EDUCATION VERSUS EXPERIENCE IN THE IT SECTOR OF UKRAINE. ON THE COSTS AND BENEFITS OF COMBINING WORKING AND STUDYING

by

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Abstract

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The Information Technology sector is becoming more and more important in the Ukrainian economy. Ukraine has the advantage of cheap labor and a strong school of quantitative sciences and has become a leading outsourcing destination. In this paper we look at key determinants of wages of the IT sector employees, which were growing at a very fast pace over the recent decade. Using a unique dataset we determine if education, work experience or a combination of both results in a higher wage. An instrumental variable regression is used in addition to a standard OLS regression. We find that work experience is a very significant determinant of future wage, with an average increase of 39.5% for the first year of experience and 16.1% and 12.7% increase for the second and third year of work experience respectively. While education by itself happens to be insignificant for IT sector workers, working in the IT sector and studying at the same time results in even higher benefits, compared to the case when a person only works. We conclude that there is some complementarity between the educational system and work experience and suggest that education should be beneficial to the future wage, if you start working early.

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GLOSSARY

DOU (DOU.UA). The largest IT sector workers community in Ukraine, previously known as developers.org.ua

IT. Information technology

IV. Instrumental variable

Outsourcing (Offshore software R&D). Outsourcing in IT is defined as developing software in countries, geographically remote from client company.

QA. Quality analyst

Tenure. Work experience in current workplace

Chapter 1

INTRODUCTION

Though being a big country with ample resources, Ukraine does not have a comparative advantage in a large number of industries. The information technology sector is one of few exceptions. In Ukraine, this sector was valued at about US $3 bn. in 2011 (Deloitte, 2012) with a growth rate of 35% in 2011. Outsourcing[1], in particular, was valued at about US $1.2 bn. in 2011 and was growing at even higher (than the IT sector on average) rate of 40%. Moreover, Ukraine is currently a leader of the industry in Central and Eastern Europe. While most analytics predict a bright future for the industry, an acute problem has emerged – the Ukrainian educational system cannot provide a foundation for the sustainable development of the IT sector. With more than 30,000 workers only in outsourcing, sustaining recent industry growth numbers of 30-40% will require an immense number of newcomers to the industry. The shortage of IT professionals is constantly increasing and has already reached hundreds of positions, with only the largest companies[2] each having several dozens of open vacancies at the moment.

Two main forces will be responsible for narrowing the gap between supply and demand of labor in the sector. Firstly, salaries of IT specialists will continue to increase, as they have been over recent years. Salaries of Ukrainian labor in the sector have significantly increased from an average of only 500 US dollars per month in 2005 to more than 1500 US dollars in 2011 (Computer Weekly, 2011; Forbes, 2012) and 1900 US dollars by the end of 2012 according to the survey

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1 Outsourcing in IT is defined as developing software in countries, geographically remote from client company. Offshore software R&D is another term, often used in this context.

2 EPAM, Luxoft, SoftServe, GlobalLogic, etc.

conducted for this research (see Chapter 3 and Appendix for more details on this survey). And while workers benefit from such a considerable rise, the Ukrainian outsourcing industry starts losing its competitiveness. The second force of adjustment is the increasing supply of labor in this sector. More and more students are considering a career in IT these days and a number of IT departments in universities and specialized IT courses have multiplied lately. While the demand for this specialized education is rather high, it is not unambiguously clear what type of education has the highest benefit for IT specialists. It could be the case that formal university education has the highest effect on the future wage, but it could be also the case that non-formal on-the-job training is more important in this sector. It is also possible that self-education has a significant effect on the salary of an individual.

There are several objectives in doing this research. One of the paper's purposes is to find if higher education in Ukraine can provide the skills considered as essential and valuable for working in the IT sector. We want to see if obtaining higher education will result in higher future wage in the IT sector. The result obtained can assist policy-makers in determining possible directions for educational development in the sector: provided that education appears to be insignificant for the future wage, a strong demand for a future thought-out educational reform is evident. In this case the educational plan should include more courses that can somehow substitute/compliment work experience.

Currently, many students in Ukraine start working while still being enrolled in a university. Clearly, such strategy can result in lower quality of the education but will result in higher work experience. Thus, the net effect is ambiguous.

So, in this paper we also want to see what the net effect of working while studying is and if students will benefit from such an approach. If we find the evidence that work experience during studying increases future wage, future educational programs should be reconsidered to include some kind of practical sessions jointly with private companies. This can somehow compensate the lack of real work experience for many graduates.

The current literature has a significant amount of research on the effect of experience and schooling on wage. Yet, the effect of combining the two has not been in the focus of academic works. In this paper we want to add to the existing academic literature by studying the effect of working and studying at the same time. As already argued the effect is not unambiguous and determining the effect would expand current knowledge on the topic.

The role of education and human capital in determining wages was developed in seminal works of Mincer (Mincer, 1958, 1974) and Becker (Becker, 1962). They noticed that wages were highly dependent on the level of previous training and learning a person acquired. In this research we want to estimate how previous learning and training influences wages in the IT sector. And at first, we need to distinguish between different types of learning. According to the main classification (OECD definition) the learning process can usually be divided into three main types – formal, non-formal and informal:

- Formal learning is regarded as learning provided by educational institutions leading to certification. Here we mostly focus on education provided by different universities.

- Non-formal learning occurs in formal learning environment but with no formal recognition. These could include IT seminars, workshops or short subject courses. A person with higher working experience is also more likely, on average, to have broader non-formal education.

- And the last but not least is the informal education, which can be very significant for IT skills. These could include participation in open-source programming, working on own projects, reading subject-specific materials, etc. In this paper we measure informal education as the amount of self-education of a person.

Using the methodology of Mincer's wage regression, we can estimate how wages in the industry are influenced by different forms of education of IT employees, as well as by work experience in the sector. Using data from the recent Ukrainian online-survey[3] of IT sector specialists conducted by DOU.ua[4] we try to estimate the effect of formal education, self-education and experience on wages of IT personnel.

