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Zusammenfassung:

In this paper I scrutinize the impact of employment on time-to-degree in Higher Education. In contrast to the previous literature, I look at different types of working while being enrolled at university. Using the German Socio-Economic Panel (GSOEP), I find that full-time employment and part-time employment significantly decreases the probability of graduating from university at any point of enrollment.

JEL Klassifikation : C33, C41, I21, I22, I28
Schlüsselwörter : Duration analysis, costs of education
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The Effects of Employment on Time-to-Degree in Higher Education: Does the Type of Employment matter? *

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June 23, 2005

Abstract

In this paper I scrutinize the impact of employment on time-to-degree in Higher Education. In contrast to the previous literature, I look at different types of working while being enrolled at university. Using the German Socio-Economic Panel (GSOEP), I find that full-time employment and part-time employment significantly decreases the probability of graduating from university at any point of enrollment.

Keywords: Duration analysis, costs of education

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1 Introduction

Working while being a student is a common phenomenon these days. Among American students, 80 percent are working either part- or full-time during their studies.[1] In Germany the proportion of working students has increased to a level of 68 percent in the last few years.[2]

One economic explanation for the students' behavior relies on the existence of imperfect capital markets. Students cannot borrow money unrestrictedly. Hence, they are forced to fund their studies partly by themselves when their expenditures exceed their income.[3]

The aim of enhancing his or her job market prospects justifies another reason for being employed as a student. Students either work in order to send a signal to their prospective employers or to accumulate firm specific human capital.

At the first glance, doing research on completion time does not seem to be an exciting topic since we do not find any spectacular abnormalities for traditional countries, like the US or the UK. But when we look at other European countries, this picture changes dramatically.[4] Table 1 presents graduation times for some selected OECD-countries. Germany, Spain and Finland are characterized by a large time span between enrolment and graduation. An investigation of the German higher education seems particularly interesting since the Supreme court recently ruled that the Federal States may have the power to introduce tuition fees. One aim of this policy covers the reduction of completion time at German universities. The policymakers expect that

[1]See NCES (2003a).

[2]See GFMER (2003).

[3]The latter is usually determined by parental transfer and governmental subsidies.

[4]See also OECD (2003), OECD (1998) and NCES (2003b).

higher costs provide an incentive to attain a degree more quickly. Contrarily, opponents argue that higher costs force the student to devote more time being employed in order to finance his or her study and consequently, the completion time will increase. This paper refers to the latter and tries to give some insights about the possible negative effects of tuition fees on completion time.

The effect of employment while in school has been broadly investigated. However, in the previous literature authors focused mainly on the effect of employment on return to schooling and on school grades. Papers by Ruhm (1997), Light (2001), Häkkinen (2004) and Hotz, Xu, Tienda, and Ahituv (2002) find a positive effect of employment on return to schooling. The impact on grades is analyzed by Hood, Craig, and Bruce (1992), Paul (2001), Light (2003) and Ehrenberg and Sherman (1987). In most cases, these studies disclose a negative effect on school performance.[5]
There is only little work done in the analysis of the effect of employment on time-to-degree in higher education. Studies of undergraduates are investigated by Häkkinen and Uusitalo (2003) and the NCES (2003b). The former analyzes a student aid reform in Finland. The authors conclude that the policy failed to reduce the completion time. The report by the NCES consists in a comprehensive work about bachelor degree recipients in the US. Moreover, there are few papers about time-to-degree for PhD students. A paper by Ehrenberg and Mavros (1995) analyzes the effect of student aids on time-to-degree of PhDs at Cornell University. The authors detect a reducing effect of the reform on graduation time throughout all fields. Papers by Booth and Satchell (1995) and Ridder and van Ours (2001) investigate PhD programmes in the UK and the Netherlands, respectively. However, none of

[5]Ehrenberg and Sherman (1987) find a positive effect for an on-campus job.

these studies includes working effects on completion time.
An attempt to analyze the effect of employment on completion time has been done by Ehrenberg and Sherman (1987). Using the National Longitudital Survey of the High School Class of 1972, the authors figure out that undergraduates who worked 20 hours a week off campus in October 1975 had an 8.7 point lower probability of graduating by October 1976. Finally, Siegfried and Stock (2001) also find a slightly negative effect of working on the hazard rate for graduation. The authors regard PhD-students in the US who have taken jobs before graduating. However, Siegfried and Stock (2001) may not come up with true effect of working, as they estimate the coefficient for employment with a duration model based on a Weibull distribution. Using such a standard approach does not consider unobserved heterogeneity in the sample.

In this paper, I utilize a discrete-time model to investigate the effect of different types of employment on completion time. Using semi-parametric and non-parametric maximum likelihood-estimation (NPMLE), I find that there is a highly negative effect of full-time employment on the hazard rate for graduation. The effect for part-time employment reveals to be negative as well. However, the impact on graduation at any point of enrollment is not as strong for being employed part-time. These results are in a line with the theoretical result that students who are employed part-time can compensate the working hours with less leisure time whereas full-time working students reduce their studying time per unit of time rather than resigning their leisure consumption.
Since working while in college occurs mostly through personal circumstances (e.g. financial constraints, compulsory internship) and as we are focusing on employment only during the term, an endogeneity problem seems almost

negligible. However, we also use IV estimation for our part-time employment variable in order to test our results obtained from the duration analysis.
The remainder of the paper is organized as follows: Section 2 describes briefly the German Higher Education System and the data. Section 3 constitutes the theoretical analysis. The results of the estimations are presented in Section 4 before Section 5 concludes.

2 The Data and the German Higher Education System

The data which I used for the empirical analysis stems from the German Socio-Economic Panel (GSOEP). The GSOEP is a household panel conducted on an annual basis since 1984. I restrict my analysis to 4500 households covering people in West Germany and exclude households with a head of foreign nationality. The observed sample guarantees that all individuals face the same education system and hence, I avoid a measurement error from institutional differences.[6]
My final working sample contains 17,903 observations which can be divided into individual spells which are complete, right-censored and right-censored through drop-out.[7] In the cross-sectional level, the numbers correspond to 105 completed spells, 61 drop-outs and 103 right-censored spells.

