The impact of anti-COVID policies on the number of applicants for unemployment benefit in face-to-face and remote work spectrum

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<draft>

Abstract

Workers whose job related on face-to-face communications (F2F) were affected by anti-COVID policies much heavier than other categories. Jobs that could be conducted remotely (home based or HB) were supposed to decrease the number of applicants for unemployment benefit. Empirical justification bases on DD estimates of the number of monthly applications in pre-lockdown and lockdown periods of January 2020–May 2020 for occupations categorised by F2F score and HB dummy. Gender specific effects were different, affecting at most low-skilled women. Whereas for men, the effect was the highest for medium-skilled workers when opportunity to work remotely was accounted. Opportunity to conduct work remotely somewhat affected the number of medium-skilled female applicants, by 7.7 pp. Whereas for men this was the major contributor 57.3 pp. And the group of medium-skilled worker in total was affected at most. High-skilled female workers were more affected than male. For women it was crucial not to be able to work remotely being in F2F intense jobs. For men, it was not important.

Introduction

COVID-19 has led to a global shortfall in jobs, dramatically affecting work practices and skyrocketing unemployment rate. According to ILO (2021b), in 2020 unemployment rates increased at most in high-income countries and lower-middle-income countries like Russia. Anti-COVID policies has brought a new categorisation of jobs by putting workers at risk of unemployment. Kniffin et al. (2021) classified vulnerability of workers relative to a possibility of working from home, being employed in essential business, or in non-essential that was the prime subject to business closures and workers' lay-off. Anti-COVID policies made jobs that rely on face-to-face communication or close physical interaction especially unsafe as putting workers and clients at risk

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of contracting Covid-19. This, in turn, led to a significant reduction of such jobs increasing unemployment.

Anti-COVID policies has increased interest in the study of remote works that flourished due to social distance requirements. Although the substantial rise of projects implemented on online labour platforms, increasing, and extending remote work opportunities, has already been observed since 2017 (ILO 2021a). In particular, already before the lockdown platform work spread remarkably in such sectors as software development, multimedia, writing and translation, sales and marketing, and data support (ILO 2021a). Mainly platform work was distributed in Asia and much less in other continents (ibid).

Russia, as other countries, has developed policies dampening the effect of anti-COVID policies on population wellbeing. Unemployment allowance was increased doubling the pre-lockdown size. Together with facilitating application process, it yielded in a sharp rise of the number of applicants. Therefore, it is impossible to find a clean effect of anti-COVID policies on unemployment. However, by distinguishing categories of unemployed the effect can be extracted for more vulnerable groups compared to others as all of them were evenly exposed to the unemployment policies.

The study analyses how the social distancing in response to anti-COVID policies affected the number of applicants for unemployment benefit across job and skill types in Russia. Workers whose remote work could be established with a substantial difficulty, because of their high involvement into a face-two-face interaction, are hypothesised to be affected to a greater extent. To measure the effect, I compose F2F score and a dummy for HB on the base of the descriptions of professions in All-Russian Classifier of Workers' Professions, Employee Positions and Wage Grades[2]. DD estimates of the number of monthly applications in pre-lockdown and lockdown periods of January 2020–May 2020 for occupations categorised by F2F score and a dummy for HB allow measuring the effect of anti-COVID policies on F2F groups and taken into account for work from home opportunities decreasing risk of the number of applicants for unemployment benefit.

[2] OKPDTR, Obshcherossiyskiy klassifikator professiy rabochikh, dolzhnostey sluzhashchikh i tarifnykh razryadov. Source: https://profstandart.rosmintrud.ru/obshchiy-informatsionnyy-blok/spravochniki-i-klassifikatory-i-bazy-dannykh/okpdtr/

Literature

COVID-19 crisis is a completely new phenomenon altering by its effect economic crises known before. The main difference is the uncertain duration of the pandemic. Studies of the impact of anti-COVID policies on unemployment rates are scarce. It is presented by research agenda (Blustein et al. 2020, Kniffin et al. 2020), world-wide projections (Chodorov-Reich and Coglianese 2020; Hatayama et al. 2020; ILO 2021a; ILO 2021b), theoretical modelling (Gallant et al. 2020, Koren and Pető 2020), and by quite a few empirical papers, which establish some results for several countries (Germany: Bauer and Weber 2020; the UK: Houston 2020; the U.S.: McFarland 2020; Montenovo et al. (2020); the U.S., Germany, and Singapore: Reichelt 2021). The main concern is expressed towards vulnerable groups in the labour market, migrants, ethnic groups, women.

Empirical findings show that anti-COVID policies led to a considerable increase in inflows from employment into unemployment in April 2020. For example, in Germany, the increase was about 60% (Bauer and Weber 2020). Houston (2020) argue that pre-lockdown regional unemployment was a stronger predictor compared with the sectoral structure of unemployed in the UK. Montenovo et al. (2020) study early lockdown consequences in the US and occupational, sectoral division together with gender and ethnicity/race serve as predictors of unemployment in lockdown. They find women are more affected by lockdown.

Interest of researchers lay in projecting in the aspect of how many jobs can be done at home at the time of anti-COVID policies. On one hand, remote works require little communication and can be performed even more effectively on distance (Kniffin et al. 2021, McFarland 2020). On another hand, team work has also successfully moved in online communications (Mak and Kozlowski 2019). Dingel and Neiman (2020) basing on Occupational Information Network (O*NET) classification find that 37% of jobs in the USA can be accomplished entirely at home. Using O*NET, Avdiu and Nayyar (2020) and Mak and Kozlowski (2019) establish that face-to-face jobs do not completely oppose home-based jobs. Avdiu and Nayyar (2020) find that F2F interactions that alter HB are essentially presented in lower paid and female jobs. Montenovo et al. (2020) using O*NET classification find that job losses were more considerable for those whose work related to face-to-face communication and could not been performed remotely. McFarland (2020) examines 14 firms job openings and applications in terms of possibilities for employees to work remotely or face-to-face. They find that firms offering HB jobs experienced an increase in the number of applications and job openings, whereas F2F type of firms did not significantly change the number of job openings during lockdown.

Hatayama et al. (2020) employ skills surveys from 53 countries to evaluate possibilities to working from home. They predict that the level of economic development of the country should be an important factor to extent HB jobs. The proportion of women, college graduates and formal workers in the labour force are expected to correlate with the number of HB jobs in lockdown.

