60%	19.61%	4.82%
Uni:Law	20.58	3.28%	6	5.26%	34.51%	23.92%
Uni:Economics	19.67	5.27%	6	1.69%	19.44%	8.26%
Uni:Manufacturing Engin.	18.57	3.19%	6	3.37%	10.23%	5.68%
Uni:Computer Science	17.67	3.49%	6	2.95%	13.36%	2.77%
AppSc:Business	17.43	3.44%	4	6.31%	16.57%	4.49%
AppSc:Industrial Engin.	17.41	3.30%	4	1.28%	10.53%	2.22%
AppSc:Manufacturing Engin.	17.32	3.76%	5	4.94%	10.82%	2.64%
AppSc:Finance and Insurance	17.31	0.81%	4	1.27%	8.70%	55.49%
Uni:Teaching	16.95	2.48%	5	7.30%	3.75%	70.05%
AppSc:Management Science	16.59	0.78%	3	3.98%	1.39%	82.69%
AppSc:Computer Science	15.61	4.21%	5	2.58%	10.85%	1.85%
Uni:Political Science	15.15	7.32%	6	0.72%	21.27%	8.06%
AppSc:Construction Engin.	14.86	6.41%	5	3.21%	22.51%	5.28%
Voc:Business	13.77	7.50%	3	7.98%	12.85%	1.98%
Uni:Social Work	13.62	7.36%	6	0.45%	9.56%	10.38%
AppSc:Social Work	13.01	3.36%	4	1.74%	7.23%	7.23%
Voc:Chemical Engin.	12.55	7.08%	3	1.67%	6.13%	2.15%
Voc:Medical Services	11.58	4.48%	3	2.98%	29.04%	1.35%
Voc:Construction Engin.	11.23	10.16%	3	5.69%	26.50%	2.56%
Voc:Hotel Restaurant	11.19	13.00%	3	1.60%	18.38%	0.55%
Voc:Media	10.96	10.30%	3	2.64%	30.97%	0.43%
Voc:Gardening	9.44	8.05%	3	0.83%	31.21%	0.34%

Source: Numbers based on German Micro Census, years 2005-2009.

Table A4: Characteristics: Selected fields of education, Women

	Hourly earnings (Euro)	Share of unempl. (%)	Length of education (years)	Share of students within degree (%)	Share of self-employed (%)	Share of civil servants (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Uni:Dentistry	20.65	3.94%	6	1.33%	77.69%	0.61%
Uni:Medicine	17.70	4.33%	6	7.24%	31.38%	2.36%
Uni:Teaching	15.18	2.60%	5	22.47%	2.59%	68.48%
Uni:Law	15.09	5.22%	6	5.51%	22.67%	25.84%
Uni:Business	14.00	6.33%	6	6.61%	10.18%	4.15%
Uni:Economics	13.73	7.69%	6	1.70%	10.95%	6.84%
AppSc:Computer Science	13.58	10.05%	5	0.76%	5.43%	0.86%
Uni:Computer Science	13.28	5.37%	6	0.83%	8.40%	2.47%
AppSc:Management Science	13.25	1.05%	3	4.82%	0.65%	76.81%
Uni:Manufacturing Engin.	13.23	7.08%	6	0.69%	8.23%	3.66%
AppSc:Finance and Insurance	13.03	1.09%	4	1.43%	3.17%	60.33%
Uni:Political Science	13.02	9.78%	6	0.72%	15.62%	6.01%
AppSc:Business	12.34	5.07%	4	7.30%	7.66%	3.96%
AppSc:Social Work	11.65	4.85%	4	6.22%	6.53%	5.68%
Uni:Social Work	11.47	7.18%	6	1.79%	7.14%	6.21%
AppSc:Manufacturing Engin.	11.11	9.92%	5	0.76%	9.60%	1.98%
AppSc:Construction Engin.	10.90	12.34%	5	1.37%	11.65%	5.66%
Voc:Chemical Engin.	10.55	6.33%	3	1.62%	4.33%	0.87%
Voc:Personal Services	10.25	10.77%	3	0.95%	8.31%	9.85%
Voc:Business	10.06	8.69%	3	12.90%	5.66%	0.91%
Voc:Media	9.98	10.29%	3	1.96%	20.30%	0.30%
Voc:Medical Services	9.57	5.92%	3	12.02%	11.89%	0.53%
Voc:Textile	8.99	14.72%	3	0.94%	17.48%	1.29%
Voc:Dentistry	8.72	6.46%	3	1.26%	7.32%	0.22%
Voc:Beauty	8.00	13.12%	3	1.22%	32.59%	0.49%

Source: Numbers based on German Micro Census, years 2005-2009.