The GSOEP provides rich information about students' and parental in-

[6]For instance people in East Germany went through another education system which demands different requirements.
[7]Right-censoring occurs because there is no observation after the last college observation of an individuum.

formation. In my analysis, I control for gender, *male*, students entrance age (in months), *age*, the average proportion in each unit of time during the terms which was devoted to full- or part-time employment ,[8] *fullworkterm, partworkterm*, the year of enrollment (1 corresponds to the year 1983), *Startyear*, being pregnant while in college, *child1*, the father's and mother's educational background, *fatheredu_low, motheredu_low*, as well as, the institution and the subject of enrollment.[9] In addition, the data allows to identify the students' completion time[10] on a monthly basis.

As we receive full information only from the completed spells, I use those observations for the descriptive statistics. Table 2 presents the minimum, maximum and mean value of each variable. We see that the average duration of obtaining a degree is almost six years in Germany. Moreover, the table shows the average proportion of time which was devoted to part-time and full-time work during the terms. As expected, part-time employment occurs more frequently than full-time working which is on average merely observable in 3.9 percent of the entire term time.

Since graduation time various enormously among students, Table 3 shows the mean length for the different subgroups. Females are faster than their male peers while graduate at university need more time than peers at other institutions.[11] Moreover, in particular fathers' education matters for the graduation time. Finally, among the subjects, it seems that students in Medicine and Social Science graduate faster than their peers in Science and Engineering. However, since the number of observations in any subjects is very small, the

[8]The distinction arises by different weekly work intensities. Full-time working usually corresponds to an employment of more than 35 hours per week.

[9]Since the last two variables are only available for students who have attained their degree, I am using a dummy for the missing values.

[10]Completion time is defined by the difference between the observed month of obtaining first degree and the first month of enrollment.

[11]Other institutions refer mainly to technical colleges.

study does not attempt to infer any generalized results.
What can we say about the characteristic of students who are working either part-time or full-time? Table 4 presents the quantity of full- and part-time employment for different explanatory variables. Among the different variables, full-time employment appears more distinctive than part-time work. For instance, mainly Engineering, Law and Economic students are working full-time during term, whereas the subjects are less distinguished for part-time employment.

The main characteristic of the German Education System is that students usually do not have to pay any tuition fees.[12] Furthermore, there is no constraint for a German student to finish his or her study within a certain time. Hence, German students are in a position to organize their college time by themselves. If we apply this decision process to each unit of time while in college, we obtain the following equation:[13]

$$1 = t^w + t^g + t^l \tag{2.1}$$

During college, student's time is generally devoted to work t^w, study t^g and leisure t^l. The working component can be divided into work which is caused by financial shortages and work that simplifies the labor market entry.
In addition, the German higher education system is marked by large term breaks. The students have two term-breaks which last two months in spring and almost three months at the end of summer. Clearly, the major trade-off between each single activity in equation (2.1) is mainly given during terms. In term breaks, a student is not forced to invest in study as much time as

[12]There are some exceptions in different federal states, like tuition fees after achieving a certain time of enrollment.
[13]See also Amann (2004).

during the terms and hence, it is more likely for him or her to work or to consume leisure. Therefore, I focus my analysis on employment which occurs during the terms.

Finally, in certain subjects there are compulsory internships for students. Those internships last usually six months and proceed normally in the last third of being enrolled.

Figure 2.2 indicates that full-time employment takes place mostly at the end of college time. Taking into account that compulsory internships have been done mainly at the end of enrollment, the graph merely confirms this aspect. In contrast, Figure 2.1 shows that part-time employment happens at the beginning and the end of college time. The high peak at the beginning of enrollment is probably caused by the abrupt change in students' financial situation. Moreover, college freshmen are probably more risk-averse and hence, they are prone to work. The high density of part-time work at the end of the enrollment time could be caused by different circumstances: First, it is more likely to find a job after a certain time. Secondly, part-time employment functions as a means to accumulate firm-specific human capital and finally, it becomes very popular in Germany to take a rest after graduation, hence, part-time work at the end of enrollment provides also pecuniary means to finance this favored time.

The variables of interest are *fullworkterm* and *partworkterm*. These variables present the average intensity of work in each single month while lectures take place. First, this specification guarantees that we take into account the cumulative effect of working and secondly, the specification provides an estimation of the intended effects which does not hinge on time trends of being employed.[14]

[14] For instance, the intensity of full-time working increases at the end of college time.

3 The theoretical framework

In this section, I present the theoretical approach which explains the methods used to obtain the empirical results.[15]

In the model, the data set is structured in person-month form, i.e. for each individual I have several months of observation. Hence, the time axis is partitioned into a number of non-overlapping monthly intervals where the interval $a_j = (a_{j-1}, a_j]$ begins at the instant after the interval $a_{j-1} = (a_{j-2}, a_{j-1}]$.[16]

The hazard for the jth interval is defined as

$$\begin{aligned} h(a_j) &= Pr(a_{j-1} < T \leq a_j \mid T > a_{j-1}) \\ &= \frac{Pr(a_{j-1} < T \leq a_j)}{Pr(T > a_{j-1})} \\ &= \frac{S(a_{j-1}) - S(a_j)}{S(a_{j-1})} \\ &= 1 - \frac{S(a_j)}{S(a_{j-1})}. \end{aligned} \tag{3.2}$$

We can now express the discrete time survivor function in term of hazard rates. The probability of surviving a certain time span equals the product of nongraduation within each single interval over the entire time span.[17]

$$\begin{aligned} S_j &= (1 - h_1)(1 - h_2)...(1 - h_{j-1})(1 - h_j) \\ &= \prod_{k=1}^{j}(1 - h_k). \end{aligned} \tag{3.3}$$

[15] The approach which I use for my analysis is fairly standard. See among others Han and Hausman (1990).

[16] The time index corresponds to the end of an interval.

[17] Since we have a unit length for our interval, I relabel the hazard rate for the jth interval in h_j.

Thus, the discrete time failure function is

$$F_j = 1 - \prod_{k=1}^{j}(1 - h_k) \tag{3.4}$$

and the discrete time density function is derived by

$$\begin{aligned} f_j &= Pr(a_{j-1} < T \leq a_j) \\ &= \frac{h_j}{1 - h_j}\prod_{k=1}^{j}(1 - h_k). \end{aligned} \tag{3.5}$$

I use standard Kaplan-Meier-estimation for a discrete time model to obtain Figure 3.3 and Figure 3.4. In the following section, I utilize these results for the specification of an appropriate hazard rate.