Face-to-face interaction between workers is conceptualized by Charlot and Duranton (2004) as "face-to-face meetings, word-of-mouth communication, and direct interactions". Oldenski (2012) scores importance of F2F contacts extending them on worker–client interaction for occupations classified in O*NET. The classification categorises contacts into ''contact with others (face-to-face, by telephone, or otherwise)'', ''face-to-face discussions'' and ''physical proximity'', by which it is not possible to distinguish between F2F and a contact on distance. Avdiu et al. (2020) measure F2F intensity categorising contacts into "(a) establishing and maintaining personal relationships; (b) assisting and caring for others; (c) performing for or working directly with the public; and (d) selling to or influencing others." Boeri (2020) employs O*Net classification with information from a survey of the Italian Statistical Office and Institute for the development of professional training of workers (INAPP) and their own personal assessment to "specify whether face-to-face contact is required or whether it can also be done online". Using O*NET, Leibovici et al. (2020) classify US economic sectors and states in the contexts of being essential and presented by contact-intensive occupations likely to be relatively more affected by the COVID-19 pandemic.

The report (WB 2017) reveals variety of jobs that could be performed at home and dynamics in the structure of such works. In 2000s there were mainly self-employed manual workers with a low education and freelancers who despite relatively good education also belonged to the fringe of the labour market not having guaranteed earnings. In 2010s, platform work provided opportunities of working from home to an increasing share of formally employed office workers.

Lockdown and unemployment in Russia

In Russia, the macroeconomic changes of 2020 consisted of COVID-19 impact and a shock related to oil prices slump, like in other countries relying heavily on hydrocarbons export (WB 2020a). The overall unemployment rate (ILO classification) increased from 4.6% in February 2020 to 5.8% in April 2020, reaching maximum 6.4% in August-September 2020 (Fig. 1). These figures correspond to a drop in the monthly average number of employed by 1.1% with a maximum 1.3% (Rosstat). Approximately each third job was reduced in manufacturing, construction, retail, and hospitality services that were difficult to perform on HB basis (WB 2020b). Whereas ICT, civil and health services experienced an increase in the number of jobs (ibid). As in other countries, young people aged 20–29 years old were hit at most and women outnumbered among unemployed (Morozov 2020). Kapeliushnikov (2020) points that it is difficult to estimate the precise unemployment rate by several reasons, among which are the tension in the labour market and national policies, in particular, "the managerial and financial capacities of the Public Employment Service (PES), responsible for supporting the unemployed" (ibid) affecting the proportions of applicants for unemployment allowance and those remained hiddenly unemployed. Therefore, the real figures on unemployment could vary from 7% to 26% outreaching the crisis numbers of the late 1990s (ibid). Kapeliushnikov (2020) explains fluctuations in registered unemployment "by the managerial and financial capacities of the PES, responsible for supporting the unemployed, rather than by the real state of the labour market."

Kapelyushinkiov (2020) projects a higher rise in unemployment in those regions where small and micro-enterprises accounted for a significant share of the economy as they had a greater institutional flexibility to reduce the number of employed. The prediction meets the figures that the larger shares of unemployed were observed in well-developed and highly populated Central and North Western federal districts with the largest share of total unemployed as of September 2020 (29%) (WB 2020b). Russia's Kaliningrad exclave was affected by anti-COVID-19 national and subnational policies much greater because of its specialisation on transport of goods and raw materials across borders that had been closed (Yemelyanova and Lyalina 2020). In terms of production, "regions with high share of mineral resource extraction suffered the most", whereas North Caucasian regions specialising on food production showed positive dynamics (WB 2020b)

Russian authorities adopted social distancing and mobility restrictions that implied national holydays for all sectors of the economy from March 27 to May 11, 2020. Then, the restrictions were moved on subnational level and meant mobility restrictions for seniors (65+) and enacting holydays restricting economic activity. Subnational anti-COVID policies were imposed in mostly populated regions. Moscow closed schools, universities, fitness facilities, beauty salons, shops, restaurants, cafes and bars (but not pharmacies and grocery stores) (WB 2020a) in some regions the restrictions lasted until July and were resumed in October – November 2020.

In response to anti-COVID-19 policies many countries established temporary instruments to stabilize financial markets (e.g., WB 2020a), support business, and wellbeing of households hurt by lockdown. An increase in unemployment allowance became one of the main instruments adopted. This policy itself affected labour market situation. In the US, an increase of unemployment benefits up to $600 per week had a tremendous effect on desire not to go back to work for 70% of unemployed (Greszler 2020). Another labour market related policy is a small business support. Bartik et al. (2020) find that a possibility to get a small business subsidy (‘cash in hand’) affected the desire of a firm owner to remain open regardless to the reduction in the demand for a firm service or production “as personal concerns about public safety dominated in the effect”.

The Russian Government established both economic activity support policies and income support for the unemployed. In April 2020 the federal minimum unemployment benefit (UB) has been increased substantially. Until December 31, 2020, the maximum level was 12,130 (US$157) against its previous level 8,000 (US$103) roubles and reached 20,000 roubles combined with subnational policies (Kapeliushnikov 2020, WB 2020a). After March 1, 2020, a newly unemployed person was granted a maximum UB regardless his or her former earnings and a paid period increased from 6 to 9 months. ‘Stay-at-home’ requirement significantly reduced transaction costs coming from a mandatory renewal of unemployment registration in-person twice a month. Unemployed parents were granted additional allowance 3,000 roubles for three months (April to June 2020), and overall parents of children aged under 3-year-old (5,000 roubles for three months) and under age 0–16 – 10,000 roubles for three months per child during June – August 2020 (WB 2020a). Thus, the financial incentives to register as unemployed increased dramatically. By early projections, the lockdown total support of households would account for 0.68% of GDP with the 0.09% in UB and vast majority of payments to families with children (0.58%) in 2020 (ibid). Prior to anti-COVID policies, less than 5% of workers where home-based (ILO). This number is relatively low, as there are countries with over than 15% of HB workers (ibid). Gezici and Ozay (2020) find that categories of workers whose occupation and skills potentially allowed working via a platform were less likely to become unemployed.

Research Strategy

Anti-COVID policies directly affected those who could not perform their working duties while following social distance requirements. The imposed restrictions slowed down economic activity and the number of jobs reduced dramatically in most of economic sectors (except for health care, ICTs…) through the decrease in demand. Therefore, there is an indirect effect of anti-COVID policies. Together with anti-COVID policies, other macroeconomic shocks and labour market policies affected unemployment growth. The aim of the study is evaluation of the direct effect of anti-COVID policies on the number of applicants for unemployment benefit ruling out other effects.

