DETERMINANTS OF SALARY EXPECTATIONS OF UKRAINIAN JOBSEEKERS USING A FREELANCE DIGITAL PLATFORM

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Abstract

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Online job sector has been developing rapidly attracting workers from all over the world. Ukrainians appear to be among leaders in terms of workers involved in the freelancing and total hours worked, especially in the IT sphere. However, in a line with the availability of appealing opportunities, the freelance platforms are poorly regulated. In order to contribute to the issue of finding the proper policy intervention, this thesis investigates the question of the wage determinants of online jobseekers using the data from a digital work platform. The regression analysis suggests that the gender gap in terms of expected wage occurs for the older workers but remains insignificant for younger ones. In addition, wage expectations of the older cohort of freelancers are more sensitive to the economic factors of the living region. Apart from the above, online platform's distinctive features such as customer reviews on the freelancers' performance also seem to be important in wage setting.

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Chapter 1

INTRODUCTION

Digital job platforms form relatively new part of job market that has not been studied well. In contrast to regular jobs, digital ones provide workers with the opportunity to find and perform job online regardless of the location of the customer. This introduces new form of work that may substitute regular job or complement to it, either way benefiting workers by giving the opportunity to choose. Most freelancers decide on the number of hours they work, particular working time, place and conditions and set their own prices for the services. The concept comes to be especially interesting for Ukrainians as it opens borders towards the possibility to work for contractors from developed countries where wages are higher. The investigation into Ukrainian job market shows that Ukraine is placed first in Europe and the fourth in the world in "work on digital labour platforms" category. Moreover, Ukraine ranks first in the world in "IT freelance". According to the data, more than 3% of the Ukrainian workforce perform some online work (Aleksynska et al. 2018).

Availability and expansion of the online work affects economy of Ukraine but appear to be not regulated yet. Some freelancers suffer from lack of social securities like helplessness regarding contractor pay evasion or absence of insurance (Aleksynska et al. 2018). Moreover, freelancers from Ukraine mostly perform high-skill macro-tasks as opposed to workers from other developing countries mainly working on micro-tasks with little qualification needed. However, digital workers from Ukraine on average earn much less than the freelancers from the richer part of the world do even if they possess equal capability of performing the job. At the same time, number of digital workers increases and newcomers from Ukraine and other developing countries tend to enter the market with lower reservation wage causing the further fall. (Aleksynska et.al. 2019).

These and other possible issues should be encountered by the proper policy intervention. However, the entire system of online work should be analyzed in detail to be able to make corresponding regulations. Improving online working conditions will also positively affect overall workers' life satisfaction and may positively affect willingness to stay in Ukraine, lowering working population's urge to migrate. In the meanwhile, government may introduce proper tax system and social securities to benefit in the same manner as it does from the ordinary job market.

To contribute to the issues mentioned above, this research studies the questions of the determinants of the expected wages in the digital job market. The analysis of the observable patterns in the market may help to understand the piece of freelancers' decision-making process that lies behind setting the expected wage. Particularly, we analyze portion of Ukrainian freelance market concerning workers' expected wage, field of work, work experience, age, gender, location influence (GRP per capita and unemployment rate), amount of positive reviews and some other controls. To do so, the regression analysis suggested by general approach from literature is used. The results on such selection of variables suggest explanation of differences mainly occurred from the explicit qualities of a person rather than the analysis concerning all the possible implicit factors (preliminary wage, unemployment duration, education, personal preferences, possessed information about the market, etc.)

The findings may be useful for the policy making regarding improving digital working conditions by revealing the freelancers' wage aspiration patterns and magnitudes caused by observable changing (aging, increase in experience) and constant (gender) factors. Such information along with the description of the particular platform related to this study also may become helpful for employers by introducing possible substitutability between in-office workers and online freelancers. On its turn, workers may benefit as well by getting acknowledged about the possibilities and features of online work.

Digital-work-related literature is advancing rapidly and one of the most recent ILO paper written on March 2019 discusses the conditions freelancers have working online and questions of digital job matching in Ukraine. In a line with previous investigations, there already exists a well-structured discussion towards Ukrainian digital labor market. In this paper we complement existing literature by providing the regression analysis of observable determinants of the expected salary on the market.

The findings of this study are mainly in a line with the known features of the digital job market. The estimation results suggest gender expected pay gap. Portion of the difference in expected wages is explained by the work choice and age difference but some part remains enduring. Another concern that exists is age and its role on forming wage expectations, as generally in Ukrainian job market workers suffer from widespread age discrimination. The findings also show that this tendency lower expected wage of online workers as well. Additionally, it is evident that freelancers' amount of reviews received have positive and strong impact on their formation of the wage expectations. However, the effect is different among age groups being stronger for the older cohort. This finding confirms that the effect of rating systems affects digital job market. Age of a freelancer appear to be a vital parameter not only in terms of its direct effect but also in a way different age groups set their expectation regarding wage.

The structure of this paper is as follows: Chapter 2 describes the literature on the job search theory, gender expected pay gap and digital work features; Chapter 3 provides the methodology and model specification; Chapter 4 presents data sources, descriptive statistics of the variables; Chapter 5 is devoted to empirical results and corresponding discussion; Chapter 6 generalizes all findings and provides a brief discussion of possible implementations.

Chapter 2

LITERATURE REVIEW

This section is devoted to the review of the articles that are helpful for deep understanding of the matter and needed to construct the proper estimation model. It discusses both theoretical and empirical studies.

The topic of the research of the salary expectation is not new to the literature. However, under the context of digital work it appears to have some noticeable differences.

2.1 Theoretical framework: Job search theory

J.J. McCall (1970) suggested a model that is now referred to as 'job search model' where he describes the way to estimate how people form expectations on their salaries to take up the job having imperfect information. According to the theory, people form so-called 'reservation wage' that determines whether they will take up the job once they are offered one. The main idea is lying in the tradeoff between accepting the offer or staying unemployed for longer for the chance of receiving offer with higher wage.

Mortensen (1986, 2001) has improved the model by analyzing bigger set of possible outcomes and variation. The most noticeable changes he take into consideration are aimed to make the model closer to reality and more empirically analyzable. He take away the infinite horizon principle (assumption of infinite life) and suggests models that cover more modern markets.