3.1 The regression model

As already mentioned, the data which I use is structured in panel form. We observe person i from month k=1 through to the end of the jth month. At the end of this follow-up time, the spell is either completed ($c_i = 1$), or right censored ($c_i = 0$). The likelihood contribution for a censored spell is given by the discrete time survivor function

$$L_i = Pr(T_i > j) = S_{ij} = \prod_{k=1}^{j}(1 - h_{ik}). \tag{3.6}$$

The contribution for each completed spell is given by the discrete time density function

$$L_i = Pr(T_i = j) = f_{ij} = \frac{h_{ij}}{1 - h_{ij}} \prod_{k=1}^{j} (1 - h_{ik}). \tag{3.7}$$

The likelihood function for the entire sample is

$$\begin{aligned} L &= \prod_{i=1}^{n} [Pr(T_i = j]^{c_i} [Pr(T_i > j)]^{1-c_i} \\ &= \prod_{i=1}^{n} [\frac{h_{ij}}{1 - h_{ij}} \prod_{k=1}^{j} (1 - h_{ik})]^{c_i} [\prod_{k=1}^{j} (1 - h_{ik})]^{1-c_i} \\ &= \prod_{i=1}^{n} [(\frac{h_{ij}}{1 - h_{ij}})^{c_i} \prod_{k=1}^{j} (1 - h_{ik})]]. \end{aligned} \tag{3.8}$$

Expression (3.8) implies

$$logL = \sum_{i=1}^{n} c_i log(\frac{h_{ij}}{1 - h_{ij}}) + \sum_{i=1}^{n} \sum_{k=1}^{j} log(1 - h_{ik}). \tag{3.9}$$

Now, I define a new binary variable y_{ik}. The properties of y_{ik} are

$$\begin{aligned} y_{ik} &= 1 \quad \text{if} \quad c_i = 1 \quad \wedge \quad k = T_i \\ y_{ik} &= 0 \quad \text{otherwise.} \end{aligned} \tag{3.10}$$

Inserting y_{ik} into (3.9) yields

$$\begin{aligned} logL &= \sum_{i=1}^{n} \sum_{k=1}^{j} y_{ik} log(\frac{h_{ik}}{1 - h_{ik}}) + \sum_{i=1}^{n} \sum_{k=1}^{j} log(1 - h_{ik}) \\ &= \sum_{i=1}^{n} \sum_{k=1}^{j} [y_{ik} log h_{ik} + (1 - y_{ik}) log(1 - h_{ik})]. \end{aligned} \tag{3.11}$$

Expression (3.11) corresponds to a standard likelihood function for a binary regression model in which y_{ik} is the dependent variable.

3.2 The specification of the hazard function

In the above subsection, we have seen that we can estimate our parameter of interest with a binary regression model. To specify this model completely, we have to determine the type of the hazard function h_{ik}.
Considering the proportional hazards (PH) specification for a continuous time model, we obtain for the hazard rate $\lambda(t, x)$

$$\lambda(t, x) = g(x)\lambda_0(t), \tag{3.12}$$

where $g(x) = exp(\beta' x)$ with $\beta' x = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_m x_m$ and $\lambda_0(t)$ denotes the baseline hazard function.
We know that the survivor function for a continuous time model is given by

$$S(a_j, x) = exp[-\int_0^{a_j} \lambda(u, x)du]. \tag{3.13}$$

The PH assumption implies that

$$S(a_j, x) = exp[-\int_0^{a_j} \lambda_0(u, x)dug(x)]. \tag{3.14}$$

Hence, introducing the discrete time hazard function $h(a_j, x)$ yields

$$h(a_j, x) = 1 - exp[g(x)(\int_0^{a_j-1} \lambda_0(u, x)du - \int_0^{a_j} \lambda_0(u, x)du)]. \tag{3.15}$$

Equation (3.15) implies that

$$log(-log[1 - h(a_j, x)]) = \beta' x + \gamma_j, \tag{3.16}$$

where $\gamma_j = log \int_{a_j-1}^{a_j} \lambda_0(u, x)du$. Thus, γ_j is the log of the difference between the integrated baseline hazard evaluated at the end of the interval (a_{j-1}, a_j) and the beginning of the interval. Equation (3.16) implies

$$h(a_j, x) = 1 - exp[-exp(\beta' x + \gamma_j)]. \tag{3.17}$$

Finally, we have to specify γ_j. A discrete time model approach leads easily to a semi-parametric analysis as restrictions on the baseline hazard are not necessary. Since Figure 3.4 indicates that the hazard function varies only in a certain time span and my data set is relatively small, I use a piece-wise constant baseline hazard specification. For this reason, I create nine dummy variables ($durat1 - durat9$) which indicate the range of time in which the graduation occurs.

3.3 Controlling for unobserved heterogeneity

However, using such a standard approach to investigate the different effects on graduation does not take into account heterogeneity within the sample. Individuals are different in many attributes. I summarize all possible unobservable effects in the variable v. Comprising these attributes, I solve the following model

$$log(-log[1 - h(a_j, x)]) = \beta' x + \gamma_j + u, \tag{3.18}$$

where $u = log(v)$. Once we introduce unobserved heterogeneity into our model, we have several possibilities to solve the above model. Either one assumes a certain distribution for v or does not. I estimate the model in both ways. First, I assume a normal distribution for v and secondly, I use a non-parametric approach which was pioneered by Heckman and Singer (1984).[18]

The model of a non-parametric maximum likelihood estimation (NPMLE) is based on the following idea:

Suppose there two types of individuals. Then, the likelihood function is

$$L = \pi L_1 + (1 - \pi)L_2, \tag{3.19}$$

where

$$L_1 = (\frac{h_1(j, X)}{1 - h_1(j, X)})^c \prod_{k=1}^{j} [1 - h_1(k, X)] \tag{3.20}$$

and

$$L_2 = (\frac{h_2(j, X)}{1 - h_2(j, X)})^c \prod_{k=1}^{j} [1 - h_2(k, X)]. \tag{3.21}$$

π depicts the probability of belonging to type 1 and c is the censoring indicator. Introducing N latent classes, the likelihood contribution for a person with spell length j is

$$L = \sum_{n=1}^{N} \pi_m L(\lambda_m), \tag{3.22}$$

[18]As in other papers, I also have estimated the model assuming a gamma distribution for the unobservable term. Since the results have shown similar results, I only discuss the above specifications.

where λ_m are the N mass point parameters describing the support of the discrete multinomial distribution. π_m depicts the corresponding probabilities.