Face-to-face interaction is determined as contacting with others, clients, or co-workers face-to-face, by telephone, or otherwise on the purpose of performed working duties regardless of whether it requires physical proximity or not. F2F score (*F2F*) corresponds to F2F intensity as an expected fraction of working time spent in F2F interaction. This measure, therefore, does not allow capturing the effect of anti-COVID policies restricted F2F interaction based on physical proximity. Second indicator, home based work score (*HB*) measures a fraction of working time that can be conducted on distance regardless of whether it requires F2F interaction or not. NHB score employed in the analysis is the reverse of *HB*, $NHB=1-HB$. This measure itself is invariant to anti-COVID policies. However, social distance restrictions generated a great demand on platform work, transforming opportunity into reality. Based on two scores, a score that measures F2F interaction intensity without opportunity to work remotely (*FNH*) is composed as

$$FNH=I(F2F>F2F_{cr})\cdot I(NHB > NHB_{cr}),$$

where I is an indicator function (1 - yes, 0 - no). This is expected to capture the effect of anti-COVID policies distinguishing the group that was directly affected and the group that was affected indirectly by the general economic recess.

Despite a great interest to the effect of anti-COVID policies on labour market, there are no studies that would answer a question how anti-COVID policies affected the number of applicants for unemployment benefit in Russia. I address this question by comparing the number of applicants for unemployment benefit in a treated group of workers with F2F-intense occupations and a group of workers, who were less exposed to the policies. I hypothesise a substantial increase in the number of applicants from the treated group. Being an exogenous shock, the effect of pandemics can be evaluated by difference-in-difference approach (DD).

The effect is evaluated in the presence of confounding factors. Firstly, the number of non-essential jobs that could not be performed remotely was also reduced due to a normative request from the government to decrease the number of employed (offline) by 30%. Women are more often work in F2F-intense jobs (teachers, nurses); therefore, gender is another confounder. Thirdly, the level of education predicts a possibility to be performed on platform regardless to the intensity of face-to-face interaction.

DD is a common approach to capture the direct effect of a policy by eliminating confounding factors common for the control and the treated group. It has been employed for evaluation anti-COVID policies. Fairlie et al. (2020) employ DD to weekly application rates to establish the differences in the impact of anti-COVID policies on minority groups.[3] Gezici and Ozay (2020) use DD exploring the differences in the likelihood of unemployment across racial/ethnic groups in USA. Bauer and Weber (2020) apply DD for the groups selected by the degree of sector value added affected by the closures.

Identification

In the base model, the monthly regional number of applicants is regressed on binary variables derived as high/low scores, pre- and lockdown periods, and their interaction (Eq. 1). Triple difference is estimated in expectation that the effect of anti-COVID policies is different across education levels. The extended specification includes age groups (16-24, 25-44, 45-59, 60+), wage group (below median, third and fourth quartiles), and sectoral variables. For robustness check, binary variables computed from F2F and HB scores are included in the model separately instead of FNH variables.

$$
\begin{aligned}
\log(number\ of\ \ applications)_{it} &= \alpha + \sum_j F2F_i\beta_{j2} + \sum_j T_t\beta_{j3} + \sum_j F2F_i \cdot T_t\ \beta_{j4} \\
&+ \sum_j NHB_i\delta_{j2} + \sum_j T_t\delta_{j3} + \sum_j NHB_i \cdot T_t\ \delta_{j4} + \\
&+ \sum_j NFH_i\varphi_{j2} + \sum_j T_t\varphi_{j3} + \sum_j NFH_i \cdot T_t\ \varphi_{j4} + X_iT_t\gamma + \eta_i + \varepsilon_{it}
\end{aligned} \qquad (1)
$$

where *F2F*, *NHB*, and *NFH* are transformed into binary indicators with a threshold established on the base of preliminary analysis. *T* is a time specific effect. *X* – covariates that potentially have different contribution before/after treatment.

The effect of intensity of F2F type of work as the average treatment effect on the treated taking the treated and the control individuals with identical characteristics is as follows

[3] They employ Blinder-Oaxaca decomposition and discontinuous random coefficient growth curve model as well.

$$\begin{aligned}\mathrm{ATET}_{F2F} &= \mathrm{E}(\log(\textit{number of applications}_i) \mid T=1, F2F_i=1, \textit{Education}=j) - \\ &- \mathrm{E}(\log(\textit{number of applications}_i) \mid T=0, F2F_i=1, \textit{Education}=j) = \\ &= \beta_{j3} + \beta_{j4}\end{aligned}$$

Similar, the contribution of low possibilities to work remotely is

$$\mathrm{ATET}_{NHB} = \delta_{j3} + \delta_{j4}$$
$$\mathrm{ATET}_{FNH} = \varphi_{j3} + \varphi_{j4}$$

Data Features

Data contain individual characteristics of applicants for UB from March 2019 to December 2020. The original set is about 5,600,000 records. Only 1,240,683 newly opened cases (applications) allow identifying F2F and HB values. Nonresponse bias increases with time as the proportion of applicants declared their previous professional occupation drops from 42.3% in March 2019 to 1.9% in November 2020 (Fig. 2).

I follow Boeri (2020) and Montenovo et al. (2020) to construct F2F and HB values of job characteristics to estimate differences in risks of job loss related to the intensity of face-to-face contacts and ability to work remotely. Then, data are aggregated by region, sector[4], F2F score, HB dummy, and whether the job is within health sector (1), or somewhere else (0). This allows comparing the numbers of applicants in the aggregated groups in pre-lockdown period and during the lockdown. The number of applicants is employed instead of duration of unemployment, often analysed in labour market studies (e.g., Chodorow-Reich and Coglianese 2020), as the latter can be biased by large prevalence of cases opened before the lockdown and by national policies that made formal unemployment status more attractive in this period.

First, jobs are rated from 0, 0.1 to 1 by F2F and HB. Correlation between F2F and HB indices in February 2020 (microdata) was 0.194. Top/bottom 10% list by F2F intensity is presented in Appendix Table A1. Then data are aggregated by region, sector, gender, level of education (primary, secondary, university), F2F score, HB score, and whether the job is within health sector (1), or

[4] Codes correspond to OKVED, the Russian Classification of Economic Activities. Source: Obshcherossiyskiye klassifikatory, zakreplennyye za Minekonomrazvitiya Rossii http://economy.gov.ru/minec/activity/sections/classificators/index

somewhere else (0). In total, the studied sample consists of 225,000 aggregate records. F2F score takes values between 0 and 1 by step 0.1 and is subject to scaling, therefore several thresholds cutting off the treated and the control group are tested. The results show that the threshold F2F = 0.6 provides the most dramatic raise in the number of applications in April 2020 (Fig. 3). It is used to distinguish F2F workers and the control groups in the descriptive statistics.[5] F2F are NHB are transformed into low 0 (0–0.5), or high 1(0.6–1). Fig. 3 demonstrates that prior to implementation of anti-COVID policies F2F workers were less likely to apply for UB. However, since April 2020 their numbers remarkably exceeded the numbers of unemployed in the control group. To December 2020, the difference disappears that can be explained by abolishing several policies supporting unemployed people.

