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Research Article

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Failing Young and Temporary Workers? The Impact of a Disruptive Crisis on a Dual Labour Market

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Abstract: We study the impact of the pandemic crisis using monthly data covering the universe of individuals registered as unemployed in mainland Portuguese municipalities, complemented with electronic payments, linked employer–employee data, and furlough records. Event study designs identify a sharp increase in unemployment, driven mostly by termination of temporary contracts, and a decrease in new job placements. With triple difference-in-differences, we show that the effects are stronger in more dual municipal labour markets, i.e. with a higher share of temporary jobs, concentrated in young workers and middle educated individuals. The asymmetries are exacerbated by the duality of the municipal labour market.

Keywords: Covid-19, unemployment, difference-in-differences, dual labour market, regional impacts, Portugal

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1 Introduction

In most countries of the Eurozone, with the exception of Greece and Spain, employment in 2017 had mostly reached the 2006 levels. However, the composition of employment changed: the share of temporary workers has increased (Weel 2018). In Portugal, the unemployment rate in 2019 was 6.6%, and the share of temporary workers 22%, i.e. twice the OECD average. Therefore, compared with the financial and sovereign debt crisis of 2008–2012, the disruptive pandemic crisis of 2020 hit a structurally different (dual) labour market and, moreover, was met with massive public spending aimed at the protecting the so-called *matching capital* between workers and firms (Dias et al. 2020, Mayhew and Anand 2020). Several European countries (e.g. France, Germany, the Netherlands, Portugal, Sweden, Spain, Switzerland, and the UK) implemented furlough schemes, most of them prohibiting firms from dismissing workers while the support lasted. By May 2020, about 50 million workers were supported by such job retention schemes (OECD 2020).[1] Portugal is a Eurozone member severely affected by the pandemic crisis (GDP contraction of 8.4% in 2020), with a generous coverage of the furlough policy (a peak of 1.2 million workers, or one fourth of the workforce (Banco de Portugal 2020). As a consequence, the unemployment rate in 2020 reached 7%, barely above the 2019 level. This stability hides considerable heterogeneous effects. Indeed, job separations can only occur in firms that do not benefit from support, or through terminations of temporary contracts in the remaining ones, thus leaving the self-employed and temporary workers in a vulnerable position (Mayhew and Anand 2020). This naturally raises the question of the impact of the crisis on temporary workers.

We use difference-in-differences event studies, and triple difference regressions, to address the following research questions. First, we estimate the causal impact of the pandemic (and subsequent restrictive policies) on jobless claims and job placements. Second, we investigate the uneven impacts along the gender, age, and education level of the workers. Finally, we show how the duality in municipal labour markets amplifies both the magnitude and the asymmetry of the effects.

Our data covers all individuals formally registered as unemployed with the Portuguese Public Employment Service, aggregated at the municipal level, in all the 278 mainland municipalities, between October 2016 and August 2020.[2]

1 By contrast, in the US, unemployment grew to over 30 million in just one month.

2 By definition, joblessness claims only include individuals in the labour force, therefore we do not tackle the participation margin, i.e. exits from the labour force.

We complement this with several other data sources, including the Labour Force Survey, pre-shock linked employer–employee data, electronic payments data, and Google mobility reports.

Our main findings are as follows. Firstly, the pandemic caused a rise on year-on-year growth rates of registered unemployment from 27 percentage points in April up to 38 percentage points in July, and a severe drop of 63 percentage points in new job placements in April. Secondly, we find evidence that the duality mediated the impact of the crisis on employment. Between March and May, there was a sharp increase in the number of jobless claims filed because workers were dismissed from their (permanent or temporary) job or because their temporary contract ended. Almost two thirds of job separations until September 2020 are due to termination of temporary contracts. Moreover, we find that the shock is larger in municipalities with a higher share of temporary workers: an increase of one standard deviation (8%) in the share of temporary workers increases joblessness claims by 11.6%.

Thirdly, we demonstrate that the impact on unemployment was 20.8% and 25.8% larger for workers who are less than 25 years old, and between 25 and 34 years old, respectively, when compared with the reference group used in the regressions, i.e. older than 55. We document an inverted u-shape impact of education on unemployment, with the highest impact concentrated on individuals with lower (15%) and upper secondary education (17.5%), *vis-à-vis* the highly educated ones. While we find no evidence of gender differences in unemployment, we document an additional drop in new job placements of women compared to men. Lastly, asymmetric effects are amplified by the duality of municipal labour markets. In particular, an increase of one standard deviation in the share of temporary contracts causes a rise of 12.6%, between 14% and 17%, and between 12% and 13% in the number of unemployed people who are female, younger than 34, and have secondary education.

The literature on the economic impacts of Covid-19 has uncovered large impacts on the labour market. Alstadsæter et al. (2020) find that 12% of the labour force filed jobless claims in the first weeks of the crisis in Norway. Cajner et al. (2020) analyse US administrative payroll data and show that aggregate employment decreased by 21% through late-April, with slight signs of recovery only by late-June. Various authors documented severe drops in job posts (Bamieh and Ziegler 2020; Hensvik et al. 2020) and a decrease in hirings on the period following lockdown (Betcherman et al. 2020). Lafuente et al. (2022) find that, in the early period of the pandemic crisis, permanent workers adjusted more the hours-per-worker (i.e. the intensive margin) than the temporary ones, while the reverse is true for the extensive margin. Using job vacancy data collected in real-time by the Burning Glass Technologies platform, Forsythe et al. (2020) find that, in the US, job postings collapsed by 44% between February and April 2020. Coibion et al. (2020) used scan data in April 2020 to show that job loss in the US was larger than new unemployment claims, with many workers moving into inactivity. For Canada, Jones et al. (2020) found new vacancies recovered in June, from 50% to around 80% of the pre-pandemic level.

A number of papers present convincing evidence of the unequal labour market impacts of the pandemic on temporary workers. Couch et al. (2020) use the Current Population Survey to show how the black-white unemployment gap increased to levels resembling those of the Great Recession. Casarico and Lattanzio (2020) uses administrative data on a sample of contracts for the first quarter of 2020 in Italy to find that temporary workers are 8 p.p. more likely to lose their job, contrary to older and highly educated workers, who are more protected against job loss. Herzog-Stein et al. (2022) also show that, in Germany, the labour adjustment used the temporary workers margin. Papers based on survey data that confirm the larger effect on temporary workers include Adams-Prassl et al. (2020a, 2020b), Kikuchi et al. (2021) and Aum et al. (2021) in the UK, USA, and Germany, Japan, and South Korea. Younger workers are shown to be the most affected in Canada by Lemieux et al. (2020), Japan by Kikuchi et al. (2021), and the US by Cho and Winters (2020), Cortes and Forsythe (2022) and Montenovo et al. (2020). Female self-employed are found to be more affected by Graeber et al. (2021), using survey data from Germany. Other papers that show a disproportionate impact on female workers include Kikuchi et al. (2021) for Japan and Cortes and Forsythe (2022) for the US. Alon et al. (2020) find that women were more struck by the crisis in the US, contrary to Hupkau and Petrongolo (2020) who find no significant job loss differences between genders in the UK. Survey data also indicates that less educated, lower income and minority workers in the US are more affected (Cho and Winters 2020). Moreover, Botha et al. (2021), using Australian data, shows that the subjective (financial) well-being is affected by the shock. Adams-Prassl et al. (2022) document strong heterogeneity of the possibility of remote working across industries and occupations in the US and the and Montenovo et al. (2020) add that workers in jobs that are more compatible with remote work fared better. Similarly, Bonacini et al. (2021) shows that remote work favours male, older, high-educated, and high-paid employees.

Two papers follow an approach closer to ours. Meekes et al. (2020) implements a triple difference-in-differences strategy with administrative data from Statistics Netherlands and document large impacts on the employment, working hours, and hourly wages of non-essential workers, particularly the female ones, and on employment and working hours of essential workers who are single parents. Kalenkoski and Wulff (2020) implement triple difference-in-differences specifications using the US Current Population Survey and find that the impact on employment and working hours was larger for coupled women than for coupled men, and smaller for single women than for single men.[3]

The paper offers four main contributions. Firstly, we show how the duality of the labour market magnifies the impact and the asymmetry of the labour market shock caused by the onset of the pandemic. Secondly, we estimate asymmetric effects along gender, education, and age, adding to the existing causal evidence on gender and marital or child rearing status (Adams-Prassl et al. 2020a, 2020b; Kalenkoski and Wulff 2020), gender and type of occupation (Meekes et al. 2020), and ethnicity (Couch et al. 2020). Thirdly, we rely on administrative data that covers the universe of newly registered unemployed workers in Portugal, while most of the papers rely on survey data, with the exception of, e.g. Casarico and Lattanzio (2020) and Meekes et al. (2020).

We also discuss possible mechanisms of adjustment, and argue that we can interpret our results as evidence that furlough schemes do not insure some segments of the labour market against the negative shock of the pandemic crisis.[4] This last contribution relates our paper to the discussion in Giupponi et al. (2022), who argue that furlough and (extended) unemployment insurance are complementary policies. Similarly, Birinci et al. (2021) claim that furlough-type policies are preferred to extended unemployment insurance in isolation, but complementary when used simultaneously, as they cater to different groups of workers. A smaller furlough coverage is sufficient to protect the *matching capital* of *high-productivity* jobs, and avoid locked-in effects after the crisis.[5]

The remainder of this paper is structured as follows. Section 2 describes the Covid-19 shock in Portugal and the main policy responses, and proceeds by discussing the data (Subsection 3.1) and the methodology used (Subsection 3.2). Section 4 discusses the aggregate effects of the shock, and Subsection 4.2 highlights the mediating effect of labour market duality. Heterogeneous effects are shown in Section 5 and Section 6 discusses possible mechanisms. Finally, Section 7 concludes.

3 Cho and Winters (2020) use a similar strategy on the Current Population Survey, and show that employment decreased more in metropolitan areas.

4 Ferreira et al. (2020) monitor the policies implemented in Portugal and highlight that they do not address the income losses of all vulnerable groups. Boeri and Brücker (2011) show that firms that rely heavily on temporary employment are less likely to take-up furlough policies, possibly because it is less costly for them to rely on the dismissal margin to adjust to the shock.

5 A related discussion that focuses exclusively on unemployment insurance is provided by Mitman and Rabinovich 2021, who compare the optimal unemployment insurance in a Covid-type of shock depending on the commitment technology of the government.

2 An Asymmetric Shock in a Dual Labour Market

2.1 Covid-19 in Portugal and Policy Responses

The government closed schools and imposed circulation restrictions on the border with Spain shortly after the first confirmed Covid-19 case on March 2nd 2020. On March 18th, the President declared the State of Emergency, which lasted until May 3rd, when it was substituted by a less severe but still fairly constrained State of Calamity. As a consequence, all retail was shutdown, with the exception of supermarkets, pharmacies, and gas stations. Restaurants were only allowed to serve take-away. Further restrictions on circulation and mandatory homeworking for compatible jobs were also decreed.[6]

The strong impact on the Portuguese economy is documented in Carvalho et al. (2020), using data from electronic purchases. They provide causal estimates of decreases in year-on-year growth rates of 16, 37, and 28 percentage points on overall purchases in March, April and May, respectively. The authors also show that the impact was very uneven across sectors. The Hospitality sector (including restaurants, coffee shops and accommodation), Fashion and Beauty, and Transportation were among the most affected. The differential impact across sectors induced asymmetric effects of the crisis. Average wages in the Hospitality, and Fashion and Beauty sectors are smaller than the national average. The share of low educated and foreign workers in Restaurants is higher than the national average. At the same time, 2022, show that the sectorial composition of the municipal economies leads to asymmetries in the geographic effect of the crisis.[7] Importantly, as shown in Peralta et al. (2021), the incidence of non-permanent contracts in these sectors was larger than for the overall economy.

These sizeable consequences were met with policies targeting the labour market, of which we highlight three. Firstly, the Portuguese Covid-19 special furlough scheme was implemented on March 26th The scheme covered labour costs for the whole duration of compulsory shut-down, and was in place until July 2022.[8] Administrative data from Social Security shows that 1.2 million workers were supported,

6 Portugal is one of the European countries where self-imposed social distancing started earlier, with people avoiding to go out to restaurants eight days before the government mandated its closure (Midões 2020).

