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ABSTRACT

Economic Shocks and Worker Careers: Has the COVID-19 Pandemic Affected Transitions Out of Unemployment?*

Temporary economic shocks can have enduring effects on individuals and their career trajectories. This paper investigates the labour market effects of the Covid- 19 pandemic on newly unemployed individuals, the underlying mechanisms as well as occupation-specific effect heterogeneity. The results indicate long-lasting earnings losses due to the pandemic, which can be explained by a decline in employment in the short run and a decline in wages in the longer run. We further find that the lower the lockdown work ability of a worker's previous occupation, the greater the adverse effects of the pandemic.

JEL Classification: J23, J62, J64

Keywords: economic shocks, COVID-19, unemployment, worker careers, occupations

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1 Introduction

Being exposed to temporary economic shocks can have long-lasting scarring effects on individuals and their careers. Prime examples include being displaced from one's job (Jacobson et al., 1993; Schmieder et al., 2023), being exposed to a recession as a labour market entrant (Oreopoulos et al., 2012; Schwandt and von Wachter, 2019) or throughout one's career (Huckfeldt, 2022) as well as experiencing youth unemployment (De Fraja et al., 2021). The Covid-19 pandemic also represents an adverse shock on the labour market (Adams-Prassl et al., 2020; Albanesi and Kim, 2021). However, the extant literature on the labour market consequences of the pandemic has so far focused to a large extent on the period immediately following its emergence (e.g., Forsythe et al., 2020; Cortes and Forsythe, 2022) as well as on occupational differences in the ability to work from home (e.g., Dingel and Neiman, 2020). What is still lacking is a thorough analysis of the longer-term effects of being exposed to the pandemic on individual labour market outcomes, such as earnings, employment and wages, and their underlying mechanisms.

In this paper, we aim to close this research gap. To study the effects of the Covid-19 pandemic, we adopt a difference-in-differences framework and compare the employment trajectories of individuals who became unemployed shortly before the start of the pandemic to individuals who became unemployed three years earlier. From the perspective of an individual, the emergence of the pandemic and its subsequent development were unforeseen and we therefore treat them as an exogenous event. Specifically, we conceptualise the adverse nature of the Covid-19 pandemic as a sudden and temporary worsening of the prospects of finding a new job that emerged in Spring 2020, which is driven by a reduction in the number of job vacancies coupled with an increase in the number of job seekers. Individuals in the treatment group are, therefore, exposed to a less favourable environment to find a new job compared to the control group, potentially leading to longer periods of non-employment or selection into lower-quality jobs. Both of these outcomes constitute possible reasons for lasting adverse labour market effects.

What sets the Covid-19 pandemic apart from other shocks is its specific occupational dimension. The implementation of various containment measures as well as changes in consumer behaviour meant that occupations which were based on inter-personal contact, such as in hospitality or other services, experienced a stronger deterioration in employment prospects compared to occupations which allowed for working from home or were otherwise considered essential. As such, the Covid-19 pandemic provides a setting with exogenous variation in the extent to which job finding prospects were affected across occupations. Individuals who used to work in occupations that were less suited to be carried out under lockdown conditions were more adversely affected by the pandemic, regardless of their personal characteristics or the type of firms they used to work for. These individuals could expect to remain unemployed for longer or to have to search for a new job in a different occupation in which their previous work experience was potentially less relevant. Moreover, the lack of job prospects of these individuals might also reduce their bargaining position in any new job, potentially leading to lower wages. We study the heterogeneous impact of the pandemic in a difference-in-difference-in-differences framework that uses the variation in an occupation's suitability to being carried out under lockdown conditions as a continuous treatment intensity measure.

Our empirical analysis is based on administrative data from the Integrated Employment Biographies (IEB) which cover the (near) universe of labour market participants in Germany, supplemented with establishment information such as size, sector and the use of short-time work during the pandemic. From this data set, we define a treatment group consisting of all individuals who became unemployed during the first half of February 2020 after being employed at the same firm and in the same occupation for at least three months previously. We compare the trajectories of various labour market outcomes of the treatment group to a control group of individuals who became unemployed in the same month three years earlier. We observe the treatment (control) group at half-monthly intervals until the end of 2022 (2019), which exceeds what other pandemic-related studies have done so far. The composition of the treatment and the control group is very similar with respect to individual, establishment and job characteristics which provides support for our empirical approach of using inflows into unemployment from an earlier period as the control group. We further improve the balancing of key characteristics by applying inverse propensity score weighting. To assess the occupational dimension of the pandemic, we leverage the fact that individuals were employed in different occupations before becoming unemployed which differed in their ability to continue operating under lockdown conditions, which we measure using the lockdown work ability (LWA) index (Palomino et al., 2020).

Consistent with existing literature (e.g., Forsythe et al., 2020), we first document that in Germany the start of the pandemic also coincided with a drop in the (seasonally adjusted) number of vacancies, while at the same time the number of unemployed job seekers increased. The resulting decrease in the number of vacancies per job seeker implies that individuals who became unemployed shortly before the pandemic were exposed to more adverse conditions with respect to finding a new job. While the number of vacancies and the ratio of vacancies to unemployed job seekers already started to decrease earlier, the pandemic led to a further pronounced drop in both quantities. Moreover, we show that the sudden deterioration was greater in those occupations that are characterised by a limited ability to be carried out under lockdown conditions, implying that the prospects for reemployment varied across occupations.

Based on our empirical approach, we then show that the Covid-19 pandemic has had significant adverse effects on earnings. Specifically, we find that over the whole period after becoming unemployed, treated individuals experience an earnings loss that is, on average, about 4,900 € greater than for the control group, which amounts to a proportional increase in lost earnings of about 15%. Two findings are remarkable: First, the sharpest reduction in earnings among the treatment group is observed during the peak of the pandemic - from March 2020 to May 2020. Second, for the subsequent time, earnings losses (relative to the control group) are considerably smaller but remain with a loss of 6.1% statistically significant at the end of 2022.

The observed loss in earnings may be due to adjustments in employment or wages. We show that in the short run, earnings losses are predominantly due to a decrease in the number of days in employment. During the year 2020, treated individuals spent, on average, about one day per half-month period more out of employment than the control group, while towards the end of the sample period, we find no significant difference in the employment losses of both groups. By contrast, we find that, conditional on being employed, the pandemic led to a lasting decrease in wages, implying that, in the longer run, the larger earnings loss of the treatment group is also due to a higher probability of receiving a lower wage after finding a new job.

We take care to rule out alternative explanations for why employment trajectories developed less favourably among the treatment group. On the one hand, we provide evidence that the magnitude of the negative effects on earnings, employment and wages cannot simply be explained by a general worsening of aggregate labour market conditions that occurred over the time period between individuals in the control and the treatment group becoming unemployed. On the other hand, we show that lost earnings and wages do not merely reflect the wide-spread use of short-time work during the pandemic.

In order to gain a deeper insight into the documented short-term employment losses and long-term wage losses, the paper sheds light on their mechanisms. In the case of employment, the greater reduction in the number of days in employment is almost exclusively due to more time spent in unemployment rather than to a withdrawal from the labour market. To further analyse the wage mechanisms, we apply a decomposition based on Gelbach (2016). The main driver of the pandemic-induced wage losses is that treated individuals, on average, take up jobs that are further down the within-occupation wage distribution than individuals in the control group. This finding is remarkable as newly unemployed individuals who are exposed to the pandemic are also found to move to occupations with higher average wages.

In a next step, we analyse the patterns of occupational mobility that occurred among individuals who lost their job before the start of the pandemic. In addition to more often moving to occupations with a higher mean wage, we find that, on average, treated individuals tend to switch to occupations with a higher LWA index. This finding is consistent with the fact that employment prospects deteriorated in low-LWA occupations as a result of the pandemic. Moreover, this finding might suggest that treated job seekers used occupational mobility to reduce their exposure to the consequences of the pandemic. It may also reflect a change in preferences or attitudes to risk among job seekers. However, our findings also suggest that changing occupations during the pandemic came at a cost. We find that occupational movers take up jobs at a lower rank of the occupational wage distribution and earn lower wages (compared to movers in the control group) than occupational stayers.

In the second part of the paper, we show that the Covid-19 pandemic had a distinct occupational angle. Specifically, we find that workers who used to be employed in occupations that were less suited to operating under lockdown conditions and who were thus exposed to a greater reduction in their reemployment prospects experienced significantly greater negative effects on their labour market trajectories. Treated individuals who used to work in occupations whose LWA index was lower by 0.1 units than the mean experienced an additional pandemic-induced earnings loss amounting to about 12% compared to individuals from occupations with a mean LWA. While these individuals also experienced a greater reduction in employment, our results indicate that it is the additional wage loss that stands out. That wage losses among job seekers who were exposed to the pandemic become larger the less these individuals' former occupations are suited to lockdown conditions can primarily be ascribed to finding jobs that are further down the occupational wage distribution. To further support the finding that the size of the adverse effects depends on the LWA of a worker's pre-unemployment occupation, we provide evidence that the difference in effect size cannot be explained by differences in other characteristics between workers who used to be employed in low- or high-LWA occupations.

Our study contributes to different strands of the literature. First, it contributes to the literature on exposure to temporary economic shocks which analyses the short- and long-term effects on earnings and employment histories after an unexpected job loss (e.g. due to a mass layoff) (see, e.g., Jacobson et al., 1993; Davis and von Wachter, 2011; Lachowska et al., 2020; Schmieder et al., 2023), during the financial crisis (Campos-Vazquez et al., 2023) or while entering the labour market during a recession (see, e.g., Oreopoulos et al., 2012; Altonji et al., 2016). Overall, these studies find that individuals who are exposed to economic shocks experience long-lasting reductions in earnings. There is evidence that the earnings losses are highly cyclical, resulting mainly from wage declines during recessions (Schmieder et al., 2023). We also document a long-lasting negative wage effect during the economic downturn caused by the Covid-19 pandemic. However, while much of the literature documents losses in firm wage premiums as an important mechanism (see, e.g., Gulyas and Pytka, 2020; Fackler et al., 2021; Schmieder et al., 2023), we rather find that in the course of the pandemic downward movements in occupational rank are an important driver of wage losses.

Second, our paper contributes to the narrower Covid-literature. In contrast to previous studies on the labour market effects of the Covid-19 pandemic from an aggregate perspective (Adams-Prassl et al., 2020; Cajner et al., 2020; Coibion et al., 2020; Forsythe et al., 2020), we extend an individual-level analysis to the longer term. Our findings of the strong effect of the Covid-19 pandemic on earnings losses in the first months is consistent with results from the individual-level analysis of Andersen et al. (2022). In their study of individuals who lost their job during March 2020 until August 2021 in Finland, they find that there is a significant drop in earnings in the first two months after becoming unemployed and earnings remain at a lower level. However, the authors are only able to follow unemployed individuals for a maximum of six months. Adermon et al. (2023) study the effects of the pandemic on earnings losses in Sweden until the end of 2021. In particular, by comparing earnings of individuals who were employed before the onset of the pandemic with the earnings of individuals of the previous years, they find that the pandemic has led to an earnings loss of 2.7%. The smaller earnings loss as compared to our estimates can be explained by the fact that Adermon et al. (2023) do not only focus on earnings of individuals who became unemployed but also consider individuals who stay in employment during the pandemic. In comparison to those two studies, our 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, as we concentrate only on individuals who became unemployed shortly before the outbreak of Covid-19. Moreover, we are able to dig deeper into the underlying mechanisms, such as employer or occupational switches, and to assess the pandemic-specific effect heterogeneity of occupations.

Thereby, we also contribute to the literature on the occupation-specific effects of the pandemic: 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. Similar to the findings in our 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 (2021) 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 occupational level, whereas this paper considers the individual perspective.

The unexpected occupation-specific change in employment prospects provides an interesting environment in which the jobs considered by the unemployed are affected differently. Since alternative occupations and related jobs that they would usually consider may also be affected, unemployed workers from occupations severely affected by lockdown restrictions must consider other options. In turn, job seekers might have redirected their search to occupations which are less affected (see, e.g., Hensvik et al., 2021; Bauer et al., 2023), but where they lack experience. However, Carrillo-Tudela et al. (2023), for instance, document that a large proportion of unemployed individuals also continued targeting declining occupations and industries during the pandemic. Fewer job offers and a potentially worse bargaining position might explain the documented wage losses due to the pandemic. In this way, our third contribution refers to the broader literature on outside options[1] by examining a situation in which the portfolio of suitable jobs changes exogenously and comes along with long-lasting labour market consequences.

This paper is structured as follows: Section 2 gives a short overview of the development

[1]For studies on the impact of information about job opportunities on job search see, e.g., Altmann et al. (2018); Belot et al. (2019); Gee (2019). For studies looking explicitly at outside options in the labor market see, e.g., Caldwell and Danieli (2024); Schubert et al. (2024) and for studies using worker flows to determine the size of the relevant labour market see, e.g., Manning and Petrongolo (2017); Nimczik (2023).

of the Covid-19 pandemic in Germany. Section 3 describes the data, the definition of the treatment and the control group as well as their comparability through inverse propensity score weighting. Section 5 analyses the effect of the pandemic on earnings, employment and wages and assesses potential mechanisms, while Section 6 evaluates whether the size of the effects differ between occupations depending on their LWA. Section 7 concludes.

2 The Covid-19 pandemic in Germany

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

Although the first Covid-19 case in Germany was registered on the 27$^{\text{th}}$ of January 2020, the beginning of the Covid-19 pandemic can be assigned to early March 2020, when the number of Covid-19 cases started to increase and the first social distancing measures were implemented. Officially, the pandemic ended in April 2023. During the beginning of the pandemic, the German economy was hit by the strongest shock since the financial crisis with 5% of employees losing their jobs and an earnings loss of 20% for workers who remained in employment (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. This scheme allowed firms to let their employees work fewer hours with the Federal Employment Agency partly covering the workers' wage loss, which helped to avoid additional layoffs.

In total, there were two strict lockdowns in Germany: the first lockdown was announced by the German government on the 16$^{\text{th}}$ of March 2020 and was implemented six days later, ending on the 4$^{\text{th}}$ of May 2020. The second lockdown lasted from the 2$^{\text{nd}}$ of November 2020 until the beginning of March 2021. Both lockdowns were similar in terms of restrictions regarding social distancing measures and closing of facilities.[2] These restrictions therefore affected occupations differently: while employees in occupations with high contact intensity or without the possibility to work from home were less likely to be able to work during the lockdown, employees in occupations of systemic relevance or with the possibility to work from home were more likely to be able to work.

The pandemic also had a negative impact on individual employment prospects, as demand for labour declined and the number of job seekers increased, especially among those occupations for which working from home was less possible. Panel (a) of Figure 1 shows the development of vacancies registered with the Federal Employment Agency between January 2017 and December 2022, while panel (b) shows the ratio of registered vacancies to unemployed job seekers.[3] Figure 1 presents the total series (black diamonds) as well as

[2] Shops, schools, businesses in hospitality, hairdressers and leisure facilities were closed, whereas facilities of systemic relevance such as pharmacies or supermarkets remained open. Additionally, the government implemented the obligation that all employees who were able to do so should work from home.

[3] Each series is shown in residualised form to account for seasonal fluctuation. Specifically, we regress each series on calendar year and month dummies and subtract the latter.

the series for occupations with a high lockdown work ability (LWA) (blue dots) and for occupations with a low LWA (red triangles). The LWA index, defined by Palomino et al. (2020), measures the possibility of a specific occupation to operate during a lockdown (see Section 3.2.2 for a detailed description). Occupations with a high LWA are, for example, occupations in the IT or healthcare services, while occupations in the hospitality or construction have a low LWA.

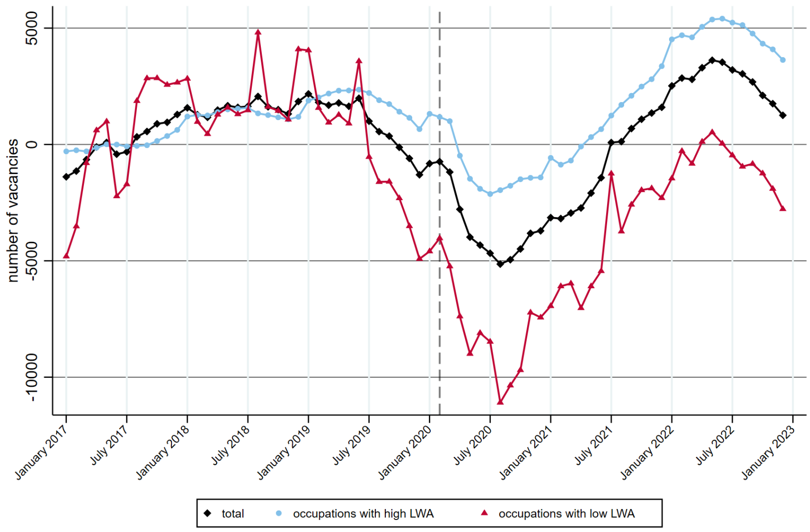
While during the onset of the Covid-19 pandemic between March and May 2020 the number of total vacancies as well as the vacancies to job seekers ratio fell sharply, the reduction was stronger for occupations with a low LWA in comparison to occupations with a high LWA. Even though vacancies subsequently started to recover and eventually exceeded their pre-pandemic level during the year 2022[4], the recovery was less pronounced among low-LWA occupations. The ratio of vacancies to job seekers, however, has also fully recovered for the low-LWA occupations. This upward trend is reversed from June 2022 which might be related to the Russian invasion of Ukraine and the ensuing effect on the global economy. Furthermore, it is noticeable that, despite fluctuations, the development of vacancies and the vacancies to job seekers ratio appears to have been quite similar for low-LWA and high-LWA occupations in the pre-pandemic years and only began to diverge in the second half of 2019. The pandemic, however, exacerbates this divergence which suggests that the differential development in labour market opportunities by occupational LWA does not only reflect a continuation of diverging pre-pandemic trends.

In conclusion, Figure 1 shows that the negative impact of the pandemic on employment prospects is concentrated at its onset and is less pronounced towards the following years. This development illustrates that the pandemic created (temporarily) unfavourable conditions for those searching for employment in the spring of 2020, especially for occupations with a low LWA. Hence, the Covid-19 pandemic may have led to longer periods of job search or a higher incidence of occupational mobility of individuals displaced from jobs in occupations with a lower LWA, which can be costly due to longer unemployment periods or human capital being only partly transferable (Gathmann and Schönberg, 2010).

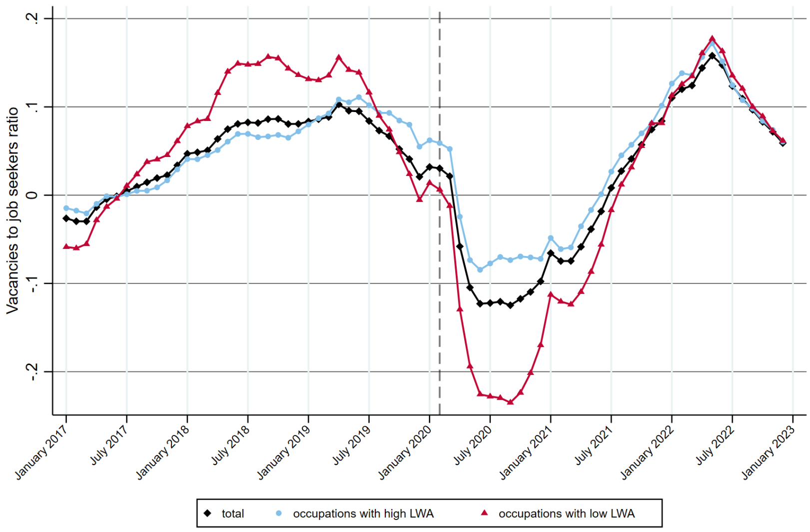
3 Data

This section begins with a description of the data source for our analysis and continues with a definition of the treatment and control groups. We then introduce the main outcome variables and the lockdown work ability index, which is used as a measure of treatment intensity in the second part of the paper. The section concludes with the balancing results for both groups, which are crucial for our identification strategy.

[4]During this period, governmental containment measures were gradually eased, for example by the reopening of hairdressers, gastronomy and schools.



(a) Vacancies



(b) Vacancies to job seekers ratio

Figure 1: The effect of the Covid-19 pandemic on vacancies and job seekers

Note: Figure 1 shows the development of registered vacancies (panel (a)) and the development of the ratio of registered vacancies to unemployed job seekers (panel (b)) in Germany. Both have been residualised to account for seasonal fluctuation. For this purpose, each series is regressed on dummies for calendar years and months and the estimated coefficients of the latter are then subtracted. The reference period is January 2017. Occupations with a low (high) lockdown work ability (LWA) correspond to the first (last) quartile of the (unweighted) LWA distribution across occupations. Note that for unemployed job seekers the targeted occupation is used for any occupational analysis.
Source: Federal Employment Agency, 2023.

3.1 Defining treatment and control group

The 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).[5] The IEB contains 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, skill and nationality), the data include not only daily information on employment relationships (e.g., job characteristics such as daily wage, marginal versus regular employment), and occupations, but also information on unemployment spells, participation in measures of active labour market policy or receipt of transfer payments. Detailed information on establishment characteristics such as industry, number of employees and place of work stem from the Establishment History Panel (BHP). We also have information on the total number of workers in short-time work in each establishment in each month based on records of the Federal Employment Agency.

To identify the effect of the Covid-19 pandemic on worker careers, the analysis focuses on individuals who became unemployed shortly before the start of the pandemic[6] and were therefore subsequently exposed to the economic shock. In particular, we consider individuals who became unemployed during the first half of February 2020[7] as the treatment group and compare them to a control group of individuals who became unemployed in the same month in 2017. Even though the first Covid-19 case was registered at the end of January 2020 in Germany, there had only been 18 confirmed cases with a Covid-19 infection by the end of February 2020 and (lockdown-)restrictions were not expected at that time. Hence, it is likely that firms did not anticipate the subsequent development of the pandemic and did not lay off their employees. Moreover, February 2020 is chosen rather than an earlier month to ensure that as many unemployed individuals as possible in the treatment group are exposed to the pandemic. Results using flows into unemployment from other months are discussed in Section 5.4.3.

Furthermore, the sample is restricted to individuals with a certain degree of labour market attachment, i.e. for whom becoming unemployed is likely to have an impact on their subsequent employment trajectory. In detail, we only retain those unemployed individuals who were employed at least from November in year $t-1$ to the 31[st] of January in year t in the same occupation and same establishment, so that the first possible day in unemployment is the 1[st] of February in year t (t refers to the year 2020 for the treatment group and 2017 for the control group). This restriction is similar to the restrictions in the

[5] IAB Integrated Employment Biographies (IEB) V17.00.00-202212. For a description of the IEB, see Oberschachtsiek et al. (2009).

[6] In this study, unemployed individuals 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.

[7] As the pandemic officially started in March 2020 following a rapid increase in infection rates and the imposition of containment measures, inflows into unemployment during that month may already have been due to the pandemic.

job displacement literature (see, e.g., Jacobson et al., 1993; Davis and von Wachter, 2011; Lachowska et al., 2020; Schmieder et al., 2023), according to which workers have to be in a stable employment relationship at the same employer. Focusing on individuals with a stable employment pattern ensures that unemployment represents a potentially severe disruption. In this way, we 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. Robustness checks with respect to the beginning of prior employment are discussed in Section 5.4.3. Further details on the construction of the sample are described in Appendix Section A.1.

In total, the sample consists of 66,199 individuals in the control and 66,070 individuals in the treatment group. Next, we aggregate the daily information to a panel of half-monthly periods ranging from September $t-1$ to December $t+2$.[8]

3.2 Variables

3.2.1 Main outcome variables

In our empirical analysis, we focus on the main outcome variables earnings, employment and wages. The administrative data allow use to record all relevant outcomes (and control variables) within each half-month period, so employment is measured as the number of days an individual is employed within a half-month period. Depending on the period, the maximum value of employment is between 13 and 16 days. Total employment comprises different forms of employment. We are, however, also able to compute the number of days in, for example, regular or marginal employment per period.

Information on the wage is only available as an average daily wage, as the IEB do not include information on hourly wages or working hours. Note that the wage for individuals who are not employed is set to missing, which means any analysis of wages is conditional on employment. Moreover, we deflate wages using the consumer price index as in Dauth and Eppelsheimer (2020). The consumer price index is additionally adjusted, since there were uncommonly high changes in the inflation rate between the years 2020 and 2021 and especially between 2021 and 2022. This, in turn, leads to a drop in the estimated wage development at the turn of the year from 2021 to 2022, as can be seen in Figure B14 in the Appendix. To avoid these jumps, which reflect changes in consumer prices rather than wage changes, we use the consumer price index from a single year to adjust the wages in the treatment and the control group, respectively. In particular, we use the index from 2017 to deflate wages after 2017 for individuals in the control group and the index from 2020 for wages after 2020 for individuals in the treatment group. Earnings are derived as the product of the number of days in employment in the respective half-month period and the daily wage. Individuals who are not employed or who leave the labour market in a given period receive earnings of zero.

[8]Monthly observations are distinguished by a "first half" which spans the period from the 1^{st} to the 15^{th} of each month and by a "second half" which spans the period from the 16^{th} to the end of each month. This results in a range of 13 to 16 days per period.