Geographical distribution of applicants is consonant with reported in WB (2020a). Distribution of applications by OKVED and F2F for the period exactly before (February 2020) and after (April 2020) is shown in Table 1. Comparison by education (the proportions of people with primary, secondary, and tertiary education), age groups (younger than 25, 25–44, 45–59, age of retirement) and salary (dummies for belonging to a certain quartile in the total distribution over the considered period) across F2F and HB groups identifies several potential risk factors increasing likelihood of application for UB (Table 2). In F2F group, the proportion of applicants aged 25–44 increased from 56% to 68%, whereas the proportion of applicants in the group of 45–59 decreased from 40.9% to 28.7% after lockdown. Although women expectedly outnumber in F2F occupations, there were no significant changes in gender, education. There was an increase in the number of low paid applicants (wage in below median) in both F2F and control groups after lockdown.

Because data present newly made applications, they skyrocket in April-May 2020 and sharply decrease after, as those who applied earlier and remained unemployed are not observed. The quality of response to the professional occupation question drops over time from 40-42% in 2019 to 29-36 in January-May 2020 and to 11-23% in June-September. Therefore, the period of analysis is “Before: January-February 2020” and “After: April-May 2020”. Fig A1 and A2 present the structure of applicants by F2F, HB and before/after period.

[5] In regression analysis F2F scores are employed, which means varying amount of treatment.

Results

The main findings are that for women the effect of F2F intensive work was an additional factor in the growth of the number of applicants during April-May 2020 after anti-COVID policies had been enacted. The greatest increase was among low-skilled female workers, 27pp. Medium – 9.1 pp, high – 16.4 pp (Table 3 and Table A2 Panel A in the appendix). However, jobs not assumed to be conducted remotely for low-skilled women were likely to be in essential types of jobs, as NHB decreased the number of applicants, by 20.1 pp. For medium-skilled women NHB was positively associated with the log number of applicants, by 7.7 pp. F2F intensive jobs that could not be performed remotely had a contribution for women with university education, by 19.4 pp. As NHB is insignificant when FNH is included, likely the remote jobs are F2F intense in this category.

Similar to female group, low-skilled men in F2F intense jobs were harmed by policies to a greater extent by 21.8pp (Table 4 and Table A2 Panel B in the appendix). The contribution to the number of applicants is high for men with secondary and tertiary education, if possibility to work remotely is controlled. The ATETs are 46.1 pp and 19.9 pp respectively. In contrast to female groups, for low-skilled men opportunity to work remotely was not important. Whereas for medium-skilled – crucial for not intense F2F professions, as $ATET_{NHB}$=57.3 pp. For high-skilled men contributions of F2F and NHB are moderate 19.9 pp and 18 pp. They do not have a joint effect possibly categorising high-skilled vulnerable jobs either in high F2F and low NHB or otherwise.

Conclusion

This study evaluates the impact of anti-COVID policies on the number of applicants for unemployment benefit exploring the effects of a degree of face-to-face contacts and a possibility to work remotely. The results help in understanding of a mechanism through which labour market adjusted to anti-COVID policies.

After enacting anti-COVID policies in March 2020, workers of face-to-face intense professions experienced a dramatic increase in the number of applicants to PES. Gender specific effects were different, affecting at most low-skilled women. Whereas for men, the effect was the highest for medium-skilled workers when opportunity to work remotely was accounted. Opportunity to conduct work remotely somewhat affected the number of medium-skilled female applicants, by 7.7 pp. Whereas for men this was the major contributor 57.3 pp. And the group of medium-skilled worker in total was affected at most. High-skilled female workers were more affected than male. For women it was crucial not to be able to work remotely being in F2F intense jobs. For men, it was not important.

In contrast to expectation of Avdiu and Nayyar (2020) for the US that because F2F interactions that alter HB are essentially presented in lower paid and female jobs, they would be more affected. The estimates show that men with secondary education seem to be the most affected category (have to be estimated in one regression).

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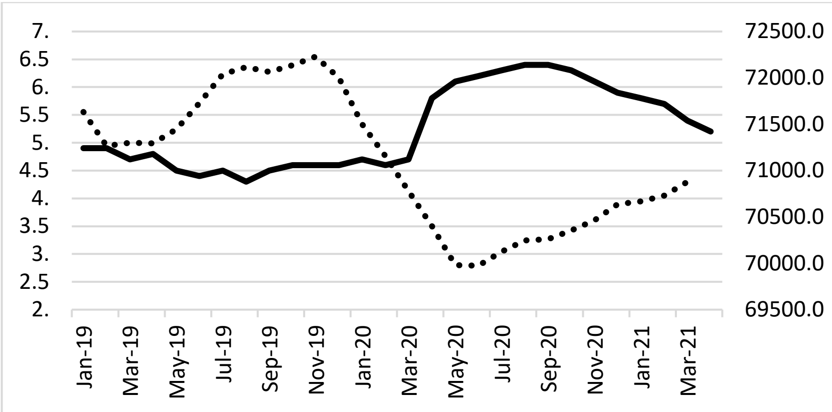

Figure 1 Unemployment rate (ILO) and the number of employed in Russian Federation

Note: Dashed line depicts the 3-month average number of employed in thousand people aged 15–72 years old. Solid line depicts the monthly unemployment rate among 15–72 years old by ILO methodology in per cent.