7 Carvalho et al. (2022) results are reminiscent of Cho et al. (2021), who find that the employed-at-work rate decreases more in larger metropolitan areas than in non-metropolitan areas in the US.

8 This scheme is a simplification of the pre-pandemic one, which was lengthier and more restrictive.

mostly concentrated in the Retail and Hospitality sectors.[9] Firms that benefited from the furlough policy *could not* dismiss workers on permanent contracts. They could, however, choose not to renew temporary contracts, stop hiring workers with no formal contract, and not replace workers who depart voluntarily.[10]

The bulk of the effects on unemployment should arise from these margins by recipient firms, or from firms that did not qualify or apply for the scheme. Importantly, furlough allows firms to suspend employment contracts or reduce employees' working hours, with social security covering two-thirds of the wage. Therefore, keeping the workers is costly.

Secondly, remote work was made compulsory for compatible occupations. Survey data from Statistics Portugal shows that there were around 1 million remote workers in the Spring of 2020, mostly highly educated and high-income ones. Their average wage was 50% higher than that of non-remote workers, and 70% of them had a higher education degree.

Finally, access to unemployment benefits was eased as of July 25, encompassing permanent or temporary employees, and halving the minimum qualifying contract duration in the past 24 months. Since our period of analysis ends in August, this legal change is unlikely to affect the flows of unemployed individuals. Moreover, mandatory job search and training were suspended between March and May.

2.2 Labour Market in Portugal

Permanent workers in Portugal benefit from one of the highest levels of employment protection across the OECD, which, according to the European Commission, increases both the reluctance of firms to hire permanent employees (European Commission 2018) and the importance of non-permanent employment (OECD 2017).

Figure 1 shows that temporary employment, i.e. wage and salary workers whose job has a pre-determined termination date, accounts for 22% of all employees in Portugal, above the OECD average of 12%, and only exceeded by Spain (27%) and Poland (24%). This makes Portugal an interesting laboratory to study the impact of a major disruptive shock (such as the pandemic), with policies that create asymmetric incentives regarding job separations for different types of workers.

Moreover, legal restrictions on nominal wage cuts, combined with the long recent period of low inflation, leave employers with little margin to adjust real

9 Appendix Figure C.1 presents the evolution in the number of firms and workers under the furlough policy between April and October 2020.

10 Firm survey data from Statistics Portugal collected in 2020 shows that 77% of the firms that took up the furlough scheme claim that they would have reduced employment by an average of 19%.

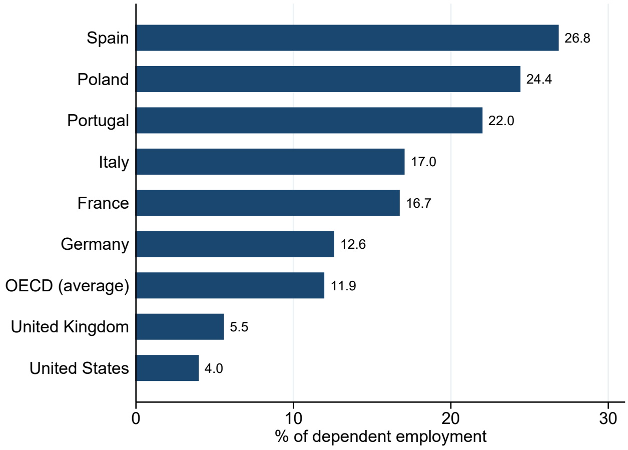


Figure 1: Share of temporary employment (as % of employees), 2018. **Source:** OECD.

wages. As a consequence, in periods of crisis, employment (and especially temporary employment) becomes the main margin of adjustment (Carneiro et al. 2014; Martins and Portugal 2019).

This is confirmed by Figure 2, constructed with data from the Labour Force Survey. It shows that the YoY quarterly change in employment in 2020 was positive in the first quarter and only marginally negative in the second, for permanent workers, in sharp contrast with the strongly negative for temporary ones.

Importantly, temporary contracts are more prevalent in some groups of the population, as shown in Figure 3, which displays the share of temporary employment as a percentage of total employment between the first quarter of 2018 and

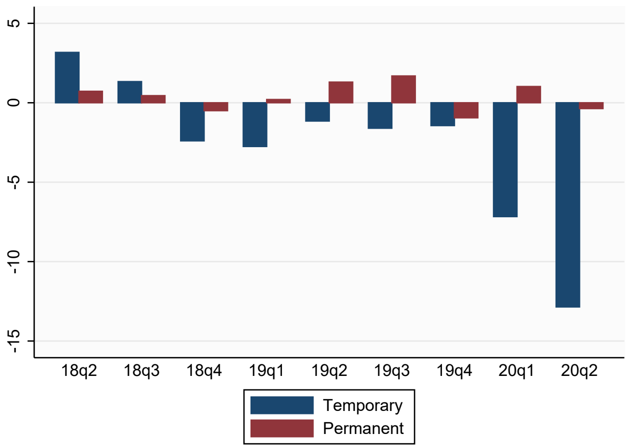


Figure 2: YoY change in temporary and permanent contracts. Source: Labour Force Survey (Statistics Portugal).

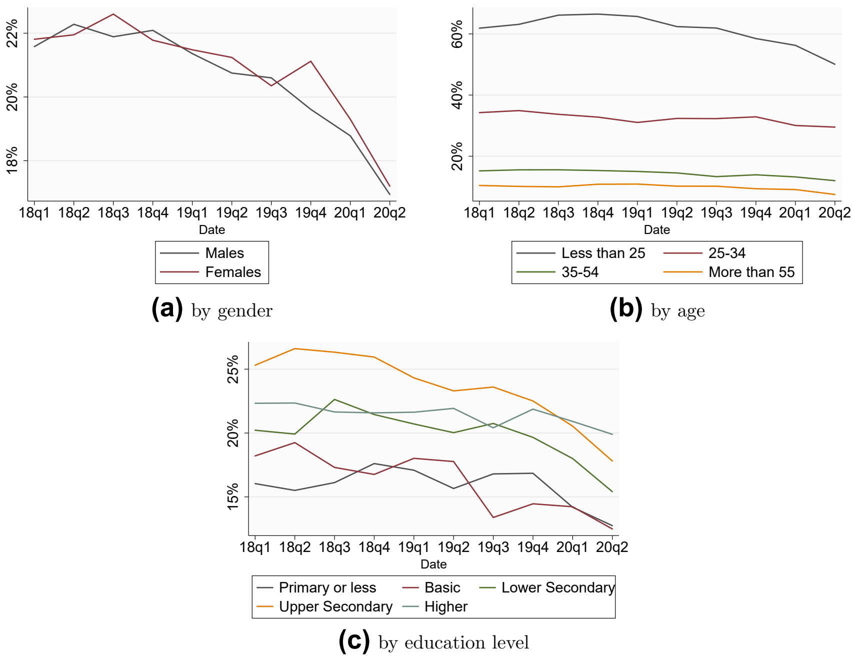


Figure 3: Temporary employment in Portugal. Source: Labour Force Survey (Statistics Portugal).

the second quarter of 2020, split by gender, age, and education level. Given the concentration of low and medium skilled workers in this group, they face significant difficulties in finding a new job (Blanchard and Portugal 2017), and are prone to be long-term unemployed. In sum, the characteristics of the labour market place some workers in a more vulnerable position in the face of a crisis.

According to panel (a), the share of temporary contracts decreased in 2020, without any consistent difference between female and male workers. The age differences, shown in panel (b), are the most striking. The share of workers aged less than 25 years old with temporary contracts is around four times that of those older than 35. In the 25–34 age interval, the prevalence of temporary work is twice as much as that of the older individuals. Finally, from panel (c) it is clear that temporary employment is more prevalent among individuals with upper secondary education. The fact that individuals with basic, primary education, or less, represent the group with the lowest share of temporary contracts is mostly driven by age. These education levels are more common in the oldest cohorts, who also have a more stable relationship with the labour market.

Figure 2 suggests that the decrease in temporary contracts is explained by an increase in job separations that hits them disproportionally.

3 Data and Methodology

3.1 Data

We use administrative data from *Instituto do Emprego e Formação Profissional* (IEFP), the Portuguese Public Employment Service, provided at the municipality level.[11] As of age 16, unemployed individuals must register in Public Employment Services to receive unemployment benefits and have access to active labour market policies. In return, they must comply with a personal employment plan and actively seek employment. The Public Employment Service collects job offers and advertises them both online and through its network. When offered a suitable or socially necessary job, unemployed individuals must accept the offer, or they risk losing the benefit.[12]

Jobless individuals have two incentives to register: qualify for the active labour market policies, and receive unemployment benefits, when eligible. Between 1999 and 2019, the number of individuals registered at the Public Employment Services represented an average of 94% of the unemployed population (according to Statistics Portugal).[13]

IEFP provides monthly data on the number of unemployed individuals registered and the number of new job placements that take place for those registered at one of the job centers distributed across the country. Our sample comprises data on the 278 municipalities of the Portuguese mainland between October 2016 and August 2020.[14] We drop September in the four years, given our identification strategy, explained in Subsection 3.2.

11 Unemployment can be measured from Labour Force Surveys or administrative data from registrations in Public Employment Services. The former are not representative at the municipal level.

12 Socially necessary jobs are temporary work opportunities filled by unemployed individuals to satisfy social or collective needs of non-profit public or private entities.

13 This figure averages out asymmetries in different periods. For instance, during the crisis, in 2011 and 2012, the share of unemployed registered at the Public Employment Services is 77%.

14 Portugal is divided in 308 municipalities, 278 in the Portuguese mainland and 30 in the Autonomous Regions of Madeira and Azores. IEFP only provides municipal data for mainland Portugal.

Data on the unemployed is split into gender, age group, and education level. Data for job placements is disaggregated by gender. We also use data on the main reasons for registration at the job centers, i.e. dismissals, voluntary quits, mutual agreement dismissals, end of temporary jobs, self-employment or former inactivity.[15] It is worth noticing that while data on unemployment refers to the situation at the end of each month (*stock*), data on job placements and the motives for registering at IEFP refers to the movement throughout the month (*flow*). Summary statistics of all variables for the average municipality are provided in Table 1.

The average number of adults registered in Public Employment Services per municipality is 1274, with a minimum of 23 and a maximum of around 26 thousand. The number is higher for females and adults between 35 and 54 years old, when compared to males and other age categories, respectively. Registrations also vary according to the level of education, with those with upper secondary education having the highest number of registrations. The average number of job placements per month and municipality is 24.

In terms of motives to register at the IEFP, end of temporary job is the most frequent (on average 73 people per municipality), followed by dismissal from previous job (19) and the registration of formerly inactive worker (15). Finally, we note that job placements are very low when compared to the flow of registrations at the Public Employment Service.

We complement the unemployment data with four further data sources.[16] Firstly, we use the last available wave of *Quadros de Pessoal* (2018), a linked employer–employee dataset covering the universe private-sector firms based in Portugal with at least one wage earner, aggregated to the municipal level. We retrieve the share of temporary workers per municipality and per sector and we also use it to relate temporary jobs to the working-from-home measure of Dingel and Neiman (2020). At the municipal level, the average share of temporary employment contracts is 33%, with a standard deviation of 8%.

Secondly, we use municipal-level data from SIBS (acronym for *Sociedade Interbancária de Serviços*, in Portuguese), which manages the integrated banking network in Portugal, comprising Automated Teller Machines (ATM), Point-of-sales (POS) terminals, and other electronic payment technologies such as mobie e-money. SIBS is the largest player in the electronic payments market and it runs

15 Former inactive workers are workers who were out of the labour force for a period of time and start to actively seek employment again. A broad category of "other reasons", such as re-registrations after non-compliance with requirements, being an ex-migrant or reaching the end of military service was dropped.

16 Table B.1, in Appendix B, summarizes the main variables, data sources, observation level and, when applicable, the manipulations necessary for the analysis.

Table 1: Descriptive statistics.