Further advancement towards econometrical way to analyze the issue was made by Andrew Chester and Tony Lancaster (1983). The paper considers ways of analysis of the data on worker' reservation wage and the formation of the required questions to be included in the surveys for the best unbiased estimations. The authors take deep investigation into the perception of the survey questions and proper ways to give the analysis.

2.2 Empirical analysis of the offline job market

One of the users of the articles above was Prasad (2000). The author gives an overview on the approach that he finds the most fitting for the study on micro data from German Socio-Economic Panel and the estimates of the model. The results have important implications for interpreting trends in wage shares, capital-labor ratios and aggregate unemployment.

Among impactful studies regarding the empirical analysis of the 'offline market', noticeable mention is Sarah Brown (2009). Using panel data, the author studies general determination of reserved and expected wages with even bigger set of controls to estimate the across countries expectations. The paper provides useful discussion on robustness of the model and its application. It is also evident that omitting variables used for controlling between countries allows to change set of variables used for the research of one country.

One of the most recent researches is made by Jian Gao et al. (2018). In the paper authors estimated the effect of height on salary expectations with other control variables. The model includes controls that are believed to be most impactful determinants and at the same time can be found on the freelance websites. Also authors discuss robustness of their model and provide its reasoning.

2.3 Overview of the digital platforms

As for the digital work, Janine Berg (2016) represented freelancers survey summary of 2015. The findings are helpful for tracking the development of the digital platform. At the time of investigation, organization of crowd work did not provide U.S with decent work opportunities. It was found that workers were more concerned about alternative way to earn money by ordinary jobs and they felt unresponsiveness of the platforms.

Another article considering aspects of digital work is written by Abi Adams (2017). The focus of the study is to check for gender inequality in the online job market. The idea is to let men and women perform the work to the employer who does not know the gender and compare payments for the quality of work. The results showed 18% average gap between genders. For the reasons of housekeeping task distractions, authors suggest implementing institute policies that address the sexual division of labor in the household.

The most disclosing article about Ukrainian digital job market is written by Mariya Aleksynska et al. (2018). The paper describes analysis of the survey conducted regarding online working condition, payment and jobs satisfaction. The results show that overall level of payments and work flexibility lead to high level of job satisfaction comparing to ordinary jobs as only 5% reported that they feel dissatisfied. It suggests that beneficial opportunities of the platform attract workers. Most importantly, the paper also reveals obstacles freelancers face.

'Job quality in the platform economy' (2018) is an ILO report Prepared for the Meeting of the Global Commission on the Future of Work. Article analyzes the spread of digital platform and suggests questions to consider regarding regulations in the sphere.

Lastly, the most recent paper is written by Mariya Aleksynska et al. (March 2019). The article is very relatable as it discusses the most recent challenges

Ukrainian digital market goes through and possible failures that may take place in case of lack of regulations. This study also present important descriptive statistics regarding the digital market and its state. The findings are mentioned through over this research and many conclusions are built with the support of the overview.

C h a p t e r 3

METHODOLOGY

In this section we describe a model able to capture the effects of parameters that are believed to affect expected wages starting with the relatable literature theory and getting to the adjustments made due to the particular goals and opportunities.

The theoretical model described in the work of McCall, 'The job search theory' represents the problem of a proper time to choose to take up the working offer to maximize utility:

An unemployed worker receives in each period a job offer with wage W_t. At time t, the worker has two choices:

1) Accept the offer and work permanently at constant wage W_t

2) Reject the offer, receive unemployment compensation c, and reconsider next period

The wage sequence $\{W_t\}$ is assumed to be iid with probabilities $p_1,\ldots,p_n$ where p_i's are probabilities of observing wage offer $W_t = w_i$ in the set $w_1,\ldots,w_n$. The worker is infinitely lived and aims to maximize the expected discounted sum of earnings.

This sum is:

$$E\sum_{t=0}^{\infty}\beta^{t}Y_{t}$$

Where β lies in (0,1) and is called a discount factor. The smaller is β, the more the worker discounts future utility relative to current utility. The variable Y_t is income, equal to his wage W_t when employed or unemployment compensation c when unemployed. Hence, the trade off is: waiting too long for a good offer is costly, since the future is discounted but accepting too early is costly, since better offers might arrive in the future.

In order to optimally trade off current and future rewards, we need to think about two things: the current payoffs we get from different choices and the different states that those choices will lead to next period (either employment or unemployment). To weigh these two aspects of the decision problem, we need to assign values to states. Let V(w) be the total lifetime value accruing to an unemployed worker who enters the current period unemployed but with wage offer w in hand. More precisely, V(w) denotes the value of the objective function when an agent in this situation makes optimal decisions now and at all future points in time

$$V(w) = \max\left\{\frac{w}{1-\beta}, c + \beta \sum_{i=1}^{n} V(w_i)p_i\right\} \tag{1}$$

From here we can obtain the rule for the optimal reservation wage:

$$\bar{w} \coloneqq (1-\beta)\{c + \beta \textstyle\sum_{i=1}^{n} V(w_i)p_i\} \tag{2}$$

Hence, we can compute this reservation wage if we can compute the value function. However, the trick is to model the value function properly. In reality, it is more relatable to think of the value function as of set of explicit and implicit factors that drive the decision process regarding valuation of own wage.

One particular model we refer to that is both theoretically derived and empirically applied for ordinary market uses the following version of econometric model (Prasad, 2000):

$$\begin{aligned}
\log(Reservation\ Wage) \\
&= \beta_1 + \beta_2 Apprenticeship \\
&+ \beta_3 Vocational\ Training \\
&+ \beta_4 University\ Degree + \beta_5 Age \\
&+ \beta_6 Age^2/100 + \beta_7 Male + \beta_8 Married \\
&+ \beta_9 Household\ Head + \beta_{10} Kids \\
&+ \beta_{11} Home\ Ownership \\
&+ \beta_{12} Other\ Emp.Person(s) in\ Household \\
&+ \beta_{13} log\ Net\ Household\ Income \\
&+ \beta_{14} UIBenesits/Assistance \\
&+ \beta_{15} Unemployment\ Rate \\
&+ \beta_{16} Regional\ Unemployment\ Rate + \boldsymbol{\beta}\ Years \\
&+ \epsilon
\end{aligned} \tag{4}$$

However, analyzing the key factors that affect expected wage freelancers stated on their profile pages in possible only by working with the data that is observable. The information set is limited and there is no access to some implicit variables that are widely used in analysis of expected wages. Those omitted influential parameters are education, unemployment duration, preliminary wage, marital status and number of children in the family. Indeed, considering analysis of the expected wage in an ordinary job market, lack of those variables may cause strong estimation bias. However, the job market of this paper's interest is digital and this fact changes the pattern of influence towards other and new factors.

