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## The Covid-19 Pandemic and Transitions out of Unemployment

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# The COVID-19 pandemic and transitions out of unemployment \*

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## Abstract

So far, the short-term effects of the Covid-19 pandemic on the labour market have been widely analysed but much of the pandemic's longer-term impact is not understood. Therefore, this paper investigates the longer-term effects of the Covid-19 pandemic on transitions out of unemployment and subsequent labour market biographies in Germany. Additionally, since the pandemic affected occupations differently (e.g. depending on the possibility to work from home), the existence of heterogeneous effects across occupations is assessed. All in all, the results show that the pandemic led to a strong and persistent earnings loss, which can mainly be explained by a reduction in employment in the short-run and by a reduction in wages in the long-run. Moreover, examining the heterogeneity across occupations indicates that the magnitude of these effects differs by occupations in which the unemployed previously worked.

Keywords: Covid-19 pandemic, unemployment, employment biographies, occupations  
JEL: J23, J62, J64

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# 1 Introduction

The Covid-19 pandemic represents one of the greatest and unique economic shocks since World War II. It has led to a severe tightening of labour market conditions: For instance, [Forsythe et al. \(2020\)](#) find for the U.S. labour market that the pandemic resulted in a large increase in unemployment, whereas at the same time the number of new recruitments decreased. A large body of studies has shown that exposure to temporary economic shocks can have long-lasting consequences. For example, being displaced from one's job is associated with earnings losses of about 15-20% even five years after displacement ([Jacobson et al., 1993](#); [Lachowska et al., 2020](#)). Likewise, individuals that enter the labour market during a recession experience persistent reductions in earnings ([Oreopoulos et al., 2012](#); [Schwandt and von Wachter, 2019](#)).

The Covid-19 pandemic is a special economic shock, because something comparable regarding its extent and its impact on the labour market has not happened before. The pandemic's impact on labour market outcomes differs from previous economic shocks ([Albanesi and Kim, 2021a](#)) and, in particular, the pandemic did not affect everyone equally. For instance, there is evidence that the pandemic brought about a stronger increase in unemployment claims for occupations and sectors in leisure, hospitality or non-essential retail than for occupations and sectors in nursing or essential retail ([Forsythe et al., 2020](#); [Beland et al., 2020](#)). Hence, it is likely that the effect of the pandemic is more pronounced for certain occupations: while labour demand shrank mainly in occupations which were hit by lockdowns, labour demand in occupations with the possibility to work from home or a high systemic importance was less negatively affected.

So far, the short-term effects of the pandemic on the labour market have been analysed but much of the pandemic's longer-term impact is not understood. Therefore, the aim of this paper is in a first step to investigate the longer-term consequences of the Covid-19 pandemic on transitions of newly unemployed (back) into employment and, in a second step, to assess the existence of heterogeneous effects across occupations that the unemployed used to work in. These analyses are important, since if the pandemic has prolonged the duration of unemployment which may reduce the probability of finding a job permanently, the pandemic may result in persistent scarring effects and a rise in long-term unemployment.

In doing so, the paper makes the following contributions: first, it does not exclusively focus on the short-term effects of the Covid-19 pandemic on labour market outcomes, but additionally expands the analysis by investigating effects of the pandemic in the longer run by taking almost two years after the onset into account. Second, this paper assesses the heterogeneity of effects across the occupations that the unemployed used to work in before the start of the pandemic. Third, this analysis ensures that the estimated effects on labour market outcomes are not influenced by the indirect effect that individuals might become unemployed due to the pandemic. Instead, the analysis concentrates only on individuals who became unemployed shortly before the outbreak of Covid-19. And finally, this is

the first study in Germany which relies on administrative data of the full population of newly unemployed individuals. This has the advantage that the data is of high quality and consists of a high number of observations which makes detailed analyses of heterogeneities and mechanisms possible.

The empirical analysis uses administrative social security data from the Integrated Employment Biographies (IEB). The IEB provide detailed information about the universe of labour market participants in Germany. Based on the IEB data, a bi-weekly panel is constructed which tracks the labour market biographies of individuals who became unemployed in February 2020 as well as a control group of individuals who entered unemployment in February 2018.

The identification strategy of this paper employs a difference-in-differences event-study-design. In particular, this means that individuals who became unemployed shortly before the onset of the Covid-19 pandemic in 2020 (treatment group) are compared to individuals who became unemployed in the same month two years earlier (control group). It is crucial that entering unemployment takes place before the beginning of the pandemic so that the pandemic can be used as an exogenous shock. February is defined as the month shortly before the pandemic, since during that time infection rates were moderate and the German government did not implement any social distancing measures before March 2020.

Overall, the results show that the Covid-19 pandemic had significant adverse effects on various outcomes such as earnings, employment or wages of unemployed individuals. Regarding earnings two findings are remarkable: first, at the peak of the pandemic — from March 2020 to May 2020 — there is the largest (average) earnings loss among the treatment group, which reaches a value of 191.59 € in half of a month. Second, for the rest of the sample period, the reduction in earnings starts to diminish but without reaching the level of the control group so that a persistent (significant) earnings loss still remains at the end of 2021. In total, this results in an earnings loss of 5,539 € over the whole sample period, which means an average loss of 120 € in every half of a month.

There are two potential drivers of the observed earnings loss: a reduction in employment on the one hand and a reduction in wages on the other hand. Exploring these mechanisms reveals that the negative effect on earnings is primarily due to a reduction in the number of days in employment. The decrease in employment leads to a total loss of 44.9 days (over the whole period) and an average of about 1 day per half a month. Though, from the beginning of 2021 onwards, a decrease in wages starts to explain an increasing share of the earnings effect. Additionally, this paper documents the mechanisms behind the employment and wage reduction by investigating changes in type of employment and occupational mobility.

As outlined above, the effects of the Covid-19 pandemic on earnings, employment and wages may differ by occupation. This paper finds evidence that there is heterogeneity in the size of the effect of the pandemic between occupations which the unemployed previously worked in. While there is a (clear) negative effect of the pandemic on earnings in the pooled model, the occupation-specific effects range from a total loss of 11,959.92 € until

the end of 2021 (construction scheduling, architecture and surveying) to 1,211.40 € (safety and health protection, security and surveillance). Regarding employment, the results provide a similar picture: unemployed individuals who previously worked in tourism, hotels and restaurants faced the largest decrease in employment (-73.38 days in total), whereas unemployed individuals who were previously employed in medical and health care occupations experienced a much lower decline (-13.72 days in total). With respect to wages, the pandemic has either a (significant) negative effect on the most affected previous occupations (occupations in construction scheduling, architecture and surveying) or no effect for the least affected occupations (occupations in safety and health protection, security and surveillance).

This paper relates to two strands of literature: first, the literature regarding the labour market effects of the Covid-19 pandemic and, second, the literature assessing the labour market consequences of exposures to (temporary) adverse shocks. Recent research has been focusing on the short-term effects of the Covid-19 pandemic on labour market outcomes. A key finding in the U.S. context is that employment decreased strongly (Cajner et al., 2020; Coibion et al., 2020), while unemployment increased sharply (Coibion et al., 2020; Forsythe et al., 2020; Adams-Prassl et al., 2020). Moreover, labour market participation has been found to drop (Coibion et al., 2020) and job vacancy postings decreased (Forsythe et al., 2020). There is also evidence to suggest that this effect differs by ethnicity (Fairlie et al., 2020) or gender (Albanesi and Kim, 2021b). For Germany, Adams-Prassl et al. (2020) find that 5% of workers lost their jobs (which is relatively small in comparison to the U.S. (20%) or the UK (17%)).

In a more closely related paper, Adermon et al. (2022) investigate the effect of the Covid-19 pandemic on earnings and the role of the welfare state in Sweden. Specifically, the authors use a difference-in-differences event-study design to compare the earnings of individuals who were employed before the onset of the pandemic with the earnings of individuals of the previous years. Overall, they find that the pandemic has led to an earnings loss of 2.7%. The size of the earnings loss differs from the estimated earnings loss of 23% in this paper which can be explained by the fact that Adermon et al. (2022) do not only focus on earnings of individuals who became unemployed but also consider individuals who stay in employment during the pandemic.

Moreover, the extant literature also provides evidence that the effects of the pandemic differ across occupations: Cortes and Forsythe (2022) analyse the distributional (heterogeneous) effects of the pandemic on employment by occupation, industry or socio-economic status and find that the effect is more pronounced in lower-paying than in higher-paying occupations. Interestingly, similar to the findings in this paper, they show that while the employment loss is large at the beginning of the pandemic, the effect gets smaller after April 2020. Other papers such as Beland et al. (2020) or Albanesi and Kim (2021a) also show that labour market outcomes decreased more strongly in occupations with a higher contact intensity and where working from home was not feasible than in occupations with systemic relevance or with the possibility to work from home. However, those studies focus

on the short-term effects of the pandemic on an aggregated level, whereas this paper also considers longer-term effects on individuals and subsequent employment histories.

In addition to the literature on the effects of the Covid-19 pandemic, this paper also relates to the job-displacement literature where the short- and long-term effects on earnings and employment histories after an unexpected job loss (e.g. due to a mass layoff) are analysed (see, e.g., [Jacobson et al., 1993](#); [Davis and von Wachter, 2011](#); [Lachowska et al., 2020](#); [Schmieder et al., 2022](#)). Overall, these studies find that individuals who are exposed to job loss experienced a long-lasting reduction in labour market outcomes such as earnings or wages (compared to their counterparts who did not lose their job). Usually, earnings losses can be attributed to an employment reduction in the short run and a wage reduction in the long run. This pattern is similar to the findings of this paper in which the earnings loss at the onset of the pandemic can mostly be explained by a decrease in days in employment, whereas the relevance of the wage reductions becomes more relevant towards the end of 2021.

This paper is structured as follows: Section 2 gives a short overview of the development of the Covid-19 pandemic in Germany, before it moves on to describe the data and the empirical identification strategy. Then, Section 4 analyses the effect of the pandemic on earnings, employment and wages and goes into further detail by investigating possible mechanisms behind the observed reduction in employment and wages. Since the effect of the Covid-19 pandemic might vary across occupations, Section 4 expands the analysis by examining the heterogeneous effects by different occupations. Section 6 concludes.

## 2 Data

### 2.1 The Covid-19 pandemic in Germany

To understand the impact of the Covid-19 pandemic on labour market prospects for the newly unemployed and the construction of the sample for the empirical analysis, this section provides a short overview of the outbreak of the pandemic and the public containment measures that were implemented in Germany.

The beginning of the Covid-19 pandemic in Germany can be assigned to the registration of the first Covid-19 case on the 27<sup>th</sup> of January 2020. For the following period of 2020 to 2021, the Covid-19 pandemic can be divided into five different phases according to the extent of governmental containment measures. The first phase began with the implementation of social distancing measures on the 11<sup>th</sup> of March 2020 and the first lockdown<sup>1</sup> on the 22<sup>nd</sup> of March 2020. Thereafter, a phase of easing of the governmental measures<sup>2</sup> during summer 2020 followed, which, in light of increasing Covid-19 infections in autumn 2020, turned into the third phase that was characterised by a second lock-

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<sup>1</sup>The first lockdown was announced by the German government on the 16th of March 2020 and was implemented six days later.

<sup>2</sup>In the first place hairdressers, gastronomy and schools were allowed to reopen.

down<sup>3</sup>. The second lockdown lasted from 2<sup>nd</sup> of November 2020 until the beginning of March 2021. During the fourth phase, the lockdown restrictions were again lifted, before restrictions were tightened in autumn 2021 due to a new rise in infections, but without the implementation of a new lockdown (fifth phase).

The lockdown restrictions in Germany included social distancing measures and the closing of all shops, schools and leisure facilities. However, facilities of systemic relevance were excluded from these restrictions and thus facilities such as pharmacies or supermarkets remained open, while businesses in hospitality, hairdressers or shops (except supermarkets) had to close. Additionally, the government implemented the obligation that all employees who were able to do so should work from home. Consequently, the restrictions affected occupations differently: while employees in occupations with high contact intensity or without the possibility to work from home could not work during the lockdown, employees in occupations of systemic relevance or with the possibility to work from home were still able to work. This might have had negative effects on labour demand in these occupations which in turn limited the opportunities for the unemployed to find a new job in such an occupation. These individuals may then had to look for a job in a different occupation, which may be costly in terms of longer search or a lower wage in the new job.

During that time, the German economy was hit by the strongest shock since the financial crisis with 5% of employees losing their jobs (Adams-Prassl et al., 2020). In comparison to other countries, though, the economic shock in Germany was buffered by an extensive use of short-time work schemes, which allowed firms to let their employees work fewer hours and thus avoid potential layoffs (Adams-Prassl et al., 2020).

## 2.2 Defining treatment and control group

This empirical analysis is based on administrative social security data provided by the Institute of Employment Research (IAB), the research institute of the German Federal Employment Agency. Specifically, the analysis uses data from the Integrated Employment Biographies (IEB), which covers The IEB consists of all labour market participants in Germany except for the self-employed, civil servants and military service members. In addition to individual characteristics (e.g. gender, age, vocational degree and nationality), the data include daily information on job characteristics such as daily wages, type of employment (e.g. marginal versus employment with social security contributions) and occupation, establishment characteristics such as industry, number of employees and place of work but also information on unemployment spells, participation in measures of active labour market policy or receipt of transfer payments.

The aim of this paper is to investigate the effects of the Covid-19 pandemic on the labour market prospects of individuals who became unemployed shortly before the start of the pandemic and were as such exposed to an exogenous shock. It is important that these individuals entered unemployment before the beginning of the pandemic so that

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<sup>3</sup>The second lockdown was comparable to the first lockdown with respect to restrictions.

the former constitutes an exogenous shock. This would ensure that any effects on labour market outcomes are due to the subsequent exposure to the pandemic and not additionally influenced by a transition into unemployment which was induced by the pandemic. In practice, however, the implementation might lead to problems, which will be discussed in further detail in Section 3. The group of individuals who became unemployed before the start of the pandemic are then compared to a control group of individuals who entered unemployment in the same period (month) two years before<sup>4</sup>. The empirical strategy is explained in further detail in Section 3.

February 2020 is defined as the period shortly before the beginning of the pandemic, because infection rates in Germany started to increase rapidly during the first half of March 2020 and social distancing measures and lockdown measures were announced thereafter (see Section 2.1). Even though the first Covid-19 case was registered at the end of January 2020 in Germany, by the end of February there had only been eighteen confirmed cases with a Covid-19 infection and (lockdown-)restrictions were not expected at that time. Hence, it is likely that firms did not anticipate any economic downturn due to the pandemic and its measures and did not have to lay off their employees.

