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Understanding How Job Retention Schemes Reshape the Within-Occupation Skill Profile of Employees within Firms

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Abstract

This study draws on employer-employee data for Latvia to investigate how participating in a job retention scheme (JRS) impacts the within-occupation composition of skills in participating firms. The findings of this research reveal that involvement in JRS positively affects the likelihood of employees retaining their employment with the same firm after the end of the programme. This positive effect is independent of the employee's skill level. However, individuals that perform higher-skilled tasks in the same occupation are less likely to participate in the JRS because of legal restrictions on the maximum amount of the benefit and the income replacement rate. Taken together, these findings suggest that JRSs may have a detrimental impact on the within-occupation composition of the skills of the workforce at the firms that participate in such schemes.

Keywords: Job retention scheme, short-term work scheme, Covid-19, employment, skills

JEL Codes: E24, H12, J62, J68

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1 Introduction

Employment protection policies were widely adopted during the Great Recession in 2008–2009, and use of them surged during the Covid-19 pandemic in 2020–2021, when the job retention scheme (JRS) emerged as a primary crisis response measure in Europe. Many countries introduced such schemes for the first time (Drahokoupil and Müller 2021; OECD 2020), with the consequence that there was wide variation in scheme names, regulatory frameworks, and the share of jobs covered within the economies concerned (Fischer and Schmid 2021). More than 15% of German employees and around one third of employees in France and Italy were enrolled in a JRS in April 2020 (Giupponi and Landais 2023).

A JRS offers crucial benefits for employers, such as allowing them to retain skilled and loyal employees during economic downturns, and avoiding the costs associated with hiring and firing. The advantages for employees include increased job security and being able to avoid periods of unemployment. Our previous research (Benkovskis et al. 2023) demonstrates that participating in a JRS has a positive and statistically significant impact on employment for firms that persists for at least several months after they receive the support. Employment growth at firms that participate in a JRS is approximately 25% higher than that at similar firms that do not participate. This effect stems from a reduction in the likelihood of firms becoming inactive and from there being fewer layoffs at firms that remain active.

However, JRSs also present a trade-off. While government support can boost the chances of a firm surviving, safeguard the human capital of the firm, and mitigate the underuse of resources that economic disruption causes, it may also obstruct the cleansing effect of crises, which would normally drive resources towards more productive uses (Caballero and Hammour 1996). The resource reallocation effect of JRSs is complex. A JRS can affect how labour is reallocated between industries or occupations (Barrero et al. 2020), and it can also influence how labour is reallocated between firms within an industry (Giupponi and Landais 2023, Meriküll and Paulus 2023). Furthermore, a JRS can alter the skill composition of the workforce at a firm within occupational groups by affecting the incentives for hiring or separation. While this may not be a typical reallocation effect, changes in the within-occupation skill composition are an additional channel through which a JRS can affect productivity by altering the proportion of employees at a participating firm that perform skilled tasks. To the best of our knowledge, no studies have examined this aspect of the JRS effect.

This study employs comprehensive administrative employer-employee data for Latvia from 2019–2020 and uses local projection difference-in-differences estimation, and matching techniques to examine how the idle-time allowance, or furlough scheme, impacted the within-occupation skill composition of labour at firms that participated in the scheme during the first year of the Covid-19 pandemic. We restrict our sample only to employees working for firms that actually participated in the JRS and so were eligible to receive the support. Doing this improves the identification of the causal effect considerably.

The key findings of this study suggest that the JRS may have an adverse impact on the proportion of skilled employees within given occupations in firms that received JRS support. We find that participation in the JRS positively affects how likely employees are to remain employed with the same firm, and that, remarkably, this positive effect is independent of the skill level of the employee who receives the JRS benefits. However, the probability of skilled workers receiving support from the JRS is lower, possibly because there were legal restrictions on the maximum amount paid as a benefit and on the income replacement rate.

The remainder of the study is structured as follows. Section 2 reviews the related literature. Section 3 outlines the details of the JRS in Latvia, Section 4 introduces the dataset used in the study, and Section 5 lays out the methodology used. Section 6 presents the estimation results and checks the robustness of the findings, while the last Section concludes.

2 Literature Review

Short-time work (STW) schemes, such as wage subsidies and job retention schemes (JRSs), are designed to hold the relationship between employers and their employees stable in the face of economic disruption. They preserve the human capital match that is specific to a firm and prevent the need for costly layoffs, and rehiring and retraining processes. How effective these schemes are depends heavily on their design, as they need to strike a balance between preserving employment and allowing creative destruction to function (Eichhorst et al. 2022).

2.1 STW schemes before the Covid-19 pandemic

A significant amount of research has been built on the experience gained in several OECD economies during the global financial crisis, particularly Germany and France, which have a long tradition of

STW programmes. The empirical evidence gathered on the impact of STW during the Great Recession points overall to it having a positive effect on the number of jobs saved (see Balleer et al. 2016, Gehrke and Hochmuth 2021 and Hijzen and Martin 2013). STW schemes are less effective when there is not a recession or if there is a structural shock rather than a cyclical one. Brey and Hertweck (2020) show for example that the effect of STW schemes is strongest when GDP growth is deeply negative, adding that the use of STW policies should be boosted at the beginning of a recession and reduced quickly once the recovery starts. Continuing a scheme during the recovery may slow down job creation in the recovery (Hijzen and Martin 2013). Firms that use STW schemes are significantly less likely to lay permanent workers off in response to a negative shock, though there is no impact for temporary workers (Lydon et al. 2019, Basso et al. 2023).

The estimates of STW effects that are based on the firm-level data in the earlier literature are, however, not unambiguously positive. Calavrezo et al. (2010) find for example that the exit rate of French firms which received subsidies for STW in 2000 to 2005 was higher than that for comparable firms which did not receive the support. Similarly, Arranz et al. (2021) suggest that participants in STW schemes are about 5 percentage points less likely to still be working with the same employer one year later than are similar workers, and this negative effect on participation increases over time.

A few studies focus on how heterogeneous the effects of STW schemes are. Tracey and Polachek (2020) examine the impact of the US Short-Time Compensation programme and show that it may affect firms differently depending on their industry, labour costs, and degree of workforce stability, and whether they are subsidised by the tax system. Giupponi and Landais (2023) provide evidence about the reallocation effect of short-time schemes in Italy, focusing specifically on the Great Recession and using firm-level and administrative data. Their study reveals that labour hoarding schemes can indeed give rise to issues with reallocation, and that the magnitude of these issues depends on the criteria for selecting the firms that participate in the programme. The study employs various indicators for the productivity of firms before the crisis, and demonstrates that firms in the lowest quartile for productivity before the crisis were nearly four times as likely as firms in the highest quartile to accept the benefits during the crisis. Consequently, the scheme may have preserved employment in firms with low productivity, sustaining inefficient matches and generating negative reallocation effects in the labour market.

2.2 JRSs and their effectiveness during the Covid-19 pandemic

Another body of research that is closely related to our study has investigated the economic consequences of the Covid-19 pandemic (Baek et al. 2021, Fadejeva et al. 2022, Coibion et al. 2020b, Coibion et al. 2020a, Cox et al. 2020, Horvath et al. 2023, Maloney and Taskin 2020) and the impact on employment and household income of the JRSs that were introduced in a large number of countries during the Covid-19 crisis (Chudik et al. 2021, Ostry et al. 2021, Gourinchas et al. 2021, Larrimore et al. 2022). This body of work can be categorised into three streams by the type of data used and the methodology employed:

- Macro-level studies, encompassing cross-region variation for the Kurzarbeit programme in Germany (Aiyar and Dao 2021) and model simulations for the JRS in France (Albertini et al. 2022) and the Kurzarbeit programme in Germany (Christl et al. 2023), as well as several JRSs in EU countries (Lam and Solovyeva 2023).
- Firm-level analysis of the Paycheck Protection Programme (PPP) in the United States (Autor et al. 2022), JobKeeper in Australia (Watson et al. 2022), several JRSs in European countries such as Estonia (Meriküll and Paulus 2022), Latvia (Benkovskis et al. 2023), or Portugal (Kozeniauskas et al. 2022).
- Employee-level research for the UK, investigating how the Covid-19 crisis impacted employment differently across different age groups, genders, and ethnicities, and studying the role of the Coronavirus Job Retention Scheme (CJRS) in alleviating these effects (Crossley et al. 2021).

Overall, the studies have shown that JRSs have been effective at maintaining employment levels. However, the positive impact of JRSs was not uniform across industries, companies, or individuals. Benkovskis et al. (2023) find that participation in a JRS had a more pronounced impact in sectors where the proportion of highly skilled employees was higher, and a less pronounced impact in service sectors with high levels of interpersonal contact. Fernández-Cerezo et al. (2023) find that the JRS in Spain was not able to protect jobs fully at firms that had a larger share of temporary workers. Crossley et al. (2021) demonstrate that the UK's Coronavirus Job Retention Scheme (CJRS) provided substantial protection for vulnerable population groups who were particularly susceptible to unemployment during the pandemic, including individuals under the age of 30 and ethnic minorities. Similar evidence is also provided by Gaudecker et al. (2020) for the Netherlands, Schröder et al. (2020) for Germany, and Alstadsæter et al. (2020) for Norway.

Despite their success at preserving jobs, JRSs have not been without their costs. These costs include the deadweight or windfall costs that arise when a JRS saves jobs that would have been retained in the absence of the scheme (see Watson et al. 2022 for Australia and Autor et al. 2022 for the US).

2.3 JRSs and resource reallocation

Recessions can have a positive impact on an economy by forcing resources to be reallocated from less productive uses to more productive ones. This theory is known as creative destruction, and was originally conceptualised by Schumpeter et al. (1939).

Several papers argue that Covid-19 acted as a persistent negative shock with the potential to lead to resource reallocation. Low-skilled workers in the United States transitioned to higher-skilled positions, sought opportunities for remote work, or faced unemployment or inactivity (Forsythe et al. 2022, Pizzinelli and Shibata 2023, Barrero et al. 2021). In the United Kingdom meanwhile, there was substantial disparity in how employment changed across occupations. Those workers who were able to do so, shifted towards expanding industries and occupations that demand higher skills, pay higher wages, and allow remote work. Conversely, workers on the fringes of the labour market remained concentrated in declining industries (Carrillo-Tudela et al. 2023).

Other studies present a different view however, arguing that the reallocation shock was temporary. Following the initial downturn in April 2020, the cumulative reallocation of resources in the United States gradually decreased by December 2020 (David 2021). In any case, a substantial portion of the reallocation during the pandemic appears to have occurred within sectors, as firms adjusted the internal composition of their workforce (David 2021, Barrero et al. 2020).

If Covid-19 was indeed a persistent shock, JRSs may have come at an additional cost by obstructing the efficient reallocation of jobs, potentially slowing down the economic recovery. Casarico and Lattanzio (2022) find, for example, that layoffs and resignations declined significantly in Italy at the beginning of the pandemic because of the protection policies of the government. This decline particularly affected individuals with lower educational attainment and those working in high-contact occupations that were not amenable to remote work.

Few papers so far have examined the reallocation of resources between firms by productivity during the Covid-19 pandemic. Understanding the types of firms that are most likely to take up government support is crucial for evaluating how effective that support is and what unintended consequences it might have. The evidence is inconclusive. Meriküll and Paulus (2023) use firm-level data for Estonia and find that there was no selection of firms into the support by productivity. Similarly, Harasztosi et al. (2022) do not find any evidence that the support was tilted towards firms that were already weak before the crisis. Neither does the recent paper by Cooper et al. (2024) find that policy interventions have any strong effects on aggregate productivity or on the extent of factor misallocation. In contrast, some studies, such as Kozeniauskas et al. (2022) and Morikawa (2021), show that the firms that obtained support were less productive, which implies there was misallocation of resources.

Our study makes a step forward. It uses a detailed employee-level dataset to investigate the impact of JRSs on the skill composition of labour at firms receiving support form a JRS during the Covid-19 crisis. Autor and Handel (2013) show that skills and earnings may vary significantly between the workers at a firm who are in the same occupation. Stinebrickner et al. (2019) distinguish more clearly between the various high-skilled tasks and low-skilled tasks that are performed by employees in the same occupational group. They show that highly skilled tasks are paid substantially more than low-skilled tasks. Differentiating the tasks performed within separate occupations by their skill level is crucial for understanding differences between workers in productivity and wages. The composition of labour within occupations may consequently be a significant determinant of firm productivity. Our study investigates how the likelihood of employees participating in the JRS varies across employees with different within-occupation skill levels. The study also examines how the impact of participation in the JRS on employment varied across different within-occupation skill groups. By answering these two questions, the study aims to identify the effect of the JRS on the composition of labour skills within a firm, and consequently on its productivity. To the best of our knowledge, this specific aspect remains unexplored in the existing literature.