3.2.2 Lockdown work ability (LWA)

Since unemployed individuals face different labour market situations during the pandemic depending on the occupation in which they were previously employed in (as outlined in Figure 1), the extent to which the individuals are affected by the pandemic is captured by a treatment intensity, specifically the "lockdown work ability" (LWA) index for occupations proposed by Palomino et al. (2020). This index consists of three components: the possibility to work from home, whether occupations were considered essential or had to close during the lockdown. Thus, the LWA index has the advantage that it does not only consider the ability to work from home as a measure for how strongly an occupation is affected by the pandemic, but also takes into account whether people in an occupation were allowed to continue working during the pandemic. For example, some occupations, such as medical and health care occupations, offer only limited possibilities to work from home, but at the same time those occupations remained open during lockdown because of their systemic relevance. Using only a working from home index would therefore incorrectly measure the degree of occupational exposure to the pandemic. These components then form an index that ranges from zero (low LWA) to one (high LWA) for each occupation. For details on the construction see Appendix Section A.4.

3.3 Comparing treatment and control group

For the empirical approach, it is necessary that the treatment group is comparable to the control group regarding observable and unobservable characteristics. To ensure comparability, inverse propensity score weighting is used as a balancing procedure on pre-unemployment characteristics, which is explained in Appendix Section A.3 in further detail. The weighting variables include personal characteristics (e.g., age, skill and gender), job and firm characteristics (e.g., employment type, firm size, sector) as well as variables from the employment biography (e.g., duration in unemployment, experience). All of these variables are measured in the first half of November $t-1$, i.e. three months before the transition into unemployment, when, by definition, every individual in the sample is employed. Table A2 in the Appendix shows the full list of weighting variables and balancing tests. The estimation results based on different sets of characteristics included in the propensity score estimation are discussed in Section 5.4.

Table 1 shows selected descriptive statistics for treated (column (1)), weighted control (column (2)) and unweighted control individuals (column (3)) who became unemployed in the first half of February.[9] Additionally, in column (4) the standardised differences between the means of the treatment and weighted control group are displayed.[10]

As can be seen from Table 1, differences between individuals in the treatment and the control group are already relatively small before applying the weighting procedure, which

[9]Notice that the variables shown in Table 1 are not necessarily all used in the weighting procedure.

[10]The standardised difference is defined as $\Delta_X = \left(\bar{X}_1 - \bar{X}_0\right) / \left((S_1^2 + S_0^2)/2\right)^{0.5}$, where $\bar{X}_w$ is the sample mean of the treated ($w = 1$) or control ($w = 0$) individuals and S_w^2 are the respective sample variances.

suggests that the composition of the unemployed is comparable despite being three years apart. These differences, though, are further reduced after weighting. The standardised difference is relatively small and below the rule of thumb of 0.1 as suggested by Austin (2011), indicating that a balance between the treatment and the control group is achieved. For example, individuals in the treatment as well as in the (weighted) control group are, on average, 39 years old, around 60% are male and they are mostly middle-skilled.[11] Moreover, at the time of matching, 93% are in regular employment (i.e. they are employed subject to social security contributions) and 75% have experienced unemployment before.

While treatment and control group are balanced with respect to various worker and establishment characteristics, we find a difference in the (consumer price-adjusted) daily wage rate of approximately 4 €, which corresponds to a relative difference of around 5.6%. This finding may raise the concern that there are differences between both groups (even if the standardised difference is below 0.1). However, we argue that this difference predominantly reflects real wage growth that took place between the years 2016 and 2019 (see Appendix Section A.3.1). The absence of structural differences in the two groups' wages is also supported by the fact that measures of unobserved worker and firm quality, which are derived from an AKM wage decomposition (Abowd et al., 1999) on the basis on the full working population in Germany and the period from 1995 until 2019, do not show any significant differences. This suggests that individuals in the treatment and the control group differ neither with respect to unobserved worker quality nor to the unobserved quality of the firm at which they worked before becoming unemployed.

4 Empirical strategy

4.1 Estimation: baseline model

The empirical approach to identify the effect of the Covid-19 pandemic on the employment trajectories of newly unemployed individuals is to use a difference-in-differences (DiD) event-study design combined with inverse propensity score weighting. The idea behind this approach is that the pandemic was unexpected, so that individuals who became unemployed shortly before its onset were exposed to a sudden worsening of their labour market prospects compared to individuals who became unemployed three years earlier. It is crucial that the individuals entered unemployment *before* the beginning of the pandemic, because this ensures that any effects on labour market outcomes are only due to the subsequent exposure to the pandemic, which allows to identify the effect of the pandemic. We use the following model to estimate the effect of the pandemic on the labour market outcomes of newly unemployed individuals:

$$y_{i,p} = \alpha_i + \sum_{\tau \neq -1} \gamma_\tau I(\tau = p) + \sum_{\tau \neq -1} \beta_\tau I(\tau = p) I(D_i = 1) + \varepsilon_{i,p}. \tag{1}$$

[11] The skill groups are defined as follows: low-skilled individuals have no vocational degree, middle-skilled have a vocational degree and high-skilled have a tertiary degree (e.g., university degree).

Table 1: Descriptive statistics

	(1) Treatment	(2) Control (weighted)	(3) Control (unweighted)	(4) Standard. diff.
Socio-demographic characteristics (at the time of matching)				
Age	39.194	39.207	39.674	-0.001
	(12.422)	(12.258)	(12.259)	
Male (fraction)	0.612	0.613	0.592	-0.002
	(0.487)	(0.487)	(0.491)	
Foreign (fraction)	0.244	0.246	0.180	-0.005
	(0.429)	(0.431)	(0.384)	
Low skilled (no completed apprenticeship, fraction)	0.153	0.154	0.132	-0.003
	(0.360)	(0.361)	(0.339)	
Middle skilled (completed apprenticeship, fraction)	0.594	0.592	0.673	0.005
	(0.491)	(0.492)	(0.469)	
High skilled (tertiary education, completed)	0.172	0.171	0.148	0.001
	(0.377)	(0.377)	(0.356)	
Current employment (at the time of matching)				
Current wage	77.658	73.751	71.414	0.084
	(47.204)	(46.009)	(43.509)	
Current earnings	1,164.863	1,106.262	1,071.214	0.084
	(708.061)	(690.128)	(652.642)	
In regular employment (fraction)	0.933	0.930	0.928	0.012
	(0.250)	(0.255)	(0.258)	
In full-time employment (fraction)	0.654	0.652	0.657	0.003
	(0.476)	(0.476)	(0.475)	
Very small establishment (less than 10, fraction)	0.205	0.202	0.216	0.008
	(0.404)	(0.402)	(0.411)	
Small establishment (10-49, fraction)	0.303	0.302	0.287	0.001
	(0.459)	(0.459)	(0.453)	
Medium-sized establishment (50-249, fraction)	0.285	0.287	0.261	-0.004
	(0.452)	(0.452)	(0.439)	
Large establishment (more than 250, fraction)	0.201	0.203	0.169	-0.005
	(0.400)	(0.402)	(0.375)	
Estimated AKM firm effect	-0.157	-0.173	-0.186	0.059
	(0.264)	(0.263)	(0.261)	
Employment biography				
Work experience	11.961	11.757	12.357	0.021
	(10.098)	(9.723)	(9.532)	
Tenure in current establishment	3.017	3.072	3.186	-0.011
	(5.177)	(5.101)	(5.130)	
Tenure in current occupation	5.732	5.802	5.941	-0.010
	(7.164)	(7.201)	(7.153)	
Number of job changes	3.259	3.008	3.112	0.069
	(3.677)	(3.666)	(3.566)	
Being unemployed before (fraction)	0.759	0.752	0.779	0.016
	(0.428)	(0.432)	(0.415)	
Employed in manufacturing sector (fraction)	0.394	0.395	0.404	-0.002
	(0.489)	(0.489)	(0.491)	
Employed in service sector (fraction)	0.598	0.597	0.584	0.002
	(0.490)	(0.490)	(0.493)	
Estimated AKM worker effect	4.364	4.372	4.359	-0.022
	(0.376)	(0.373)	(0.353)	
N	66,070	66,199	66,199	

Notes: Columns (1) to (3) show the mean value and standard deviation (in parentheses) of individual characteristics that are measured at the first half of November $t-1$ (the point for the weighting). Column (4) reports the standardised difference between columns (1) and (2), which is defined as $\Delta_X = \left(\bar{X}_1 - \bar{X}_0\right) / \left((S_1^2 + S_0^2)/2\right)^{0.5}$, where $\bar{X}_w$ is the sample mean of the treated ($w = 1$) or (weighted) control ($w = 0$) individuals and S_w^2 are the respective sample variances. Note that the observations for the AKM worker and firm fixed effects are smaller than the reported number of observations. Not all shown characteristics, such as current wages, establishment size or AKM firm effects, are used in propensity score weighting. For the full list of propensity score weighting variables see Table A2 in the Appendix.
Source: IEB, BHP, own calculations.

$y_{i,p}$ is the outcome of individual i at time p, α_i is an individual fixed effect, accounting for differences in time-invariant unobservable characteristics between the treatment and the control group, D_i represents the treatment dummy which takes the value 1 if the individual became unemployed in February 2020 and is thus exposed to the pandemic (and 0 otherwise) and $\varepsilon_{i,p}$ is a random error term. p measures half-month periods and runs from -10 to 68, which means that the treatment group is observed from September 2019 until December 2022 and the control group from September 2016 until December 2019. For a fixed point in time τ, γ_τ is the average change in the value of the outcome variable for the control group relative to the reference period (conditional on fixed effects) and β_τ is the average difference in the change of this outcome between the treatment and the control group at that point in time. The inclusion of individual fixed effects ensures that identification of the parameter of interest, β_τ, is based on the within-variation in the outcome variables for treated and control individuals. In a dynamic setting, $\sum_{\tau>0}\gamma_\tau$ provides an estimate of the cumulative expected deviation of the outcome variable from its value at the reference period over the whole treatment period for individuals in the control group. In our DiD setting, this quantity provides the counterfactual change in the outcome for the treatment group if the pandemic had not taken place. Correspondingly, $\sum_{\tau>0}\beta_\tau$ shows by how much the cumulative deviations differ between the treatment and the control group. The latter quantity, therefore, provides a measure of the cumulative effect of the pandemic on the corresponding outcome. To support the assumption of a common trend, β_τ should be close to zero for $\tau < 0$. In the following section, we will use average measures computed over the whole treatment period as well as over different sub-periods to quantify the effect of the pandemic on different outcomes.

The first identifying assumption of our empirical approach is that from the perspective of the individuals, the Covid-19 pandemic and its timing were unforeseen. We therefore assume that becoming unemployed during the first half of February 2020 is not the result of strategic behaviour on the part of individuals.[12] The second identifying assumption is that the observed labour market trajectories of the control group provide a valid approximation of the counterfactual trajectories for the individuals of the treatment group that would have taken place had the Covid-19 pandemic not occurred. To provide support for this approach, we sample inflows into unemployment from the same month which should reduce compositional differences related to seasonal fluctuations. More importantly, we are able to show that, even without applying weighting, individuals in the treatment and the control group are already very similar with respect to the composition of observable individual, firm and job characteristics. Applying our IPW approach further reduces any differences between the two groups (see Section 3.3). Moreover, our event-study approach allows us to assess the existence of differences in outcome trends during the pre-unemployment period, which would be an indication that both groups were on different trajectories be-

[12] This contrasts, for example, with approaches taken in the literature on the consequences of entering the labour market during a recession, where individuals have discretion with respect to when they enter the labour market and thus may choose to delay entry to avoid unfavourable conditions (Kahn, 2010).

fore becoming unemployed. A potential challenge to identification is that individuals in the treatment group were exposed to less favourable labour market conditions - regardless of the Covid-19 pandemic - compared to individuals in the control group. Figure 1 shows that the worsening in labour market conditions already started setting in before the start of the pandemic. While this concern is not considered in our baseline event-study model, we explicitly address it in Section 5.4.1 and show that our estimated effects of the Covid-19 pandemic cannot be explained merely by a general worsening of labour market opportunities.

4.2 Estimation: heterogeneous effects model

An important feature of the Covid-19 pandemic is its occupational dimension which meant that some occupations could more easily adapt to lockdown conditions than others. The second part of the paper therefore addresses heterogeneous effects of the pandemic across occupations. The basic idea is that unemployed individuals face different labour market situations (during the pandemic) depending on the occupation which they were previously employed in and in which they are likely to search for reemployment. Based on the evidence in Figure 1, we expect that the adverse effects of the Covid-19 pandemic are more pronounced for individuals who used to work in occupations that are less suited to being carried out under lockdown conditions.

To asses these heterogeneous effects, Equation 1 is extended to a difference-in-difference-in-differences model which includes a measure of treatment intensity, the "lockdown work ability" (LWA) index proposed by Palomino et al. (2020). This index uses properties of occupations (such as the possibility to work from home and whether an occupation is defined as being essential) as a measure for how strongly an occupation is affected by lockdown restrictions. The extended model reads as follows:

$$\begin{aligned} y_{i,p} =& \alpha_i + \sum_{\tau \neq -1} \gamma_\tau I(\tau = p) + \sum_{\tau \neq -1} \beta_\tau I(\tau = p) I(D_i = 1) + \\ & \sum_{\tau \neq -1} \delta_\tau I(\tau = p) \overline{LWA^*}_{o(i)} + \sum_{\tau \neq -1} \phi_\tau I(\tau = p) I(D_i = 1) \overline{LWA^*}_{o(i)} + \varepsilon_{i,p} \end{aligned} \tag{2}$$

In particular, Equation 2 includes additional interactions with $\overline{LWA^*}_{o(i)}$ which varies by the occupation $o(i)$, in which individual i was employed before becoming unemployed. To ease the interpretation of the results of the empirical analysis, we first transform the LWA index by defining $LWA^* = 1 - LWA$, so that higher values indicate a lower lockdown work ability.[13] Second, we adjust the transformed variable by subtracting the mean over all occupations ($\overline{LWA^*}$), so that $\overline{LWA^*}$ takes a value of zero for occupations with the mean value of LWA.

[13]Our hypothesis is that workers who used to be employed in occupations with a lower LWA experienced greater (negative) effects from being exposed to the pandemic. After transforming the LWA variable, the estimated coefficients directly show the additional effect associated with a *reduction* in LWA.

The coefficients γ_τ and β_τ (and their sums) now represent the effects for individuals who used to work in occupations with a mean value of LWA. For a fixed point in time τ, δ_τ captures the effect of a marginal increase in the inverse LWA on the respective outcomes for individuals in the control group. ϕ_τ is the average difference between treated and control individuals for those who used to be employed in marginally more exposed occupations. We refer to this quantity as the excess effect of the pandemic as it measures by how much the effect of the pandemic is predicted to change for a marginal reduction in the LWA of an individual's pre-unemployment occupation. This quantity captures the heterogeneous effect of the Covid-19 pandemic. In a dynamic setting, $\sum_{\tau>0}\delta_\tau$ describes the cumulative deviation of outcomes from the reference period for individuals in the control group who were initially employed in marginally more exposed occupations, while $\sum_{\tau>0}\phi_\tau$ describes the cumulative differential development of outcomes between treated and control individuals initially employed in marginally more exposed occupations. Given the hypothesis that labour market opportunities for individuals who used to be employed in more exposed occupations are reduced more, we expect the adverse effects of the pandemic to increase in magnitude as LWA becomes smaller.

When estimating Equation 2, we use variation in the assignment of workers to occupations before becoming unemployed. While sorting into occupations is itself not random, we assume that selection into occupations in the treatment group was not driven by expectations concerning the heterogeneous effect of the pandemic on different occupations. Moreover, since the LWA is a continuous variable, Equation 2 has to fulfil stronger parallel trend assumptions (Callaway et al., 2024): Not only do the treatment and control groups have to display parallel trends on average, but also the trends of individuals from lower- and higher-LWA occupations have to be similar. Section 6.3.1 provides analyses on the validity of the stronger parallel trends assumption.

5 The labour market effects of the Covid-19 pandemic

In this section, the labour market effects of the Covid-19 pandemic on earnings and its two components, employment and wages, are investigated. In order to get a better understanding of the effects on employment and wages, potential mechanisms are further analysed.

5.1 Earnings

The estimated effects of the Covid-19 pandemic on earnings over time are shown in Figure 2. The horizontal axis measures event-time, where t indicates the year in which the transition into unemployment occurs. The dashed vertical line indicates the period in which individuals became unemployed (first half of February 2017 for the control group and 2020 for the treatment group). The vertical axis displays the estimated difference in the change in earnings at every point τ (relative to the reference period) between the treatment and the control group, $\hat{\beta}_p$ of Equation 1.

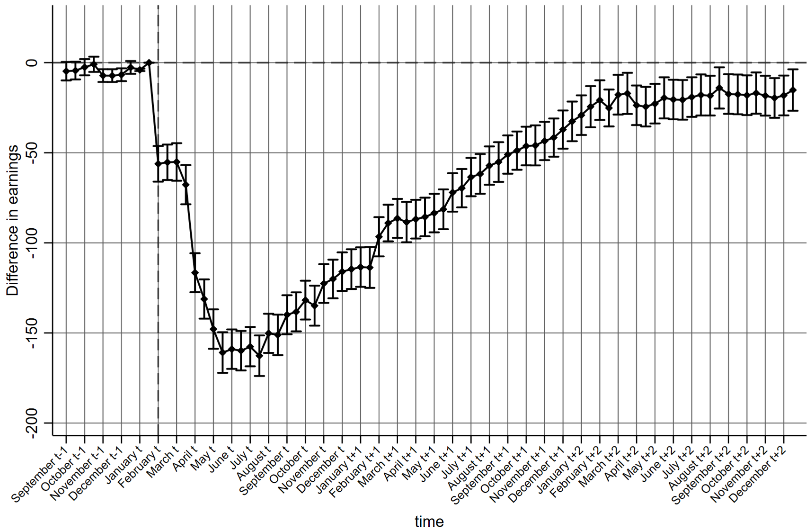


Figure 2: The effect of the Covid-19 pandemic on earnings

Note: Figure 2 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings as dependent variable. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence intervals which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

As can be seen in Figure 2, in the periods before the transition into unemployment the estimated coefficients for earnings are very similar for the treatment and the control group. Therefore, there seems to be no evidence for a differential development of earnings between the two groups leading up to the transition into unemployment. This, in turn, provides support for the hypothesis that the development of earnings of the treatment group would have been similar to the control group had the pandemic not occurred. At the moment of the transition into unemployment, there is a substantial drop in earnings for the treatment group relative to the control group. Since the pandemic sets in during the first half of March 2020 (March t), the difference between treated and control individuals might suggest that unemployed individuals in 2020 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. The negative effect reaches its maximum between June and July 2020 with an average earnings loss (relative to the reference period) of around 162 € 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 the earnings of newly unemployed individuals.

After remaining almost constant up to the end of July, the earnings gap between treated and control individuals starts to decrease steadily. However, earnings losses compared to the control group do not fully disappear by the end of the observation period. Column (1) of Table 2 depicts the estimated effects for earnings over different periods. In addition to the average effect over the whole period, Table 2 also shows the treatment effects averaged over five separate time periods: pre-pandemic (September 2019 to January 2020), from February to May 2020, from June to September 2020, from October to December 2020 and for the year 2021 and the year 2022. As can be seen, in 2022, the adjustment stops and an average earnings gap of about 20 € or 6.1%[14] still remains throughout the year. This suggests that the pandemic had a lasting negative earnings effect on those individuals who became unemployed shortly before its start. In total, the estimated cumulative earnings loss amounts to almost 4,900 € over the whole treatment period (70 periods meaning 35.5 months) or about 70 € per half-month. This translates into an average earnings gap of 15% ($\frac{-69.65}{-451.306}$).

Table 2: The effect of the Covid-19 pandemic on the main outcomes

	(1) Earnings	(2) Days in employ-ment	(3) Log wages	(4) Hypo-thetical earnings
Average				
Treatment period	-69.654***	-0.573***	-0.010**	-57.155***
	(4.871)	(0.033)	(0.005)	(3.906)
Treatment period ($\hat{\gamma}$)	-451.306***	-7.024***	0.052***	-519.439***
	(3.824)	(0.025)	(0.004)	(3.090)
Pre-treatment period	-4.015**	0.022***	-0.001	-2.100***
	(1.553)	(0.007)	(0.002)	(0.556)
Feb-May 2020	-98.829***	-0.731***	0.003	-94.035***
	(5.010)	(0.030)	(0.006)	(4.681)
Jun-Sep 2020	-152.317***	-1.705***	-0.001	-147.438***
	(5.412)	(0.042)	(0.005)	(4.876)
Oct-Dec 2020	-123.294***	-1.300***	-0.009*	-116.238***
	(5.425)	(0.044)	(0.005)	(4.805)
2021	-68.779***	-0.533***	-0.017***	-48.833***
	(5.203)	(0.039)	(0.005)	(4.224)
2022	-19.838***	0.000	-0.011**	-8.318**
	(5.398)	(0.039)	(0.005)	(4.132)
Cumulative				
Treatment period	-4,875.759***	-40.079***	-0.719**	-4,000.820***
	(340.975)	(2.289)	(0.332)	(273.441)
N	10,583,520	10,583,520	6,747,890	10,583,520

Notes: Table 2 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1, with earnings, days in employment, log wages (conditional on employment) as well as hypothetical earnings as the dependent variable. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\beta}_p$ for specific time periods, the (treatment) effect averaged over the whole period and the baseline estimate for the control group averaged over the whole period ($\hat{\gamma}$). Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

Earnings depend on employment as well as on wages, implying that a reduction in

[14] Average earnings loss in 2022: $\frac{-19.84}{-324.379} = 0.061$, where 324.379 is the average earnings loss for the control group in 2022.

earnings can be due to a reduction in employment or a reduction in wages, or both. Therefore, the question arises to what extent the observed earnings loss can be ascribed to reductions along these two margins. To answer this question, the following section will analyse the effect of the Covid-19 pandemic on employment and wages.

5.2 Employment and wages

One explanation for the earnings loss is a reduction in employment. To evaluate the impact of the Covid-19 pandemic on employment, Equation 1 is estimated using the number of days in employment as the dependent variable.[15] Analogously to Figure 2, panel (a) of Figure 3 shows the corresponding effects on days in employment. The Covid-19 pandemic significantly reduced the number of days in employment among the treatment group relative to the control group. The effect is most pronounced between May and July 2020. This development is similar to the evolution of earnings, though employment recovers faster than earnings and reaches the same level as the control group towards the beginning of 2022. In total, the treated individuals experienced, on average, a loss of about 40 days in employment over the treatment period compared to the control group, which corresponds to a loss of almost 0.6 days per half a month (see column (2) of Table 2). Thus, the Covid-19 pandemic has, on average, increased the loss in employment by about 8.2% ($\frac{-0.573}{-7.024}$) compared to the control group.

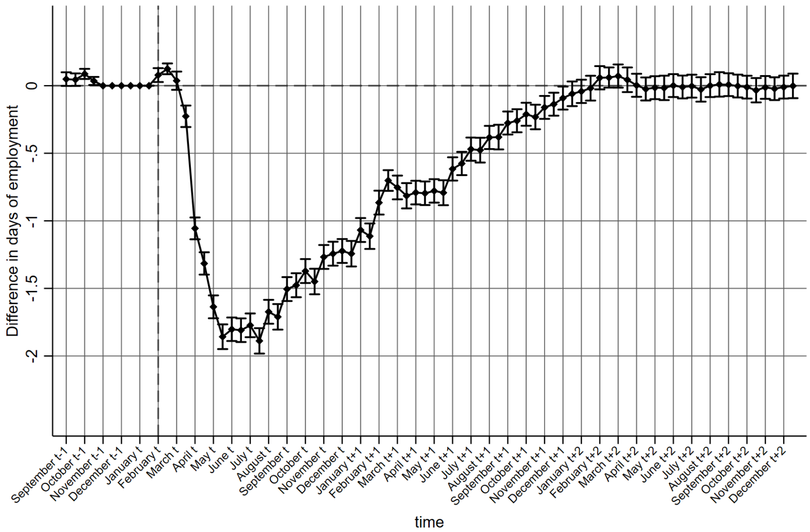
Wages, in contrast, do not follow the same downward trend at the onset of the pandemic, as can be seen from panel (b) of Figure 3.[16] Instead, the wage effects fluctuate in sign during the first weeks following the transition into unemployment before turning positive between April and June 2020. Subsequently, the coefficient estimates steadily decrease in magnitude, turning negative in August 2020, leading to a significant wage penalty in 2021, before stabilising at a level of an average wage loss of 1.1% in 2022 (see column (3) of Table 2). These findings suggest that, in the longer run, the Covid-19 pandemic significantly reduced wages and that this loss contributed to the reduction in earnings.

Before examining the role of employment and wages in explaining the earnings loss in more detail, the temporary increase in wages has to be explained. This increase can be attributed to a positive selection of individuals in the treatment group who quickly find new employment. In normal times, some individuals stay unemployed, while individuals with higher wage potential are over-represented among those who find employment more quickly. The pandemic and the resulting worsening of labour market conditions reduced the number of reemployed individuals to those with even higher wage potential. We assess this selection into employment by using the estimated worker fixed effects from the AKM wage decomposition: Figure B3 in the Appendix depicts the development of the estimated AKM worker fixed effects.[17] For the period from April to June 2020, which coincides with

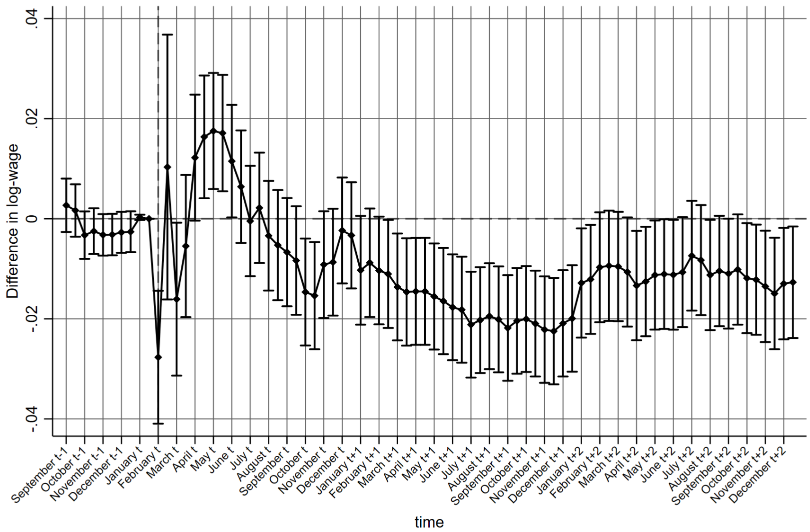
[15] If a person is not employed, the employment variables take on a value of zero.