To construct the sample for the empirical analysis, all individuals are identified who became unemployed<sup>5</sup> in February 2018 (control group) or in February 2020 (treatment group)<sup>6</sup>. Using the full labour market biographies of these individuals, the daily information is aggregated to a half<sup>7</sup> monthly panel data up until the end of December 2021. In doing so, we retain information on, for instance, how many days individuals were employed during each half-month period.

Furthermore, we restrict the sample to those unemployed individuals who were employed at least from November in year  $t - 1$  to the 31<sup>st</sup> of January in year  $t$  so that the first possible day in unemployment is the 1<sup>st</sup> of February in year  $t$ . This restriction is similar to the restrictions in the job-displacement literature (see, e.g., [Jacobson et al., 1993](#); [Davis and von Wachter, 2011](#); [Lachowska et al., 2020](#); [Schmieder et al., 2022](#)) in which the treatment group has to be in a stable employment relationship at the same employer. Focusing on individuals with a stable employment pattern ensures that job loss represents a potentially severe disruption. Another reason for this restriction is that a sample which also includes individuals who were already unemployed in January is more selective. Individuals with certain characteristics (such as high motivation) are more likely to find a new job after unemployment faster than others and might therefore be employed in February

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<sup>4</sup>The cohort of individuals entering unemployment in 2018 are chosen as a control group because the individuals in that group are not affected by the pandemic throughout the whole period of observation.

<sup>5</sup>In this study, the unemployed are defined as those for whom the status “unemployed and searching for work” is recorded. Individuals who are sick (for more than *six* weeks during unemployment), only registered as “searching for work” but not unemployed or without a status are excluded.

<sup>6</sup>Note that individuals who became unemployed in February 2018 as well as in February 2020 are only part of the control group.

<sup>7</sup>To capture the daily changes in the unemployment data, the monthly observations are further distinguished by a “first half” which spans the period from the 1<sup>st</sup> to the 15<sup>th</sup> of each month and by a “second half” which spans the period from the 16<sup>th</sup> to the end of each month (which varies by month). This results in a range of twelve to fifteen days per period.



so that they would not be included in the sample. Thus, unemployed individuals who find a new job more slowly would then be over-represented in our sample. Hence, the paper focuses on investigating only individuals with a relatively short time in unemployment before the onset of the pandemic. The month November is chosen as the date from which the individuals have to be at least employed in the same occupation by the same establishment in order to make the sample not too restrictive and to exclude individuals who frequently switch their employment status and who may display a different pattern of search activity over their spells of employment and unemployment. Further details of the construction of the sample are shown in the Appendix [A.1](#).

After applying these restrictions, the total sample consists of 95,366 observations in the control group and 99,493 observations in the treatment group. By construction of the half-monthly data set, individuals can become unemployed either in the first or in the second half of February. The majority of the observed individuals became unemployed in the first half of February with 71,062 in the control and 72,535 in the treatment group. In the following, the analysis will focus on the unemployed of the first half, since the unemployed of the second half differ in observable characteristics from the unemployed of the first half of February and there seems to be underlying heterogeneity between both groups. Descriptive statistics and analyses based on the second half can be found in the appendix *[forthcoming]*.

Table [1](#) shows descriptive statistics for treated and control individuals who became unemployed in the first half of February<sup>8</sup>. As can be seen from Table [1](#), individuals in the treatment as well as in the control group are on average 38 years old, around 60% are male, they are mostly middle skilled<sup>9</sup> (60%), they spent, on average, more than twenty days in unemployment and switched 0.33 times the employer<sup>10</sup> during the year before the start of the unemployment spell in February.

The restriction regarding the length of the previous employment spell may raise the concern that the sample is selective, for instance, with respect to individuals with a higher probability for finding a job. As a comparison to the full sample of individuals who were employed at least one day before becoming unemployed, Table [A2](#) in the appendix shows that the individuals in the actual sample differ only in their attachment to the labour market (which they do per definition) but not in terms of individual characteristics such as age, gender or education. Hence, it can be concluded that there are no substantial differences.

For the empirical approach of the paper, it is necessary that the treatment group is comparable to the control group and that there are (on average) no systemic differences between the groups. To test this hypothesis, Table [1](#) illustrates the difference and the p-values of the corresponding t-test (equality of means) in Column 4. There is a statistically

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<sup>8</sup>Employment characteristics refer to the last employment period (15<sup>th</sup> to the 31<sup>st</sup> of January).

<sup>9</sup>The skill groups are defined as follows: low skilled individuals have no vocational degree, middle skilled have a vocational degree but no tertiary education and high skilled have a tertiary degree (e.g. university degree).

<sup>10</sup>An employer switch is defined as a switch of an establishment.

Table 1: Descriptive statistics

	Treatment	Control	Difference	p-value
Age	38.286 (13.012)	38.519 (12.913)	-0.233	0.001
Gender	0.605 (0.489)	0.588 (0.492)	0.016	0.000
Foreign	0.184 (0.387)	0.162 (0.369)	0.022	0.000
Low skilled	0.219 (0.414)	0.203 (0.414)	0.016	0.000
Middle skilled	0.607 (0.488)	0.640 (0.480)	-0.033	0.000
High skilled	0.174 (0.379)	0.157 (0.364)	0.016	0.000
Tenure (in days)	1062.462 (1741.804)	1031.124 (1670.617)	31.338	0.001
Previous wage	70.273 (46.506)	64.675 (43.575)	5.598	0.000
Regular employment	0.841 (0.366)	0.838 (0.368)	0.003	0.183
Marginal employment	0.060 (0.237)	0.066 (0.248)	-0.006	0.000
Duration of unemployment before (in days)	21.301 (51.273)	25.582 (55.748)	-4.281	0.000
Number of job changes	0.336 (0.602)	0.293 (0.563)	0.043	0.000

Notes: The first two columns show mean values and standard deviations (in parentheses) of individual characteristics that are measured at the second half of January (the last period in employment). The third column reports the difference in means and the fourth column shows the p-value of the hypothesis test that the corresponding difference is equal to zero.

Source: IEB, own calculations.

significant difference for almost all characteristics between the treatment and the control group. However, this might not be an issue for two reasons: first, statistical significance of the difference might be due to the large number of observations and second, the difference itself is very small. For example, the treatment and the control group are both on average 38 years old with only a very small difference of 0.177 years. Thus, it can be argued that there are no substantial differences between the treatment and control group regarding most of the observable characteristics. Though one exception has to be made: there is a difference of 5€ in daily wages. Consequently, some underlying differences cannot be completely ruled out. To ensure comparability the treatment and the control group are matched on pre-displacement characteristics by inverse propensity score weighting, which will be explained in further detail in the next subsection.

### 3 Identification strategy

#### 3.1 Inverse propensity score weighting

The inverse propensity score weighting (IPW) approach aims at making the treatment group comparable to the control group in terms of observable characteristics (see e.g. [Wooldridge, 2007](#)). Comparability is achieved by placing lower weights on outcomes of control individuals that are over-represented and by up-weighting the outcomes of those that are under-represented in terms of observable characteristics in either group. The weights are determined by the propensity score, or the probability of belonging to the treatment group ( $T = 1$ ), given observed covariates  $x$ :  $p(x) = P(T = 1|X = x)$ . While treated observations receive a weight of one, formally weights for the control group are given by  $\frac{\hat{p}(x_i)}{1-\hat{p}(x_i)}$ , where  $\hat{p}(x_i)$  is the predicted probability of belonging to the treatment group conditional on observed characteristics  $x_i$ .

The individual probability of belonging to the treatment group is estimated by means of a logit model, given a detailed set of observed individual, job and firm characteristics. These variables are measured at the first half of November, such that their levels are not affected by future treatment. In particular, the following matching variables are chosen: Occupation (dummies for 2-digit occupations), age (dummies for quartiles), gender (dummy), foreign (dummy), skill (dummy for three qualification levels), experience (dummies for quartiles), type of current employment (dummies for marginal or regular as well as part-time or full-time), duration in current regular and marginal employment (continuous in days)<sup>11</sup>, sector (dummies for 1-digit sector classification), establishment size (dummies for  $< 10$ ,  $10-49$ ,  $50-249$ ,  $\geq 250$ ), labour market regions (dummies)<sup>12</sup> and number of job changes (dummies for none, 1 or  $\geq 2$ )<sup>13</sup>.

In order to test for balance, we compare the differences in means after weighting

<sup>11</sup>The time of the duration refers to one year before entering unemployment.

<sup>12</sup>See [BBSR \(2021\)](#) for the mapping of counties to labor market regions.

<sup>13</sup>For the observed period one year before entering unemployment around 77% had no and around 20% only one job change.

between individuals of the treatment and the control group. The balancing tests for the baseline specification can be found in Table A3 in the Appendix. The table shows the p-values of a standard t-test (column (4)) as well as the standardized differences (column (5)). The standardized differences in covariate means ( $\Delta_X$ ) between treated and weighted control observations can be interpreted as a scale-free measure of balancing (see e.g., Austin, 2011; Guo and Fraser, 2014).<sup>14</sup> Since there is no universally agreed criterion for how small the standardized difference must be to provide balance, we apply the rule of thumb of  $\Delta_X < |0.1|$  as suggested by Austin (2011). The standardized differences between treated and control observations are very close to zero and in each case the standardized difference is smaller than the threshold value. We estimate different specifications to examine the sensitivity of the choice of covariates included in the estimations (for details see Section A.5).

The overlap assumption requires some randomness in the treatment assignment, meaning that we need to observe persons with identical characteristics in both states. To check whether the overlap assumption holds, we compare the distribution of the estimated propensity scores for the treatment and the control group. Figure A4 in Appendix shows the distribution and suggests that we have sufficient overlap in our sample.

### 3.2 Estimation

The empirical approach to identify the effect of the Covid-19 pandemic on labour market outcomes of newly unemployed individuals is to use a difference-in-differences (DiD) event-study design combined with inverse propensity score weighting (from the previous Section). The idea behind this approach is that the pandemic and the extent of its effects on the labour market were unexpected so that everyone who became unemployed shortly before the onset of the pandemic faced a sudden worsening of their labour market prospects compared to individuals who became unemployed two years earlier. Thus, for those individuals the Covid-19 pandemic represents an exogenous shock, which allows to identify the effect of the pandemic on their subsequent labour market biographies.

The group of individuals who entered unemployment in February 2020 constitute the treatment group. Their outcomes are compared to a control group of individuals who became unemployed during February 2018. This has the advantage that time-constant seasonal (un-)employment effects can be eliminated. However, the underlying assumption here is that in the absence of the Covid-19 pandemic, the outcomes of both groups would have, on average, developed in the same way. Testing this assumption is impossible but a similar pre-trend in outcomes could be a hint that this assumption holds.

In particular, the following model is used to estimate the effect of the pandemic on the labour market outcomes of initially unemployed individuals:

<sup>14</sup>The standardized difference is defined as  $\Delta_X = (\bar{X}_1 - \bar{X}_0) / ((S_1^2 + S_0^2)/2)^{0.5}$ , where  $\bar{X}_w$  is the sample mean of treated ( $w = 1$ ) or control ( $w = 0$ ) observations and  $S_w^2$  are the respective sample variances (Austin, 2011). The advantage of  $\Delta_X$  over the usual  $t$ -statistic is that it does not mechanically increase with the sample size and therefore avoids exaggerating small imbalances that would still appear significant in a  $t$ -test.

$$y_{i,t} = \alpha_i + \sum_{\tau \neq -1} \gamma_\tau I(t = \tau) + \sum_{\tau \neq -1} \beta_\tau I(t = \tau) I(T_i = 1) + \varepsilon_{i,t} \quad (1)$$

$y_{i,t}$  is the outcome of individual  $i$  at time  $t$ ,  $\alpha_i$  is an individual fixed effect,  $T_i$  the treatment dummy which takes the value 1 if the individual is exposed to the pandemic (and 0 otherwise) and  $\varepsilon_{i,t}$  is a random error term.  $t$  runs from -5 to 24 covering the time period of roughly two years<sup>15</sup>. For a fixed point of time  $\tau$ ,  $\gamma_\tau$  is the average value of outcomes for the control group relative to the reference period (conditional on fixed effects) and  $\beta_\tau$  the average difference between the treatment and the control group at that point in time. In a dynamic setting this means that  $\sum_{\tau > 0} \gamma_\tau$  describes the average deviation of outcomes from the reference period, whereas  $\sum_{\tau > 0} \beta_\tau$  describes the average difference in the outcome per time period between treatment and control group. Thus,  $\beta_\tau$  represents the effect of the Covid-19 pandemic. If the common trend assumption is satisfied, it is expected that  $\beta_\tau$  is zero for  $\tau < 0$ .

The second part of the paper investigates the occupation-specific effect of the pandemic. For this purpose, Equation 1 is estimated separately for all individuals who initially worked in occupation  $o$ . The effect  $\sum_{\tau > 0} \beta_{\tau,o}$  then describes the different development of outcomes between treatment and control group over time for occupation  $o$ . Occupations are defined at the 2-digit level which comprises 36 different occupations.

This approach might have the problem of underlying time trends. This means that there might be some underlying time trend such as some business-cycle effects or a general worsening of labour market conditions which are independent of the Covid-19 pandemic and lead to a (general) reduction in outcomes as compared to the control group.

## 4 The labour market effects of the Covid-19 pandemic

In this section, the labour market effects of the Covid-19 pandemic on earnings, employment and wages are investigated and in order to get a better understanding of the relevance and magnitude of the effects of the pandemic, these effects are compared to those of the financial crisis [*forthcoming*], before we analyse the effects by occupations are analysed in Section 5. If the pandemic delays the transition of individuals in the treatment group into employment, a reduction in earnings compared to the control group would be expected.

### 4.1 Earnings

The estimated effects of the Covid-19 pandemic on earnings,  $\hat{\beta}_t$  over time are shown in Figure 1<sup>16</sup>. The horizontal axis measures event-time. The value of zero refers to the period during which individuals became unemployed (first half of February 2018 for the control group and 2020 for the treatment group). The vertical axis displays the estimated

<sup>15</sup>This means that the treatment group is observed from September 2019 until December 2021 and the control group from September 2017 until December 2019.

<sup>16</sup>The bars represent 95%-confidence intervals.

difference in earnings between the treatment and the control group.