The main regression is a 2SLS instrumental variable regression where we use a dummy of parents working (or being educated) in the IT sector, as an instrument for education. The age of the first computer program written is used as a proxy for ability. We also run an OLS regression additionally to the IV estimation.

Our results show that education is, on average, not significant for the IT sector workers. Both OLS and IV regressions result in non-significant coefficients for education. Work experience is much more important for this sector with an average increase of 39.5% for the first year of experience and 16.1% and 12.7% increase for second and third years of work experience respectively. This means that educational system of Ukraine in general is currently not capable of providing the skills which can be most useful for the IT sector employment. Thus, most graduates start learning almost from scratch at their working place

[3] The survey is held in May and December of every year since December 2010. We will be using the data from the Dec 2012 – Jan 2013 survey, in which we have been able to include questions needed for this research

[4] DOU.ua is the largest community of the IT sector specialists in Ukraine. Currently, the number of members reaches 40,000 people

and future wage is on average not determined by the education obtained. At the same time, we do not distinguish IT education and other degrees due to the specification of the data. Thus, it can be the case that some good IT programs do exist in Ukraine, but they are not numerous enough in the data.

An interesting result is discovered in the case of an early career start (beginning of the career while still studying). The efficiency of education could decreases if a person works and studies and could result in lower wage in future. However, what this paper shows is that while education being insignificant in determining wage, combining studying with working can result in additional benefits. Every additional year of working and studying at the same time results in a 3% increase of the future wage additionally to the wage increase due to the higher work experience (39.5% for the first year of work experience). Thus, an early career start in the IT sector is a good strategy (in terms of future wage) for students even if it can result in a lower quality of education obtained.

The structure of the paper is the following. We proceed with the chapter on literature review. Next sections contain data description, empirical model, discussion of the results and conclusions.

Chapter 2

LITERATURE REVIEW

The importance of human capital in determining wages was primarily developed in the seminal works of Jacob Mincer and Gary S. Becker. The first ground-breaking paper (Mincer, 1958) introduces the model of how people are compensated for different levels of training (years of schooling). The next very important work in this field is Becker's research on the investment in human capital (Becker, 1962). The theoretical concept of returns to additional year of schooling is usually attributed to this paper. These papers are usually considered to be the ground-breaking works for the theory of human capital and a starting point for further research in the field, as well as for our paper.

The empirical background for our work is taken from Mincer's book (Mincer, 1974) where the well-known Mincer wage regression (Mincer equation, Mincer model) was first introduced. The model represents a regression of natural logarithm of earnings on the number of years of education and work experience in the labor market (also, experience squared was used in the original model).

Hundreds and thousands of papers were written using the above-mentioned wage regression and methodology, proposed by Mincer. The model is not perfect, though. Many researchers pointed out flaws in the methodology and possible ways of solving the problems. First of all, while deriving the model, some strong assumptions are used: no cost of schooling, no income tax, linearity of wage in schooling, etc. Evidence is provided that not all of these assumptions hold and this can greatly affect the estimates of returns to schooling (Heckman et al., 2006; Heckman, 2008; etc.). In particular, many works argued that the effect of schooling was not linear (Hungerford and Solon, 1987; Heckman et al., 1996).

There is also evidence that using Mincer's methodology on more recent data (US decennial censuses held after 1960) does not support the original conclusions, because of the changing wage structure[5] and/or imperfection of the original model (Katz and Autor, 1999; Heckman, 2003; Heckman, 2006). At the same time, Card and Krueger (Card and Krueger, 1992) conclude that earnings to education relationship is close to log-linear, with almost no differences comparing to the more advanced linear-spline approach. Moreover, the wage structure in the US is becoming more stable now, after a period of instability at the end of the previous millennium (Card and DiNardo, 2002). Considering other assumptions of the model, we should note, that the logarithmic form of wages was also chosen to be the most appropriate (Heckman and Polachek, 1974; Fortin and Lemieux, 1998).

In current study we are trying to explore the effects of education and experience on wages in the IT sector of Ukraine. Having data on different educational variables, experience and personal characteristics we can construct a model, similar to Mincer's regression. According to previous studies (Coupé and Vakhitova, 2011) returns to schooling are relatively low in transition countries and in Ukraine, particularly. The authors find that economic boom of 2003-2007 in Ukraine changed little, since returns to education remained low even after economic upturn. In our work, we will try to concentrate on the IT sector and see if returns to schooling are also low for this particular industry in Ukraine.

It is thought that success of the IT industry in Ukraine was mainly due to the high-skilled labor (CEEOA, 2010; Deloitte, 2012). But at the same time, the educational system in Ukraine has only few IT specializations with most IT employees having a math or engineering background (Ukrainian Hi-Tech Initiative, 2007). Modern computer technologies are rarely taught in the

[5] In US, particularly

universities and practitioners are almost never employed. Future specialists are often selected by IT companies because of high creativity and analytical skills rather than computer science knowledge (Ukrainian Hi-Tech Initiative, 2007). Thus, nowadays, education itself, rather than providing information about IT skills of an individual, might represent a sign that a person is eligible for work in the sector.

At the same time, a shortage of IT specialists in Ukraine is predicted to be one of the main trends in the industry for the next decade (CEEOA, 2010). This can be another reason why educational reform is needed for the IT sector. And while some reforms (improvement of IT education, attraction of youth to the IT industry and matching education to the needs of IT labor demand) are currently in development specifically for this sector, no major changes are seen up to date (Ukrainian Hi-Tech Initiative, 2012). As already mentioned, practical skills are not typically taught in universities in Ukraine. It is likely that lack of such skills in formal education could result in lower skills of graduates pursuing work in the IT sector. In current work we also want to estimate if working (in the IT sector) and studying at the same time can result in future benefits in wage for an individual, even after accounting for extra effect of additional work experience. If this happens to be true, we can argue that more practical skills similar to those acquired during working are essential to be added to the curriculum of Ukrainian universities.