Source: Federal State Statistics Service. https://rosstat.gov.ru/

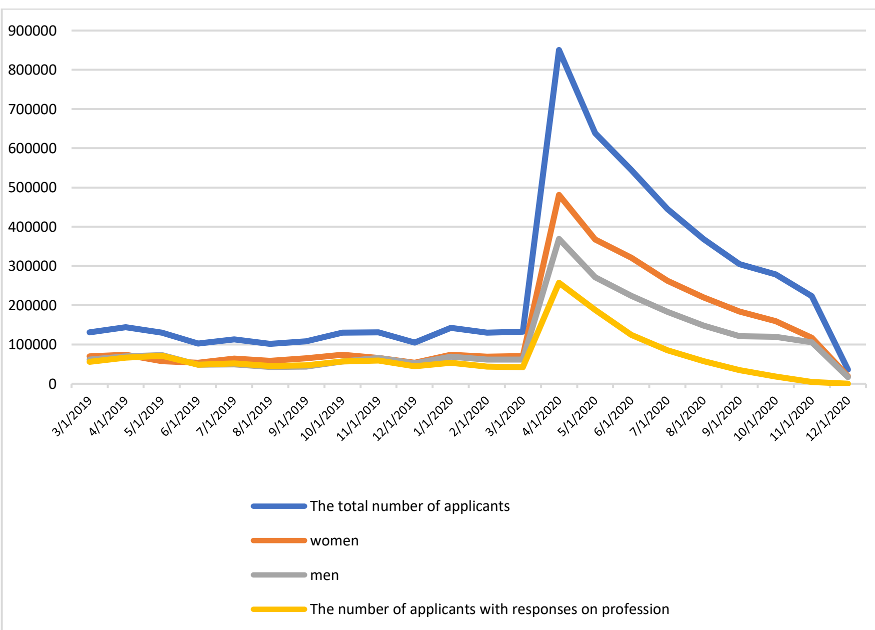

Figure 2 The number of applicants for UB by gender and response on profession in the last job.

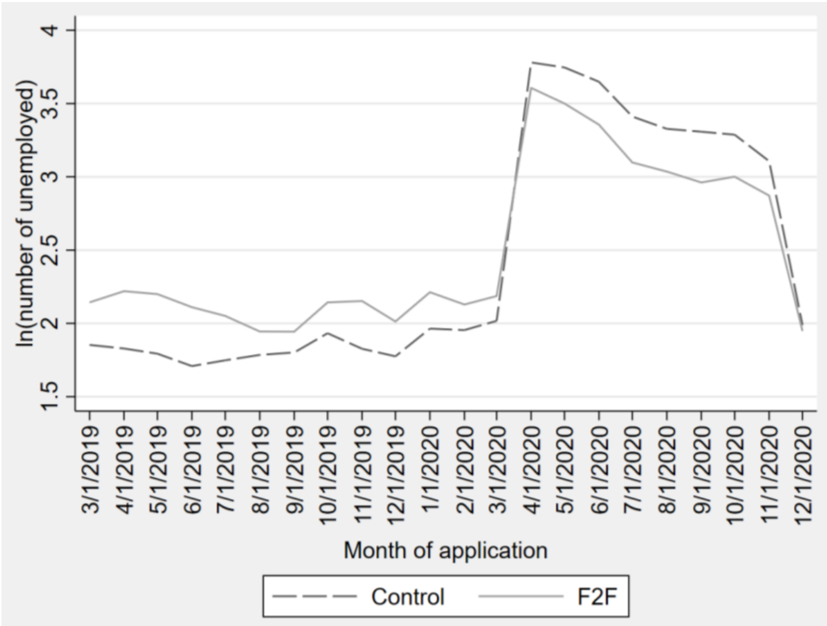

Figure 3 The log number of unemployed by groups and month of application (threshold F2F=0.6)

Source: Constructed by the author.

Table 1 Sectoral structure of applicants by F2F/control in February 2020 (before) and April 2020 (after)

	Feb-20	
Sector	F2F	Control
Администрация	1310	1344
Водоснабжение		
Госуправление, военная безопасность, соцобеспечение		
Добыча полезных ископаемых		11
Домашние хозяйства		13
Здравоохранение	89	155
Информация и связь		53
Культура и спорт	7	
Наука		
Недвижимость		
Обеспечение электроэнергией		266
Обрабатывающие производства	19	1770
Образование	355	
Общепит и гостиницы	46	487
Прочее	1222	10392
Сельское хозяйство		90
Строительство		114
Торговля	3414	9
Финансы		1706
Экстерриториальные организации		
	Apr-20	
Sector	**F2F**	**Control**
Администрация	32042	18861
Водоснабжение		
Госуправление, военная безопасность, соцобеспечение	1	
Добыча полезных ископаемых		66
Домашние хозяйства		187
Здравоохранение	737	424
Информация и связь		603
Культура и спорт	106	34
Наука		
Недвижимость		
Обеспечение электроэнергией		1283
Обрабатывающие производства	787	12949
Образование	2785	
Общепит и гостиницы	1804	6161
Прочее	20868	39672
Сельское хозяйство		98
Строительство		1127

Торговля	39881	61
Финансы		14099
Экстерриториальные организации		

Table 2 Structure of applicants by F2F (threshold F2F=0.6), age, gender, education and wage before/after (Feb-2020 to Apr-2020)

	Before, Feb-20		After, Apr-20	
	Control	F2F	Control	F2F
Education				
Primary	22.6%	15.3%	19.6%	16.3%
	(28.1%)	(23.1%)	(21.3%)	(18.2%)
Secondary	40.1%	40.6%	43.0%	41.5%
	35.0%	35.8%	32.2%	29.3%
Tertiary	15.6%	24.7%	16.3%	22.7%
	32.5%	34.7%	29.0%	26.6%
Male	50.1%	5.4%	49.1%	6.1%
	44.7%	12.0%	44.2%	12.2%
Age				
Younger than 25 years old	1.4%	7.0%	2.7%	11.7%
	7.6%	14.3%	9.8%	19.7%
25–44	56.2%	76.6%	68.0%	77.3%
	32.8%	26.6%	28.0%	26.0%
45–59	40.9%	16.5%	28.7%	11.0%
	32.2%	24.3%	27.7%	20.8%
retired	1.5%	0.0%	0.5%	0.0%
	5.5%	0.1%	1.5%	0.0%
Salary				
1st and 2nd quartiles	47.5%	42.4%	53.2%	57.2%
	31.4%	32.9%	24.5%	23.9%
3d quartile	23.2%	28.3%	23.6%	23.0%
	23.3%	27.7%	18.7%	18.1%
4th quartile	27.8%	27.1%	20.6%	16.6%
	29.0%	31.0%	19.6%	16.5%