3 Job Retention Schemes in Latvia

The JRS in Latvia was introduced at the onset of the Covid-19 pandemic and remained available only during specific periods when the economy was restrained by the pandemic and under the corresponding government-imposed restrictions. Two distinct types of JRS were provided. The first was the idle-time allowance, which was granted to furloughed employees. It aimed to protect employment and prevent lay-offs at firms that were suffering from a decline in revenue because of the pandemic. The first instalment of the idle-time allowance was distributed between 14 March 2020 and 30 June 2020, which roughly covers the first wave of the Covid-19 outbreak.[1] The programme was introduced again from November 2020 to June 2021. The second JRS was the wage subsidy, which aimed to cover the costs of employees who were working shorter hours rather than being idle. The wage subsidy programme ran between November 2020 and June 2021, and again in October 2021 and November 2021.

The idle-time allowance was set at 75% of the average monthly remuneration of the employee receiving it, but not exceeding 700 euros. Employees receiving the allowance were not permitted to work and could not be fired within a month after the application for the allowance was submitted. To qualify for the allowance, firms had to prove that they had suffered a drop in turnover of at least 30% from the average monthly revenue in 2019 or from the average revenue across their active months from 1 January 2019 to 1 March 2020. The threshold for a decline in turnover was lowered to 20% if the firm met one of the criteria that exports of goods and services in 2019 were at least 10% of the total turnover or were at least 500,000 euros, the average monthly gross remuneration in 2019 was at least 800 euros, or long-term investments in fixed assets as at 31 December 2019 were at least 500,000 euros.

Equally, the JRS legislation listed 14 reasons that made firms ineligible to participate in the scheme, including minor tax arrears of more than 1000 euros, or being in active bankruptcy proceedings. A further condition for eligibility was that the drop in income had to have been caused by the pandemic. This, together with the temporary nature of the scheme, may have reduced the chance of the JRS being abused by firms that were already facing structural problems before the Covid-19 pandemic and were trying to postpone layoffs (an issue raised by Calavrezo et al. 2010).

It is important to note that the eligibility criteria were settled at the level of the firm, and if a firm satisfied the criteria, all of its employees were eligible for the idle-time allowance up to the cap of 700 euros.[2] The application for the idle-time allowance was made by the firm, and the firm was free to choose which employees the application would cover.

[1] See the law "On Measures for the Prevention and Suppression of Threat to the State and Its Consequences Due to the Spread of Covid-19", https://likumi.lv/ta/en/en/id/313373-on-measures-for-the-prevention-and-suppression-of-threat-to-the-state-and-its-consequences-due-to-the-spread-of-covid-19.

[2] For employees employed by multiple employers, only the primary employer was eligible for the idle-time allowance. If the primary employer was not identified, the allowance was paid to the first employer to submit an application.

High infection rates and restrictions imposed by the government led to the idle-time allowance programme being reactivated in late November 2020 with some changes to the eligibility criteria, such as an adjustment to the reference period for the decline in turnover, and to the size of the idle-time allowance, which was now set at 70% of the average monthly remuneration within the range of 500–1000 euros. Furthermore, the government introduced a second programme of wage subsidies. The subsidy was set at 50% of the average salary of the employee concerned in August, September and October 2020, but it could not exceed 500 EUR. The firm had to pay the difference between the subsidy and the full-time wage. This programme also obliged the employer to retain the employee for at least a month after applying for the subsidy. During the second wave of the Covid-19 pandemic as a result, firms in Latvia could apply for two JRSs, one for idle employees and the other for employees with a reduced number of working hours. Both programmes remained in operation until June 2021, and the wage subsidy programme was reactivated again in October 2021.

4 Data description

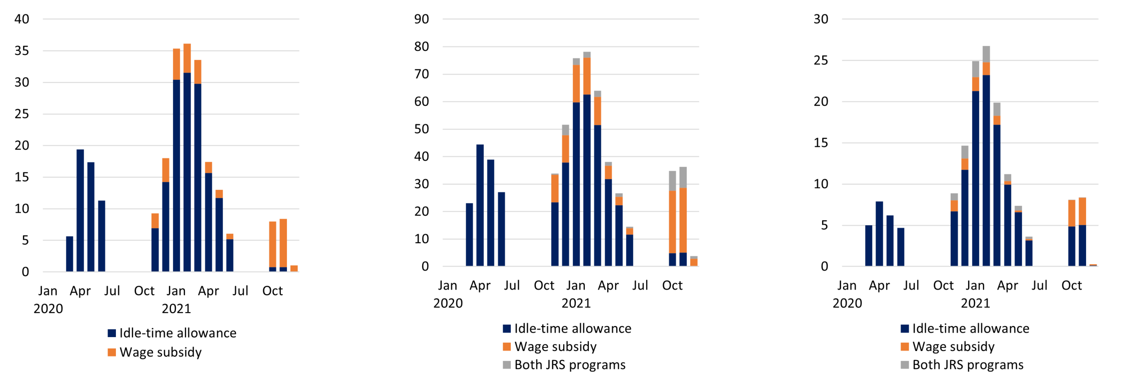
To analyse how the JRS impacted employment, we use the dataset of recipients of JRS benefits on a monthly basis provided by the State Revenue Service (SRS) of Latvia. This anonymised dataset contains information about the amount of support received by each employee working in a particular firm for each month.

We limit our analysis to the first wave of the Covid-19 pandemic in March–September 2020. The first wave was an unexpected shock, while subsequent waves of infections, restrictions on mobility, and corresponding government support were largely expected by economic agents. In addition, the idle-time allowance was the only JRS support programme during the first wave (see Figure 1 for the JRS support in Latvia in 2020–2021), since wage subsidies and other non-JRS support instruments such as grants to firms were only introduced in November 2020. This means that we do not need to separate the economic effect of the idle-time allowance from the effect of other government support programmes during the first wave of the Covid-19 pandemic. Since the wage subsidies and the grants to firms were quite large and many firms participated in both JRSs and non-JRS programmes, the effect of the idle-time allowance programme from the first wave is difficult to detect after October 2020 because of the later waves of restrictions and overlapping support programmes. We therefore restrict our analysis to the short-run effect of the JRS in March–June 2020.

The expenditure on idle-time allowances during the first wave was relatively small and totalled around 55 million EUR. The number of firms and employees covered by the JRS was not negligible, as it reached 5000-8000 firms, or 3-4% of all economically active firms, and 20,000-45,000 employees, or 3-7% of all private sector employees every month in March–June 2020 (see Figure 1). The programme covered 4–5 employees on average at each participating firm.

Figure 1: JRS coverage in Latvia, January 2020–December 2021

(a) Total expenditure on the JRSs, EUR million | (b) Number of employees covered by the JRSs, thousand | (c) Total numbers of legal entities in the JRSs, thousand



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Legal entities include the self-employed. The wage subsidy programme was introduced in November 2020 and was not available during the first wave of the Covid-19 pandemic.

To get information about firms and employees, we link the JRS database with several anonymised employer-employee and firm-level datasets provided by the SRS and the Central Statistical Bureau of Latvia, which give us monthly employer-employee data, annual balance sheet data, profit and loss statements, and business registry data. All the databases are linked using the anonymised IDs of firms and employees.

The SRS employer-employee data come from an extensive administrative dataset that encompasses all employees in Latvia. This administrative dataset contains the monthly gross wage for all employees reported by firms to Latvia's tax authorities, but excluding the self-employed. In addition to income data, the dataset includes hours worked, the age and gender of each employee, a flag on the salary tax booklet denoting that this is the primary place of work of the employee, and the employment status as ordinary employee, working pensioner, or some other category.

The monthly income dataset is complemented by another employer-employee database that records any changes in an employee's status, such as hiring, firing, transfer to a new position, or parental leave. The information is recorded only during the month when any change occurs. Since

July 2015, the information set has also incorporated a six-digit employee occupation code that aligns with the Latvian classification of professions. The first four digits of the occupation code coincide with the International Standard Classification of Occupations (ISCO-08) four-digit codes. Although the changes in an employee's status are updated quite infrequently and the occupation codes are not available before June 2015, we are able to infer information about occupations for a large number of entries within the monthly dataset of employer-employee gross income in 2019–2020. We make the assumption that an employee's occupation remains unchanged from the moment they are hired or transition to a new position until there is a change in their status. Likewise, we can retrospectively track the occupation of an employee who terminated their contract with an employer because we know their profession at the moment the contract is terminated.

The employer-employee data are linked to firm-level variables for 2019–2020, which are taken from the annual balance sheets, the profit-loss statements, and the business registry. The employer-employee data are also linked with the dataset of recipients of JRS benefits. The results of linking the databases are given in Table A.1 in Appendix A. It appears that 38.3% of the legal entities that participated in the idle-time allowance programme in March–June 2020 are not represented in the employer-employee database. Legal entities that are absent from the employer-employee dataset tend to be small and young, and more than a third of such legal entities are not present in the annual financial database containing balance sheets and profit-loss statements either (see Table A.2 in Appendix A). There are two reasons that could explain the absence of these legal entities from the employer-employee database. The first is that data reporting for very small firms is weak, but the second and more important reason is that the majority of these legal entities are self-employed people who are not included in employer-employee database.[3] The numerical losses of legal entities participating in the JRS are not negligible, but the data losses are minor for the number of employees participating in the JRS at 8.8% and for the aggregate value of the idle-time allowance at only 7.3%. The summary statistics of the main variables used in the analysis can be found in Table A.3 in Appendix A.

The employer-employee database contains some information about the employee, including their age and gender. Records about the changes in an employee's status allow the experience of the em-

[3]The self-employed were also eligible for the idle-time allowance under Republic of Latvia Cabinet Regulation No. 179 "Regarding the Allowance for Idle Time for the Self-employed Persons Affected by the Spread of Covid-19", https://likumi.lv/ta/en/en/id/313680-regulations-regarding-the-allowance-for-idle-time-for-the-self-employed-persons-affected-by-the-spread-of-covid-19

ployee in their job to be imputed.[4] Many important characteristics of the employee are missing though, including information on their formal education attainment and abilities. Given the limitations of our dataset, it is not possible to measure the skills of employees directly.[5] We consequently proxy the skill level by the full-time equivalent (FTE) gross wage. Some studies (such as Davis and Haltiwanger 1991, Kremer and Maskin 1996, Autor et al. 1998 and Dunne et al. 2004) use a similar approach, as there is a positive relationship between wages and productivity (Dunne et al. 2004), which some authors attribute to the complementarity between technology and highly skilled labor (see Acemoglu and Autor 2011).

However, wages also incorporate a significant firm-specific component that reflects factors such as the firm's compensation practices, rent-sharing arrangements, and the bargaining power of employees within the organisation. To address these challenges we follow Iranzo et al. (2008) among other papers and use the employee-specific wage component of the Abowd et al. (1999) wage equation as a proxy for the skills of employees in the robustness analysis.

Our analysis focuses specifically on firms that received the JRS support during the first wave of the pandemic. All the employees within these firms were eligible for the idle-time allowance programme, but not all such employees received the support. Table 1 provides some summary statistics for the participation in the idle-time allowance programme by industry. The total value of the benefits was highest in the Accommodation and Food (I) sector, as that was severely impacted by the crisis. Manufacturing (C), Trade (G) and Other Services (S) also received a substantial amount of support. The same industries got the largest amount of support in terms of the number of firms and employees covered. The proportion of employees who received the allowance within the firms got support appears to be more homogeneous within each industries, as it ranges from approximately one third in Construction and Trade to around half in Accommodation and Food, and Other Services. This means that even at firms in the sectors most affected by the crisis, only half of the employees participated in the idle-time allowance programme. The employees covered by the programme received the support for an average of two months out of the four from March to June 2020.

Table 2 provides similar statistics for selected occupations. The JRS support was not uniformly distributed across occupations, with personal services workers at 51% and sales workers at 52%,

[4] Trimmed for experience exceeding six years (72 months).