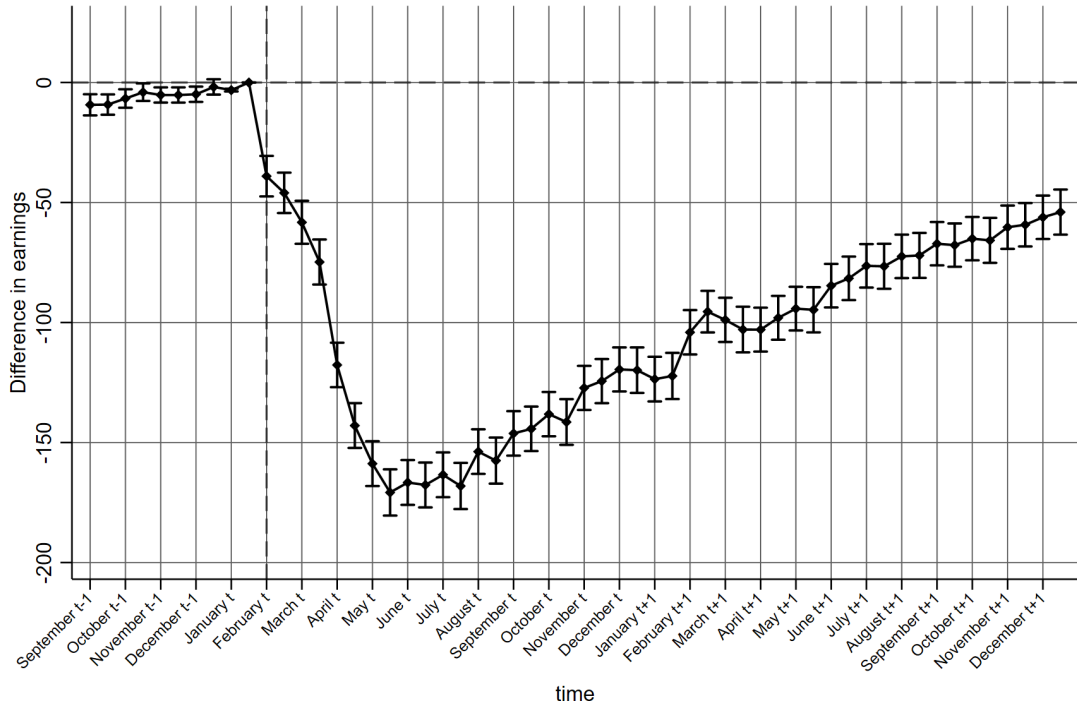


Figure 1: The effect of the Covid-19 pandemic on earnings

Note: Figure 1 shows the estimated coefficients  $\beta_t$  from Equation 1 when earnings are used as the dependent variable. They represent the differential development of earnings in the treatment group relative to the control group.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

As can be seen in Figure 1, in the periods before the transition into unemployment takes place, there is only a small and statistically insignificant difference between the earnings of the treatment and the control group. Therefore, there is no evidence for a differential development of earnings between the two groups leading up to transition into unemployment, which, in turn, may provide support to the hypothesis that the development of earnings of the treatment group would have been similar to that of the control group in the absence of the pandemic. At the moment both treatment and control group are entering unemployment, there is a substantial drop in earnings for the treatment group. Since the pandemic set in at first half of March 2020 (March  $t$ ), this difference between the treated and the control individuals suggests that unemployed individuals in 2020 might already faced less favourable prospects of finding employment compared to the control group. However, the drop in earnings becomes even larger at the peak of the pandemic between March 2020 and April 2020, when the first lockdown was implemented, which presumably also reduced labour demand and the posting of vacancies. The negative effect reaches its maximum May with an earnings loss of 192.5€ compared to the control group in only half of a month. Thus, there is evidence that the Covid-19 pandemic had a (significant) negative

impact on (newly) unemployed individuals.

After remaining almost constant up to the first half of August, the earnings gap between treatment and control group started decreasing slowly, which partly slowed down during the second lockdown which was in place from November 2020 to March 2021. However, earnings losses compared to the control group never fully disappear which suggests that the pandemic had a lasting negative earnings effect on those individuals who became unemployed shortly before its start. At the end of the period of observation, an absolute earnings gap of 68.59€ still remains. In total, the estimated cumulative earnings loss amounts to 5,539€ over the whole post-treatment period (45 periods meaning 22.5 months) or 120€ per half-month which translates into a relative earnings loss of around 23%<sup>17</sup>.

These findings are qualitatively similar to findings of the job displacement literature (see, e.g., [Jacobson et al., 1993](#); [Davis and von Wachter, 2011](#); [Lachowska et al., 2020](#); [Schmieder et al., 2022](#)), which provides evidence that an unforeseen job displacement leads to a permanent earnings loss. While in the short-run the earnings loss after displacement is relatively high with 49%, in earnings tend to recover in the longer run, though without reaching the earnings level of their counterparts in the control group. A persistent earnings loss of 15 to 20% remains (see, e.g., [Jacobson et al., 1993](#); [Davis and von Wachter, 2011](#); [Lachowska et al., 2020](#); [Schmieder et al., 2022](#)). It needs to be mentioned that the size of the short-run effect in the job displacement literature is substantially higher than in this paper. However, it has to be kept in mind that the unemployed of the treatment group in the job displacement literature are compared to a group of individuals who are still employed, whereas in this paper the unemployed of the treatment group are compared to another cohort of unemployed individuals. The difference in the size of the effects can partly be explained by these different control groups.

Despite the difference in the size of the effect on earnings between the job displacement literature and this paper, the evolution of the earnings loss is comparable. Earnings, though, depend on employment as well as on wages, implying that a reduction in earnings can be due to a reduction in employment or a reduction in wages or both. One of the main findings in the job displacement literature is that the earnings loss can be attributed to a reduction in employment in the short-run and a reduction in wages in the long-run. Therefore, the question arises to what extent a reduction in employment or wages can explain the earnings loss due to the Covid-19 pandemic.

To answer this question, [Figure 2](#) displays the previously discussed coefficient estimates which are based on an individual's actual earnings (black line). In addition, [Figure 2](#) plots the effect on "hypothetical" earnings that are computed by holding the wage constant to the pre-pandemic value (as observed in period  $t = -1$ ) and multiplying it with the observed days in employment (blue line). The closer the two coefficient plots are, the larger the part of the reduction in earnings in the treatment group that can be ascribed to a reduction in employment (vis-à-vis the control group), while a gap between the two

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<sup>17</sup>Average earnings loss:  $\frac{120}{(120+406)} = 0.228$ , where 406 is the average earnings loss for both groups.

plots would indicate that the reduction is due to changes in wages.

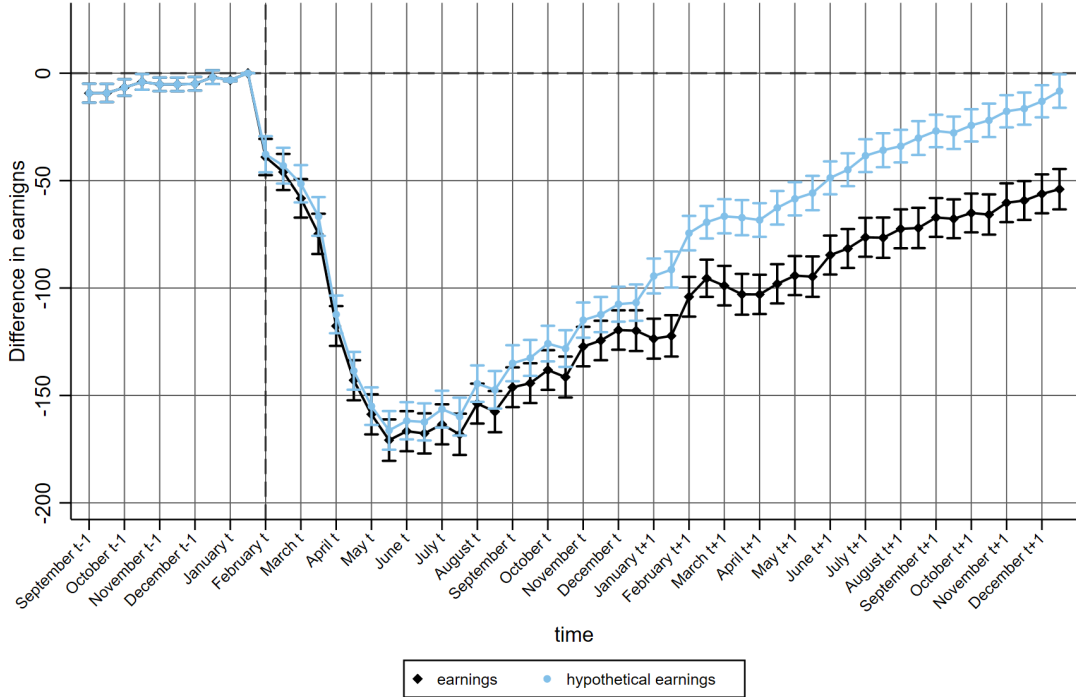


Figure 2: The effect of the Covid-19 pandemic on (hypothetical) earnings

Note: Figure 2 shows the estimated coefficients  $\beta_t$  from Equation 1 when earnings and “hypothetical” earnings are used as the dependent variable. “Hypothetical” earnings refer to a variable in which the wages are held fixed to the value observed in period  $t = -1$ .  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

As shown in Figure 2 for the first half of the estimated effects on the hypothetical earnings are very close to the estimated effect on actual earnings suggests that a reduction in employment plays a bigger role in explaining the observed earnings losses than a reduction in wages. However, subsequently, the magnitude of the effects starts to diverge more, indicating that now a reduction in wages is primarily responsible for the sluggish recovery of the earnings loss. This pattern is again similar to the (above described) findings of the job displacement literature. In order to get a better understanding of the drivers of the earnings losses, the effect of the Covid-19 pandemic on employment and on wages will be examined in further detail in the next sections.

## 4.2 Employment

As discussed in the Section 4.1, a reduction in employment might explain the substantial earnings losses shortly after the onset of the Covid-19 pandemic. To evaluate the impact on employment<sup>18</sup>, Equation 1 is estimated using the number of days in employment as

<sup>18</sup>The number of days not being employed are counted as zero days in employment.



the dependent variable. Analogously to Figure 1, Figure 3 shows the corresponding effects on days in employment. The Covid-19 pandemic has significantly reduced the number of days in employment among the treatment group relative to the control group. This effect is more pronounced during the first lockdown between March 2020 and August 2020 with a maximum loss of 2.1 days in half a month. This development seems to be similar to the evolution of earnings (Figure 1), though employment recovers faster than earnings and reaches nearly the same level as the control group towards the end of the sample period. In total, the treated individuals experienced, on average, a loss of about 45 days in employment over the treatment period compared to the control group, which corresponds to a loss of approximately 1 day per half a month. Consequently, the huge drop in earnings is mostly explained by a reduction in employment.

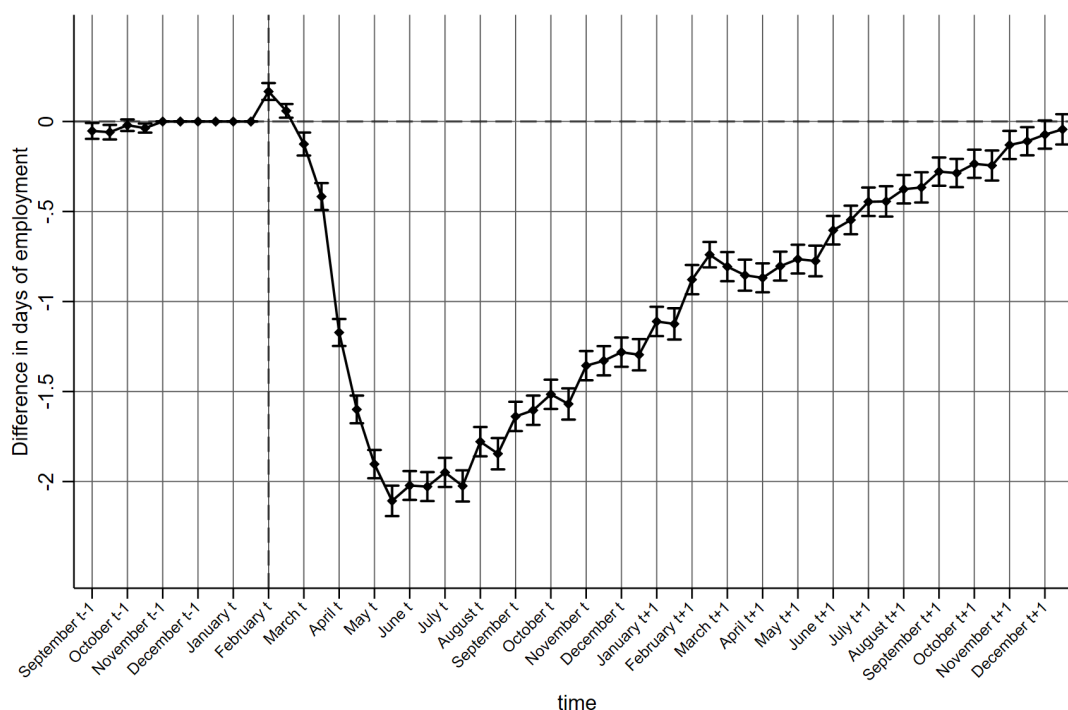


Figure 3: The effect of the Covid-19 pandemic on days in employment

Note: Figure 3 shows the estimated coefficients  $\beta_t$  from Equation 1 when days in employment are used as the dependent variable.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

To further investigate the development of employment and to shed light on the underlying mechanisms, the impact of the Covid-19 pandemic on the type of employment (marginal or regular employment) and on the hours worked (full- or part-time employment) will be analysed in the following.

The development of the number of days in regular (light blue line) and marginal (red line) employment is shown in Figure 4. Additionally, the development of total days in em-

ployment (black line) of Figure 3 is plotted for comparison. On the one hand, the Covid-19 pandemic had a significant negative effect on days in regular employment which experienced a huge drop from March 2020 to June 2020. This means that at its maximum during the first half of June the treatment group experienced a reduction in regular employment of 2 days compared to the control group. Overall, this development is very similar to the development of the total days in employment which indicates that the reduction of employment during the pandemic is mainly due to a reduction in regular employment. After this sharp drop, days in regular employment start to adjust slowly to the level of the control group without reaching its initial level and with a further short decrease around April 2021. On the other hand, the Covid-19 pandemic has a small, but significant positive effect on days in marginal employment in the very first periods after becoming unemployed. This implies that, in comparison to the control group, the treatment group initially spent more time in marginal employment. However, from April 2020 onwards, days in marginal employment also started to decline due to the pandemic (but not to the same extent as the drop in regular employment) and stayed at this reduced level until April 2021. This is followed by a recovery resulting in a higher level compared to the control group, indicating that the Covid-19 pandemic has led to a shift from regular employment to marginal employment. This development can also be seen at the point when the black line crosses the light blue line, when employment starts to recover faster than regular employment due to the increase in marginal employment.