Table 3 ATET postEstimates. Women

	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
F2F_prim	0.349***	0.027	0.338***	0.028	0.339***	0.028	0.237***	0.069	0.236***	0.069	0.271***	0.068	0.27***	0.068
sec	0.183***	0.022	0.185***	0.022	0.186***	0.022	0.067	0.053	0.067	0.053	0.092*	0.053	0.091*	0.053
high	0.254***	0.022	0.255***	0.022	0.256***	0.022	0.098**	0.04	0.098**	0.04	0.164***	0.042	0.164***	0.042
NHB_prim			-0.185***	0.037	-0.186***	0.037	-0.239**	0.05	-0.241***	0.05	-0.2***	0.052	-0.201***	0.052
sec			0.082***	0.029	0.082***	0.029	0.025**	0.037	0.024	0.037	0.078*	0.041	0.077*	0.041
high			0.024	0.024	0.024	0.024	-0.081**	0.033	-0.081**	0.033	-0.04	0.037	-0.04	0.037
FNH_prim							0.121	0.075	0.123	0.075	0.069	0.075	0.071	0.075
sec							0.142**	0.059	0.144**	0.059	0.114*	0.059	0.116	0.059
high							0.226	0.048	0.227***	0.048	0.193***	0.05	0.194***	0.05
Covariates x Time					age groups				age groups				age groups	
					wage groups				wage groups				wage groups	
											okved		okved	

Table 4 ATET postEstimates. men

	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
F2F_prim	0.169***	0.04	0.174***	0.042	0.176***	0.042	0.136	0.092	0.142	0.092	0.213**	0.091	0.218*	0.091
sec	-0.046	0.034	0.012	0.035	0.01	0.035	0.326***	0.096	0.324***	0.096	0.465***	0.096	0.461***	0.096
high	0.017	0.033	0.076	0.035	0.075	0.035	0.177***	0.067	0.178***	0.067	0.199***	0.069	0.199***	0.069
NHB_prim			0.023	0.051	0.027	0.051	0.001	0.069	0.008	0.069	-0.035	0.069	-0.03	0.069
sec			0.354***	0.051	0.351***	0.051	0.535***	0.073	0.532***	0.073	0.577*	0.074	0.573***	0.074
high			0.197***	0.039	0.199***	0.039	0.264***	0.054	0.268***	0.054	0.177**	0.058	0.18***	0.058
FNH_prim							0.049	0.103	0.043	0.103	0.078	0.103	0.074	0.103
sec							-0.361***	0.103	-0.361***	0.103	-0.419***	0.103	-0.414***	0.103
high							-0.141*	0.078	-0.143	0.078	0.027	0.08	0.026	0.08
					age groups				age groups				age groups	
					wage groups				wage groups				wage groups	
women											okved		okved	

Appendix

Table A1

Panel A Bottom 10% of F2F intensity

profession_employment	name_okved	F2F	HB	F2F_alter	HB_alter
Системный администратор	Обрабатывающие производства	0	1	0.8	1
Авербандщик	Культура и спорт	0.1	0	0.1	0
Аппаратчик (различных технологических процессов)	Обрабатывающие производства	0.1	1	0.1	0
Бетонщик	Финансы	0.1	0	0.1	0
Бортпроводник	Обрабатывающие производства	0.1	0	0.8	0
Вязальщик (прутков и проволоки, схемных шгутов, кабелей и шнуров)	Обрабатывающие производства	0.1	0	0	0
Гардеробщик	Культура и спорт	0.1	0	0.8	0
Горничная	Обрабатывающие производства	0.1	0	0	0
Горнорабочий	Добыча полезных ископаемых	0.1	0	0	0
Грузчик	Прочее	0.1	0	0.1	0
Дворник	Прочее	0.1	0	0.1	0
Дизайнер	Прочее	0.1	1	0.1	1
Дизайнер (художник) компьютерной графики	Информация и связь	0.1	1	0.5	1
Дорожный рабочий	Строительство	0.1	0	0.1	0

Panel B Top 10% by F2F intensity

profession_employment	name_okved	F2F	HB	F2F_alter	HB_alter
Ассистент (в сфере искусства и кино)	Культура и спорт	0.8	1	0.5	0.5
Буфетчик	Общепит и гостиницы	0.8	0	0.8	0
Вожатый (в т.ч. старший)	Образование	0.8	1	1	0
Инспектор	Администрация	0.8	1	0.8	0
Инструктор, тренер	Культура и спорт	0.8	1	1	0
Преподаватель в учреждении высшего образования	Образование	0.8	1	1	1
Преподаватель в учреждении дополнительного образования	Образование	0.8	1	1	0.5
Преподаватель общеобразовательного учреждения	Образование	0.8	1	1	0.5
Сотрудник государственного органа	Госуправление, военная безопасность, соцобеспечение	0.8	1	0.5	0.5
Сотрудник дошкольного образовательного учреждения	Образование	0.8	1	1	0
Социальный работник	Образование	0.8	0	1	0.5
Специалист	Прочее	0.8	1	0.1	0.5
Торговый представитель	Торговля	0.8	0	0.8	1
Юрист	Прочее	0.8	1	0.8	1
Врач	Здравоохранение	0.9	1	0.8	0.5
Приемщик товаров, заказов, багажа	Прочее	0.9	0	0.8	0