The effect of non-university formal education, such as certifications and trainings, is usually associated with positive effect on wage for IT sector workers. For example, Vakhitova (2006) finds a positive wage premium associated with Microsoft IT certification. And Borghans and Haelermans (2012) find positive effect of on-the-job trainings on wage.

Since formal and non-formal education can only partially explain the difference in wages of employees we also want to focus on the effect of informal education. Loewenstein and Spletzer (1994) looked into the effect of different measures of both formal and informal training. They found positive and significant estimates with the effect of informal training being even higher than for formal training. Rather than assessing the effect of informal training, researchers often discuss why people participate in informal training. Generally, a positive correlation between the level of schooling and investment into informal education is found (Fahr, 2005). This paper also finds a positive correlation between the time spent on reading technical literature (which in this case is considered as informal education) and wage. There is a scarce amount of works on this topic, which is probably due to the number of problems that arise while assessing the effect of self-education on wage. A major problem that arises here is the subjectivity of assessing the number of hours spent on self-education by survey-participants. The results of such bias will be discussed in the following chapters.

Therefore, by doing this research we want to add to the existing knowledge by answering three different questions. First of all, we want to see if formal education can affect future wage of an IT sector employee in Ukraine or in other words – if education matters for determining future salary. Then we want to see if it can be beneficial for a person to start his work in the IT sector before graduating. In this way a person may not only acquire more work experience, but also can possibly gain from an early carrier start. And lastly, we want to see if the effect of self-education is significant in determining wage. While mostly the results are relevant to the case of Ukraine, we can possibly conclude on similar effect in countries with similar state of education and IT sector (such as Russia, Belarus, etc.).

C h a p t e r 3

DATA DESCRIPTION

The data for this research were collected in a joint project of the author and DOU.ua – the largest community of IT specialists in Ukraine. An online survey is held semiannually by this community since December 2010. The last round took place in late December 2012 – early January 2013. Additional questions of our interest on education and on personal characteristics were incorporated into the survey specifically for this research. More details about the survey are available in the Appendix.

The sample was the highest of all surveys by DOU, with data having more than 4100 observations (the May 2012 survey was filled by 3500 participants). The survey also includes standard questions, usually asked by DOU, such as wage, position, company size, city, etc.

Of course, some selection bias may appear because the survey is conducted by a single community through the online survey. Still, it is reasonable to assume that all IT specialists use Internet and DOU.ua is the largest, and probably the only considerable IT community in the Ukrainian web space. The survey was advertised extensively and it was hard to miss the announcement. Thus, we have two possible selectivity biases. The first one is connected with the fact that only active members do fill in the survey. And the second bias can be connected with the fact that the survey is filled more by people who possess more free time and, thus, are likely to have lower wage.

To address these problems we compare the results obtained by other IT sector surveys in Ukraine or other types of data. For example, different descriptive statistics can be obtained from Ukrainian recruiting agencies reports. One study held in the first half of the year 2012 (IT Catalogue, 2012) shows a similar wage structure in the IT sector even after looking into the specific categories. While the size of the sample in this survey is not known, the differences in wages for the main categories are minor when comparing to our data. For example, the difference in wages of business analysts, system administrators and designers between this survey and our data is around 10%. At the same time the IT Catalogue survey shows about 10% to 15% higher salaries for QA Engineers when compared with the relevant May 2012 DOU.ua survey and 5% higher salaries for Java Software Engineers (see Table 2 for precise numbers). The higher numbers for these positions can be attributed to the fact that the IT Catalogue survey was based on salaries for open positions, which usually provide slightly higher salaries than industry average ones due to the high growth of the sector. Current workers are usually bound by a contract and do not have the same bargaining possibilities in the short-term as new workers do.

Another survey of the year 2011 held by a recruiting portal (Rabota.ua and Luxoft Personnel, 2011) is not easily comparable in terms of wages. While this survey was also held in 2011, it corresponds to average salaries for 2011, but not for December 2011 salaries, as the relevant DOU data do (and is not perfectly comparable because of a high rate of salary growth in the sector). Yet, it shows almost the same distribution of age and positions in the IT sector in Ukraine as our survey does (see Table 3 for precise numbers). Thus, while the bias can still occur because of the selection process, there is some evidence that survey results are consistent with the previous data.

Of course, all surveys on salaries can be biased in the same way, but a population survey for this sector is not available in Ukraine. Since the studies mentioned earlier are sometimes based on the data from recruiting agencies (which collect data from open vacancies and employees demands), we can assume they are free from the bias which our data can have. No doubt, other problems can arise for this type of research, such as small sample size, mismatch between the actual wage offered and the wage reported in the vacancy, mismatch of wages of current workers and those applying for a new job, etc. And while the difference between salaries of the available report (IT Catalogue, 2012) can be argued to be slightly dissimilar from our data, the difference is not zero. Certainly, obtaining actual data for this sector is arguably impossible, considering the fact that most workers of the IT sector in Ukraine are not employed according to all official legislations and thus, the population data is impossible to obtain. According to our knowledge, the data we use is the largest, most recent and most complete dataset of individuals working in the IT sector in Ukraine.

The data collected include the following information to be used in the regression: person's net wage (after taxes), age, position, programming language used (for relevant positions), work experience, tenure (work experience in current workplace), education level, English level competence and awareness, city of employment, size of the employee's company. We also have information about the amount of hours a person spends on self-education during a month and information about the period of time a person was working (in the IT sector) and studying at the same time if it was the case. Finally, we know that if at least one of the person's parents was ever employed in the IT sector or educated as an IT specialist (this information is to be used as an instrumental variable in our regression) and the age of the first computer program written (as proxy for ability).

Experience variable is given in the following way. If work experience is between 3 month and 10 years, a discrete variable (with a segmentation of 3 month – for example, 6 years and 9 month, or 1 year and 3 month of work experience) is used to denote experience. If experience is less than 3 months, a dummy variable is used. Also, if work experience is larger than 10 years, another dummy variable is used to denote work experience. The same can be said about the tenure variable, which is identified in an identical way.

