

The role of wage subsidies in the Macedonian labour market*

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Abstract

The main rationale for wage subsidies is giving job opportunities to workers who would otherwise remain unemployed or take jobs that do not exploit their potential productivity. The aim of this paper is to evaluate the wage subsidy programme in North Macedonia for the period 2018-2019 in order to provide a sound basis for its redesign in the times of Covid-19 crisis. The Propensity score matching is used as a principal estimation method. Moreover, we further explore the impact of the wage subsidies on the outcome variables for particular disadvantaged segments by disaggregation of the average treatment effect on treated individuals. The evaluation reveals improvement of the wage subsidy program in 2019 relative to 2018. However, having in mind the impact of the Covid-19 pandemics, there is a room for redesign of this measure by improving its targeting and conditions for retaining the subsidised jobs in the long run.

Keywords: wage subsidy, labour market, unemployment, COVID-19

Introduction

Active labour market measures (ALMMs) aim at bringing unemployed back to work by improving the functioning of the labour market. The active labour market policies have multiple purposes such as: increasing output and welfare by putting unemployed to work maintain the size of the effective labour force by counteracting high unemployment, help reallocate labour between different segments by improving employability of the labour force, alleviate the moral-hazard problem of unemployment insurance etc. (Martin, 2000). The majority of these measures are general-purpose, i.e. serve relatively broad target population. However, often programs are designed for specific groups in the labour market considered as vulnerable segments. The current Covid-19 crisis offer unique opportunities for innovation and reset of social objectives and to experiment with different ALMMs.

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Persistently high unemployment in many countries, tight government budgets and the existing scepticism regarding the effects of active labour market policies are the reason for growing interest in evaluating these measures (Hujer and Caliendo, 2000). The main challenge in carrying out effective impact evaluation is to identify the causal relationship between the program and the outcomes of interest. With respect to this, there exist contrasting positions on the effectiveness of active labour market programs. On one hand, proponents of these programs argue that they are both necessary and useful for reducing unemployment. On the other hand, the opponents demonstrate that active labour market programs are provided at high opportunity costs to other social programs and labour market efficiency as a whole (Dar and Tzannatos, 1999; Kluve, 2006; Escudero, 2018).

The importance of active labour market policies for North Macedonia can be viewed from two different perspectives. First, the role of the active labour market policies receives greater weight when skill obsolescence is higher *i.e.* when the long-term unemployment prevails over the short-term unemployment. Second, the aspiration of the country in the near future to start negotiations for EU accession imposes ambitious objectives in terms of attaining international labour market competitiveness. With this in mind, we can argue that investment in human capital becomes increasingly valuable and implies a need for reforms of active labour market policies (Nikoloski, 2021).

Even though the implemented ALMMs in North Macedonia are characterized with high level of transparency and accountability, there is a lack of their rigorous assessment. To our knowledge, there are two published impact evaluations performed for selected number of active labour market programs: First, for the period 2008-2012 financed by the ILO, and second for the period 2018-2019 (Mojsoska Blazevski and Petreski, 2015; Nikoloski, 2021). The findings show mixed results in the way that some programs bring comparatively better outcomes for the program participants relative to non-participants. However, the analyses identified programs that were not effective in improving the labour market outcomes of the participants.

One of the widely used ALMMs are the wage subsidies that lower the cost of a company to hire particular worker, which should lead to an increase in employment. The main rationale for wage subsidies is giving job opportunities to workers who would otherwise remain unemployed or take jobs that do not exploit their potential productivity. In the absence of wage subsidies, these workers are likely to face long spells of unemployment or inactivity that reduce their human capital. Most of the evaluations of wage subsidy programs focus on high income countries and have shown large variation in results, which depends on the specificities of the design (Katz, 1996; Jaenichen and Gesine, 2007; Bernhard *et al.*, 2008; Almeida *et al.*, 2014). For instance, Schünemann *et al.* (2011) do not find significant impact of wage subsidies for long-term unemployed workers in Germany on

the employment outcomes. Similarly, Huttunen *et al.* (2010) find out that the Finish subsidy system has no effects on the employment rate. In addition, Bördős *et al.* (2015) in their comprehensive analysis of wage subsidies for youth workers find out that modest pay roll tax cuts in developed countries leads to negligible employment gains and are cost ineffective. However, in middle-income countries wage subsidies in the form of payments to firms lead to sizeable employment gains in the short run.

During the Covid-19 pandemics as part of a wider range of policy measures to counteract the economic and labour market effects of the crisis, many countries adopted the strategy of implementing temporary wage subsidies (ILO, 2020a). Although the temporary wage subsidies are not a new policy instrument, the scale of their use in the pandemic crisis is unprecedented. In contrast to targeted subsidies that aim to encourage firms to employ specific categories of workers such as youth, long-term unemployed, or workers with disabilities, temporary wage subsidies are used in times of crisis to save jobs and help enterprises to retain as many employees as possible. However, the analyses suggest that as economic conditions improve, temporary wage subsidy schemes will be gradually integrated with the pre-existing systems (Linden *et al.*, 2021).

The need to assess the effects of wage subsidy programme in North Macedonia stems from the fact that public funds are limited and spent at a time of an economic crisis as well as increased risk of poverty due to the Covid-19 pandemics. Although ESA successfully copes with the implementation of planned ALMMs including the wage subsidy programme, there still exist a lot of challenges regarding the redesign of the actual and introduction of new measures (Nikoloski *et al.*, 2023). The aim of this paper is to evaluate the wage subsidy programme in North Macedonia for the period 2018-2019 in order to provide a sound basis for its redesign in the times of Covid-19 crisis. The paper is structured as follows. In section 1 we present the characteristics of the wage subsidy programme in North Macedonia followed by section about the data and sample used for the analysis. The variables under consideration and estimation technique are elaborated in Section 3 and Section 4 respectively. The estimation results are presented in Section 5, followed by an analyses of the cost effectiveness and the impact of Covid-19 pandemics. In the last section are presented the concluding remarks and the policy recommendations.

1. Characteristics of the wage subsidy programme in North Macedonia

The efforts to increase employment and reduce social exclusion in North Macedonia continue to be high priority due to the need for reducing unemployment, especially among vulnerable groups.

In this context, the process of planning, design and implementation of ALMMs has been continually performed since 2007 (Nikoloski, 2021). Among the implemented measures, the usual types of measures are provided on regular basis, while the others are provided sporadically. As regular, we can consider the following ALMMs: subsidies for employment, trainings for known employers, trainings for advanced IT skills and trainings for jobs on demand. The non-regular ALMMs are quite heterogeneous and sometimes they have been provided for only couple of years such as trainings for specific fields or specific support for firms regarding new job openings (Krstevska and Ilievska, 2018).