[16] Wages are conditional on employment. Estimation of the wage effects is therefore restricted to those observations where individuals are employed for at least one day during a half-month period.

[17] The results are derived from using the estimated AKM worker fixed effects as the dependent variable



(a) Days in employment



(b) Log wages

Figure 3: The effect of the Covid-19 pandemic on employment and wages

Note: Figure 3 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with days in employment (panel (a)) and log wages (panel (b)) as dependent variables. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence intervals which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

the positive wage effects in panel (b) of Figure 3, the average AKM worker fixed effect is significantly higher in the treatment group than in the control group (relative to the period before becoming unemployed). This suggests that selection of individuals with higher unobserved wage components among the treatment group are likely to explain the temporary wage increase. Note, that the positive and significant impact on the AKM worker fixed effect disappears in later periods which indicates that selection into employment is unlikely to explain wage differences in the longer run.

To get a deeper understanding of the relative contributions of employment and wages to the earnings losses, we perform two analyses. First, we compare the developments of earnings and "hypothetical" earnings. Second, we conduct a formal decomposition of earnings losses into an employment, a wage and a covariance component based on the corresponding analysis in Schmieder et al. (2023).

Hypothetical earnings are computed by holding the wage constant to the pre-pandemic value of November $t-1$ (as observed in period $p = -6$) and multiplying it with the observed days in employment for all observations in the treatment and the control group. This implies that changes in the hypothetical earnings variable can be ascribed to changes in employment. The results from estimating Equation 1 using hypothetical earnings as the dependent variable can be seen in column (4) of Table 2. The closer the coefficient estimates of earnings and hypothetical earnings are, the larger the part of the reduction in earnings among the treatment group that can be ascribed to a reduction in employment (vis-á-vis the control group). In contrast, a gap between the two coefficient estimates would indicate that the reduction in earnings is due to changes in wages. Comparing columns (1) and (4) of Table 2 shows that throughout 2020 the average effects of the pandemic on earnings and hypothetical earnings are close to each other. Specifically, the effect on hypothetical earnings amounts to about 95% of the effect on earnings in each of the three periods in 2020, indicating that a reduction in employment drives the reduction in earnings.

However, from 2021 onward, the estimated effects start to diverge more substantially: the ratio of the two average effects amounts to about 71% in 2021 and falls to 42% in 2022. The reduction in the explanatory share of the earnings losses that can be ascribed to employment losses mirrors the development shown in Figure 3. While the employment penalty experienced by the treatment group is steadily decreasing in size through 2021 and is close to zero in 2022, the wage penalty increases in size and remains negative in 2022. This leads to the conclusion that earnings losses are mainly explained by a reduction in employment during 2020, but as the subsequent recovery of employment is much faster than that of earnings, a greater part of the earnings loss can be ascribed to wage losses during the years 2021 and 2022.

The results of the formal decomposition of the earnings loss into the part related to employment, the part related to wages and the part related to the covariance between

in the estimation of Equation 1. As the AKM effects do not vary over time, the individual fixed effects have to be dropped from the model.

employment and wages is displayed in Figure B4 in the Appendix. Following (Schmieder et al., 2023), the analysis is restricted to employed individuals, which means that the coefficient estimates of earnings differ from the development of actual earnings in Figure 2. By comparing the size of these effects in 2020, it can be concluded that employed individuals experienced a smaller earnings loss of about 40 €, on average, than employed and unemployed individuals together who experience a loss of about 130 €. The results of this decomposition indicate that only for a short period immediately after the transition into unemployment a large share of the decrease in earnings is the result of extensive-margin employment losses. Throughout the following period, though, the loss in earnings is mainly due to wage reductions. Employment as well as the covariance component do not play a substantial role in explaining earnings losses. Therefore, for employed individuals, the development of earnings is mostly explained by wages.

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., 2023), which provide 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% (Couch and Placzek, 2010), 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 10 to 20% still remains even five years after displacement (see, e.g., Jacobson et al., 1993; Davis and von Wachter, 2011; Lachowska et al., 2020; Schmieder et al., 2023). Although the evolution of the earnings loss is comparable, the size of the effect in the job displacement literature is substantially higher than in this paper. However, it has to be kept in mind that in this literature displaced workers are compared to a group of individuals who remain employed, whereas in this paper the unemployed of the treatment group are compared to another cohort of unemployed individuals. Our findings are also in line with the job displacement literature regarding the driving factors of earnings: employment and wages. The observed earnings loss can be attributed to a decline in employment in the short run. While employment quickly recovers to the level of the corresponding control group, the remaining loss of earnings is due to a longer-lasting wage reduction.

Two questions now arise: what is behind the decrease in employment and what is the reason for the longer-run reduction in wages? In the following, potential mechanisms behind these developments will be discussed in further detail.

5.3 Mechanisms

5.3.1 Employment

Especially, in its beginning, the Covid-19 pandemic led to a substantial decrease in employment. Figure B5 and Table B6 in the Appendix provide further information on the different labour market states that are responsible for the longer period of non-employment. Two conclusions can be drawn: First, the Covid-19 pandemic led to a shift into unemployment.

This effect is more pronounced at the onset of the Covid-19 pandemic[18] and diminishes around the end of 2020. Over the whole period, the unemployment effect, on average, amounts to 0.8 days per half a month and 58.4 days over the whole sample period. Second, the effect on leaving the labour market or being in other labour market states such as participating in a measure of active labour market policy or being on benefit receipt is first negative, but quickly adjusts to the level of the control group. Consequently, the flip-side of the pandemic's negative effect on employment is an increase in time spent unemployed rather than exiting the labour market or taking part in a policy measure.

5.3.2 Wages

The previous section has shown that the pandemic led to negative and significant wage effects throughout 2021 and, partly, 2022. The purpose of this section is to assess possible mechanisms behind these wage losses which are based on evidence from the displacement literature: (i) occupational mobility (**?**), (ii) moving to lower-paying occupations, firms or sectors (Schmieder et al., 2023), (iii) the loss of firm-specific wage premia (Fackler et al., 2021), (iv) finding employment further down the occupational wage distribution (Blien et al., 2021) and (v) downgrading to lower-paying forms of employment, such as part-time employment (Farber, 2017). We evaluate the role of these mechanisms in two ways: First, we estimate Equation (1) separately using a measure of each of these mechanisms as the dependent variable. The results of these estimations are summarised in Table 3, while the event-study plots can be found in Figure B6 in the Appendix. Second, we take into consideration that these measures are correlated and conduct a Gelbach-decomposition (Gelbach, 2016) to quantify the relevance of each measure for the pandemic-induced wage losses.

According to **?**, the costs of job loss can be primarily ascribed to finding a new job in a lower-quality occupation. In a first step, we therefore assess whether the pandemic has led to increased occupational mobility. Column (1) of Table 3 shows the estimated effects on the probability of being employed in a different 2-digit occupation compared to the occupation prior to unemployment. Over the treatment period, the pandemic has increased the probability of being employed in a different occupation by about 3.1 percentage points per half-month period. This effect is statistically significant and implies that the probability of working in a different occupation is about 6% ($\frac{0.031}{0.497}$) greater among the treatment group than the control group. Moreover, the size of this effect appears to be roughly constant throughout the whole treatment period, which suggests that moving to a different occupation is unrelated to the fact that finding employment is initially more selective among the treatment group (see panel (a) of Figure B3 in the Appendix and the discussion in Section 5.2).

Moving to a different occupation by itself provides no information about the wage that

[18]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, individuals in the treatment group can also be one more day unemployed compared to individuals in the control group.

individuals can expect to earn in their new occupation. To further assess whether the pandemic has led to reallocation towards better- or lower-paying occupations, we show, in a second step, results for the time-invariant occupational mean wage in column (2) of Table 3.[19] Since the mean wage does not change over time within the treatment and the control group, the results exclusively reflect changes in the allocation towards occupations between workers in the treatment and the control group.

Throughout the whole treatment period, the pandemic induces reallocation to higher-paying occupations. Individuals in the treatment group tend to be employed in occupations that pay a mean wage that is higher by about 0.8 percentage points, on average, than among individuals in the control group. This effect is relatively large as it implies that the average change in the occupational mean wage is greater by more than 70% ($\frac{0.008}{0.011}$) compared to the change in the occupational mean wage for individuals in the control group. Thus, these results suggest that the wage losses experienced by the treatment group are not due to reemployment in lower-paying occupations during the pandemic. To better understand the type of occupations in which individuals find employment again, panel (a) of Figure B.13.3 in the Appendix shows the estimated coefficients with LWA as the dependent variable. The results suggest that treated individuals are more likely to be employed in an occupation with a higher LWA than control individuals. This finding is consistent with the evidence presented earlier that a decrease in the number of vacancies in low-LWA occupations negatively affected the prospects of finding a new job in these occupations.

We evaluate the question of reallocation along two further dimensions in columns (3) and (4) of Table 3, where we show results for the mean wage by firm and by sector. These results are less clear-cut than in the case of occupational mean wages. During the year 2020, the pandemic appears to have led to reallocation towards better-paying firms and sectors. A possible explanation for this is that individuals in the treatment group who find a job are initially positively selected compared to the control group, as evidenced by the higher AKM worker fixed effect. If there is positive assortative matching between workers and firms in the labour market, as recent evidence suggests (Dauth et al., 2022), one would expect higher-quality workers to be working at better-paying firms or sectors. In the longer run, the point estimate turns negative and, in most cases, statistically significant indicating that the pandemic eventually led to a reallocation towards lower-paying firms and sectors.

[19]Mean wages for occupations, firms and sectors are computed from the universe of employees using data from 2016 (control group) and 2019 (treatment group), respectively. Choosing these years ensures that mean wages are not affected by pandemic-induced mobility. Columns (1)-(6) of Table B7 in the Appendix show the corresponding results when mean wages are computed from either the year 2016 or 2019 for both groups. For the firm-level mean wage, the estimated coefficients are partly larger in magnitude when mean wages refer to the year 2019, but otherwise the results are are very similar to those shown in Table 3.

Table 3: Wage adjustments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Mean wage				Downgrading		
	Occupational mobility	Occupation	Firm	Sector	AKM firm effect	Occupational rank	Marginal	Part-time
Average								
Treatment period	0.031***	0.008***	-0.000	-0.005***	-0.003*	-1.178***	-0.004***	0.009***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.165)	(0.001)	(0.003)
Treatment period ($\hat{\gamma}$)	0.497***	0.011***	0.018***	0.005***	-0.000	2.136***	0.051***	-0.014***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.124)	(0.001)	(0.002)
Pre-treatment period	0.001	0.000	0.001**	0.001***	0.000	-0.149**	0.000	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.058)	(0.000)	(0.000)
Feb-May 2020	0.034***	0.008***	0.024***	0.010***	0.008***	-0.864***	-0.008***	0.005
	(0.004)	(0.002)	(0.004)	(0.003)	(0.002)	(0.186)	(0.002)	(0.003)
Jun-Sep 2020	0.031***	0.008***	0.013***	0.005*	0.003	-1.017***	-0.007***	0.005
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.180)	(0.001)	(0.003)
Oct-Dec 2020	0.031***	0.008***	0.007*	-0.001	-0.002	-1.273***	-0.008***	0.004
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.179)	(0.001)	(0.003)
2021	0.032***	0.009***	-0.006	-0.010***	-0.007***	-1.740***	-0.006***	0.009***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.177)	(0.001)	(0.003)
2022	0.029***	0.006**	-0.010**	-0.011***	-0.006***	-0.750***	0.002	0.012***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.186)	(0.001)	(0.003)
N	6,747,890	6,715,320	6,177,056	6,655,717	5,754,885	6,715,320	6,747,890	6,747,890

Notes: Table 3 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with occupational mobility, occupational mean log wage, sector mean log wage, firm mean log wage, AKM firm fixed effects, rank in the occupational wage distribution, downgrading from regular into marginal employment as well as downgrading from full-time into part-time employment as dependent variables. All variables are conditional on employment. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\beta}_p$ for specific time periods, the (treatment) effect averaged over the whole period and the baseline estimate for the control group averaged over the whole period ($\hat{\gamma}$). Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

Additionally, treated individuals do not only tend to move to lower-paying firms but also to firms that pay a lower wage premium. Column (5) of Table 3 reports results for the AKM firm effects: especially in the years 2021 and 2022, the pandemic led to a reallocation of workers to firms offering significantly lower wage premia. Overall, the findings in columns (3) to (5) suggest that changes in the composition of firms and sectors which workers are employed at after entering unemployment, may explain part of the negative wage effects in the longer run, whereas the pattern of reallocation across occupations appears to be at odds with the estimated wage effects.

To shed further light on the reallocation to higher-paying occupations, we analyse the implications for an individual worker's wage, as workers do not necessarily receive the occupational mean wage. It is possible that due to the loss of occupation-specific human capital or the deterioration of bargaining positions due to the reduced labour market tightness individuals find new jobs further down the occupational wage distribution. To evaluate this, we use the universe of employees to, first, compute wage distributions for each 2-digit occupation in a reference year and to, second, identify the percentile of each worker's job in the occupational wage distribution.[20] The results in column (6) of Table 3 show that, while the pandemic led to reallocation to higher-paying occupations, it also pushed treated individuals further down the occupational wage distribution. Over the whole treatment period, the average change in the position in the occupational wage distribution is about 1.2 percentage points lower than in the control group per half-month period, while larger effects are observed especially for the year 2021.

The question now arising is whether these losses in the occupational wage rank can be attributed only to those individuals who change occupation or whether they are also found among individuals who remain in their occupation. To this end, we estimate the effect of the pandemic on log wages, occupational mean wage and occupational wage rank separately for individuals who in January 2022 are employed in a different occupation ("movers") and those who are employed in the same occupation ("stayers").[21] The event-study plots for occupational movers and non-movers are shown in Figure B7 in the Appendix. As can be seen, the wage losses and losses in the occupational wage rank are more pronounced for occupational movers which suggests that this group mainly drives the negative effect on wages. The positive effect on the occupational mean wage can also be attributed to movers.

Finally, we investigate whether the negative wage effects might be related to downgrading into lower-paid forms of employment. Column (7) of Table 3 shows results for downgrading into marginal employment which is often paid at the minimum wage level (Minimum Wage Commission, 2023). The dependent variable takes the value one if the

[20] The occupational wage distribution is computed by using data from November of the years 2016 and 2019 for the control group and the treatment group, respectively. Results when either 2016 or 2019 is used to compute the distribution for treatment as well as control group can be found in columns (7) and (8) in Table B7

[21] We choose the year 2022 as at this point the positive selection of employed individuals among the treatment group is no longer observable, while there is a negative wage effect of the pandemic.

person is now marginally employed and was initially regular employed and zero otherwise. The results reveal that downgrading into marginal employment is, on average, less likely for the treatment group. The effect is more pronounced during 2020, indicating that those individuals who quickly find a job after the onset of the pandemic remain in the same employment type or are able to leave their marginal employment relationship and transition to regular employment. However, this effect disappears in 2022. By contrast, results in column (8) show that the probability for downgrading into part-time employment (after initially holding a full-time job), is, on average, more likely among the treatment group, especially during the years 2021 and 2022.

Each of the variables shown in Table 3 represents a potential explanation for the documented wage loss among individuals in the treatment group compared to the control group. A limitation of the analysis is, however, that it does not account for the potential correlation between the different variables. For example, a firm's mean wage may be relatively low because its workforce consists predominantly of occupations that have a low average wage.

To quantify the contribution of the different variables shown in Table 3 towards the wage loss among the treatment group, we follow Schmieder et al. (2023) and estimate an extended baseline model where we include these variables as additional control variables. We expect that if these variables are relevant for explaining the wage loss among treated individuals, their inclusion in the wage model should reduce the size of the estimated coefficients $\hat{\beta}_p$ in Equation (1). In contrast to Schmieder et al. (2023), we choose not to estimate several models with different combinations of additional control variables, but instead estimate a single model that contains all additional control variables and then perform a decomposition based on Gelbach (2016) to estimate the contribution of each variable to the change in the estimated coefficients of the baseline compared to the model with the additional control variables. Further details on the decomposition can be found in Section B.5 in the Appendix.

Figure 4 shows the decomposition based on Gelbach (2016). In particular, it displays the difference between the estimated coefficients, $\hat{\beta}_p$, from the baseline model and the model including the additional control variables (black line). The fact that this difference is mostly negative illustrates that the inclusion of the additional control variables reduces the magnitude of the estimated effects of the pandemic.

Moreover, Figure 4 shows the contribution of the different control variables to this difference. It provides three insights: First, at the beginning of the pandemic the contribution of occupational mobility and marginal employment is positive. This is in line with the results of Table 3 that individuals who lost their job shortly before the start of the pandemic were less likely to take up a new job in marginal employment for most of the sample period and that observed occupational mobility among the treated put upward pressure on the wages of the treatment group compared to the control group. Second, the excess wage loss of the treatment group can almost exclusively be attributed to the fact that the change in the position in the occupational wage distribution was less favourable among the treatment than the control group. Up to the end of year 2021, the contribution of the occupational rank variable is more negative than the estimated difference between the baseline model and the extended baseline model, which suggest that part of the negative consequences of taking up lower-paying jobs within occupations is partly compensated by moving to occupations that pay more on average and a lower incidence of marginal employment. However, towards the end of 2022 the contribution of marginal employment takes on an increasing share in explaining the wage loss. While changes in jobs *between* occupations contributed positively to the wages of treated individuals (relative to the control group), changes in jobs *within* occupations contributed negatively. This is consistent with the results shown in Table 3 that the change in the occupational rank developed significantly less favourably in the treatment than the control group. Third, differences in the incidence of part-time work as well as taking up employment in firms with different mean wages do not contribute to the difference in the estimated average wage effects of the treatment and the control group, ceteris paribus. This suggest that the negative and significant effects that are shown in Table 3 for these two variables are likely to reflect correlation with the other variables in Table 3.

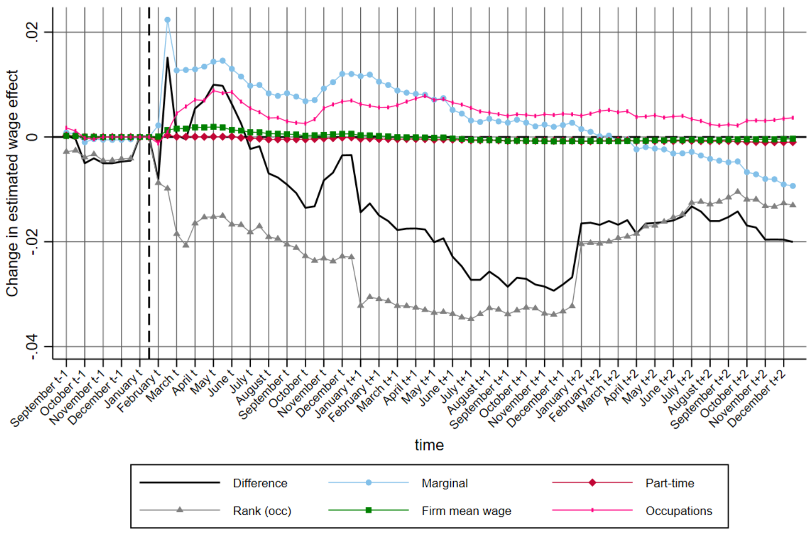


Figure 4: Decomposition of the wage effect

Note: Figure 4 shows the change in the estimated wage effect when additional control variables are added to the baseline model of Equation 1 (solid line). Moreover, it shows how much each additional control variable (or set of control variables) contributes to this change: downgrading into marginal employment (circles), downgrading into part-time employment (diamonds), rank in the occupational wage distribution (triangles), firm mean wage (squares) and occupation dummies (X). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019.
Source: IEB, BHP, own calculations.

5.4 Robustness

5.4.1 Pre-pandemic weakening of the labour market

The underlying assumption of our empirical DiD model is that in absence of the pandemic the average outcomes for the treatment and the control group would developed along the same path. One concern might be that the post-unemployment development of the outcomes of the control group is not a good approximation of the counterfactual development of the treatment group due to changes in aggregate labour market conditions. Specifically, the increasingly slack labour market that is already visible before the start of the pandemic in the form of a declining number of vacancies and the ratio of the vacancies to job seekers in Figure 1 might hint at less favourable labour market conditions, even if the pandemic had not occurred.

To address this concern, we conduct a linear extrapolation of the treatment effects that are based on a rolling set of treatment and control groups. If there is a steady worsening of labour market conditions, we would expect that the post-displacement outcomes of newly unemployed individuals become less favourable over time. Linear extrapolation of this development then provides an estimate of the counterfactual scenario if the pandemic had not occurred. To do this, we first estimate Equation (1) over a one-year window separately for three cohorts, c, of matched individuals who became unemployed during the first half of February 2017, 2018 and 2019 (treatment group) or 2016, 2017 and 2018 (control group). Regressing the estimated coefficients β_p^c on a linear trend and extrapolating this by one year, yields the estimate of the counterfactual scenario that captures the gradual worsening of labour market conditions. Finally, these values are compared to the coefficient estimates for one year only from estimating the model using the newly unemployed individuals from the year 2020 (treatment group) and 2019 (control group).

The results of the extrapolation are presented in Figure B8 in the Appendix. The main finding for earnings and employment is that although a part of the negative effects can be ascribed to a worsening of the labour market, the extrapolation does not pick up the sharp drop that occurred shortly after the start of the pandemic. For wages, the estimated counterfactual is relatively close to the estimated effects of the pandemic. However, as can be seen in panel (b) of Figure 3, the wage effects are negative mainly during the years 2021 and 2022. A detailed description of the extrapolation can be found in Appendix Section B.6.

5.4.2 Short-time work

Short-time work schemes were heavily used in Germany, as well as in other countries, to buffer the pandemic's adverse impact on employment (Giupponi and Landais, 2022). Since the incidence of short-time work was minimal in the years preceding the start of the Covid-19 pandemic, one concern is that the estimated differences in the employment trajectories of treatment and control group are related to the use of short-time work schemes. For example, the negative earnings and wage effects might reflect the fact that short-time work schemes typically do not provide a full compensation of the wage loss due to reduced working hours.

While we have no information about whether and to what extent an individual worker was placed on short-time work, we have information about whether establishments used short-time work at a monthly level. Consistent with our expectation that short-time work is far less relevant for the control group than the treatment group, we find that 28% of the individuals in the treatment group were employed at least once at firms that used short-time work over the whole treatment period compared to only 2% of individuals in the control group.

To assess the impact of short-time work on our results, we create an additional sample that only includes individuals who were never employed at an establishment that used short-time work. As shown in Figure B9 in the Appendix, we also find negative effects on all three outcomes - earnings, employment and wages - and qualitatively similar developments among those individuals who never worked at establishments that used short-time work schemes. This implies that the less favourable development of the employment trajectories among the individuals of the treatment group are not entirely due to the use of short-time work.

5.4.3 Other robustness checks

We present the results of additional robustness checks in the Appendix. These refer to the estimation sample, the inverse propensity score weighting and the inflation adjustment.

Sample. The results in the paper are based on individuals who became unemployed during the first half of February after being continuously employed from at least November. We also estimate the effects on earnings, employment and wages using samples that are based on different requirements concerning the prior duration of employment, the later transition into unemployment in the second half of February and a longer duration in unemployment. Figures B10, B11 and B12 show similar results as in the baseline specification.

Weighting. Our IPW approach uses a broad set of control variables for the estimation of the propensity score including socio-demographic, employment biography, job and firm characteristics. We show that the effects on earnings, employment and wages are qualitatively similar, but larger in magnitude when no weights are used. Moreover, we show that when smaller sets of control variables are included in the propensity score estimation, the results fall between those obtained from models without weights and those from the baseline specification. Results are shown in Figure B13.

Inflation adjustment. The consumer price index that we use for the inflation adjustment of wages increases considerably in 2022 compared to the previous years. Moreover, no comparable increase applies to the control group. Applying the actual consumer price index leads to substantially larger negative effects on wages for the treatment group, which, however, mainly reflect a reduction in purchasing power. For this reason, we apply the index from the year 2021 (2018) for all years in which the treatment (control) group is observed. For completeness, we show the results on wages when the actual consumer price index is used in Figure B14.

6 Occupation-specific effects of the Covid-19 pandemic

The results in Section 5 provide evidence that the Covid-19 pandemic led to an increase in the costs of being unemployed in terms of earnings, employment and wage losses. Besides, occupations are differently affected by the pandemic. Therefore, in this section, we investigate whether and to what extent the effects of the pandemic differ between occupations. Specifically, this is done by comparing the effects for individuals who used to be employed in occupations with different degrees of LWA, as outlined in Section 4.2. We assess the differences in the impact of the pandemic on the three main outcomes (earnings, employment and wages) along the LWA distribution based on the estimation of Equation 2 and evaluate whether differences in effect sizes also reflect differences in the relative importance of the underlying mechanisms.