The jobs that freelancers perform are temporary and time restricted. A customer that hires a worker expects the task to be performed right away. The impression that the profile page set up is the only decision-making driving mechanism. There is also no interview or training in a line with the requested project. Hence, the ability to learn or train new skills (the justification for using education parameter in ordinary models) appear to have much less impact. Moreover, most high-skilled jobs represented on the portal are parts of IT sphere. Corresponding jobs are known to be more dependent on skills rather than on education and 69% of employers in Ukraine usually do not even request any education information from potential workers (Carpio et al. 2017). Furthermore, Ukraine is known to have very high share of population with higher education (27%), taking place among the most highly educated countries (Barro-Lee Database). Adding it up to very low willingness to mention education level by freelancers themselves, the education parameter is considered of low impact to the model.

Another noticeable difference between ordinary and digital job market is availability of workers' reviews. Each freelancer's page has ranking that is visible to any user visiting his page. The portal creates it by using the amount of each worker's positive reviews. This ranking also influences the order in which freelancers are represented when customer searches for their stated specialization. In fact, people with big amount of reviews are first ones to be shown on the search page. It is also known that reviews on the internet are highly impactful for decision making around goods or services they relate to (Tom Collinger et al. 2017). For these reasons, the model includes positive reviews that workers are rated with. The specification is categorical, divided in four parts: amount of reviews 1-5; 6-15; 16-40 and 41+ with zero reviews as base value. This particular division is used due to equal share of observations for each group.

Age, gender and experience are personal characteristics included in the model based on the literature evidence of their importance. Unemployment rates and Gross Regional Product are economic factors considered meaningful as well. For better scaling, GRP per capita coefficient is taken in the logarithmic form. The model also has a set of specializations to control for wage differentials across jobs.

The core of the model has been taken from combining the model (4) and research on the height condition in China by Jian Gao et al. (2018) as the models are consistent with the economic theory of expected wage estimation and has the structure that can be replicated by scrapped data. Original OLS model in the article has been then adjusted by adding the variables described above while taking the education off. It takes form as follows:

$$\begin{aligned}\log(\text{wage}) = {} & \beta_0 + \beta_1 Age + \beta_2 Age^2 + \beta_3 Male + \beta_4 Experience \\ & + \beta_5 Experience^2 + \beta_6 \log GRPpc + \beta_7 Unemploy \\ & + \sum_{i=8}^{11} \beta_i\, ReviewCategory + \sum_{i=12}^{31} \beta_i\, Specialization \\ & + \epsilon\end{aligned} \tag{5}$$

where 'log(wage)' is logarithm of the wage that person stated as desirable; 'Age' and 'Age^2' are age in years and its square term; 'Male' is gender dummy and equal 1 for males; 'Experience' and '$Experience^2$' are number of years freelancer stated as his experience and its square term; 'log(GRPpc)' is the logarithmic form of GRP per capita in the living region; 'Unemploy' is level of unemployment in a living region in percent; sum of 'ReviewCategory' is set of dummy variables standing for one of 4 groups of review amounts: (1-5), (6-15), (16-40), 41+; sum of 'Specialization' is a vector of specializations.

More extensions of the model are used to capture better picture of actual effects that take place on the platform. Particularly, we build the model without including specialization vector to see how it affects gender pay gap. The difference in case of occurrence suggests that some portion of expectation divergences are explained by women job specialization choice. Apart from that, we analyze the model divided in two age groups. Younger workers with age up to 30 and older ones with age greater than 30. The reason for this particular division is explained by the fact that the two groups show different patterns and are almost equally divided in terms of observations.

Chapter 4

DATA DESCRIPTION

Freelancers have their own pages on different platforms with very dissimilar information lists. They work by performing projects that are offered from temporary contractors. Each website has its own requirements regarding information that workers have to mention. Getting the proper data to fit the model requires finding digital platforms that represent all the specified variables and then scrapping it. There are around 10 platforms that Ukrainians mention as their best choice for freelancing (Aleksynska, 2018). However, the information provided on most of them usually appear to be insufficient in terms of the amount of variables. Specifically, the websites fail to display one or more parameters from the following list: wage expectation, age, location or experience. The data that fit the best have been scrapped from the website "fl.ru" in February-March 2019. Thus, all the observations take place in that period.

After clearing (observations with age higher than 80, wage more than 200$/h in 7-12$/h field, experience higher than age, etc.) the data consist of 2400 Ukrainian freelancers. Digital workers live in over 130 localities and all together make each region of Ukraine represented with the range from 5 to 586 workers (Figure 1). 87% of freelancers live in the oblast centers.