The planned active labour market programs and measures in North Macedonia are systematized in the Operational Plan (OP), which is prepared on yearly basis by the ESA. The OP is an official document that contains detailed explanation of each ALMM including the eligibility criteria, the number of beneficiaries (participants), the selection procedures etc. In the realisation of the OP are involved different institutions such as ESA, Ministry of Labour and Social Affairs, educational organisations etc. Furthermore, the OP encompasses the financial framework with indicated costs and financial sources for each ALMM. The guiding principles in the realization of the ALMMs according to the OP is providing gender balance and representation of youth (aged under 29) for at least 30 percent.

In this context, the wage subsidies in North Macedonia are used to promote integration into the labour market of specific groups of workers that usually face employment difficulties. Particularly, the target groups are the following types of workers: long-term unemployed, youth (under 29), older workers (above 50), social assistance beneficiaries, single parents, disabled people, some ethnic minorities (Roma), homeless persons, persons without elementary education, former drug abusers etc.

The eligible companies for wage subsidies are micro, small and medium enterprises, social enterprises, civil and non-profit organisations that carry out economic activities, newly created enterprises within the self-employment programme as well as individual unemployed persons. The eligible companies are informed about the programme by a public announcement, while individual unemployed are directly contacted by using the ESA registry. After selecting the successful submissions, ESA signs with the beneficiary companies contracts that contain the terms and conditions.

The selection criteria generally consider the employers. First, the total number of employees in the company has not be lower then the average number of the full-time employees in the previous year. Second, the company should has settled all obligations regarding payments of salaries and social security contributions. Third, the company should not have financial debts in the previous year.

Fourth, the employer has to have at least one employed person with permanent (open-ended) contract. Fifth, the number of newly hired workers by the wage subsidy program in the company may not exceed 50% of the average number of employed in the previous year and may not by greater than five persons by one employer.

The wage subsidies in North Macedonia are granted for a limited period of 3, 6 or 12 months. A follow-up period of further employment is obligatory after the expiration of the subsidy. For instance, the employer is obliged to keep the beneficiary worker for a total period of: (i) 9 months in the case of receiving wage subsidies for a period of 3 months, (ii) 18 months in the case of receiving wage subsidies for a period of 6 months, and (iii) 30 months in the case of receiving wage subsidies for a period of 12 months. If a beneficiary worker is dismissed within this period for reasons attributable to the employer, the employer has to reimburse part of the subsidy.

The monthly amount of the wage subsidy in 2018-2019 was 310 EUR. Hence, the total financial support for a period of 3 months was 930 EUR, for 6 months was 1.860 EUR, while for 12 months was 3.720 EUR. Having in mind that the gross minimum wage for the same period was around 300 EUR, the monthly wage subsidy provided possibility for paying the beneficiaries higher then the minimum wage.

When the Covid-19 pandemics hit the Macedonian economy in March 2020, the Government approached the World Bank in search of co-financing support for the implementation of a wage subsidy scheme. The scheme was designed to provide salary subsidies to adversely affected firms for three months (April, May and June) to enable these firms to meet their immediate liquidity needs, retain employees, encourage operational upgrading, and spur an economic recovery. This support covered 50% of social contributions from employees for viable firms in tourism and transport as the hardest hit sectors during the pandemic. Accordingly, approximately 20,000 companies benefitted from this wage subsidy scheme, helping over 120,000 employees (World Bank, 2020). Having in mind that jobs in the informal sector were not eligible for this measure, it is assumed that it assisted a number of informal jobs to formalize (ILO, 2020b; ETF, 2021; Finance Think, 2021).

2. Data and sample

The data for the analyses are provided from two sources: the registry of the Employment Service Agency as administrative data and a survey carried out on a sample of wage subsidy beneficiaries. There are several advantages of using administrative data for policy research such as: its superior quality, exhaustive coverage, representativeness etc. (Pierre, 1999). However, the ESA registry does

not contain data on all considered attributes. In order to obtain information for additional attributes that are not provided by the ESA registry, an additional telephone survey was carried out during September 2021, covering a sample of participants (treatment group) and non-participants (control group).

The sample for analysis consists of treatment and control groups. The treatment group comprises persons who were wage subsidy beneficiaries. On the other hand, the control group comprise persons who applied but have not been selected. The figures regarding the sample size for the treatment and control groups are reported in Table 1. In addition to response rate, we present the rates of unreached participants and control group applicants and the rates of rejection.

Table 1. Total number and sample size of the treatment and control groups

	Wage subsidy p	program 2018	Wage subsidy program 2019		
	Treatment	Control	Treatment	Control	
Database from ESA	1206	531	1945	281	
Sample size	261	121	234	82	
Response rate (percent)	21.7	22.8	35.8	40.2	
Unreached rate (percent)	55.6	52.5	33.9	33.3	
Rejection rate (percent)	22.7	24.7	30.3	26.5	

Source: own calculations

The number of planned subsidised jobs in 2018 according to the OP was 570, while there were actually provided 1206 subsidies (which is more than double). Accordingly, the number of planned wage subsidies in 2019 was increased to 1419, while the ESA actually provided 1945 subsidies. The control groups of workers were considerably smaller than treatment groups, consisting of 531 and 281 applicants in 2018 and 2019 respectively.

The attrition is a problem because we might expect the employment outcomes of individuals who refuse to be surveyed or who cannot be found to differ from those who are interviewed. A typical approach has been to compare attrition rates in the treatment and control groups, and then do a bounding exercise if the attrition rates vary (often the control group is slightly less likely to respond). This type of differential response would bias the estimated treatment effect upwards, overstating the impact of training (McKenzie, 2017). A second issue with the use of survey measures of employment is the possibility that those in the treatment groups over-report their employment outcomes to express their appreciation for being given the program, while those in the control group potentially underreport these outcomes.

3. Variables under consideration

The analysis is based on observing a wide range of possible outcomes obtained from the ESA Registry or from the survey. The following possible 8 outcomes may arise: Employed person, other person who search for job, unemployed person, unknown status, founder, manager, founder and manager, death or retirement. In addition, from the survey carried out on a sample of participants and control group applicants we provide information about the following outcome measures:

- Currently employed defined according to the standard ILO definition and further is disaggregated to the following categories: employer, employed, self-employed and unpaid family worker;
- Currently unemployed which correspond to the ILO definition of a person who does not have a job, is searching for job and is available to take a job within four weeks;
- Inactive correspond to the ILO definition of inactivity, or more precisely categorizes those who have not searched for a job at least four weeks;
- Type of contract permanent (open-end), temporary (close-end), seasonal or no contract if the person is employed informally;
- Monthly salary earned on the current job for employed persons or monthly wage earned on
 the last employment for those who are unemployed. Instead of asking the respondents about
 the exact amount of monthly salary, we assign them to classes with predefined ranges;
- Changes in financial conditions after the participation in the program or after the cut-off point for the applicants from the control group. The possible outcomes are categorized as: better, same or worse.
- Changes in employment prospects after the participation in the program or after the cut-off point for the applicants from the control group. The possible outcomes are categorized as: better, same or worse;
- Job search effort assessed on a five point Likert scale with five options from 'do not search at all' to 'search to great extent';
- Emigration intention assessed on a five point Likert scale with five options from 'do not plan at all' to 'plan to great extent'.
- Similarly, to outcome indicators, the explanatory variables are obtained from the ESA Registry or by the survey. The variables under consideration are the following:
- Demographic (age, gender, urban/rural, marital status, disability) all of these variables
 except the marital status are provided from the ESA registry; the marital status of respondents
 has been provided from the survey;

- Household characteristics Number of household members, Number of household members under 15, Number of employed household members, Number of unemployed household members, Number of retired household persons; this information is provided from the survey;
- Human capital (education) the education level is categorized in the broad education groups: primary, secondary, higher (2 years), higher (4 years) and specialization which corresponds to the post-graduate and doctoral levels;
- Previous work experience provided from the ESA registry and measured number of months;
- Unemployment history duration of unemployment prior to application or participation in the program; this information is provided from the ESA registry.