To uncover effect heterogeneity by the LWA of a worker's previous occupation, we use LWA as a continuous treatment variable. To support the validity of this approach, we show that individuals in the treatment and control group are well-balanced along the occupational LWA distribution (see Table A5 in the Appendix). Moreover, we also estimate our baseline model (Equation 1) separately for workers who used to be employed in occupations with different degrees of LWA. The event-study plots can be found in Figure B15 in the Appendix. Crucially, the ordering of the effect sizes is consistent with the results that we obtain from estimating Equation 2.

6.1 Earnings, employment and wages

Table 4 summarises the results of estimating Equation (2) for the three main outcomes in two different ways. Odd-numbered columns show $\hat{\phi}_p$, i.e. the change in the effect of the pandemic that is associated with a reduction in the LWA of the occupation that a person was initially employed in by 0.1 units. To better illustrate its magnitude, even-numbered columns report the additional effect associated with a reduction in LWA by 0.1 units relative to the effect estimated for individuals who used to be employed in an occupation with a mean LWA ($\frac{\hat{\phi}_p}{\hat{\beta}_p}$).[22] The event-study plots showing $\hat{\phi}_p$ can be found in Figure 5.

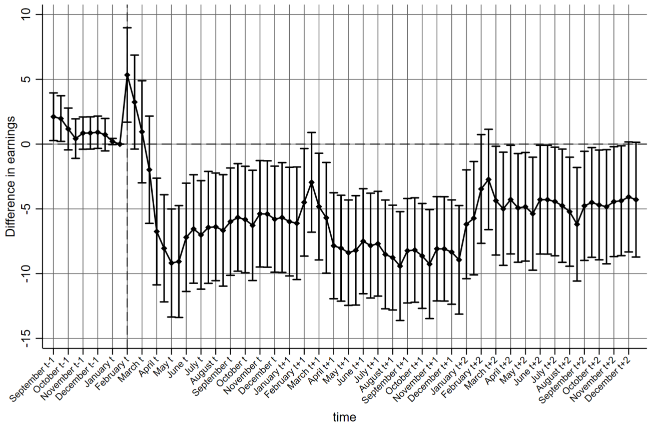
Taking heterogeneity by occupations into account reveals that individuals who used to be employed in occupations with a lower LWA experience long-lasting and statistically significant additional earnings loss. According to column (1) of Table 4, a reduction in LWA by 0.1 units is predicted to increase earnings losses, on average, by 7.91 € per half-month or by about 553.86 € over the whole treatment period. Column (2) shows that

[22] We provide descriptive statistics of the LWA variable in Table A3 in the Appendix, which can be used to compute the size of the additional effect for other changes in the LWA of a worker's initial occupation, such as the standard deviation or the inter-quartile range.

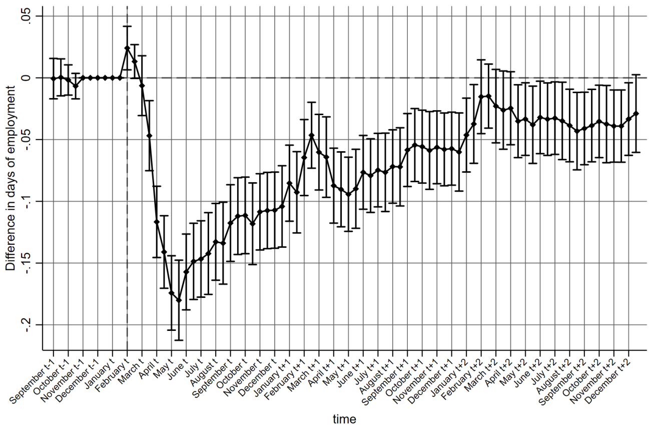
this excess earnings loss amounts to about 11.8% compared to individuals who used to be employed in an occupation with mean LWA. The corresponding development of excess is displayed in Panel (a) of Figure 5. To further illustrate the size of the excess earnings penalty, we refer to individuals who initially were employed in gastronomy occupations, which have an LWA that is about one standard deviation(about 0.3 units) below the mean. For these individuals, the excess earnings loss amounts to, on average, 23.73 € (7.91 $\times$ 3) per half-month or 1661.58 € over the whole treatment period.

In contrast to constant additional earnings losses over the whole period, the additional effect on employment is more pronounced at the onset of the pandemic and then diminishes in the longer run, as can be seen in panel (b) of Figure 5. In particular, column (3) of Table 4 shows that the additional employment loss associated with a reduction in LWA by 0.1 units is 0.08 days per half-month between February and May 2020. This increases to 0.14 days per half-month between June and September 2020, before decreasing in magnitude until the end of the treatment period. Over the whole treatment period, the additional employment loss amounts to 6.45 days, which translates to an excess loss of approximately 17.1% compared to individuals who used to work in an occupation with mean LWA. Individuals who were previously working in gastronomy occupations experience and additional earnings loss of an average reduction of 0.28 days (0.092 $\times$ 3) per half-month or almost 20 days over the whole treatment period (6.452 $\times$ 3).

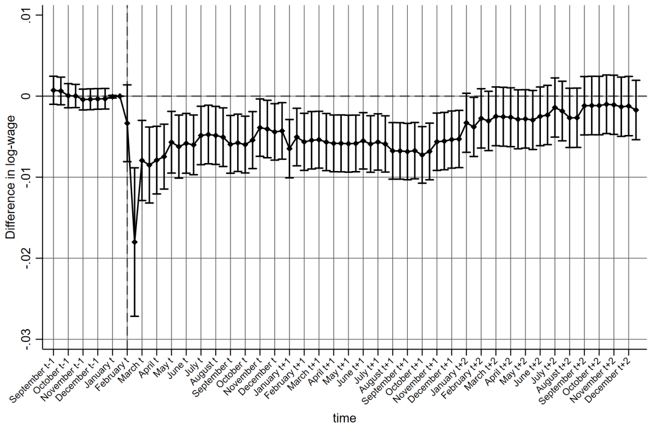
Column (5) of Table 4 shows that individuals who used to work in occupations with a lower LWA also experience an additional wage loss. On average, a reduction in LWA by 0.1 units leads to an additional reduction of 0.5 percentage points per half-month among employed workers, which corresponds to an increase of almost 60% compared to the pandemic effect on workers who used to be employed in occupations with a mean LWA (column (6)). While the additional wage loss is statistically significant until the end of 2021, it becomes insignificant throughout the year 2022. In contrast to the findings on the overall pandemic effect on wages (see Section 5.2), the additional effect is always negative. This is also illustrated by panel (c) of Figure 5, which shows that individuals who previously worked in occupations with a lower LWA and who find a new job between February and May 2020 faced additional wage reductions instead of a wage increase as panel (b) in Figure 3 would have suggested. To return to the example: individuals who were previously employed in the gastronomy face an additional wage loss of 1.5 percentage points (0.005 $\times$ 3) per half-month.



(a) Earnings



(b) Days in employment



(c) Log wages

Figure 5: The heterogeneous effect of the Covid-19 pandemic by LWA

Note: Figure 5 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the worker level.
Source: IEB, BHP, own calculations.

Table 4: Effect heterogeneity by LWA: main outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Earnings		Days in employment		Log wages		Hypothetical earnings	
	absolute	relative	absolute	relative	absolute	relative	absolute	relative
Average								
Treatment period	-7.912***	0.118	-0.092***	0.171	-0.005***	0.593	-5.881***	0.106
	(1.795)		(0.011)		(0.002)		(1.433)	
Pre-treatment	0.923*	-0.207	-0.001	-0.039	-0.000	0.007	0.239	-0.108
	(0.548)		(0.002)		(0.001)		(0.204)	
Feb-May 2020	-3.186***	0.033	-0.078***	0.113	-0.008***	-1.027	-2.656	0.029
	(1.871)		(0.011)		(0.002)		(1.751)	
Jun-Sep 2020	-6.486***	0.043	-0.136***	0.083	-0.005***	-2.353	-5.549***	0.038
	(2.073)		(0.015)		(0.002)		(1.8609)	
Oct-Dec 2020	-5.723***	0.047	-0.109***	0.088	-0.005***	0.727	-4.460**	0.039
	(2.080)		(0.015)		(0.002)		(1.828)	
2021	-7.500***	0.115	-0.070***	0.141	-0.006***	0.421	-4.046**	0.086
	(1.982)		(0.014)		(0.002)		(1.606)	
2022	-4.668**	0.266	-0.033**	-2.038	-0.002	0.222	-3.115*	0.458
	(2.064)		(0.014)		(0.002)		(1.586)	
Cumulative								
Treatment period	-553.858***	0.118	-6.452***	0.171	-0.316***	0.593	-411.655***	0.106
	(125.668)		(0.792)		(0.109)		(100.288)	
N	10,583,520		10,583,520		6,747,890		10,583,520	

Notes: Table 4 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 with earnings, days in employment, log wages and hypothetical earnings as dependent variables. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\phi}_p$ and the ratio $\frac{\hat{\phi}_p}{\hat{\beta}_p}$ for specific time periods and the (treatment) effect averaged over the whole period. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

Finally, to get a better understanding of what drives the additional earnings effect, column (7) of Table 4 shows the results for hypothetical earnings for which wages are held constant at the level that is observed in November of the year $t-1$. Over the whole treatment period, the additional effect on hypothetical earnings is only 5.88 € per half-month as opposed to 7.91 € for actual earnings. This indicates that the major part of the additional earnings loss is explained by the additional loss in employment. However, employment does not exclusively drive the additional earnings loss and, in particular, the part of the additional earnings effect that can be ascribed to an additional reduction in employment becomes smaller during 2021 and 2022 (both absolutely and proportionately).

All in all, these results show that not only did the pandemic adversely affect the job prospects of newly unemployed individuals, it did so unequally, depending on an individual's previous occupation. Individuals who used to be employed in occupations that were less suited to be carried out under lockdown conditions experienced additional losses in terms of earnings, employment and wages that are economically and statistically significant. These findings are consistent with the hypothesis that the employment prospects of individuals who used to work in occupations that were less amenable to being carried out under lockdown conditions, were more exposed to the pandemic. However, it is unclear, what drives the additional employment and wage effects. Therefore, the next section provides further information on the mechanisms underlying these effects.

6.2 Mechanisms

6.2.1 Employment

The majority of the excess employment loss can be explained by an increase in the effect on unemployment. Table B9 in the Appendix displays the change in estimated effect of the pandemic on days in unemployment, days out of the labour market and other labour market states based on Equation 2. The shown effects are associated with a reduction in LWA of a worker's previous occupation by 0.1 units. During the onset of the pandemic, there is a strong increase in the additional effect on the number of days in unemployment followed by an adjustment towards the level of the control group which is not reached at the end of 2022. As can be seen in Appendix Figure B16, this additional effect on unemployment mirrors the development and almost the effect size of the additional effect on employment in Panel (b) of Figure 5. The effects on days out of the labour market or other states mostly, though, remain statistically insignificant. Thus, this confirms the finding that the additional employment reduction can mostly be explained by a shift to unemployment.

6.2.2 Wages

To shed further light on the mechanisms behind the additional wage reduction, we replicate the analysis from Section 5.3.2 and assess the relevance of the same set of variables as in Table 3 for the excess wage effect. The results for the absolute and the relative effects are summarised in Table 5.

According to the results in column (1), a reduction in the LWA of an individual's initial occupation makes it more likely for that individual to subsequently work in a different occupation. Specifically, we find that a reduction in LWA by 0.1 units increases the probability of working in a different occupation by a further 0.7 percentage points per half-month, on average. This represents a proportional increase of the pandemic's effect by about 26% compared to individuals who used to work in an occupation with the mean LWA. Panel (b) of Figure B.13.3 in the Appendix shows that the pandemic additionally increases the probability of being employed in an occupation with a higher LWA as before for treated individuals from occupations with a 0.1 lower LWA as compared to treated individuals with a mean LWA.

Similar to the findings for the overall effect on mean wages in occupations, the additional effect is also positive and mostly significant at the 10% level. However, although this might implicate a positive effect on wages of individuals from occupations with a lower LWA, their rank within the wage distribution of occupations is significantly lower than for individuals from occupations with a higher LWA as shown in column (11) of Table 5. In particular, individuals of the treatment group from occupations with a 0.1 lower LWA experience an excess loss in their position in the occupational wage distribution of 0.29, on average, which is an additional loss of 27% relative to the loss of the rank of treated individuals with a mean LWA. Therefore, this loss in the position in the occupational wage distribution might contribute to the additional wage loss of low LWA occupations.

Firms also seem to play a role in explaining the additional wage loss: while the excess effect on mean wages of firms shows little variation across time, it is negative and, in most cases, statistically significant at the 5% level. This indicates that individuals from occupations with a 0.1 lower LWA are employed in firms that pay on average a 0.2 percentage points lower mean wage. However, firms seem only to have an influence on that dimension in explaining the additional wage loss, since there is no or only a very small effect on firm premia, as can be seen in column (9) of Table 5. Sectors also do not play any role in explaining the additional wage loss (see column (7) from Table 5).

Finally, columns (13) to (16) show results if individuals from occupations with lower LWA experience downgrading into marginal or part-time employment in comparison to individuals from occupations with a higher LWA. The additional effect of the pandemic on transitions into marginal employment is positive, constant and significant at the 5%-level throughout the whole period, but rather small. This indicates that a decrease in the LWA of 0.1 is associated, on average, with a 0.1 percentage points increase in the probability of being marginally employed if the individual has been regular employed before the pandemic. Although the additional effect on part-time employment is also positive and constant at 0.001 throughout the period, it remains statistically insignificant.

Table 5: Effect heterogeneity by LWA: wage adjustments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
			Mean wage										Downgrading			
	Occupational mobility		Occupation		Firm		Sector		AKM firm effect		Occupational rank		Marginal		Part-time	
	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.
Average																
Treatment period	0.007***	0.264	0.001*	0.161	-0.002**	-2.055	-0.001	0.111	-0.001	0.258	-0.287***	0.272	0.001***	-0.238	0.001	0.070
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.054)		(0.000)		(0.001)	
Pre-treatment period	0.000	0.071	0.000**	0.646	0.000**	0.390	0.000	0.152	0.000	0.846	-0.006	0.043	-0.000	-0.107	-0.000	0.108
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.019)		(0.000)		(0.000)	
Feb-May 2020	0.006***	0.202	0.001*	0.181	-0.003**	-0.105	0.000	0.019	-0.001	-0.100	-0.350***	0.493	0.002***	-0.226	0.001	0.307
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.062)		(0.001)		(0.001)	
Jun-Sep 2020	0.007***	0.264	0.001*	0.164	-0.002*	-0.172	-0.000	-0.063	-0.001*	-0.341	-0.292***	0.321	0.001**	-0.130	0.001	0.104
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.060)		(0.000)		(0.001)	
Oct-Dec 2020	0.008***	0.291	0.001	0.135	-0.002	-0.217	-0.000	0.202	-0.001*	0.698	-0.280***	0.240	0.001	-0.076	0.000	0.046
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.060)		(0.000)		(0.001)	
2021	0.008***	0.262	0.001*	0.134	-0.003**	0.661	-0.001	0.120	-0.001	0.145	-0.359***	0.227	0.001**	-0.182	0.000	0.056
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.059)		(0.000)		(0.001)	
2022	0.006***	0.250	0.001	0.140	-0.003**	0.424	-0.001	0.082	-0.001	0.112	-0.173***	0.258	0.001**	0.833	0.000	0.036
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.063)		(0.000)		(0.001)	
N	6,715,320		6,715,320		6,177,056		6,655,717		5,754,885		6,715,320		6,747,890		6,747,890	

Notes: Table 5 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 with occupational mobility, occupational mean log wage, sector mean log wage, firm mean log wage, AKM firm fixed effects, rank in the occupational wage distribution, downgrading from regular into marginal employment as well as downgrading from full-time into part-time employment as dependent variables. All variables are conditional on employment. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\phi}_p$ and the ratio $\frac{\hat{\phi}_p}{\hat{\beta}_p}$ for specific time periods and the (treatment) effect averaged over the whole period. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

To assess the relevance of the individual mechanisms for the excess wage effect associated with having been employed in an occupation with lower LWA, we again apply the Gelbach-decomposition. However, rather than incorporating the decomposition into the extended model of Equation (2), we first estimate the model separately for individuals who used to be employed in low-LWA (below the 25% quantile), medium-LWA (between the 25% and 75% quantile) and high-LWA (above the 75% quantile) occupations, respectively. Next, we extend these models by including the outcomes from Table 5 as additional control variables and then compute the contribution of each of these outcomes to the change in the estimated wage effects. The results are shown in Figure B18 in the Appendix.

For low-LWA occupations (panel (a)), we find that until the end of 2021, the negative wage effects can be almost exclusively ascribed to finding a new job that is further down the occupational wage distribution. From the end of 2021, a higher probability of working in marginal employment and occupational mobility also contribute to the negative wage effects. The results for medium-LWA occupations (panel (b)) resemble the results from the decomposition across all individuals: while individuals tend to find jobs that a further down the occupational wage distribution, these effects are partly compensated by a lower probability of working in marginal employment and by moving to occupations that pay higher average wages. Finally, individuals who used to work in high-LWA occupations experience a more favourable development of wages than the corresponding control group. Panel (c) shows that this is due to a lower probability of working in marginal employment, the observed pattern of occupational mobility and - in the first year of the pandemic - the taking up of new jobs further up the occupational wage distribution.

6.3 Robustness

6.3.1 Parallel trends assumption

In Section 4.2, we discussed that the estimation of Equation 2 requires stricter parallel trend assumptions. To assess the non-occurrence of parallel trends, first, the continuous treatment variable of Equation 2 is replaced by a dummy, which divides all individuals into low- and high-LWA categories at certain thresholds of the LWA distribution (namely the 33%- and the 75%-quantile) as in Bauernschuster et al. (2015). Figure B20 in the Appendix provides evidence that for all three main outcomes - earnings, employment and wages - there are mostly no significant deviations from zero before the transition into unemployment in February t independent of the threshold. Second, Equation 1 is estimated for the following different subset of the LWA distribution: low LWA, medium LWA as well as high LWA. This would give insights into the behaviour of trends for those different quantiles. The results which are presented in Appendix Figure B15 confirm that there seems to be no diverging trends for all three groups.

6.3.2 Confounding variables

There might be the concern that the documented effect heterogeneities by LWA are actually due to heterogeneities in other variables. Following this thought, Table A5 in the Appendix shows that there are differences between individuals who were previously employed in occupations with different degrees of LWA. In particular, individuals from low-LWA occupations are more likely to be male, low-skilled and to have previously worked in smaller firms. In order to investigate whether the documented heterogeneous effects of LWA are due to differences in other variables, interaction terms of gender, skill level and firm size (measured at the matching point in November $t-1$) with the treatment dummy, the event time and a combination of both are additionally included in Equation 2. Figure B21 in the Appendix shows that our results hold even with these additional control variables. Thus, we conclude that the results in Section 6.1 represent genuine heterogeneity across occupations.

7 Conclusion

Being exposed to temporary economic shocks can have long-lasting consequences for individual employment trajectories. In this paper, we investigate the effects of an economic shock, namely the Covid-19 pandemic, on labour market outcomes for individuals who became unemployed shortly before the onset of the pandemic and face a labour market that is disrupted by the pandemic. Using German social security data from the Integrated Employment Biographies (IEB), we employ a difference-in-differences event study design to identify not only the overall effect of the pandemic on earnings, employment and wages, but also the additional effect resulting from the occupations in which people were previously employed and which are affected differently by the pandemic.

The results indicate that the pandemic led to a strong and significant reduction in earnings in the first year of the pandemic in comparison to individuals who became unemployed in 2017. Although the effect on earnings starts to diminish in the longer run, an earnings gap of 6.1% still remains at the end of 2022. The total earnings loss amounts to 4,876 €, which translates into an average loss of 140 € per month during the period from February 2020 to December 2022. This reduction in earnings is mainly driven by a reduction in employment in the short run, but while employment fully recovers, the long-lasting earnings loss can be explained by a decrease in wages.

Analysing the mechanisms behind the wage loss in the longer run, reveals that while treated individuals are on average 3.1 percentage points more likely to switch occupations, most of the wage reduction can be assigned to reemployment at a lower rank within the occupational wage distribution. This indicates that even if the pandemic has not led to a substantial lower level of employment in the longer run, it led to a monetary downgrading of the new employment relationships in comparison to normal times.

We further find that additional to the overall earnings loss there is an excess loss in earnings depending on the lockdown work ability (LWA) index of occupations the individuals were previously employed in: treated individuals from occupations with a 0.1 lower LWA index experience, on average, an additional earnings loss of 554 € over the whole treatment period, which means an average additional earnings loss of 16 € per month. This corresponds to a total earnings loss of 5,430 € for individuals from 0.1 lower LWA occupations. The additional effect can be explained by both a reduction in employment and wages.

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 the unemployed of a specific group of occupations. 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 2022.

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APPENDIX FOR ONLINE PUBLICATION

The material contained in this document represents an Appendix to the paper "Economic shocks and worker careers: Has the Covid-19 pandemic affected transitions out of unemployment?". It provides supplementary information related to the data and to empirical results.

A Data appendix

A.1 Data preparation

This section provides further details about how the sample in this paper is constructed. The empirical analysis uses administrative microdata based on the Integrated Employment Biographies (IEB), which are provided by the Institute of Employment Research (IAB), the research institute of the German Federal Employment Agency. The IEB covers the universe of labour market participants in Germany (with the exception of the self-employed and civil servants). Based on this dataset, in the following it is described how a panel dataset with half-month observations is created.

Two challenges arose during the data preparation: 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 (most of) the decision rules suggested 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 do not contain the main (regular and marginal) employment or the main unemployment information ("unemployed and searching for work") 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 retired. 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 are defined. For being in either group, certain criteria had to be fulfilled: First, individuals had to be registered unemployed in February 2017 or in February 2020. Registered unemployed means that individuals had to be registered as unemployed and are searching for a job. Individuals who have been registered as unemployed in 2017 as well as in 2020 are only considered in 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 31st of January before becoming unemployed. This means that all individuals whose employment spell ends before the 31st 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. Fourth, during the employment period from November to February, individuals in the sample had to be employed in the same establishment and same occupation. Thus, individuals who switch either their establishment or their occupation or both were excluded from the sample.

Taken the sample restrictions together gives a sample of 172,631 individuals in total, 132,797 in the first half (treatment and control group) and 39,834 in the second half of February (treatment and control group). Due to weighting procedure, some individuals do not receive a weight, thus the sample is further reduced to 132,294 in the first half and 33,308 in the second half of February.

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 (see Table 1 in the paper), they are on average a little younger, more often low skilled, earn less, a higher share has a migration background and they are more likely to have been unemployed before.

Table A1: Descriptive statistics: second half of February

	(1) Treatment	(2) Control (weighted)	(3) Control (unweighted)	(4) Standard. diff.
Socio-demographic characteristics (at the time of matching)				
Age	37.460	37.294	37.413	0.014
	(12.001)	(11.677)	(11.773)	
Male (fraction)	0.638	0.639	0.620	-0.002
	(0.481)	(0.480)	(0.485)	
Foreign (fraction)	0.302	0.306	0.215	-0.009
	(0.459)	(0.461)	(0.411)	
Low skilled (no completed apprenticeship, fraction)	0.196	0.195	0.171	0.002
	(0.397)	(0.397)	(0.376)	
Middle skilled (completed apprenticeship, fraction)	0.589	0.584	0.679	0.012
	(0.492)	(0.493)	(0.467)	
High skilled (tertiary education, completed)	0.108	0.108	0.097	-0.000
	(0.310)	(0.310)	(0.297)	
Current employment (at the time of matching)				
Current wage	65.006	60.636	60.902	0.119
	(38.245)	(35.245)	(34.085)	
Current earnings	975.089	909.538	913.524	0.119
	(573.670)	(528.681)	(511.271)	
In regular employment (fraction)	0.891	0.887	0.888	0.012
	(0.312)	(0.317)	(0.316)	
In full-time employment (fraction)	0.647	0.638	0.660	0.019
	(0.478)	(0.481)	(0.474)	
Very small establishment (less than 10, fraction)	0.205	0.207	0.211	-0.004
	(0.404)	(0.405)	(0.408)	
Small establishment (10-49, fraction)	0.322	0.327	0.292	-0.011
	(0.467)	(0.469)	(0.455)	
Medium-sized establishment (50-249, fraction)	0.304	0.298	0.292	0.013
	(0.460)	(0.457)	(0.455)	
Large establishment (more than 250, fraction)	0.167	0.166	0.173	0.002
	(0.373)	(0.372)	(0.378)	
Estimated AKM firm effect	-0.222	-0.244	-0.240	0.088
	(0.247)	(0.247)	(0.244)	
Employment biography				
Work experience	9.688	9.455	10.139	0.027
	(8.715)	(8.395)	(8.312)	
Tenure in current establishment	1.751	1.663	1.805	0.028
	(3.307)	(3.046)	(3.279)	
Tenure in current occupation	4.249	4.186	4.416	0.011
	(5.815)	(5.733)	(5.853)	
Number of job changes	3.290	2.988	3.174	0.080
	(3.922)	(3.619)	(3.657)	
Being unemployed before (fraction)	0.818	0.806	0.836	0.031
	(0.386)	(0.396)	(0.370)	
Employed in manufacturing sector (fraction)	0.128	0.121	0.113	0.021
	(0.334)	(0.326)	(0.317)	
Employed in service sector (fraction)	0.426	0.437	0.443	-0.021
	(0.495)	(0.496)	(0.497)	
Estimated AKM worker effect	4.269	4.281	4.288	-0.041
	(0.306)	(0.298)	(0.288)	
N	18,331	14,977	14,977	

Notes: Columns (1) to (3) show the mean value and standard deviation (in parentheses) of individual characteristics that are measured at the first half of November $t-1$ (the point for the weighting). Column (4) reports the standardised difference between columns (1) and (2), which is defined as $\Delta_X = \left(\bar{X}_1 - \bar{X}_0\right) / \left((S_1^2 + S_0^2)/2\right)^{0.5}$, where $\bar{X}_w$ is the sample mean of the treated ($w = 1$) or (weighted) control ($w = 0$) individuals and S_w^2 are the respective sample variances. Note that the observations for the AKM worker and firm fixed effects are smaller than the reported number of observations. Not all shown characteristics, such as current wages, establishment size or AKM firm effects, are used in propensity score weighting. For the full list of propensity score weighting variables see Table A2.
Source: IEB, own calculations.