3.4 Controlling for possible endogeneity

A proper empirical analysis is marked by unbiased estimation results. The cause for bias arises mainly through endogenous variables in the regression. Since we are particularly interested in the employment variables, the endogeneity problem does not seem to be a major issue. From GFMER (2003) we know that 56 percent of all employed students have to work in order to finance their living costs. The report also shows that students from mainly a poor social background are forced to work. If we take into account that students may attempt to work during term breaks and that students face compulsory internships in certain subjects, there is not much space left for working during the term which is based upon a voluntary basis. The data reveals that this fact holds in particular for full-time employment.[19] Full-time working occurs rarely and Table 4 reveals that the type of subject captures most of the explanation for being full-time employed. Furthermore, different peer group pressure within the subjects accounts certainly for these sizable differences as well. In general, full-time work during the term seems to be explained by circumstances rather than by personal unobserved characteristics.

In the case of part-time work, the endogeneity problem appears to be different. It may occur that students are part-time employed during the term due

[19]GFMER (2003) confirms that working above 35 hours is not a common phenomenon. Only three percent of the students bear such a high intensity of work.

to differences in skills, since the burden of being part-time employed is much less than in the case of full-time employment. To control for this possible endogeneity problem for part-time employment, I use a standard IV approach with the following identification strategy. First, consider a linear equation model

$$y = a_0 + a_1 x_1 + a_2 partworkterm + u, \tag{3.23}$$

where y depicts the length of being enrolled, x_1 presents a vector of covariates and u contains all omitted variables like ability or motivation. Yet, it is most likely that u is correlated with *partworktime*, as it could be that only the intelligent students bear the burden of being employed during the term. Obviously, OLS estimation of (3.23) results in inconsistent estimators of all the a. Therefore, I use the method of instrumental variables (IV) in order to solve the problem of an endogenous explanatory variable. This method requires a variable (instrument) z which entails the following two characteristics. First, Cov(z,u)=0, or in other words, z is an exogenous variable in equation (3.23). Secondly, the relation between z and *partworkterm* is

$$partworkterm = b_0 + b_1 x_1 + b_2 z + e, \tag{3.24}$$

where e is uncorrelated with the explanatory variables and $b_2 \neq 0$.
In my case, I utilize the fact that part-time employment during term is partly explained by financial shortages. Therefore, I use the number of people living in the same household as a valid instrument. The idea behind this is fairly simple. The higher the number of people the lower the expected parental al-

lowance for enrolled students and hence, the higher the likelihood to work.[20] Furthermore, there is no evidence that there is a correlation between the unobservables and the used instrument.[21]

4 Estimation Results

In order to avoid distortion of the results , I have only used the completed and right-censored spells for the regression since the drop-outs represent a specific kind of people. The results of the semi-parametric and NPMLE-estimation are presented in Table 5. The first column shows the estimation results of the semi-parametric approach. The estimation reveals that both type of employment decreases the hazard rate for graduation at each month of enrollment. However, the impact of full-time work is much stronger than for being employed part-time. The interpretation of the presented numbers is that students who are working full-time each single month have a hazard rate of 4.7 percent of those students who do not work at all. Considering part-time employment, the hazard rate is 33.3 percent, respectively. The result seems to be fairly intuitive and may be explained within a theoretical framework in which a student maximizes his or her utility through the optimal choice of leisure time. Students who are working part-time have less time for their study. However, those student may have the chance to give up a fraction of their leisure time in order to catch up partly the missed studying time.

[20] OLS estimation reveals a positive effect between the instrument and part-time employment.

[21] However, IV estimation deals more as an attempt to take into account possible endogeneity rather than a prober method to solve an endogeneity problem within a duration analysis.

Hence, the impact of part-time employment is comparably weak for this type of employment. In the case of full-time employed students, the theory confirms the observed results as well since those students are not willing to compensate the missed studying time through the remaining leisure time. Obviously, the marginal utility of leisure consumption for this type of student is enormous.[22]

In contrast to many other empirical papers in education in which the mother's education mostly matters, it seems that if we consider graduation time in HE a crucial variable is the father's education level. An explanation for this result is certainly the importance of financial support from the parents which depends essentially on father's income.[23] The rest of the explanatory variables describes the effect of being enrolled in a certain subject at a certain institution. Since we compare these variables with the missing groups, all coefficients were found to be positive. Finally, our dummy time variables indicate the observed inverted U-shaped hazard rate curve.[24]

In order to control for endogeneity of part-time employment, I use only the completed spells. Table 6 shows the results of the IV estimation. I still find that both types of employment increases the graduation time, whereas part-time employment turns out to be insignificant. Clearly, since we have now a relatively small sample, our standard errors become large which may lead to the obtained result.

[22] For the entire model, see Amann (2004)

[23] I have also used parental profession level variables to estimate the effect on graduation and I have received similar results.

[24] For the NPMLE estimation I only use six dummy time variables in order to reduce the rank of dimension. Moreover, less than six dummies may allow for no precise capture of the hazard function.

4.1 The Predicted Effect on Time-to-Degree

Since policymakers are interested in the effect on graduation time, I exploit the result from the above regressions in order to predict the impact of both types of employment on time-to-degree.

Taking all mean values from the covariates and varying the intensities of employment for both types lead easily to figure 4.5 and figure 4.6. Obviously, the higher the intensities the higher the probability of nongraduation at each month of enrollment. Interestingly, the impact of full-time employment seems to be more severe at a higher level. In contrast, the reduction of graduation time by varying part-time employment is higher at the lowest level. This observation is confirmed by figure 4.7 and figure 4.8. The increment of the expected time-to-degree rises with increasing full-time employment. Conversely, there is a diminishing increment of the completion time with increasing part-time working.

5 Conclusion

Being employed as a student is a common status nowadays, and it is mainly caused by financial needs or by firm-specific human capital accumulation. This study discloses that the effects of employment on the graduation time depend crucially on the type of employment. Full-time employment decreases the hazard rate much stronger than part-time employment. The reason for the differences in the results by employment types may be explained by the choice of an optimal leisure consumption. If there is high intensity of work, students reduce their studying time in any point of enrollment instead of resigning their leisure time. In contrast, part-time employment still permits a sufficiently high consumption of leisure. Hence, it may occur that these students consume less leisure in order to catch up their missed studying time. Furthermore, the decrement of leisure time may provide incentives to graduate earlier. In sum, the impact of part-time employment reveals to be significant, but relatively weak compared to being employed full-time.