Here we need to mention the issue considering the collected data. Since specific IT education (such as, for example, bachelor or master in Computer Science) is currently only beginning to develop in Ukraine on a large scale and most employees of the sector have technical or math background, no distinction was made in the field of the obtained education. In other words, the education variable can refer to the background in any major and not only IT related spheres. Respondents were asked what education they had. According to the Ukrainian law, a person is obligated to obtain secondary education. So, possible options included secondary education, unfinished degree (or still in the process of obtaining a degree), master degree, two higher educations and PhD.

In regressions a discrete variable of years of schooling was used to denote education, which was approximated by the average number of years it takes to obtain each of the degrees mentioned above. This approximation was done in order to have the ability to use instrumental variable for education, as discussed in the methodology section. Since this estimation may not be perfect, we have also used current dummy variables in the similar regressions to make a robustness check. All our conclusions appeared to remain the same and thus, such approximation should not bias the inferences of this research.

The variation of all variables is substantial. About 47% of all respondents are employed in Kyiv, with the second largest city for the IT sector being Kharkiv with about 16% (See Figure 1 for details). Wage distribution can be seen in Figure 2. Average net (after tax) salary in the sector is close to US$ 1900 per month after taxes, with an average wage in Kyiv of about US$ 2200 per month (the highest average among Ukrainian cities). The age of participants is distributed between 16 and 57 years with a mean of about 27 and standard deviation of 4.4, meaning that most employees in the sector are young professionals. About 81% of respondents already have higher education, with 17% still in the process of studying (or having dropped out before finishing university). Almost 95% of respondents report to have the English language level higher than elementary, with more than 40% reporting the advanced or higher than average level.

About 31% of the sample didn't combine studying and working in the IT sector. At the same time, 17% simultaneously worked and studied for three years or more.

Due to the exclusion of females from regressions (we focus on the regressions for males only since there are only a small number of females in the sample) and some missing observations on our instrumental variables the final dataset to be used in the regression consists of 3386 observations.

More detailed descriptive statistics is available in Table 1.

Chapter 4

METHODOLOGY

In the paper an augmented Mincer model regression is used. The regression equation has the following form:

$$\ln(w_i) = a + \mathbf{B} \cdot \mathbf{X}_i + \mathbf{C} \cdot \mathbf{E}_i + \mathbf{D} \cdot \mathbf{Educ}_i + e_i \quad (1)$$

where

w – wage,

X – matrix of employee characteristics, including experience, the second order polynomial of experience, tenure, position, age, level of English language competence

E – matrix of employer characteristics, such as city, size of the company

Educ – matrix of educational variables, including formal (university) education, time spent on self-education, and the time-period, when a person was studying and working at the same time.

This functional form goes back to Mincer's work on returns to schooling (Mincer, 1974). As in Mincer's paper we also use the logarithm of wage, years of schooling, work experience and work experience squared. We also add additional explanatory variables which include tenure, position, age, etc. A proxy and an instrumental variable are used to increase the accuracy of estimates.

An endogeneity problem can appear in the classical Mincer regression. The first reason for this is that ability is typically an omitted variable. To decrease the possible bias because of the omitted ability we use a proxy variable for ability. Respondents were asked at what age they had written their first computer program. We think that this information can be correlated with their ability (and talent) to work in this sector and so, can be used as a proxy for ability.

Also, a problem can arise in the case of reverse causality of wage and studying. When a person works and studies at the same time, a high wage is likely to influence him to drop out of the university. To address this issue we are going to use an instrumental variable. In the survey, respondents were asked if at least one of the parents is/was working in IT sector or had education connected with the sector. In this case, parents can influence the decision of a person to continue studying either because of the pressure of getting a degree or because of higher wealth of the family. We also assume that parents' education should not be correlated with the error term (that is, there is no compelling reason for parents' education to affect a person's wage except through its effect on the person's education). And thus, this variable could be used as an instrument of our variable, responsible for education.

Thus, we use a 2 SLS Instrumental Variable regression in this paper. We also run a usual OLS regression to check if our results will be also consistent in this case.

To check the power of our instrumental variable we run first step of instrumental variable regression. The first step is to regress the endogenous variable (education) on all explanatory variables and the instrument, which in our case is parents' education/work in the IT sector:

$$\text{Education} = a + \beta * Instrument + \mathbf{B} \cdot \mathbf{X}_i + e_i \tag{2}$$

where $\mathbf{X}_i$ is the matrix of all exogenous variables.

The output of the regression and corresponding tests are given in Table 6. The R2 of this regression is 15% and the instrument is significant at 10% significance level, but not at 5% (p-value is 0.075). Tests for the first stage of the 2SLS regression (reduced form equation estimation) suggest that the instrument is either weak or marginally weak. This is why finding a stronger IV would be beneficial for further research on the topic.

As already mentioned, we also run a simple OLS regression. It appears that all of the inferences remain the same for the case of simple OLS and 2SLS IV regression.

Chapter 5

RESULTS

We start by performing a simple descriptive analysis for mean wage for different educational categories. The results are given in Table 4. Having secondary education or two diplomas of higher education appears to be statistically identical to having a higher education in terms of wage. At the same time, those with higher education earn less money than those with a PhD and more than those who are still studying. We also perform a descriptive analysis for mean wage for the different amount of work experience (Table 5). In this case a clear pattern is obvious. More work experience result in higher wage and all results are highly significant.

Thus, while such a simple analysis provides us with some conclusions we now start from deeper analysis by using IV and OLS regressions which includes other explanatory variables and should yield more robust results.

As mentioned in the previous section we use the instrumental variable regression to determine the effect of education, experience and other variables of interest on wage. We also use the age of the first computer program written as proxy for ability and parent's education or work in the IT sector as an instrumental variable for education (see Chapter 4 for more details). Other variables included into the regression include experience, education, tenure (work experience at current workplace), age, amount of time spent on self-education, position (and programming language for relevant positions), city of employment, size of the company of employment and English level competence. We also include the variable responsible for overlap in working and studying. This variable is measured as a period of time during which a person was studying at a university and working in the IT sector.