Figure 5 displays the effects of the pandemic on days in full- (light blue line) and part-time (red line) employment next to the effects on total days in employment (black line) shown in Figure 3. The trajectory of days in full-time employment closely follows the development of regular employment with a strong reduction at the beginning of the Covid-19 pandemic and a recovery towards the end of the sample period. However, the magnitude of the effect of the pandemic on days in full-time employment is smaller. Although the majority of the reduction in total employment can be attributed to the reduction in full-time employment, the reduction in part-time employment also plays an important part. Even if part-time employment increases shortly after the beginning of the unemployment spell (in comparison to the control group), the pandemic has led to a significant and persistent reduction in the number of days in part-time employment. Recovery occurs slowly, but the end of 2021, it passes the initial level of the control group. Again, it can be concluded that the Covid-19 pandemic induced a shift away from full-time employment to part-time employment.

All in all, the Covid-19 pandemic led to a rapid drop in the number of days in employment which is mostly driven by a reduction in regular and full-time employment. Thus, the question arises what happened to those people who did not find a job again: do they remain in unemployment or do they leave the labour market?

Figure 6 sheds light on this question: For the sample period it plots the evolution of the number of days in different labour market states: being unemployed (blue line), being out of the labour market (red line), participating in measures of active labour market

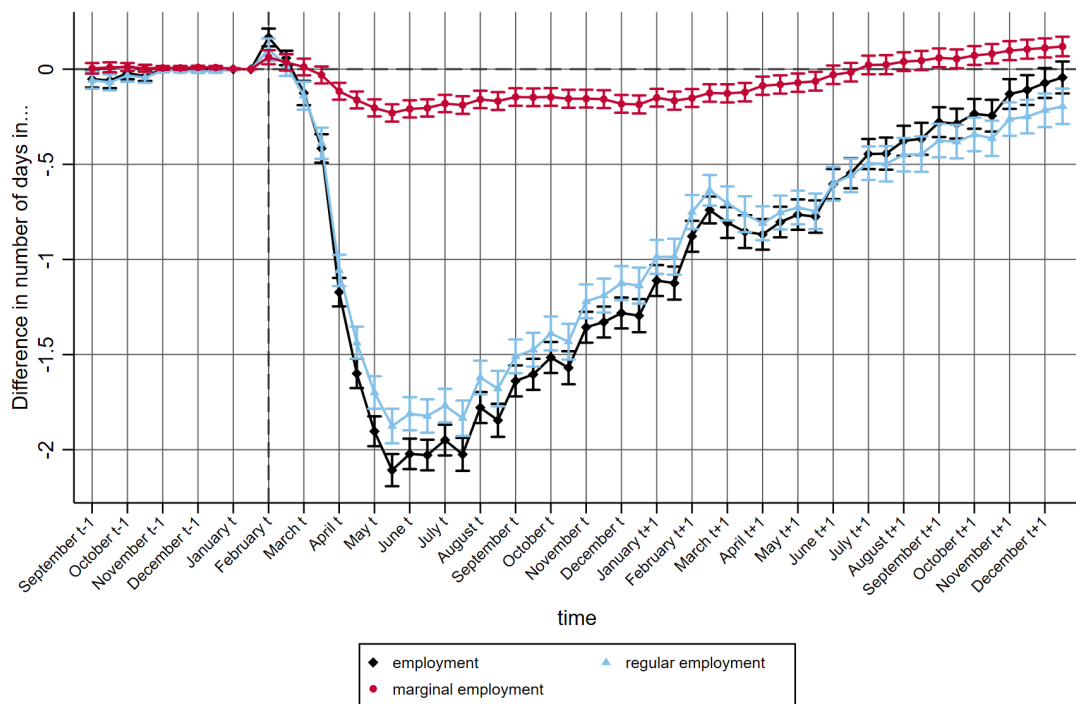


Figure 4: The effect of the Covid-19 pandemic on days in different types of employment

Note: Figure 4 shows the estimated coefficients  $\beta_t$  from Equation 1 when days in different types of employment are used as the dependent variable. Regular employment refers to employment that is subject to social security contributions.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

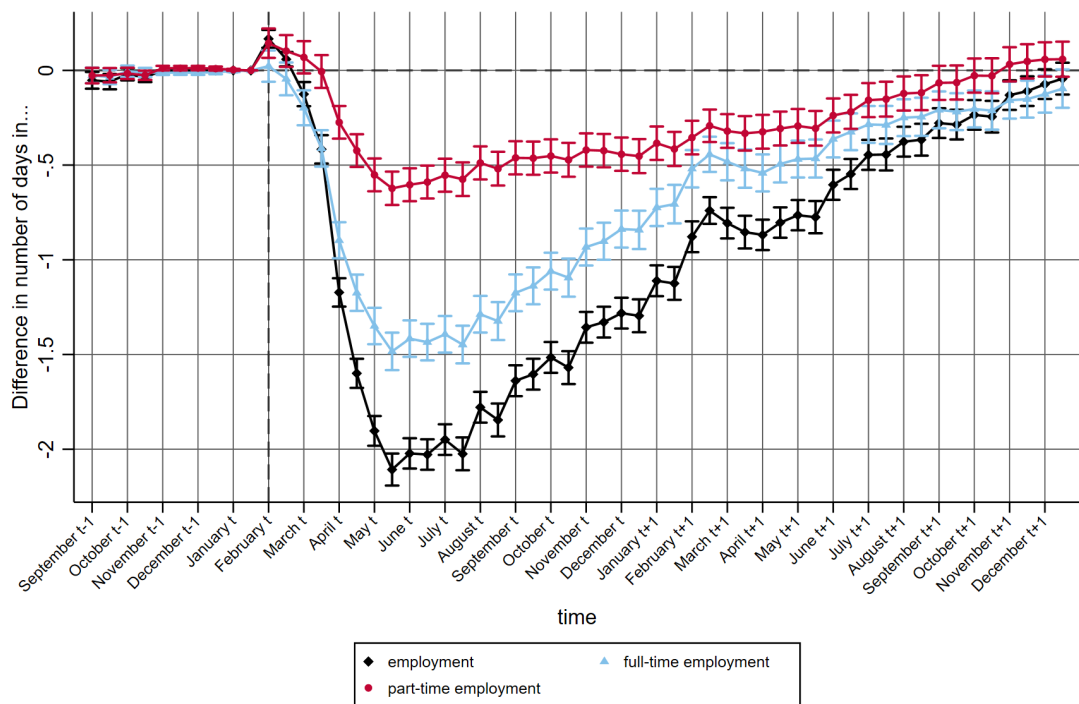


Figure 5: The effect of the Covid-19 pandemic on days in employment by full-time status

Note: Figure 5 shows the estimated coefficients  $\beta_t$  from Equation 1 when days full-time and part-time employment are used as the dependent variables.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

policy (grey line) or receiving transfer payments (black line). It is important to note that the number of days cannot be cumulated in each period and compared with the number of days in employment since some of these labour market states take place at the same time. For example, individuals can be unemployed while at the same time receiving transfer payments and (or) participating in a policy measure.

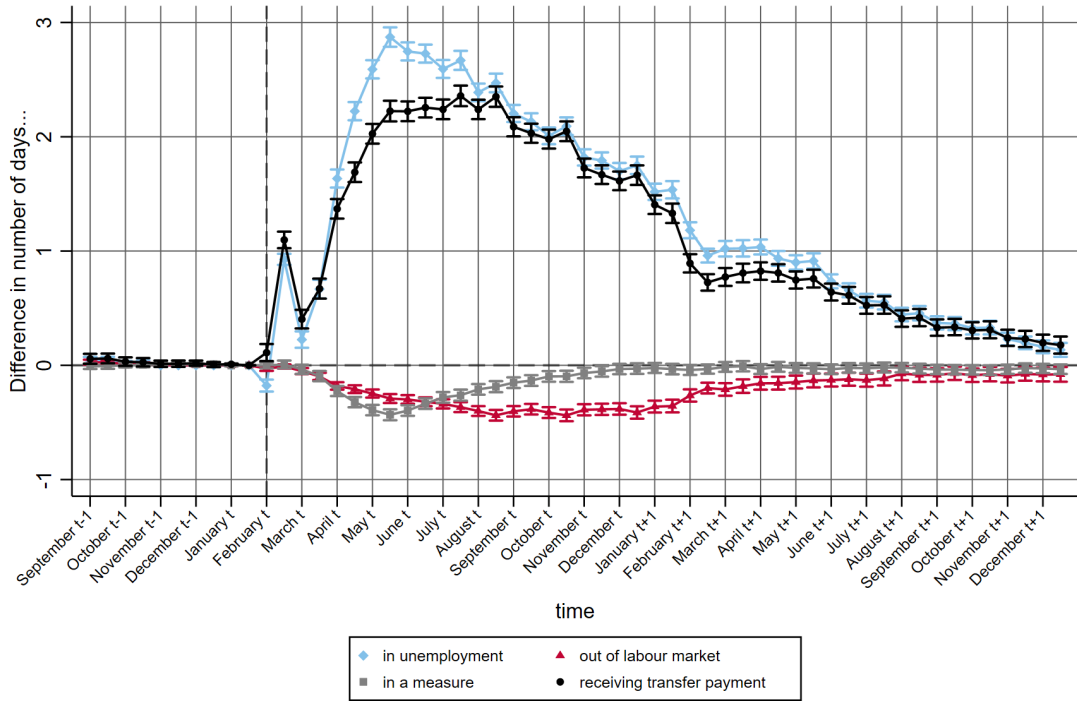


Figure 6: The effect of the Covid-19 pandemic on days in different labour market states

Note: Figure 6 shows the estimated coefficients  $\beta_t$  from Equation 1 when days full-time and part-time employment are used as the dependent variables.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

The largest difference between treatment and control group can be seen for the number of days in unemployment. Following the start of the Covid-19 pandemic, there is a sharp increase in the number of days that individuals from the treatment group spend in unemployment (compared to the control group)<sup>19</sup>. Over the whole period, excess unemployment among the treatment group, on average, amounts to 1.2 days per half-month and 56.6 days over the whole sample period. In comparison to the average and total days in employment, the values of days in unemployment are larger indicating that there is a shift to more unemployment due to the pandemic. After May 2020, when lockdown restrictions were lifted, the effect on the days in unemployment starts to decrease slowly and almost reaches the level of the control group by the end of 2021.

<sup>19</sup>The jump between February and March  $t$  can be explained by the data: since the days in unemployment are measured in absolute terms and the month February has an additional day in 2020, the treatment group has also 1 more day in which they can be unemployed compared to the control group.

The effects on the number of days of benefit receipt display a similar pattern to the days in unemployment, with the exception that they plateau at a maximum of around 2.3 days. This similarity can be explained by the fact that in Germany most of the unemployed also receive benefits. However, the black line is slightly below the blue line which indicates that some individuals who were unemployed receive no benefits.

It is remarkable that the Covid-19 pandemic reduced the number of days out of the labour market (relative to the control group). This is in contrast to findings from the U.S. (Coibion et al., 2020; Albanesi and Kim, 2021a; Fairlie et al., 2020) which provide evidence that during the first months of the Covid-19 pandemic, more people left the labour market or went into early retirement after a job loss instead of becoming unemployed. The difference in terms of days out of the labour market between the treatment and the control group is relatively small at a level of 0.4 days per half a month, before disappearing in March 2021.

Comparable to the days out of the labour market, the number of days in a measure of active labour market policy also decreased due to the Covid-19 pandemic relative to the control group. The decrease is quite small with a maximum of around 0.3 days and it lasts only from April 2020 up to September 2020. From period 8 onward the pandemic has no effect on the days participating in a policy measure.

To sum up, the Covid-19 pandemic resulted in a large increase in the number of days in unemployment (leading to longer durations in unemployment) and a simultaneous increase in days receiving transfer payments, whereas at the same time the pandemic did hardly affect the participation in a labour market measure or leaving the labour market.

### 4.3 Wages

As discussed in Section 4.2, the recovery of employment cannot fully explain the sluggish recovery of earnings described in Section 4.1. However, a decrease in wages towards the end of the observation period might be the reason for the slow recovery of earnings.

Therefore, Figure 7 shows the effect of the Covid-19 pandemic on log wages. In contrast to earnings, wages decline sharply in the first periods after the transition into unemployment followed by a temporary jump back to the initial level. This temporary jump might be explained by a positive selection of those individuals who find a new job quickly. While in the first periods most of the individuals in the sample stay unemployed, some rather productive individuals might find a new job during the period from April to June  $t$ , which might result in a temporary increase in wages. Thereafter, wages start to decrease<sup>20</sup> steadily without any adjustment towards the end of the sample period. Thus, this ongoing reduction in wages might be responsible for the persistent earnings loss.