Considering the latest political developments within the German higher education system, this paper provides evidence that the introduction of tuition fees may not affect strongly the completion time when the weekly intensity of working remains low. This suggests that the education of students from poor socioeconomic backgrounds should be provided through governmental subsidies.

In general, colleges have to decide whether they want to educate students with general human capital or provide a system in which the student can also accumulate firm specific human capital. If the former applies, universities ought to use a rigid system in which a student accumulates his or her required human capital as fast as possible. Thus, the accumulation of firm-specific human capital in the form of compulsory internships should take place outside of the college system.

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Country	Age of new entrants*	Age of graduates*
Belgium	18.8	22.8
Finland	21.6	27.6
Germany	21.4	28.9**
Spain	19.0	25.1
UK	19.4	22.0***
US	19.3	22.0***

*The Median attaining a diploma degree.
** On average.
*** For bachelor degree.
Sources: Education at a Glance (1998, 2003), Federal Statistical Office Germany, NCES.

Table 1: Age of entrants and graduates in higher education across OECD-countries

Table 2: Descriptive Statistics

variable	**min**	**max**	**mean**	**N**
Length	34	149	68.74286	105
fullworkterm	0	1	.039031	105
partworkterm	0	1	.1247525	105
age	250	466	276.9714	105
Startyear	3	15	7.019048	105
male	0	1	.6285714	105
child1	0	1	.0285714	105
unidegree	0	1	.5428571	105
nounidegree	0	1	.4571429	105
Medicine	0	1	.0571429	105
Humanities_Edu	0	1	.0571429	105
Science	0	1	.1619048	105
Law_Econ	0	1	.247619	105
Engineering	0	1	.0571429	105
Social_Science	0	1	.0571429	105
Others	0	1	.3619048	105
fatheredu_low	0	1	.352381	105
motheredu_low	0	1	.4	105

Source:GSOEP

Table 3: The mean length of enrollment (in months).

Variable	**Length**
male	72.151
female	62.974
nochild1	68.509
child1	76.666
fatheredu_high	62.455
motheredu_high	65.809
fatheredu_low	80.297
motheredu_low	73.142
nounidegree	64.541
unidegree	72.280
Medicine	62.166
Humanities_Edu	73.166
Science	78.823
Law_Econ	68.076
Engineering	75.667
Social_Science	59.166
Others	65.447

Table 4: The mean proportion of time spent at work.

Variable	**Full-time**	**Part-time**
male	0.058	0.152
female	0.006	0.077
nochild1	0.040	0.125
child1	0	0.084
fatheredu_high	0.026	0.102
motheredu_high	0.044	0.107
fatheredu_low	0.062	0.166
motheredu_low	0.030	0.150
nounidegree	0.015	0.109
unidegree	0.058	0.137
Medicine	0.004	0.066
Humanities_Edu	0.012	0.108
Science	0.005	0.129
Law_Econ	0.095	0.140
Engineering	0.087	0.042
Social_Science	0.022	0.078
Others	0.019	0.144

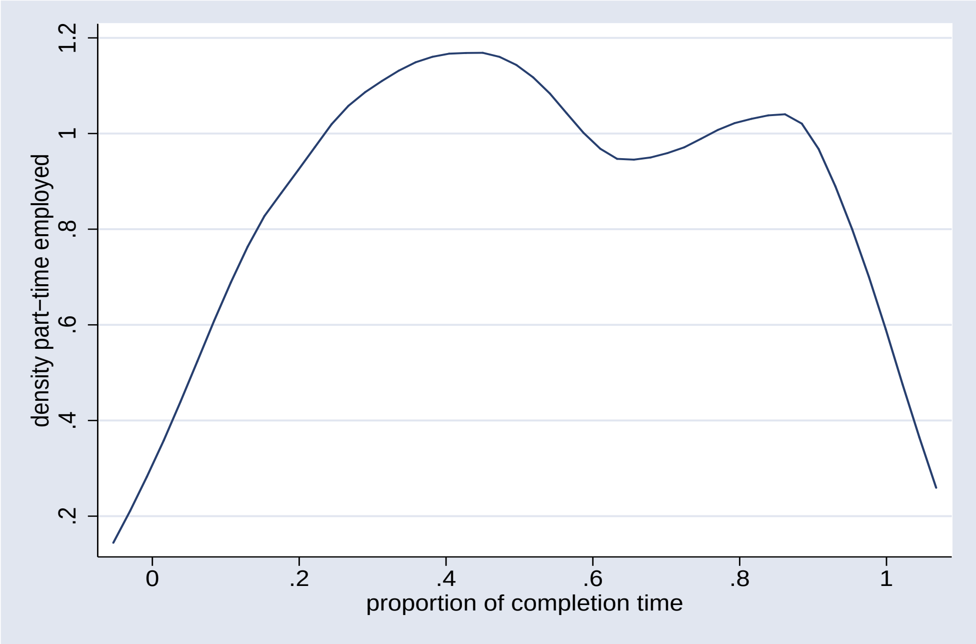

Figure 2.1: Part-time employment in colleges.

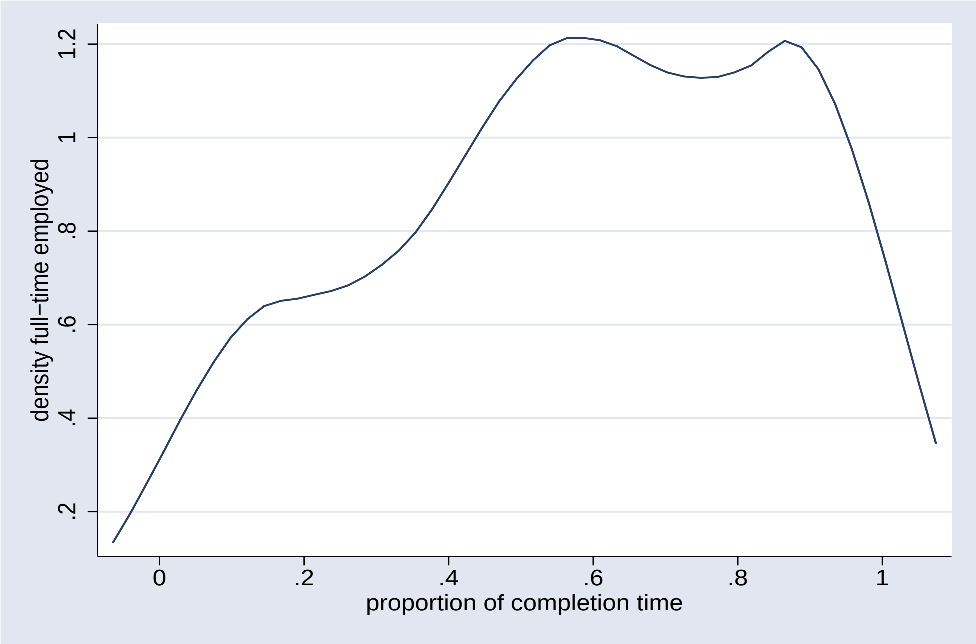

Figure 2.2: Full-time employment in colleges.