Table A5: Mincer wage regression: Men, Women and technical fields

	Men		Women		Technical fields (men)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Age X Voc. Educ.	0.04**	0.003	0.044**	0.004	0.044**	0.002
Age X Uni. of AppSc.	0.047**	0.003	0.040**	0.005	0.044**	0.010
Age X University	0.070**	0.006	0.068**	0.007	0.061**	0.006
Age^2Xvoc	−0.000**	0.000	−0.000**	0.000	−0.000**	0.000
Age^2Xappsc	−0.001**	0.000	−0.000**	0.000	−0.001**	0.000
Age^2Xuni	−0.001**	0.000	−0.001**	0.000	−0.001**	0.000
German	0.121**	0.010	0.112**	0.017	0.140**	0.011
Married	0.210**	0.005	0.006	0.006	0.192**	0.007
Part-time work	0.117**	0.024	0.236**	0.020	−0.009	0.034
Married X Part-time	−0.036*	0.018	−0.194**	0.015	−0.031	0.027
Tenure	0.013**	0.001	0.015**	0.001	0.014**	0.001
$Tenure^2$	−0.000**	0.000	−0.000**	0.000	−0.000**	0.000
University of Applied Science:						
Architecture	1.171**	0.072	1.263**	0.091	1.258**	0.067
Business	1.348**	0.070	1.379**	0.090	.	.
Chemical Engin.	1.344**	0.071	.	.	.	.
Computer Science	1.330**	0.068	1.462**	0.091	.	.
Construction Engin.	1.202**	0.073	1.252**	0.088	1.300**	0.068
Educational Science	.	.	1.232**	0.085	.	.
Electrical Engin.	1.326**	0.072	.	.	1.415**	0.067
Finance and Insurance	1.319**	0.070	1.370**	0.088	.	.
Industrial Engin.	1.397**	0.069	.	.	.	.
Management Science	1.282**	0.070	1.388**	0.089	.	.
Manufacturing Engin.	1.338**	0.072	1.272**	0.089	1.430**	0.067
Maths	1.275**	0.072	1.283**	0.088	.	.
Precision Engin.	1.303**	0.072	.	.	1.396**	0.068
Social Work	1.096**	0.073	1.274**	0.087	.	.
Supply Engin.	1.327**	0.072	.	.	1.415**	0.067
University						
Anglistic	0.685**	0.143	0.681**	0.155	.	.
Architecture	0.592**	0.145	0.625**	0.153	1.264**	0.180
Biology	0.664**	0.142	0.706**	0.153	.	.
Business	0.875**	0.141	0.805**	0.151	.	.
Chemical Engin.	0.746**	0.145	0.717**	0.155	.	.
Chemistry	0.800**	0.145	0.752**	0.156	.	.
Computer Science	0.833**	0.138	0.774**	0.154	.	.
Construction Engin.	0.660**	0.144	0.626**	0.155	1.335**	0.180
Dentistry	0.975**	0.146	1.025**	0.155	.	.
Economics	0.783**	0.145	0.720**	0.157	.	.
Educational Science	0.594**	0.147	0.680**	0.157	.	.
Electrical Engin.	0.712**	0.145	.	.	1.391**	0.179
Geo Science	0.616**	0.144	0.670**	0.153	.	.
German Literature	0.577**	0.146	0.683**	0.155	.	.
History	0.585**	0.144	0.679**	0.155	.	.
Industrial Engin.	0.840**	0.141	.	.	.	.
Law	0.807**	0.143	0.798**	0.153	.	.
Manufacturing Engin.	0.784**	0.144	0.662**	0.157	1.457**	0.181
Maths	0.774**	0.145	0.755**	0.156	.	.
Medicine	0.947**	0.145	0.982**	0.155	.	.
Music	0.519**	0.145	0.586**	0.156	.	.
Physics	0.796**	0.144	.	.	.	.