In order to evaluate the targeting of the ALMMs with respect to vulnerable and marginalised groups, we pay particular attention to the coverage of specific categories of workers. As marginalised groups are considered the following: unemployed without work experience, youth (aged under 25), female, those living in rural areas and very-long-term unemployed (those who search for job more than 4 years). Additionally, as a disadvantaged groups can be considered disabled people and some ethnic minorities such as Roma, but their underrepresentation in some ALMMs prevents us from undertaking more detailed analyses.

The participants in the ALMMs are assessed with respect to their satisfaction with the provided training or wage subsidy. Particularly they are questioned about the gained knowledge and skills, the appropriateness of the applied training methods, the usefulness of the training materials, the appropriateness of the training environment and whether they would apply for another ALMM. In the case of wage subsidies the satisfaction is assessed with respect to the job, salary, on-the-job training and superiors. For the purpose of evaluation we use a five point Likert scale in the gradation from 'not satisfied at all' to 'satisfied to great extent'. Having in mind the circumstances engendered by the Covid-19 pandemics, the participants and ALMM applicants have been assessed whether the pandemics imposed a need for new skills. As possible outcomes we assume an increased demand for the following skills: foreign languages, basic IT skills, advanced IT skills, e-commerce, e-banking etc.

4. Estimation technique

Part of the differences in labour market outcomes between ALMMs participants and the control group is due to the differences in their socio-demographic characteristics. A similar explanation could be offered for the different outcomes across the various programs (aside from the differences stemming from the characteristics and intensity of programs). Given that the treatment and control

groups are likely to differ in their observable and unobservable characteristics, a comparison of their employment outcomes can be biased. Specifically, better employment outcomes can be expected for individuals with higher levels of education, those who have prior work experience, those with shorter unemployment spells and so on. In other words, program participants may have better employment outcomes not because of the effectiveness of the programs but because of their better characteristics. Thus, if the groups systematically differ in these characteristics, the differences in employment outcomes may be due to these differences, rather than to differences in program effects.

The analysis is be based on quasi-experimental approach where programs are evaluated expost. Namely, because the control group does not exist, it must be created and matched as closely as possible to the observed characteristics of those who participated in the program. These methods are called quasi-experimental, because they attempt to recreate a situation similar to a controlled experiment. In this case there is no single method that is preferable in all circumstances, and various alternative techniques can be applied (Caliendo and Hujer, 2005; Gertler *et al.*, 2016).

The Propensity score matching is used as a principal estimation method. This method is based on the assumption that differences between participants and non-participants that jointly determine their decision to participate and the outcome of interest are all observable in the data. Matching therefore results in comparing participants with non-participants, giving more weight to the non-participants that are most similar to participants. In this context, a logistic regression is used in order to calculate the propensity scores. The outcomes of participants and non-participants with similar propensity scores are compared to obtain the program effect. The technical aspects of estimation based on propensity score matching procedure is developed within the Roy-Rubin framework*.

There are several matching algorithms suggested in the literature such as: nearest-neighbour matching, radius calliper matching and Kernel matching (Loi and Rodrigues, 2012). The choice of the matching algorithm is not trivial since it involves trade-off between bias and variance. The quality of the matching procedure is evaluated on the basis of its capability in balancing the control and treatment groups with respect to the covariates used for the propensity score estimation. The basic idea is to compare the distribution of these covariates in the two groups before and after matching on the propensity score.

Let denote with Y^T the outcome when the person gets the treatment, whereas Y^C denotes the outcome when person does not participate in the ALMM (comparison group). Additionally, we

¹ Developed by A.D. Roy and D.B. Rubin.

introduce a binary assignment indicator D that determines whether the individual gets the treatment (D=1) or not (D=0). The average treatment effect of the treated (ATT) is defined as follows:

$$ATT = E(Y^T - Y^C | D=1) = E(Y^T | D=1) - E(Y^C | D=1)$$

ATT shows the expected effect of the program for those persons who actually participated. However, we cannot observe the counterfactual $E(Y^C|D=1)$ i.e. the average outcome of those persons who participated in the program had they not participated. Thus, without further assumption ATT is not identified. But if we can observe all factors that jointly influence outcomes and participation decision, then conditional on these factors (X), the participation decision and the outcomes are independent.

The propensity score matching method creates a comparison group from untreated observations by matching treatment observations to one or more observations from the untreated sample, based on observable characteristics. The propensity scores are used to select the comparison group for each treatment group according to the following three steps:

- First, a logistic regression model is estimated for each ALMM in which the dependent variable is dichotomous, taking the value 1 for those who took part in the intervention, and 0 if they did not. The explanatory variables include all observables that may affect participation, but that are not affected by the intervention;
- Second, the output from these selection models are used to estimate choice probabilities conditional on X (the so-called propensity scores) for each treatment and potential comparison group member. Hence, an individual's propensity score is the fitted value from the participation equation. Having calculated the propensity scores for all observations, the region of common support is identified;
- Third, for each treatment group member is selected potential comparison group member based on their propensity scores.

Once the matching is done, a test is performed for balance by comparing the mean characteristics of treatment and comparison groups. There should be no significant difference in average characteristics between the two groups. Finally, the impact estimate is calculated by first calculating the difference in between the indicator for the treatment individual and the average value for the matched comparison individuals, and second, by averaging over all these differences.

There are several pros and cons using the propensity score matching method. On one hand it is characterised with its simplicity in computing the standardised bias and joint significant test. Furthermore, the matching method does not require any functional form assumption for the outcome equation and therefore, it is not susceptible to misspecification bias along that dimension. However,

in practice it may be the case that some of the participants do not have matched counterparts in the pool of non-participants with similar propensity scores. In technical terms, it is possible a lack of common support, or lack of overlap between the propensity scores of the participants in the program and those of the pool of non-participants. Having in mind these characteristics of the propensity score matching method, for checking the robustness of the estimates alternative methods for estimation are applied as well.