	Obs.	Mean	St. deviation	Min.	Max.
Unemployment (stock)					
Total	12,232	1273.6	2359.5	23	25,796
By gender					
Male	12,232	567.4	1091	12	13,000
Female	12,232	706.2	1274.8	7	13,895
By age					
Less than 25 years old	12,232	137.1	218.6	1	2961
Between 25 and 34 years old	12,232	238.2	442.4	1	5953
Between 35 and 54 years old	12,232	549.8	1069.5	8	12,163
More than 55 years old	12,232	348.5	650.7	5	6437
By education					
Primary education (1st–4th grade) or less	12,232	315.4	585.3	5	7341
Basic education (5th–6th grade)	12,232	187.6	356.5	2	4690
Lower secondary (7th–9th grade)	12,232	250.5	441.7	4	4928
Upper secondary (10th–12th grade)	12,232	342	635.2	5	7181
Higher education	12,232	178.1	412.1	0	6157
Job placements (flow)					
Total	12,232	23.9	35.3	0	494
By gender					
Male	12,232	11.1	17.9	0	234
Female	12,232	12.8	19.2	0	273
Motive to register at IEFP (flow)					
Dismissed from previous job	12,232	18.8	36.9	0	831
Voluntarily quit previous job	12,232	7.3	11.8	0	132
Mutual agreement dismissal	12,232	5.3	12.2	0	189
End of temporary job	12,232	73.2	135.3	0	2625
Former inactive worker	12,232	15	26	0	369
Self-employed	12,232	1.5	3.4	0	48
Share of temporary contracts (2018)	12,232	0.33	0.08	0.16	0.69

Observations are at the year-month-municipality level. Age bins reflect the availability of data.

the interbank compensation system through a contract with the Portuguese Central Bank.[17] The data comprises electronic payments, i.e. payments with bank cards, including those with contactless technology, and several digital money solutions (both mobile phone and net banking based), made in Portugal, by domestic and foreign costumers.[18] This data allows us to compute a real-time measure of the crisis per sector of activity.

Thirdly, we use sectoral-level administrative data from the Ministry of Social Security and Employment on the number of workers benefiting from the furlough scheme implemented by the Portuguese government per sector of activity. Finally, we use individual data from the Labour Force Survey between the first quarter of 2018 till the second quarter of 2020 to highlight some stylized facts about the impact of the Covid-19 crisis.

3.2 Methodology

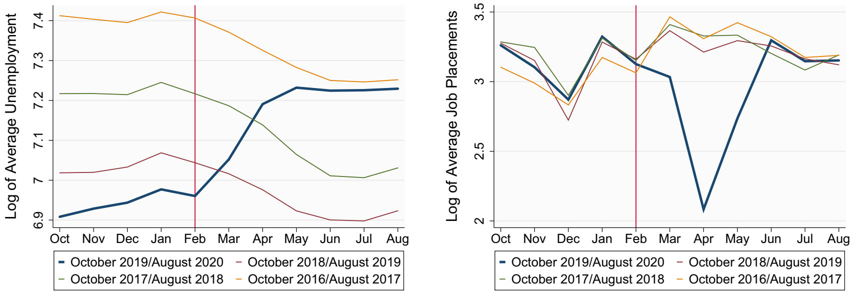
We implement a difference-in-differences (DiD) event study. In Section 5, we use triple difference-in-differences to assess the role of duality and exploit heterogeneous effects. Our identification strategy is easily explained by analysing Figure 4. The treatment and comparison groups are sets of months. The treatment group is represented by the blue lines in both panels, i.e. it comprises the months between October 2019 and August 2020. The comparison group comprises the remaining lines, i.e. the same sequence of months lagged one, two, or three years, respectively. The treatment period includes the months between March and August for all the years between 2017 and 2020.

The identifying assumption is that, absent the pandemic, and the implemented policies (detailed in Subsection 2.1) the year-on-year growth rate between the month of March (resp., April, May, June, July, and August) 2020 and the corresponding month in 2019 would be equal to a weighted geometric mean of the year-on-year growth rates for the same month, lagged between 1 and 3 years. Thus, the treatment group (Oct. 2019–Aug. 2020) can be decomposed into two parts, the *pre-treatment period* (Oct. 2019–Jan. 2020), used to assess parallel trends, and the *treatment period* (Mar. 2020–Aug. 2020), used to assess the impact of the pandemic.

The evidence in Figure 4 suggests that the outcome variables are on parallel trends prior to the shock. We provide a more formal test in Section 4 below, in which we run event studies for these outcome variables, using the same set of months for the control and treatment groups. Figures C.3–C.5 in the Appendix C

17 85% of SIBS is owned by the five biggest Portuguese banks.

18 Electronic payment operations includes purchases, bill payments, mobile top-ups, payments to government, public transport tickets, and others.



(a) Unemployment **(b)** New Job Placements

Figure 4: Identification strategy. Time-series of Log of average unemployment and new job placements. The blue line represents the period between October 2019 and August 2020 (the treatment group), of which October 2019 to January 2020 correspond to the pre-treatment period, and March 2020 to August 2020 correspond to the treatment period. The remaining lines represent the control group, i.e. the same series lagged one (Oct. 2018–Aug. 2019), two (Oct. 2017–Aug. 2018) and three (Oct. 2016–Aug. 2017) years.

show analogous evidence with the unemployed split by gender, age, and education levels.

The treatment period begins in March 2020. Recall that the first case was diagnosed on March 2nd. Carvalho et al. (2022) show that there is no evidence of changed behavior in electronic purchases before March. This is confirmed by Google mobility data shown in Figure C.2 (borrowed from Carvalho et al. 2022) that displays no evidence of changes in mobility in February or the first two weeks of March. Moreover, note that around the Carnival holiday of February 24, we observe a downward peak in workplaces and retail, accompanied by a mirror increase in parks and other open areas. This is convincing evidence that the country was living a normal life at the end of February. Hence, we rule out potential anticipatory behaviours that would threaten our identification strategy.

3.2.1 Aggregate Effects

We begin by estimating the following event study equation:

$$\ln(y)_{imt} = \gamma_i + \delta_m + \lambda\,\mathbb{1}_T + \sum_{m\in\{1,3,\ldots,12\}} \beta_m \mathbb{1}_T + \epsilon_{imt} \tag{1}$$

where $\ln(y)_{imt}$ corresponds to natural log of unemployment or new job placements at the job centers of municipality i, in month m and year

$t \in \{2016, 2017, 2018, 2019, 2020\}$. Municipal, γ_i, and month, δ_m, fixed effects are also included. February is the omitted month, since it is the one just before the start of the crisis.

The treatment indicator, $\mathbb{1}_T$ takes the value one for the months between October 2019 and August 2020. As explained above, the identifying assumption for the estimation of (1) is that, if the pandemic had not occurred, the monthly year-on-year change between March 2020 and March 2019 would have been parallel to a weighted geometric mean of the year-on-year change of the previous three years for the same month, and analogously for the remaining months between April and August. Thus the parallel trend assumption implies that $\hat{\beta}_1, \hat{\beta}_{10}, \hat{\beta}_{11}$, and $\hat{\beta}_{12}$ must not be statistically different from zero. The error term is given by ϵ_{imt}. Standard errors are clustered at time period (month, year) and NUTS II level.[19]

We show in the Appendix that $\hat{\beta}_m$ can be written as

$$\ln\left(\frac{1+g_m^{20,19}}{1+g_2^{20,19}} \cdot \sqrt[3]{\frac{\left(1+g_m^{19,18}\right)^2}{\left(1+g_2^{19,18}\right)^2} \cdot \frac{1+g_m^{18,17}}{1+g_2^{18,17}}}\right), \tag{2}$$

where $g_m^{t,t-1}$ stands for the month m YoY growth rate between years t and $t-1$. In order to provide estimates of the impact of Covid-19 in the YoY growth rates for each month from March 2020 onward, we use (2) to correct for seasonality. More specifically, we use the empirically observed YoY growth rates between 2019 and 2018, and between 2018 and 2017, to replace for the cubic root term.[20]

Please note that these impacts are best interpreted as lower bounds of the impact of the pandemic crisis and the lockdown strategies implemented as a result, since the labour-market policies enacted in the first weeks of the crisis aimed at mitigating the severity of the repercussions.[21]

3.2.2 The Role of Duality

We quantify the role of the duality of the labour market in our results in Subsection 2.2. We begin by estimating (1) for transitions into unemployment, i.e. motives for new registrations, in Subsection 4.1.

19 Mainland Portugal is divided in 5 NUTS II regions: Norte, Centro, Área Metropolitana de Lisboa, Alentejo and Algarve.

20 Please refer to the Appendix A for details.

21 Bourdin et al. (2021) show that the implementation of a lockdown at the beginning of March 2020 was an effective policy measure to slow down the spread of the virus in Italy.

We then use the following triple difference-in-differences specification, in Subsection 4.2.

$$\begin{aligned}\ln(y)_{imt} = \gamma_i + \delta_m + \lambda \mathbb{1}_T + \alpha_0 \mathbb{1}_T \,\text{temp}_i + \alpha_1 \mathbb{1}_{m\geq 3} \,\text{temp}_i \\ + \alpha_2 \mathbb{1}_{m\geq 3} \mathbb{1}_T + \alpha_3 \mathbb{1}_{m\geq 3} \mathbb{1}_T \,\text{temp}_i + \epsilon_{imt}\end{aligned} \tag{3}$$

where $\ln(y)_{imt}$ is, respectively, the log of the number of unemployed individuals in municipality i, month m, year t, or the number of unemployed individuals for each possible motives to register; temp_i is the share of workers with temporary contracts in the private sector of each municipality i in 2018. This specification allows us to test if the duality of municipal labour markets, proxied by the share of temporary workers in the municipality, amplifies the impacts of the pandemic.

In this case, our coefficient of interest is α_3, and it gives us the effect of the Covid-19 pandemic on municipal unemployment when the share of temporary workers increases by 1 p.p. Since we control for municipality fixed effects and temp_i is time invariant, we do not include it alone in the regression.

3.2.3 Heterogeneous Effects

In Section 5, we explore heterogeneous effects along each dimension of our data (gender, age, and education). We use a triple difference-in-differences strategy. The following equation is estimated for the gender dimension:

$$\begin{aligned}\ln(y)_{kimt} = \alpha + \gamma_i + \delta_m + \lambda \mathbb{1}_T + \beta_0 \mathbb{1}_f + \beta_1 \mathbb{1}_T \mathbb{1}_f + \beta_2 \mathbb{1}_{m\geq 3} \mathbb{1}_f \\ + \beta_3 \mathbb{1}_{m\geq 3} \mathbb{1}_T + \beta_4 \mathbb{1}_{m\geq 3} \mathbb{1}_T \mathbb{1}_f + \epsilon_{kimt}\end{aligned} \tag{4}$$

Where $\ln(y)_{kimt}$ is the (log of) number of unemployed people of gender $k \in \{\text{female}, \text{ male}\}$, in municipality i, month m, and year t, $\mathbb{1}_{m\geq 3}$ is an indicator for the months of March and subsequent, $\mathbb{1}_f$ is female indicator, and the remaining variables are defined as in (1). We estimate a similar equation for three age categories (in which the reference category is above 55), and for the four education levels (in which the reference category is higher education). Our coefficient of interest is β_4, and it gives the differential impact of the pandemic crisis on females. The results are presented in Subsection 5.1.

Finally, we analyse whether the duality of the labour market amplifies the heterogeneous impacts. This is done by estimating (3) for sub-samples according to gender, age, and education level, in Subsection 5.2.

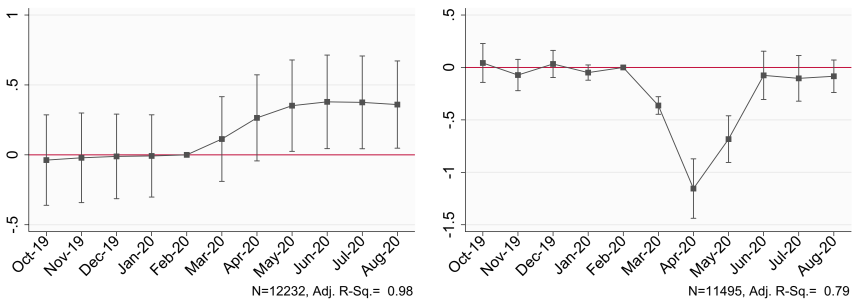
4 The Aggregate Shock and Labour Market Transitions

In this section, we present our results for the impact of the pandemic on the labour market. We start by using (1) to estimate the impact of the pandemic crisis on registered unemployment and new job placements. The coefficient estimates for β_m are depicted in Figure 5. All our coefficient plots display the 95% confidence intervals.