Similar to the effects of job loss, the Covid-19 pandemic led to a permanent wage loss among individuals who were initially unemployed in the longer run which contributed to a lasting earnings loss, despite the recovery of employment at the end of 2021. This pattern

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<sup>20</sup>The jump between the second half of December  $t$  and January  $t + 1$  might be explained by a strong change in the inflation rate between 2020 and 2021

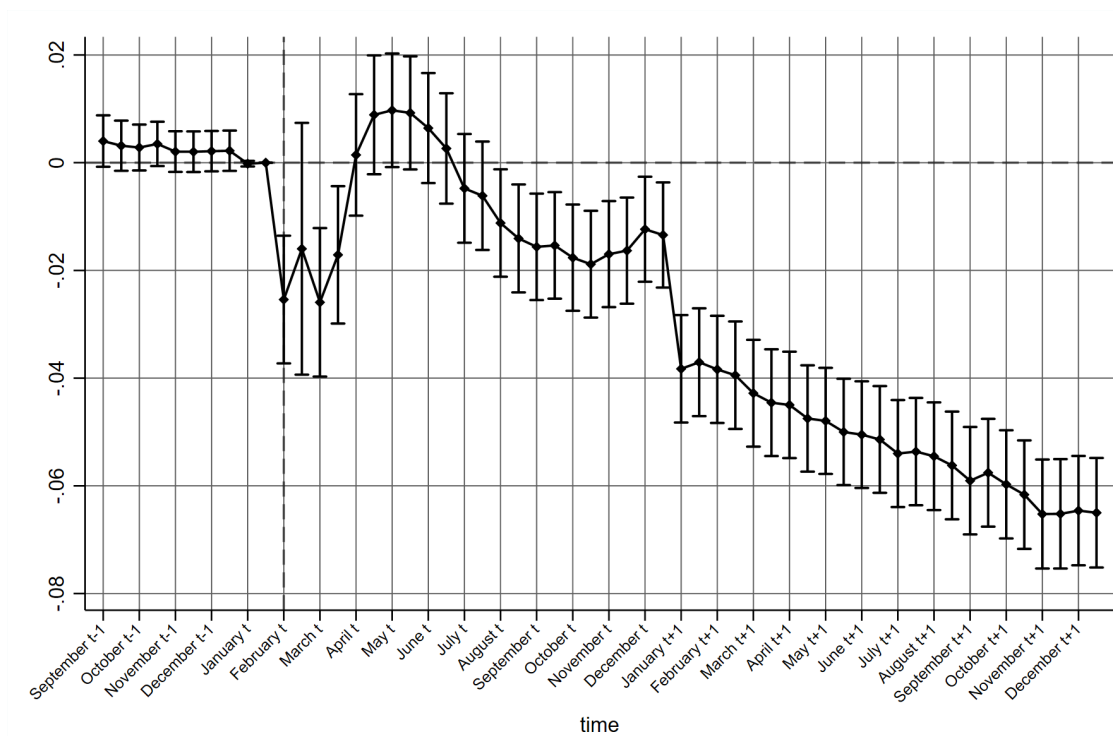


Figure 7: The effect of the Covid-19 pandemic on log wages

Note: Figure 7 shows the estimated coefficients  $\beta_t$  from Equation 1 when average daily wages are used as the dependent variable.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

is again similar to the findings of the job displacement literature. As an explanation for this persistent wage loss the literature suggests, for instance, a worsening of match quality between worker and employers, employer fixed effects (Lachowska et al., 2020) or establishment wage premia (Schmieder et al., 2022). Another possible explanation is proposed by Huckfeldt (2022) who finds that a substantial part of the persistent wage loss is due to a switch to lower-paying occupations after a job loss. The question now arising is what can explain the long-term reduction in wages. In the following, two possible mechanisms will be investigated in further detail: first, changes in the type of employment and hours worked and, second, occupational mobility.

The reason for a reduction in wages might be that in the long-run more individuals again find employment, but in lower-paying jobs. The analyses of changes in types of employment and hours worked in Section 4.2 have shown that marginal as well as part-time employment were less affected by the Covid-19 pandemic than regular and full-time employment and that at the end of 2021 marginal employment experienced a (minor) increase in days employed compared to the control group. Since marginal and part-time employment are typically (in most of the cases) those employment relationships with lower wages, the shifts from regular to marginal and from full-time to part-time employment might explain the permanent wage reduction.

Another possible mechanism behind the wage effects refers to occupational mobility. According to Huckfeldt (2022), the permanent wage reduction after job loss can be explained by a switch to lower-paying occupations. The motivation to change the occupation during the pandemic is very high, since many occupations such as occupations in restaurants, hotels or tourism were not allowed to operate due to lockdown restrictions, whereas occupations such as occupations in offices (with the possibility to work from home) could continue to operate. Consequently, switching from those affected to non- (or hardly) affected can be quite attractive.

Figure 8 shows the effect of the Covid-19 pandemic on occupational mobility. Here occupational mobility is defined as the number of days the individuals are working in an occupation which differs from their occupation prior to unemployment<sup>21</sup>. Overall, the results indicate that the Covid-19 pandemic increased the number of days that an individual is employed in a different occupation. The effect is quite small: over the whole observation period, the treatment group spent an average of 0.45 more days per period and a total of 20.8 more days in a different occupation than the control group. In comparison, the average days in another occupation for both treatment and control group are 6.6 days in half a month. Hence, it can be concluded that the Covid-19 pandemic did not increase occupational mobility to a large extent. Despite the small size of the (average) effect, it is noteworthy that in the first periods after the transition into unemployment the number of days increased up to a maximum of 0.88 days per period. Since around that time the lockdown restrictions have been in place, it can be argued that the Covid-19 pandemic

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<sup>21</sup>Note that occupations are classified at the 2-digit level.



increased occupational mobility at least at its beginning. These results, though, have to be interpreted with caution because the pre-trend of occupational mobility differs significantly between the treatment and the control group. However, this difference is relatively small.

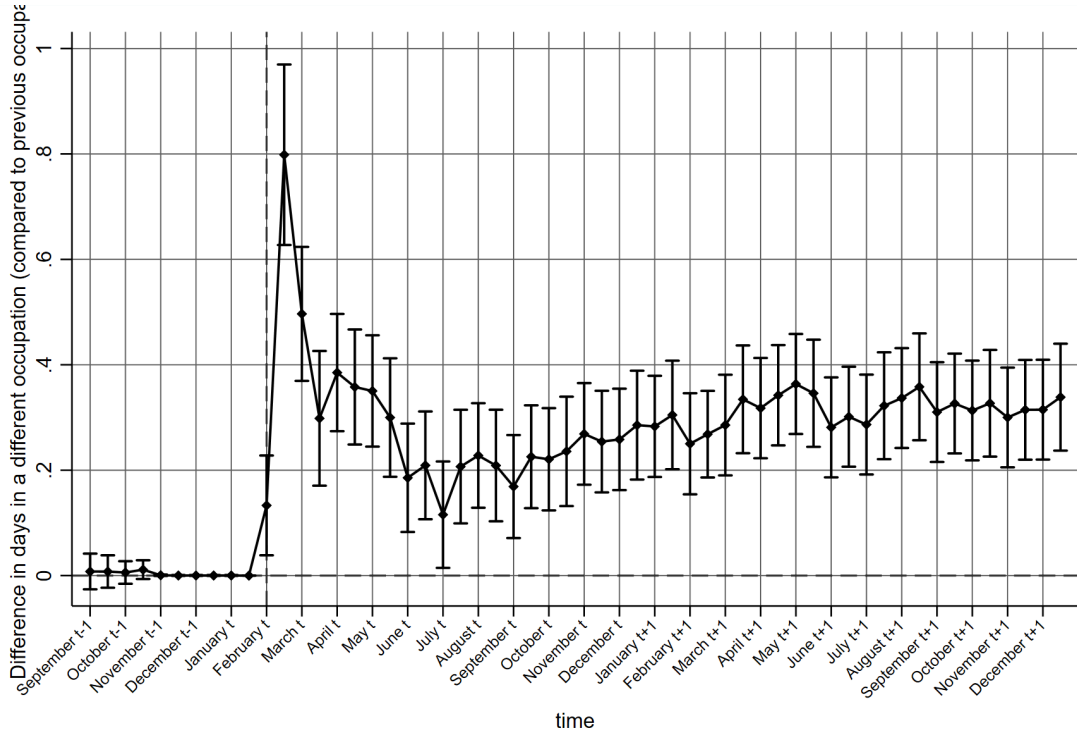


Figure 8: The effect of the Covid-19 pandemic on days in employment in a different occupation

Note: Figure 8 shows the estimated coefficients  $\beta_t$  from Equation 1 when the number of days that an individual is employed in a different occupation in in period  $t = -1$  is used as the dependent variable.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

## 5 Occupation-specific effects of the COVID-19 pandemic

The results in Section 3 showed that the Covid-19 pandemic had a considerable negative effect on labour market outcomes such as earnings, employment or wages; especially in the short run. Besides, there might be heterogeneity in these effects depending on the occupation the unemployed were employed in before becoming unemployed. Recent research found evidence that the impact of the pandemic varies by occupation and that this variation depends on certain characteristics of the occupations such as the possibility to work from home, intensity of contact to others, systemic relevance (Adams-Prassl et al., 2020; Albanesi and Kim, 2021a; Beland et al., 2020; Cortes and Forsythe, 2022). For example, their results indicate that the increase in unemployment is higher in occupations without the possibility to work from home than in occupations in which working-from-home is

possible.

The reason behind this is that occupations consist of different tasks. On the one hand, some tasks can be performed from home, whereas others cannot (Dingel and Neiman, 2020). Hence, during the lockdown restrictions, employees working in occupations that consist mainly of tasks which can be done at home could continue working while employees in other occupations were not able to do so to the same extent. On the other hand, different tasks imply a different intensity of (physical) contact and employees in occupations with a high contact intensity were not allowed to work due to the lockdown restrictions (e.g. closings of shops or the gastronomy) (Albanesi and Kim, 2021a; Beland et al., 2020). However, this does not necessarily apply to every occupation: employees in some occupations such as medical and health care occupations were allowed to continue to work during lockdown restrictions because these occupations are essential (of high systemic relevance). Therefore, those occupations with high contact intensity were less negatively affected by the pandemic.

In addition, the pandemic may have changed the labour demand for individual occupations which, in turn, might influence the chances to find a job in these occupations. Since the unemployed in sample of this paper were employed in various occupations before the start of their unemployment spell and are likely to search in this area for re-employment<sup>22</sup>, they face different labour market prospects depending on their previous occupations. Thus, the Covid-19 pandemic might have different effects on their labour market outcomes.

Therefore, in this section the occupation-specific effects of the pandemic will be investigated. The hypotheses are that, on the one hand, unemployed individuals who were previously employed in occupations with the possibility to work from home or of systemic relevance were less affected by the pandemic and, on the other hand, unemployed individuals previously employed in occupations without the possibility to work from home or of systemic relevance were more affected. In this connection it is important to mention, that there is no selection into potentially more or less affected occupations, because individuals in the sample started working in their occupation before the beginning of the pandemic.

## 5.1 Earnings

In this section, the analysis begins with the examination of the occupation-specific effects of the pandemic on earnings in order to get a deeper understanding of the existence and magnitude of heterogeneity, before the next two sections go into further detail by investigating the two drivers of earnings, namely employment and wages.

To assess how the impact of the pandemic differs by occupation, Equation 1 is estimated separately for every occupation. The average and cumulative earnings effects are reported in Table 2. The results for the five most affected and the five least affected occupations are shown in Table 2. Overall, the Covid-19 pandemic has decreased earnings for all unemployed individuals independent of their previous occupation, however, there

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<sup>22</sup>In Section 4.3 it has been found that occupational mobility before transitioning into unemployment was very low.

are significant differences in the magnitude of the reduction in earnings: unemployed individuals who were previously employed in the least affected occupations, namely in *safety and health protection, security and surveillance*<sup>23</sup> experienced the smallest reduction in earnings by 27.21 € in half a month on average and 1,211.40 € in total over the full post-treatment period, whereas unemployed individuals who were previously employed in the most affected occupations, namely in construction, scheduling, architecture and surveying, experienced a reduction in earnings by 259.84 € per period on average and 11,959.92 € in total. The latter is remarkable since these values describe the reduction in earnings which is due to the Covid-19 pandemic and which the treatment group faces additionally to the average reduction in earnings of -579 € due to a transition into unemployment over the whole period of almost two years.

Table 2: Occupations with the highest/lowest effects on earnings

Most affected occupations			
Rank	Occupation	Average effect	Cumulative effect
1	Construction scheduling, architecture and surveying	-259.84	-11,959.92
2	Technical research and development, construction	-237.48	-10,641.41
3	Mathematics, biology, chemistry and physics	-231.30	-10,385.25
4	Product design, artisan craftwork and fine arts	-227.22	-10,228.53
5	Computer science, information and communication	-216.00	-9,701.90
Least affected occupations			
Rank	Occupation	Average effect	Cumulative effect
1	Geology, geography and environmental protection	-4.48	-168.82
2	Safety and health protection, security and surveillance	-27.21	-1,211.40
3	Education and social work, housekeeping, and theology	-57.85	-2,605.57
4	Cleaning services	-58.77	-2,640.70
5	Medical and health care	-63.77	-2,885.31

Notes: Table 2 shows the average and the cumulative values of  $\hat{\beta}_t$  from Equation 1 when earnings are used as the dependent variable. The model is estimated separately by the occupations which individuals are employed in before the start of the pandemic.

Source: IEB, own calculations.

However, Table 2 only displays average and cumulative effects, but these effects may vary over time. In order to get a better understanding of the evolution of these occupational effects, Figure 9 shows the estimated effects for the most affected and the least affected occupations over time. The evolution of the effects for occupations in *safety and health protection, security and surveillance*<sup>24</sup> represents the upper bound, while the lower bound is given by occupations in *construction, scheduling, architecture and surveying*. While the effect of the Covid-19 pandemic on earnings for the least affected occupations is close to zero and (mostly) insignificant over the whole period, the effect for the most affected occupations follows the known pattern of a sharp decrease at the onset of the pandemic and

<sup>23</sup>While occupations in *geology, geography and environmental protection* are the least affected, they will not be investigated further since the total number of observations for the treatment as well as the control group are too low (165 for both). This low number of observations also results in wide confidence intervals, which makes the estimates for these occupations statistically insignificant in most cases.

<sup>24</sup>Occupations in *safety and health protection, security and surveillance* are chosen instead of occupations in *geology, geography and environmental protection*, since the former have a changing and insignificant evolution with very large confidence intervals.

an adjustment for the rest of the period, yet having a higher magnitude with a maximum of around 400€ per period. Hence, it can be concluded that the highest reduction in earnings occurs directly after the transition into unemployment (during the onset of the pandemic).

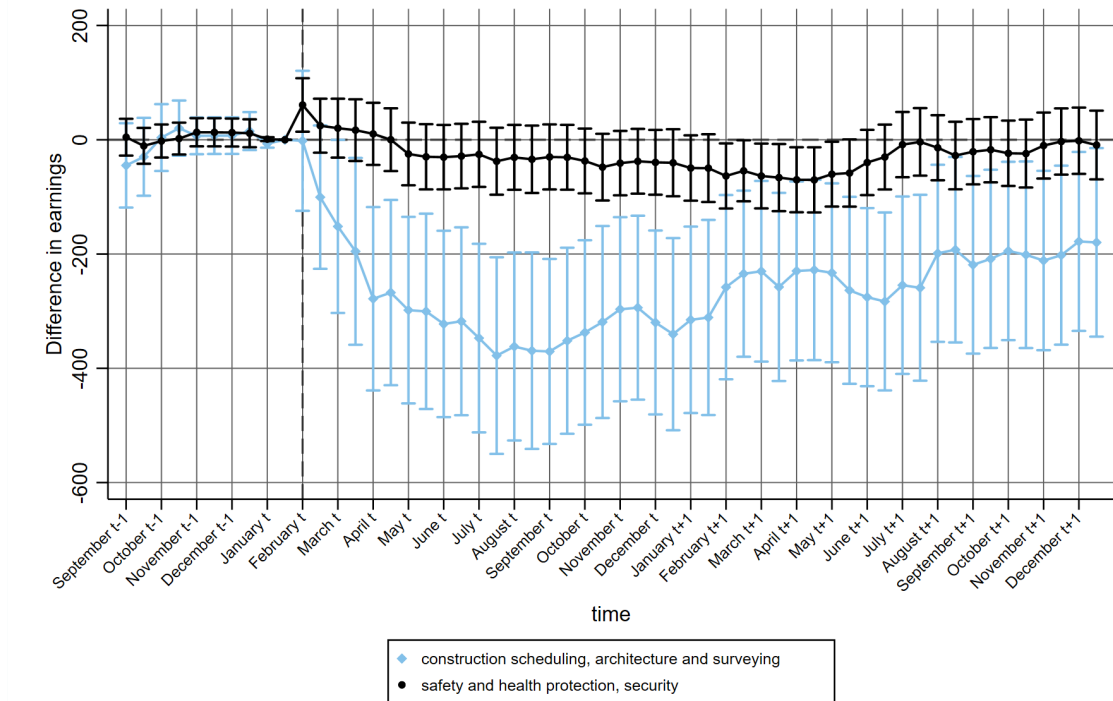


Figure 9: The effect of the Covid-19 pandemic on earnings (most and least affected occupations)

Note: Figure 9 shows the estimated coefficients  $\beta_t$  from Equation 1 when earnings are used as the dependent variable for individuals that are employed in the most or least affected occupations before the start of the pandemic.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

## 5.2 Employment

The analysis in the previous section showed that while the pandemic’s effect on earnings was negative and significant in most cases, there is a considerable spread in terms of the magnitude of these effects. However, as outlined in Section 4.1, earnings depend on employment and on wages. Therefore, in this section the effect of the pandemic on the number of days in employment will be further investigated before the next section turns to the analysis of wage effects.