5. Evaluation of the wage subsidy program

For the wage subsidy programme, we determine what outcome would have been for a program beneficiary after participation in the program compared with the counterfactual outcome i.e. if the person had not participated in the program. The difference between the observed outcome and the counterfactual outcome is used as a measure of the impact of the program. One of the main issues in the sample selection is the so-called selection bias, which may affect the accuracy of the estimates. Selection bias means that a better outcome for the participants compared to the non-participants may be observed due to differences in the characteristics of the persons in the two groups and not to participation in the program.

Furthermore, we estimate the individual probabilities to participate to the program, depending on a set of observable characteristics. This is conducted through using standard Probit regression on the treated and the non-treated individuals. The estimated coefficients will provide insights in the factors influencing selection into treatment, but may also capture factors of attrition from the survey, i.e. factors explaining differential non-response rates in the treatment and in the control group. According to the estimated Probit model is than calculated the propensity score for each individual in the treatment and comparison group.

The propensity scores are used to match participants with comparable non-participants. For each treated individual, we look for the one individual among non-participants who is the closest neighbour in terms of the predicted probability of being treated. In other words, for each pair comprising a participant and a non-participant, the absolute difference in terms of the estimated propensity to participate in a certain treatment is minimized. To ensure that the matched pairs have reasonably similar probabilities to be treated, we exclude participants for whom the predicted probability to be in the program is larger than for any individual in the comparison group. In this way we achieve common support. Alternative matching procedures are used as robustness checks.

Moreover, we further explore the impact of the wage subsidies on the outcome variables for particular disadvantaged segments by disaggregation of the average treatment effect on treated individuals. In this context, particular attention is paid to youth, female, unemployed from rural areas, without work experience and being very-long-term unemployed. The disaggregation is performed only for those outcome variables where statistically significant impact has been identified.

Finally, we conduct evaluation of the matching quality. A way to do so is to compare the standardized mean bias before matching to the standardized mean bias after matching. In addition, we also re-estimate the propensity score on the matched sample to compute the pseudo-R² before and after matching. The number of observations that are off common support in absolute and relative term is also presented as an additional indicator of matching quality. In what follows, we separately evaluate the wage subsidy programmes in 2018 and 2019.

5.1. Wage subsidy program in 2018

From Table A1 (Annex A), in 2018 statistically significant positive difference is observed with respect to the number of the unemployed household members, primary education and short-term unemployment, while negative difference is observed with respect to age, marital status, number of persons under 15 and number of employed in household.

According to Table A2 in Annex A, age, education level and previous unemployment history have statistically significant impact on the probability to enjoy benefit from wage subsidies. Namely, younger unemployed, those with primary education and short-term unemployment are more likely to be wage subsidies beneficiary.

Table 2. Wage subsidies 2018, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	-0.163	-0.085	0.048	0.064	-3.42	-1.34
Unemployed	0.092	0.093	0.026	0.018	3.50	5.14**
Salary	-19.038	211.267	306.046	431.011	-0.06	0.49
Permanent contract	-0.325	-0.298	0.056	0.080	-5.77	-3.72**
Better financ. cond.	0.009	0.016	0.039	0.058	0.24	0.27
Better empl. prosp.	0.051	0.039	0.037	0.049	1.41	0.80
Search for job	0.023	-0.008	0.043	0.067	0.52	-0.12
Intend to emigrate	0.027	0.020	0.015	0.008	1.82	2.25**

Note: */**/*** indicate significance at 10/5/1 percent level respectively.

As displayed by Table 2, wage subsidies have statistically significant positive impact on unemployment and on intention to emigrate, while they have negative impact on the probability of having permanent contract. In addition, the matching quality is good since the percent of mean bias reduction is 42.8%, the pseudo-R² in the case of matched samples is more than double compared to unmatched samples, while only 1% of the observations are off common support.

We further evaluate the impact of the wage subsidy programme in 2018 with respect to the impact of wage subsidies on disadvantaged groups (Annex A, Table A3). Youth are better off than mature unemployed vis-à-vis probability of being unemployed and having permanent employment contract, but express higher intention to emigrate. Female are better off than male unemployed vis-à-vis probability of being unemployed, worse off with respect of probability of having permanent employment contract, and express lower intention to emigrate. Unemployed from rural areas are worse off than those from urban areas vis-à-vis probability of being unemployed and having permanent employment and express slightly higher intention to emigrate. Unemployed without work experience are better off than those with work experience vis-à-vis probability of being unemployed and having permanent employment contract, and express lower intention to emigrate. The very-long-term unemployed are worse off compared to those with shorter spells of unemployment regarding the probability of having permanent contract. In addition, we present the propensity score density functions and the quality of the matching (Annex A, Figure A1 and Figure A2 respectively).

5.2. Wage subsidy program in 2019

From Table B1 presented in Annex B, we can observe that statistically significant difference between the treatment and control group is found for the following observables: age, gender and previous work experience.

According to Table B2 (in Annex B), only age appears to have statistically significant impact on the probability to enjoy benefit from wage subsidies. Namely, an additional year increases the probability to be wage subsidies beneficiary.

According to Table 3, wage subsidies have statistically significant positive impact on salary and perception for better financial conditions, while negative impact on the probability of being unemployed and the intention to emigrate. In addition, the matching quality is good since the percent of mean bias reduction is 56.6%, the pseudo-R² in the case of matched samples is more than four times higher compared to unmatched samples, while 18.7% of the observations are off common support.

Table 3. Wage subsidies 2019, treatment effects on outcome variables

Outcome variables	Differ	Difference		d error	t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	-0.006	0.029	0.039	0.056	-0.15	0.52
Unemployed	-0.089	-0.121	0.022	0.051	-4.03	-2.37**
Salary	1314	1382	505.113	648.636	2.60	2.13^{**}
Permanent contract	-0.065	-0.094	0.061	0.085	-1.07	-1.11
Better finan. cond.	0.078	0.064	0.032	0.029	2.40	2.19^{**}
Better empl. prosp.	0.058	0.040	0.035	0.040	1.67	1.00
Search for job	-0.052	-0.052	0.057	0.082	-0.91	-0.64
Intend to emigrate	-0.282	-0.260	0.059	0.086	-4.74	-3.03**

Note: */**/*** indicate significance at 10/5/1 percent level respectively.

Similar to the previous analysis, we make inference with respect to the impact of wage subsidies on disadvantaged groups (Table B3, Annex B). Youth are better off than mature unemployed vis-àvis probability of being unemployed and expecting better financial condition but they have lower monthly salary and lower intention to emigrate. Female are better off than male unemployed vis-àvis probability of being unemployed, they have similar expectations for the financial conditions and intention to emigrate, but they are worse of regarding the level of monthly salary. Unemployed from rural areas are worse off than those from urban areas vis-à-vis perception of the financial conditions, they manifest lower intention to emigrate and they have lower level of monthly salary. Unemployed without work experience are worse off than those with work experience vis-à-vis probability of being unemployed, they have lower level of monthly salary and intention to emigrate, but they expect better financial conditions. The relative position of the very-long-term unemployed is not possible to be assessed because of their low representation among participants in the wage subsidy program. The propensity score density functions and the quality of the matching are presented on Figure B1 and Figure B2 respectively (Annex B).