A.3 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 ($D = 1$), given observed covariates x: $p(x) = P(D = 1|X = x)$. 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 establishment 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: male (dummy), skill (dummy for three qualification levels), age (dummies for quartiles), foreign (dummy), wage growth between the years 2016 and 2017 for the control group and between 2019 and 2020 for the treatment group (dummy for deciles), type of current employment (dummies for marginal or regular as well as part-time or full-time), establishment size (dummies for four categories), experience (dummies for quartiles), tenure in current occupation (dummy for quartiles), duration in previous unemployment (dummy for quartiles), establishment change before the matching point (dummy) and sector (dummies for 3 sector classification). The estimation of the propensity score is stratified on the level of 2-digit occupations.

In order to test for balance, we compare the differences in means after weighting between individuals of the treatment and the control group. The balancing tests for the baseline specification can be found in Table A2. The table shows the mean values of various characteristics that were used for the weighting for the treatment group (column (1)), the unweighted control 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 standardised difference between the treatment and the (weighted) control group are displayed. The standardised differences in covariate means (Δ_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).[23] Since there is no universally agreed criterion for how small the standardised difference must be to provide balance, we apply the rule of thumb of $\Delta_X < |0.1|$ as suggested by Austin (2011). Without weighting, the difference between treatment and

[23] The standardised difference is defined as $\Delta_X = \left(\bar{X}_1 - \bar{X}_0\right) / \left((S_1^2 + S_0^2)/2\right)^{0.5}$, 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 Δ_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.

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 standardised differences). However, differences in two quartiles of unemployment experience are still significant at conventional significance levels, but the standardised difference is smaller than 0.1 which does not indicate an economically significant difference between the treatment and control group. Overall, the sample appears to be balanced.

Table A2: Balancing table

	Treatment	Control		Difference	
		Unweighted	Weighted	P-value	Standardised
	(1)	(2)	(3)	(4)	(5)
Worker variables (contemporaneous)					
Male	0.612	0.592	0.613	0.718	-0.002
Low skilled	0.153	0.132	0.154	0.624	-0.003
Middle skilled	0.594	0.673	0.592	0.385	0.005
High skilled	0.172	0.148	0.171	0.793	0.001
Missing skill	0.082	0.046	0.084	0.205	-0.007
Age (1^{st} quartile)	0.242	0.234	0.242	0.805	0.001
Age (2^{nd} quartile)	0.257	0.244	0.258	0.595	-0.003
Age (3^{rd} quartile)	0.245	0.257	0.245	0.891	-0.001
Age (4^{th} quartile)	0.256	0.265	0.255	0.671	0.002
Foreign nationality	0.244	0.180	0.246	0.412	-0.005
Missing nationality	0.001	0.001	0.001	0.528	-0.003
Worker variables (employment biography)					
2019(16)/2020(17) wage growth (1^{st} decile)	0.104	0.096	0.104	0.830	0.001
2019(16)/2020(17) wage growth (2^{nd} decile)	0.097	0.103	0.097	0.855	0.001
2019(16)/2020(17) wage growth (3^{rd} decile)	0.096	0.104	0.095	0.460	0.004
2019(16)/2020(17) wage growth (4^{th} decile)	0.097	0.103	0.097	0.743	0.002
2019(16)/2020(17) wage growth (5^{th} decile)	0.060	0.140	0.061	0.769	-0.002
2019(16)/2020(17) wage growth (6^{th} decile)	0.131	0.068	0.133	0.198	-0.007
2019(16)/2020(17) wage growth (7^{th} decile)	0.106	0.095	0.105	0.919	0.001
2019(16)/2020(17) wage growth (8^{th} decile)	0.103	0.097	0.103	0.764	-0.002
2019(16)/2020(17) wage growth (9^{th} decile)	0.104	0.096	0.104	0.811	-0.001
Marginal employment	0.067	0.072	0.070	0.025	-0.012
Regular employment	0.933	0.928	0.930	0.027	0.012
Full-time employment	0.654	0.657	0.652	0.564	0.003
Part-time employment	0.346	0.343	0.348	0.564	-0.003
Very small establishment (less than 10, fraction)	0.205	0.216	0.202	0.162	0.008
Small establishment (10-49, fraction)	0.303	0.287	0.302	0.909	0.001
Medium-sized establishment (50-249, fraction)	0.285	0.261	0.287	0.508	-0.004
Large establishment (more than 250, fraction)	0.201	0.169	0.203	0.362	-0.005
Missing establishment size	0.006	0.067	0.006	0.522	0.004

Experience (1^{st} quartile)	0.271	0.229	0.272	0.643	-0.003
Experience (2^{nd} quartile)	0.248	0.252	0.249	0.854	-0.001
Experience (3^{rd} quartile)	0.237	0.263	0.237	0.865	0.001
Experience (4^{th} quartile)	0.244	0.256	0.243	0.619	0.003
Tenure (last occupation) (1^{st} quartile)	0.257	0.242	0.259	0.455	-0.004
Tenure (last occupation) (2^{nd} quartile)	0.257	0.243	0.256	0.893	0.001
Tenure (last occupation) (3^{rd} quartile)	0.235	0.266	0.235	0.871	0.001
Tenure (last occupation) (4^{th} quartile)	0.251	0.249	0.250	0.645	0.003
Duration in unemployment (1^{st} quartile)	0.259	0.236	0.265	0.020	-0.013
Duration in unemployment (2^{nd} quartile)	0.261	0.241	0.259	0.382	0.005
Duration in unemployment (3^{rd} quartile)	0.244	0.257	0.240	0.076	0.010
Duration in unemployment (4^{th} quartile)	0.236	0.266	0.236	0.782	-0.002
Establishment switch before matching	0.019	0.017	0.019	0.631	0.003
Occupations					
Agriculture, forestry, farming	0.008	0.011	0.008	1.000	-0.000
Gardening, floristry	0.011	0.013	0.011	1.000	0.000
Production, processing of raw materials	0.004	0.006	0.004	1.000	0.000
Plastic-making, -processing, wood-working, -processing	0.020	0.019	0.020	1.000	0.000
Paper-making, -processing, printing, technical media design	0.011	0.011	0.011	1.000	0.000
Metal-making, -working, metal construction	0.049	0.039	0.049	1.000	-0.000
Technical machine-building, automotive industry	0.048	0.038	0.048	1.000	0.000
Mechatronics, energy electronics, electrical engineering	0.022	0.021	0.022	1.000	0.000
Technical research, development, construction, production planning,	0.021	0.016	0.021	1.000	0.000
Textile-, leather-making, -processing	0.005	0.004	0.005	1.000	0.000
Food-production, -processing	0.047	0.053	0.047	1.000	0.000
Construction scheduling, architecture, surveying	0.004	0.005	0.004	1.000	-0.000
Building construction	0.023	0.032	0.023	1.000	-0.000
Interior construction	0.023	0.034	0.023	1.000	-0.000
Building services engineering, technical building services	0.019	0.022	0.019	1.000	0.000
Mathematics, biology, chemistry, physics	0.009	0.007	0.009	1.000	-0.000
Geology, geography, environmental protection	0.001	0.001	0.001	1.000	-0.000
Computer science, information, communication technology	0.016	0.012	0.016	1.000	-0.000
Traffic, logistics	0.104	0.091	0.104	1.000	0.000
Drivers and operators of vehicles and transport equipment	0.047	0.048	0.047	1.000	0.000
Safety and health protection, security, surveillance	0.015	0.021	0.015	1.000	-0.000
Cleaning services	0.053	0.051	0.053	1.000	0.000

Purchasing, sales, trading	0.029	0.026	0.029	1.000	-0.000
Retail trade	0.086	0.093	0.086	1.000	0.000
Tourism, hotels, restaurants	0.055	0.054	0.055	1.000	-0.000
Business management, organisation	0.100	0.104	0.100	1.000	-0.000
Financial services, accounting, tax consultancy	0.017	0.018	0.017	1.000	-0.000
Law and public administration	0.011	0.012	0.011	1.000	0.000
Medical and health care	0.035	0.032	0.035	1.000	0.000
Non-medical healthcare, body care, wellness, medical technicians	0.021	0.022	0.021	1.000	0.000
Education, social work, housekeeping, theology	0.032	0.031	0.032	1.000	-0.000
Teaching, training	0.020	0.018	0.020	1.000	0.000
Philology, literature, humanities, social sciences, economics	0.003	0.002	0.003	1.000	0.000
Advertising, marketing, commercial, editorial media design	0.023	0.022	0.023	1.000	0.000
Product design, artisan craftwork, fine arts, making of musical inst	0.002	0.002	0.002	1.000	0.000
Performing arts, entertainment	0.004	0.005	0.004	1.000	0.000
Sectors					
Agriculture	0.008	0.012	0.008	0.972	-0.000
Manufacturing	0.394	0.404	0.395	0.781	-0.002
Service	0.598	0.584	0.597	0.775	0.002
N	66,070	66,199	66,199		

Notes: The table reports descriptive statistics that refer to the time before the onset of unemployment (November 2019 for the treatment group and November 2016 for the control group): mean in the treatment group (column (1)), mean in the control group (column (2)), weighted mean in the control group (column (3)), p-value for the null hypothesis of equality between the mean in the treatment group and the weighted mean in the control group (column (4)), standardised difference between the mean in the treatment group and the weighted mean in the control group (column (5)).

Source: IEB, BHP, own calculations.

The overlap assumption requires some randomness in the treatment assignment, meaning that we need to observe persons with identical characteristics in the treatment and control group. To check whether the overlap assumption holds, we compare the distribution of the estimated propensity scores for both groups. Figure A1 shows 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 overlap assumption.

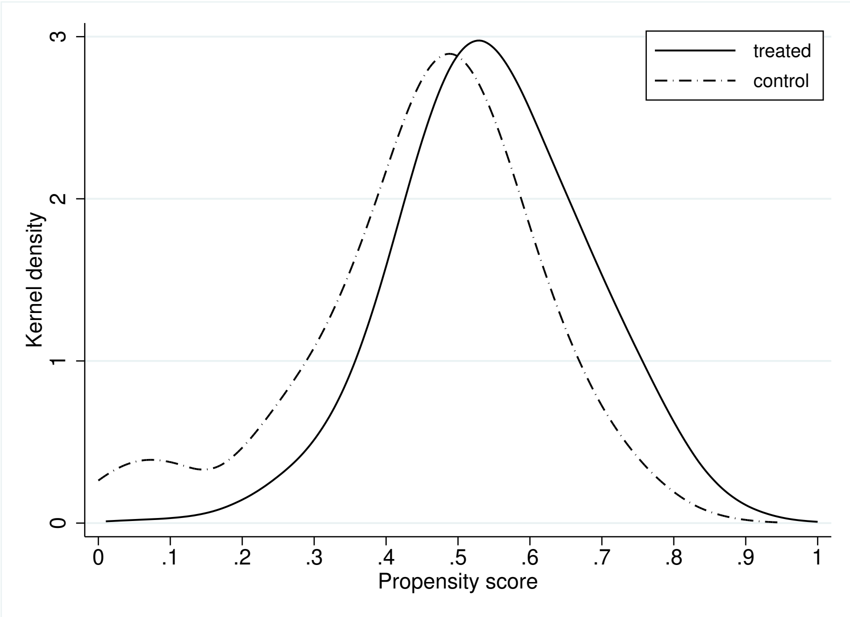


Figure A1: Overlap after inverse propensity score weighting

Note: Figure A1 shows the estimated propensity score for the treatment and the control group.

A.3.1 Wage differences between treatment and control group

Table 1 in the paper shows that individuals in the treatment group, on average, earn in November $t-1$ a significantly higher daily wage compared to the control group, even when matching weights are used. We argue that this difference reflects real wage growth that took place between the years 2016 (the year before which individuals in the control group became unemployed) and 2019 (the corresponding year for individuals in the treatment group) rather than any difference in the composition of the two groups.

To assess this hypothesis, we compute the change in the mean real wage for each occupation between 2016 and 2019 based on the universe of employees. Figure A2 shows that almost all occupations experienced an increase in mean real wages over this period. This increase was especially pronounced among a number of lower-wage occupations, such as *cleaning services* or *non-medical healthcare occupations*, which likely reflects binding increases in the minimum wage during the period. The employment-weighted average across all occupations is 4.6%. Using the occupational employment shares of the treatment group in 2019 as weights, the average real wage growth amounts to 4.9%. This values is very close to the difference in the mean real wage between the treatment and the control group that is shown in Table 1 in the paper.

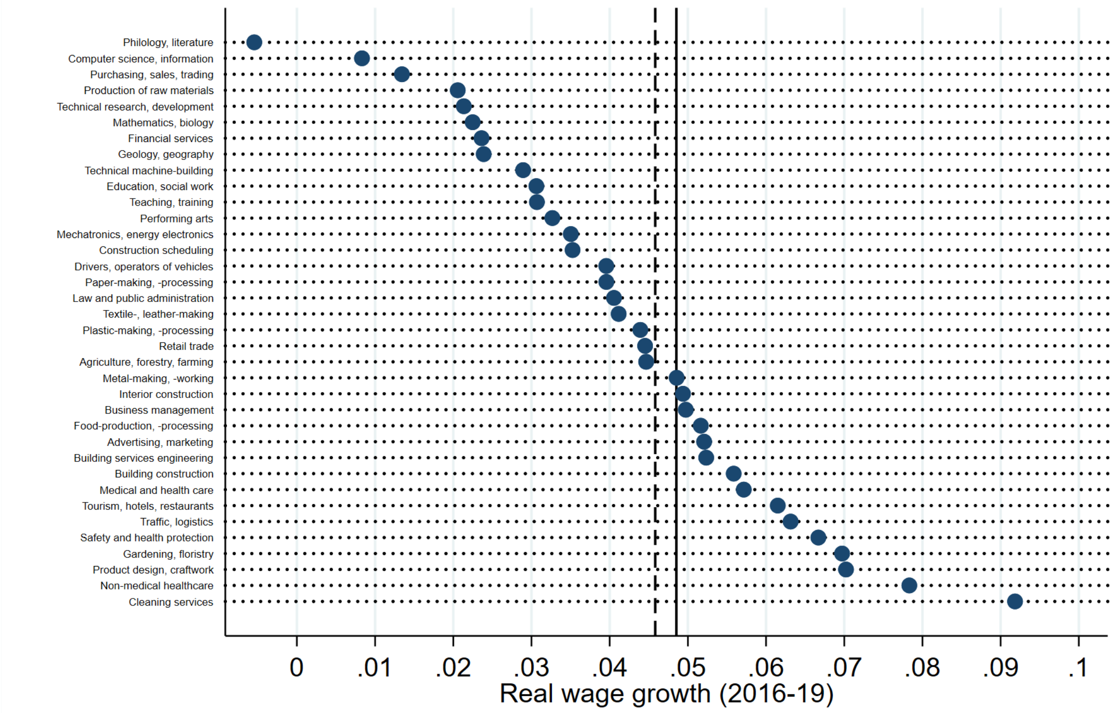


Figure A2: Change in real wage by occupation

Note: Figure A2 shows the change in mean real wages between 2016 and 2019 for each 2-digit occupation (occupational titles are shortened due to space constraints). The average change in the mean real wage is represented by the dashed line, while the solid line represents the weighted average based on the occupational employment shares in the treatment group.
Source: IEB, own calculations.

A.4 Lockdown work ability index (LWA)

A.4.1 Construction

The LWA index consists of three components: the possibility to work from home (H), whether occupations are essential (E) or had to close (C) during the lockdown.[24] All indicators rage from 0 to 1, where 0 indicates that an occupation is not essential, not closed or can not be carried out from home and 1 indicates that an occupation is essential, closed or suitable for working from home. The LWA index is generated by the following formula similar to Palomino et al. (2020):

$$LWA_o = \begin{cases} E_o + (1 - E_o)H_o & E_o = e \\ (1 - C_o)H_o & C_o = c \\ H_o & E_o \neq 0 \wedge C_o \neq 0 \end{cases} \tag{3}$$

o is the occupation at the 2-digit KldB level, $e \in (0; 1]$ denotes the extent to which an occupation is essential and $c \in (0; 1]$ denotes whether an occupation was closed during the pandemic. Thus, the LWA index captures the ability to work during the pandemic based on the extent to which tasks can be done from home. Additionally, if the occupation is essential (or partly essential), then it is able to operate, regardless of its working from home potential. However, if the occupation is closed, then only the part of the occupation which is not closed is able to operate to the extent of the working from home potential. The LWA index ranges from 0 (low LWA) to 1 (high LWA). Table A3 displays the corresponding mean, the standard deviation and the distribution of LWA across occupations.

Table A4 shows occupations and their corresponding LWA index ranked from occupations with a high to occupations with a low LWA. Occupations with a high LWA are occupations in computer science, information or communication technology or medical and health care occupations, while occupations with a low LWA are occupations in the field of construction or occupations in tourism, hotels and restaurants.

[24] Similar to Palomino et al. (2020), the working from home indicator is based on Dingel and Neiman (2020), which is derived by the composition of tasks with working from home possibilities for each occupation via O*Net. Values for essential or closed occupations at the 2-digit ISCO-08 level are based on the decision by the Spain and Italian government (though Palomino et al. (2020) use these values also for Germany) and are transformed to the 2-digit KldB (36 different occupations) used in this paper. The values for essential and closed occupations were transformed from 2-digit ISCO-08 into 5-digit KldB and then aggregated into 2-digit KldB by weighting the relative employment size of the 5-digit occupations. After the aggregation some occupations have a value greater than zero in the essential as well as the closed index. This is by definition of the index not possible. To adjust this we set every index to zero if it is smaller than a threshold of 0.1 (which is arguably close to zero). After applying this rule, three occupations remained with this conflict: occupations in food-production and -processing, in non-medical healthcare, body care, wellness and medical technicians and in education and social work, housekeeping, and theology. By comparing them to similar occupations, we manually set either the essential or the closed index to zero.

Table A3: Descriptive statistics of LWA

	LWA
Mean	0.396
Standard deviation	0.299
Percentile 10	0.060
Percentile 25	0.127
Percentile 75	0.680
Percentile 90	0.824

Notes: Table A3 reports the statistical properties of the lockdown work ability (LWA) index.
Source: Dingel and Neiman (2020); Palomino et al. (2020), own calculations.

Table A4: Occupations ranked by LWA

Occupation	LWA
Computer science, information and communication technology	0.98
Medical and health care occupations	0.95
Gardening and floristry	0.88
Teaching and training	0.82
Agriculture, forestry and farming	0.82
Business management and organisation	0.72
Philology, literature, humanities, social sciences, and economics	0.71
Non-medical healthcare, body care, wellness and medical technicians	0.70
Financial services, accounting and tax consultancy	0.68
Law and public administration	0.68
Safety and health protection, security and surveillance	0.65
Advertising and marketing, in commercial and editorial media design	0.52
Purchasing, sales and trading	0.50
Construction scheduling, architecture and surveying	0.48
Technical research and development, construction, and production planning and scheduling	0.47
Geology, geography and environmental protection	0.45
Traffic and logistics (without vehicle driving)	0.40
Product design, artisan craftwork, fine arts and the making of musical instruments	0.39
Mathematics, biology, chemistry and physics	0.33
Performing arts and entertainment	0.26
Education and social work, housekeeping, and theology	0.22
Papermaking and -processing, printing, and in technical media design	0.20
Cleaning services	0.20
Textile- and leather-making and -processing	0.20
Plastic-making and -processing, and wood-working and -processing	0.17
Food-production and -processing	0.15
Sales occupations in retail trade	0.13
Mechatronics, energy electronics and electrical engineering	0.13
Drivers and operators of vehicles and transport equipment	0.10
Building construction above and below ground	0.10
Technical occupations in machine-building and automotive industry	0.10
Tourism, hotels and restaurants	0.07
Production and processing of raw materials, glass- and ceramic-making and -processing	0.06
Metal-making and -working, and in metal construction	0.02
Building services engineering and technical building services	0.02
Interior construction	0.00

Notes: Table A4 shows the lockdown work ability (LWA) index by 2-digit occupation.
Source: Dingel and Neiman (2020); Palomino et al. (2020), own calculations.

A.5 Descriptive statistics by quantile of the LWA distribution

Table A5: Descriptive statistics: individuals from low-, medium- and high-LWA occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Low LWA (25%-Quantil)			Medium LWA (25%-75%-Quantil)			High LWA (75%-Quantil)		
	Treatment	Control	Standard. diff.	Treatment	Control	Standard. diff.	Treatment	Control	Standard. diff.
Socio-demographic characteristics (at the time of matching)									
Age	39.047	39.104	-0.005	38.754	38.776	-0.002	40.281	40.221	0.005
	(12.672)	(12.522)		(12.408)	(12.230)		(12.066)	(11.919)	
Male (fraction)	0.836	0.835	0.003	0.565	0.566	-0.003	0.428	0.430	-0.005
	(0.371)	(0.372)		(0.496)	(0.496)		(0.495)	(0.495)	
Foreign (fraction)	0.275	0.278	-0.007	0.278	0.278	-0.001	0.134	0.138	-0.011
	(0.447)	(0.448)		(0.448)	(0.448)		(0.341)	(0.345)	
Low skilled (no completed apprenticeship, fraction)	0.164	0.166	-0.006	0.187	0.188	-0.002	0.068	0.068	-0.000
	(0.370)	(0.372)		(0.390)	(0.391)		(0.252)	(0.252)	
Middle skilled (completed apprenticeship, fraction)	0.688	0.684	0.010	0.563	0.561	0.004	0.539	0.539	-0.001
	(0.463)	(0.465)		(0.496)	(0.496)		(0.499)	(0.498)	
High skilled (tertiary education, completed)	0.057	0.057	-0.000	0.147	0.148	-0.001	0.365	0.362	0.007
	(0.232)	(0.232)		(0.354)	(0.355)		(0.481)	(0.480)	
Current employment (at the time of matching)									
Current wage	74.846	70.857	0.110	70.486	67.377	0.069	95.910	90.467	0.09
	(36.869)	(35.520)		(45.600)	(44.705)		(56.336)	(55.295)	
Current earnings	1,122.694	1,062.858	0.110	1,057.286	1,010.656	0.069	1,438.654	1,357.007	0.098
	(553.037)	(532.797)		(684.003)	(670.575)		(845.040)	(829.427)	
In regular employment (fraction)	0.935	0.932	0.010	0.917	0.914	0.013	0.963	0.960	0.015
	(0.247)	(0.251)		(0.275)	(0.281)		(0.189)	(0.196)	
In full-time employment (fraction)	0.775	0.774	0.002	0.593	0.591	0.004	0.627	0.626	0.002
	(0.418)	(0.418)		(0.491)	(0.492)		(0.484)	(0.484)	
Very small establishment (less than 10, fraction)	0.235	0.232	0.008	0.166	0.164	0.007	0.248	0.244	0.009
	(0.424)	(0.422)		(0.372)	(0.370)		(0.432)	(0.430)	
Small establishment (10-49, fraction)	0.344	0.343	0.000	0.284	0.283	0.002	0.289	0.290	-0.002
	(0.475)	(0.475)		(0.451)	(0.451)		(0.453)	(0.454)	
Medium-sized establishment (50-249, fraction)	0.262	0.261	0.002	0.318	0.321	-0.006	0.247	0.250	-0.007
	(0.440)	(0.439)		(0.466)	(0.467)		(0.431)	(0.433)	
Large establishment (more than 250, fraction)	0.152	0.157	-0.014	0.226	0.227	-0.002	0.209	0.209	-0.001
	(0.359)	(0.363)		(0.418)	(0.419)		(0.407)	(0.407)	
Estimated AKM firm effect	-0.181	-0.200	0.069	-0.171	-0.186	0.057	-0.097	-0.110	0.052
	(0.270)	(0.271)		(0.257)	(0.256)		(0.262)	(0.260)	
Employment biography									
Work experience	12.100	11.949	0.015	11.066	10.882	0.019	13.627	13.315	0.031
	(10.165)	(9.824)		(9.901)	(9.516)		(10.195)	(9.811)	
Tenure in current establishment	3.164	3.387	-0.042	2.687	2.678	0.002	3.510	3.489	0.004
	(5.241)	(5.482)		(4.895)	(4.596)		(5.596)	(5.516)	
Tenure in current occupation	5.831	5.983	-0.021	4.955	5.008	-0.008	7.206	7.205	0.000
	(7.221)	(7.411)		(6.488)	(6.482)		(8.112)	(8.060)	
Number of job changes	3.315	3.015	0.081	3.167	2.957	0.055	3.379	3.102	0.082
	(3.821)	(3.564)		(3.673)	(3.893)		(3.492)	(3.288)	
Being unemployed before (fraction)	0.780	0.769	0.027	0.775	0.768	0.015	0.698	0.696	0.006
	(0.414)	(0.422)		(0.418)	(0.422)	(0.409)	(0.459)	(0.460)	
Employed in manufacturing sector (fraction)	0.436	0.440	-0.007	0.170	0.162	0.020	0.121	0.120	0.003
	(0.496)	(0.496)		(0.376)	(0.369)		(0.326)	(0.325)	
Employed in service sector (fraction)	0.561	0.558	0.007	0.829	0.836	-0.020	0.851	0.852	-0.002
	(0.496)	(0.497)		(0.377)	(0.370)		(0.356)	(0.355)	
Estimated AKM worker effect	4.303	4.314	-0.041	4.314	4.325	-0.027	4.551	4.551	-0.001
	(0.270)	(0.262)		(0.374)	(0.370)		(0.442)	(0.449)	
N	19,247	19,590		31,568	31,223		15,368	15,390	

Notes: For three different subsets of the LWA distribution - low, medium and high - the first two columns show the mean value and standard deviation (in parentheses) of individual characteristics that are measured at the first half of November $t-1$ (the point for the weighting). The third column reports the standardised difference between the first two columns, which 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 the treated ($w = 1$) or (weighted) control ($w = 0$) individuals and S_w^2 are the respective sample variances. The subsets are defined by the quantiles of the LWA distribution: low LWA below the 25% quantile, medium LWA between the 25% and the 75% quantile as well as high LWA above the 75% quantile. Note, that the observations for the AKM worker and firm fixed effects are smaller than the reported number of observations.
Source: IEB, BHP, own calculations.