[5] However, such a measure would primarily assess formal skills, which may not fully capture innate abilities or informal skills, such as job accuracy or communication proficiency (Iranzo et al. 2008).

Table 1: The idle-time allowance support by selected industries

Industry (NACE 2.0)	Value, EUR million	Number of firms	Number of employees	Average number of months getting JRS support	Share of employees getting JRS support, % in total employment	Share of employees getting JRS support, % at JRS firms
(A) Agriculture	0.2	64	286	2.27	0.5	43.6
(C) Manufacturing	7.6	556	9,942	1.94	4.2	45.2
(F) Construction	0.8	189	973	2.00	0.8	31.5
(G) Trade	6.9	1,285	8,354	2.00	2.8	35.4
(H) Transportation	3.5	341	3,694	2.29	2.8	41.1
(I) Accommodation and food	14.9	914	12,821	2.90	26.8	49.8
(J) Information and communication	0.9	161	979	2.15	1.6	32.6
(L) Real estate	0.5	105	473	2.56	1.2	36.8
(M) Professional services	1.6	382	1,244	2.50	2.8	29.0
(N) Administrative services	2.8	360	2,164	2.84	4.0	38.0
(R) Arts, entertainment and recreation	2.3	357	2,901	1.84	24.4	25.3
(S) Other services	5.5	301	4,005	3.10	5.3	56.7

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: The table reports the numbers for the idle-time allowance programme in March–June 2020.

together with other contact-intensive employee categories, being more likely to be covered by the programme. Being employed in those professions at a firm that received the support did not guarantee that people would participate in the idle-time allowance programme however, as approximately half of eligible employees got the support regardless of their occupation.

Table 2: The idle-time allowance data by selected occupations

Occupation (ISCO-08)	Value, EUR million	Number of employees	Average number of months getting JRS support	Share within JRS firms, %
(24) Business and Administration Professionals	0.7	512	2.38	33.7
(33) Business and Administration Associate Professionals	1.5	1,366	2.28	42.3
(42) Customer Services Clerks	2.2	1,557	3.13	58.5
(43) Numerical and Material Recording Clerks	0.7	687	2.10	41.4
(51) Personal Services Workers	3.6	3,409	2.80	53.6
(52) Sales Workers	2.0	2,620	2.04	44.0
(72) Metal, Machinery and Related Trades Workers	0.7	857	2.01	46.7
(75) Food Processing, Woodworking and Other Craft Workers	0.6	819	1.88	45.9
(83) Drivers and Mobile Plant Operators	0.7	826	2.19	36.0
(91) Cleaners and Helpers	1.1	1,041	2.84	47.7
(93) Labourers in Construction, Manufacturing and Transport	0.9	1,236	1.96	44.2
(94) Food Preparation Assistants	0.7	798	2.78	57.3

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: The table reports the numbers for the idle-time allowance programme in March–June 2020. Note that occupation of employees was not detected for a large number of observations in the dataset, so the numbers are indicative.

Finally, Figure A.1 in Appendix A compares the distribution of some worker characteristics for employees who participated in the JRS and those that did not. Figure A.1a uncovers that employees who participated in the idle-time allowance programme tended to have a potential ratio of 75% for the idle-time allowance to their gross wage more often than employees who did not participate. This follows from the gross wage of participating employees in the second half of 2019 being lower (Figure A.1b) as the rules were that the idle-time allowance equalled 75% of the gross wage but could not exceed 700 euros, so employees with gross wage above 933.33 euros got relatively less in idle-time allowance support. It appears that firms were less willing to apply for the support for employees with high salaries because the ratio of the benefit to the gross wage was unfavourable. Figures A.1c and A.1d show that even after the number of hours worked is accounted for, participants in the JRS tended to have lower wages. Using FTE wages as a proxy of skills suggests that low-skilled employees tended to be more likely to participate in the idle-time allowance programme, possibly because of the ceiling of 700 euros. We investigate this possibility in Section 6.2.

5 Methodology

5.1 Local projection difference-in-differences analysis

We follow the recent approach of Dube et al. (2023) and combine the local projection (LP) method with the difference-in-differences (DiD) approach to so that we use the LP-DiD estimation technique with control variables in order to uncover the effect of the JRS program on the probability of a worker to staying employed inat the same firm:

$$E_{i,j,t+h} - E_{i,j,t-1} = \beta_{0,h} + \delta_{1,h}\Delta JRS_{i,j,t} + \beta_{1,h}X_{i,j,t-1} + \beta_{2,h}X_{i,t-1} + \beta_{3,h}X_{j,t-1} + \epsilon_{i,j,t}, \tag{1}$$

where $E_{i,j,t}$ is a binary variable that is 1 if employee i works at firm j during period t. We define t as the period March–June 2020, when the idle-time allowance support was granted during the first wave of the pandemic. Period $t-1$ is defined as the period before the pandemic, so $E_{i,j,t-1}$ denotes whether employee i worked at firm j in February 2020, just before the start of the pandemic and the introduction of the idle-time allowance programme. We restrict our sample to the firms that participated in the idle-time allowance programme in March–June 2020, so that all employees were eligible for the support in time t. We also exclude observations for employees who had more than one place of employment within a single month. Moreover, we only include workers that were employed before the pandemic at firms that participated in the JRS, so $E_{i,j,t-1} = 1$ for all i and j. There are two reasons for this restriction. The first is that the regulation stated that the disbursement of the idle-time allowance for the firm would be discontinued if the firm hired new employees while receiving the support.[6] Firms participating in the JRS were consequently strongly discouraged from hiring new employees in March–June 2020. Although new employees could be

[6] Section 14(1) of the law "On Measures for the Prevention and Suppression of Threat to the State and Its Consequences Due to the Spread of Covid-19".

hired starting from July 2020, this happened infrequently (see Benkovskis et al. 2023). The second reason is that even if any new employees were hired, they were not eligible for the idle-time allowance in March–June 2020, making this group of employees useless for the DiD analysis. We define $t + h$ as a post-treatment period lasting until the start of the second wave of the Covid-19 pandemic and the JRS support in November 2020, and we focus in this on August, September and October 2020, so $h = 2, 3, 4$ in the monthly frequency. July 2020 is excluded from the analysis because of the legal requirement that employees could not be laid off in the next month after they had received the idle-time allowance.

$JRS_{i,j,t}$ denotes binary variable that is 1 for employees from firm j that received the idle-time allowance in period t. $JRS_{i,j,t-1} = 0$ for all firms and employees as the idle-time allowance was not introduced before March 2020, so $\Delta JRS_{i,j,t} = JRS_{i,j,t}$. We also control for a number of covariates and $X_{i,j,t-1}$ includes various employee-employer pair characteristics such as the full-time equivalent gross wage (FTE gross wage), the average hours worked relative to the full-time equivalent (average FTE), the ratio of the potential value of the JRS to the average gross wage in the second half of 2019,[7] and worker experience in months at the given firm and occupation before the start of the pandemic. Lastly, $X_{i,j,t-1}$ includes the set of four-digit occupation fixed effects. Some covariates like age and gender are employee-specific ($X_{i,t-1}$), while industry and firm size class effects are firm-specific ($X_{j,t-1}$). Given that $E_{i,j,t-1} = 1$ and $JRS_{i,j,t-1} = 0$ for all i and j, equation (1) can be simplified as follows ($\delta_{0,h} = \beta_{0,h} + 1$):

$$E_{i,j,t+h} = \delta_{0,h} + \delta_{1,h} JRS_{i,j,t} + \beta_{1,h} X_{i,j,t-1} + \beta_{2,h} X_{i,t-1} + \beta_{3,h} X_{j,t-1} + \epsilon_{i,j,t}. \tag{2}$$

All employees that were employed at firms that participated in the JRS in February 2020 are either treated ($\Delta JRS_{i,j,t} = JRS_{i,j,t} = 1$) or clean ($JRS_{i,j,t+h} = 0$) controls, and can be used in the regression in equation (2) (see Dube et al. 2023). To check the heterogeneity of the effect of participating in the idle-time allowance on the probability of staying employed at the same firm, we add the interaction term:

$$E_{i,j,t+h} = \delta_{0,h} + \delta_{1,h} JRS_{i,j,t} + \delta_{2,h} JRS_{i,j,t} X_{i,j,t-1} + \beta_{1,h} X_{i,j,t-1} + \beta_{2,h} X_{i,t-1} + \beta_{3,h} X_{j,t-1} + \epsilon_{i,j,t}. \tag{3}$$

By interacting the treatment variable $JRS_{i,j,t}$ with the log of the FTE gross wage before the pandemic, we examine whether the impact of the JRS on employment differs across skills, which are proxied by the logarithm of the FTE gross wage. The heterogeneity of how the programme

[7]We use the second half of 2019 instead of February 2020 to make the definitions closer to those used in the regulations.

impacted employment by workload is accounted for by the interaction with the logarithm of average FTE before the pandemic.

5.2 Linear probability model of participation in the JRS

To understand the drivers of the decision of firms to apply for the JRS support for a particular employee we use the Linear Probability Model (LPM):[8]

$$JRS_{i,(j,k)} = \beta X_{i,(j,k)} + \mu_j + \mu_k + \epsilon_{i,(j,k)}, \tag{4}$$

where the binary variable $JRS_{i,(j,k)}$ equals 1 if employee i from firm j in occupation k participated in the idle-time allowance programme in March–June 2020. Since we have only one treatment period of four months, we estimate the LPM as the cross-section regression and the subscript t becomes redundant. Like in the LP-DiD analysis, $X_{i,(j,k)}$ represents a vector encompassing the employee's characteristics, including the potential value of the idle-time allowance for employee i and variables that determine the potential value of the allowance. These control variables include the FTE gross wage, the average FTE in the second half of 2019, demographic factors such as age and gender, the employee's employment status, and the submission status of the payroll tax booklet, indicating whether firm j is the primary employer.[9] To account for unobservable firm characteristics, we incorporate the firm fixed effect μ_j, while μ_k controls for variations between four-digit occupations. By including both fixed effects, the estimates of β require at least two employees within each single occupation and firm: one who participated in the JRS and another who did not. It is important to note that including fixed effects leads to a marked reduction in the number of observations used for the estimates of β, particularly for smaller firms, as they do not employ many employees within each profession. As before, our analysis only considers employees who were employed in February 2020 by firms that participated in the JRS in March–June 2020, and we exclude observations for employees who had more than one place of employment within a single month.

[8]We use LPM instead of a probit or logit specification because of the presence of the firm and occupation fixed effects.

[9]This affects the personal income tax rate applied to income received by an employee at the selected workplace.

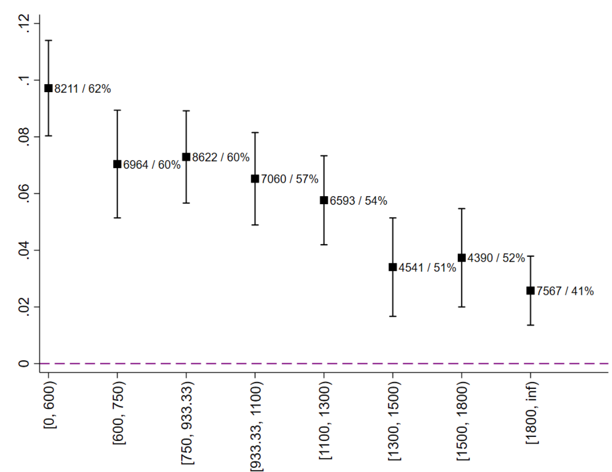
6 Empirical results

6.1 The probability of staying employed

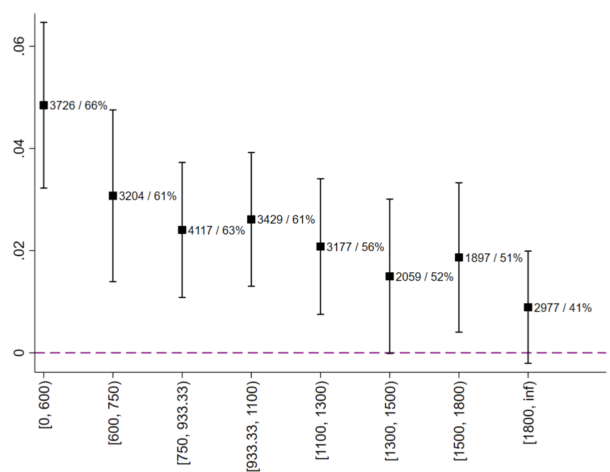
We begin by analysing whether employees that received the idle-time allowance, who are the treated employees, exhibit a greater probability of staying employed in October 2020 at the same JRS-participant firm than employees that did not receive the support, who are untreated employees. First, we merely estimate the differences in probabilities at different FTE gross wage intervals.[10] Figure 2a covers all the employees for whom data on the FTE gross wage in the second half of 2019 are available, while Figure 2b shows a smaller sample of employees for whom the data on covariates, including occupations, needed to estimate equation (2) are available.