Continued on next page

	Men		Women		Technical fields (men)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Political Science	0.611**	0.142	0.760**	0.151	.	.
Psychology	0.735**	0.146	0.785**	0.155	.	.
Regional Science	0.586**	0.145	0.653**	0.154	.	.
Social Work	0.464**	0.147	0.576**	0.156	.	.
Supply Engin.	0.784**	0.144	.	.	1.453**	0.182
Teaching	0.645**	0.147	0.788**	0.156	.	.
Vocational Education						
Accounting	1.196**	0.070	1.117**	0.059	.	.
Anglistic	.	.	1.196**	0.061	.	.
Beauty	.	.	0.871**	0.059	.	.
Business	1.170**	0.070	1.111**	0.060	.	.
Chemical Engin.	1.129**	0.070	1.135**	0.060	.	.
Computer Science	1.202**	0.067	.	.	.	.
Construction Engin.	1.008**	0.071	.	.	1.155**	0.097
Dentistry	.	.	0.959**	0.060	.	.
Educational Science	.	.	1.059**	0.059	.	.
Electrical Engin.	1.130**	0.070	.	.	1.264**	0.097
Finance and Insurance	1.246**	0.069	1.171**	0.059	.	.
Gardening	0.865**	0.071	.	.	.	.
Hotel Restaurant	1.023**	0.070	1.027**	0.060	.	.
Management Science	1.177**	0.069	1.123**	0.059	.	.
Manufacturing Engin.	1.170**	0.071	1.111**	0.061	1.314**	0.097
Marketing	.	.	1.164**	0.060	.	.
Maths	1.286**	0.071	.	.	.	.
Media	1.027**	0.069	1.101**	0.060	.	.
Medical Services	1.052**	0.070	1.051**	0.058	.	.
Nursing	1.054**	0.071	1.111**	0.059	.	.
Office Assistant	.	.	1.040**	0.059	.	.
Personal Services	.	.	1.026**	0.060	.	.
Precision Engin.	1.108**	0.071	.	.	1.253**	0.097
Public Security	1.165**	0.070	.	.	.	.
Social Work	.	.	1.094**	0.059	.	.
Supply Engin.	1.080**	0.071	.	.	1.228**	0.097
Textile	.	.	0.955**	0.062	.	.
Tourism	.	.	1.057**	0.059	.	.
Trade and Logistic	1.102**	0.069	1.065**	0.059	.	.
Transport	1.181**	0.070	1.136**	0.060	.	.
Transport Engin.	1.051**	0.071	.	.	1.194**	0.097
Year dummies	yes		yes		yes	
Region dummies	yes		yes		yes	
N	120,441		84,261		39,522	

S.E. calculated using the delta method. Significance levels: † : 10% $*$: 5% $**$: 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Table A6: Returns to field of education: Men

	$\gamma = 1$			$\gamma = 1.03$		
	Rank	Return $E[\hat{R}_j] - \overline{\hat{R}}$	S.E.	Rank	Return $E[\hat{R}_j] - \overline{\hat{R}}$	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Uni:Dentistry	1	10.941^{**}	0.609	1	4.020^{**}	0.337
Uni:Medicine	2	10.226^{**}	0.552	4	3.672^{**}	0.313
AppSc:Industrial Engin.	3	6.600^{**}	0.646	2	3.984^{**}	0.269
Uni:Business	4	6.447^{**}	0.519	11	1.848^{**}	0.265
Uni:Computer Science	5	4.854^{**}	0.504	12	1.077^{**}	0.234
AppSc:Management Science	7	4.804^{**}	0.687	3	3.890^{**}	0.308
AppSc:Business	8	4.509^{**}	0.629	5	2.936^{**}	0.268
AppSc:Finance and Insurance	9	4.272^{**}	0.685	6	2.815^{**}	0.298
Uni:Law	10	3.924^{**}	0.563	17	0.626^{**}	0.302
Uni:Manufacturing Engin.	14	3.045^{**}	0.529	24	0.201	0.294
Uni:Economics	18	2.260^{**}	0.567	30	-0.175	0.315
AppSc:Manufacturing Engin.	21	1.810^{**}	0.528	15	0.809^{**}	0.239
AppSc:Computer Science	23	1.357	0.700	18	$0.586^{\dagger}$	0.281
Uni:Teaching	27	-0.252	0.721	32	-0.708	0.407
Voc:Business	39	-3.052^{**}	0.647	31	-0.185	0.286
AppSc:Construction Engin.	42	-4.562^{**}	0.521	46	-2.328^{**}	0.245
Voc:Chemical Engin.	44	-4.621^{**}	0.659	37	-0.986^{**}	0.292
Uni:Political Science	46	-5.192^{**}	0.529	54	-3.777^{**}	0.280
AppSc:Social Work	50	-5.931^{**}	0.682	45	-2.299^{**}	0.325
Voc:Medical Services	55	-7.003^{**}	0.697	44	-2.205^{**}	0.316
Voc:Media	59	-9.951^{**}	0.671	53	-3.702^{**}	0.297
Voc:Construction Engin.	60	-10.690^{**}	0.567	57	-4.079^{**}	0.259
Uni:Social Work	61	-10.929^{**}	0.697	62	-6.554^{**}	0.374
Voc:Hotel Restaurant	62	-10.957^{**}	0.561	58	-4.212^{**}	0.242
Voc:Gardening	63	-15.977^{**}	0.633	63	-6.781^{**}	0.287
Total number of Fields	63			63		

S.E. calculated using the delta method. Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Notes: Columns 1 to 3 give the excess returns when the capital value of each field is not discounted ($\gamma = 1$). Columns 4 to 5 show the values when log-earnings are discounted with a rate of $\gamma = 1.03$. Only selected fields are depicted. A full list of field is given in A12.