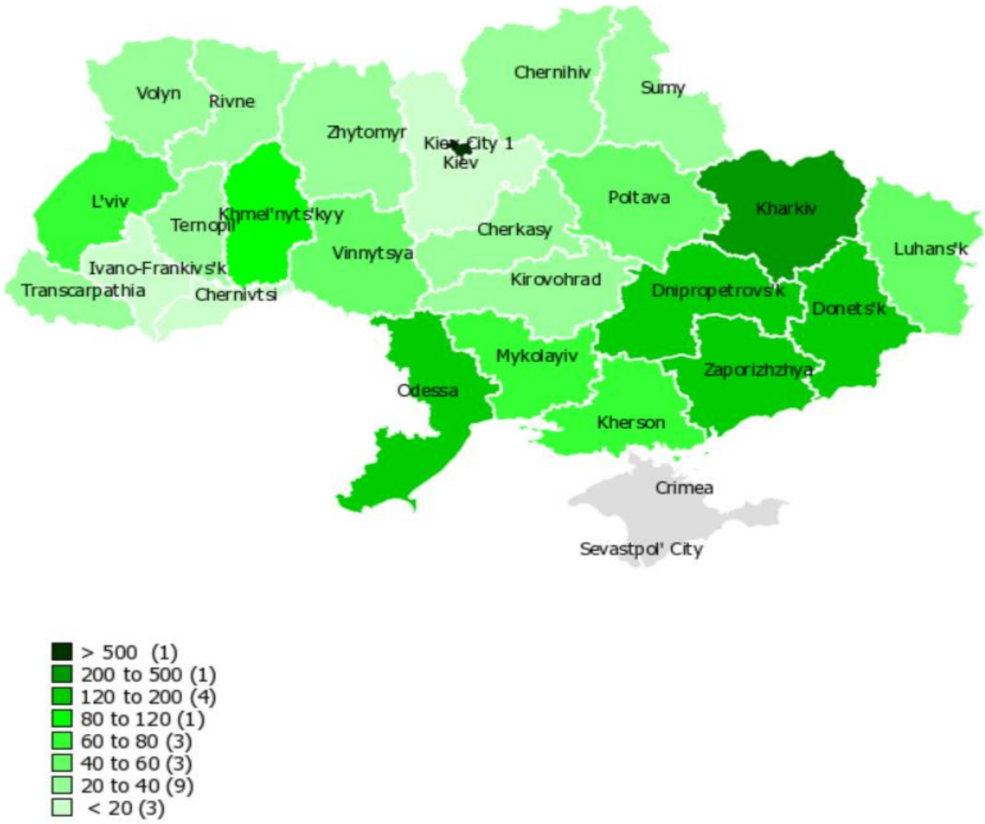

Figure 1. Map of distribution of digital workers from the sample over Ukraine.
Source: Scrapped data from 'fl.ru' on February-March, 2019.

The platform represents 20 different job specializations that can be done online. Number of specialists vary from 4 to 892 (Figure 2). The highest share of freelancers work in the Website Development sphere and perform tasks associated with making websites, filling them with the content, fixing respective issues and creating designs. The lowest share belongs to the Information System jobs involving system and database administrating. Represented jobs on the platform are mostly of IT sphere which is in a line with general structure of Ukrainian freelancing.

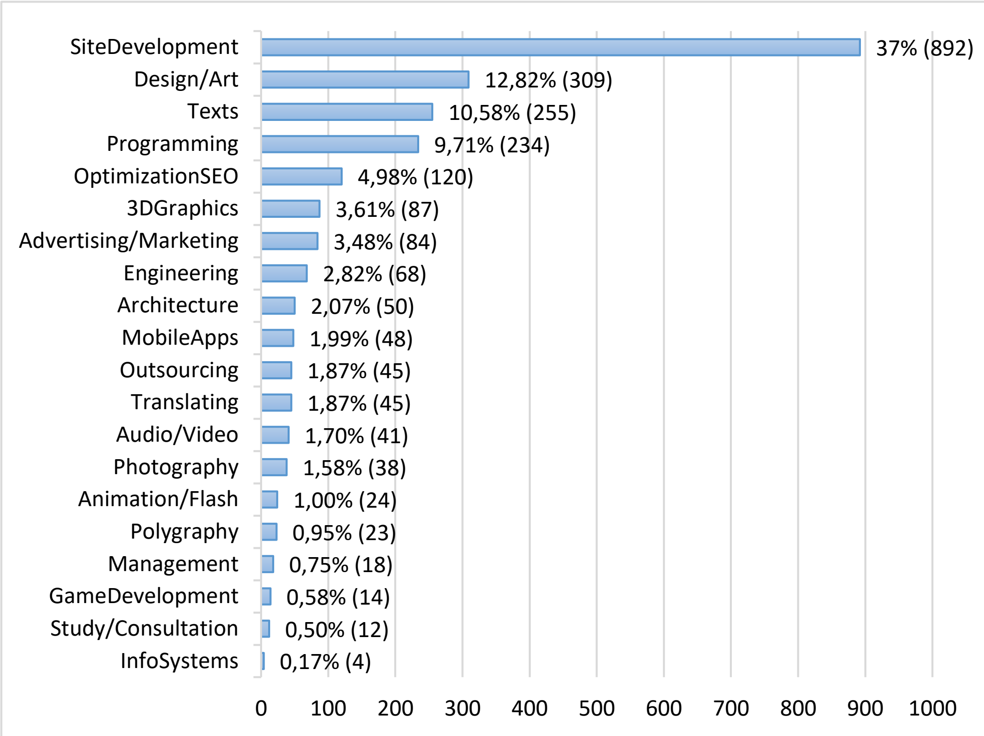

Figure 2. Composition of freelancers by desired sector

Source: Scrapped data from 'fl.ru' on February-March, 2019.

The dependent variable – wage is the hourly rate of payment that freelancers stated on the website as their aspiration for performing the respective job projects. Besides, the portal allows to extract data on their age, gender, location, experience and number of reviews with the rating. Average expected wage among all specializations varies from 7,53$/h in translation field to 19,71$/h in information systems. Overall mean wage is 10,79$/h. (Figure 3).