Figure 2: Difference in the average probability of staying employed at the same firm for treated employees and untreated employees in October 2020, by FTE gross wage rate in the second half of 2019

(a) Employees with data on the FTE gross wage in 2019H2
(53,948 employer-employee pairs)



(b) Employees with all data available
(24,586 employer-employee pairs)



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: FTE gross wage intervals are on the X axis, difference in average probability of staying employed is on the Y axis. Squares denote point estimates, lines stand for confidence intervals (±2 s.d.). The numbers on each line reflect the number of observations and the percentage of treated employees in the group.

As explained in Section 4, the information on occupations is imputed from the database on changes in the status of employees. Unfortunately though, we are able to impute the four-digit occupation for fewer than half of the employees in our dataset.[11] There are two major factors that explain these data losses. The first is that we cannot impute the occupation of employees who did

[10] These FTE gross wage intervals are 0-600, 600-750, 750-933.33, 933.33-1100, 1100-1300, 1300-1500, 1500-1800, and above 1800 EUR.

[11] There are some data losses because information on age, gender, NACE industry, or size of firm is missing, but these losses are minor.

not have any changes in their status or occupation after the occupation variables first appear in the dataset in mid-2015, meaning that workers with a long work tenure tend to be missing from our analysis. The second is the non-reporting of occupation information by small firms, which biases our analysis towards the larger entities. The workers that we have were employed in February 2020 by firms that participated in the JRS, so each employee in this sample is eligible to participate in the idle-time allowance programme. The differences in the average probabilities are positive and statistically significant for all wage groups, so participation in the idle-time allowance programme is associated with a higher probability of staying at the same firm in the short run following the end of the programme. The relationship is substantially more pronounced for employees with lower wages, for whom the difference in the probability of staying employed is close to 10 percentage points, while the difference for employees with an FTE gross wage above 1800 euros is only 3 percentage points (see the average probabilities separately for employees which did or did not receive the idle-time allowance in Figure B.1 in Appendix B). Comparing the two figures reveals that the difference in the average probability of staying employed gets smaller for the smaller sample that was used in the econometric estimation, and even becomes statistically insignificant for the employees with the highest FTE gross wage. This suggests that the difference in the probability of staying employed increases with tenure, but decreases with firm size.

To provide evidence on the difference in the probability of remaining employed for different skill levels within occupations, we proceed to estimate equation (2), while controlling for occupations, and also for other worker characteristics like age and gender, and firm factors, like industry and firm size. We address the heterogeneity of the JRS support effect by using the interaction terms (see equation (3)). The results are reported in Table 3.

The relation of participation in the idle-time allowance programme with the probability of employment appears to be positive, statistically significant and persistent beyond the end of the first wave of the pandemic. These results confirm the findings of Benkovskis et al. (2023) at the firm level, which were that firms that received the idle-time allowance were less likely to cut employment after the end of the first wave of the pandemic, and that this effect persisted for several months after the end of the programme. Our results imply that the positive effect on employment was also observed at the employee level. We next examine whether the effect of participating in the JRS differs across skills within occupational groups. If it is higher for employees with lower skills, then participation in the idle-time programme may alter the composition of the workforce in favour of

Table 3: Probability of staying employed at the same firm

	Aug 2020	Sep 2020	Oct 2020
JRS participation (dummy)	0.343***	0.238***	0.185***
	(0.043)	(0.040)	(0.040)
... x Log of FTE wage in 2019H2	-0.032***	-0.021***	-0.015***
	(0.006)	(0.005)	(0.005)
... x Log of FTE in 2019H2	-0.072***	-0.058***	-0.051***
	(0.014)	(0.014)	(0.015)
Log of FTE wage in 2019H2	0.027***	0.015**	0.010
	(0.007)	(0.007)	(0.007)
Log of FTE in 2019H2	0.069***	0.066***	0.061***
	(0.014)	(0.014)	(0.014)
Log of potential JRS value to wage in 2019H2	0.004	-0.008	-0.015*
	(0.008)	(0.008)	(0.008)
Female (dummy)	0.004	0.008**	0.011***
	(0.003)	(0.003)	(0.004)
Age	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Log of experience in job position in Feb 2020	0.015***	0.016***	0.017***
	(0.002)	(0.002)	(0.002)
Ordinary status in 2019H2 (dummy)	-0.001	0.001	-0.005
	(0.007)	(0.006)	(0.006)
Salary tax booklet in 2019H2 (dummy)	-0.001	0.001	-0.005
	(0.004)	(0.004)	(0.004)
Occupation fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Firms size fixed effects	Yes	Yes	Yes
Firm fixed effects	No	No	No
R^2	0.102	0.084	0.085
Number of employees	24,586	24,586	24,586

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if the employee stayed in the same firm, 0 otherwise. The sample includes only employees from the model for the probability of participating in the JRS: workers that were employed in firms that participated in the JRS in March–June 2020, all necessary variables available. The sample excludes employees that were employed at more than one firm during any month in 2019–2020. * p<0.10, ** p<0.05, *** p<0.01

employees performing low-skilled tasks at the firms that received support. The results reported in Table 3 indicate that the difference in the probability of staying employed is statistically smaller for employees with high full-time equivalent wage rates for their job. Assuming that the FTE gross wage rate reflects each employee's skills, we may conclude that the difference in the probability of staying employed is lower for skilled employees. These results are robust to dropping employees whose FTE gross wage rate falls below the 10th percentile or exceeds the 90th percentile (see Table B.1 in Appendix B). We also split the sample into employees who could get the JRS support at the maximum of 75% of their gross wage, meaning employees with a gross wage below 933.33 euros, and employees with a lower potential ratio of the JRS allowance ratio to their wage rate, meaning employees with a gross wage above 933.33 euros (Table B.2 in Appendix B). It appears that the JRS effect is somewhat more pronounced for employees receiving it who are at the 75% threshold. This result is in line with the decline in the JRS effect for highly skilled workers illustrated previously (Figure 2).

Finally, we control for the heterogeneity of the JRS effect on employment by the hours worked. The coefficient before the interaction term for this shows that the difference in the probability of staying employed is statistically smaller for employees with a higher workload, meaning those employed full time rather than part time.

All in all, the difference in the probability of staying employed for treated and untreated employees is greater for employees with lower skills, which may indicate that the JRS has a negative effect on the within-occupation skill composition of labour at the firms receiving it. We cannot make any causal interpretation based on the results from Figure 2 or Table 3. The participation of employees in the idle-time allowance programme was not random, since the employees were appointed to the programme by the employer. Although we already control for occupation and other firm and employee characteristics in the LP-DiD regression analysis, the endogeneity of the treatment variable may not be fully accounted for, perhaps because of non-linearities or unobservables. In order to understand the relationship between participation in the idle-time allowance programme and the probability of staying employed, we need to investigate the factors behind the selection of employees into the programme.

6.2 Probability of participating in the JRS

We use the LPM from equation (4) to understand which employee characteristics were positively associated with the probability of an employee being nominated for the idle-time allowance support by a firm participating in the JRS. The estimation results are presented in Table 4 consisting of three columns. The first column incorporates the total potential value of the benefits an employee could receive given their wage rate in the second half of 2019. The second column breaks this value down by separating out the wage rate corresponding to a full-time job and the average number of hours worked relative to full-time hours. The third column adds an additional dimension by controlling for the income replacement rate offered through the idle-time allowance.

It is important to remember that all the workers in our sample were employed in February 2020 by the firms that later participated in the idle-time allowance programme, and so all those workers were eligible for the support. While all the firms participating in the JRS faced a severe decline in turnover, that decline could differ across firms and so vary the incentive to apply for the support. In order to control for any firm-related factors, we include the firm fixed effect into the regression. Acknowledging that some professions were more vulnerable to the pandemic and the restrictive

Table 4: Probability of participating in the JRS at the employee level

Determinants	(1)	(2)	(3)
Log of potential JRS value	0.0278***	-	-
	(0.0103)	-	-
Log of FTE wage in 2019H2 (skills proxy)	-	-0.0575***	0.0341*
	-	(0.0114)	(0.0165)
Log of average FTE in 2019H2	-	0.00865	0.0400***
	-	(0.0100)	(0.0108)
Log of potential JRS value to wage in 2019H2	-	-	0.1701***
	-	-	(0.0220)
Female (dummy)	0.0486***	0.0411***	0.0379***
	(0.0085)	(0.0086)	(0.0086)
Age	-0.00429**	-0.00259	-0.00250
	(0.00186)	(0.00188)	(0.00187)
Age^2	0.00005**	0.00003	0.00003
	(0.00002)	(0.00002)	(0.00002)
Log of experience in job position in Feb 2020	-0.00797**	-0.00306	-0.00441
	(0.00404)	(0.00407)	(0.00407)
Ordinary employee's status in 2019H2 (dummy)	0.0921***	0.0990***	0.0870***
	(0.0180)	(0.0180)	(0.0180)
Salary tax booklet in 2019H2 (dummy)	0.0286***	0.0319***	0.0287***
	(0.0099)	(0.0099)	(0.0099)
Firm fixed effect	Yes	Yes	Yes
Occupation fixed effect (4-digit ISCO-08)	Yes	Yes	Yes
Number of observations	24,586	24,586	24,586
R^2	0.446	0.446	0.448

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if the employee participated in the JRS in March–June 2020, 0 otherwise. The sample only includes workers that were employed in firms that participated in the JRS in March–June 2020. The sample excludes employees that were employed at more than one firm during any month in 2019–2020. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

measures introduced because of it, we also include the four-digit occupation fixed effect. Finally, we include all the employee-level variables available in our datasets, such as gender, age, experience and status.

The regression in column (1) is based on the simple idea that a firm participating in the JRS would maximise the amount of JRS support available for their employees, meaning workers that could get a larger potential value in benefits would be more likely to participate in the JRS. The coefficient before the variable for this is indeed positive and statistically significant, but employees with different skill levels could still get the same potential value from the idle-time allowance. To account for this, we decompose the potential value of the JRS support into three components, which are the employee's FTE gross wage, the employee's workload as the ratio of the hours they worked to full-time equivalent hours, and the potential JRS coverage, or the potential benefit an employee would get as a ratio to their gross wage.[12] More specifically, the logarithm of the potential JRS benefit is decomposed into the logarithm of the FTE gross wage, the logarithm of average FTE, and the logarithm of the potential JRS value to the gross wage in the second half of 2019. Note

[12]The ratio declines for employees whose gross wage is above 933.33 EUR.

that there is no perfect multicollinearity between these three variables because of the 700-euro cap (see Table B.3 and Figure B.2 in Appendix B), more so given that the gross wage of approximately half of the employees in our dataset exceeds the threshold of 933.33 euros.

We only account for two components of the JRS value, these being the logarithm of the FTE gross wage as our proxy for skills, and the employee's workload. The estimation results after controlling for firm characteristics, occupation, demographic variables, and employment status reveal a negative conditional correlation between FTE wages and the probability of the employee participating in the JRS (see column (2)). This shows that relatively more skilled workers in the same occupation had a smaller probability of getting the idle-time allowance. This does not mean that firms were not willing to support skilled workers, but rather on the contrary, the results for all three components reported in column (3) show that firms actually value skills and tended to apply for the JRS support for more skilled workers once the income replacement rate guaranteed by the allowance is taken into account. Although firms exhibit a greater willingness to support skilled employees, the legal ceiling of 700 euros on the value of the benefit reduces the relative value of the potential benefits for the skilled employees with higher pay and encourages the targeting of the JRS support to low-skilled employees.

6.3 DiD estimation using the sample of matched firms

To mitigate the selection bias in the results reported previously in Table 3 and to confirm the causal effect of JRS support on employment, we use the propensity score matching technique. We apply the matching approach using the kernel method with a calliper of 0.0075. Matching is conducted among employees within the same industry, firm size class, and occupation.