Table A7: Returns to field of education: Women

	$\gamma = 1$			$\gamma = 1.03$		
	Rank	Return $E[\hat{R}_j] - \overline{\hat{R}}$	S.E.	Rank	Return $E[\hat{R}_j] - \overline{\hat{R}}$	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Uni:Dentistry	1	13.206^{**}	0.842	1	4.994^{**}	0.408
Uni:Medicine	2	11.377^{**}	0.858	3	4.110^{**}	0.413
AppSc:Management Science	3	7.220^{**}	1.195	2	4.800^{**}	0.560
Uni:Teaching	4	6.370^{**}	1.102	5	2.401^{**}	0.540
AppSc:Finance and Insurance	5	4.366^{**}	1.184	4	2.570^{**}	0.548
Uni:Law	6	3.846^{**}	0.932	11	0.466	0.436
Uni:Business	7	3.718^{**}	0.867	12	0.405	0.402
AppSc:Business	8	3.380^{**}	0.981	6	2.076^{**}	0.439
AppSc:Computer Science	9	2.950^{**}	0.885	8	1.108^{*}	0.387
Uni:Computer Science	10	2.824^{**}	0.855	14	-0.028	0.404
Uni:Political Science	14	0.791	0.853	24	$-1.007^{\dagger}$	0.397
Uni:Economics	16	-0.063	0.867	29	-1.423^{**}	0.423
AppSc:Social Work	21	-0.850	1.096	16	-0.045	0.522
Uni:Manufacturing Engin.	25	$-2.096^{\dagger}$	0.816	39	-2.407^{**}	0.401
Voc:Chemical Engin.	27	$-2.142^{\dagger}$	0.961	13	0.027	0.478
Voc:Business	35	-3.908^{**}	0.960	22	-0.874	0.476
AppSc:Manufacturing Engin.	40	-4.511^{**}	0.762	44	-2.567^{**}	0.357
Voc:Media	44	-4.855^{**}	0.935	28	-1.357^{*}	0.464
Uni:Social Work	46	-5.465^{**}	1.091	54	-4.038^{**}	0.522
Voc:Medical Services	47	-5.540^{**}	1.082	33	-1.708^{*}	0.541
AppSc:Construction Engin.	50	-6.047^{**}	0.807	49	-3.323^{**}	0.382
Voc:Hotel Restaurant	52	-7.639^{**}	0.890	46	-2.778^{**}	0.441
Voc:Personal Services	53	-8.099^{**}	1.056	47	-3.012^{**}	0.531
Voc:Dentistry	54	-9.579^{**}	1.002	53	-3.769^{**}	0.499
Voc:Textile	55	-12.167^{**}	0.837	55	-5.087^{**}	0.416
Voc:Beauty	56	-15.164^{**}	0.924	56	-6.617^{**}	0.459
Total number of Fields	56			56		

S.E. calculated using the delta method. Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Notes: Columns 1 to 3 give the excess returns when the capital value of each field is not discounted ($\gamma = 1$). Columns 4 to 5 show the values when log-earnings are discounted with a rate of $\gamma = 1.03$. Only selected fields are depicted. A full list of field is given in A13.

Table A8: Returns to field of education: Controlling for work-status, Men

	Rank	Return $E[\hat{R}_j] - \overline{\hat{R}}$	S.E.
	(1)	(2)	(3)
Uni:Dentistry	1	5.244**	0.365
Uni:Medicine	2	4.141**	0.314
AppSc:Industrial Engin.	3	4.128**	0.244
AppSc:Business	4	3.140**	0.243
Voc:Maths	5	2.484**	0.241
AppSc:Management Science	8	2.296**	0.518
Uni:Business	10	2.023**	0.251
AppSc:Finance and Insurance	11	1.955**	0.397
Uni:Computer Science	12	1.200**	0.211
AppSc:Manufacturing Engin.	16	0.933*	0.216
AppSc:Computer Science	17	0.744*	0.259
Uni:Law	18	0.655†	0.323
Voc:Business	26	0.024	0.255
Uni:Economics	29	−0.089	0.311
Voc:Chemical Engin.	34	−0.880**	0.264
Voc:Medical Services	41	−1.779**	0.276
Uni:Teaching	42	−2.004**	0.558
AppSc:Construction Engin.	43	−2.110**	0.228
AppSc:Social Work	47	−2.343**	0.301
Uni:Political Science	54	−3.683**	0.274
Uni:German Literature	59	−4.377**	0.383
Uni:Music	60	−4.854**	0.344
Uni:History	61	−4.897**	0.327
Voc:Gardening	62	−6.301**	0.252
Uni:Social Work	63	−6.653**	0.372
Total number of Fields	63		