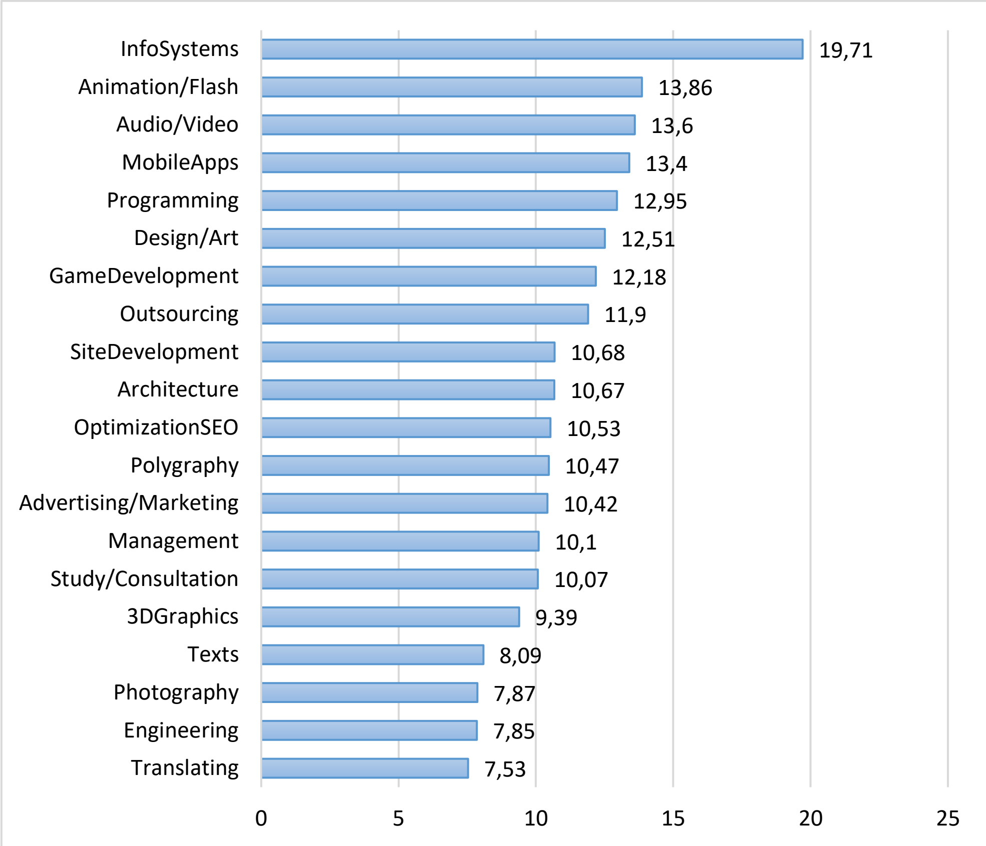

Figure 3. Average wage expected in the desired sector
Source: Scrapped data from 'fl.ru' on February-March, 2019.

Males and females have different preferences regarding job specialization (Figure 4). While there are 81,4% males in the sample, share of female workers in different jobs vary from 0 to 43,3%. Women tend to choose work that requires lower skill involvement and hence lower payment. Those are: working with texts, translating, making designs, taking photos, etc. (Figure 5). As opposed to the females, male workers tend to work in higher skill-demanding jobs like app development, website creating, programming and game development.

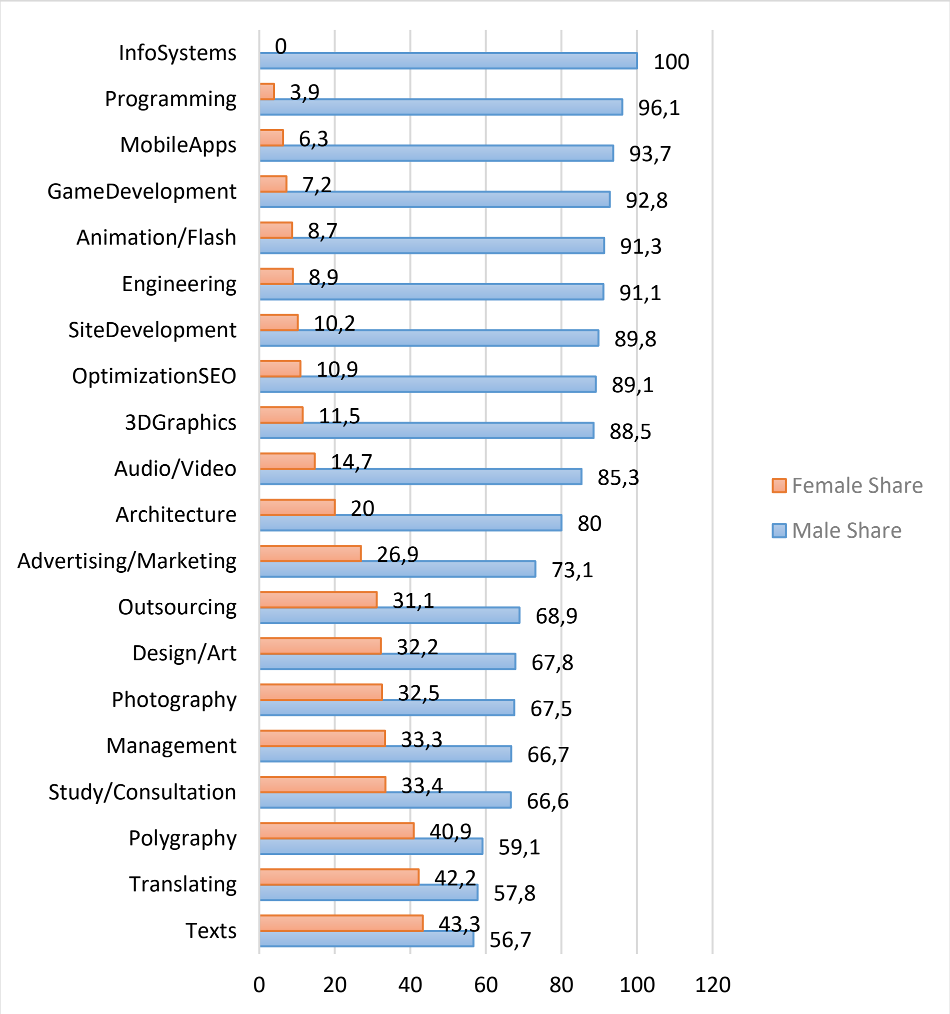

Figure 4. Distribution of the gender preferences in the desired sector

Source: Scrapped data from 'fl.ru' on February-March, 2019.

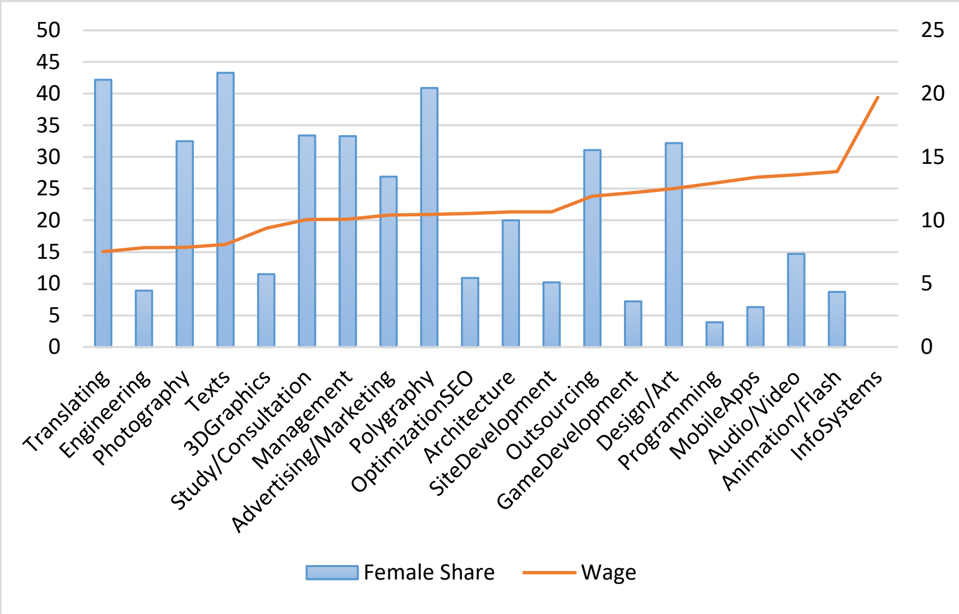

Figure 5. Female concentration compared to average expected wage in the desired sector

Source: Scrapped data from 'fl.ru' on February-March, 2019.