B Results appendix

B.1 AKM worker effect

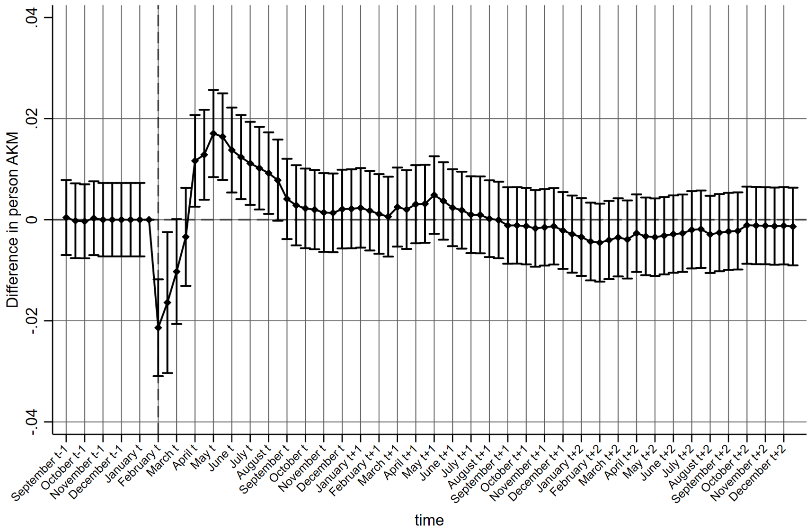


Figure B3: The effect of the Covid-19 pandemic on AKM worker effects

Note: Figure B3 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with the AKM worker effect as dependent variable. The variable is conditional on employment. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.2 Earnings decomposition

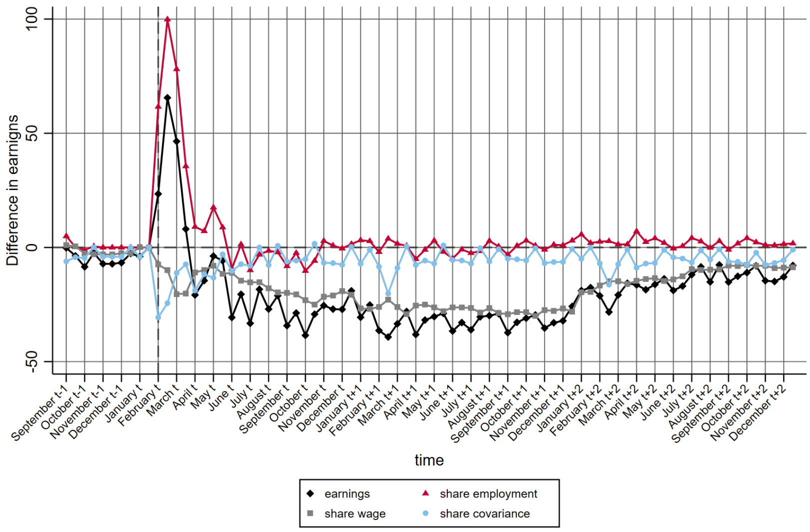


Figure B4: Earnings decomposition

Note: Figure B4 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings conditional on employment (black) as dependent variable as well as the decomposition following (Schmieder et al., 2023) into the shares of the explaining variables employment (red), wage (grey) and their corresponding covariance (blue). The estimation is weighted by the inverse propensity score. 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 individual level.
Source: IEB, BHP, own calculations.

B.3 Employment mechanisms

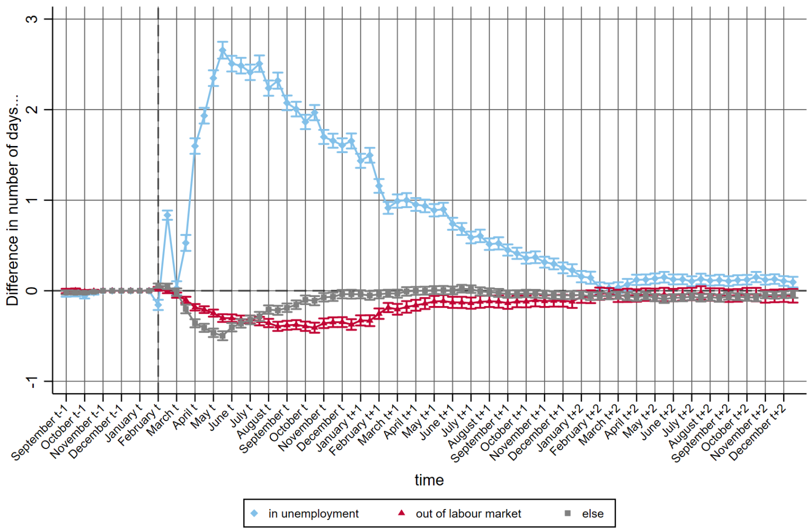


Figure B5: The effect of the Covid-19 pandemic on other labour market states

Note: Figure B5 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with days in unemployment, days out of the labour market as well as the remaining labour market status (which includes days in a measure, days receiving transfer payments and days registered in the unemployment data but not being unemployed) as dependent variables. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level. Note that individuals can be in several labour market states at the same time, but the figure shows only one state per individual per period.
Source: IEB, BHP, own calculations.

Table B6: Employment adjustments

	Days in unemployment	Days out of the labour market	Days in other states
Average			
Treatment period	0.835***	-0.156***	-0.092***
	(0.021)	(0.023)	(0.012)
Treatment period ($\hat{\gamma}$)	3.280***	1.978***	0.965***
	(0.015)	(0.018)	(0.010)
Pre-treatment period	-0.013**	-0.001	-0.007**
	(0.005)	(0.003)	(0.003)
Feb-May 2020	1.221***	-0.134***	-0.231***
	(0.031)	(0.014)	(0.016)
Jun-Sep 2020	2.319***	-0.347***	-0.267***
	(0.039)	(0.021)	(0.020)
Oct-Dec 2020	1.741***	-0.371***	-0.071***
	(0.038)	(0.026)	(0.022)
2021	0.709***	-0.154***	-0.021
	(0.027)	(0.028)	(0.017)
2022	0.111***	-0.047	-0.064***
	(0.022)	(0.033)	(0.016)
Cumulative			
Treatment period	58.438***	-10.916***	-6.442***
	(1.464)	(1.591)	(0.864)
N	10,583,520	10,583,520	10,583,520

Notes: Table B6 shows the estimated coefficients of $\hat{\beta}_p$ from Equation 1 with days in unemployment, out of the labour market as well as the remaining labour market status (which includes days in a measure, days receiving transfer payments and days registered in the unemployment data but not being unemployed) as dependent variables. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\beta}_p$ for specific time periods, the (treatment) effect averaged over the whole period and the baseline estimate for the control group averaged over the whole period ($\hat{\gamma}$). Standard errors clustered at the individual level are in parentheses. Note that it is possible that individuals are in several labour market states at the same time, but Table B6 show only one labour market per individual per period. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

B.4 Wage mechanisms

B.4.1 Reference year of wage distributions

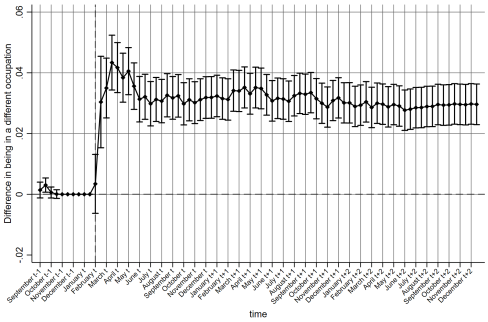
The mean wages of occupations, sectors and firms as well as the wage distribution within occupations are calculated on the basis of two separate years for the treatment (2019) and the control group (2016). Table B7 presents the results when instead of those two separate years the same year - 2016 or 2019 - for the treatment and control group is used.

Table B7: Wage adjustments: constant year of wage distributions

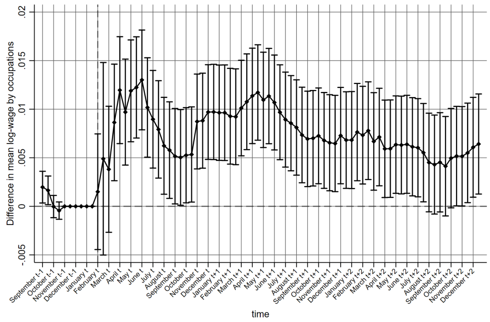
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean wage						Occupational rank	
	Occupation		Firm		Sector			
	2016	2019	2016	2019	2016	2019	2016	2019
Average								
Treatment period	0.008***	0.008***	-0.024***	0.014***	-0.006**	-0.006**	-1.095***	-1.111***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.002)	(0.165)	(0.163)
Treatment period ($\hat{\gamma}$)	0.011***	0.011***	0.018***	0.003	0.005***	0.005***	2.136***	2.069***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.002)	(0.002)	(0.124)	(0.122)
Pre-treatment period	0.000	0.000	-0.000	0.002***	0.001***	0.001***	-0.012	-0.028
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.058)	(0.058)
Feb-May 2020	0.008***	0.008***	0.011**	0.021***	0.009***	0.009***	-0.759***	-0.812***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.187)	(0.184)
Jun-Sep 2020	0.008***	0.008***	-0.007	0.021***	0.004	0.004	-0.832***	-0.881***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.181)	(0.178)
Oct-Dec 2020	0.008***	0.008***	-0.018***	0.018***	-0.002	-0.002	-1.095***	-1.148***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.181)	(0.177)
2021	0.009***	0.009***	-0.033***	0.011**	-0.010***	-0.010***	-1.622***	-1.656***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.178)	(0.175)
2022	0.007***	0.006***	-0.034***	0.011**	-0.010***	-0.010***	-0.767***	-0.733***
	(0.003)	(0.002)	(0.005)	(0.006)	(0.003)	(0.003)	(0.187)	(0.185)
N	6,715,320	6,715,320	4,225,042	4,106,833	6,655,597	6,655,554	6,715,320	6,715,320

Notes: Table B7 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with occupational mean log wage, sector mean log wage, firm mean log wage and rank in the occupational wage distribution as dependent variables, where the mean log wages and the rank in the occupational wage distribution are calculated on the basis of all employed individuals in Germany for November 2016 and 2019. All variables are conditional on employment. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\beta}_p$ for specific time periods, the (treatment) effect averaged over the whole period and the baseline estimate for the control group averaged over the whole period ($\hat{\gamma}$). Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

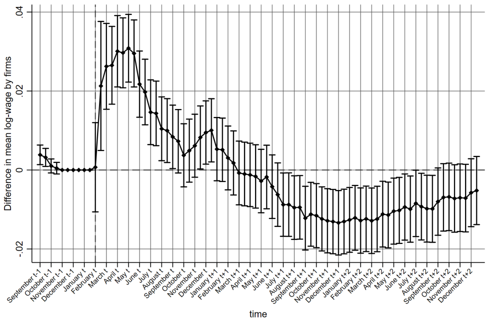
B.4.2 Event study plots



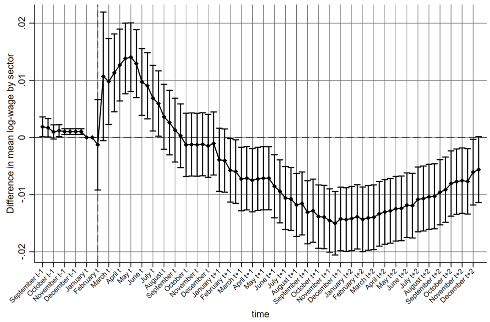
(a) Occupational mobility



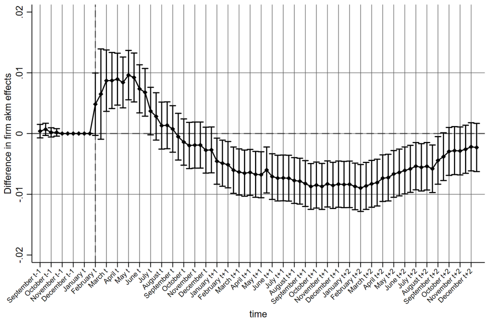
(b) Mean wage (occupation)



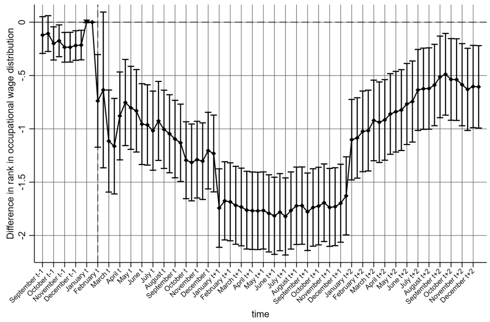
(c) Mean wage (firm)



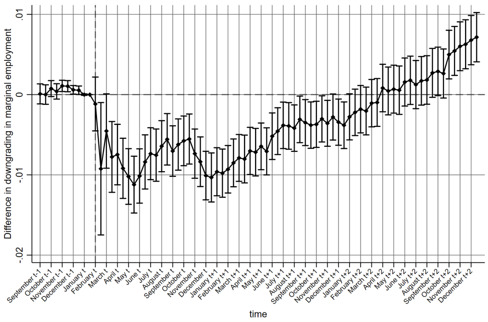
(d) Mean wage (sector)



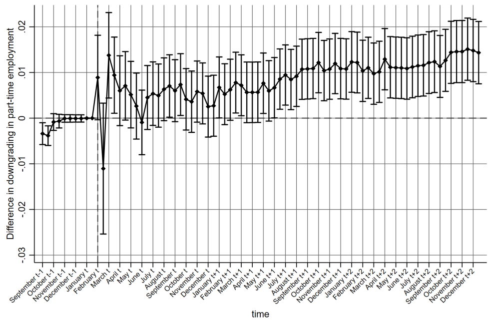
(e) AKM firm effect



(f) Occupational rank



(g) Downgrading (marginal)



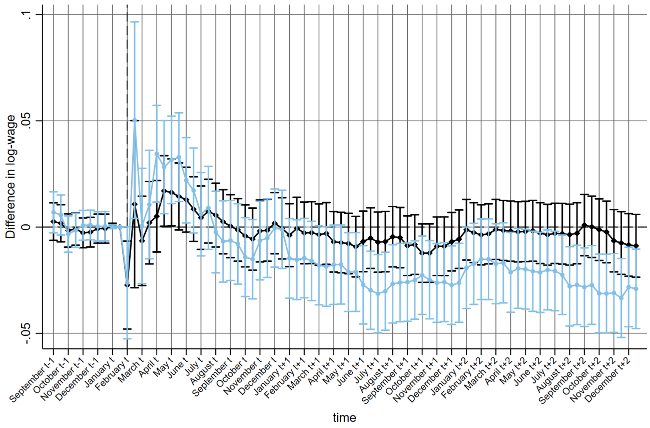
(h) Downgrading (part-time)

Figure B6: Wage mechanisms: event study plots

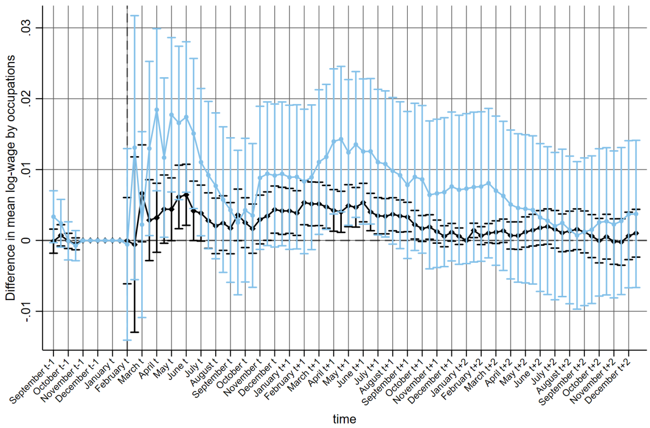
Notes: Figure B6 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with occupational mobility (panel (a)), occupational mean log wage (panel (b)), firm mean log wage (panel(c)), sector mean log wage (panel (d)), AKM firm fixed effects (panel (e)), rank in the occupational wage distribution (panel (f)), downgrading from regular into marginal employment (panel (g)) as well as downgrading from full-time into part-time employment (panel (h)) as dependent variables. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence intervals which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.4.3 Occupational mobility

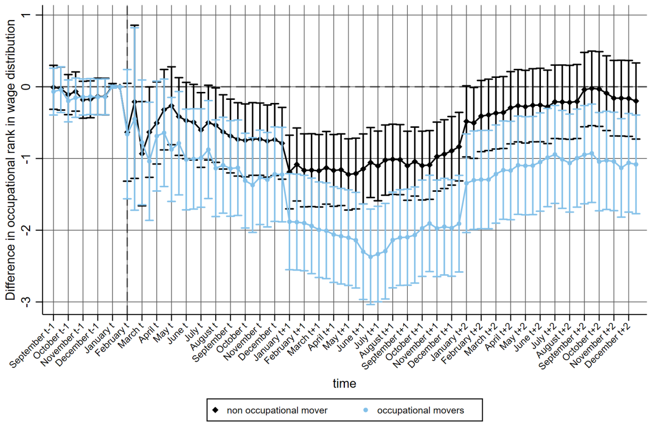
To investigate whether wage loss can be attributed to individuals who switch their occupation, the sample is split into "occupational mover" who are employed on January $t+2$ in a different occupation and "non occupational mover" who are employed on January $t+2$ in the same occupation as before their transition into unemployment. January $t+2$ is chosen as the reference date, because around that time the difference in the employment between treatment and control group has disappeared. Thus, individuals of the treatment and control group are comparable in terms of employment. Note that it is possible that before and after this reference date individuals are allowed to switch their occupations. Weights via inverse propensity score weighting are then computed separately for the groups of occupational mover and non occupational mover. Figure B7 shows the estimated coefficients β_p from Equation 1 for log wages, the mean occupational log wage and the rank of the occupational wage distribution for occupational mover (blue line) and non occupational mover (black line).



(a) Log wage



(b) Occupational mean wage



(c) Occupational wage rank

Figure B7: The effect of the Covid-19 pandemic on earnings, employment and wages – Occupational mobility

Note: Figure B7 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with log wages (panel (a)), occupational mean log wage (panel (b)) and rank in the occupational wage distribution (panel (c)) as dependent variables. Estimates are shown for individuals who are employed in the same occupation in January t as in November $t-1$ (non occupational mover, black line) and individuals who are employed in a different occupation in January t as in November $t-1$ (occupational mover, blue line). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.5 Gelbach decomposition

For the decomposition, we first estimate Equation 1 using the log daily wage as dependent variable and store the estimates of the average excess wage loss among individuals in the treatment group for each event time, $\hat{\beta}_p$.[25] We then estimate the extended model and store the corresponding estimates, $\hat{\beta}^*_p$. In the extended model, we additionally control for the (time-invariant) mean wage of the firm in which individual i is employed at time p (corresponding to column (3) in Table 3), indicators for marginal and part-time employment (columns (7) and (8)), the rank of an individual's wage in the occupational wage distribution (column (6)) as well as occupation dummies to capture the effects of changes in the occupational mean wage as well as of occupational mobility (columns (1) and (2)). Figure 4 in the paper shows that the size of the estimated wage loss among treated individuals (compared to individuals in the control group) decreases in magnitude in the extended model compared to the baseline model. For most points in time, we no longer find significant differences between the wages of the individuals in the treatment and the control group once the additional control variables are included. We interpret this finding as evidence that the included variables are associated with the wage loss among treated individuals that we identify in the baseline model without control variables.

We proceed to compute the difference in the estimated coefficients from the two models, $\hat{d}_p = \hat{\beta}_p - \hat{\beta}^*_p$, and compute which part of this difference can be attributed to each of the additional control variables in the extended model. Figure 4 in the paper shows the difference between the coefficient estimates of the two models (in black) as well as the part of this difference that can be assigned to the additional control variables.

B.6 Counterfactual employment trajectories in the absence of the Covid-19 pandemic

According to the results in Section 5 in the paper, individuals who became unemployed shortly before the onset of the Covid-19 pandemic in Germany subsequently experienced a more adverse development of their employment trajectories than observationally identical individuals from the control group. One concern is that these adverse effects are not the result of the pandemic, but rather reflect a general worsening of labour market opportunities. Figure 1 in the paper provides some support for this hypothesis as it shows that the number of vacancies was already decreasing before the start of the pandemic.

To assess this hypothesis empirically, we construct a counterfactual development of the main labour market outcomes (earnings, employment and wages) that is based on a linear extrapolation from pre-pandemic years. Specifically, we estimate Equation 1 separately for three cohorts of individuals who became unemployment during the first half of February in the years 2017, 2018 and 2019, respectively (the corresponding control groups entered unemployment during the first half of February 2016, 2017 and 2018) as well as for the cohort 2020 (control group: 2019). For each cohort we employ the weighting procedure

[25] The estimated coefficients are identical to those shown in the bottom panel of Figure 3 in the paper.

that is described in Section 3.3 in the paper to ensure comparability of treatment and control group in terms of observable characteristics. Table B8 shows that both groups are balanced for each cohort.

Compared to the analysis in the paper where we observe individuals up to year $t+2$ after becoming unemployed, individuals are only followed until the end of the year in which they entered unemployment for the extrapolation analysis. We do this for two reasons: First, the largest effects can be found during the first year, so that focusing on this year appears to be most relevant. Second, a longer period of observation would have required us to use earlier cohorts to ensure that the period of observation for these cohorts does not cover the Covid-19 pandemic. This would have increased the risk of differences in the composition of the unemployed between cohorts as earlier cohorts are subject to other labour market shocks.

We start by estimating separate models for each cohort c using earnings, days in employment and log wages as dependent variables:

$$y_{i,p}^c = \alpha_i^c + \sum_{\tau \neq -1} \gamma_\tau^c I(\tau = p) + \sum_{\tau \neq -1} \beta_\tau^c I(\tau = p) I(D_i = 1) + \varepsilon_{i,p}^c \tag{4}$$

After storing the coefficient estimates, $\hat{\beta}_p^c$, for the three pre-pandemic cohorts (2017, 2018, 2019), we estimate an auxiliary model in which we regress the estimated coefficients on a constant and a linear time trend:

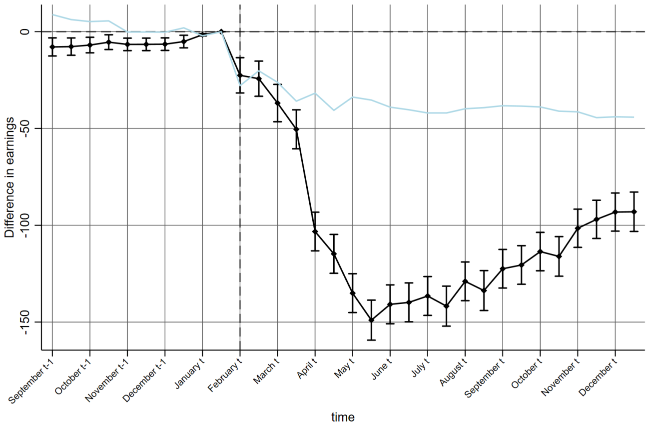
$$\hat{\beta}_p^c = \alpha^c + \beta^c p + \epsilon_p^c \tag{5}$$

Based on the estimated coefficients from Equation 5, we then compute the linear extrapolation of the estimates $\hat{\beta}_p^c$ for the pandemic cohort 2020. Based on the assumption that the employment trajectories of newly unemployed individuals in 2020 would have followed the (linear) path of the three preceding cohorts, these predicted values present the counterfactual employment trajectories in the absence of the Covid-19 pandemic. Finally, we compare the predicted path of the different labour market outcomes with the corresponding coefficient estimates that are obtained when estimating the model for the 2020 cohort.