S.E. calculated using the delta method. Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Notes: Excess returns are calculated using a discount rate of ($\gamma = 1.03$). The additional control variables in the wage equation are indicator variables for self-employment and civil service status. Only selected fields are depicted.

Table A9: Returns to field of education: Controlling for work-status, Women

	Rank	Return $E[\hat{R}_j] - \overline{\hat{R}}$	S.E.
	(1)	(2)	(3)
Uni:Dentistry	1	5.769^{**}	0.372
Uni:Medicine	2	4.672^{**}	0.286
AppSc:Business	3	2.626^{**}	0.296
Voc:Finance and Insurance	4	2.033^{**}	0.347
AppSc:Management Science	5	1.948^{**}	0.565
AppSc:Computer Science	7	1.726^{**}	0.263
Uni:Business	9	0.876^{**}	0.251
Voc:Chemical Engin.	10	$0.762^{\dagger}$	0.308
AppSc:Finance and Insurance	11	0.674	0.497
Uni:Computer Science	15	0.499	0.267
AppSc:Social Work	16	0.449	0.347
Uni:Teaching	19	0.100	0.569
Uni:Law	20	0.055	0.318
Voc:Business	21	-0.180	0.307
Uni:Political Science	26	$-0.640^{\dagger}$	0.258
Voc:Medical Services	29	-0.986^{*}	0.354
Uni:Economics	33	-1.120^{**}	0.329
AppSc:Manufacturing Engin.	40	-2.031^{**}	0.250
Voc:Personal Services	47	-2.765^{**}	0.375
AppSc:Construction Engin.	49	-2.938^{**}	0.270
Voc:Dentistry	50	-3.054^{**}	0.327
Uni:Social Work	54	-3.634^{**}	0.371
Voc:Textile	55	-4.495^{**}	0.288
Voc:Beauty	56	-5.981^{**}	0.325
Total number of Fields	56		

S.E. calculated using the delta method. Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Notes: Excess returns are calculated using a discount rate of ($\gamma = 1.03$). The additional control variables in the wage equation are indicator variables for self-employment and civil service status. Only selected fields are depicted.

Table A10: Standardized Returns, Men

	Rank	Standardized Return Sj	*S.E.*
	(1)	(2)	(3)
AppSc:Management Science	1	2.836**	0.225
AppSc:Industrial Engin.	2	2.082**	0.140
AppSc:Finance and Insurance	3	1.719**	0.182
Uni:Medicine	4	1.608**	0.137
Uni:Dentistry	5	1.529**	0.128
AppSc:Business	6	1.435**	0.131
Uni:Business	11	0.826**	0.119
Uni:Computer Science	12	0.574**	0.125
AppSc:Manufacturing Engin.	15	0.430**	0.127
AppSc:Computer Science	18	0.336**	0.161
Uni:Law	20	0.260**	0.125
Uni:Economics	30	−0.074	0.134
Voc:Business	31	−0.092	0.143
Uni:Teaching	35	−0.449	0.258
Voc:Chemical Engin.	37	−0.612**	0.181
Voc:Medical Services	43	−1.199**	0.172
AppSc:Construction Engin.	45	−1.257**	0.132
Uni:Political Science	50	−1.709**	0.127
AppSc:Social Work	51	−1.732**	0.245
Uni:Regional Science	59	−2.228**	0.169
Uni:Music	60	−2.411**	0.165
Uni:History	61	−2.566**	0.167
Uni:Social Work	62	−4.059**	0.232
Voc:Gardening	63	−4.323**	0.183
Total number of Fields	63		

S.E. calculated using the delta method. Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Notes: Excess returns and risk are calculated using a discount rate of ($\gamma = 1.03$). Only selected fields are depicted. A full list of field is given in A12.