Table 3 shows the average (by half a month) and the cumulative effect (over the whole period of 22.5 months) of the Covid-19 pandemic on the number of days in employment for the five most and the five least affected initial occupations are excluded. Overall, the effect

of the pandemic leads to a reduction in employment for all occupations<sup>25</sup>. It ranges from an average reduction in days in employment of 1.64 days in half a month for occupations in tourism, hotels and restaurants to 0.31 days in half a month for medical and health care occupations, which results in a total loss of 73.38 and 13.72 days, respectively.

Table 3: Occupations with the highest/lowest effects on days in employment

Most affected occupations			
Rank	Occupation	Average effect	Cumulative effect
1	Tourism, hotels and restaurants	-1.64	-73.38
2	Philology, literature, humanities, social sciences	-1.51	-67.88
3	Food-production and -processing	-1.45	-64.85
4	Building construction above and below ground	-1.41	-63.46
5	Product design, artisan craftwork and fine arts	-1.27	-57.29
Least affected occupations			
Rank	Occupation	Average effect	Cumulative effect
1	Geology, geography and environmental protection	1.91	86.17
2	Medical and health care	-0.31	-13.72
3	Education and social work, housekeeping, and theology	-0.44	-19.36
4	Teaching and training	-0.52	-22.84
5	Advertising and marketing, commercial and editorial media design	-0.57	-25.36

Notes: Table 3 shows the average and the cumulative values of  $\hat{\beta}_t$  from Equation 1 when days in employment are used as the dependent variable. The model is estimated separately by the occupations which individuals are employed in before the start of the pandemic.

Source: IEB, own calculations.

The estimated effects regarding the types of previous occupations listed in Table 3 are for the most as well as the least affected occupations as expected: the most affected occupations have in common that they do not offer the possibility of working-from-home and therefore could not operate under lockdown restrictions such as *tourism, hotels and restaurants or food-production and -processing*. The least affected occupations are either essential such as *medical and health care occupations* and *teaching and training* or lend themselves to working-from-home such as *advertising and marketing, commercial and editorial media design*.

The results in Section 4.2 showed that the substantial reduction in employment occurred during the onset of the pandemic. Therefore, the evolution of the effect on employment for occupations in *tourism, hotels and restaurants* as well as for *medical and health care* occupations is displayed in Figure 10. In both cases, there is a negative employment effect for individuals who used to be employed in either occupation, but the magnitude of this effect differs: while individuals in *medical and health care* occupations lose at most 1 day in employment (during a half month period) due to the Covid-19 pandemic, individuals in occupations in the area *tourism, hotels and restaurants* experience a loss of nearly 4 days at maximum. It is remarkable that while there was high demand for *medical and health care* occupations during the pandemic, individuals who previously worked in those occupations still experienced a reduction in employment relative to the control group.

From November 2020 onwards, the differential effect on employment for individuals ini-

<sup>25</sup>As outlined in Section 5.2 occupations in *geology, geography and environmental protection*

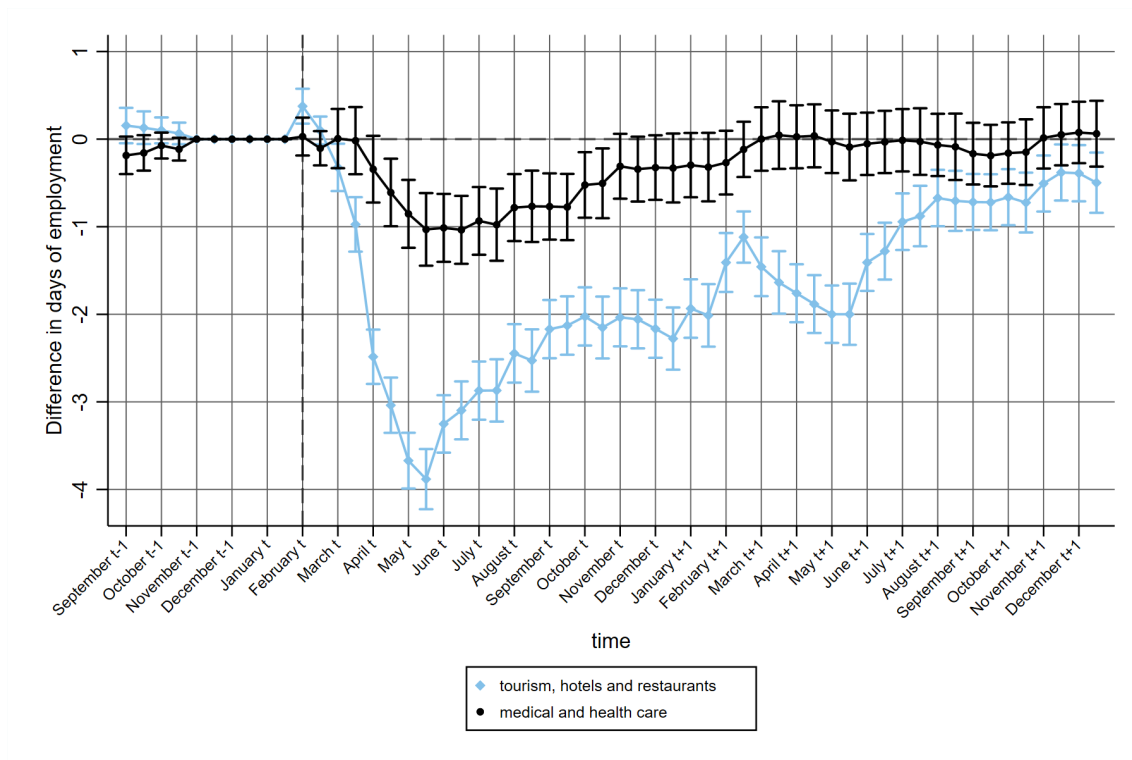


Figure 10: The effect of the Covid-19 pandemic on days in employment (most and least affected occupations)

Note: Figure 10 shows the estimated coefficients  $\beta_t$  from Equation 1 when days in employment are used as the dependent variable for individuals that are employed in the most or least affected occupations before the start of the pandemic.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

tially employed in medical and health care occupations takes the form of an almost flat line around zero and thus the Covid-19 pandemic has no (significant) effect anymore. Although employment starts to recover also for occupations in tourism, hotels and restaurants, it decreased again between March 2021 and June 2021 before finally starting to adjust but without reaching its initial level. This second reduction overlaps with the second lockdown in Germany which ended before April 2021 (see Section 2.1).

All in all, it can be concluded that the unemployed who previously worked in occupations which were affected by lockdown restrictions or have no possibility to work from home experienced employment losses greater than the unemployed who previously worked in occupations which have the possibly to work from home.

### 5.3 Wages

Finally, in this section the effect of the Covid-19 pandemic on log wages is analysed for the different occupations. The results of the ranking of the five most and five least affected occupations which the individuals were initially employed in are shown in Table 4. Overall, the effect on log wages differs considerably between the most and the least affected occupations: while individuals from the five most affected occupations experience a wage decline (at maximum on average of 14% in half a month), those from the least affected have no change in wages or even a slight wage increase over the whole analysed time period (at maximum on average of 7% in half a month). Hence, there is strong heterogeneity in the effect of the pandemic on log-wages.

Table 4: Occupations with the highest/lowest effects on log wages

Most affected occupations			
Rank	Occupation	Average effect	Cumulative effect
1	Geology, geography and environmental protection	-0.18	-8.29
2	Construction scheduling, architecture and surveying	-0.15	-6.70
3	Metal-making and -working, and in metal construction	-0.14	-6.19
4	Textile- and leather-making and -processing	-0.09	-4.13
5	Mathematics, biology, chemistry and physics	-0.09	-4.01
Least affected occupations			
Rank	Occupation	Average effect	Cumulative effect
1	Safety and health protection, security and surveillance	0.07	3.31
2	Tourism, hotels and restaurants	0.01	0.53
3	Financial services, accounting and tax consultancy	0.01	0.34
4	Medical and health care	0.00	-0.16
5	Teaching and training	0.00	-0.22

Notes: Table 4 shows the average and the cumulative values of  $\hat{\beta}_t$  from Equation 1 when log wages are used as the dependent variable. The model is estimated separately by the occupations which individuals are employed in before the start of the pandemic.

Source: IEB, own calculations.

Regarding the composition of the most and least affected previous occupations, three conclusions can be drawn: first, previous occupations which belong to the five least (most) affected occupations regarding earnings also appear in the five least (most) affected occupations regarding wages. Second, occupations that are not suitable for working-from-home

are among the most affected such as occupations in *metal-making and -working*, and in *metal construction* or in *textile- and leather-making and -processing*. At the same time, occupations that offer the possibility to work from home or can be categorised as essential are ranked among the least affected such as *medical and health care occupations* or occupations in *financial services, accounting and tax consultancy*. Third, treated individuals who were previously employed in occupations in *tourism, hotels and restaurants* experienced no wage decrease and are ranked among the least affected previous occupations. The latter is quite remarkable, since these occupations were heavily affected by lockdown restrictions and this group had the strongest reduction in employment. On the one hand, these occupations are typically lower-paying (often at the minimum wage level), so significant wage reductions might not have been possible. For these occupations, a reduction in wages/earnings therefore is primarily possible through a reduction in employment, as shown in Section 5.2. On the other hand, on account of the limited possibilities to work during the phase of lockdown restrictions, the observed individuals who previously worked in these occupations, might have switched to higher-paying or less-affected occupations. Furthermore, in the end of 2021, there was a shortage of workers in hospitality occupations which also might explain the (insignificant) wage increase.

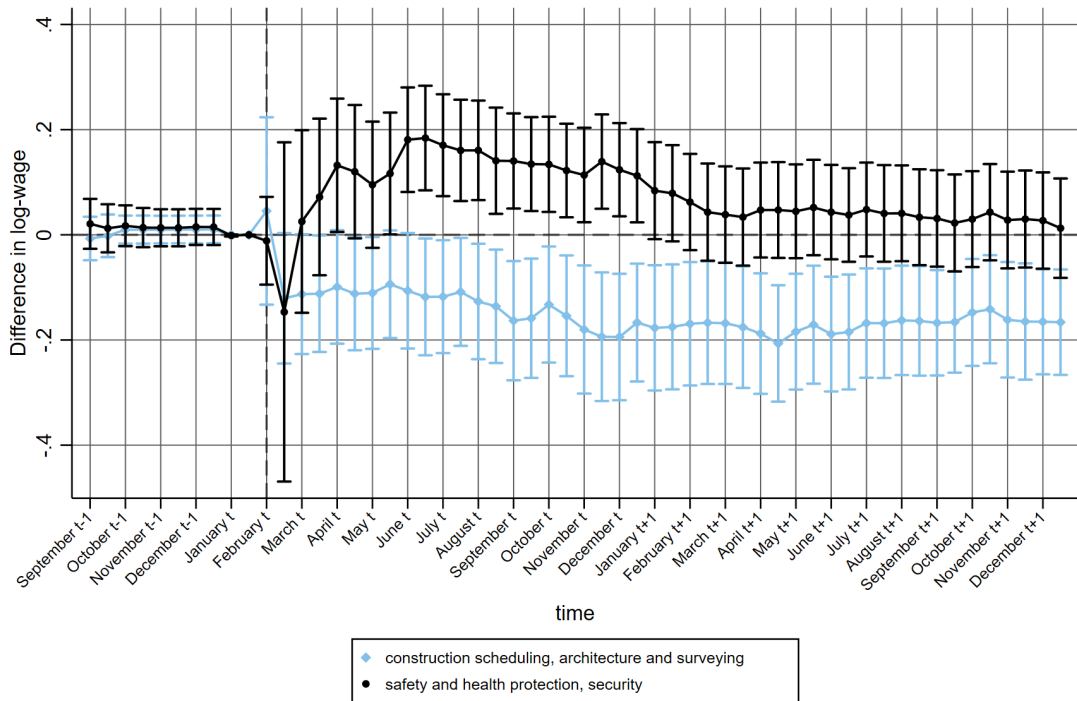


Figure 11: The effect of the Covid-19 pandemic on log wages (most and least affected occupations)

Note: Figure 11 shows the estimated coefficients  $\beta_t$  from Equation 1 when average daily wages are used as the dependent variable for individuals that are employed in the most or least affected occupations before the start of the pandemic. Individuals in the control group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.



However, these are only average and cumulative effects which ignore developments over time, and therefore Figure 11 illustrates the evolution of the most and least affected occupations over time. Occupations in *safety and health protection, security and surveillance* represent the upper bound of the evolution of the effect of the pandemic on wages. Before the transition into unemployment takes place, there is no (significant) difference between the treatment and the control group, but with the beginning of the Covid-19 pandemic in March 2020, log wages started to increase. After reaching a maximum of 22%, wages returned slowly back to their initial level and the difference between the treatment and control group becomes insignificant at the beginning of 2021. By contrast, the effect of the Covid-19 pandemic on wages for *construction scheduling, architecture and surveying*, which represents the lower bound, is negative and statistically significant over time. In particular, individuals who were employed in this occupation experienced a constant wage reduction of 14% (compared to the control group).