To proceed with the LP-DiD estimation of equations (2) and (3), it is crucial to ensure that the matching process yields satisfactory results that allow comparison between the employees who received the idle-time allowance and those who did not. The quality of the matching is assessed in Table 5. The pre-matching analysis reveals significant statistical differences across various observable characteristics between the treated employees who are covered by the JRS, and the control employees who are not. Specific differences are that the treated employees had lower full-time equivalent wage rates, worked fewer hours, and had a lower income replacement rate than the control group. However, after the matching process, the differences in the means between the treated employees and the matched control employees become statistically insignificant at a 90% confidence level for all variables except age, for which the difference remains statistically significant but is small in economic terms. Similar conclusions about the quality of matching arise from Figure B.3 in Appendix B, which compares the distribution of several variables for the unmatched and matched samples. This indicates that the matching procedure successfully addresses the initial disparities, resulting in the treated and control groups having comparable characteristics.

Table 5: Quality of matching: t-tests

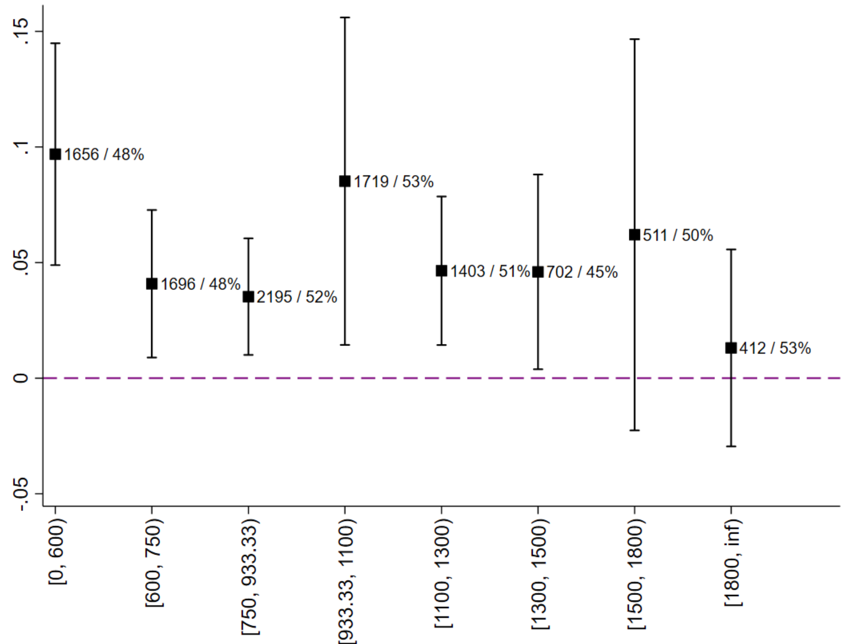
Variable		Unmatched			Matched	
	Treated	Control	p-value	Treated	Control	p-value
Log of potential JRS value	6.192	6.265	0.000	6.209	6.195	0.043
Log of FTE wage in 2019H2 (skill proxy)	6.865	7.013	0.000	6.776	6.763	0.054
Log of average FTE in 2019H2	-0.264	-0.243	0.000	-0.212	-0.215	0.566
Log of potential JRS value to wage in 2019H2	-0.409	-0.505	0.000	-0.355	-0.353	0.420
Female (dummy)	0.657	0.545	0.000	0.742	0.739	0.649
Age	42.79	43.40	0.000	41.93	42.77	0.000
Log of experience in job position in Feb 2020	3.051	3.075	0.018	3.065	3.067	0.889
Ordinary employee's status in 2019H2 (dummy)	0.956	0.934	0.000	0.980	0.980	0.959
Salary tax booklet in 2019H2 (dummy)	0.866	0.859	0.000	0.980	0.980	0.959
Number of employees on support	14,219	10,746	-	6,187	4,107	-
Number of employees off support	-	-	-	7,930	-	-

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Matching performed using the kernel method with a 0.0075 calliper. Employees are matched within the same industry (4-digit NACE), firm size class (less than 10 employees, 10-49 employees, 50-249 employees, 250 employees or more) and occupation (4 digit ISCO-08). The table reports the mean values and a corresponding p-value for the two-sample t-test.

Using the propensity score matching technique means there is a substantial loss of observations as approximately 55% of treated employees remain off support. This is because we were not able to find a good enough match for more than half of the employees receiving the JRS support. Some attention should be devoted to these employees as they will not appear in our subsequent analysis. Figure B.4 in Appendix B compares the distribution of some characteristics of the treated employees who were or were not receiving the support. We lose the recipients of JRS support who are employed in small firms, are older and are more skilled. Since we match within the same industry, firm size class, and occupation, it is difficult to find a good match for employees in rare and highly specific skilled occupations. Table B.4 in Appendix B shows that we were able to find good matches for most of the more common occupation groups, such as Personal Services Workers (51), Sales Workers (52), and Food Preparation Assistants (94), while matching was very poor for such groups as Science and Engineering Associate Professionals (31), Business and Administration Associate Professionals (33), and Numerical and Material Recording Clerks (43). The results reported below are consequently based mostly on the data for the more common occupations.

We next estimate the average effect of treatment on the treated (ATT) for the probability of staying employed at the same firm at different FTE gross wage intervals. The ATT is estimated for employees that are comparable across a whole range of observables. These employees share the same occupation, come from similar firms that participated in the JRS, and have comparable skills, workload and demographics, and so the probability of untreated employees participating in the idle-time allowance programme is almost identical, which removes the selection bias. It is possible that the estimation results could be biased because of unobservable factors, but the bias should not be large since all the employees at firms in the JRS were eligible to participate in the programme.[13]

Figure 3: Average effect of treatment on the treated (ATT) for the probability of staying employed at the same firm in October 2020, by FTE gross wage rate in the second half of 2019, matched sample



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: FTE gross wage intervals are on the X axis, ATT on the Y axis. Squares denote point estimates, lines stand for confidence intervals (2 s.d.). The numbers on each line reflect the number of observations and the percentage of treated employees in the subsample.

The ATT for the probability of staying employed shown in Figure 3 is positive and statistically significant for most of the wage groups, indicating an effect of about five percentage points. Although some heterogeneity can be observed across different wage groups, as the evidence for participation in JRS having a positive effect on employment is weak for employees with higher remuneration, the difference between wage groups is not statistically significant (see also Figure B.5 in Appendix B).

Next, we estimate equation (2) for the sample of matched employees, including covariates and interaction terms. The estimation results reported in Table 6 cconfirm that even after various

[13] We control for the firm fixed effects at the level of decision making when modelling the probability of participation.

individual factors are controlled for, the positive impact on employment persists for employees who are covered by the JRS. Specifically, JRS beneficiaries were more likely than non-participants to maintain their employment after the end of the first wave of the pandemic. However, once we narrow our sample down to matched employee pairs, the interaction term between JRS participation and the FTE gross wage rate becomes statistically insignificant, suggesting that the effect of the JRS on employment does not depend on within-occupation skills, at least for the employees in the more common occupations in the larger firms.

Table 6: Probability of staying employed at the same firm, matched sample

	Aug 2020	Sep 2020	Oct 2020
JRS participation (dummy)	0.318**	0.238*	0.258*
	(0.142)	(0.131)	(0.135)
... x Log of FTE wage in 2019H2	-0.019	-0.017	-0.021
	(0.020)	(0.019)	(0.019)
... x Log of FTE in 2019H2	-0.138***	-0.073*	-0.073*
	(0.041)	(0.039)	(0.040)
Log of FTE wage in 2019H2	0.028	0.024	0.031
	(0.023)	(0.021)	(0.022)
Log of FTE in 2019H2	0.133***	0.106***	0.120***
	(0.042)	(0.039)	(0.040)
Log of potential JRS value to wage in 2019H2	-0.011	-0.020	-0.013
	(0.034)	(0.032)	(0.033)
Female (dummy)	0.028	0.035*	0.037*
	(0.019)	(0.019)	(0.019)
Age	-0.001*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Log of experience in job position in Feb 2020	0.019***	0.014***	0.013**
	(0.006)	(0.005)	(0.005)
Ordinary status in 2019H2 (dummy)	0.006	0.011	-0.024
	(0.030)	(0.026)	(0.017)
Salary tax booklet in 2019H2 (dummy)	-0.017	-0.007	0.002
	(0.010)	(0.010)	(0.011)
Occupation fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Firms size fixed effects	Yes	Yes	Yes
Firm fixed effects	No	No	No
R^2	0.143	0.115	0.122
Number of employees	10,294	10,194	10,294

Source: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if the employee stayed at the same firm, 0 otherwise. The sample includes only matched employees. * p<0.10, ** p<0.05, *** p<0.01

In summary, our findings indicate that participating in the JRS positively affects the likelihood of employees maintaining their employment with the same firm in the immediate aftermath of the end of the programme. This effect is independent of the skill level of the employees. At the same time, skilled employees tend to be less likely to receive JRS support because of the programme's benefit ceiling and the regressive income replacement rate. Taken together, these findings suggest that the JRS may negatively affect the within-occupation skill composition of the workforce in firms that benefit from the programme.

6.4 Robustness checks

We conduct several robustness checks for our results. For the first, we employ an alternative matching technique, as we use the one nearest neighbour approach instead of the kernel method, and set a calliper value at 0.005 instead of 0.0075. As previously, matching is conducted within the same industry, firm size class, and occupation. The quality of matching is similar to that reported in Section 6.3.[14] The results of the LP-DiD regression using the alternative matching technique are reported in the first three columns of Table 7. They point to a similar conclusion, that participation in the JRS increases the probability of staying at the same firm in the short run, but this impact is not contingent upon different wage levels.

Table 7: Probability of staying employed at the same firm

	Matching, 1 nearest neighbour			LP-DiD with firm fixed effects		
	Aug 2020	Sep 2020	Oct 2020	Aug 2020	Sep 2020	Oct 2020
JRS participation (dummy)	0.321*	0.230	0.276*	0.516***	0.328**	0.307**
	(0.174)	(0.155)	(0.160)	(0.151)	(0.149)	(0.150)
... x Log of FTE wage in 2019H2	-0.019	-0.017	-0.023	-0.041*	-0.027	-0.025
	(0.025)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
... x Log of FTE in 2019H2	-0.141***	-0.065	-0.073*	-0.176**	-0.089**	-0.086**
	(0.046)	(0.042)	(0.043)	(0.040)	(0.040)	(0.041)
Log of FTE wage in 2019H2	0.015	0.019	0.032	0.107**	0.085***	0.087***
	(0.028)	(0.024)	(0.025)	(0.029)	(0.027)	(0.027)
Log of FTE in 2019H2	0.123***	0.091**	0.117***	0.192***	0.162***	0.165***
	(0.047)	(0.041)	(0.043)	(0.041)	(0.041)	(0.041)
Log of potential JRS value to wage in 2019H2	-0.016	-0.027	-0.014	0.055	0.025	0.017
	(0.038)	(0.034)	(0.035)	(0.040)	(0.038)	(0.037)
Female (dummy)	0.019	0.026	0.030*	0.031	0.037	0.037
	(0.018)	(0.017)	(0.018)	(0.024)	(0.024)	(0.024)
Age	-0.001	-0.000	-0.000	-0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of experience in job position in Feb 2020	0.027***	0.020***	0.018***	0.014**	0.009	0.006
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Ordinary status in 2019H2 (dummy)	0.008	0.007	-0.026	0.022	0.014	-0.018
	(0.034)	(0.029)	(0.021)	(0.034)	(0.027)	(0.018)
Salary tax booklet in 2019H2 (dummy)	-0.018	-0.009	0.001	-0.009	0.003	0.007
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	No	No	No
Firms size class fixed effects	Yes	Yes	Yes	No	No	No
Firm fixed effects	No	No	No	Yes	Yes	Yes
R^2	0.151	0.119	0.128	0.414	0.355	0.363
Number of employees	7,862	7,862	7,862	10,294	10,294	10,294

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if the employee stayed in the same firm, 0 otherwise. The sample only includes employees from the model for the probability of participating in the JRS: workers that were employed at firms that participated in the JRS in March–June 2020, all necessary variables available. The sample excludes employees that were employed at more than one firm during any month in 2019—2020. * p<0.10, ** p<0.05, *** p<0.01

The second check is that we incorporate firm fixed effects in the LP-DiD regressions, which we estimate for a sample of matched employees. The results are reported in the last three columns of

[14] The results are available upon request.