The 2SLS regression output can be seen in Table 7. There are 3386 observations in this regression and the R^2 is 56%. We also provide the output of a simple OLS regression in this table.

As can be seen from the output table, education is found to be not significant. The same result holds if we include education as dummy variables for a particular degree (as it was asked in the survey, see Chapter 3 for more details) and not as an average number of years studied. See Table 8 for the results of this regression. Thus, education effect on future wage appears to be insignificant.

Contrary to education, experience effect is highly significant both statistically and economically. Experience also has a diminishing effect. The first year of experience in the IT sector adds on average 39.5% to wage. This includes the fact that those, having less than 3 month work experience have on average 16% less wage, possibly because of probation periods, internships, etc. The second and third years of experience result in 16.1% and 12.7% wage increase respectively. The diminishing effect becomes prevailing after 7 years of work experience. See Figure 3 for the graph of work experience effect on wage.

Thus, work experience appears to be highly significant both economically and statistically. At this point, working in the IT sector happens to be more beneficial for future wage than studying. The effect of tenure, depending on regression, appears to be either insignificant or small. The only significant variable is the dummy, corresponding to less than three month tenure. It is significant at 5% and positive, meaning that company newcomers are likely, in average, to get a slightly (about 7%) higher wage, possibly due to the constant high pace growth of the sector.

At the same time, while education appears to have insignificant effect on wage, coefficient on combining studying and working is highly significant and positive in all regressions. On average, every year of combining studies and work in the IT sector results in a 3% wage increase. Since this gain adds to the usual work experience increase, a person who combines work and studies will receive a higher wage comparing to those who only work or those who only study. This finding can be probably attributed to the fact that those, who work and study at the same time learn better how to manage their time due to the higher work load. They can also extract only the most important things from their studies and concentrate on the most useful subjects, since they have some insights of what is important in the IT sector.

Several conclusions can be made from these results. First, education in Ukraine in general cannot independently provide the skills valued by employers. As mentioned in Chapter 2, education has become more like a signal that a person is eligible for work in the sector rather than an indicator of person's knowledge. This suggestion was concluded by another implication from our data: it appeared that while small companies (less than 10 people employed) account for about 22% of all employees, they employ about 45% of those with only secondary education. This suggests that while education does not affect your wage if you are already in a particular company, having a degree may increase your chances of getting a job in a larger company. According to our data, people employed in companies with 50 to 100 employees are paid, on average, 8% more than those working in companies of 10 to 50 employees and 17% more than those working in small companies with less than 10 employees. The difference between wage of employees working in companies with 50 to 100, 100 to 200, 200 to 1000 and more than 1000 employees appeared to be statistically non-significant. Thus, having a degree actually may aid you in getting a job in a larger company but your wage there would be the same as of your co-workers with no degree.

At the same time this means that while education itself does not provide you with the additional benefits for work in the IT sector, it is still beneficial to get a degree if you also start your work working in the IT sector as early as possible. Such strategy can result in the highest future benefits for your wage, suggesting some complementarity between the educational system and work experience, if you combine these two at the same time.

Figure 4 illustrates a relative increase in wage for several possible scenarios. The most beneficial scenario is studying and starting to work from the beginning of the studies. If we assume that higher education will be completed in six years, wage after graduation should on average be 253% higher comparing to the one before entering the university. Just working for the same six years will result in 217% increase in wage. Studying for two years and starting work only in the third year of education will on average result in 221% higher wage, which is even more than in "only work" scenario. Since education appeared to be non-significant in our analysis, concentrating only on studying will not increase your future wage. Clearly, combining work and education is very beneficial for future wage, even in the case of a later career start (like in the case of working from year 3). Many Ukrainian students follow exactly this scenario. They start combining work and studies after few years of studies at the university. Our findings suggest that this strategy should be helpful and not chosen randomly. It helps not only make both ends meet during the studies but it is also likely to be beneficial for future salary.

Coefficient of self-education (monthly hours spent on self-education) appeared to be insignificant in every regression. Such inference is opposite to common knowledge that time spent on self-education is beneficial for wage and career growth. This result can be explained by the data issues connected to the question of self-education. People were asked to assess how many hours a month they spent on self-education. Even though some explanation was given about how to define self-education (time, spent on reading technical literature; studying programming languages; etc.), the definition was not complete. Many people skipped this question and many gave the answer not comparable to the number of hours in a month. So, there is some evidence that people did not treat this question seriously and we have received errors in our variables. If errors were random, attenuation bias appears, thus diluting coefficients towards zero.

Another variable, which appeared to be highly significant and positive, is English language competence and awareness. Those, who claim to have advanced English level competence on average, receive 11% more than those, who claim to have higher than average level, 21% more than those with average level, 32% and 54% more than those, who have lower than average and elementary levels respectively.

Chapter 6

CONCLUSIONS

The growth of wages in the IT sector of Ukraine was tremendously high over the recent decade. This is why, the importance of investigating the factors that determine wages in the sector is higher than ever. This study looks at several possible determinants of wages.

First of all, previous work experience appears to be the most significant factor that determines your wage in this sector. On average, the first year of experience in the IT sector adds 39.5% to the current wage. This additional effect is diminishing and both the second and third year of experience result in 16.1% and 12.7% wage increase respectively. At the same time, the effect of tenure appears to be either insignificant or very small.

Secondly, while education appears to be insignificant on its own, the effect of working in the IT sector and studying at the same time appears to be significant and positive. We conclude that there is some complementarity between the educational system and work experience. On average, every year of combining studies and work in the IT sector results in a 3% wage increase. Figure 4 illustrates a relative increase in wage for several possible scenarios. Clearly, the most beneficial strategy, in terms of future wage, is studying and starting work in the sector as soon as possible.