Table A11: Standardized Returns, Women

	Rank	Standardized Return Sj	$S.E.$
	(1)	(2)	(3)
AppSc:Management Science	1	3.697**	0.431
Uni:Medicine	2	2.059**	0.207
Uni:Dentistry	3	1.941**	0.158
AppSc:Finance and Insurance	4	1.819**	0.388
Uni:Teaching	5	1.394**	0.313
AppSc:Business	6	1.159**	0.245
AppSc:Computer Science	9	0.576*	0.201
Uni:Law	11	0.214	0.201
Uni:Business	12	0.207	0.205
Voc:Chemical Engin.	13	0.016	0.286
Uni:Computer Science	14	−0.017	0.240
AppSc:Social Work	16	−0.031	0.360
Voc:Business	23	−0.526	0.287
Uni:Political Science	24	−0.536**	0.211
Uni:Economics	27	−0.694**	0.206
Voc:Medical Services	35	−1.075*	0.340
AppSc:Manufacturing Engin.	42	−1.415**	0.197
Voc:Personal Services	47	−1.614**	0.285
AppSc:Construction Engin.	51	−1.930**	0.222
Voc:Dentistry	53	−2.301**	0.304
Uni:Social Work	54	−2.868**	0.371
Voc:Textile	55	−2.892**	0.237
Voc:Beauty	56	−3.336**	0.232
Total number of Fields	56		

S.E. calculated using the delta method. Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Source: Estimation based on German Micro Census, years 2005-2009.

Notes: Excess returns and risk are calculated using a discount rate of $\gamma = 1.03$. Only selected fields are depicted. A full list of fields is given in A13.

Table A12: Returns and standardized Returns to field of education: All fields, Men

	Returns $E[\hat{R}_j] - \overline{\hat{R}}$			Standardized Returns Sj		
	Rank	Return	S.E.	Rank	Return	S.E.
Uni:Dentistry	1	4.020**	0.337	5	1.529**	0.337
AppSc:Industrial Engin.	2	3.984**	0.269	2	2.082**	0.269
AppSc:Management Science	3	3.890**	0.308	1	2.836**	0.308
Uni:Medicine	4	3.672**	0.313	4	1.608**	0.313
AppSc:Business	5	2.936**	0.268	6	1.435**	0.268
AppSc:Finance and Insurance	6	2.815**	0.298	3	1.719**	0.298
Voc:Maths	7	2.363**	0.270	10	1.179**	0.270
AppSc:Supply Engin.	8	2.323**	0.256	7	1.343**	0.256
AppSc:Electrical Engin.	9	2.275**	0.252	8	1.305**	0.252
Voc:Finance and Insurance	10	2.189**	0.314	9	1.208**	0.314
Uni:Business	11	1.848**	0.265	11	0.826*	0.265
Uni:Computer Science	12	1.077**	0.234	12	0.574†	0.234
Uni:Industrial Engin.	13	1.055**	0.262	13	0.517†	0.262
AppSc:Chemical Engin.	14	0.909**	0.252	14	0.501†	0.252
AppSc:Manufacturing Engin.	15	0.809**	0.239	15	0.430	0.239
Voc:Accounting	16	0.792*	0.282	16	0.387	0.282
Uni:Law	17	0.626†	0.302	20	0.260	0.302
AppSc:Computer Science	18	0.586†	0.281	18	0.336	0.281