The first important remark is that in both cases the estimates for β_m, where $m \in \{1, 10, 11, 12\}$, are not statistically different from zero; in other words, the parallel trends assumption is verified, which validates our identification strategy and shows that our results reflect the causal impact of Covid-19 on the variables of interest, as explained in Subsection 3.2.

In order to better interpret Figure 5, note that it displays the point estimates (and respective confidence intervals) for the difference in the outcome variables between the months of October 2019 to August 2020 and the geometric average of the same months in the past three years, as per (1). The fact that the estimated coefficients in the pre-treatment period are not statistically different from zero confirms that the outcome variables are on parallel trends. This is a more formal confirmation of the visual evidence in Figure 4.

Panel (a) in Figure 5 shows a strong impact on unemployment following the lockdown period that began in March 2020. The increase is persistent but more pronounced until June, and stabilizes thereafter. In terms of job placements, Panel (b) presents a colossal drop of new placements, especially in April, followed by a recovery in May and June and a subsequent stabilization. Although between June



(a) Unemployment **(b)** New Job Placements

Figure 5: Event study aggregate effects.

and August the point estimates are not statistically different from zero, they are still negative.

Table 2 displays the net effect of the pandemic on the YoY growth rates, computed as explained in Appendix A. The YoY growth rates of unemployment increased gradually over time, from 27 p.p. in April, up to 39 p.p. and 38 p.p. in June and July, respectively. The sharp decline of new job placements shown in Panel (b) on Figure 5 corresponds to a 63 p.p. drop in April. From June onward, the impact has been attenuated but is still negative. These effects are consistent with the deep lockdown in April and the slow restart of the economic activity during the summer.

We perform robustness tests to (i) further assert that the parallel trend assumption holds and (ii) show that the remaining coefficient estimates are stable across different specifications. The results are shown in Appendix Figure C.6. We also use (1) to analyse regional differences on unemployment across the five Portuguese mainland NUTS II regions, shown in the Appendix (Figure C.7 and Table B.2, respectively).

4.1 Transitions in a Dual Labour Market

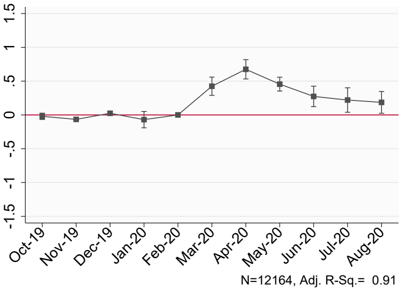
We now analyse the evidence about the reasons that led the individuals to register with the Public Employment Service during the Covid crisis. Since these are flow variables, the results measure the impact on new unemployment each month, net of composition effects.

Table 2: Event study aggregate effects: magnitudes.

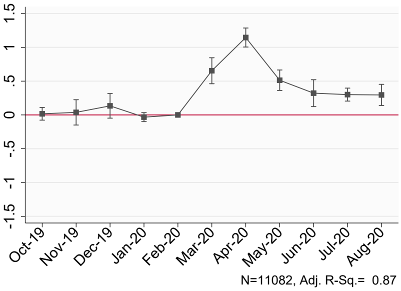
Dep. var.:	Log of unemployment			Log of job placements		
	Point estimate (1)	*t*-stat (2)	Effect (p.p.) (3)	Point estimate (4)	*t*-stat (5)	Effect (p.p.) (6)
Mar-20	0.113	1.04	10.67	−0.363	−12	−23.55
Apr-20	0.265	2.39	26.92	−1.155	−11.31	−62.74
May-20	0.352	2.99	37.25	−0.683	−8.53	−43.14
Jun-20	0.379	3.15	39.06	−0.075	−0.91	−3.37
Jul-20	0.375	3.14	38.42	−0.104	−1.33	−8.48
Aug-20	0.360	3.2	35.5	−0.084	−1.5	−0.23

Point estimates are the coefficients β_m from (1). The effect is given by $\left(1 + g_2^{20,19}\right)(\vartheta_m - 1)$. Please refer to Appendix A for more information.

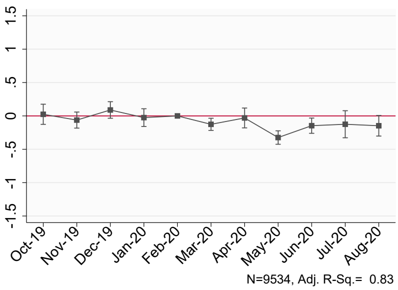
The data splits the motives into four categories that are explicit job separations (end of temporary contract, dismissal, voluntary quit, mutual agreement dismissal) and two additional categories for transition from inactivity and registration of self-employed. Figure 6 shows the event study for each motive. The evidence confirms the importance of temporary contracts for the transitions during this period. The most important ones, for the purposes of our analysis, are the first two. Note that



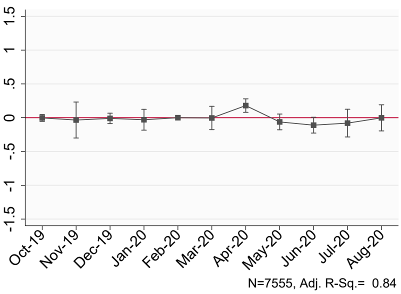
(a) End of temporary contract



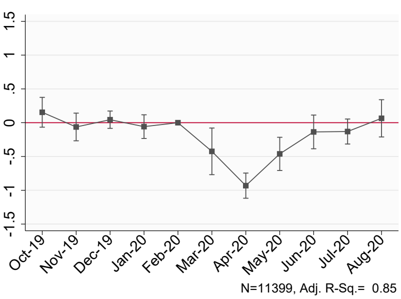
(b) Dismissed from previous job



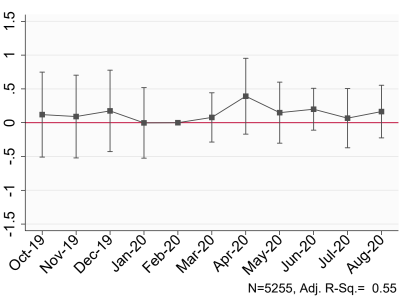
(c) Voluntarily quit previous job



(d) Mutual agreement dismissal



(e) Former inactive worker



(f) Self-employed

Figure 6: Motives to register with IEFP.

dismissals also include temporary workers who are dismissed before the end of the contract. The pandemic had no sizeable impact on the remaining transitions, except for the drop in inactive workers that register as job-seekers, which is a natural consequence of the lockdown period.

Panels (a) and (b) exhibit very clear spikes in terminations of temporary contracts and dismissals, respectively, lasting until the end of the analysed period. The effects were particularly strong in April, with YoY growth rate increases of 87 p.p. and 216 p.p. for end of temporary contracts and dismissals, respectively. Although the effect is lower for termination of temporary contracts, the base effect is much stronger (Figure C.8 in Appendix C shows that almost two thirds of job separations in 2020 are due to the termination of temporary contracts.)[22]

4.2 Duality in Municipal Labour Markets and the Pandemic Shock

We now explore whether unemployment is driven by municipal heterogeneity in the dual nature of the labour market, i.e. we analyse the possibility that municipalities with a higher share of temporary contracts are more impacted by the crisis. We use the municipal share of temporary contracts in 2018, the last available year. As we show in Figure C.9, in Appendix C, this share is strongly correlated with that of previous years, which suggests that we capture a structural feature of the local labour markets.

Table 3 shows the estimate of α_3 in Eq. (3) for the stock of unemployed (column 1). The estimate indicates that there are more registrations at the Public Employment Services in municipalities with a higher share of temporary employment. The number of newly registered unemployed increases by 1.5% with an increase of 1 p.p. in the share of temporary workers in a municipality. Alternatively, a one standard deviation (8%) increase in the share of temporary contracts amounts to an 11.6% change in the number of registries. This effect is sizeable, particularly given that the average share of temporary workers is 33%.

Columns 2 to 8 report similar regressions where the outcome variable is the flow of monthly registrations by motive, for all the motives shown in Figure 6. Results show that new registrations in Public Employment Offices due to the termination of temporary contracts are higher in municipalities with a higher share of temporary workers. The interaction with the share of temporary contracts is not significant for the remaining motives. This provides further evidence that temporary workers were more severely affected by job loss during the early months of the pandemic.

22 The causal impacts of Covid-19 on all variables are shown in Appendix Table B.3.

Table 3: Share of temporary contracts and the Covid-19 crisis.

	Log of						
		Motives to register as unemployed (flow)					
	Unemployment (stock)	**End of temp. contract**	**Dismissed**	**Voluntary quit**	**Mutual ag. dismissal**	**Former inactive**	**Self-employed**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$\mathbb{1}_{m\geq 3} \times \mathbb{1}_T \times \text{temp}_i$	1.452*	1.343*	1.272	0.254	0.444	−0.255	0.105
	(0.57)	(0.58)	(0.8)	(0.32)	(0.72)	(0.2)	(0.5)
Number of obs.	12,232	12,164	11,082	9534	7552	11,399	5253
R-squared	0.976	0.907	0.859	0.819	0.839	0.817	0.552

Standard errors (in parenthesis) are clustered at NUTS II and time period (month, year) level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Heterogeneity along Gender, Age, and Education

In Subsection 2.2, we document the unequal distribution of temporary contracts. We now show that the pandemic shock hit these workers asymmetrically.

5.1 Heterogeneous Effects of Covid-19 on the Labour Market

In this section, we use a triple difference-in-differences strategy to explore the heterogeneous effects of the Covid-19 shock on the outcomes of interest for (i) gender, (ii) age groups, and (iii) education levels. Results are reported in Table 4. As mentioned in Subsection 3.1, data on new job placements is only disaggregated by gender, thus the heterogeneity in terms of age and education focuses exclusively on unemployment.

Columns 1 and 2 of Table 4 report the estimates of β_3 and β_4 from (4) for the gender heterogeneity specification, where β_4 represents the additional impact for females. In all specifications, the estimates of β_3 represent the impact for the reference group. When we estimate heterogeneous impacts other than gender, we expand the interaction of β_4 to include a full set of interactions for each category, i.e. three coefficients instead of one for the age specification (column 3 of Table 4), and four for the education one (column 4 of Table 4).

Results for gender heterogeneity indicate that Covid-19 increased male unemployment by 33.8% (column 1) and decreased new job placements by 24.1% (column 2) between March and August 2020. Taken together, our results show that women were most severely hit by the pandemic: while there is no statistically significant difference in unemployment, women suffer an additional drop of 17.5% in placements after March, when compared to men. The absence of gender differences in unemployment is in line with the findings of Casarico and Lattanzio (2020) for Italy, and Hupkau and Petrongolo (2020) for the UK. The negative effect that we identify on placements suggests that women are less likely to find a job following an unemployment episode during the pandemic; this adds to the long list of differential gender impacts due to a higher proportion of female workers in the most affected industries (ILO 2017), disproportionate take up of household chores and childcare after school closures and work from home restrictions (Del Boca et al. 2020; Farré et al. 2020).

To study the impact on different age groups, we use the unemployed aged more than 55 as the reference group. Our findings in column 3 of Table 4 show this is the least affected group. There is a very strong impact on youth unemployment after

Table 4: Triple DD on unemployment and new job placements, by gender, age and education level.