Table 7. The results are similar to those obtained earlier even after firm specific unobservables are controlled for.

The final check of the robustness of our findings uses an alternative measure of the skills of employees. Instead of using FTE gross wages directly, we estimate an employee-specific component or employee fixed effect for the seminal wage equation of Abowd et al. (1999):[15]

$$\ln W_{i,j,t} = \theta_i + \psi_j + \beta X_{i,t} + \epsilon_{i,j,t}, \tag{5}$$

where $W_{i,j,t}$ is the annual full-time equivalent gross wage of employee i working at firm j in year t, $X_{i,t}$ includes the age of the employee and year fixed effects, ψ_j denotes the firm fixed effect, while θ_i is an employee fixed effect. Further, we use the estimated employee fixed effect, $\widehat{\theta_i}$, as a proxy for unobserved skills of employees, further denoted as the AKM skills proxy. The procedure for finding this is that we first replace the logarithm of the FTE gross wage with the AKM skills proxy in the linear probability model (see the results in Table 8). The conclusions remain unchanged even though there are fewer observations. Firms tend to apply for the idle-time allowance programme for higher skilled employees less frequently (column (2)), but this result reverses when the ratio of the potential allowance to the gross wage is controlled for (column (3)). In other words, firms would nominate skilled employees for the JRS if there were no benefit ceiling.

The next step is that we re-estimate the LP-DiD regressions (equation (2)) both for a broad sample of employees and for a sample of matched employees.[16] The estimation results (reported in Table 9) indicate that the effect of the JRS on the probability of employment does not differ by skills in either sample, thus confirming our baseline estimations.

[15] We estimate the wage equation using the full annual employer-employee dataset for 2015-2020.

[16] The quality of the matching is similar to the baseline results, available upon request.

Table 8: Probability of participating in the JRS at the employee level using the AKM skills proxy

Determinants	(1)	(2)	(3)
Log of potential JRS value	0.0278***	-	-
	(0.0103)	-	-
AKM skills proxy	-	-0.0601***	0.0300*
	-	(0.0138)	(0.0177)
Log of average FTE in 2019H2	-	0.0147	0.0100
	-	(0.0120)	(0.0123)
Log of potential JRS value to wage in 2019H2	-	-	0.1676***
	-	-	(0.0206)
Female (dummy)	0.0486***	0.0368***	0.0315***
	(0.0085)	(0.0093)	(0.0093)
Age	-0.00429**	-0.01063***	-0.00234
	(0.00186)	(0.00269)	(0.00311)
Age^2	0.00005**	0.00006***	0.00001
	(0.00002)	(0.00002)	(0.00003)
Log of experience in job position in Feb 2020	-0.00797**	-0.00284	-0.00049
	(0.00404)	(0.00442)	(0.00441)
Ordinary employee's status in 2019H2 (dummy)	0.0921***	0.0843***	0.0835***
	(0.0180)	(0.0191)	(0.0190)
Salary tax booklet in 2019H2 (dummy)	0.0286***	0.0257***	0.0253***
	(0.0099)	(0.0114)	(0.0114)
Firm fixed effect	Yes	Yes	Yes
Occupation fixed effect (4-digit ISCO-08)	Yes	Yes	Yes
Number of observations	24,586	21,775	21,775
R^2	0.446	0.453	0.455

Sources: Central Statistical Bureau of Latvia and the State Revenue Service

Note: Dependent variable equals 1 if the employee participated in the JRS in March–June 2020, 0 otherwise. The sample includes only workers that were employed at firms that participated in the JRS during March–June 2020. The sample excludes employees that were employed at more than one firm during any month in 2019–2020. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Probability of staying employed in the same firm using the AKM skills proxy

	Unmatched employees			Matched employees		
	Aug 2020	Sep 2020	Oct 2020	Aug 2020	Sep 2020	Oct 2020
JRS participation (dummy)	0.119***	0.088***	0.077***	0.166***	0.112***	0.109***
	(0.014)	(0.014)	(0.014)	(0.039)	(0.038)	(0.038)
... x AKM skills proxy	-0.004	-0.000	0.002	-0.008	-0.003	-0.001
	(0.002)	(0.002)	(0.002)	(0.008)	(0.007)	(0.007)
... x Log of FTE in 2019H2	-0.070***	-0.054***	-0.053***	-0.111**	-0.060	-0.068
	(0.016)	(0.016)	(0.016)	(0.045)	(0.043)	(0.043)
AKM skills proxy	-0.001	-0.001	0.000	0.010	0.016	0.026
	(0.006)	(0.006)	(0.006)	(0.026)	(0.026)	(0.027)
Log of FTE in 2019H2	0.060***	0.058***	0.058***	0.073	0.069	0.091**
	(0.015)	(0.014)	(0.014)	(0.047)	(0.044)	(0.042)
Log of potential JRS value to wage in 2019H2	-0.015**	-0.016**	-0.017***	-0.016	-0.013	-0.002
	(0.006)	(0.006)	(0.006)	(0.029)	(0.028)	(0.028)
Female (dummy)	0.003	0.007*	0.009**	0.028	0.035*	0.039*
	(0.004)	(0.004)	(0.004)	(0.021)	(0.021)	(0.021)
Age	-0.001	-0.000	0.000	-0.000	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Log of experience in job position in Feb 2020	0.014***	0.015***	0.016***	0.012**	0.008	0.019*
	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.005)
Ordinary status in 2019H2 (dummy)	-0.009	-0.004	-0.011*	-0.010	0.014	-0.020
	(0.007)	(0.007)	(0.006)	(0.034)	(0.033)	(0.019)
Salary tax booklet in 2019H2 (dummy)	-0.004	-0.004	-0.002	-0.020*	-0.011	0.001
	(0.004)	(0.004)	(0.004)	(0.034)	(0.033)	(0.019)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firms size class fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
R^2	0.106	0.089	0.090	0.139	0.120	0.123
Number of employees	21,775	21,775	21,775	9,231	9,231	9,231

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if employee stayed in the same firm, 0 otherwise. The sample only includes employees from the model for the probability of participating in the JRS: workers that were employed in firms that participated in the JRS during March–June 2020, all necessary variables available. The sample excludes employees that were employed at more than one firm during any month in 2019–2020. * p<0.10, ** p<0.05, *** p<0.01

7 Conclusions

This study aims to address a gap in the literature by examining how employment protection programmes impact the within-occupation skill composition of the workforce in participating firms. Previous research has primarily focused on how employment protection programmes influence the reallocation of labour between firms, but the changes in skill composition in participating firms have been largely overlooked. This study uses a detailed employer-employee dataset from Latvia and reveals that participation in the JRS during the Covid-19 pandemic negatively affected the within-occupation skill profile of the workforce at firms that participated in the JRS.

Notably, our findings demonstrate that this adverse effect does not stem from the JRS being less effective for high-skilled employees, but rather it is a consequence of a design feature that was common to most of the JRSs introduced during the pandemic, which was the maximum allowance that an employee could receive. Our results indicate that while firms are more inclined to support employees who perform higher-skilled tasks within the same occupation group, the ceiling on the legal allowance reduces the relative value of the potential benefits for skilled, highly paid workers, and steers the JRS support towards low-skilled employees. These findings suggest that the choice of the maximum allowance plays a crucial role in how JRSs shape the skill profile of the workforce within participating firms. While we acknowledge that it may be necessary from a fiscal perspective to introduce a maximum allowance, policymakers should carefully consider the potential adverse impact that doing so could have on skill composition when they design employment protection programmes.

It is crucial to recognise that the impact we observed in this study is a short-term one. JRSs may inadvertently support jobs that are not viable in the long run or that would have survived even without the intervention. Additionally, workers enrolled in a JRS are less inclined to pursue alternative employment opportunities with more promising long-term prospects. This dynamic could potentially hinder structural transformations within the economy, slowing down the process of productive reallocation. Furthermore, we are unable to assess the overall impact on productivity and welfare. To do so, we would need to examine the subsequent career trajectories of the employees who did not participate in the JRS and who left the firm during the pandemic. This topic remains a subject for future research.

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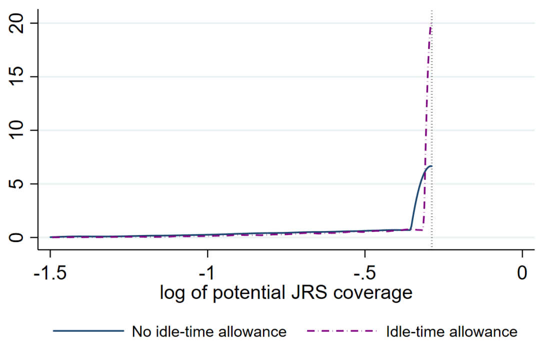
Appendices

A Data Description

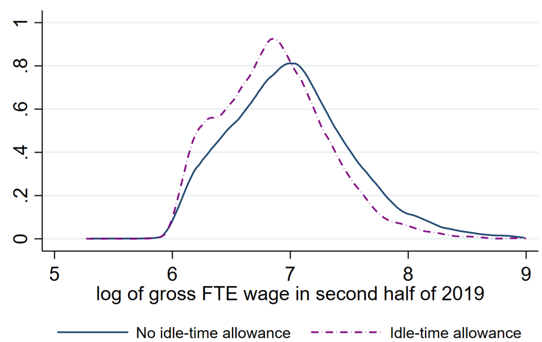
Figure A.1: Wage, skills and JRS coverage of employees participating and not participating in the JRS

(a) Distribution of JRS coverage (the ratio of the potential allowance to the gross wage in the 2nd half of 2019)

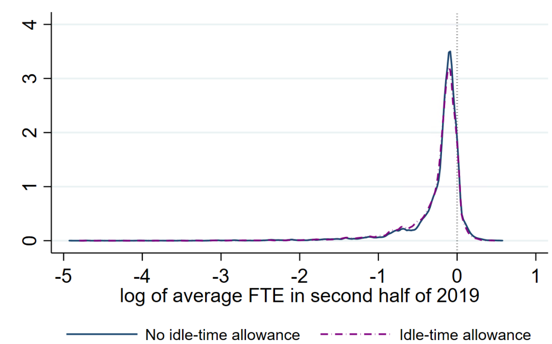


(b) Distribution of the gross wage in the 2nd half of 2019

(c) Distribution of the FTE gross wage in the 2nd half of 2019 (proxy for skills)



(d) Distribution of average FTE in the 2nd half of 2019



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: The sample includes workers that were employed at firms that participated in the idle-time allowance programme in March—June 2020, employed in February 2020 at firms that participated in the JRS, and where all the data needed for the regression analysis were available. We removed all employees that had more than one working place within any single month in 2019-2020. Vertical lines correspond to 75% JRS coverage and 100% FTE.

Table A.1: Linking the employer-employee database with idle-time allowance data (March–June 2020)

	Total	Linked with EE database	Not linked with EE database	% lost
Number of unique legal entities	9,136	5,637	3,499	38.3
Number of unique employees	55,182	50,324	4,858	8.8
Number of monthly observations	133,475	120,807	12,668	9.5
Value in million EUR	53.7	49.8	3.9	7.3

Sources: Central statistical Bureau of Latvia and the State Revenue Service
Note: Observations were linked using anonymised IDs of firms and employees. EE refers to the employer-employee database.

Table A.2: Legal entities participating in the idle-time allowance programme (March–June 2020)

	Present in EE database	Not present in EE database
Number of unique legal entities	5,637	3,499
Number of firms present in financial database	5,439	1,208
Share present in financial database, %	96.5	34.5
Average employment in 2019	17.4	3.25
Median employment in 2019	5	2
Average registration year	2007.1	2013.2

Sources: Central statistical Bureau of Latvia and the State Revenue Service
Note: Observations were linked using anonymised IDs of firms and employees. EE refers to the employer-employee database.