Informal education, measured as self-education (time, spent on participation in open-source programming, reading subject-specific materials, etc.) was found to be insignificant, possibly because of errors in variables that determine self-education. English language competence and awareness in contrast are highly significant and positive, with those who claim to have advanced English knowledge earning, on average, 54% more than those with elementary level.

We have also run a simple OLS regression in this work. While the relative size of coefficients slightly changes in case of OLS regression, significance and signs of coefficients remain the same, and thus, our inferences do not change.

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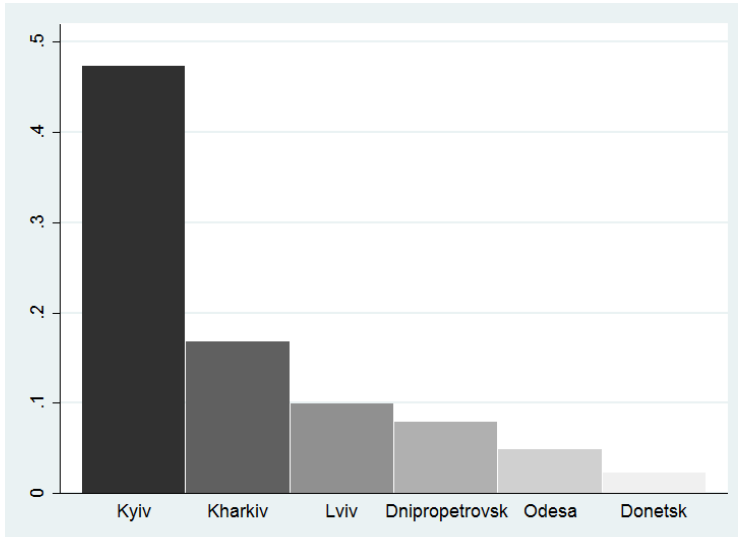