Average age and experience show variation across specializations as well (Figures 6 and 7 in Appendix). Information on Gross Regional Product per capita and unemployment rates is taken from Ukrstat most recent data (Ukrstat, 2018).

General statistical summary of variables is provided in the table below (Table 1).

Table 1. Descriptive statistics of the variables impacting expected wage

VARIABLES	N	mean	sd	min	max
Wage	2,411	10.79	8.923	0.151	150
Age	2,411	31.87	7.233	17	73
Gender (=1 if male)	2,400	0.814	0.389	0	1
Experience	2,411	6.308	3.997	2	40
Positive Reviews	2,411	25.81	68.21	0	967
GRP per capita	2,411	83,730	62,739	14251	191,736
Unemployment	2,411	8.374	2.946	5,2	15.90

Chapter 5

EMPIRICAL RESULTS

In this section we discuss possible model specifications to provide the most unbiased estimations and capture effects of the model parameters and post estimation results.

Over all variations of the models, there are several of them that represent the best way to analyze the patterns and magnitudes in the digital job platform. The main (1) model (Table 2) is exactly the one described in the methodology section. The results suggest that expected wage is negatively related to age and model (2) (Table 2) indicates that squared term of age is insignifficant while F-test for joint significance also confirms that. This implies that age is not specified parabolically but rather linearly with negative slope. Hence, this would mean that increase in age is associated with decrease in expected wage over entire age interval from the beginning. However, models (4) and (5) (Table 3) test this inference by doing the same regression over two different age intervals, before and after 30. The lower age interval regression (4), as opposed to main with age squared term (2) reveal that at this interspace age is described parabolically with cut-off point at the age of 24, meaning that expected wage increases up to this age and then goes down. On its turn, the upper interspace analysis suggests same parabolical specification for age but with the opposite signs. This means that starting from age of 30, workers tend to lower their wage expectations with each extra year comparing to younger workers but with diminishing returns. The cut-off point in this case is 54 years, however there are almost no observations with higher age, so it simply indicates the end of the interval.

Table 2. OLS regression coefficients. Models (1)-(3)

Dependent Variable: log(expected wage)			
	(1)	(2)	(3)
VARIABLES	Main	Age^2 included	No Specialization
Age	-0.00868***	0.00453	-0.0123***
	(0.00238)	(0.0129)	(0.00239)
Age^2		-0.000184	
		(0.000176)	
Male	0.115***	0.115***	0.209***
	(0.0393)	(0.0393)	(0.0379)
Experience	0.0940***	0.0902***	0.0936***
	(0.00895)	(0.00965)	(0.00909)
$Experience^2$	-0.00257***	-0.00238***	-0.00248***
	(0.000369)	(0.000413)	(0.000378)
Log GRP per capita	0.0976***	0.0985***	0.0919***
	(0.0273)	(0.0273)	(0.0279)
Unemployment	-0.0184***	-0.0184***	-0.0199***
	(0.00644)	(0.00644)	(0.00659)
Positive Reviews 1-5	0.129***	0.126***	0.143***
	(0.0422)	(0.0423)	(0.0429)
Positive Reviews 6-15	0.162***	0.157***	0.162***
	(0.0479)	(0.0481)	(0.0489)
Positive Reviews 16-40	0.158***	0.154***	0.152***
	(0.0435)	(0.0437)	(0.0442)
Positive Reviews 41+	0.375***	0.371***	0.371***
	(0.0442)	(0.0443)	(0.0445)
Specializations	YES	YES	NO
Constant	0.774***	0.558	1.188***
	(0.270)	(0.340)	(0.270)
Observations	2,394	2,394	2,394
R-squared	0.193	0.194	0.141

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3. OLS regression coefficients. Models (4)-(5)

Dependent Variable: log(expected wage)		
	(4)	(5)
VARIABLES	Age < 30	Age >= 30
Age	0.374***	-0.0646**
	(0.130)	(0.0253)
Age^2	-0.00760***	0.000601**
	(0.00261)	(0.000303)
Male	0.0857	0.140***
	(0.0617)	(0.0515)
Experience	0.105**	0.0722***
	(0.0461)	(0.0113)
$Experience^2$	-0.000857	-0.00195***
	(0.00407)	(0.000456)
Log GRP per capita	0.0865**	0.0982***
	(0.0403)	(0.0370)
Unemployment	-0.0125	-0.0238***
	(0.00970)	(0.00863)
Positive Reviews 1-5	0.0283	0.176***
	(0.0664)	(0.0552)
Positive Reviews 6-15	0.0439	0.226***
	(0.0778)	(0.0611)
Positive Reviews 16-40	0.0611	0.199***
	(0.0680)	(0.0580)
Positive Reviews 41+	0.251***	0.409***
	(0.0677)	(0.0600)
Specializations	YES	YES
Constant	-4.077**	2.144***
	(1.652)	(0.619)
Observations	1,014	1,380
R-squared	0.212	0.222

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Male coefficient in the main model (1) has positive and signifficant sign, suggesting gender pay gap in expected wage of around 11%. Comparing it with the model that does not include specializations (3) (Table 2), this coefficient is higher by 0.095 (80%), implying that to some extend gender pay gap is expained by women job preferences. Overview of the gender parameter over two age groups implies that main portion of inequalities appear on the older age interspace (5) being signifficant and higher than in main model, while being lower and insignificant on the other interspace (4).

Experience coefficient is positive and signifficant in every model, suggesting overal increase in expected wage starting from the initial point of 9% for each extra year of experience. However, it also has diminishing returns and the cut-off point of 18 years of experience in the main model (1) and upper age interspace (5). For the age group of lower than 30, the quadratic term is insignifficant implying that experience has no cut-off point there as well as more or less constant returns.