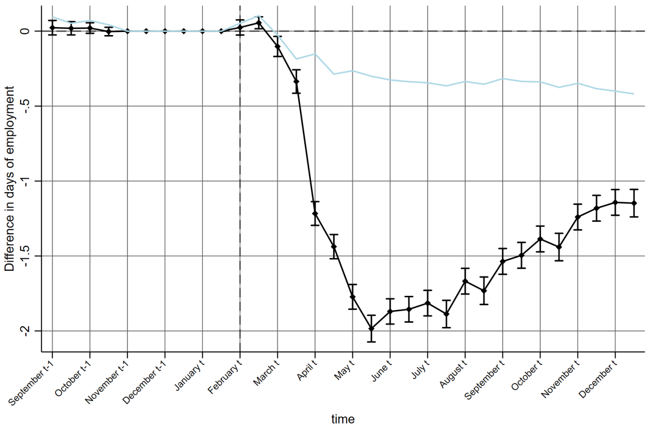
Table B8: Descriptive statistics: different cohorts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2017			2018			2019			2020		
	Treatment	Control	Standard. diff.	Treatment	Control	Standard. diff.	Treatment	Control	Standard. diff.	Treatment	Control	Standard. diff.
Socio-demographic characteristics (at the time of matching)												
Age	39.594	39.561	0.003	39.423	39.339	0.007	39.331	39.293	0.003	39.223	39.291	-0.005
	(12.266)	(12.272)		(12.349)	(12.273)		(12.365)	(12.301)		(12.379)	(12.328)	
Male (fraction)	0.581	0.580	0.001	0.589	0.589	0.002	0.604	0.602	0.004	0.596	0.597	-0.001
	(0.493)	(0.494)		(0.492)	(0.492)		(0.489)	(0.490)		(0.491)	(0.491)	
Foreign (fraction)	0.181	0.182	-0.002	0.209	0.209	-0.001	0.227	0.228	-0.001	0.246	0.245	0.001
	(0.385)	(0.386)		(0.407)	(0.407)		(0.419)	(0.419)		(0.431)	(0.430)	
Low skilled (no completed apprenticeship, fraction)	0.133	0.134	-0.003	0.144	0.144	-0.001	0.145	0.146	-0.002	0.154	0.153	0.001
	(0.339)	(0.340)		(0.351)	(0.351)		(0.352)	(0.353)		(0.361)	(0.360)	
Middle skilled (completed apprenticeship, fraction)	0.664	0.663	0.002	0.634	0.634	0.001	0.612	0.612	0.000	0.585	0.585	-0.001
	(0.472)	(0.473)		(0.482)	(0.482)		(0.487)	(0.487)		(0.493)	(0.493)	
High skilled (tertiary education, completed)	0.155	0.154	0.003	0.163	0.163	0.001	0.174	0.173	0.003	0.177	0.178	-0.001
	(0.362)	(0.361)		(0.370)	(0.369)		(0.379)	(0.378)		(0.382)	(0.382)	
Current employment (at the time of matching)												
Current wage	67.673	66.411	0.030	68.699	67.002	0.040	71.615	69.897	0.039	72.853	71.552	0.029
	(42.003)	(42.256)		(41.568)	(42.660)		(41.147)	(44.079)		(45.017)	(44.939)	
Current earnings	1,015.096	996.163	0.030	1,030.486	1,005.034	0.040	1,074.232	1,048.459	0.039	1,092.794	1,073.279	0.029
	(630.051)	(633.841)		(639.896)	(617.209)		(661.182)	(647.903)		(675.257)	(674.078)	
In regular employment (fraction)	0.925	0.925	0.002	0.927	0.927	0.001	0.928	0.928	0.003	0.931	0.930	0.005
	(0.263)	(0.264)		(0.260)	(0.260)		(0.258)	(0.259)		(0.254)	(0.256)	
In full-time employment (fraction)	0.646	0.642	0.010	0.644	0.642	0.003	0.653	0.652	0.002	0.641	0.642	-0.001
	(0.478)	(0.479)		(0.479)	(0.479)		(0.476)	(0.476)		(0.480)	(0.479)	
Very small establishment (less than 10, fraction)	0.248	0.242	0.015	0.230	0.230	0.001	0.222	0.222	-0.000	0.206	0.204	0.005
	(0.432)	(0.428)		(0.421)	(0.421)		(0.416)	(0.416)		(0.405)	(0.403)	
Small establishment (10-49, fraction)	0.306	0.304	0.004	0.301	0.301	-0.001	0.297	0.298	-0.002	0.306	0.306	-0.001
	(0.461)	(0.460)		(0.459)	(0.459)		(0.457)	(0.457)		(0.461)	(0.461)	
Medium-sized establishment (50-249, fraction)	0.267	0.272	-0.011	0.280	0.280	0.000	0.281	0.281	0.001	0.285	0.286	-0.003
	(0.443)	(0.445)		(0.449)	(0.449)		(0.450)	(0.449)		(0.452)	(0.452)	
Large establishment (more than 250, fraction)	0.172	0.176	-0.011	0.183	0.182	0.001	0.194	0.193	0.002	0.197	0.197	-0.001
	(0.378)	(0.381)		(0.386)	(0.386)		(0.395)	(0.395)		(0.398)	(0.398)	
Estimated AKM firm effect	-0.186	-0.183	-0.010	-0.184	-0.187	0.014	-0.169	-0.174	0.021	-0.161	-0.171	0.039
	(0.264)	(0.264)		(0.266)	(0.263)		(0.264)	(0.263)		(0.265)	(0.267)	
Employment biography												
Work experience	12.269	12.176	0.010	11.916	11.839	0.008	11.946	11.823	0.013	11.893	11.817	0.008
	(9.573)	(9.525)		(9.710)	(9.530)		(9.921)	(9.758)		(10.056)	(9.963)	
Tenure in current establishment	3.177	3.202	-0.005	2.969	3.040	-0.014	2.951	3.024	-0.014	2.987	2.967	0.004
	(5.104)	(5.052)		(4.953)	(4.996)		(4.954)	(5.085)		(5.139)	(4.988)	
Tenure in current occupation	5.911	5.808	0.015	5.674	5.606	0.010	5.680	5.748	-0.010	5.734	5.785	-0.007
	(7.141)	(7.022)		(7.014)	(6.960)		(7.095)	(7.159)		(7.169)	(7.173)	
Number of job changes	2.728	2.658	0.022	2.731	2.673	0.018	2.790	2.699	0.028	2.885	2.795	0.027
	(3.188)	(3.102)		(3.223)	(3.186)		(3.273)	(3.238)		(3.383)	(3.311)	
Being unemployed before (fraction)	0.767	0.763	0.010	0.768	0.768	-0.000	0.766	0.767	-0.003	0.758	0.757	0.002
	(0.423)	(0.425)		(0.422)	(0.422)		(0.423)	(0.423)		(0.429)	(0.429)	
Employed in manufacturing sector (fraction)	0.396	0.395	0.001	0.379	0.379	0.001	0.395	0.394	0.000	0.379	0.380	-0.001
	(0.489)	(0.489)		(0.485)	(0.485)		(0.489)	(0.489)		(0.485)	(0.485)	
Employed in service sector (fraction)	0.593	0.594	-0.002	0.611	0.612	-0.001	0.596	0.596	-0.000	0.613	0.613	0.001
	(0.491)	(0.491)		(0.487)	(0.487)		(0.491)	(0.491)		(0.487)	(0.487)	
Estimated AKM worker effect	4.365	4.367	-0.006	4.363	4.358	0.012	4.365	4.368	-0.009	4.364	4.365	-0.003
	(0.360)	(0.357)		(0.368)	(0.354)		(0.374)	(0.371)		(0.382)	(0.386)	
N	60,808	61,001		59,690	65,548		58,113	58,210		62,393	61,347	

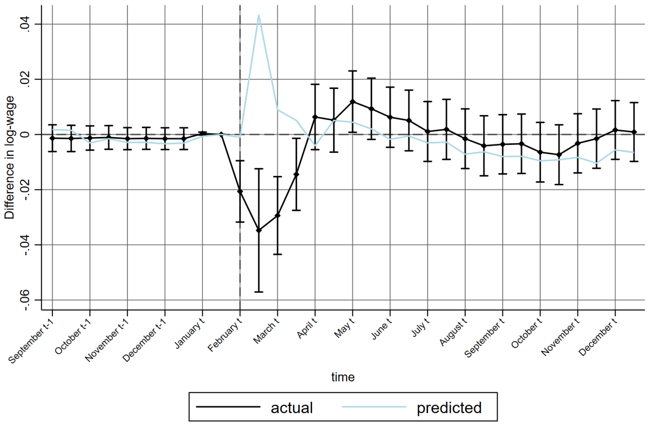
Notes: For each treatment year - 2017, 2018, 2019 and 2020 - the first two columns show the mean value and standard deviation (in parentheses) of individual characteristics that are measured at the first half of November $t-1$ (the point for the weighting). The third column reports the standardised difference between the first two columns, which is defined as $\Delta_X = \left(\bar{X}_1 - \bar{X}_0\right) / \left((S_1^2 + S_0^2)/2\right)^{0.5}$, where $\bar{X}_w$ is the sample mean of the treated ($w=1$) or (weighted) control ($w=0$) individuals and S_w^2 are the respective sample variances. The corresponding control year for the treatment year t is $t-1$. Note that the observations for the AKM worker and firm fixed effects are smaller than the reported number of observations. Source: IEB, BHP, own calculations.



(a) Earnings



(b) Days in employment

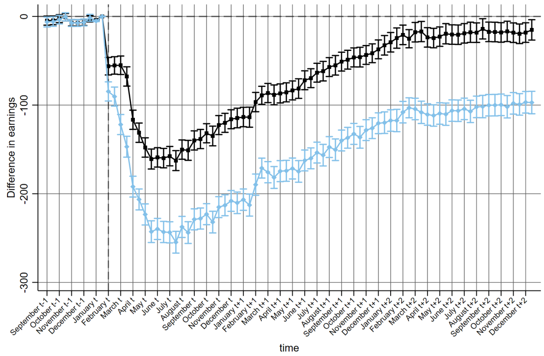


(c) Log wages

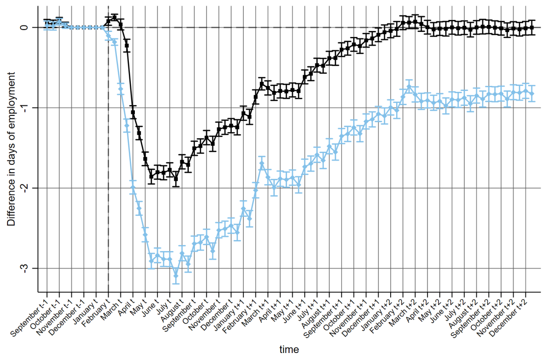
Figure B8: The effect of the Covid-19 pandemic on earnings, employment and wages – Counterfactual scenarios

Note: Figure B8 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 (black line) and the predicted $\hat{\beta}^c_p$ from Equation 5 (blue line) with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. The estimation is weighted by the inverse propensity score. t denotes the year in which the individuals in the sample became unemployed. For treated individuals t refers to the years 2017, 2018, 2019 (blue line) and 2020 (black line) and for control individuals to the years 2016, 2017, 2018 (blue line) and 2019 (black line). The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

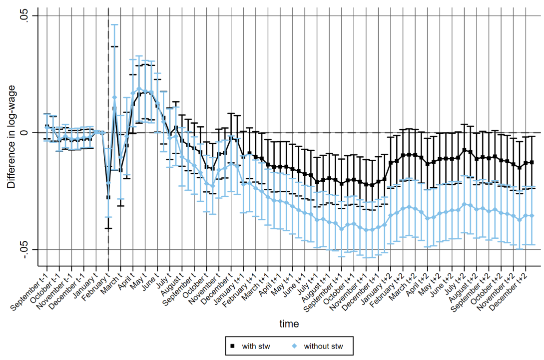
B.7 Short-time work



(a) Earnings



(b) Days in employment



(c) Log wages

Figure B9: The effect of the Covid-19 pandemic on earnings, employment and wages – Role of short-time work

Note: Figure B9 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. The black line indicates the baseline estimates and the blue line indicates the estimates for a sample restricted to individuals who never had been employed in a firm that used short-time work. The estimation is weighted by the inverse propensity score.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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

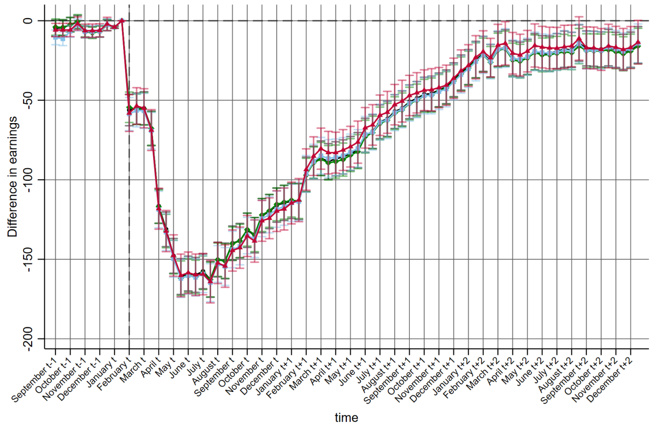
B.8 Sensitivity to changes in sample restrictions

In this section, robustness checks for different variations of the sample restrictions are presented. These include, first, different duration of employment prior to the transitions into unemployment, second, different timings of the transition into unemployment and, third, different lengths of the subsequent unemployment period.

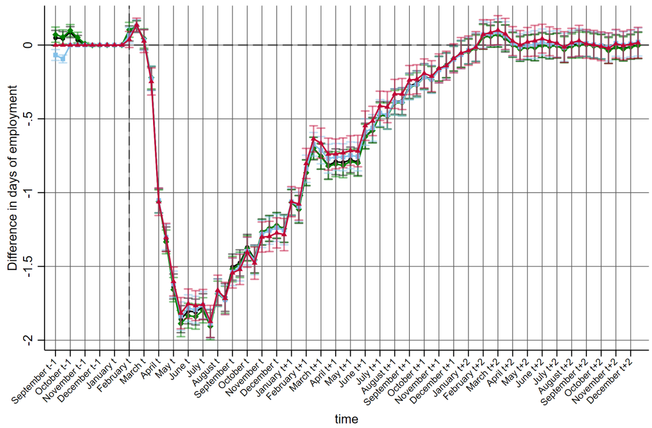
The first sample restriction implies that individuals have to be employed from at least November in the same establishment and occupation. Figure B10 shows the results for shorter (December, grey line) and longer (October, blue line; August, red line) duration in employment as well as for the baseline duration (November, black line). Overall, the estimated effects are close together indicating that longer or shorter lengths of employment do not substantially change results.

The baseline sample is restricted to individuals who enter unemployment in the first half of February. Figure B11 displays results if instead individuals who enter unemployment during the second half of February (for the treatment as well as the control group) is chosen. As can be seen, for the main outcomes - earnings, employment, wages - the negative effect size is stronger for individuals entering unemployment in the second half and seems to be visible - at least for earnings and employment - in the longer run. However, the differences are small and the overall pattern is similar compared to the baseline specification.

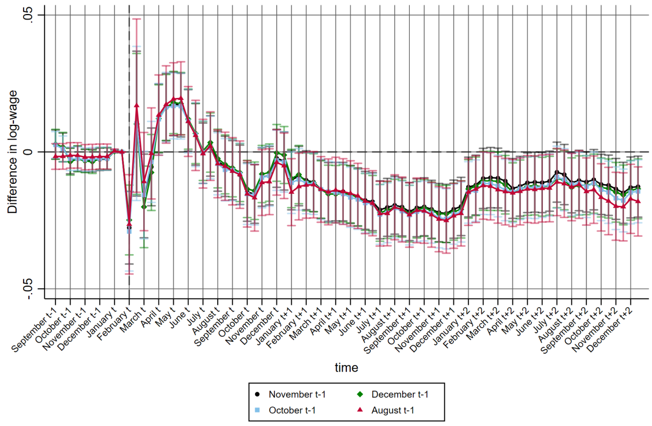
At the same time, the baseline restriction includes all individuals who have been at least one day unemployed in (the first half of) February and thus potential job-to-job transitions might be included. In order the exclude the latter, we run a separate analysis for individuals who have been at least one month (February) unemployed. Figure B12 shows that the results also do not change considerably by including this restriction (except log wages in the longer run).



(a) Earnings



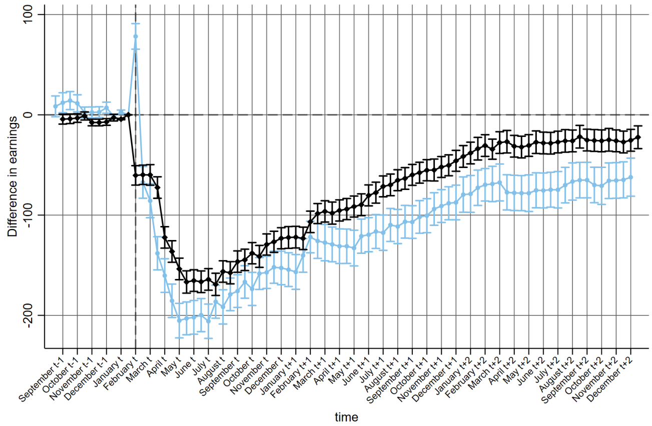
(b) Days in employment



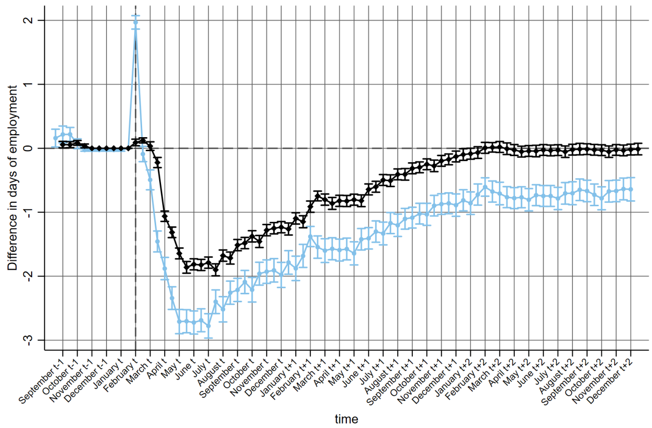
(c) Log wages

Figure B10: The effect of the Covid-19 pandemic on earnings, employment and wages – Different sample restrictions I

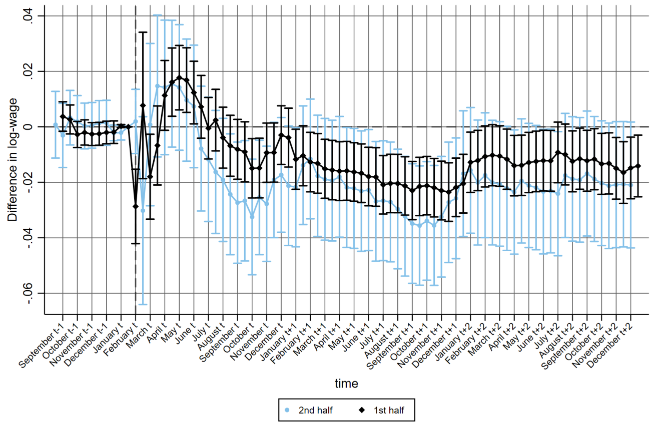
Note: Figure B10 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. Estimates are shown for different sample restrictions: individuals that were employed since December $t-1$ (green line), November $t-1$ (black line), October $t-1$ (blue line) and August $t-1$ (red line). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.



(a) Earnings



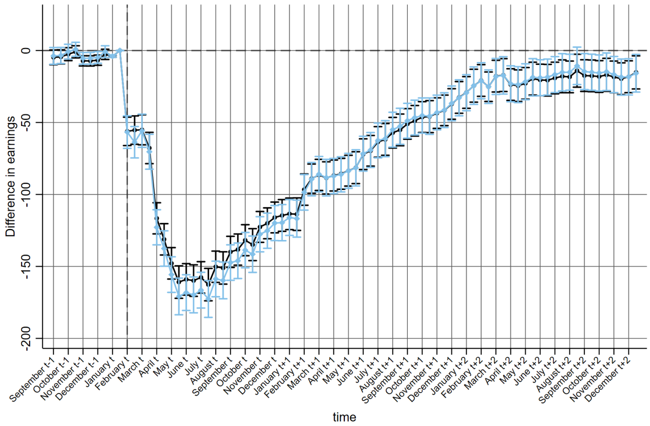
(b) Days in employment



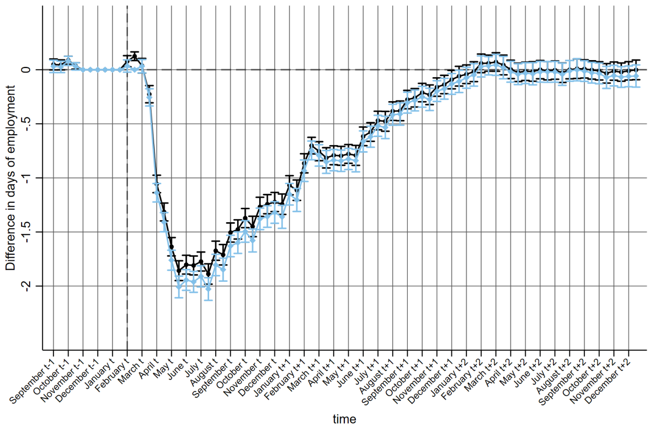
(c) Log wages

Figure B11: The effect of the Covid-19 pandemic on earnings, employment and wages – Different sample restrictions II

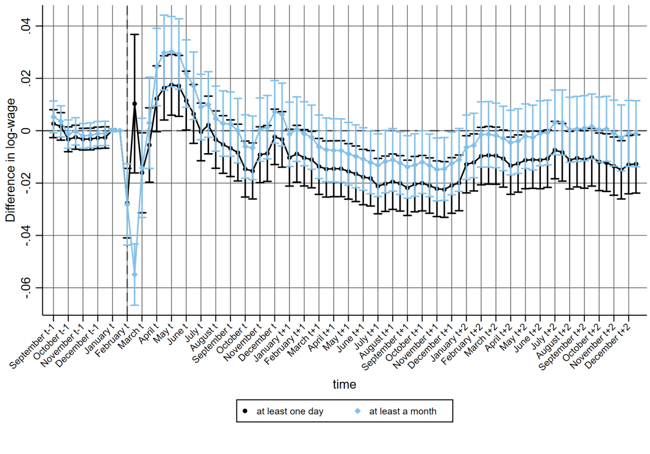
Note: Figure B11 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. Estimates are shown for different samples: individuals who became unemployed in the first half of February t (black line) and in the second half (blue line). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.



(a) Earnings



(b) Days in employment



(c) Log wages

Figure B12: The effect of the Covid-19 pandemic on earnings, employment and wages – Different sample restrictions III

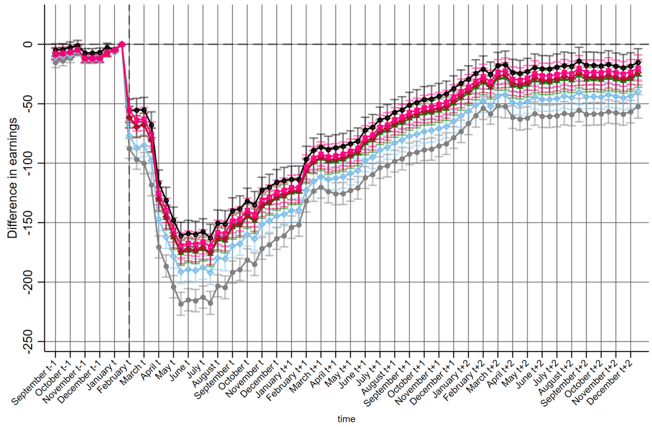
Note: Figure B12 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. Estimates are shown for different sample restrictions: individuals that were unemployed in February t at least one day (black line) or at least one month (blue line). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.9 Sensitivity to changes in the set of weighting covariates

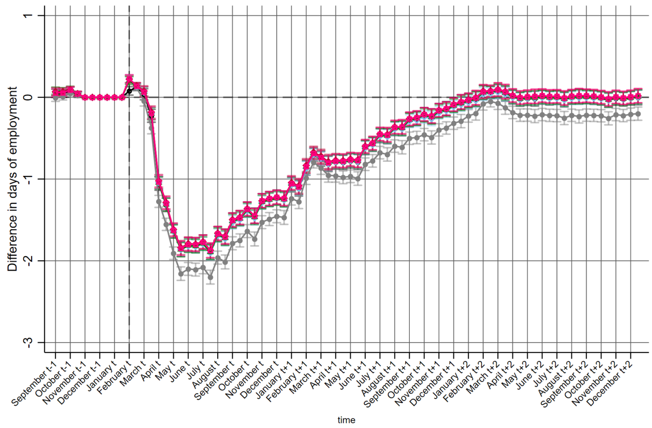
We estimate different specifications to examine the sensitivity of the choice of covariates included in the IPW approach. Figure B13 presents the results of estimating Equation 1 for earnings, days in employment and log wages using different sets of IPW covariates. The grey line shows the development of outcomes for the model without any weighting and the coloured lines add subsequently new sets of variables as weights to the unweighted estimation: socio-demographic (blue), firm characteristics (green), current employment characteristics (red) and employment biography (pink). The black line adds the wage-growth variable and then displays the final set of weighting variables of our approach.