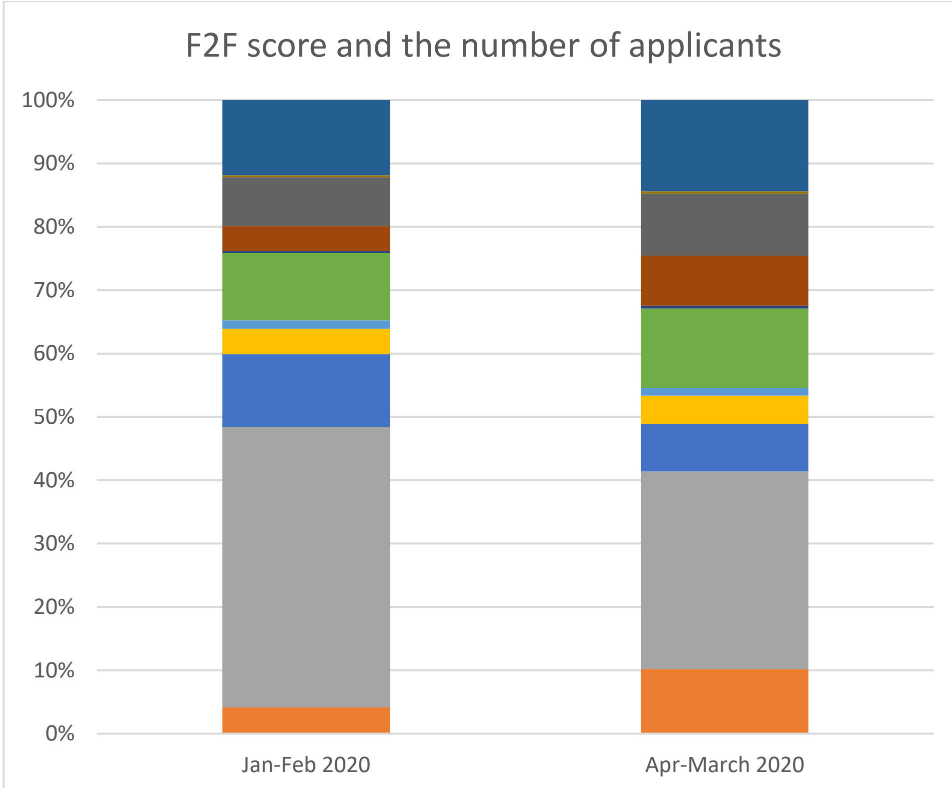

Fig A1 The structure of applicants by F2F and before/after period

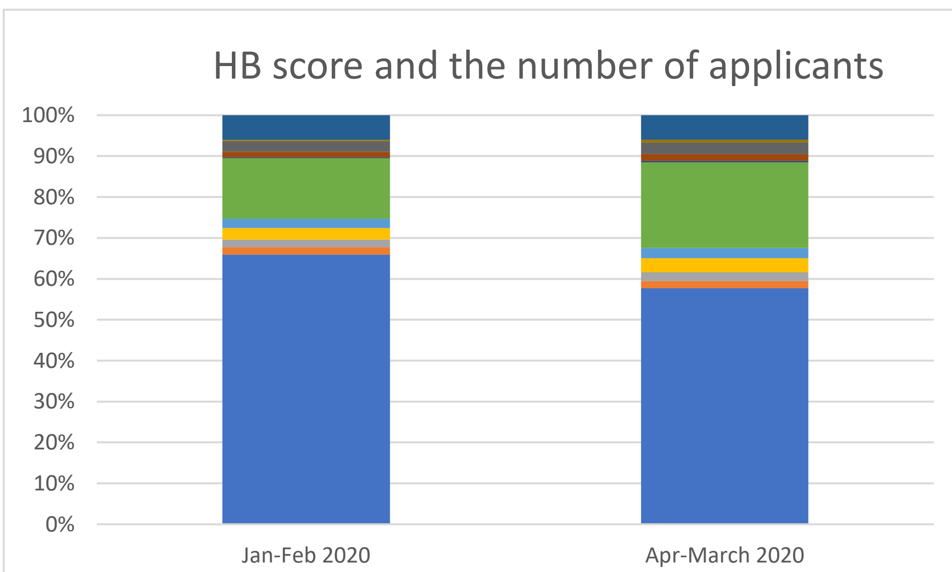

Fig A2 The structure of applicants by HB and before/after period

Table A2

Panel A Estimates. Women

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
April-May 2020	0.922***	0.792***	0.953***	0.956***	1.000***	1.004***	0.984***	0.986***
	(0.0134)	(0.0168)	(0.0366)	(0.0366)	(0.0467)	(0.0467)	(0.0503)	(0.0504)
Secondary	-0.157***	-0.0959***	-0.326***	-0.327***	-0.325***	-0.325***	-0.340***	-0.341***
	(0.0172)	(0.0216)	(0.0459)	(0.0459)	(0.0578)	(0.0578)	(0.0572)	(0.0572)
Tertiary	-0.336***	-0.319***	-0.497***	-0.499***	-0.470***	-0.472***	-0.485***	-0.488***
	(0.0174)	(0.0224)	(0.0430)	(0.0430)	(0.0542)	(0.0542)	(0.0536)	(0.0536)
F2F		0.349***	0.338***	0.339***	0.237***	0.236***	0.271***	0.270***
		(0.0275)	(0.0276)	(0.0276)	(0.0687)	(0.0687)	(0.0683)	(0.0683)
NHB			-0.185***	-0.186***	-0.239***	-0.241***	-0.200***	-0.201***
			(0.0373)	(0.0373)	(0.0500)	(0.0501)	(0.0524)	(0.0524)
FNH					0.121	0.123	0.0686	0.0707
					(0.0750)	(0.0750)	(0.0748)	(0.0748)
Secondary#F2F		-0.165***	-0.153***	-0.153***	-0.170*	-0.170*	-0.179**	-0.179**
		(0.0352)	(0.0352)	(0.0352)	(0.0870)	(0.0870)	(0.0861)	(0.0861)
Secondary#NHB			0.267***	0.268***	0.264***	0.265***	0.277***	0.278***
			(0.0471)	(0.0471)	(0.0623)	(0.0623)	(0.0616)	(0.0616)
Secondary#FNH					0.0212	0.0208	0.0449	0.0449
					(0.0951)	(0.0951)	(0.0941)	(0.0941)
Tertiary#F2F		-0.0945***	-0.0833**	-0.0834**	-0.139*	-0.138*	-0.107	-0.105
		(0.0353)	(0.0353)	(0.0353)	(0.0795)	(0.0795)	(0.0787)	(0.0787)
Tertiary#NHB			0.209***	0.210***	0.158***	0.160***	0.160***	0.161***
			(0.0443)	(0.0443)	(0.0597)	(0.0597)	(0.0592)	(0.0592)
Tertiary#FNH					0.105	0.104	0.125	0.124
					(0.0890)	(0.0890)	(0.0882)	(0.0882)
Administration		Reference						
Water supply							-0.640***	-0.642***
							(0.212)	(0.212)
Public administration, military security,							-0.378***	-0.379***
							(0.0877)	(0.0877)
Mining							-0.407	-0.408
							(0.451)	(0.451)
Households							0.266	0.264
							(0.290)	(0.290)
Health care							-0.302***	-0.303***
							(0.0542)	(0.0542)
Information and communication							-0.0387	-0.0359
							(0.0399)	(0.0399)
Culture and sports							-0.342***	-0.341***
							(0.0389)	(0.0389)
Science							-0.381*	-0.377*
							(0.219)	(0.219)
Estate							-0.796*	-0.812*
							(0.422)	(0.422)
Electricity supply							-0.574***	-0.576***
							(0.118)	(0.118)
Manufacturing industries							-0.0232	-0.0232
							(0.0253)	(0.0253)
Education							-0.119***	-0.118***
							(0.0271)	(0.0271)
Catering and hotels							0.240***	0.241***