The coefficient log(GRP per capita) over all the models implies that every 10% difference upwards in GRP per capita in a living region compared to other regions increase wage expectations by 0,9-1%. Unemployment rates have vice versa effect, lowering the expectations by 1.8-2.4% for each percentage point of unemployment in the living region. However, for lower age cohort this coefficient if insignifficant.

Positive reviews affect wage expectations in a positive way. All the following interpratations are given compared to freelancers having zero reviews. Having at least some reviews (up to 5) is associated with 13% increase in wage that freelancers expect to work for. For the intervals of moderate amount (6-40), this increase is slightly higher – 16%. The most positively reviewed freelance pages with over 40 ratings expect earning 37% more. Models (4) and (5) reveal that most impact reviews have for the older cohort of workers. The value of coefficients for them is higher by 3-4 percantage points in each category while being insignifficant in most cases and lower in 41+ category for the younger group.

However, age and experience as well as GRP per capita and unemployment rates are pairwisely correlated (with coefficients of 0,5 and -0,5 respectively and corresponidng signifficance). In order to avoid the multicollinearity bias, we consider models with separation into groups where no pairwise correlation occurs. To do so, the model (1) from Table 2 is subdivided into groups of age lower and higher than 30 and additionally, as opposed to models (4) and (5) from Table 2, only one parameter, either GRPpc or Unemployment is included and age is taken away. The respective (6)-(9) models' coefficients are represented in the Table 4.

The variable division results appear to stay consistent with the findings from previous models with some renewals. Male coefficient remains insignifficant for the younger cohort and strongly signifficance in the older one with even slightly higher value. Experience remains having positive linear increase pattern for the younger group and for older one it also remains parabollicly specified increasing with diminishing returns and cut-off point of 17 years of experience, which is 1 year lower from the models of Table 3. With excluded unemployment rates, the value of log(GRP per capita) coefficient increases by 0.34 and 0.87 percantage points (per 10% difference) for the younger and older cohors respectively comparing to previous estimates. On its turn, unemployment rates effect also show coefficient increase by 0.17 percentage points (71%) for older group and appeared signifficance for the lower one. The changes suggests even higher sensitivity towards economic factors for the older group. The coefficients of positive reviews remain relatively same.

Table 4. OLS regression coefficients. Models (6)-(9)

Dependent Variable: log(expected wage)				
	(6)	(7)	(8)	(9)
VARIABLES	Age<30& GRPpc	Age>=30& GRPpc	Age<30& Unemploy	Age>=30& Unemploy
Male	0.0763	0.146***	0.0683	0.147***
	(0.0619)	(0.0520)	(0.0618)	(0.0519)
Experience	0.116**	0.0682***	0.110**	0.0694***
	(0.0454)	(0.0109)	(0.0454)	(0.0109)
Experience^2	-0.00209	-0.00210***	-0.00156	-0.00210***
	(0.00404)	(0.000415)	(0.00404)	(0.000415)
Log GRP per capita	0.120***	0.175***		
	(0.0320)	(0.0283)		
Unemployment			-0.0266***	-0.0408***
			(0.00766)	(0.00648)
Positive Reviews 1-5	0.0368	0.202***	0.0335	0.197***
	(0.0663)	(0.0556)	(0.0664)	(0.0554)
Positive Reviews 6-15	0.0518	0.251***	0.0520	0.239***
	(0.0776)	(0.0614)	(0.0776)	(0.0612)
Positive Reviews 16-40	0.0693	0.255***	0.0663	0.229***
	(0.0678)	(0.0576)	(0.0679)	(0.0578)
Positive Reviews 41+	0.259***	0.473***	0.263***	0.451***
	(0.0676)	(0.0594)	(0.0676)	(0.0594)
Specializations	YES	YES	YES	YES
Constant	0.0481	-0.522**	1.240***	1.191***
	(0.292)	(0.230)	(0.163)	(0.117)
Observations	1,014	1,380	1,015	1,385
R-squared	0.210	0.233	0.208	0.236

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Such results suggest that older people perceive digital platforms to be driven by the ordinary job market more than younger ones do. This finding may be explained by the influence of the experience: workers that have worked more tend to pay closer attention to the economic situation and patterns that are observable on the market. Thus, this experience stands for the sensibility to the economic factors and tolerance to some job market failures (particularly gender pay gap).

Chapter 6

CONCLUSIONS

The empirical evidence from the models analyzed show that wage expectations on the Ukrainian digital job market depend on personal characteristics, economic conditions and in-platform features. It is evident that for younger cohort working online seems in a way different than it is for older one. Freelancers with age up to 30 do not have significant observed differences in wage expectations between gender groups, do not have an excess experience point and less dependent on the unemployment rates. As opposed, older group go through diminishing returns on experience, steady decrease in expected wage with aging, higher gender gap regarding expected wages and sensitivity to economic factors. This may be associated with lower familiarity with online working systems among older people and their stickiness towards experience from the ordinary job market.

Gender gap in terms of expected wages occurs for the older cohort of workers. Older women tend to lower their expectations compared to men working in the same sphere, having same age and experience. The gap changes drastically with adding specialization list. The models predict that the gap declines by 9.5% (almost twice) with having specializations included. This means that female workers tend to choose jobs that are paid less. However, other part of the gap is possibly caused by imperfect information women possess and stereotypes driven by society.

Freelancers with big amount of experience may expect lower wage than those who have less. It may be explained by the fact, that skills that are needed in the modern market (especially IT sphere) are of more 'fresh' list. Meaning that IT market is developing and require rather better adaptation and ability to learn new than stick to older knowledge. Moreover, in context of Ukraine, 25 and more years of experience it is also associated with the USSR experience that does not have much use on the freelance market nowadays.

One important feature of work online is ability to write or receive reviews through the platform. With advancing in review statistics freelancer gets higher ranking among the list of all workers in a line with higher attractiveness. This feature of platforms appears to have positive and valuable effect on the formation of the expected wage. Workers tend to expect higher wages with getting more positive reviews. Particularly, older cohort of workers rely on this feature increasing their expectations in wage as they get at least any reviews. Younger freelancers show significant difference only with attaining relatively big amount of ratings.