6. Cost effectiveness

The cost effectiveness analysis serves as a tool of economy by calculating the cost of producing of one unite of outcome. In order to carry out a cost effectiveness analysis the outcomes from the wage subsidy must be quantifiable and completely attributable to the intervention. In addition, cost effectiveness analysis obviously require accurate measure of the cost of the intervention. Two issues are fundamental to the measurement of the cost effectiveness analysis of ALMMs: first, what is the outcome? and second, when should one measure the outcome: immediately after the training or over some time period? Outcomes of interest in labour market programs typically relate to some form of

employment and might include increases in earnings, increases in hours worked, or change in job status from part-time to full-time. The cost per participant in the wage subsidy programme in 2018 was 136.970 MKD, while in 2019 it was 158.017 MKD.

Although the calculation of the net cost of activities and outputs is a very useful role for cost effectiveness analysis in program management, its most common application in the training literature calculates the cost of producing a unit of net outcome. The term 'net' indicates that the evaluator has controlled the external influences on outcomes and estimated the exact relationship between the ALMMs and the change in employment of participants. In this context, the cost per employed participant in the wage subsidy programme in 2018 was 198.507 MKD, while in 2019 it was 181.005 MKD. This measure is also known as average cost effectiveness ratio (ACER).

In order to assess whether the wage subsidy programme change its effectiveness in the course of time, we can calculate the so-called incremental cost effectiveness ratio (ICER). An incremental cost-effectiveness ratio is a summary measure representing the economic value of an intervention, compared with an alternative (comparator). It is usually the main output or result of an economic evaluation. An ICER is calculated by dividing the difference in total costs (incremental cost) by the difference in the chosen measure of treatment outcome (incremental outcome) to provide a ratio of 'extra cost per extra unit of outcome'. Hence, the ICER is calculated as a change in total cost divided by the change in the number of employed participants according to the following formula:

$$ICER = \frac{\left(Cost_{2019} - Cost_{2018}\right)}{\left(No. \text{ employed participants}_{2019} - No. \text{ employed participants}_{2018}\right)}$$

The calculated ICER for the wage subsidy programme (2019/2018) is 165.336 MKD which is lower compared to the average cost per employed participant in 2018 (198.507 MKD). Therefore, we can conclude that the cost effectiveness of wage subsidies in 2019 improved compared to 2018.

7. The impact of Covid-19

The last Covid-19 crisis exerted devastating effects on the world economy as well as the functioning of the labour markets. When the pandemic spread out around the world, the governments reacted swiftly with wide-ranging containment measures. The negative impact of this crisis is manifested as structural distortions among a number of industries and professions that will have long lasting economic consequences.

The Covid-19 crisis has stimulated many activities in the digital gig economy². The demand for gigs in many sectors and the expected ascension of several new forms of job calls for the employment of a comprehensive gig economy framework. Following the Covid-19 outbreak, many sectors in the economy are under pressure including home rental, design and crafting, simple tasks and renting. Others, such as software-based services, banking and investment services are expected to remain at the same level or even increase, while vital sectors such as service delivery are expected to rise considerably (Dhaini *et al.*, 2020, Nikoloski *et al.*, 2023).

Notwithstanding, it is expected that the recovery from the Covid-19 will last longer and will need more substantial restructuring of the economy. In this context, the most affected are the vulnerable population segments such as: women, older people, immigrants and the workers with lower levels of education and they are less likely to be reached by the mitigation and job retention measures that have been adopted in response to the Covid-19 pandemic. According to the World Bank estimates, recent poverty reduction gains in a number of countries will likely be lost because of the pandemics as firms resort to labour shedding in the most affected sectors. In addition, the mobility limitations engendered from the pandemics has considerably restricted the possibilities for circular migration and had significant adverse effects on the emigrants welfare.

Digital technologies nowadays represent a significant generator of changes in the domain of employment. In this context, the internet has opened up a wide range of opportunities for employment through providing easier access to the global labour market and developing new forms of employment. The recent studies in this domain indicate that online platforms provide job opportunities for those otherwise excluded through geographic borders, gender, or ability. Although ICTs have implied many positive effects on employment, certain studies indicate negative impacts that mainly arise from process optimization and capital-labour substitution in traditional industries. According to these insights the internet induces specific changes on the job market, such as: the end of job stability, and the rise of freelancing, self-employment and odd-jobs. However, it should be noted that arguments about net positive effects prevail indicating that new technologies generate new types of employment.

Besides the outcome variables, the success of a given ALMM depends on the satisfaction of the participants. The satisfaction of the wage subsidy beneficiaries is assessed with respect to the job, salary, on-the-job training and superiors. The results of the respondents are presented in Table 4.

2

² A gig worker is someone who is employed on a freelance basis, carrying out short-term jobs or contracts to one or more employers.

Table 4. Self-assessed satisfaction (percent)

	Job		Sal	Salary		he-job ining Sup		riors
	WS	WS	WS	WS	WS	WS	WS	WS
	2018	2019	2018	2019	2018	2019	2018	2019
Not satisfied at all	-	5.3	5.4	19.8	-	15.5	-	3.4
Not satisfied	0.5	1.0	19.9	11.1	0.5	3.9	1.4	2.9
Do not have opinion	1.4	0.5	3.2	4.4	1.8	3.9	1.4	2.9
Satisfied to less extent	32.7	2.4	40.7	9.7	16.8	8.7	21.4	5.3
Satisfied to great extent	65.5	90.8	30.8	55.1	80.9	68.1	75.9	85.5

Source: own calculations

From Table 4 we can conclude that majority of the wage subsidy beneficiaries where generally satisfied from the job, the on-the-job training and the superiors. However, lower satisfaction can be observed regarding the level of monthly salary.

The estimated extent to which Covid-19 pandemics imposed a need for new skills among wage subsidy beneficiaries and control groups is presented in Table 5.

Table 5. The extent to which Covid-19 pandemic imposed a need for new skills (percent)

	Wage s	•	Wage subsidy programme 2019		
	program	me 2018			
	Treatment	Control	Treatment	Control	
Did not impose at all	1.9	0.8	25.6	19.5	
Did not impose	31.2	27.3	3.0	-	
Do not have opinion	1.2	0.8	15.8	25.6	
Imposed to less extent	30.0	31.4	-	-	
Imposed to great extent	35.8	39.7	55.6	54.9	

Source: own calculations

According to Table 5, in 2018 dominate respondents who stated that the pandemic of Covid-19 imposed a need for new skills (to less or great extent). Among the respondents in 2019 dominate those whose skills are affected to great extend, however accompanied with considerable shares of those who responded that Covid-19 pandemic did not impose at all a need for new skills.