Dep. var.:	**Gender**		**Age**	**Education**
	Log of unemployment (1)	**Log of new job placements (2)**	**Log of unemployment (3)**	**Log of unemployment (4)**
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T$	0.338**	−0.241*	0.177**	0.239**
	(0.08)	(0.11)	(0.05)	(0.07)
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{\text{female}}$	−0.026	−0.175*		
	(0.02)	(0.08)		
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{\text{less than 25}}$			0.208**	
			(0.06)	
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{25-34}$			0.258*	
			(0.04)	
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{35-54}$			0.179*	
			(0.03)	
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{\text{Primary or less}}$				−0.037
				(0.03)
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{\text{Basic}}$				0.096**
				(0.02)
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{\text{Lower Secondary}}$				0.150***
				(0.03)
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \mathbb{1}_{\text{Upper Secondary}}$				0.175***
				(0.02)
Number of obs.	24,464	21,265	48,928	61,156
R-squared	0.968	0.725	0.953	0.930

Standard errors (in parenthesis) are clustered at NUTS II and time period (month, year) level. The omitted group is male, 55 and older, and higher education, respectively for columns 1 and 2, 3, and 4. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

March 2020, amounting to an additional increase of 20.8% and 25.8%, for individuals younger than 25, and between 25 and 34 years old, respectively. These results are consistent with the prevalence of non-permanent contracts among younger workers in Portugal documented above. Younger workers are also less unionized than older ones (Portugal and Vilares 2013) and more vulnerable to precarious working conditions.

With regards to education levels, column 4 of Table 4 shows that individuals with higher education, the reference group, experienced an increase of 23.9% in unemployment after March 2020. The differential impact of the crisis was 17.5% higher for individuals with upper secondary education, 15% for individuals with lower secondary education, and 9.6% for individuals with basic education, than for those with higher education. Individuals with less than four years of formal education do not behave differently than the highly educated ones. This may stem from the fact that these workers are concentrated in essential jobs that kept working during the lockdown; however, the lack of statistical significance may also be explained by the relatively small number of workers with this level of education.

The inverted u-shaped relationship between education levels and the labour market impact of the pandemic can be explained by the fact that workers with secondary education are usually not employed in the subset of service sectors compatible with home working, and are thus in a more vulnerable position in this crisis. Indeed, data from Statistics Portugal shows that during the second quarter of 2020, 4.7% of the employed population with lower secondary education or less was working from home, compared with 53.8% of the population with higher education degrees (INE 2020).

5.2 Does Labour Market Duality Drive the Heterogeneous Effects?

So far, we have established that (i) the increase in unemployment was higher in more dual municipal labour markets, (ii) temporary contract terminations were more pervasive in these municipal labour markets, and (iii) the impact of the crisis falls disproportionally on females (through the hiring margin), younger workers, and those with secondary education. Since these worker groups are the ones that are over-represented in temporary contracts, this also constitutes evidence that the termination of temporary contracts plays a major role in our results. We now combine the two pieces of evidence and test whether the heterogeneous impact (along gender, age, and education) is greater in municipal labour markets with a stronger duality character.

The estimates of α_3 from (3) for each group of workers are presented in Table 5. We report the tests for the null hypothesis that the estimated coefficients are equal in Tables B.4 and B.5 in the Appendix B. As regards gender, the value of the χ^2 statistic is 4.03, i.e. the coefficients are statistically different at 5%. More specifically, a one standard deviation increase in the share of temporary contracts in a dual labour market increases the number of newly registered female workers in response to the pandemic shock by 12.6%, and that of males by 10.7%.

We now analyse the results with respect to age. Interestingly, the estimated coefficients are monotonic in the age of the individuals. The tests of the difference of the coefficients in Table B.4 indicate that there is no statistical difference between the two groups who are younger than 34. Conversely, the coefficients for both these groups are different from the ones of older workers. The negative impact of the pandemic shock in dual labour markets is therefore more concentrated in younger

Table 5: Share of temporary contracts and the Covid-19 crisis.

Dep. var.:	**Log of unemployment**					
Dimension:	**Gender**		**Age**			
	Male	**Female**	**<25**	**25–34**	**35–54**	**>55**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \text{temp}_i$	1.331**	1.569*	2.065*	1.771*	1.426*	0.919*
	(0.47)	(0.66)	(0.35)	(0.36)	(0.29)	(0.19)
Number of obs.	12,232	12,232	12,232	12,232	12,232	12,232
R-squared	0.971	0.976	0.940	0.961	0.971	0.983

Dimension:	**Education**				
	Primary or less	**Basic**	**Lower sec.**	**Upper sec.**	**Higher**
	(7)	**(8)**	**(9)**	**(10)**	**(11)**
$\mathbb{1}_{m\geq3} \times \mathbb{1}_T \times \text{temp}_i$	1.156*	1.338*	1.712*	1.572*	1.219
	(0.47)	(0.58)	(0.62)	(0.60)	(0.58)
Number of obs.	12,232	12,232	12,232	12,232	12,232
R-squared	0.969	0.961	0.963	0.970	0.970

Standard errors (in parenthesis) are clustered at NUTS II and time period (month, year) level.
Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

workers. More specifically, a one standard deviation increase in the share of temporary workers leads to an increase of between 14.2% and 16.5% in the number of newly registered young workers in the Employment Office. Conversely, the impact on older workers amounts to between 7.4% and 11.4%.

Regarding education, the effect follows an inverted U-shaped pattern. In municipalities with a higher share of temporary contracts, Covid-19 impacts less severely individuals with primary education or less, and individuals with higher education. The strongest impact falls on the those with lower and upper secondary education, as the results of the tests of the equality of the coefficients reported in Table B.5 confirm. A one-standard deviation increase in the share of temporary workers in the municipality increases the number of registered unemployed people with upper and lower secondary education by 12.6% and 13.7%, respectively. The impact on highly educated workers is non significant.

These results strongly suggest that the effect of the crisis in female, young and middle-educated workers is driven by the duality of the labour market. The crisis has asymmetric effects depending on the workers' ties to the labour market, and measures like the furlough scheme do not seem to be enough to protect certain groups of the labour force.

In order to correct for possible seasonality in temporary contracts, we re-estimate the regressions excluding the municipalities in the top quartile of the distribution of tourist overnight stays, which are bound to have a peak of jobs in the Summer. The results, presented in Tables B.6 and B.7, in Appendix B, are similar to the baseline, with the exception of the gender differences, which are less precisely estimated.

6 Discussion of Possible Mechanisms

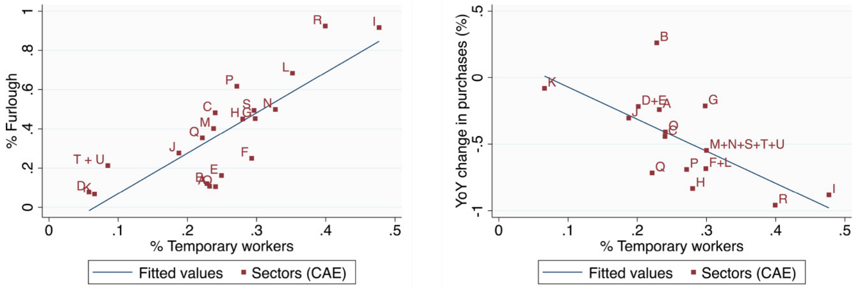
We have shown that the effects of the pandemic on unemployment are asymmetric across age, gender, and education. In addition, we show that the shock is *both* more pronounced and more asymmetric in municipalities with a more dual labour market, as measured by the share of temporary contracts in the overall labour force.

There are at least three possible mechanisms that may explain these results. First, it may be a mechanical effect of the furlough policy: given that supported firms are forbidden to dismiss workers, they use the margin of not renovating temporary contracts to adjust employment. Second, temporary workers may be more likely to work in the industries (such as retail and hospitality) that are heavily disrupted by the pandemic shock. Finally, it is possible that jobs performed by temporary workers are less suitable for working from home arrangements.[23]

We now provide suggestive evidence showing that the three mechanisms are present. Panel (a) of Figure 7 shows a stark positive correlation between the share of workers on furlough until August 2020, according to the records of the Ministry of Labour and Social Security, and the share of temporary workers per sector, measured in 2018 using administrative linked employer-employee data. This graph suggests that part of the impact is driven by the mechanical effect of the policy.

Panel (b) of Figure 7 shows that the share of temporary workers is higher in the sectors that were more hit by the crisis, as measured by the year-on-year change in electronic purchases between April 2020 and April 2019. Importantly, SIBS data covers payments with both Portuguese and foreign electronic cards. We focus on

23 Grabner and Tsvetkova (2022) highlights that the share of teleworkable jobs is linked to stronger employment resilience using data from US cities during the 2020 Covid-19 emergency. In addition, Gabe and Florida (2021) shows that requiring close physical proximity and high interaction with the public were important determinants of U.S. industry employment change in the early months of the pandemic.



(a) Prevalence of Furlough **(b)** YoY changes in purchases

Figure 7: Covid-19 crisis and the share of temporary workers, by sector. Letters A to U represent sectors of activity according to the NACE classification (sector definition in Appendix Table B.8). Panel (a) plots the correlation between the share of employees with temporary contracts (horizontal axis) in each sector and the share of employees under furlough schemes (vertical axis) in the same sector. Panel (b) plots the correlation between the percentage change in the value of electronic purchases (transactions with cards), between April 2019 and 2020; and the share of temporary workers in the same sector/group of sectors. More details about the sources of data on Appendix Table B.1. To build Panel (b) we created a correspondence between the NACE sector groups and the division provided by SIBS.

this measure because this crisis was characterised by strong limitations in contact-intensive sectors such as the specialised retail and hospitality industries, that rely on business-to-customer transactions.[24] We use April 2020 because it was the month with the sharpest contraction in electronic purchases. Therefore, temporary workers are more prevalent in the sectors that suffered the most from stay-at-home orders and the collapse of tourism (Carvalho et al. 2022). This amounts to a *sectorial effect* hitting temporary workers.

In Figure 8, we focus on 22 job occupations instead of sectors. More precisely, we rely on the analysis of jobs that can be done at home from Dingel and Neiman (2020), who computed a work-from-home measure using surveys from the Occupational Information Network (O*NET) for each possible occupation.

24 Electronic payment data is less suitable to capture contractions in business-to-business transactions.

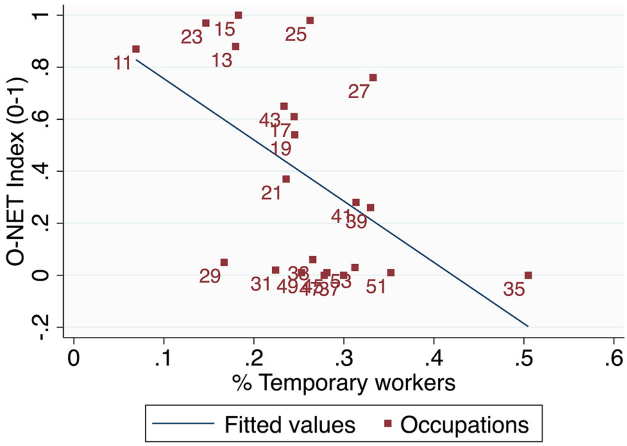


Figure 8: Remote working and the share of temporary workers, by occupation. Numbers 11 to 53 represent groups of occupations according to the ISCO classification (group definition in Appendix Table B.9). The figure plots the correlation between the O-NET index and the average share of temporary workers in each occupation group. The O-NET index is retrieved from Dingel and Neiman (2020) and indicates how amenable to remote working is each group of occupations. The share of temporary workers is obtained from GEP-MTSSS.

We combine this with the administrative linked employer-employee data, that covers the universe of private sector workers in Portugal, using the year of 2018. We then plot, for each occupation, the share of temporary contracts and the respective work-from-home measure. What we find is a striking negative correlation, showing that the jobs that are more easily prone to remote working are dominated by permanent contracts. For instance, Food Preparation and Serving is not prone to remote working, and almost half of the contracts are temporary. By contrast, Management Occupations are easy to perform in home working, and have less than 10% of temporary workers. Therefore, more-at-risk jobs were likely to be performed by temporary workers who were thus more likely to dismissed. This suggests that even in sectors that were not particularly hit by the crisis, or did not rely a lot on furlough, temporary workers may have been dismissed because of the nature of their occupations. This shows that temporary workers are also hurt by an *occupation effect*. This evidence is in line with Bonacini et al. (2021), who show that the possibility of remote working in Italy exacerbates pre-existing inequalities.