Voc:Computer Science	19	0.459	0.319	19	0.267	0.319
Voc:Public Security	20	0.458	0.312	17	0.341	0.312
Voc:Management Science	21	0.353	0.303	21	0.196	0.303
Uni:Chemistry	22	0.219	0.308	22	0.118	0.308
Voc:Transport	23	0.202	0.280	25	0.086	0.280
Uni:Manufacturing Engin.	24	0.201	0.294	23	0.106	0.294
Voc:Manufacturing Engin.	25	0.170	0.263	24	0.098	0.263
Uni:Supply Engin.	26	0.144	0.292	26	0.083	0.292
Uni:Physics	27	0.102	0.291	27	0.058	0.291
AppSc:Precision Engin.	28	−0.113	0.238	28	−0.065	0.238
Uni:Maths	29	−0.138	0.303	29	−0.071	0.303
Uni:Economics	30	−0.175	0.315	30	−0.074	0.315
Voc:Business	31	−0.185	0.286	31	−0.092	0.286
Uni:Teaching	32	−0.708	0.407	35	−0.449	0.407
Voc:Electrical Engin.	33	−0.730†	0.285	33	−0.414	0.285
AppSc:Maths	34	−0.774*	0.240	32	−0.395	0.240
Uni:Chemical Engin.	35	−0.857*	0.305	36	−0.462	0.305
Uni:Psychology	36	−0.898†	0.362	34	−0.445	0.362
Voc:Chemical Engin.	37	−0.986**	0.292	37	−0.612†	0.292
Voc:Precision Engin.	38	−1.336**	0.258	38	−0.767*	0.258
Uni:Electrical Engin.	39	−1.536**	0.289	39	−0.777*	0.289
Voc:Trade and Logistic	40	−1.688**	0.294	40	−0.860*	0.294
Voc:Supply Engin.	41	−1.841**	0.264	42	−1.020**	0.264
Uni:Anglistic	42	−1.965**	0.288	41	−0.994**	0.288
Voc:Nursing	43	−2.167**	0.309	49	−1.606**	0.309
Voc:Medical Services	44	−2.205**	0.316	43	−1.199**	0.316
AppSc:Social Work	45	−2.299**	0.325	51	−1.732**	0.325
AppSc:Construction Engin.	46	−2.328**	0.245	45	−1.257**	0.245
Uni:Biology	47	−2.456**	0.275	44	−1.235**	0.275
Uni:Construction Engin.	48	−2.549**	0.298	46	−1.280**	0.298
AppSc:Architecture	49	−2.555**	0.255	47	−1.296**	0.255
Voc:Transport Engin.	50	−2.869**	0.256	48	−1.560**	0.256
Uni:Geo Science	51	−3.404**	0.307	52	−1.852**	0.307
Uni:Educational Science	52	−3.505**	0.371	57	−2.154**	0.371
Voc:Media	53	−3.702**	0.297	53	−1.886**	0.297
Uni:Political Science	54	−3.777**	0.280	50	−1.709**	0.280
Uni:Architecture	55	−3.957**	0.308	54	−1.918**	0.308
Uni:German Literature	56	−4.036**	0.339	55	−2.050**	0.339
Voc:Construction Engin.	57	−4.079**	0.259	58	−2.221**	0.259
Voc:Hotel Restaurant	58	−4.212**	0.242	56	−2.056**	0.242
Uni:Regional Science	59	−4.344**	0.330	59	−2.228**	0.330
Uni:History	60	−4.722**	0.307	61	−2.566**	0.307
Uni:Music	61	−5.139**	0.353	60	−2.411**	0.353
Uni:Social Work	62	−6.554**	0.374	62	−4.059**	0.374
Voc:Gardening	63	−6.781**	0.287	63	−4.323**	0.287
Total number of Fields	63			63		