Furthermore, we attempt to identify the increased demand of specific skills due to the Covid-19 pandemics. The results for both the wage subsidy beneficiaries and control groups are presented in Table 6.

Table 6. Increased demand for skills due to Covid-19 pandemic (percent)

	0	Wage subsidy programme 2018		ubsidy me 2019
	Treatment Control Treatment			Control
Foreign languages	2.7	-	39.8	31.1
Basic IT skills	36.2	41.3	1.6	-
Advanced IT skills	5.4	5.0	39.1	42.2
E-commerce	2.3	-	7.0	15.6
E-banking	0.4	1.7	12.5	11.1
Other	53.1	52.1	-	-

Source: own calculations

From Table 6 we can notice that the majority of the respondents in 2019 emphasised the increased demand for advanced IT skills due to the pandemic of Covid-19. The high shares of the category 'Other' in 2018 suggest a need for more detailed inspections. In particular, some other skills engendered from the social and physical distancing may have not been anticipated. The EU experience shows that the burden of the Covid-19 social distancing falls disproportionately on vulnerable workforce groups, such as: women, older employees, the lower-educated and those employed in small enterprises. As a consequence there is an urgent need for immediate and targeted policy responses to prevent ongoing job losses and widening of labour market and social inequalities due to the pandemic.³

Conclusion

In order to answer the research question, we applied a post-program quasi-experimental evaluation method with an aim of achieving unbiased results. By using the propensity score matching technique the 'net' effects of the wage subsidy programme on the outcome variables were estimated. In addition to estimating the general effect, we disaggregated the average treatment effect on treated participants by various attributes in order to identify the particular impact of the wage subsidies on the vulnerable labour market segments. Moreover, we conducted cost effectiveness analysis with an aim to explore whether the devoted funds for the wage subsidy programme are worth with respect to the expected benefits from their implementation. Finally, the assessment of the impact of Covid-19 pandemics aims to identify needs for redesign of this programme.

The evaluation of the outcomes from the wage subsidy program reveals its improvement in 2019 relative to 2018. Namely, wage subsidies in 2018 exerted increasing unemployment associated

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³ Based on the Covid-19 social distancing risk index (COV19R), CEDEFOP.

with increasing intention to emigrate. This can be attributed to the possible job closures after the expiration of the obligatory period for retaining the subsidised workers. However, in 2019 we find out that wage subsidies exert diminishing impact on unemployment associated with positive impact on salary and negative impact on the intention to emigrate. Although, the incremental cost effectiveness ratio demonstrates improving effectiveness in 2019 vis-à-vis 2018, this ALMM is still considered as one of the most expensive measures. The cost-effectiveness analysis of the wage subsidy program needs to be accompanied by cost-benefit analysis in order to assess its beneficial effects relative to the costs. In this context, we recommend redesign of this measure by improving its targeting and conditions for retaining the subsidised jobs on the long run.

Generally, the reforms of the active labour market measures should be delivered by applying integrated and partnership-based approach and should be combined with sufficient management and implementation capacity. In addition, the reforms of active labour market policies should account for the possible complementarities with the unemployment compensation system and the existing social assistance programs. The assessment results for each particular intervention have to be used to inform policy makers whether the program has achieved the objectives and to provide information regarding the potential continuation, re-design or termination of the program.

This study demonstrated that wage subsidies do not work equally well for different individuals and further improvements of their targeting is required. Particularly, a better coverage is needed regarding disabled workers, long-term unemployed as well as representative of some ethnic minorities such as Roma. In addition, a redesign of the program is needed with respect to the eligibility requirements in order serve as a stepping-stone to more stable employment. Having in mind the positive experience from the self-employment support programme, viable business plans prepared by the applicants might ensure the long-term perspectives of the companies and might increase the probability of workers retention after the expiration of the subsidised period.

The reforms of wage subsidy programme in North Macedonia have to take into account the specific socio-economic context due to the Covid-19 pandemics, as well as the ESA capacities. The possibility of combining different programs such as wage subsidies and trainings may bring good synergies and can strengthen their individual impact (Jaenichen and Gesine, 2007). One of the main objectives of wage subsidies is to stimulate the labour demand and to provide effective matching with the supply of skills. Since de demand of skills changes as a consequence of the Covid-19 crisis, one should not be surprised if these measures show to be relatively ineffective in the new circumstances. In this context, the wage subsidy program should be accompanied by a short-term training for acquiring the necessary skills for online working.

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Annex A. Wage subsidy programme in 2018

Table A1. Wage subsidies 2018, mean comparison

Age 31.4 33.8 -2.4 Gender (1=male) 0.529 0.537 -0.008 Rural 0.257 0.256 0.001 Married 0.831 0.909 -0.078 Household size 3.70 3.91 -0.12	0.089* 0.878 0.992 0.043** 0.123 0.000*** 0.046** 0.010** 0.061* 0.015** 0.985 0.273
Gender (1=male) 0.529 0.537 -0.008 Rural 0.257 0.256 0.001 Married 0.831 0.909 -0.078 Household size 3.70 3.91 -0.12 Number of members under 15 0.80 1.17 -0.37 Number of employed members 1.83 2.03 -0.20 Number of unemployed members 0.742 0.488 0.254 Number of retired members 0.350 0.223 0.127	0.878 0.992 0.043** 0.123 0.000*** 0.046* 0.010** 0.061* 0.015** 0.985 0.273
Household size 3.70 3.91 -0.12	0.992 0.043** 0.123 0.000*** 0.046** 0.010** 0.061* 0.015** 0.985 0.273
Household size 3.70 3.91 -0.12	0.043** 0.123 0.000*** 0.046** 0.010** 0.061* 0.015** 0.985 0.273
Household size 3.70 3.91 -0.12	0.123 0.000*** 0.046** 0.010** 0.061* 0.015** 0.985 0.273
Number of members under 15 0.80 1.17 -0.37 Number of employed members 1.83 2.03 -0.20 Number of unemployed members 0.742 0.488 0.254 Number of retired members 0.350 0.223 0.127	0.000*** 0.046** 0.010** 0.061* 0.015** 0.985 0.273
Number of retired members 0.350 0.223 0.127	0.046** 0.010** 0.061* 0.015** 0.985 0.273
Number of retired members 0.350 0.223 0.127	0.010** 0.061* 0.015** 0.985 0.273
Number of retired members 0.350 0.223 0.127	0.061* 0.015** 0.985 0.273
Number of retired members 0.350 0.223 0.127	0.015** 0.985 0.273
Primary education 0.337 0.215 0.122 Secondary education 0.486 0.488 -0.001 Higher education 0.153 0.198 -0.045	0.985 0.273
Secondary education 0.486 0.488 -0.001 Higher education 0.153 0.198 -0.045	0.273
Higher education 0.153 0.198 -0.045	
Previous work experience 0.602 0.645 -0.043	0.422
Short-term unemployed 0.851 0.727 0.123	0.004***
Very-long-term unemployed 0.019 0.083 -0.063	0.003***
Youth 0.483 0.322 0.160	0.003***
Very-long-term unemployed 0.019 0.083 -0.063 Youth 0.483 0.322 0.160 Older 0.084 0.099 -0.015 Disabled 0.011 0.016 -0.005 Roma 0.038 0.058 0.020	0.636
Disabled 0.011 0.016 -0.005	0.688
Roma 0.038 0.058 0.020	0.390
treated control	p-value
Currently employed 0.670 0.603 0.067	0.202
Currently employed 0.670 0.603 0.067 Currently unemployed 0.115 0.157 -0.042 Currently unknown 0.188 0.198 -0.011	0.254
	0.807
Employed 0.690 0.851 -0.162	0.001***
Unemployed 0.091 0.000 0.091	0.001***
Salary 19528 19556 -28	0.926
Permanent contract 0.383 0.710 -0.327	0.000^{***}
Salary 19528 19556 -28 Permanent contract 0.383 0.710 -0.327 Better financial conditions 0.150 0.140 0.100 Better employment prospects 0.142 0.091 0.051	0.808
Better employment prospects $0.142 0.091 0.051$	0.160
Search for job 0.195 0.174 0.022	0.613
Intend to emigrate 0.027 0.000 0.027	0.069^{*}