7 Conclusion

In the beginning of 2020, the Coronavirus pandemic hit the world economy, and rapidly turned into the biggest shock since the Second World War. Compared with the financial and sovereign debt crisis of 2008–2012, the pandemic hit a structurally different labour market, with a much higher share of temporary employment, and, moreover, was met with massive public spending aimed at the protecting the so-called matching capital between workers and firms

In this paper, we analyse the effects of the crisis on unemployment in a country characterised by a high degree of duality in the labour market, using administrative data from *Instituto do Emprego e Formação Profissional*, that covers the universe of unemployed individuals registered at job centers from October 2016 to August 2020. We complement it with several other data sources, including the Labour Force Survey, pre-shock linked employer-employee data, electronic payments data, and Google mobility reports. Using event study difference-in-differences, we rely on the assumption that, in the absence of the Covid-19 outbreak, the monthly year-on-year change between March/August 2020 and March/August 2019 would have been parallel to a weighted geometric mean of the year-on-year change of the previous 3 years.

We document a large causal impact of the pandemic on registered unemployment, with YoY growth rate increases from 27 percentage points in April up to 39 and 38 percentage points in June and July, respectively. New job placements were also severely affected, i.e. the YoY growth rates were below pre-crisis levels from March to August, with a negative peak of 63 percentage points in April. These impacts are lower bounds, since the labour-market policies enacted in the first weeks of the crisis aimed at mitigating the severity of the repercussions.

We argue that this effect is mediated by the duality of the labour market. On the one hand, we show the prevalence of the termination of temporary contracts in the transitions into unemployment and document the destruction of temporary contracts using data from the Labour Force Survey. We then exploit municipal heterogeneity in the share of temporary contracts as a measure of the intensity of the duality of the local markets. We show that the effect of the crisis on unemployment is amplified by the share of temporary jobs.

On the other hand, we show that the impact on unemployment is more pronounced for the demographic groups that are more likely to have temporary jobs. More precisely, we show that, when compared to individuals who are older than 54, those younger than 25 and between 25 and 34 have an additional impact of 20.8% and 25.8%, respectively. In terms of education, the bulk of the effect is concentrated in individuals with lower and upper secondary education (additional 15% and 17.5%, respectively *vis-à-vis* those with higher education). We find no evidence of gender differences on registered unemployed, but women are more affected in terms of new job placements, with an additional decline of 17.5%, when compared to men. Finally, we show that these asymmetries are stronger in the municipalities with a higher share of temporary contracts, i.e. the crisis is more unequal in more dual labour markets.

We combine several data sources to present suggestive evidence that these results are driven by a combination of mechanisms. The first is the mechanical effect of furlough policies that prohibit dismissals of workers, thus creating an extra layer of protection for permanent workers, exacerbating the dual nature of the labour market. Indeed, we show that the share of workers in furlough is positively correlated with the share of temporary workers at the sectorial level. The second is a *sectorial effect*, according to which temporary workers are more prevalent in the sectors that were the most hit by the crisis, as measured by the contraction in electronic transactions with foreign and domestic cards. The third is an *occupation effect*, since occupations of temporary workers are less likely to be amenable to working-from-home arrangements.

Furlough policies maintain the *matching capital* between firms and workers in the short run, but longer periods of support can be problematic because they lock-in production factors in zombie firms. Whether the *matching capital* of permanent workers is more valuable than that of temporary ones is an open policy question. Nevertheless, furlough policies have supported a total of 1.2 million workers at the peak of the crisis, whereas unemployment never surpassed 400 thousand individuals, according to Statistics Portugal. This suggests that the policy mix was sub-optimal in the short-run, as the protection of permanent workers through furlough exacerbated the duality of the market.

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Research funding: This work was funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, LISBOA-01-0145-FEDER-022209), POR Lisboa (LISBOA-01-0145-FEDER-007722, LISBOA-01-0145-FEDER-022209) and POR Norte (LISBOA-01-0145-FEDER-022209) and the research project PTDC/EGE-ECO/31213/2017. Bruno P. Carvalho acknowledges the scientific and financial support of ECARES, Université Libre de Bruxelles, and the support from Agencia Estatal de Investigación del Gobierno de España (CEX2021-001181-M) and Comunidad de Madrid (Spain), grant EPUC3M11 (V PRICIT), and grant H2019/HUM-5891.

Appendix A: Derivation of the Impacts

Departing from Eq. (1), we can write the coefficients $\hat{\beta}_m$ as an estimate of a function of growth rates:

$$\ln\left(\sqrt[3]{\frac{1+g_m^{20,19}}{1+g_2^{20,19}}\frac{1+g_m^{20,18}}{1+g_2^{20,18}}\frac{1+g_m^{20,17}}{1+g_2^{20,17}}}\right)$$

where $g_m^{20,19}$, $g_m^{20,18}$ and $g_m^{20,17}$ represent the YoY growth rate of the outcome variable in month m, where $m \in \{3, \ldots, 8\}$, from 2019, 2018 and 2017 to 2020, respectively. This expression can be further simplified to:

$$\ln\left(\frac{1+g_m^{20,19}}{1+g_2^{20,19}}\sqrt[3]{\frac{\left(1+g_m^{19,18}\right)^2}{\left(1+g_2^{19,18}\right)^2}\frac{1+g_m^{18,17}}{1+g_2^{18,17}}}\right) \tag{5}$$

with $g_m^{19,18}$ representing the YoY growth rate of month m from 2018 to 2019 and $g_m^{18,17}$ representing the YoY growth rate from 2017 to 2018. As such, to estimate the effect of the pandemic crisis on the gross YoY growth rates $\frac{1+g_m^{20,19}}{1+g_2^{20,19}}$, we can compute:

$$\vartheta_m = \operatorname{Exp}(\hat{\beta}_m) \times \sqrt[3]{\frac{\left(1+g_2^{19,18}\right)^2}{\left(1+g_m^{19,18}\right)^2}\frac{1+g_2^{18,17}}{1+g_m^{18,17}}}$$

Hence, we use the growth rates observed in the data to correct for any possible seasonal differences between the YoY growth rates of each month m and February. Finally, we estimate the net YoY growth rates by computing $\left(1+g_2^{20,19}\right)(\vartheta_m - 1)$, with which we obtain the net impact of the crisis on the outcome variables in percentage points.

Appendix B: Additional Tables

Table B.1: Data coverage and sources.

Variable	Source	Period	Observation level	Calculations for the paper
Total registrations in unemployment centers – stock, breakdown by gender, age and education	IEFP	Monthly, Oct to Aug, 2016–2020	Municipal level	–
Total job placements – flow, breakdown by gender	IEFP	Monthly, Oct to Aug, 2016–2020	Municipal level	–
Reasons to register in the unemployment office, breakdown by 6 categories	IEFP	Monthly, Oct to Aug, 2016–2020	Municipal level	–
Share of temporary workers in the private sector.	GEP-MTSSS (*Quadros de Pessoal*)	2018	Individual level data covering all private sector firms.	Municipal level share computed by the authors.
Measure of sectors most affected by the pandemic: Value of purchases with bank cards	SIBS	Apr 2019, 2020	Municipal level monthly, by 39 sectors of activity.	YoY change in purchases aggregated at the NACE activity sector.
Prevalence of layoff by sector	MTSSS	2020	Number of firms that registered for the furlough scheme	–
Share of temporary workers as a % of total employment	Labour force survey – INE	Q1-2018 to Q2-2020	Quarterly individual data	National averages, by gender, age and education level

Table B.2: NUTS II: magnitudes.

Dep. var.:	Log of unemployment									
	Norte		Centro		Lisboa VT		Alentejo		Algarve	
	P.E. (1)	Eff. (p.p.) (2)	P. E. (3)	Eff. (p.p.) (4)	P.E. (5)	Eff. (p.p.) (6)	P.E. (7)	Eff. (p.p.) (8)	P.E. (9)	Eff. (p.p.) (10)
Mar-20	0.079	6.77	0.099	9.24	0.126	11.88	0.126	14.18	0.284	33.22
	(0.75)		(0.9)		(0.98)		(0.99)		(6.9)	
Apr-20	0.210	19.15	0.206	19.39	0.323	35.03	0.257	27.88	0.683	101.17
	(1.99)		(1.93)		(2.51)		(1.99)		(9.46)	
May-20	0.284	27.18	0.274	27.25	0.413	46.09	0.330	35.57	0.963	166.11
	(2.59)		(2.48)		(3.16)		(2.5)		(11.02)	
Jun-20	0.300	27.03	0.287	27.01	0.442	49.01	0.371	39.22	1.042	186.71
	(2.7)		(2.56)		(3.43)		(2.85)		(10.97)	
Jul-20	0.305	28.04	0.292	28.64	0.462	50.06	0.325	31.27	0.994	179.54
	(2.74)		(2.59)		(3.66)		(2.57)		(11.26)	
Aug-20	0.296	26.71	0.280	25.62	0.448	46.50	0.322	30.92	0.889	146.78
	(2.78)		(2.64)		(3.71)		(2.72)		(12.12)	

t-statistics in parenthesis. Point estimates are the coefficients β_m from (1). The effect is given by $\left(1+g_2^{20,19}\right)(\vartheta_m-1)$. Please refer to Appendix A for more information.

Table B.3: Motives for registration: magnitudes.

Dep. var.:	Log of new unemployment					
	Dismissed from previous job		Voluntarily quit previous job		Mutual agreement dismissal	
	P.E. (1)	Eff. (p.p.) (2)	P.E. (3)	Eff. (p.p.) (4)	P.E. (5)	Eff. (p.p.) (6)
Mar-20	0.654	112.52	−0.126	−6.10	−0.004	3.99
	(9.45)		(−3.85)		(−0.07)	
Apr-20	1.145	215.70	−0.031	−6.37	0.179	26.08
	(22.62)		(-0.57)		(4.98)	
May-20	0.513	72.80	−0.324	−23.31	−0.062	−10.59
	(9.4)		(−8.94)		(−1.49)	
Jun-20	0.322	55.72	−0.147	0.53	−0.110	−7.79
	(4.49)		(−3.57)		(−2.62)	
Jul-20	0.301	33.27	−0.125	−14.68	−0.080	−8.96
	(8.68)		(−1.71)		(−1.08)	
Aug-20	0.296	40.17	−0.148	−6.25	−0.002	−2.55
	(5.24)		(−2.66)		(−0.03)	

Table B.3: (continued).

Dep. var.:	Log of new unemployment					
	End of temporary job		Former inactive worker		Self-employed	
	P.E. (7)	Eff. (p.p.) (8)	P.E. (9)	Eff. (p.p.) (10)	P.E. (11)	Eff. (p.p.) (12)
Mar-20	0.424	69.58	−0.424	−25.97	0.078	24.58
	(8.73)		(−3.41)		(0.59)	
Apr-20	0.675	87.26	−0.932	−53.48	0.392	50.53
	(13.14)		(−13.89)		(1.94)	
May-20	0.455	58.00	−0.462	−29.07	0.148	18.40
	(12.34)		(−5.22)		(0.91)	
Jun-20	0.274	36.88	−0.136	−2.25	0.199	37.38
	(5.03)		(−1.52)		(1.79)	
Jul-20	0.220	19.64	−0.131	−16.53	0.067	11.82
	(3.37)		(−1.96)		(0.42)	
Aug-20	0.186	22.94	0.065	13.40	0.165	27.36
	(3.19)		(0.65)		(1.17)	

t-statistics in parenthesis. Point estimates are the coefficients β_m from (1). The effect is given by $\left(1+g_2^{20,19}\right)(\vartheta_m-1)$. Please refer to Appendix A for more information.

Table B.4: Means tests of coefficient equality, age.

	25–34	35–54	>55
<25	4.44	17.28	33.78
	(0.04)	(0.00)	(0.00)
25–34	–	8.81	26.05
		(0.00)	(0.00)
35–54	–	–	22.03
			(0.00)

χ^2 statistics. Probability > χ^2 in parenthesis.

Table B.5: Means tests of coefficient equality, education level.

	Basic	**Lower sec.**	**Upper sec.**	**Higher**
Primary or less	1.98	14.77	9.67	0.12
	(0.16)	(0.00)	(0.00)	(0.73)
Basic	–	9.38	3.56	0.39
		(0.00)	(0.06)	(0.53)
Lower sec.	–	–	1.40	5.19
			(0.24)	(0.02)
Upper sec.	–	–	–	3.53
				(0.06)

χ^2 statistics. Probability $> \chi^2$ in parenthesis.