## 6 Conclusion

This paper analyses the effect of the Covid-19 pandemic on labour market outcomes such as earnings, employment and wages for individuals who become unemployed shortly before the onset of the pandemic in 2020. The empirical analysis is based on German social security data from the Integrated Employment Biographies (IEB) and the effect is identified by a difference-in-differences event-study design, in which the treated individuals are compared to a group of individuals who became unemployed in the same month in 2018. In a first step, the aggregate effect of the Covid-19 pandemic is investigated. Results show that the pandemic led to a strong and significant reduction in earnings among the group of individuals who became unemployed shortly before the start of the pandemic. This effect is especially pronounced at the beginning of the pandemic (from March 2020 until summer 2020). In the longer run, however, earnings start to adjust and the gap between treatment and control group decreases. Consequently, the Covid-19 pandemic led to a permanent reduction in earnings for unemployed people. This reduction in earnings is mainly driven by a reduction in employment in the short run and by a (less strong) reduction in wages in the long run. These results are comparable to the findings of the job-displacement literature (see, e.g., [Jacobson et al., 1993](#); [Davis and von Wachter, 2011](#); [Lachowska et al., 2020](#); [Schmieder et al., 2022](#)). Further, mechanisms behind the reduction in employment and in wages are investigated. It can be concluded that the reduction in employment is mostly due to a reduction in regular and full-time employment, whereas the reduction in wages can partly be explained by a small but significant increase in occupational mobility and by a small shift towards reemployment in marginal and part-time employment. Moreover, the results also show that the Covid-19 pandemic increased the number of days in unemployment. This development might have prolonged unemployment duration and thus might result in more long-term unemployment due to the pandemic. In a second step, the occupation-specific heterogeneity of the effect of the Covid-19 pandemic

is analysed. The results indicate that the effect of the Covid-19 pandemic on earnings, employment or wages vary by occupation and the intensity of the effect depends on the possibility to work from home and the systemic relevance of the occupation. For instance, unemployed individuals who previously worked in hospitality occupations experienced a cumulative employment reduction of 73 days, whereas unemployed individuals who were previously employed in medical and health care occupations only faced a reduction of 12 days. Hence, the effect of the Covid-19 pandemic is heterogeneous across occupations. All in all, it can be concluded that the Covid-19 pandemic had a huge effect on the transitions of newly unemployed that lead to persistent consequences regarding labour market outcomes which are especially pronounced for unemployed of a specific group of occupations (which among others lack the possibility to work from home). These findings underline that the Covid-19 pandemic was a severe economic shock with lasting consequences and (policy) support should concentrate on those unemployed coming from the most affected occupations which were not able to recover by the end of 2021.

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## A Appendix

### A.1 Data preparation

This section provides further details about how the sample in this paper is constructed. The administrative integrated employment biographies (IEB), which are provided by the Institute of Employment Research (IAB), the research institute of the German Federal Employment Agency, is used. This dataset is a combined dataset with four different sources which have daily information on employment in the social security system and marginal employment, receipt of transfer payments (e.g. unemployment benefits and means-tested welfare benefit receipt), unemployment and participation in active labour market programs. Based on this dataset, a panel dataset with bi-monthly observations is created. Two challenges which arose during the data preparation are explained in the following: First, the challenge of parallel spells and second, the challenge of missing spells.

The challenge of parallel spells refers to the fact that at any point in time a person can have more than one record in the IEB data. For example, individuals can have more than one job at the same time or during unemployment they receive transfer payments, which creates two spells for the same time period. To keep only one observation per period for each individual, several decision rules have been developed. In doing so this paper applies the (most) common decision rules by [Dauth and Eppelsheimer \(2020\)](#). In particular, this means that in the first place all parallel spells which do not include information on employment or unemployment (such as participating in a labour market program or receiving financial transfers) are excluded. The cases in which there are parallel unemployment and/or employment spells are more difficult. Here the paper proceeds as follows: first, all spells with information that does not contain the main (regular and marginal) employment or the main ("unemployed and searching for work") unemployment information were dropped. Second, spells containing more information on other observable characteristics, e.g. vocational degree, establishment, occupation, (meaning less missings) were kept. Third, spells with a longer duration were included, however there are two exceptions: firstly, if there is an unemployment spell parallel to a marginal employment spell, the unemployment spell is kept and secondly, if there is a transition of an employment period to an unemployment period, where both spells are overlapping at some time of the transition, the overlapping employment spell is dropped. Regarding the case of two parallel employment spells with the same duration, the spell with lower daily wages, is excluded. In the end, if all of the described rules cannot be applied, one of the parallel spells is randomly chosen.

In contrast to the parallel spells the challenge of missing spells means that for some periods individuals might not have an observed spell. This happens, for instance, if the individual has left the labour market, is self-employed or got into retirement. Those missing spells are filled with "artificial" spells which contain no information but ensure that every individual has one observation for each time period.

After these data preparation steps, the treatment and control group were defined. For being in either group, certain criteria had to be fulfilled: first, individuals had to be registered unemployed in February 2018 or in February 2020. Individuals who have been registered as unemployed in 2018 as well as in 2020 are only part of the control group. The same rule is applied for individuals who became unemployed in the first as well as in the second half of February: they are only counted in the first half. Moreover, there is no restriction on the duration of the unemployment spell, which indicates that individuals who find a new job after one day in unemployment are still part of the sample. Second, individuals in the sample had to be employed at least until the 31<sup>st</sup> of January before becoming unemployed. This means that all individuals whose employment spell ends before the 31<sup>st</sup> of January were excluded whereas all individuals whose employment spell ends on some day in February are in the sample. Third, individuals in the sample have to be employed on every day at least since November of the previous year. Before that date, they are allowed to have any possible labour market status. Taken the sample restrictions together gives a sample of 194,859 individuals in total.

## **A.2 Descriptive statistics of the unemployed of the second half of February**

The descriptive statistics of those individuals who became unemployed in the second half of February are displayed in Table A1. In contrast to individuals who became unemployed in the first half of February, they are on average slightly younger, more often low skilled, earn less, a higher share has a migration background, they were on average ten days longer in unemployment and switched 0.42 times their employer in the year before their unemployment spell started.

## **A.3 Descriptive statistics of the full sample**

Table A2 shows descriptive statistics of the analysis sample in comparison to the full sample of all unemployed who were at least employed for one day before they become unemployed in February. It can be seen that in most of the characteristics the full sample is quite similar to the actual sample. However, the full sample differs regarding some employment characteristics, for example individuals of the full sample earn (substantially) less, are (a little bit) more often marginally employed and in the year before their unemployment spell starts (in February) they were, on average, almost twenty days longer in unemployment.

## **A.4 IPW: Balancing table**

Table A3 shows the mean values of various characteristics, which were used for the weighting<sup>26</sup>, as well as the wage for the treatment group (column (1)), the unweighted control

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<sup>26</sup>For clarity reason the dummies for the 258 labour market regions are omitted. It can be noted that none of the differences in the shares of the labour market regions is statistically significant. Full results are available on request.

Table A1: Descriptive statistics second half

	Treatment	Control	Difference	p-value
Age	36.06 (12.49)	36.52 (12.44)	-0.45	0.00
Gender	0.63 (0.48)	0.62 (0.48)	0.01	0.07
Foreign	0.23 (0.42)	0.20 (0.40)	0.03	0.00
Low skilled	0.29 (0.45)	0.25 (0.43)	0.03	0.00
Middle skilled	0.60 (0.49)	0.64 (0.48)	-0.04	0.00
High skilled	0.11 (0.32)	0.11 (0.31)	0.01	0.03
Tenure (in days)	640.07 (1039.36)	679.54 (1090.63)	-39.47	0.00
Previous wage	58.07 (37.81)	55.96 (35.25)	2.11	0.00
Regular employment	0.80 (0.40)	0.80 (0.40)	0.00	0.48
Marginal employment	0.09 (0.28)	0.09 (0.29)	0.00	0.05
Duration of unemployment before (in days)	30.31 (59.54)	33.75 (62.14)	-3.45	0.00
Number of job changes	0.42 (0.68)	0.36 (0.68)	0.06	0.00

Notes: The first two columns show mean values and standard deviations (in parentheses) of individual characteristics that are measured at the second half of January (the last period in employment). The third column reports the difference in means and the fourth column shows the p-value of the hypothesis test that the corresponding difference is equal to zero.

Source: IEB, own calculations.

Table A2: Descriptive statistics full sample

	Treatment	Control	Difference	p-value
Age	38.23 (12.93)	38.47 (12.82)	-0.24	0.00
Gender	0.60 (0.49)	0.59 (0.49)	0.02	0.00
Foreign	0.20 (0.40)	0.17 (0.38)	0.02	0.00
Low skilled	0.23 (0.42)	0.21 (0.41)	0.02	0.00
Middle skilled	0.61 (0.49)	0.64 (0.48)	-0.03	0.00
High skilled	0.16 (0.37)	0.15 (0.35)	0.02	0.00
Tenure (in days)	951.59 (1665.71)	919.37 (1594.87)	32.22	0.00
Previous wage	65.92 (46.69)	60.66 (46.71)	5.26	0.00
Regular employment	0.82 (0.39)	0.81 (0.39)	0.01	0.00
Marginal employment	0.09 (0.29)	0.11 (0.31)	-0.01	0.00
Duration of unemployment before (in days)	38.10 (76.09)	45.05 (82.87)	-6.95	0.00
Number of job changes	0.35 (0.63)	0.30 (0.58)	0.05	0.00

Notes: The first two columns show mean values and standard deviations (in parentheses) of individual characteristics that are measured at the second half of January (the last period in employment). The third column reports the difference in means and the fourth column shows the p-value of the hypothesis test that the corresponding difference is equal to zero.

Source: IEB, own calculations.



group (column (2)) and the weighted control group (column (3)). In addition, the p-value of a standard t-test (column (4)) as well as the standardized difference between the treatment and the (weighted) control (column (5)) are displayed. Without weighting, the difference between treatment and control group were already relatively small, by applying the weighting the differences are even smaller and statistically insignificant in each case (in terms of both p-values and standardized differences). However, one exception has to be made: the difference in wages between the treatment and the control group is still significant at conventional significance levels, but the standardized difference is smaller than 0.1 which does not indicate an economically significant difference. Overall, the sample appears to be balanced.

### **A.5 IPW: Model selection**

Figure A1, Figure A2 and Figure ?? illustrate the estimation of Equation 1 for earnings, days in employment and log wages using different sets of IPW covariates. The black line shows the development of the outcomes for the baseline model without any weighting, the green line shows the development for the set of weighting variables which are used in the paper. Overall, it can be seen that the estimation results are not materially affected by the choice of IPW variables. The same holds for the other outcomes that are investigated in the paper. Results are available upon request.

### **A.6 IPW: Overlap assumption**

To provide evidence on the overlap assumption, Figure A4 illustrates the distribution of the estimated propensity score for the treatment (solid line) and the control group (dashed line). Although the distribution of the treated individuals is slightly shifted to the right, the majority of both distributions is nearly identical, which supports the overlapping assumption.

Table A3: IPW Balancing

	Treated	Unweighted Controls	Weighted Controls	P-value	Standardized Difference
Age (1st quartile)	0.242	0.240	0.242	0.954	-0.000
Age (2nd quartile)	0.259	0.248	0.258	0.688	0.002
Age (3rd quartile)	0.245	0.253	0.245	0.968	0.000
Age (4th quartile)	0.254	0.260	0.255	0.699	-0.002
Male	0.608	0.585	0.606	0.428	0.004
Foreign	0.242	0.205	0.242	0.832	0.001
Low skill	0.149	0.140	0.149	0.848	-0.001
Middle skill	0.592	0.640	0.591	0.612	0.003
High skill	0.171	0.160	0.172	0.782	-0.002
Skill missing	0.088	0.060	0.089	0.787	-0.001
Current wage	73.308	68.145	70.338	0.000	0.068
Experience (1st quartile)	0.256	0.244	0.257	0.762	-0.002
Experience (2nd quartile)	0.252	0.248	0.251	0.726	0.002
Experience (3rd quartile)	0.242	0.258	0.242	0.744	0.002
Experience (4th quartile)	0.250	0.250	0.251	0.713	-0.002
Number of job changes: 0	0.759	0.795	0.759	0.911	0.001
Number of job changes: 1	0.206	0.178	0.206	0.930	0.000
Number of job changes: >1	0.035	0.027	0.035	0.650	-0.002
Marginal employment	0.067	0.073	0.069	0.315	-0.006
Regular employment	0.933	0.927	0.932	0.311	0.006
Duration in regular employment (in days)	240.541	233.453	239.849	0.204	0.007
Duration of marginal employment (in days)	13.918	15.618	14.133	0.466	-0.004
Full-time employment	0.652	0.641	0.650	0.351	0.005
Part-time employment	0.348	0.359	0.350	0.351	-0.005
<b>Occupation</b>					
Agriculture, forestry, farming	0.008	0.009	0.008	0.981	-0.000
Gardening, floristry	0.011	0.012	0.011	0.718	-0.002
Production, processing of raw materials	0.004	0.005	0.004	0.929	0.000
Plastic-making, -processing, wood-working, -processing	0.020	0.017	0.020	0.705	0.002
Paper-making, -processing, printing, technical media design	0.011	0.011	0.011	0.895	0.001
Metal-making, -working, metal construction	0.049	0.035	0.048	0.359	0.005
Technical machine-building, automotive industry	0.048	0.039	0.047	0.869	0.001
Mechatronics, energy electronics, electrical engineering	0.022	0.019	0.022	0.992	0.000
Technical research, development, construction, production planning	0.021	0.016	0.021	0.963	0.000
Textile-, leather-making, -processing	0.005	0.004	0.005	0.972	0.000
Food-production, -processing	0.045	0.055	0.046	0.851	-0.001
Construction scheduling, architecture, surveying	0.005	0.005	0.005	0.975	-0.000
Building construction	0.023	0.026	0.023	0.976	0.000
Interior construction	0.022	0.028	0.022	0.906	-0.001
Building services engineering, technical building services	0.019	0.021	0.019	0.926	-0.001
Mathematics, biology, chemistry, physics	0.009	0.008	0.009	0.786	-0.001
Geology, geography, environmental protection	0.001	0.001	0.001	0.861	-0.001
Computer science, information, communication technology	0.016	0.013	0.016	0.983	0.000
Traffic, logistics	0.103	0.098	0.101	0.345	0.005
Drivers and operators of vehicles and transport equipment	0.047	0.045	0.047	0.879	0.001
Safety and health protection, security, surveillance	0.015	0.020	0.016	0.761	-0.002
Cleaning services	0.053	0.053	0.054	0.621	-0.003
Purchasing, sales, trading	0.030	0.028	0.030	0.883	-0.001
Retail trade	0.086	0.094	0.086	0.998	-0.000
Tourism, hotels, restaurants	0.055	0.056	0.055	0.830	-0.001
Business management, organisation	0.101	0.105	0.101	0.938	-0.000
Financial services, accounting, tax consultancy	0.017	0.018	0.017	0.937	-0.000
Law and public administration	0.011	0.012	0.011	0.870	-0.001
Medical and health care	0.036	0.035	0.036	0.825	-0.001
Non-medical healthcare, body care, wellness, medical technicians	0.022	0.023	0.022	0.952	-0.000
Education, social work, housekeeping, theology	0.032	0.033	0.033	0.615	-0.003
Teaching, training	0.020	0.021	0.021	0.750	-0.002
Philology, literature, humanities, social sciences, economics	0.003	0.003	0.003	0.915	-0.001
Advertising, marketing, commercial, editorial media design	0.023	0.023	0.023	0.877	-0.001
Product design, artisan craftwork, fine arts, making of musical inst	0.002	0.002	0.002	0.840	-0.001
Performing arts, entertainment	0.004	0.005	0.004	0.984	-0.000
<b>Sector</b>					
Agriculture	0.008	0.010	0.008	0.955	0.000
Mining	0.001	0.001	0.001	0.942	0.000
Manufacturing	0.159	0.127	0.158	0.504	0.004
Energy	0.002	0.002	0.002	0.998	-0.000
Water	0.005	0.005	0.005	0.864	-0.001
Construction	0.068	0.077	0.068	0.903	-0.001
Retail trade	0.158	0.166	0.157	0.787	0.001
Transportation, storage	0.069	0.060	0.069	0.827	0.001
Hotelling	0.084	0.091	0.084	0.759	-0.002
ICT	0.033	0.029	0.033	0.981	0.000
Banking, insurance	0.010	0.012	0.011	0.865	-0.001
Real estate	0.010	0.010	0.010	0.988	-0.000
Technical service	0.062	0.058	0.062	0.938	-0.000
Business service	0.171	0.183	0.171	0.983	0.000
Public admin	0.012	0.018	0.012	0.841	0.001
Education	0.029	0.030	0.029	0.829	-0.001
Social, health	0.078	0.077	0.079	0.630	-0.003
Arts	0.013	0.014	0.014	0.589	-0.003
Other service	0.024	0.027	0.024	0.871	-0.001
Private households	0.003	0.003	0.003	0.679	-0.002
Other	0.000	0.000	0.000	0.959	0.000
Missing Sector	0.000	0.000	0.000	0.901	-0.001
Firm size (0-9)	0.205	0.231	0.207	0.388	-0.005
Firm size (10-49)	0.303	0.303	0.304	0.627	-0.003
Firm size (50-249)	0.286	0.279	0.285	0.761	0.002
Firm size (>249)	0.200	0.180	0.198	0.300	0.006
Missing firm size	0.006	0.007	0.006	0.779	0.002