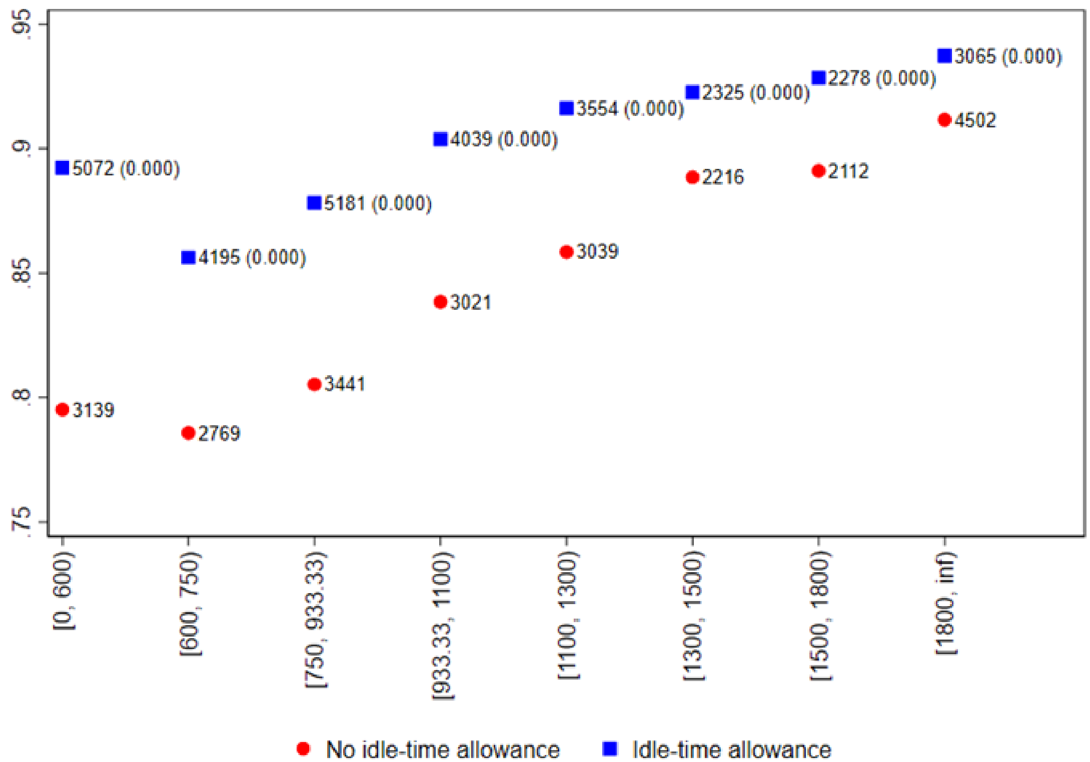
Table A.3: Summary statistics

Variable	Number of observations	Mean	Standard deviations	Min	Max
JRS participation (dummy)	59,624	0.522	0.500	0	1
JRS participation (number of months)	59,624	1.221	1.399	0	4
Log of FTE wage in 2019H2	53,948	6.952	0.528	4.5001	13.38
AKM skills proxy	50,711	0.125	1.200	-3.307	3.802
Log of FTE in 2019H2	53,948	0.802	0.210	0.00185	2.013
Log of potential JRS value to wage in 2019H2	53,948	0.655	0.150	0.0125	0.750
Female (dummy)	59,245	0.594	0.491	0	1
Age	59,245	44.42	13.75	25	82
Ordinary status in 2019H2 (dummy)	55,392	0.920	0.271	0	1
Salary tax booklet in 2019H2 (dummy)	55,392	0.857	0.350	0	1
Occupation	26,954	-	-	1112	9629

Sources: Central statistical Bureau of Latvia and the State Revenue Service
Note: The sample includes only workers that were employed at firms that participated in the JRS during March–June 2020. The sample excludes employees that were employed at more than one firm during any month in 2019–2020.

B Results

Figure B.1: Average probability of staying employed in the same firm in October 2020, by FTE gross wage rate in the second half of 2019



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Squares denote average probability values of staying employed at the same firm for employees that receive the idle-time allowance, and circles denote employees that do not receive it. Numbers denote the number of observations. Figures in brackets are the p-values of the statistical test on the difference between the probability values at each FTE gross wage rate.

Figure B.2: Potential JRS support and ratio of potential JRS value to the gross wage depending on the gross wage

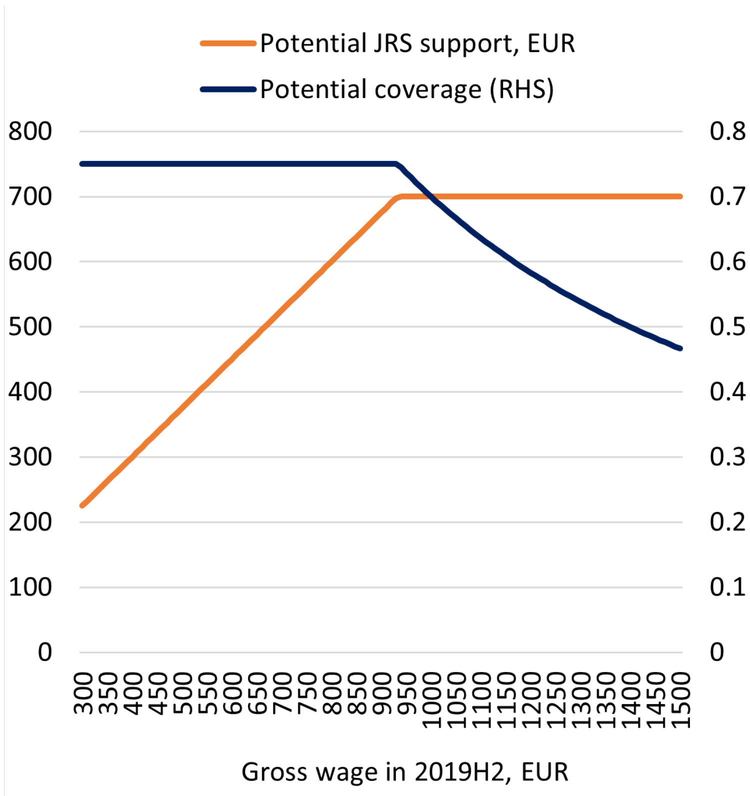
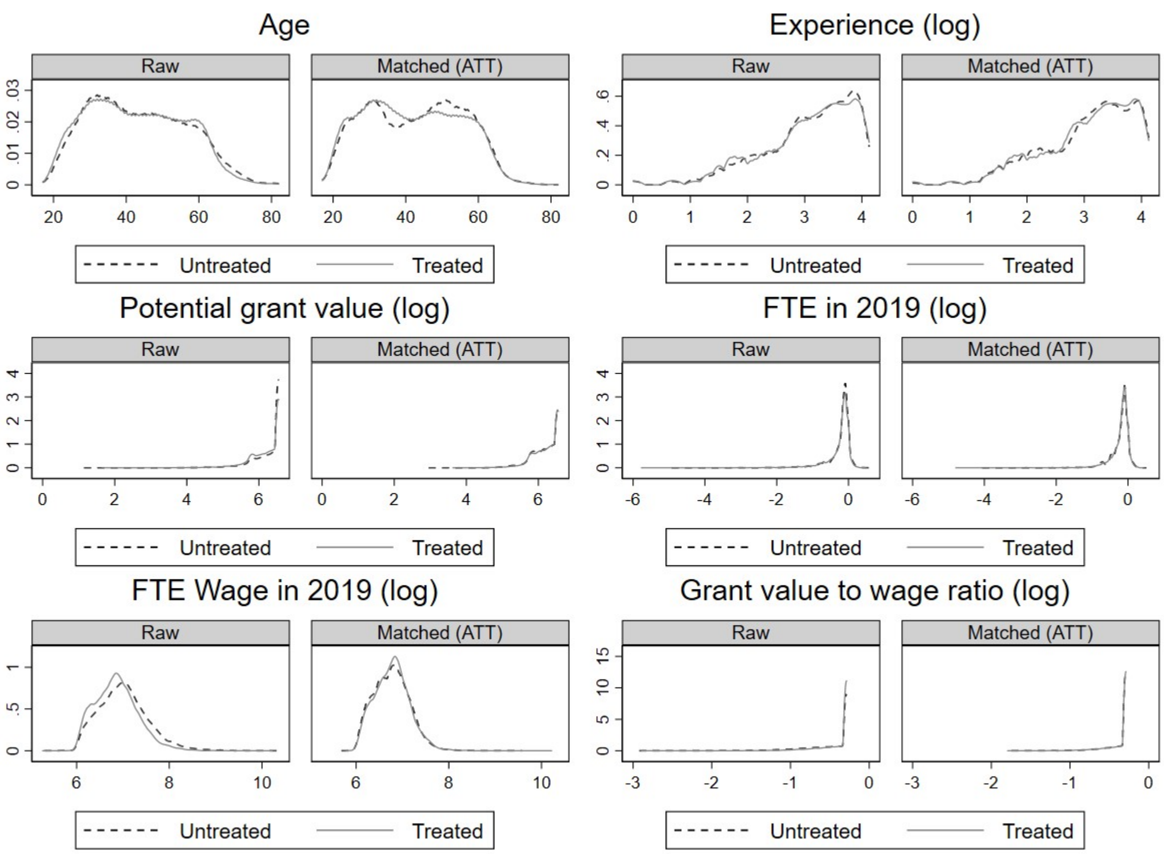
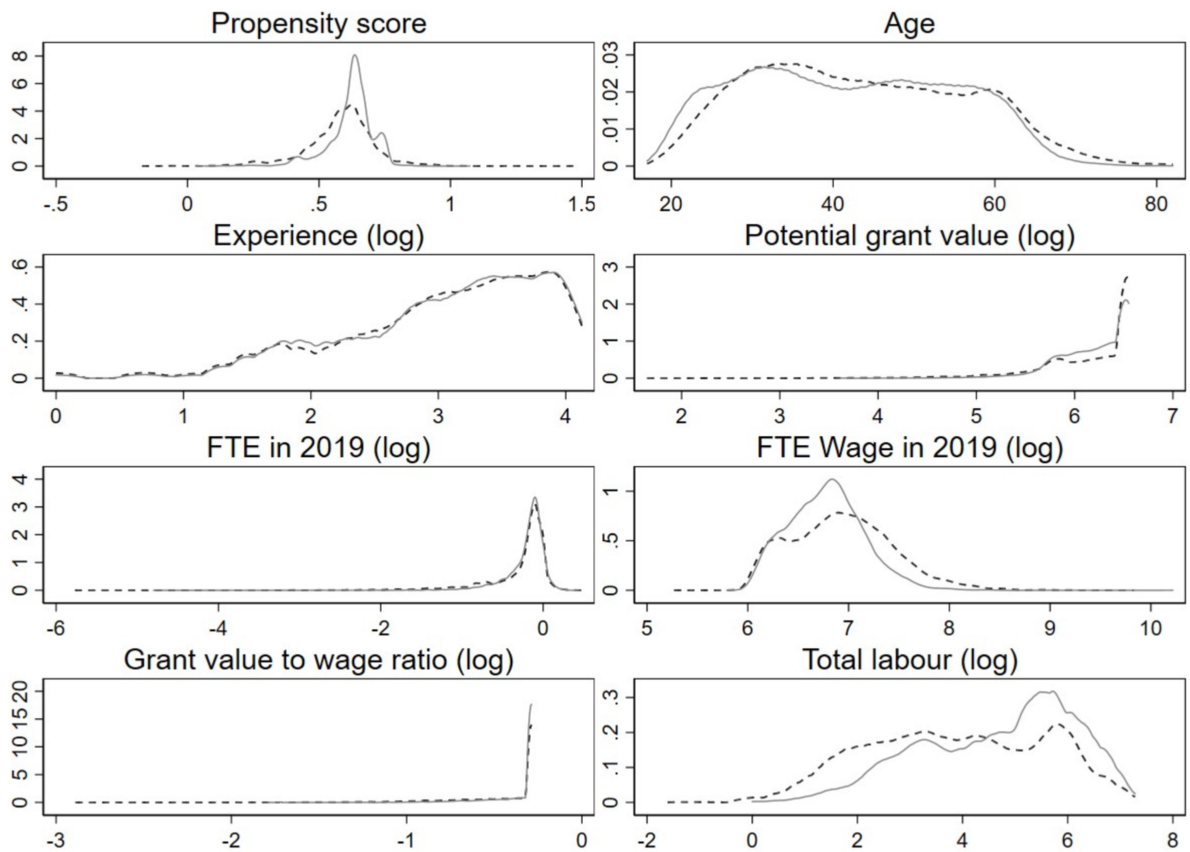