Table B.6: Share of temporary contracts and the Covid-19 crisis (sub-sample excluding the municipalities in the top quartile of the distribution of tourist overnight stays).

Dep. var.:	**Log of unemployment (1)**
$\mathbb{1}_{m\geq 3} \times \mathbb{1}_T \times \text{temp}_i$	0.962^{**}
	(0.29)
Number of obs.	9152
R-squared	0.980

Standard errors (in parenthesis) are clustered at NUTS II and time period (month, year) level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.7: Share of temporary contracts and the Covid-19 crisis (sub-sample excluding the municipalities in the top quartile of the distribution of tourist overnight stays).

Dep. var.:	**Log of unemployment**					
Dimension:	**Gender**		**Age**			
	Male (1)	**Female (2)**	**<25 (3)**	**25–34 (4)**	**35–54 (5)**	**>55 (6)**
$\mathbb{1}_{m\geq 3} \times \mathbb{1}_T \times \text{temp}_i$	1.036**	0.906*	1.429*	1.107**	0.922**	0.608*
	(0.26)	(0.36)	(0.56)	(0.34)	(0.25)	(0.23)
Number of obs.	9152	9152	9152	9152	9152	9152
R-squared	0.973	0.980	0.946	0.965	0.974	0.985

Dimension:	**Education**				
	Primary or less (7)	**Basic (8)**	**Lower sec. (9)**	**Upper sec. (10)**	**Higher (11)**
$\mathbb{1}_{m\geq 3} \times \mathbb{1}_T \times \text{temp}_i$	0.703*	0.767**	1.080**	1.151**	0.873*
	(0.29)	(0.25)	(0.28)	(0.33)	(0.37)
Number of obs.	9152	9152	9152	9152	9152
R-squared	0.971	0.965	0.968	0.974	0.970

Standard errors (in parenthesis) are clustered at NUTS II and time period (month, year) level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.8: Activity sectors (NACE, sections).

Code	**Sector**
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air-conditioning supply
E	Water supply, sewerage, waste management and remediation
F	Construction
G	Wholesale and retail trade, repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Audiovisual, broadcasting and telecommunications
K	Financial and insurance activities
L	Real estate activities

Table B.8: (continued).

Code	Sector
M	Consulting, technical and scientific activities
N	Administrative and support service activities
O	Public administration and defence, compulsory social security
P	Education
Q	Healthcare, residential care and social work activities
R	Arts, entertainment and recreation
S	Other services
T	Activities of households as employers, undifferentiated goods- and services-producing activities of households for own use
U	Activities of extra-territorial organizations and bodies.

Table B.9: Occupations' classification (ISCO, Level 2).

Code	Sector
11	Management occupations
13	Business and financial operations occupations
15	Computer and mathematical occupations
17	Architecture and engineering occupations
19	Life, physical, and social science occupations
21	Community and social service occupations
23	Legal occupations
25	Education, training, and library occupations
27	Arts, design, entertainment, sports, and media occupations
29	Healthcare practitioners and technical occupations
31	Healthcare support occupations
33	Protective service occupations
35	Food preparation and serving related occupations
37	Building and grounds cleaning and maintenance occupations
39	Personal care and service occupations
41	Sales and related occupations
43	Office and administrative support occupations
45	Farming, fishing, and forestry occupations
47	Construction and extraction occupations
49	Installation, maintenance, and repair occupations
51	Production occupations
53	Transportation and material moving occupations

Appendix C: Additional Figures

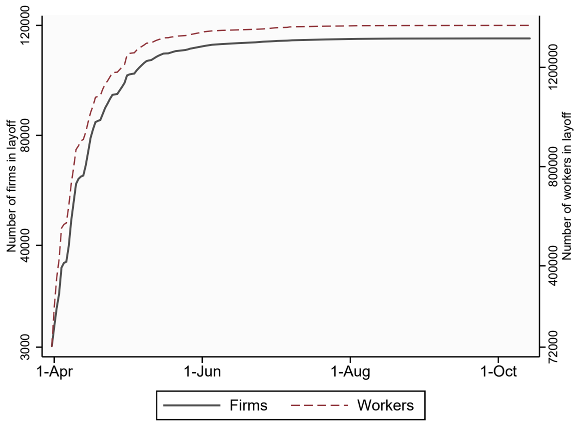


Figure C.1: Total number of firms and workers under the furlough scheme. Source: GEP/MTSSS.

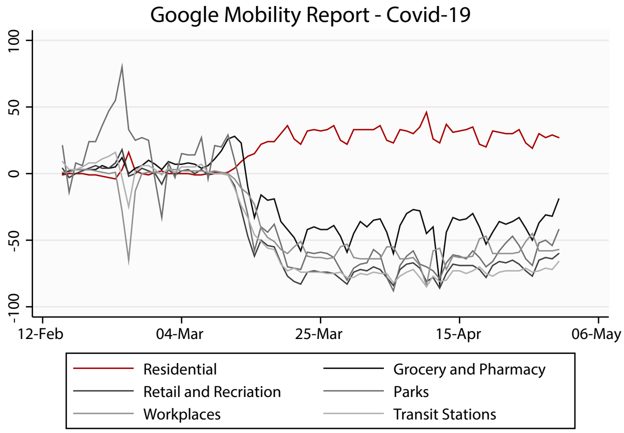
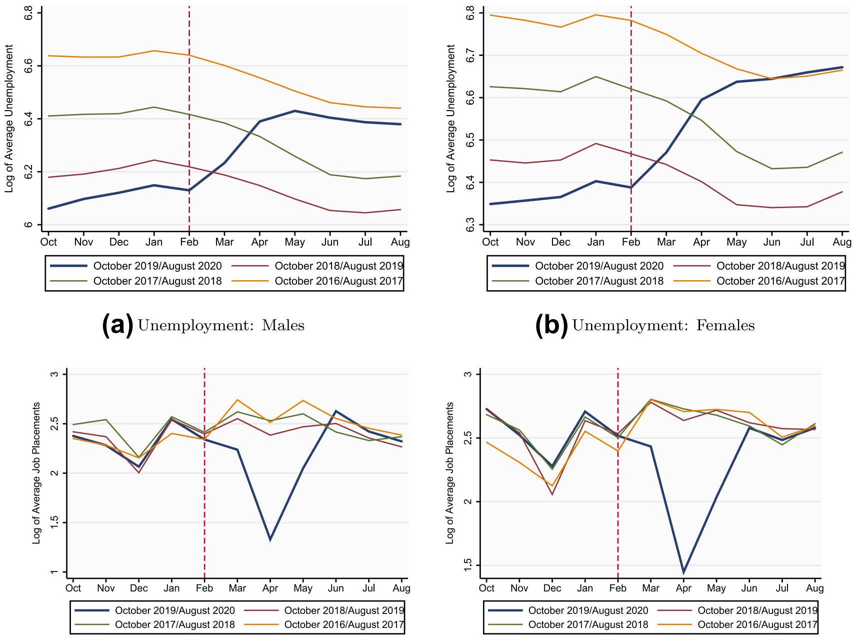


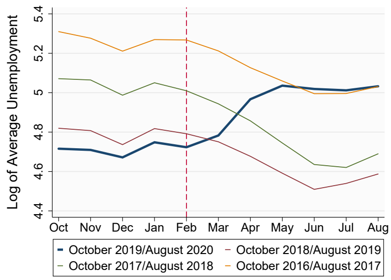
Figure C.2: Google Mobility Index: Time Series. The figure plots the time series of the Google Mobility Index, from its mobility reports, for the six available categories. Google computes this indicator taking the median value of the mobility between January 3 and February 6, 2020, as the reference period. The figure is borrowed from Carvalho et al. (2022).



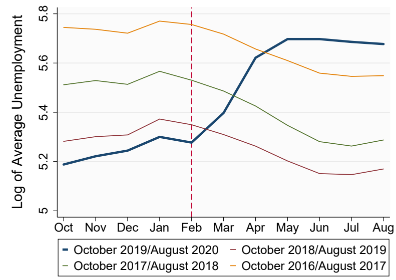
(a) Unemployment: Males **(b)** Unemployment: Females

(c) New job placements: Males **(d)** New job placements: Females

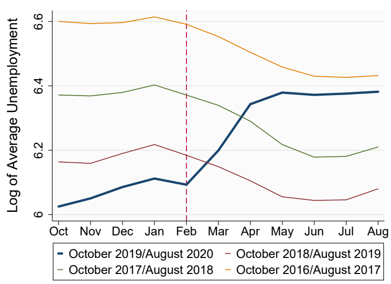
Figure C.3: Identification strategy, unemployment and new job placements by gender. Time-series of Log of average unemployment and new job placements, by gender. The blue line represents the period between October 2019 and August 2020 (the treatment group), of which October 2019 to January 2020 correspond to the pre-treatment period, and March 2020 to August 2020 correspond to the treatment period. The remaining lines represent the control group, i.e. the same series lagged one (Oct. 2018–Aug. 2019), two (Oct. 2017–Aug. 2018) and three (Oct. 2016–Aug. 2017) years.



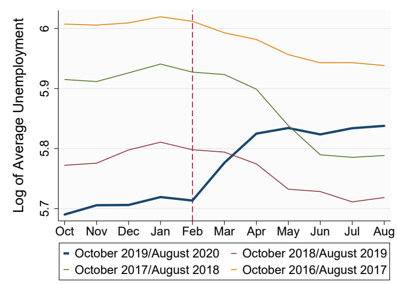
(a) Less than 25y



(b) Between 25y and 34y

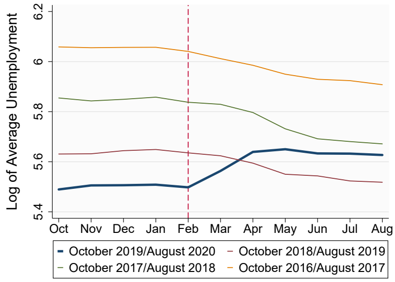


(c) Between 35y and 54y

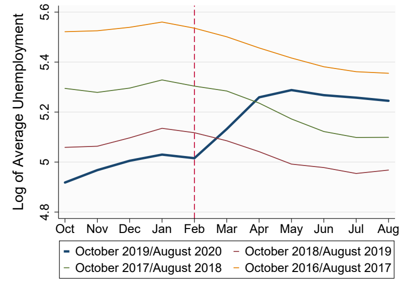


(d) More than 54

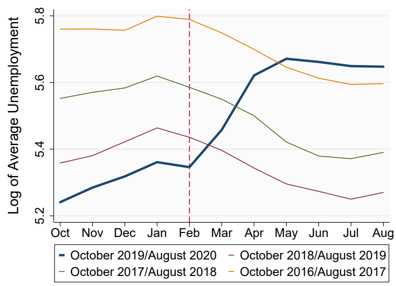
Figure C.4: Identification strategy, unemployment by age. Time-series of Log of average unemployment, by age. The blue line represents the period between October 2019 and August 2020 (the treatment group), of which October 2019 to January 2020 correspond to the pre-treatment period, and March 2020 to August 2020 correspond to the treatment period. The remaining lines represent the control group, i.e. the same series lagged one (Oct. 2018–Aug. 2019), two (Oct. 2017–Aug. 2018) and three (Oct. 2016–Aug. 2017) years.