S.E. calculated using the delta method. Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Source: Estimation based on German Micro Census, years 2005-2009

Notes: Excess returns and risk are calculated using a discount rate of $\gamma = 1.03$.

Table A13: Returns and standardized Returns: All fields, Women

	Returns $E[\hat{R}_j] - \overline{\hat{R}}$			Standardized Returns Sj		
	Rank	Return	S.E.	Rank	Return	S.E.
Uni:Dentistry	1	4.994**	0.408	3	1.941**	0.408
AppSc:Management Science	2	4.800**	0.560	1	3.697**	0.560
Uni:Medicine	3	4.110**	0.413	2	2.059**	0.413
AppSc:Finance and Insurance	4	2.570**	0.548	4	1.819**	0.548
Uni:Teaching	5	2.401**	0.540	5	1.394*	0.540
AppSc:Business	6	2.076**	0.439	6	1.159*	0.439
Voc:Finance and Insurance	7	1.225†	0.551	7	0.807	0.551
AppSc:Computer Science	8	1.108*	0.387	9	0.576	0.387
Voc:Anglistic	9	1.081†	0.470	8	0.618	0.470
Voc:Marketing	10	0.689	0.466	10	0.397	0.466
Uni:Law	11	0.466	0.436	11	0.214	0.436
Uni:Business	12	0.405	0.402	12	0.207	0.402
Voc:Chemical Engin.	13	0.027	0.478	13	0.016	0.478
Uni:Computer Science	14	−0.028	0.404	14	−0.017	0.404
Uni:Psychology	15	−0.037	0.476	15	−0.021	0.476
AppSc:Social Work	16	−0.045	0.522	16	−0.031	0.522
Voc:Transport	17	−0.060	0.467	17	−0.039	0.467
Voc:Nursing	18	−0.148	0.519	19	−0.107	0.519
Voc:Management Science	19	−0.155	0.527	18	−0.101	0.527
Voc:Accounting	20	−0.304	0.516	20	−0.174	0.516
Uni:Chemistry	21	−0.680	0.437	21	−0.374	0.437
Voc:Business	22	−0.874	0.476	23	−0.526	0.476
Uni:Maths	23	−0.884†	0.415	22	−0.478	0.415
Uni:Political Science	24	−1.007†	0.397	24	−0.536	0.397
Voc:Manufacturing Engin.	25	−1.010†	0.451	25	−0.603	0.451
Voc:Social Work	26	−1.039	0.540	28	−0.720	0.540
AppSc:Educational Science	27	−1.115†	0.501	26	−0.686	0.501
Voc:Media	28	−1.357*	0.464	29	−0.735	0.464
Uni:Economics	29	−1.423**	0.423	27	−0.694	0.423
Voc:Educational Science	30	−1.532*	0.534	37	−1.114†	0.534
Uni:Biology	31	−1.656**	0.433	30	−0.935†	0.433
Uni:Educational Science	32	−1.688**	0.511	32	−0.990	0.511
Voc:Medical Services	33	−1.708*	0.541	35	−1.075†	0.541
Voc:Trade and Logistic	34	−1.711**	0.491	33	−1.022†	0.491
Voc:Tourism	35	−1.751**	0.485	36	−1.112†	0.485
Uni:German Literature	36	−1.828**	0.453	31	−0.981†	0.453
Uni:Anglistic	37	−2.035**	0.432	34	−1.037†	0.432
Uni:Chemical Engin.	38	−2.264**	0.428	39	−1.223*	0.428
Uni:Manufacturing Engin.	39	−2.407**	0.401	38	−1.123*	0.401
Uni:Geo Science	40	−2.409**	0.448	46	−1.508**	0.448
Voc:Office Assistant	41	−2.416**	0.498	45	−1.484*	0.498
AppSc:Architecture	42	−2.425**	0.449	43	−1.434*	0.449
AppSc:Maths	43	−2.526**	0.395	40	−1.320**	0.395
AppSc:Manufacturing Engin.	44	−2.567**	0.357	42	−1.415**	0.357
Uni:History	45	−2.619**	0.426	41	−1.371*	0.426
Voc:Hotel Restaurant	46	−2.778**	0.441	44	−1.454**	0.441
Voc:Personal Services	47	−3.012**	0.531	47	−1.614*	0.531
Uni:Regional Science	48	−3.089**	0.427	49	−1.869**	0.427
AppSc:Construction Engin.	49	−3.323**	0.382	51	−1.930**	0.382
Uni:Construction Engin.	50	−3.587**	0.411	52	−2.127**	0.411
Uni:Architecture	51	−3.609**	0.412	50	−1.882**	0.412
Uni:Music	52	−3.725**	0.477	48	−1.857**	0.477
Voc:Dentistry	53	−3.769**	0.499	53	−2.301**	0.499
Uni:Social Work	54	−4.038**	0.522	54	−2.868**	0.522
Voc:Textile	55	−5.087**	0.416	55	−2.892**	0.416
Voc:Beauty	56	−6.617**	0.459	56	−3.336**	0.459
Total number of Fields	56			56		

S.E. calculated using the delta method. Significance levels: † : 10% $*$: 5% $**$: 1%

Source: Estimation based on German Micro Census, years 2005-2009
Notes: Excess returns and risk are calculated using a discount rate of $\gamma = 1.03$.

Figure B1: Age-earnings profile: Men

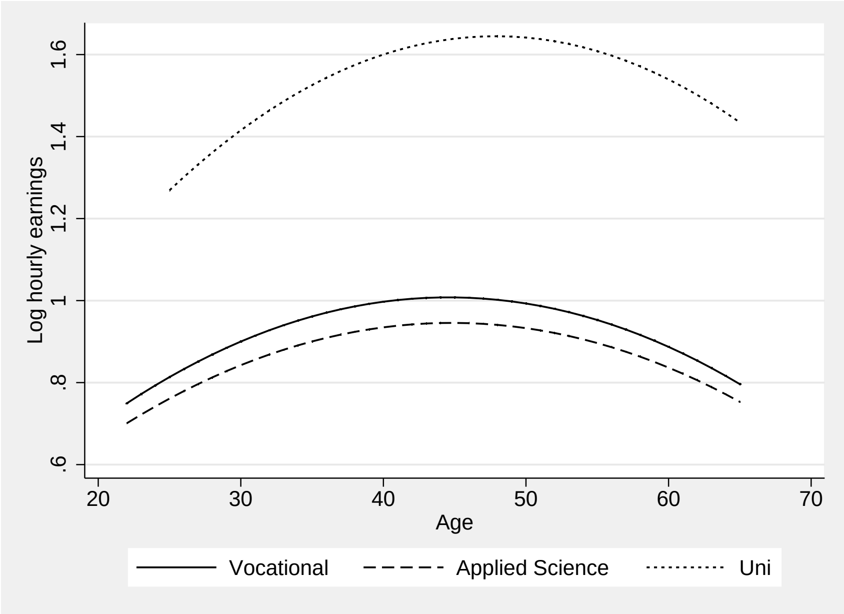

Figure B2: Age-earnings profile: Women