Compared to the estimates with weights the negative effect size of estimates without weights is stronger and long lasting. The pre-trend, though, are only close to zero and insignificant for employment and wages, for earnings there is a small and significant deviation from zero visible. Overall, it can be seen that the estimation results are not substantially affected by the choice of IPW variables. The same holds for the other outcomes that are investigated in the paper.[26]

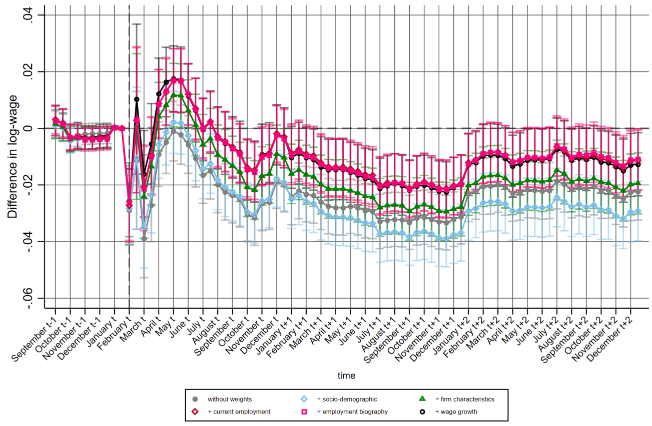
[26] Results are available upon request.



(a) Earnings



(b) Days in employment



(c) Log wages

Figure B13: The effect of the Covid-19 pandemic on earnings, employment and wages – Different weighting variables

Note: Figure B13 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. The estimation is weighted by the inverse propensity score with a growing set of variables: without weights (grey line), with socio-demographics (blue line), firm characteristics (green line), current employment characteristics (red line), employment biography (pink line) and the full set of variables (black line). 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.10 Wage variable

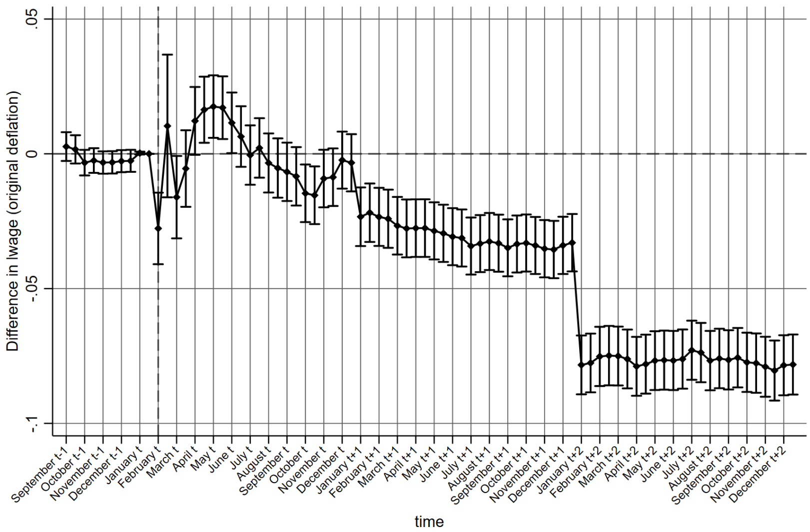
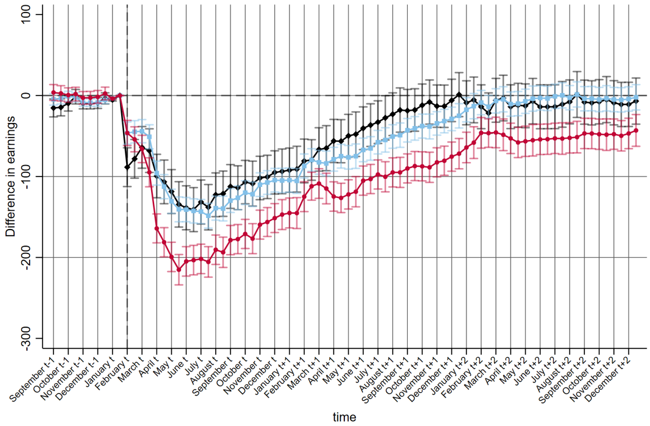


Figure B14: The effect of the Covid-19 pandemic on log wages – Original deflation

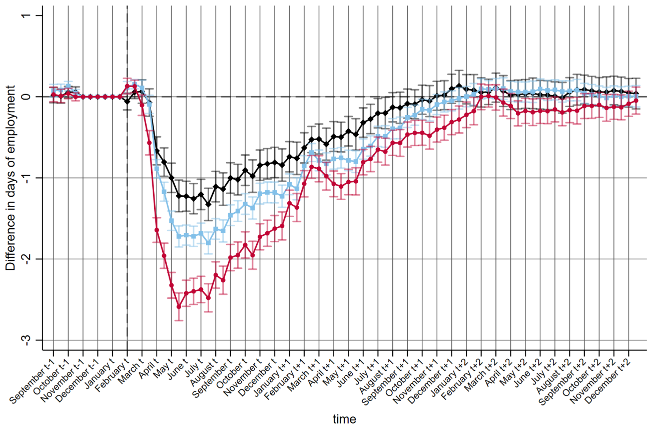
Note: Figure B14 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with log wages with the original deflation as dependent variable. The estimation is weighted by the inverse propensity score. t denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.11 Sensitivity to LWA distribution

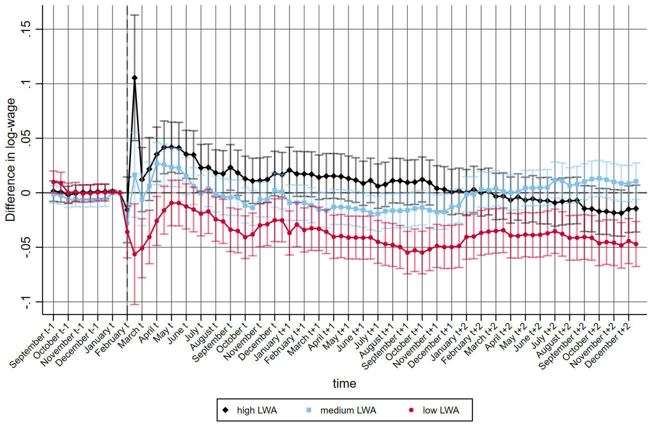
Equation 1 is estimated for the main outcomes - earnings, employment and log-wages - for different subsets of the LWA distribution. These subsets are defined at different thresholds of the LWA distribution to get a subset of individuals from low-LWA occupations (below the 25% quantile, grey line), from medium-LWA occupations (between the 25% and the 75% quantile, blue line) and from high-LWA occupations (above the 75% quantile, black line). The group of individuals from medium-LWA occupations are pooled in order to get a better understanding of less and high affected occupations.



(a) Earnings



(b) Days in employment



(c) Log wages

Figure B15: The effect of the Covid-19 pandemic on earnings, employment and wages – Different subsets of LWA distribution

Note: Figure B15 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 with earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)) as dependent variables. Estimates are shown for different subsets of the LWA distribution: low LWA (below the 25% quantile), medium LWA (between the 25% and the 75% quantile) as well as high LWA (above the 75% quantile). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.12 Occupational heterogeneity: employment mechanisms

Table B9: Effect heterogeneity by LWA: employment adjustments

	(1)	(2)	(3)	(4)	(5)	(6)
	Days in unemployment		Days out of the labour market		Days in other states	
	Abs.	Rel.	Abs.	Rel.	Abs.	Rel.
Average						
Treatment period	0.080***	0.098	0.007	-0.042	0.006	-0.058
	(0.007)		(0.008)		(0.004)	
Pre-treatment	0.002	-0.119	-0.001	1.500	0.000	-0.044
	(0.002)		(0.001)		(0.001)	
Feb-May 2020	0.067***	0.057	0.007	-0.051	0.004	-0.018
	(0.011)		(0.005)		(0.005)	
Jun-Sep 2020	0.104***	0.046	0.015*	-0.041	0.018**	-0.064
	(0.014)		(0.008)		(0.007)	
Oct-Dec 2020	0.069***	0.041	0.020**	-0.052	0.020***	-0.253
	(0.013)		(0.009)		(0.007)	
2021	0.048***	0.070	0.011	-0.069	0.011**	-0.425
	(0.009)		(0.010)		(0.005)	
2022	0.015**	0.142	0.010	-0.200	0.008	-0.122
	(0.007)		(0.012)		(0.005)	
Cumulative						
Treatment period	5.583***	0.098	0.475	-0.042	0.394	-0.058
	(0.483)		(0.564)		(0.284)	
N	10,583,520		10,583,520		10,583,520	

Notes: Table B9 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 with days in unemployment, out of the labour market as well as the remaining labour market status (which includes days in a measure, days receiving transfer payments and days registered in the unemployment data but not being unemployed) as dependent variables. The estimation is weighted by the inverse propensity score. The table displays the averaged $\hat{\phi}_p$ and the ratio $\frac{\hat{\phi}_p}{\hat{\beta}_p}$ for specific time periods and the (treatment) effect averaged over the whole period. Standard errors clustered at the individual level are in parentheses. Note that it is possible that individuals are in several labour market states at the same time, but Table B9 show only one labour market per individual per period.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: IEB, BHP, own calculations.

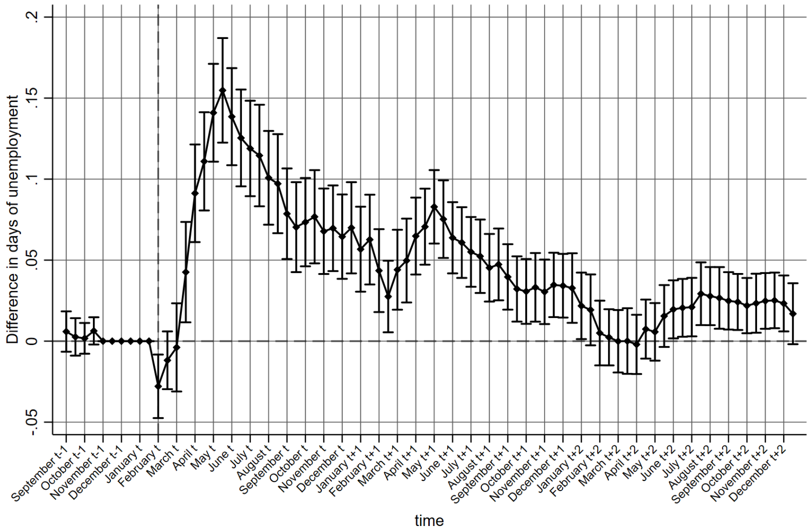
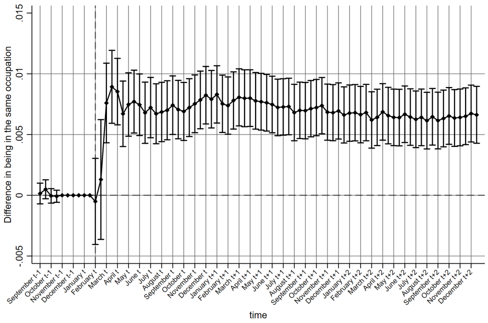


Figure B16: The heterogeneous effect of the Covid-19 pandemic by LWA on unemployment

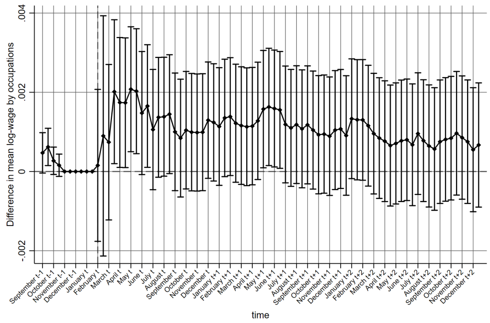
Note: Figure B16 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 with days in unemployment as dependent variable. The estimation is weighted by the inverse propensity score. t denotes the year in which the individuals in the sample became unemployed. This means that individuals in the treatment group are observed from September 2019 until December 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level. Source: IEB, BHP, own calculations.

B.13 Occupational heterogeneity: wage mechanisms

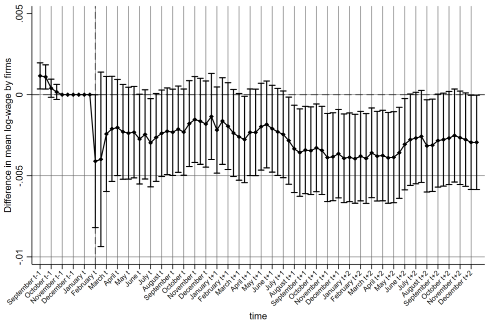
B.13.1 Event study plots by LWA



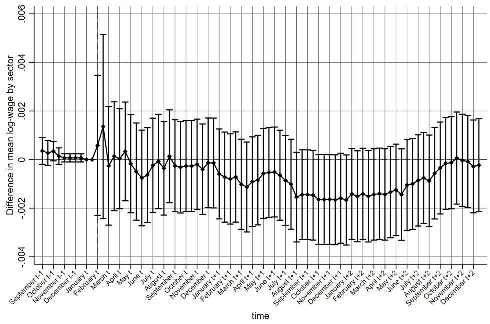
(a) Occupational mobility



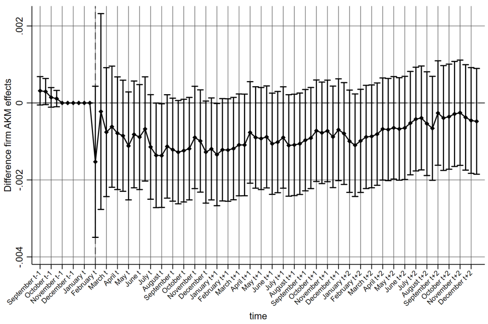
(b) Mean wage (occupation)



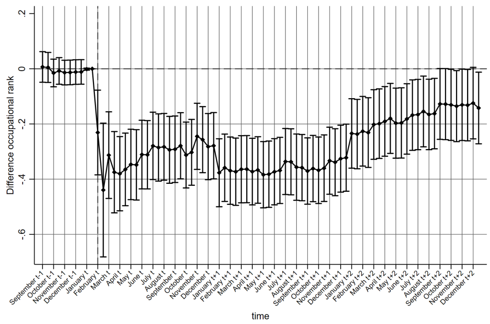
(c) Mean wage (firm)



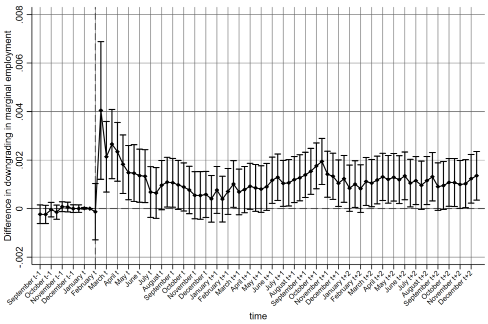
(d) Mean wage (sector)



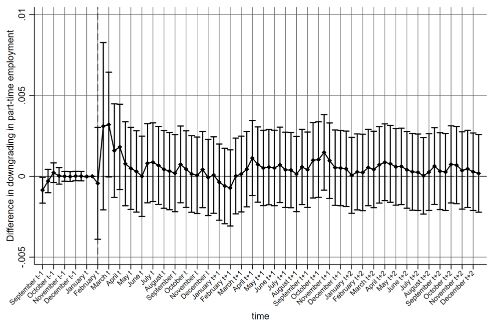
(e) AKM firm effect



(f) Occupational rank



(g) Downgrading (marginal)

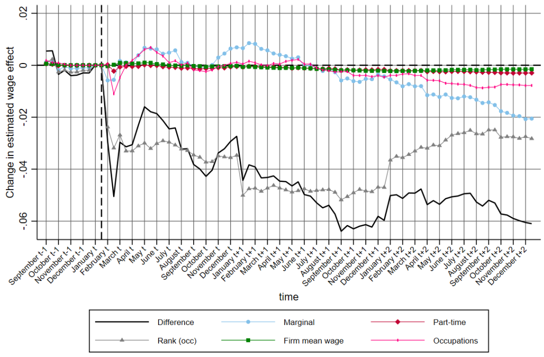


(h) Downgrading (part-time)

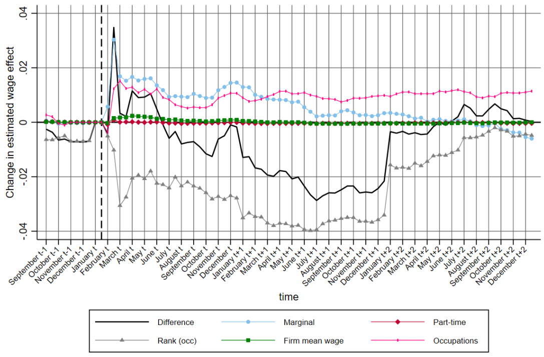
Figure B17: Wage mechanisms by LWA: event study plots

Notes: Figure B17 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 with occupational mobility (panel (a)), occupational mean log wage (panel (b)), firm mean log wage (panel(c)), sector mean log wage (panel (d)), AKM firm fixed effects (panel (e)), rank in the occupational wage distribution (panel (f)), downgrading from regular into marginal employment (panel (g)) as well as downgrading from full-time into part-time employment (panel (h)) as dependent variables. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence intervals which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

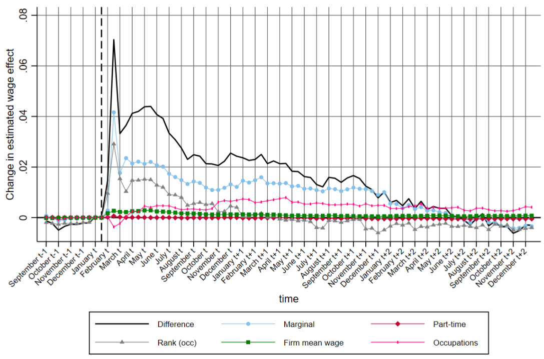
B.13.2 Gelbach decomposition by LWA



(a) Low LWA



(b) Medium LWA

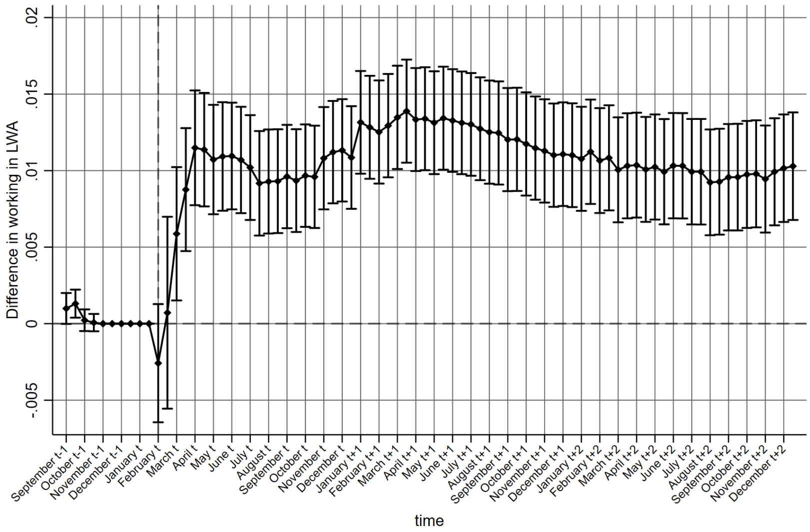


(c) High LWA

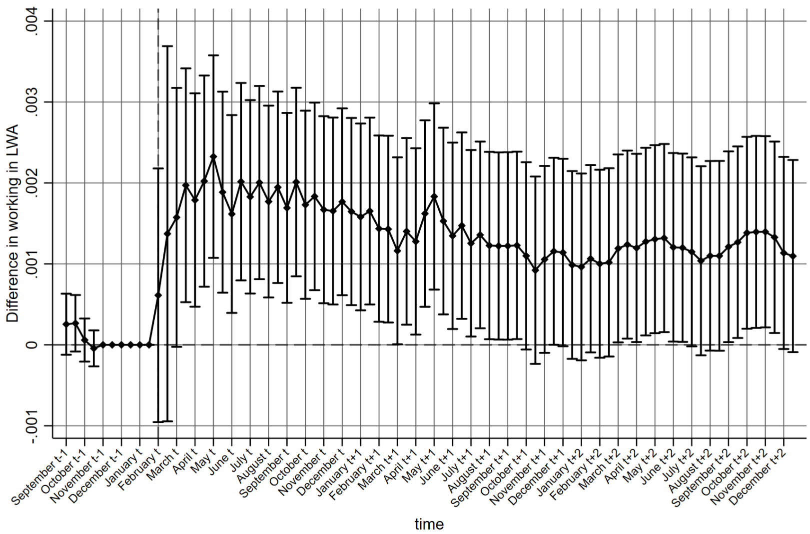
Figure B18: Decomposition of the wage effect by LWA

Note: Figure B18 shows the change in the estimated wage effect when additional control variables are added to the baseline model of Equation 1 (solid line) for different subsets of the LWA distribution: low LWA (below the 25% quantile), medium LWA (between the 25% and the 75% quantile) as well as high LWA (above the 75% quantile). Moreover, it shows how much each additional control variable (or set of control variables) contributes to this change: downgrading into marginal employment (circles), downgrading into part-time employment (diamonds), rank in the occupational wage distribution (triangles), firm mean wage (squares) and occupation dummies (X). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019.
Source: IEB, BHP, own calculations.

B.13.3 LWA as dependent variable



(a) Baseline model

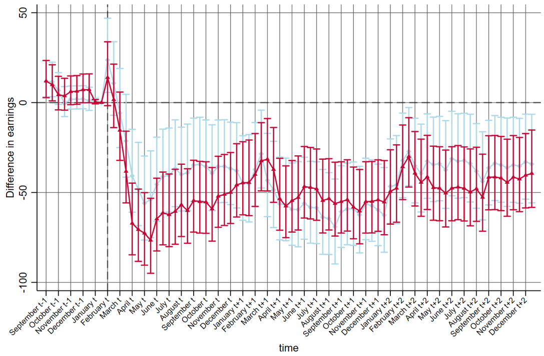


(b) Heterogeneous model

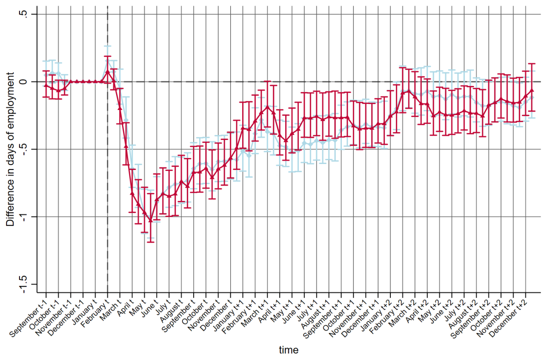
Figure B19: The effect of the Covid-19 pandemic on LWA

Note: Figure B19 shows the estimated coefficients $\hat{\beta}_p$ from Equation 1 (panel (a)) and the estimated coefficients $\hat{\phi}_p$ from Equation 2 (panel (b)) with LWA as dependent variable. The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

B.14 Occupational heterogeneity: parallel trends assumption



(a) Earnings



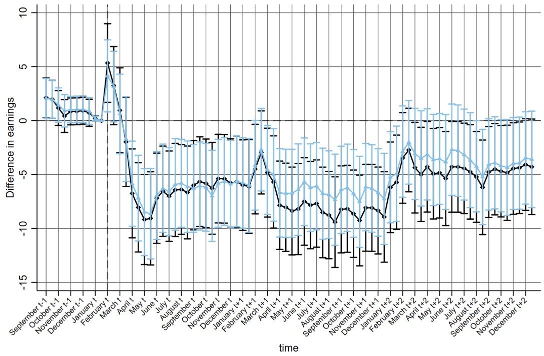
(b) Days in employment

(c) Log wages

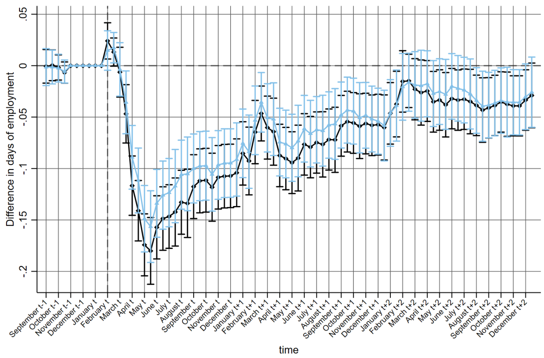
Figure B20: The effect of the Covid-19 pandemic on earnings, employment and wages – Assessing parallel trends

Note: Figure B20 shows the estimated coefficients $\hat{\phi}_p$ from an adjusted Equation 2 in which instead of the continuous (inverse) LWA index a dummy for low- (below the 33% quantile of the LWA distribution) and high-LWA occupations (above the 75%-quantile of the LWA distribution) is used. The dependent variables are earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence interval which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.

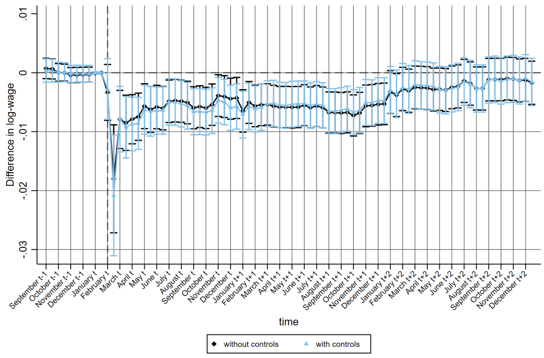
B.15 Occupational heterogeneity: accounting for confounding variables



(a) Earnings



(b) Employment



(c) Log wage

Figure B21: The effect of the Covid-19 pandemic on earnings, employment and wages - Additional control variables

Note: Figure B21 shows the estimated coefficients $\hat{\phi}_p$ from Equation 2 (blue line) as well as the coefficients from Equation 2 including interaction terms of gender, skill level and firm size (measured at the matching point in November $t-1$) with the treatment dummy, the event time and a combination of both (black line). The dependent variables are earnings (panel (a)), days in employment (panel (b)) and log wages (panel (c)). The estimation is weighted by the inverse propensity score. 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 2022, while the control group is observed from September 2016 until 2019. The vertical bars represent the 95% confidence intervals which are based on standard errors that are clustered at the individual level.
Source: IEB, BHP, own calculations.