Note: */**/*** indicate significance at 10/5/1 percent level respectively.

Table A2. Wage subsidies 2018, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
ıi.	Age	-0.0133226	0.0066667	0.046**
der	Gender (1=male)	-0.0364803	0.1462993	0.803
Socio-dem.	Rural	-0.0730476	0.1650318	0.658
\mathbf{S}_{0}	Married	-0.2010786	0.2289442	0.380
	Household size	-0.2391221	0.7231031	0.741
plo	Number of members under 15	0.0007312	0.717749	0.999
Household	Number of employed members	0.0618584	0.7214297	0.932
Hou	Number of unempl. members	0.334072	0.7218742	0.644
_	Number of retired members	0.3714028	0.6981682	0.595
al	Primary education	1.144861	0.3562483	0.001***
capital	Secondary education	0.7831719	0.3392132	0.021**
Human ca	Higher education	0.7213618	0.3631489	0.047^{**}
	Previous work experience	-0.0748539	0.1603538	0.641
Hu	Short-term un. (up to 1 year)	0.3157968	0.1857825	0.089^{*}

Note: */**/*** indicate significance at 10/5/1 percent level respectively.

Table A3. Wage subsidies 2018, disaggregated ATT for disadvantaged categories

Variables		Unemployed	Permanent contract	Intention to emigrate
_	Youth	0.071	-0.346	0.031
Age	Mature	0.112	-0.337	0.022
Gender	Female	0.082	-0.338	0.008
	Male	0.101	-0.239	0.043
Dl £ 1::	Rural	0.104	-0.439	0.030
Place of living	Urban	0.088	-0.233	0.026
***	Without	0.086	-0.271	0.019
Work experience	With	0.096	-0.348	0.032
TI	Very long-term	-	-0.400	-
Unemployment	Short-term	0.094	-0.308	0.027

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

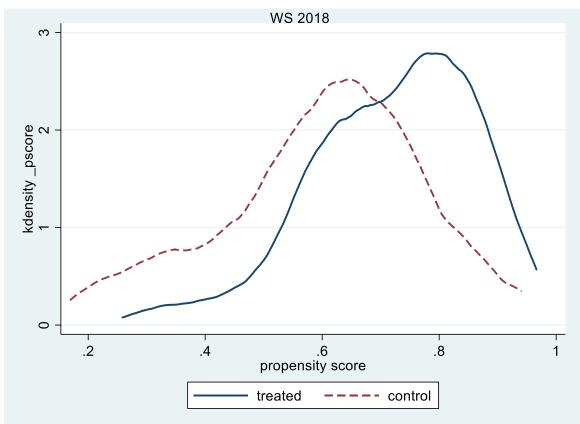
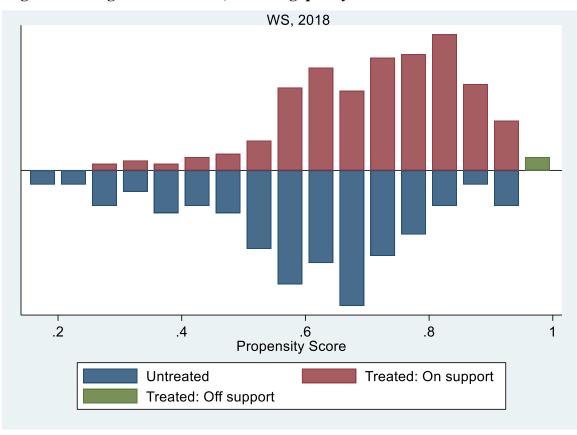