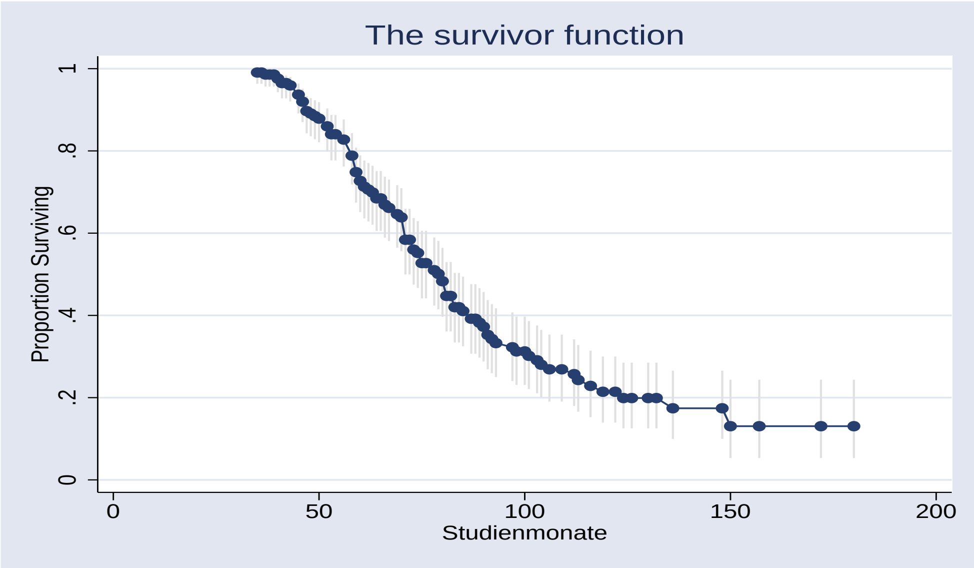

Figure 3.3: The survivor function to graduate at any month of enrollment.

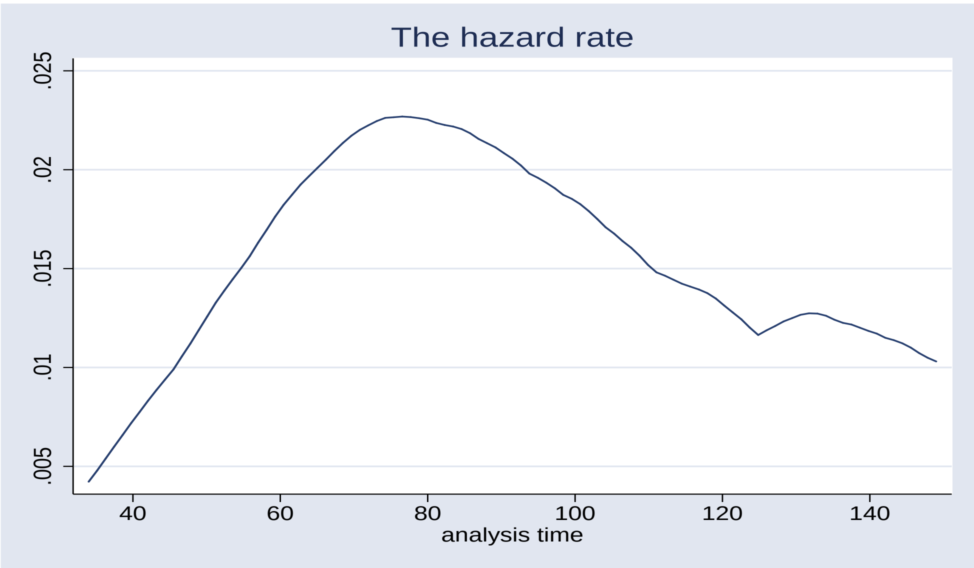

Figure 3.4: The hazard rate to graduate at any month of enrollment.