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
							(0.0303)	(0.0303)
Other							0.0167	0.0179
							(0.0214)	(0.0214)
Agriculture							-0.569***	-0.568***
							(0.0521)	(0.0521)
Construction							-0.387***	-0.386***
							(0.0595)	(0.0595)
Trade							0.141***	0.141***
							(0.0289)	(0.0289)
Finance							0.0956***	0.0953***
							(0.0353)	(0.0353)
young				-1.596		-1.604		-1.586
				(2.775)		(2.773)		(2.736)
age25_44				-1.569		-1.574		-1.559
				(2.774)		(2.772)		(2.735)
age45_59				-1.557		-1.563		-1.552
				(2.775)		(2.773)		(2.736)
wage_q12				0.0102		0.00997		0.0157
				(0.0133)		(0.0133)		(0.0131)
wage_q3				0.0241*		0.0242*		0.0261*
				(0.0138)		(0.0138)		(0.0136)
Constant	0.942***	0.939***	0.938***	2.495	0.938***	2.500	0.958***	2.504
	(0.00520)	(0.00515)	(0.00519)	(2.775)	(0.00518)	(2.772)	(0.00530)	(2.736)
Observations	33,785	33,785	33,785	33,785	33,785	33,785	33,785	33,785
R-squared	0.404	0.415	0.416	0.416	0.417	0.417	0.433	0.433
Number of panel_id	15,233	15,233	15,233	15,233	15,233	15,233	15,233	15,233

Panel B Estimates. Men

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.after2m	1.003***	0.970***	0.949***	0.948***	0.969***	0.966***	0.964***	0.962***
	(0.0158)	(0.0176)	(0.0508)	(0.0508)	(0.0662)	(0.0662)	(0.0701)	(0.0702)
Secondary	-0.139***	-0.0959***	-0.411***	-0.404***	-0.603***	-0.594***	-0.669***	-0.659***
	(0.0210)	(0.0235)	(0.0723)	(0.0722)	(0.0971)	(0.0971)	(0.0957)	(0.0957)
Tertiary	-0.358***	-0.330***	-0.482***	-0.482***	-0.562***	-0.561***	-0.539***	-0.539***
	(0.0217)	(0.0249)	(0.0639)	(0.0639)	(0.0836)	(0.0835)	(0.0823)	(0.0822)
F2F		0.169***	0.174***	0.176***	0.136	0.142	0.213**	0.218**
		(0.0398)	(0.0416)	(0.0416)	(0.0920)	(0.0919)	(0.0911)	(0.0911)
NHB			0.0230	0.0267	0.00144	0.00762	-0.0355	-0.0298
			(0.0513)	(0.0512)	(0.0687)	(0.0687)	(0.0691)	(0.0691)
FNH					0.0487	0.0429	0.0783	0.0740
					(0.103)	(0.103)	(0.103)	(0.103)
Secondary#F2F		-0.214***	-0.163***	-0.166***	0.191	0.183	0.253*	0.243*
		(0.0521)	(0.0541)	(0.0541)	(0.133)	(0.133)	(0.131)	(0.131)
Secondary#NHB			0.331***	0.325***	0.533***	0.524***	0.613***	0.602***
			(0.0726)	(0.0726)	(0.100)	(0.100)	(0.0987)	(0.0986)
Secondary#FNH					-0.410***	-0.404***	-0.497***	-0.488***
					(0.146)	(0.146)	(0.143)	(0.143)
Tertiary#F2F		-0.152***	-0.0987*	-0.101*	0.0419	0.0368	-0.0135	-0.0185
		(0.0518)	(0.0544)	(0.0544)	(0.114)	(0.114)	(0.112)	(0.112)
Tertiary#NHB			0.174***	0.172***	0.263***	0.260***	0.213**	0.210**
			(0.0645)	(0.0645)	(0.0876)	(0.0875)	(0.0863)	(0.0862)
Tertiary#FNH					-0.189	-0.186	-0.0515	-0.0476
					(0.130)	(0.129)	(0.128)	(0.128)
Administration		Reference						
Water supply							-0.895***	-0.915***
							(0.196)	(0.196)
Public administration,							-0.484***	-0.485***

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
military security,								
							(0.0704)	(0.0704)
Mining							-0.00138	-0.00192
							(0.0948)	(0.0948)
Households							0.0776	0.0722
							(0.303)	(0.303)
Health care							-0.767***	-0.757***
							(0.159)	(0.159)
Information and communication							-0.0172	-0.0185
							(0.0675)	(0.0675)
Culture and sports							-0.341***	-0.346***
							(0.0720)	(0.0719)
Science							-0.496***	-0.502***
							(0.192)	(0.192)
Estate							-0.788**	-0.799**
							(0.395)	(0.395)
Electricity supply							-0.123***	-0.120***
							(0.0387)	(0.0387)
Manufacturing industries							0.215***	0.210***
							(0.0312)	(0.0312)
Education							-0.581***	-0.587***
							(0.0663)	(0.0663)
Catering and hotels							0.233***	0.229***
							(0.0557)	(0.0557)
Other							0.118***	0.120***
							(0.0278)	(0.0278)
Agriculture							-0.644***	-0.641***
							(0.0584)	(0.0584)
Construction							0.0552	0.0569
							(0.0439)	(0.0439)
Trade							-0.00774	-0.00852
							(0.0425)	(0.0425)
Finance							-0.210***	-0.210***
							(0.0503)	(0.0503)
young				-0.0969		-0.107		-0.0727
				(0.126)		(0.126)		(0.123)
age25_44				-0.118		-0.127		-0.0945
				(0.124)		(0.124)		(0.122)
age45_59				-0.0823		-0.0916		-0.0640
				(0.124)		(0.124)		(0.122)
wage_q12				0.0296*		0.0292*		0.0310*
				(0.0162)		(0.0162)		(0.0159)
wage_q3				0.0776***		0.0773***		0.0747***
				(0.0180)		(0.0179)		(0.0176)
Constant	0.895***	0.892***	0.902***	0.980***	0.905***	0.993***	0.932***	0.988***
	(0.00669)	(0.00678)	(0.00688)	(0.124)	(0.00694)	(0.124)	(0.00715)	(0.122)
Observations	24,499	24,499	24,499	24,499	24,499	24,499	24,499	24,499
R-squared	0.435	0.436	0.439	0.440	0.439	0.441	0.463	0.464
Number of panel_id	11,790	11,790	11,790	11,790	11,790	11,790	11,790	11,790