Figure 1: Distribution of IT sector workers by main cities

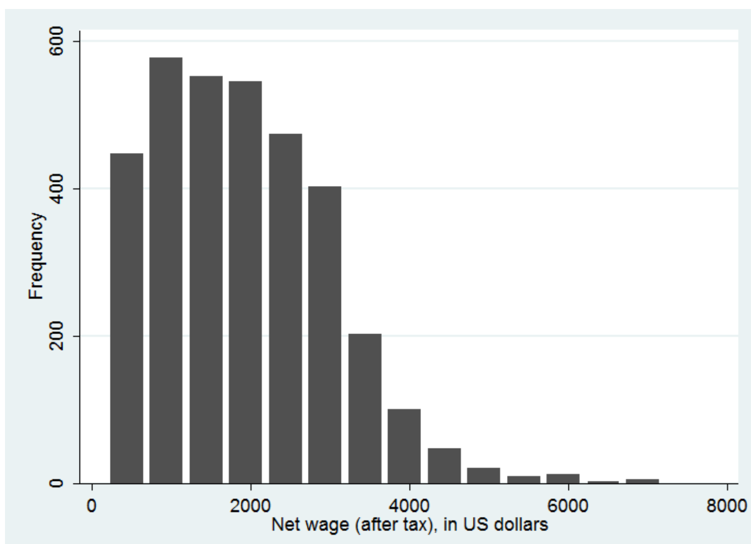

Figure 2: Distribution of wages in the IT sector, US $

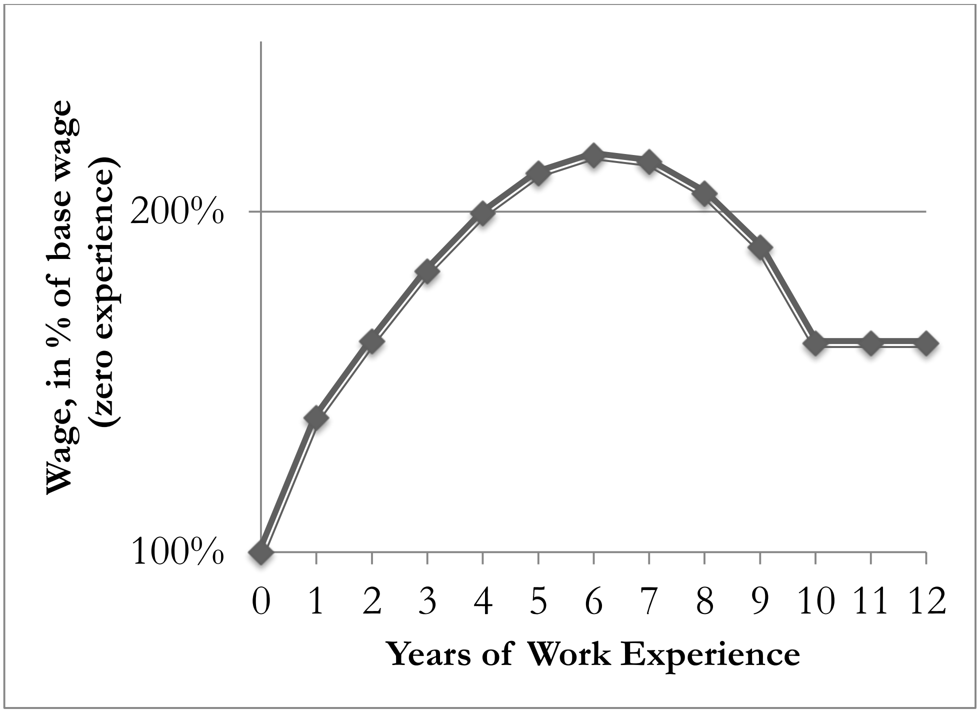

Figure 3: Effect of work experience on wage

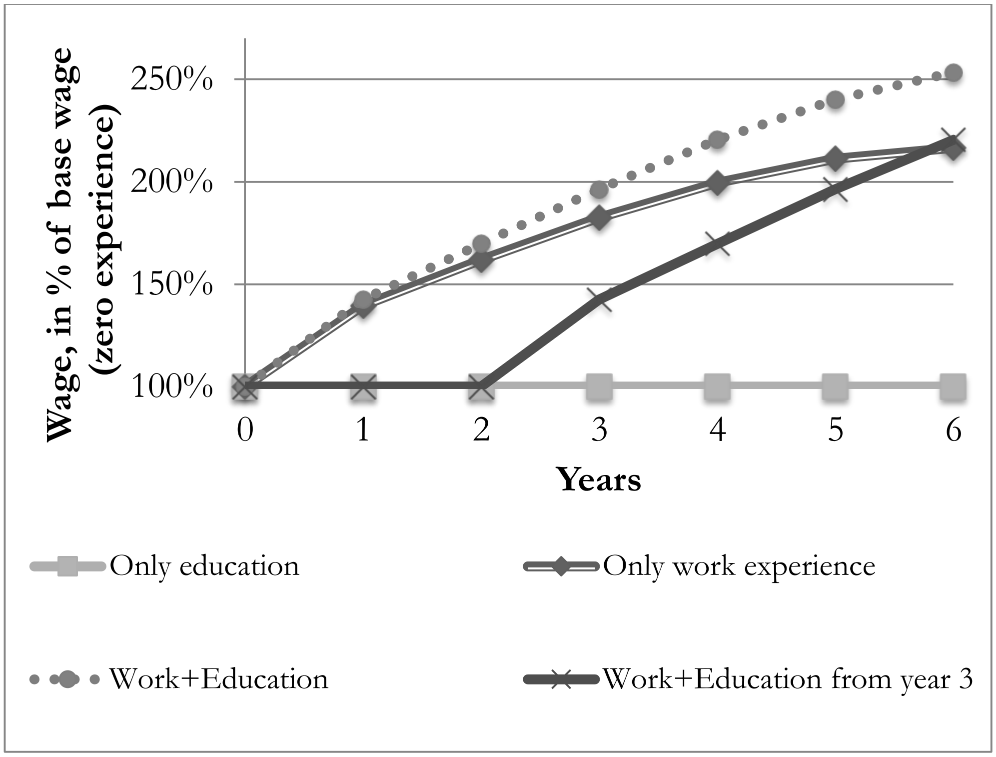

Figure 4: Wage path for different work/education scenarios

Table 1 Descriptive statistics of the dataset

Variable	Mean	Std. Dev.	Min	Max
Wage (US $, net)	1891.04	1081.32	200	7000
Experience	3.40	2.50	0	9.5
Experience < 3 month†	0.02	0.13	0	1
Experience ≥ 10 years†	0.08	0.28	0	1
Tenure	1.69	1.66	0	9
Tenure < 3 month†	0.09	0.28	0	1
Tenure ≥ 10 years†	0.01	0.09	0	1
Age	26.69	4.41	16	57
Education (Constructed variable) *	13.61	1.09	10	17
Education (Categories)	**Mean**			
Secondary	0.03			
Higher	0.73			
Unfinished higher	0.17			
Two educational degrees	0.05			
PhD	0.02			
English Language	**Mean**			
Elementary	0.05			
Lower than Average	0.18			
Average	0.38			
Higher than Average	0.30			
Advanced	0.10			
Number of observations in the dataset				**3386**

† Dummy variables

* Constructed from categorical variable using the average amount of years needed to obtain the corresponding degree: 10 years for secondary education, 14 years for both higher and two degrees (since there is no significant difference between them according to descriptive analysis), 17 years for a PhD, 12 years for unfinished higher education (average between secondary and higher).

Table 2 Relative difference of salaries on selected positions between IT Catalogue May 2012 survey and relevant May 2012 DOU.UA survey

	IT Catalogue (May 2012)		**Relevant DOU.UA Survey (May 2012)**		**Difference***	
Net Wage, $	Kyiv	Ukraine	Kyiv	Ukraine	Kyiv	Ukraine
Business analyst	$2 768.00	$2 255.00	$2 717.00	$2 475.00	2%	10%
System Admin.	$1 468.00	-	$1 590.00	$1 613.00	8%	
Designer	$1 883.00	$1 599.00	$2 105.00	$1 604.00	12%	0%
QA Engineer	$1 929.00	$1 672.00	$1 763.00	$1 441.00	9%	14%
Software Developer (Java)	$2 556.00	-	$2 435.00	$2 017.00	5%	

* Relative difference in absolute value

Table 3 Relative difference of selected descriptive statistics between Rabota.ua Luxoft Personnel 2011 Survey and relevant Dec 2011 DOU.UA survey

	Rabota.ua/Luxoft Personnel Survey (average 2011)	**Relevant DOU.UA Survey (Dec 2011)**	**Difference***
Share of QA specialists	9%	10%	11%
Share of C/C#/C++ Dev.	17%	21%	24%
Share of Web Dev.	16%	13%	19%
Share of developers of age <20	3%	2%	24%
Share of developers of age 20-25	45%	41%	9%
Share of developers of age>25	52%	55%	6%

* Relative difference in absolute value

Table 4 Descriptive analysis. Education

Education	Mean Wage	t-statistic†	Significance
Secondary	$1 830.57	1.52	
Higher	$2 001.79	-	
Two Higher	$1 976.33	0.25	
Unfinished Higher	$1 347.70	15.07	***
PhD	$2 269.00	2.28	*

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

† T-statistic of a hypothesis that difference in mean with the comparison group is zero. Comparison group is Higher education.

Table 5 Descriptive analysis. Work experience

Work Experience	Mean Wage	t-statistic†	Significance
< 3 month	$646.40	5.03	***
1 year	$1 046.26	-	
2 years	$1 390.57	5.04	***
5 years	$2 272.85	16.01	***
> 10 years	$2 993.37	21.69	***

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

† T-statistic of a hypothesis that difference in mean with the comparison group is zero. Comparison group is 1 year of experience.