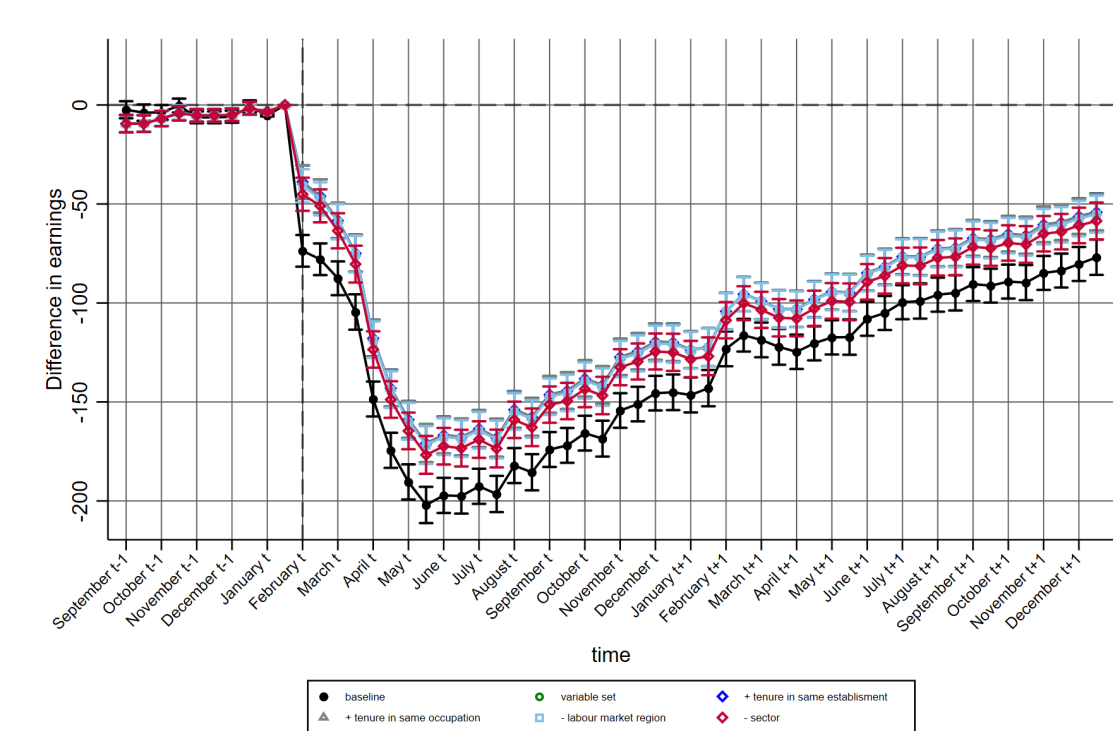


Figure A1: The effect of the Covid-19 pandemic on log wages

Note: Figure ?? shows the estimated coefficients  $\beta_t$  from Equation 1 when earnings is used as the dependent variable for different sets an matching variables.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

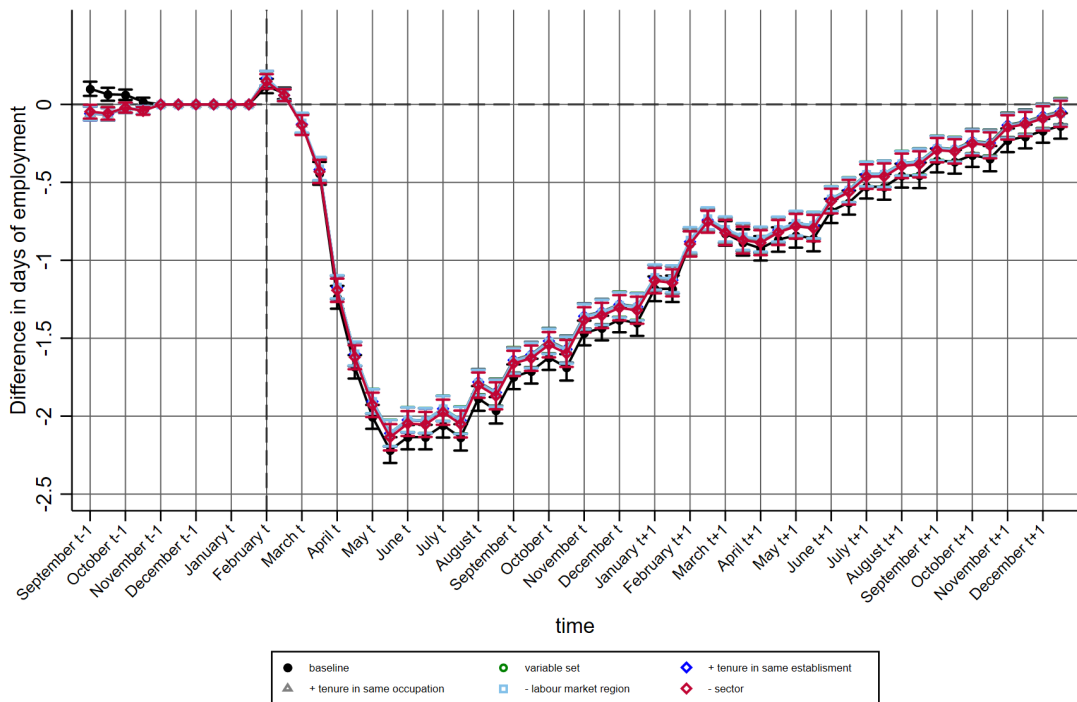


Figure A2: The effect of the Covid-19 pandemic on log wages

Note: Figure A2 shows the estimated coefficients  $\beta_t$  from Equation 1 when the number of days in employment is used as the dependent variable for different sets an matching variables.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

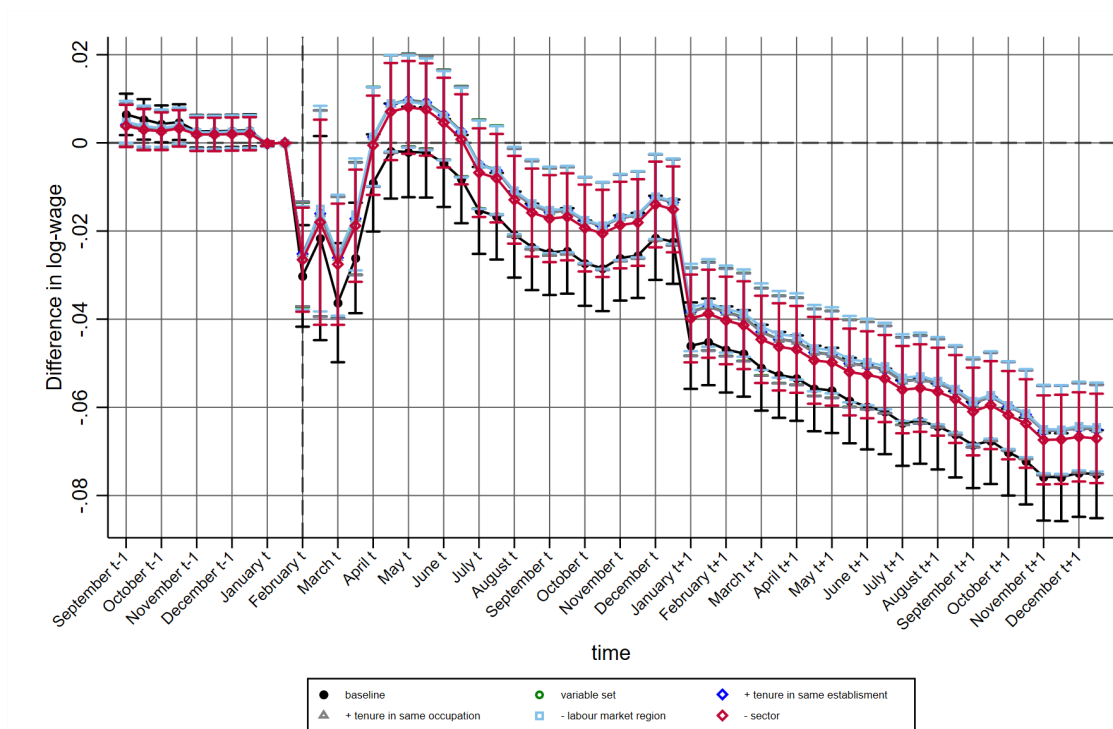


Figure A3: The effect of the Covid-19 pandemic on log wages

Note: Figure A3 shows the estimated coefficients  $\beta_t$  from Equation 1 when the log-wage is used as the dependent variable for different sets an matching variables.  $t$  denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2021, while the control group is observed from September 2017 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.

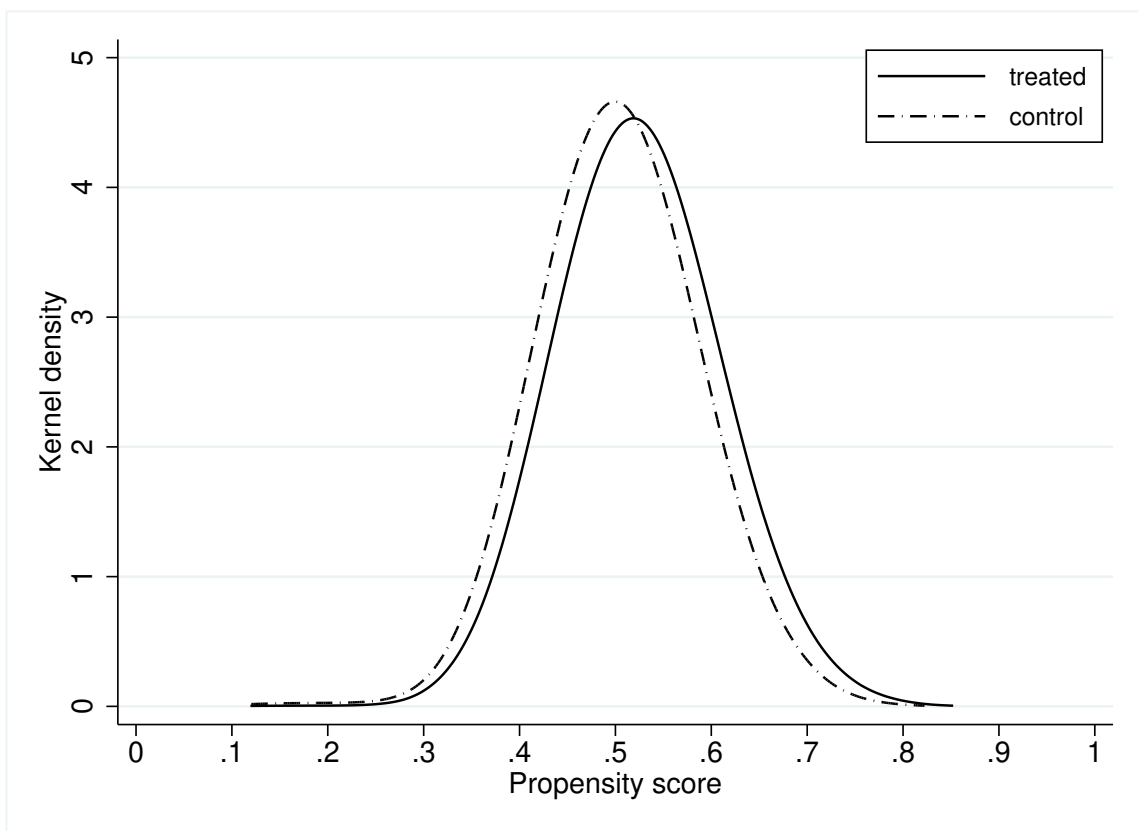


Figure A4: The effect of the Covid-19 pandemic on log wages

Note: Figure A4 shows the estimated propensity score for the treatment and the control group.