From the models, it is evident that online workers have different preferences and wage evaluation through the age interval. This finding is useful for creating the proper policies. For example, one of the concerns regarding unregulated online work is about the entrance of workers that escalate inequalities and mismatches of wage differentials. Investigating particularly the issue of gender expected pay gap, the policy maker should pay closer attention to older workers and consider regulation for this category rather than younger one. At the same time, it is necessary to take into account higher responsiveness of older group of freelancers towards economic fluctuations.

Revealed by regression analysis issues confirm concerns regarding digital job market and suggest paying closer attention towards the older cohort of online workers. Online jobs do not require workers to have strong education background. Due to the results, a potential worker may get skills required for the particular online job and gradually increase his market value by getting reviews, studying platform structure and finding the most appropriate wage. Digital job market gives Ukrainians a new set of working opportunities and further development may make it even more beneficial. Thus, further investigation and deeper analysis is required to avoid possible failures and correct existing ones.

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Appendix

DESCRIPTIVE STATISTICS

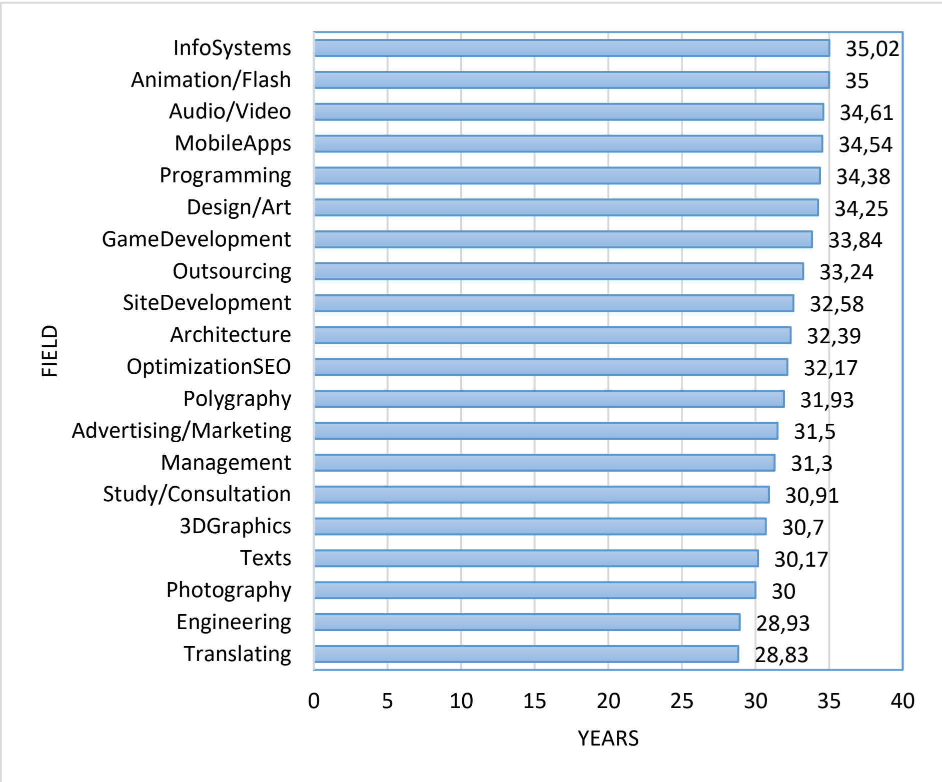

Figure 6. Average age of freelancers by desired sector

Source: Scrapped data from 'fl.ru' on February-March, 2019

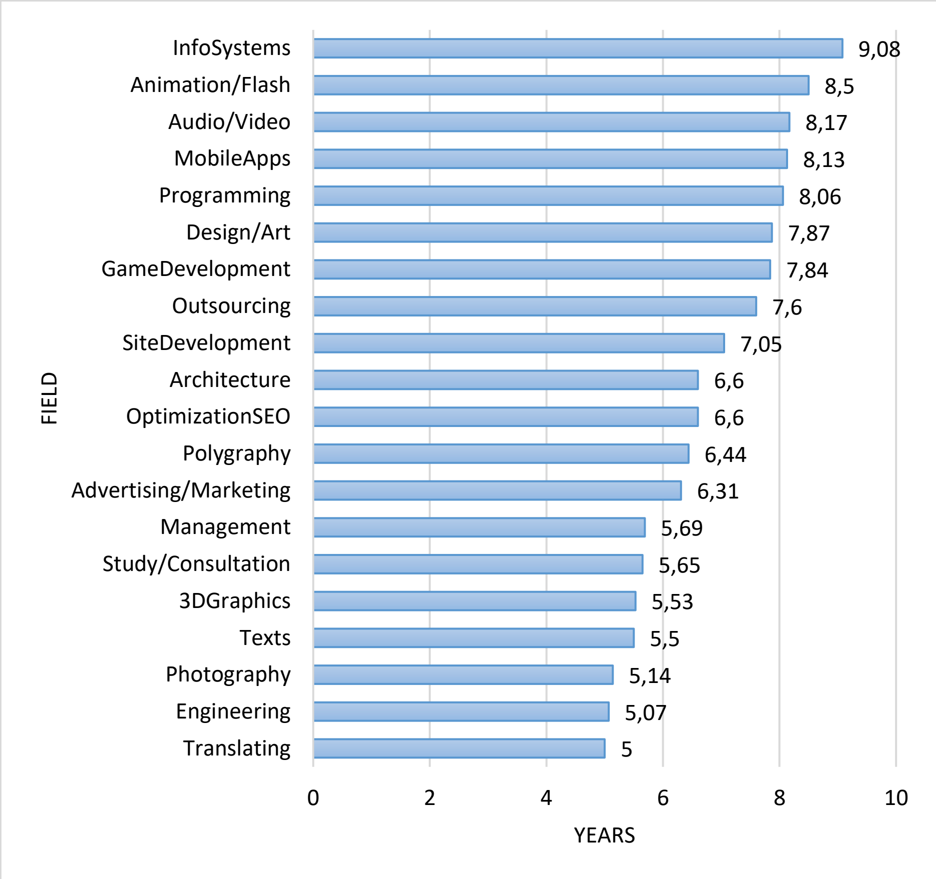

Figure 7. Average experience of freelancers by desired sector

Source: Scrapped data from 'fl.ru' on February-March, 2019