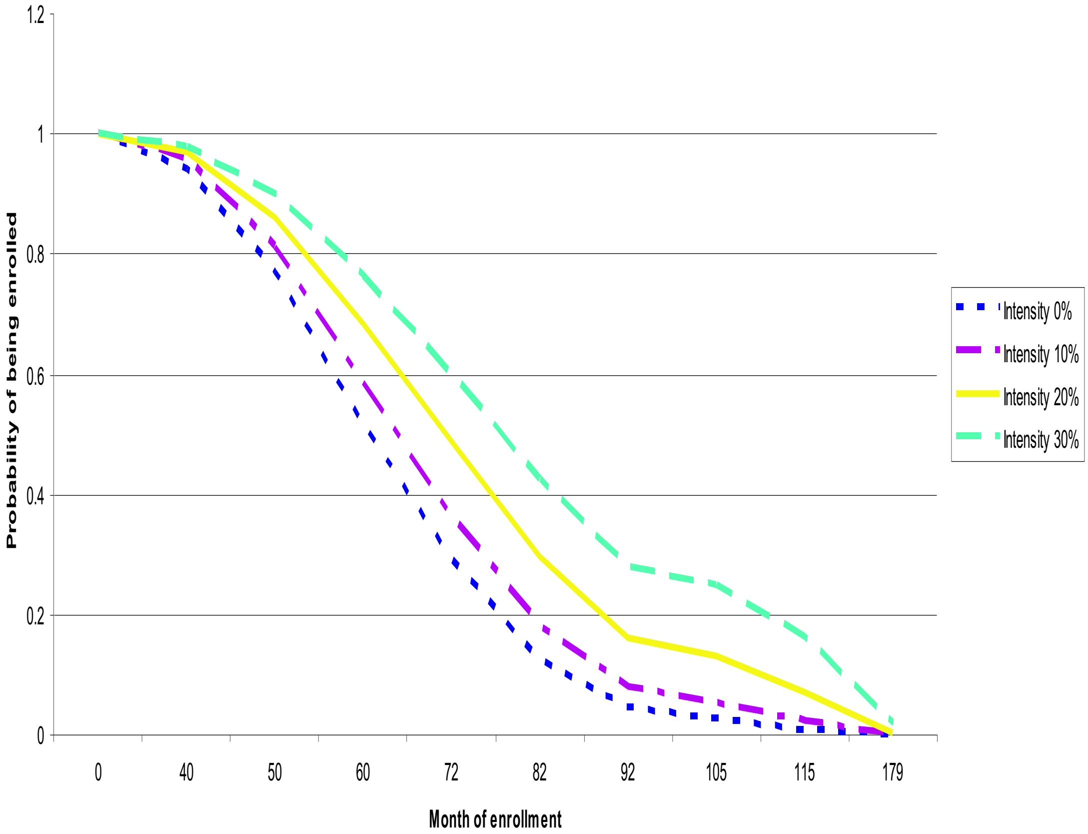

Figure 4.5: The survival function for different intensities of full-time employment

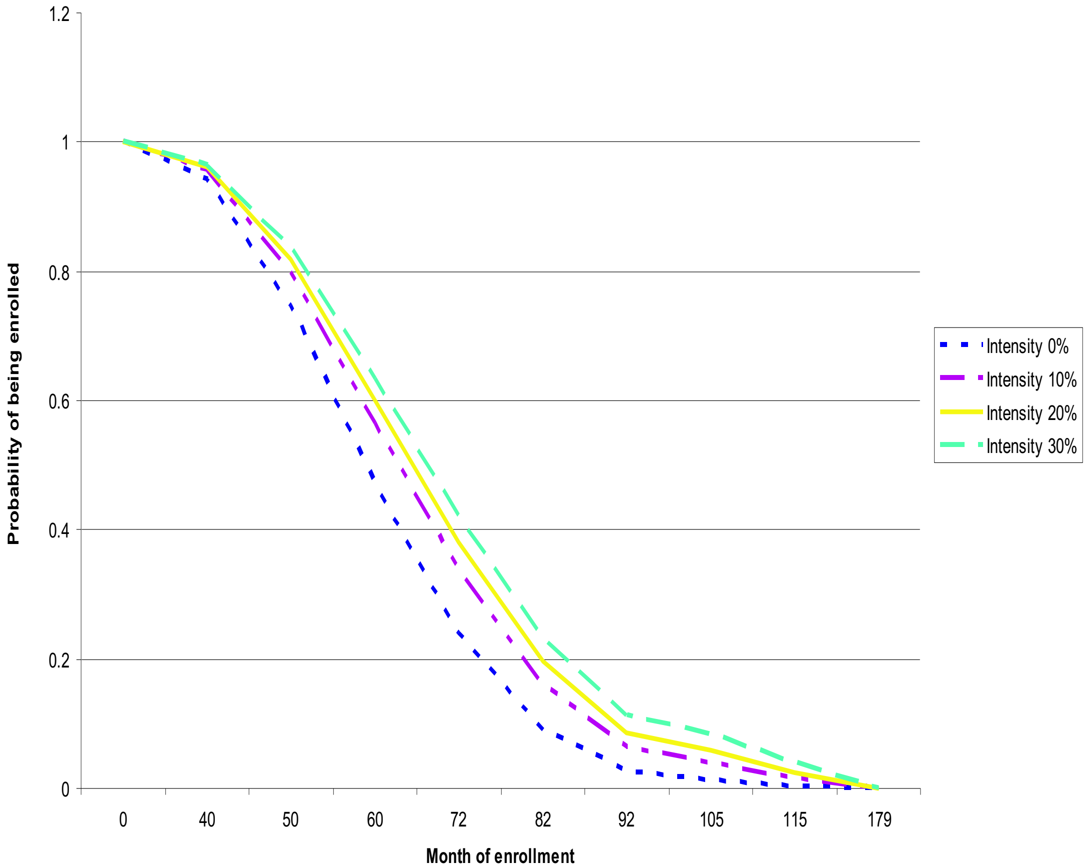

Figure 4.6: The survival function for different intensities of part-time employment