Table 6 First step IV regression

Education		OLS[6]
IV (parents' education)		0.071
	s.e.	0.040
	p-value	0.076
Work Experience		0.138
	s.e.	0.036
	p-value	0
Work Experience Squared		-0.016
	s.e.	0.004
	p-value	0
_cons		11.531
	s.e.	0.293
	p-value	0
F(72, 3313)		8.3400
Prob > F		0
Centered R^2		0.1534
Uncentered R^2		0.9947
F test of excluded instrument p-value		0.0758
Angrist-Pischke multivariate test of excluded instruments (F) p-value		0.0758
Angrist-Pischke (χ^2) test p-value		0.0726
Anderson LM statistic (Underidentification test) p-value		0.0727
Cragg-Donald Wald F statistic (Weak identification test)[7]		3.1500
Weak-instrument-robust inference. Anderson-Rubin Wald test (F) p-value		0.2167
Weak-instrument-robust inference. Anderson-Rubin Wald test (χ^2) p-value		0.2116
Weak-instrument-robust inference. Stock-Wright LM S statistic p-value		0.2117
N		3386
R2		15.3%

[6] Other explanatory variables are omitted from current output

[7] 25% maximal IV size critical value is 5.53

Table 7 Regression coefficients

Ln(wage)		OLS	IV	-		OLS	IV
Education		0.003	-0.252	Parents in IT (IV)		-0.018	-
	s.e.	0.006	0.247		s.e.	0.014	-
Work Experience		0.194***	0.229***	Self-education		0.000	-0.001
	s.e.	0.013	0.037		s.e.	0.000	0.001
Work Experience Squared		-0.013***	-0.018***	Less than 10 employees†		-0.145***	-0.170***
	s.e.	0.001	0.004		s.e.	0.022	0.036
Experience > 10 years		0.681***	0.614***	10-50 employees†		-0.067**	-0.076**
	s.e.	0.045	0.085		s.e.	0.021	0.027
Experience < 3 month		-0.183**	-0.166*	50-200 employees†		-0.011	-0.041
	s.e.	0.056	0.069		s.e.	0.021	0.038
Tenure		-0.014**	-0.009	200-1000 employees†		-0.002	0.001
	s.e.	0.005	0.008		s.e.	0.023	0.028
Tenure > 10 years		-0.135	-0.131	Lower than average††		0.132***	0.214*
	s.e.	0.075	0.091		s.e.	0.034	0.090
Tenure < 3 month		0.084***	0.067	Average††		0.222***	0.325**
	s.e.	0.025	0.034		s.e.	0.032	0.108
Age		0.012***	0.031	Higher than average††		0.298***	0.430**
	s.e.	0.002	0.019		s.e.	0.034	0.135
Overlap (combining)		0.018***	0.030*	Advanced††		0.383***	0.536***
	s.e.	0.005	0.013		s.e.	0.038	0.156
First program		-0.005**	-0.003	cons		6.061***	9.342***
	s.e.	0.002	0.002		s.e.	0.313	2.709
N		3386	3386				
R^2		70%	56%				

* p<0.05, ** p<0.01, *** p<0.001

Explanatory variables for position, programming language and city (all dummy variables) are not included in the output.

†Number of employees in the company. Omitted category is more than 1000 employees

††Elementary English level competence is the omitted category

Table 8 Regression coefficients. Education as dummy variables

Ln(wage)		OLS	-		OLS
Higher[1]		-0.048	Tenure > 10 years		-0.133
	s.e.	0.039		s.e.	0.075
Unfinished higher[1]		-0.073	Tenure < 3 month		0.084***
	s.e.	0.416		s.e.	0.025
Two higher[1]		-0.069	Age		0.012***
	s.e.	0.484		s.e.	0.002
PhD[1]		-0.015	Overlap (combining)		0.02***
	s.e.	0.058		s.e.	0.005
Work Experience		0.192***	First program		-0.005**
	s.e.	0.013		s.e.	0.002
Work Experience Squared		-0.013***	Parents in IT (IV)		-0.018
	s.e.	0.001		s.e.	0.014
Experience > 10 years		0.680***	Self-education		0.000
	s.e.	0.045		s.e.	0.000
Experience < 3 month		-0.184***	_cons		6.166***
	s.e.	0.056		s.e.	0.313
Tenure		-0.014**	-		-
	s.e.	0.005	-		-
N		3386			
R^2		71%			

* p<0.05, ** p<0.01, *** p<0.001

[1] Secondary education is the omitted category. Education appears to be insignificant for every educational category in this case.

Explanatory variables for position, programming language, city, size of the company and English level competence (all dummy variables) are not included in the output.

APPENDIX: DOU.UA AND CURRENT SURVEY

DOU.ua is by far the largest IT sector specialist community in Ukraine. It consists of more than 40,000 of registered users and of much more anonymous visitors. Five semiannual surveys of IT sector workers were held by DOU since end of 2010. Having only about 1000 respondents in the first round, the survey was expanding rapidly, reaching more than 3000 respondent in May 2012. The first four rounds of the survey had about 10 standard questions like the city of employment, experience, size of the company, salary, etc.

In November 2012, about a month before the fifth round of the survey have been held, we contacted the founder of DOU and coordinators of the survey. After some negotiations, they kindly agreed to aid in the current research and add some additional questions of our interest. The main goal was to explore the effect of education in the sector. But another objective was not to make the survey overwhelming because it could result in a smaller sample.

The fifth round was held at the end of December 2012 – January 2013 and had more than 4300 respondents – the highest result among all the rounds. This round provided information on the following characteristics:

1) Current position

2) Programming language used

3) Specialization

4) General work experience

4) Tenure – work experience in current workplace

5) Net wage (after tax) in US$

6) Change in wage during 12 most recent month

7) City

8) Company size

9) Sex

10) Age

11) Level of education

12) English language competence

13) Web services, which a person uses on permanent basis

14) Period of time, when a person was both working in the IT sector and studying

15) Age, when the first program was written

16) Does at least one parent worked or studied in the IT sector

17) Time, spent on self-education