Figure A1. Wage subsidies 2018, Propensity score density functions





Annex B. Wage subsidy programme in 2019

Table B1. Wage subsidies 2019, mean comparison

Age 32.2 27.0 5.233 0.000*** Fernate 0.423 0.549 -0.126 0.049** Rural 0.308 0.354 -0.046 0.444 Married 0.820 0.793 0.027 0.590 Household size 3.512 3.720 -0.207 0.133 Number of members under 15 0.940 1.110 -0.170 0.128 Number of employed members 1.885 1.866 0.019 0.870 Number of unemployed members 0.607 0.598 0.009 0.928 Number of retired members 0.171 0.146 0.025 0.675 Primary education 0.295 0.268 0.027 0.649 Secondary education 0.521 0.524 -0.003 0.963 Higher education 0.141 0.195 -0.054 0.246 Previous work experience 0.615 0.451 0.164 0.009*** Higher education 0.829 0.805 0.024 0.623 Very-long-term unemployed 0.038 0.024 0.014 0.551 Youth 0.393 0.500 -0.107 0.092* Older 0.094 0.000 0.094 0.004*** Outcome variables Mean treated 0.025 0.003 0.873 Outcome variables Mean treated 0.015 0.015 0.001*** Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.897 0.902 -0.005 0.889 Unemployed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000*** Permanent contract 0.258 0.324 -0.066 0.277 Permanent contract 0.258 0.324 -0.066 0.277 Better financial conditions 0.090 0.012 0.077 0.018**		Observables	Mean	Mean	Difference	p-value
Gender (1=male)			treated	control		_
Household size 3.512 3.720 -0.207 0.133	em.	_				
Household size 3.512 3.720 -0.207 0.133	p-q	· · · · · · · · · · · · · · · · · · ·				
Household size 3.512 3.720 -0.207 0.133)ci					
Number of members under 15 0.940 1.110 -0.170 0.128	Š					
Number of retired members 0.171 0.146 0.025 0.675	_	Household size	3.512	3.720	-0.207	0.133
Number of retired members 0.171 0.146 0.025 0.675	olci	Number of members under 15	0.940	1.110		0.128
Number of retired members 0.171 0.146 0.025 0.675	ısel	Number of employed members	1.885	1.866	0.019	0.870
Number of retired members 0.171 0.146 0.025 0.675	Hoı	Number of unemployed members	0.607	0.598	0.009	0.928
Secondary education 0.521 0.524 -0.003 0.963 Higher education 0.141 0.195 -0.054 0.246 Previous work experience 0.615 0.451 0.164 0.009*** Short-term unemployed 0.829 0.805 0.024 0.623 Very-long-term unemployed 0.038 0.024 0.014 0.551 Youth 0.393 0.500 -0.107 0.092* Older 0.094 0.000 0.094 0.004*** Disabled 0.021 0.024 0.003 0.873 Roma 0.026 0.049 -0.023 0.305 Outcome variables Mean treated Mean treated Control Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000***		Number of retired members	0.171	0.146	0.025	0.675
Very-long-term unemployed 0.038 0.024 0.014 0.551	tal	Primary education	0.295	0.268	0.027	0.649
Very-long-term unemployed 0.038 0.024 0.014 0.551	apit	Secondary education	0.521	0.524	-0.003	0.963
Very-long-term unemployed 0.038 0.024 0.014 0.551	n c	Higher education	0.141	0.195	-0.054	0.246
Very-long-term unemployed 0.038 0.024 0.014 0.551	Huma	Previous work experience	0.615	0.451	0.164	0.009^{***}
Youth 0.393 0.500 -0.107 0.092* Older 0.094 0.094 0.000 0.094 0.004*** Disabled 0.021 0.024 0.003 0.873 Roma 0.026 0.049 -0.023 0.305 Mean treated Mean control Difference control p-value Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000****		Short-term unemployed	0.829	0.805	0.024	0.623
Outcome variables Mean treated Mean control Difference p-value Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000***		Very-long-term unemployed	0.038	0.024	0.014	0.551
Outcome variables Mean treated Mean control Difference p-value Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000***	age	Youth	0.393	0.500	-0.107	0.092^{*}
Outcome variables Mean treated Mean control Difference p-value Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000***	/anj	Older	0.094	0.000	0.094	0.004***
Outcome variables Mean treated Mean control Difference p-value Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000***	ad	Disabled	0.021	0.024	0.003	0.873
Currently employed 0.756 0.561 0.195 0.001*** Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000***	Dis	Roma	0.026	0.049	-0.023	0.305
Currently unemployed 0.094 0.213 -0.125 0.003 Currently unknown 0.124 0.195 -0.071 0.113 Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000****		Outcome variables				_
Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000****	try	Currently employed	0.756	0.561	0.195	0.001***
Employed 0.897 0.902 -0.005 0.889 Unemployed 0.009 0.097 -0.089 0.000****	gist	Currently unemployed	0.094	0.213	-0.125	0.003
Unemployed 0.009 0.097 -0.089 0.000***	Re	Currently unknown	0.124	0.195	-0.071	0.113
		Employed	0.897	0.902	-0.005	
Salary 21050 19792 1258 0.015** Permanent contract 0.258 0.324 -0.066 0.277 Better financial conditions 0.090 0.012 0.077 0.018** Better employment prospects 0.094 0.037 0.057 0.098*		Unemployed	0.009	0.097	-0.089	0.000^{***}
Permanent contract 0.258 0.324 -0.066 0.277 Better financial conditions 0.090 0.012 0.077 0.018** Better employment prospects 0.094 0.037 0.057 0.098*	/ data	Salary	21050	19792	1258	0.015^{**}
Better financial conditions 0.090 0.012 0.077 0.018** Better employment prospects 0.094 0.037 0.057 0.098*		Permanent contract	0.258	0.324	-0.066	0.277
Better employment prospects 0.094 0.037 0.057 0.098*	rve	Better financial conditions	0.090	0.012	0.077	0.018^{**}
G ₁ Detter employment prospects 0.071 0.037 0.037	Sm	Better employment prospects	0.094	0.037	0.057	0.098^*
Search for job 0.252 0.305 -0.053 0.354		Search for job	0.252	0.305	-0.053	0.354
Intend to emigrate $0.278 0.561 -0.283 0.000^{***}$		Intend to emigrate	0.278	0.561	-0.283	0.000^{***}

Note: */**/*** indicate significance at 10/5/1 percent level respectively.

Table B2. Wage subsidies 2019, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
	Age	.0269899	.0100349	0.007***
Socio-dem.	Gender (1=male)	1998777	.1659805	0.229
cio-	Rural	.0201982	.1764942	0.909
\mathbf{S}_{0}	Married	.2412135	.256391	0.347
	Household size	7162501	.5964381	0.230
plo	Number of members under 15	.5663615	.6061233	0.350
Household	Number of employed members	.796475	.6167568	0.197
Hou	Number of unemployed members	.7551278	.6161485	0.220
	Number of retired members	.731589	.6225828	0.240
	Primary education	5897944	.5882469	0.316
ıpita	Secondary education	4735914	.5795643	0.414
Human capital	Higher education	6628186	.5957272	0.266
	Previous work experience	.2348546	.173214	0.175
Н	Short-term unemployed	.2097703	.219059	0.338

Note: */**/*** indicate significance at 10/5/1 percent level respectively.

Table B3. Wage subsidies 2019, disaggregated ATT for disadvantaged categories

Vari	ables	Unemployed	Salary	Better fin. conditions	Intent. to emigrate
	Youth	-0.055	886	0.109	-0.413
Age	Mature	-0.206	1715	0.071	-0.339
Gender	Female	-0.104	803	0.076	-0.400
	Male	-0.010	1989	0.082	-0.495
	Rural	-	885	0.127	-0.352
Place of living	Urban	-0.093	1412	0.060	-0.430
Work	Without	-0.045	219	0.101	-0.309
experience	With	-0.083	1534	0.076	-0.514
Unemployment	Very long	-	-	-	-
	Short-term	-0.072	1130	0.085	-0.400

Note: Estimation based on nearest neighbour matching only for statistically significant outcome variables.

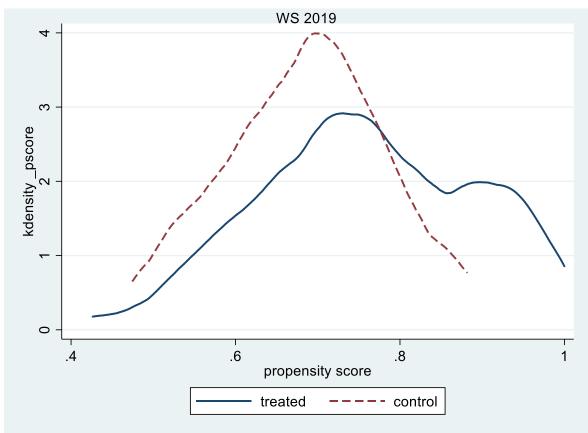


Figure B1. Wage subsidies 2019, Propensity score density functions