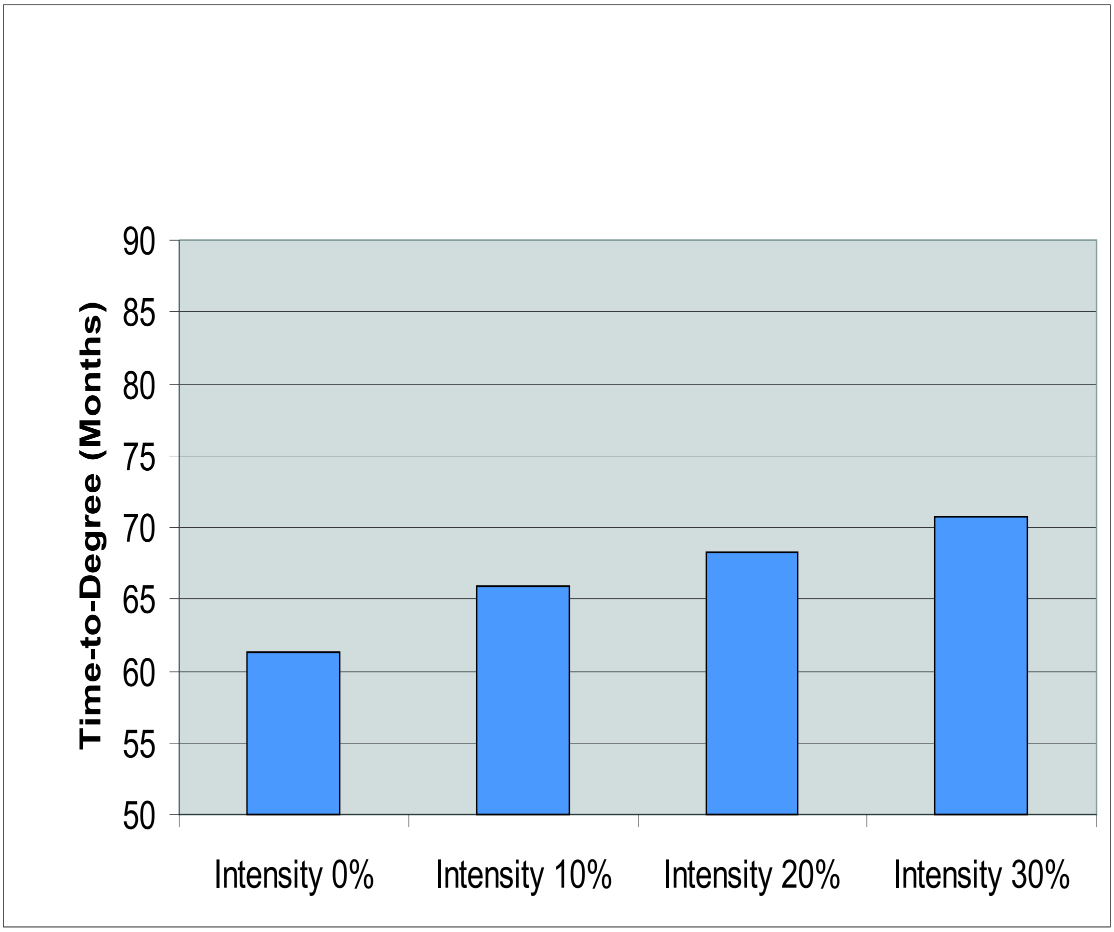

Figure 4.7: The expected time-to-degree for different intensities of part-time employment

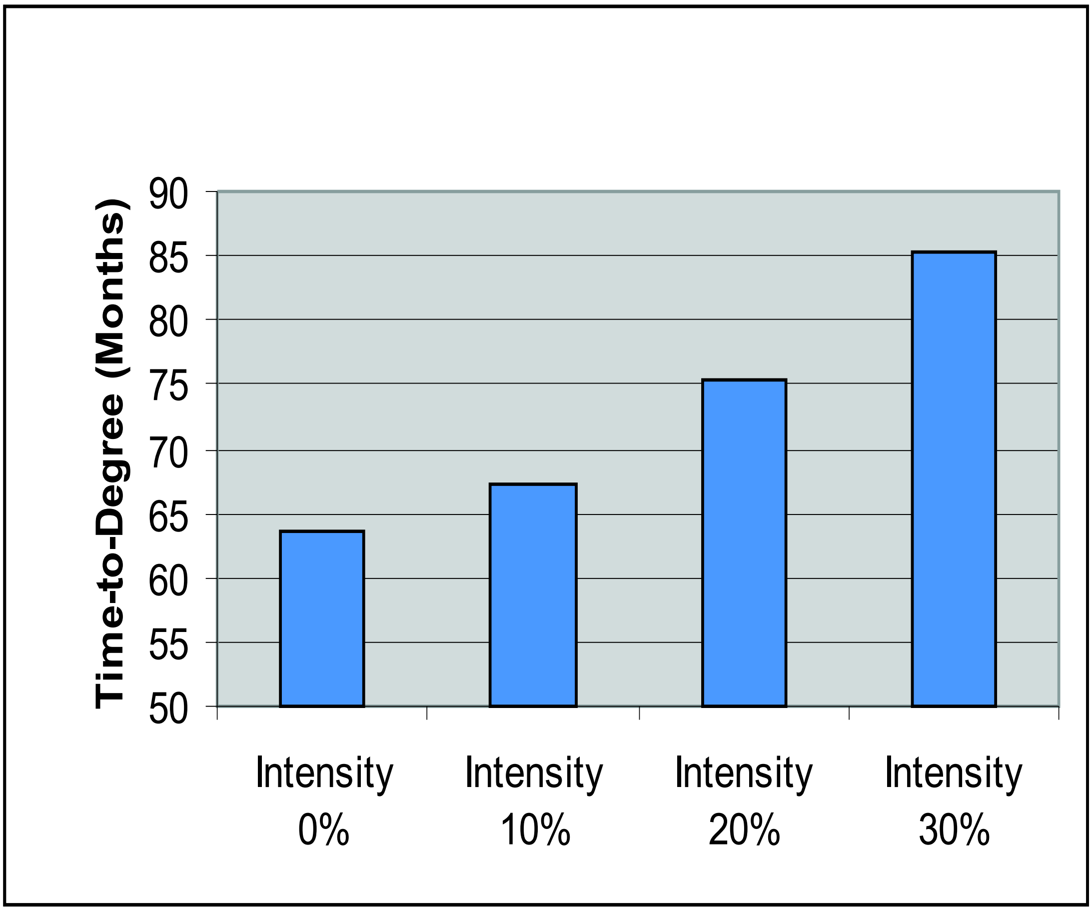

Figure 4.8: The expected time-to-degree for different intensities of full-time employment.

Table 5: Calculation of the Hazard Rates

Variable	**Hazard Rate** (Semiparametric)	**(Hazard Rate)** (Nonparametric)
fullworkterm	0.0478345***	0.0508501***
partworkterm	0.3332468**	0.3451808**
age	1.002487	1.002474
child1	0.4260842	0.4380346
male	0.6801938	0.6864206
motheredu_low	0.9170217	0.9118596
fatheredu_low	0.5793052**	0.5832302**
Startyear	0.9694272	0.9676422
nounioth	4.069258***	3.857571***
nounisocsci	2.585281	3.038413
nounieng	2.171704	2.082147
nounilaw	3.207593**	3.074202**
nounimed	15.57928**	12.70211**
unimed	4.190263**	4.189054**
unihum	4.859911***	4.807988***
unisci	2.366516**	2.322605**
unilaw	3.746169***	3.675249***
unieng	2.81197*	2.71949*
unisocsci	5.95642**	5.480844**
unioth	4.80414***	4.597003***
durat1	0.000334***	0.0003493***
durat2	0.0053024***	0.0076519***
durat3	0.010265***	0.0125918***
durat4	0.012273***	0.0233059***
durat5	0.0210926***	0.0205997***
durat6	0.0259723***	0.0308412***
durat7	0.0184904***	
durat8	0.0251796***	
durat9	0.0308118***	

Both regression are based on 13,449 observations. For the NPMLE, I use four mass points.

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 6: Controlling for Endogeneity with IV

Variable	**Coefficient**
partworkterm	27.301
fullworkterm	61.247**
age	0.011
male	-2.170
unidegree	1.802
Startyear	-1.260
child1	16.142
fatheredu_low	13.422**
motheredu_low	1.202
Medicine	-4.932
Humanities	1.370
Science	12.485
Law_Econ_Admin	1.025
Engineering	9.702
Social_Science	-8.452
Intercept	61.335*

Significance levels : $*$: 10% $**$: 5% $***$: 1%