Figure B.3: Quality of matching: distributions



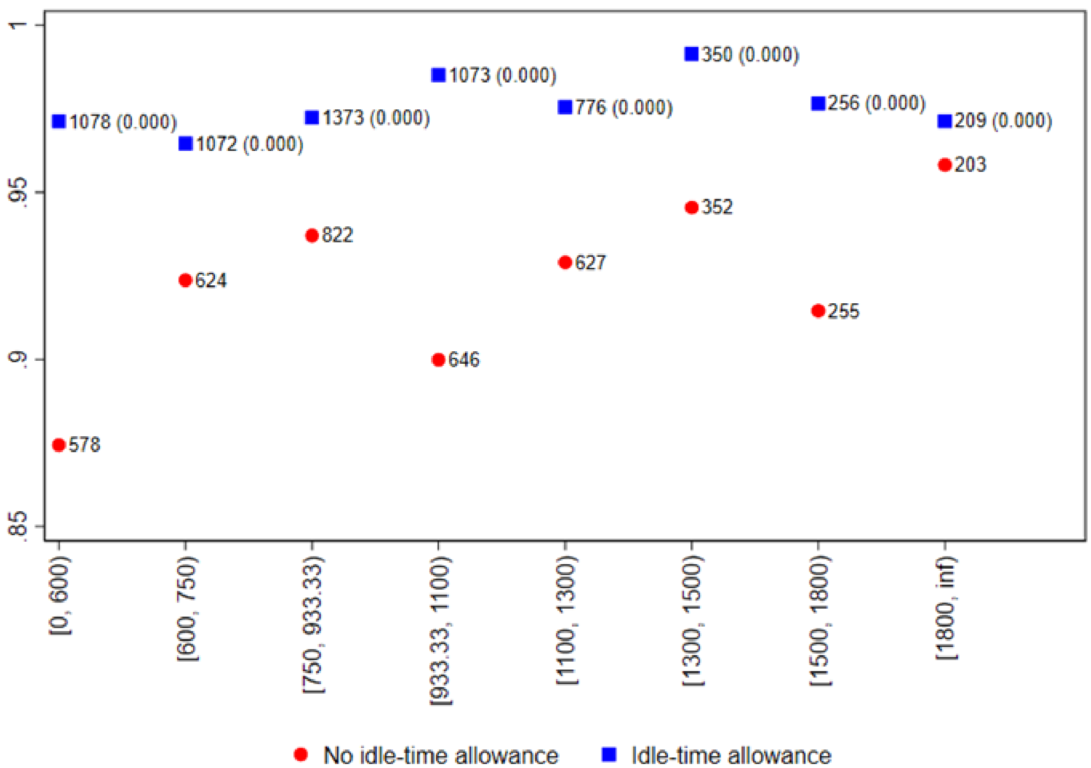
Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Matching performed using the kernel method with a 0.0075 calliper. Employees are matched within the same industry (4-digit NACE), firm size class (less than 10 employees, 10-49 employees, 50-249 employees, 250 employees or more) and occupation (4 digit ISCO-08)

Figure B.4: On support (solid) and off support (dashed)



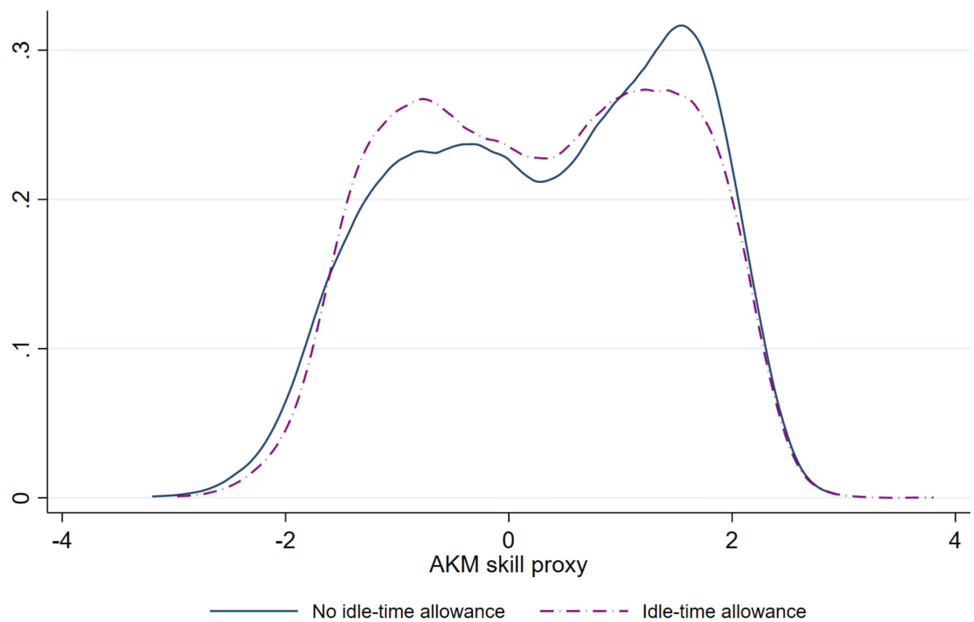
Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Matching performed using the kernel method with a 0.0075 calliper. Employees are matched within the same industry (4-digit NACE), firm size class (less than 10 employees, 10-49 employees, 50-249 employees, 250 employees or more) and occupation (4 digit ISCO-08)

Figure B.5: Average probability of staying employed at the same firm in October 2020 for the sample of matched firms, by FTE gross wage rate in the second half of 2019



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Squares (denote average probability values of staying employed in the same firm for employees that receive the idle-time allowance, and circles denote employees that do not receive it. Numbers denote the number of observations. Figures in brackets are the p-values of the statistical test on the difference between the probability values at each FTE gross wage rate.

Figure B.6: AKM skill proxy of employees participating and not participating in the JRS



Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: The sample includes workers that were employed at firms that participated in the idle-time allowance programme in March-–June 2020, employed in February 2020 at firms that participated in the JRS, and where all the data needed for the regression analysis were available. We removed all employees that had more than one working place within any single month in 2019-2020.

Table B.1: Probability of staying employed in the same firm, excluding very high and low-skilled employees
(excluding employees with FTE gross wage in the 2nd half of 2019 below 540 euros (10th percentile) and above 1920 euros (90th percentile))

	Aug 2020	Sep 2020	Oct 2020
JRS participation (dummy)	0.314***	0.224***	0.183***
	(0.071)	(0.067)	(0.067)
... x Log of FTE wage in 2019H2	-0.029***	-0.020**	-0.017*
	(0.010)	(0.009)	(0.010)
... x Log of FTE in 2019H2	-0.067***	-0.051***	-0.038***
	(0.017)	(0.017)	(0.018)
Log of FTE wage in 2019H2	0.039***	0.020*	0.017
	(0.012)	(0.011)	(0.011)
Log of FTE in 2019H2	0.068***	0.063***	0.055***
	(0.017)	(0.016)	(0.016)
Log of potential JRS value to wage in 2019H2	-0.002	-0.019	-0.020
	(0.013)	(0.013)	(0.014)
Female (dummy)	0.008**	0.013***	0.014***
	(0.004)	(0.004)	(0.004)
Age	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Log of experience in job position in Feb 2020	0.015***	0.016***	0.016***
	(0.002)	(0.002)	(0.002)
Ordinary status in 2019H2 (dummy)	-0.007	-0.002	-0.008
	(0.008)	(0.007)	(0.007)
Salary tax booklet in 2019H2 (dummy)	-0.008*	-0.004	0.000
	(0.004)	(0.005)	(0.005)
Occupation fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Firms size class fixed effects	Yes	Yes	Yes
Firm fixed effects	No	No	No
R^2	0.113	0.093	0.094
Number of employees	19,693	19,693	19,693

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if the employee stayed at the same firm, 0 otherwise. The sample includes only employees from the model for the probability of participating in the JRS: workers that were employed at firms that participated in the JRS programme during March–June 2020, all necessary variables available. The sample excludes employees that were employed at more than one firm during any month in 2019–2020. * p<0.10, ** p<0.05, *** p<0.01

Table B.2: Probability of staying employed at the same firm, depending on the potential JRS coverage

(separating employees with a potential JRS grant equalling 75% of gross wage in the 2nd half of 2019 from employees with lower potential JRS coverage (gross wage exceeding 933.33 euros))

	JRS coverage equals 75%			JRS coverage below 75%		
	Aug 2020	Sep 2020	Oct 2020	Aug 2020	Sep 2020	Oct 2020
JRS participation (dummy)	0.518***	0.309***	0.221***	0.177**	0.130	0.079
	(0.094)	(0.090)	(0.088)	(0.080)	(0.083)	(0.084)
... x Log of FTE wage in 2019H2	-0.057***	-0.031**	-0.020	-0.011	-0.007	-0.003
	(0.013)	(0.013)	(0.012)	(0.009)	(0.009)	(0.009)
... x Log of FTE in 2019H2	-0.087***	-0.063***	-0.057***	-0.052*	-0.047	-0.033
	(0.019)	(0.019)	(0.019)	(0.029)	(0.031)	(0.032)
Log of FTE wage in 2019H2	0.038***	0.019	0.009	0.008	-0.000	-0.008
	(0.012)	(0.012)	(0.011)	(0.026)	(0.026)	(0.027)
Log of FTE in 2019H2	0.072***	0.066***	0.063***	0.063*	0.063*	0.040
	(0.019)	(0.018)	(0.018)	(0.035)	(0.037)	(0.039)
Log of potential JRS value to wage in 2019H2	-	-	-	-0.018	-0.019	-0.027
	-	-	-	(0.027)	(0.026)	(0.027)
Female (dummy)	0.009	0.017***	0.024***	0.001	0.001	0.001
	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)
Age	-0.000	0.000	0.000	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of experience in job position in Feb 2020	0.015***	0.018***	0.018***	0.012***	0.011***	0.013***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Ordinary status in 2019H2 (dummy)	-0.000	0.001	-0.007	-0.004	-0.002	-0.001
	(0.009)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Salary tax booklet in 2019H2 (dummy)	-0.010*	-0.007	-0.007	-0.003	0.001	0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firms size class fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
R^2	0.124	0.102	0.102	0.115	0.123	0.124
Number of employees	14,588	14,588	14,588	9,998	9,998	9,998

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Dependent variable equals 1 if the employee stayed at the same firm, 0 otherwise. The sample includes only employees from the model for the probability of participating in the JRS: workers that were employed at firms that participated in the JRS programme during March–June 2020, all necessary variables available. The sample excludes employees that were employed at more than one firm during any month in 2019–2020. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table B.3: Correlations between potential logs of FTE gross wage, average FTE and JRS value to wage

	Log of FTE wage	Log of average FTE	Log of potential JRS value to wage
Simple correlation matrix			
Log of FTE wage in 2019H2	1.000	-	-
Log of average FTE in 2019H2	0.029	1.000	-
Log of potential JRS value to wage	-0.787	-0.210	1.000
Correlation matrix after demeaning (controlling for industry and occupation)			
Log of FTE wage in 2019H2	1.000	-	-
Log of average FTE in 2019H2	-0.116	1.000	-
Log of potential JRS value to wage	-0.678	-0.188	1.000

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: The second part of the table reports correlation coefficients for the residuals of the variables to their averages within industry/occupation pairs.

Table B.4: Employees by selected 2-digit ISCO-08 occupation groups on and off support

	On support	Off support
31 Science and Engineering Associate Professionals	31	246
33 Business and Administration Associate Professionals	126	806
42 Customer Services Clerks	522	411
43 Numerical and Material Recording Clerks	123	376
51 Personal Services Workers	1,148	731
52 Sales Workers	1,359	569
72 Metal, Machinery and Related Trades Workers	247	413
75 Food Processing, Woodworking, Other Craft Workers	318	279
81 Stationary Plant and Machine Operators	246	304
83 Drivers and Mobile Plant Operators	321	254
91 Cleaners and Helpers	265	377
93 Labourers in Mining, Construction, Manufacturing and Transport	422	528
94 Food Preparation Assistants	483	131
Total	6,187	7,930

Sources: Central Statistical Bureau of Latvia and the State Revenue Service
Note: Matching performed using the kernel method with a 0.0075 calliper. Employees are matched within the same industry (4-digit NACE), firm size class (less than 10 employees, 10-49 employees, 50-249 employees, 250 employees or more) and occupation (4 digit ISCO-08).