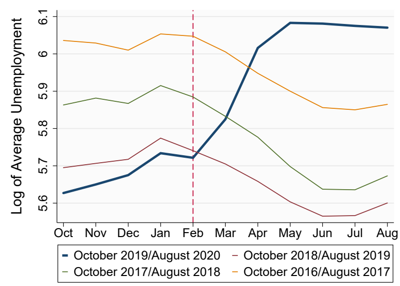
(a) Primary education or less



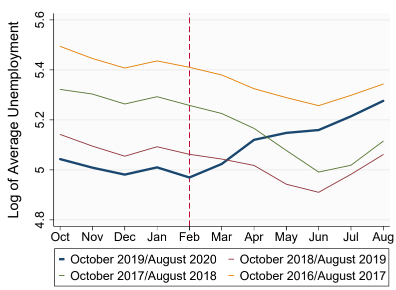
(b) Basic education



(c) Lower Secondary education

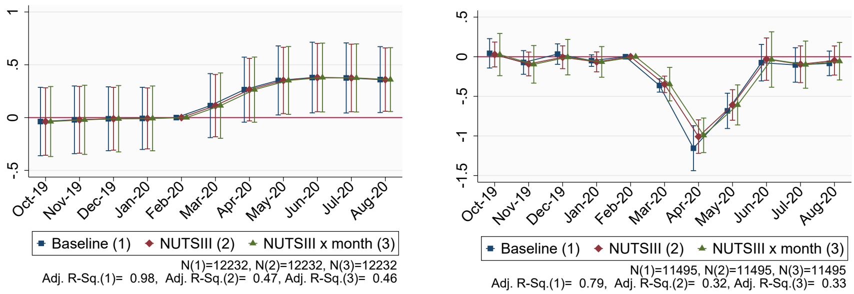


(d) Upper Secondary education



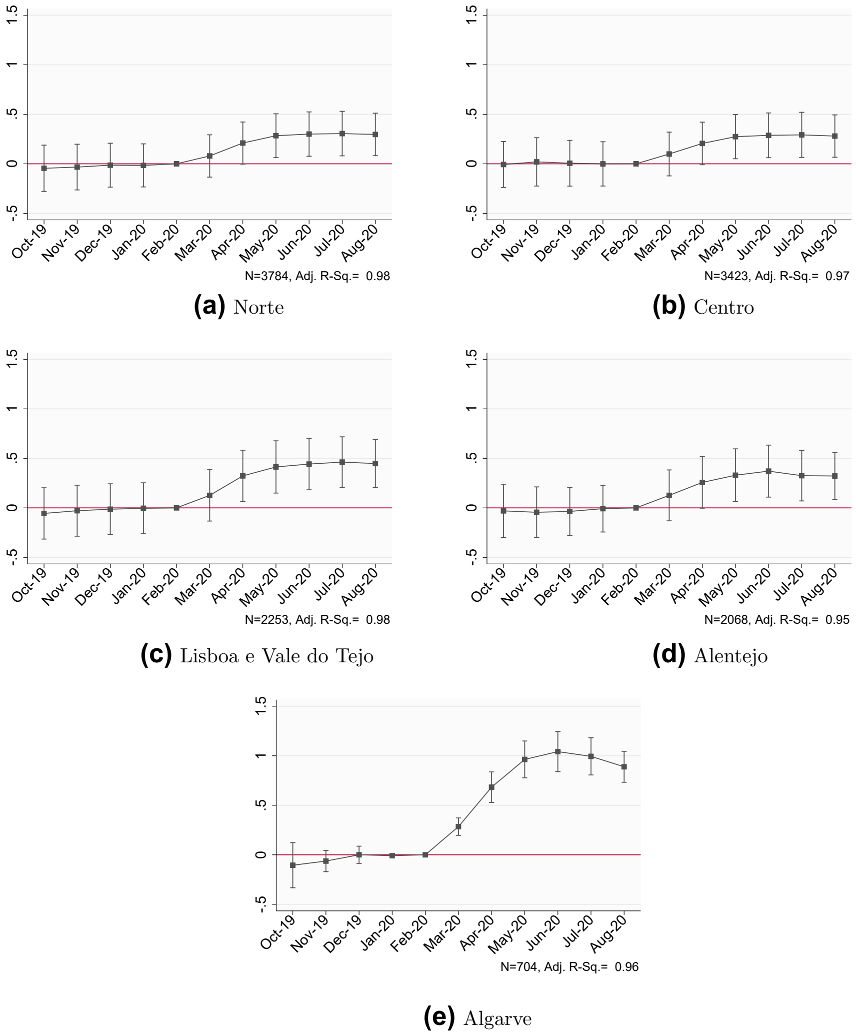
(e) Higher education

Figure C.5: Identification strategy, unemployment by education. Time-series of Log of average unemployment, by education level. The blue line represents the period between October 2019 and August 2020 (the treatment group), of which October 2019 to January 2020 correspond to the pre-treatment period, and March 2020 to August 2020 correspond to the treatment period. The remaining lines represent the control group, i.e. the same series lagged one (Oct. 2018 Aug. 2019), two (Oct. 2017–Aug. 2018) and three (Oct. 2016–Aug. 2017) years.



(a) Unemployment **(b)** New Job Placements

Figure C.6: Event study aggregate effects: different fixed effects.



(a) Norte

(b) Centro

(c) Lisboa e Vale do Tejo

(d) Alentejo

(e) Algarve

Figure C.7: Event study aggregate effects: unemployment by NUTS II region. Standard errors are clustered at the municipality (instead of NUTS II) and time period level.

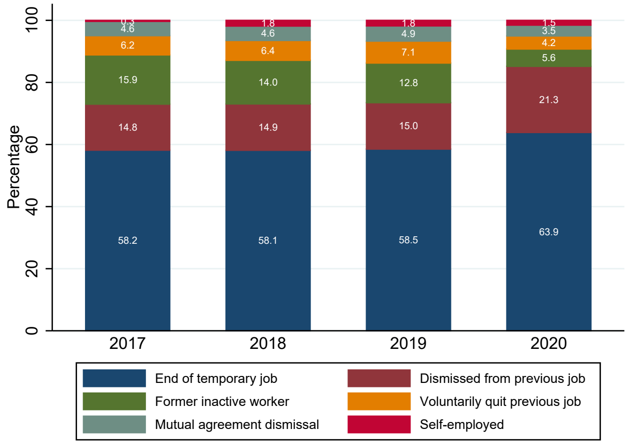
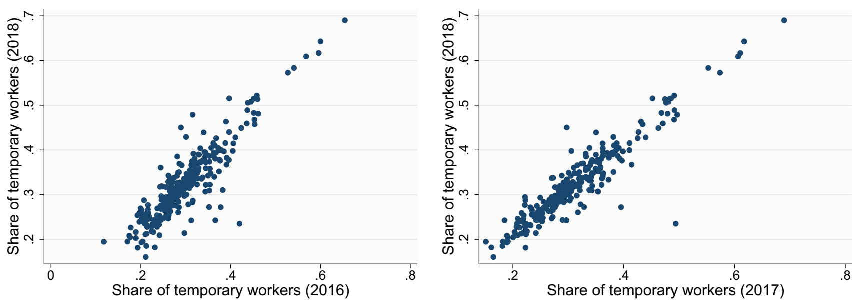


Figure C.8: Average new unemployment between March and August (% of total new registrations) by motive of registration.



(a) 2018 versus 2016 **(b)** 2018 versus 2017

Figure C.9: Scatterplot share of temporary workers.

References

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh. 2020a. “Furloughing.” *Fiscal Studies* 41 (3): 591–622.

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh. 2020b. “Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys.” *Journal of Public Economics* 189: 104245.

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh. 2022. “Work that Can Be Done from Home: Evidence on Variation within and across Occupations and Industries.” *Labour Economics* 74: 102083.

Alon, T., M. Doepke, J. Olmstead-Rumsey, and M. Tertilt. 2020. “This Time It’s Different: The Role of Women’s Employment in a Pandemic Recession.” In *Working Paper Series, No. 27660*. National Bureau of Economic Research.

Alstadsæter, A., B. Bratsberg, G. Eielsen, W. Kopczuk, S. Markussen, O. Raaum, and K. Røed. 2020. "The First Weeks of the Coronavirus Crisis: Who Got Hit, when and Why? Evidence from Norway." In *Working Paper Series, No. 27131*. National Bureau of Economic Research.

Aum, S., S. Yoon (Tim) Lee, and Y. Shin. 2021. "COVID-19 Doesn't Need Lockdowns to Destroy Jobs: The Effect of Local Outbreaks in Korea." *Labour Economics* 70: 101993.

Bamieh, O., and L. Ziegler. 2020. "How Does the Covid-19 Crisis Affect Labor Demand? an Analysis Using Job Board Data from Austria." In *IZA Discussion Papers, No. 13801*. Institute of Labor Economics.

Banco de Portugal. 2020. *Boletim Económico - Outubro 2020*. Lisbon: Banco de Portugal.

Betcherman, G., N. Giannakopoulos, I. Laliotis, I. Pantelaiou, M. Testaverde, and G. Tzimas. 2020. "Reacting Quickly and Protecting Jobs: The Short-Term Impacts of the COVID-19 Lockdown on the Greek Labor Market." In *IZA Discussion Papers, No. 13516*. Institute of Labor Economics.

Birinci, S., F. Karahan, Y. Mercan, and S. Kurt. 2021. "Labor Market Policies during an Epidemic." *Journal of Public Economics* 194: 104348.

Blanchard, O., and P. Portugal. 2017. "Boom, Slump, Sudden Stops, Recovery, and Policy Options:Portugal and the Euro." In *Working Papers 2017, No. 11*. Banco de Portugal.

Boeri, T., and H. Brücker. 2011. "Short-Time Work Benefits Revisited: Some Lessons from the Great Recession." *Economic Policy* 26: 697—765.

Bonacini, L., G. Gallo, and S. Scicchitano. 2021. "Working from Home and Income Inequality: Risks of a 'new Normal' with COVID-19." *Journal of Population Economics* 34: 303—60.

Botha, F., J. P. de New, S. C. de New, D. C. Ribar, and N. Salamanca. 2021. "Implications of COVID-19 Labour Market Shocks for Inequality in Financial Wellbeing." *Journal of Population Economics* 34: 655—89.

Bourdin, S., L. Jeanne, F. Nadou, and G. Noiret. 2021. "Does Lockdown Work? A Spatial Analysis of the Spread and Concentration of Covid-19 in Italy." *Regional Studies* 55 (7): 1182—93.

Cajner, T., L. D. Crane, R. A. Decker, J. Grigsby, A. Hamins-Puertolas, E. Hurst, C. Kurz, and A. Yildirmaz. 2020. "The U.S. Labor Market during the Beginning of the Pandemic Recession." *Brookings Papers on Economic Activity* 2020 (2): 3—33.

Carneiro, A., P. Portugal, and J. Varejão. 2014. "Catastrophic Job Destruction during the Portuguese Economic Crisis." *Journal of Macroeconomics* 39: 444—57.

Carvalho, B., S. Peralta, and J. Pereira dos Santos. 2020. "What and How Did People Buy during the Great Lockdown? Evidence from Electronic Payments." In *Covid Economics: Vetted and Real-Time Papers. Issue 28*, 119—58. Centre for Economic Policy Research.

Carvalho, B., S. Peralta, and J. Pereira dos Santos. 2022. "Regional and Sectorial Impacts of the Covid-19 Crisis: Evidence from Electronic Payments." *Journal of Regional Science* 62 (3): 757—798.

Casarico, A., and S. Lattanzio. 2020. "The Heterogeneous Effects of COVID- 19 on Labor Market Ows: Evidence from Administrative Data." In *Covid Economics: Vetted and Real-Time Papers. Issue 52*, 152—74. Centre for Economic Policy Research.

Cho, S. J., J. Y. Lee, and J. V. Winters. 2021. "Employment Impacts of the COVID-19 Pandemic across Metropolitan Status and Size." *Growth and Change* 52 (4).

Cho, S. J., and J. V. Winters. 2020. "The Distributional Impacts of Early Employment Losses from COVID-19." In *GLO Discussion Paper Series, No. 554*. Global Labor Organization.

Coibion, O., Y. Gorodnichenko, and M. Weber. 2020. "Labor Markets during the COVID-19 Crisis: A Preliminary View." In *Working Paper Series, No. 27017*. National Bureau of Economic Research.

Cortes, G. M., and E. Forsythe. 2022. "Heterogeneous Labor Market Impacts of the COVID-19 Pandemic." *ILR Review* 76 (1): 30—55.

Couch, K. A., R. W. Fairlie, and H. Xu. 2020. "Early Evidence of the Impacts of COVID-19 on Minority Unemployment." *Journal of Public Economics* 192: 104287.

Del Boca D., N. Oggero, P. Profeta, and M. C. Rossis. 2020. "Women's Work, Housework and Childcare, before and during COVID-19." *Review of Economics of the Household* 18: 1001–17.

Dias, M. C., R. Joyce, F. Postel-Vinay, and X. Xu. 2020. "The Challenges for Labour Market Policy during the COVID-19 Pandemic." *Fiscal Studies* 41.

Dingel, J. I., and B. Neiman. 2020. "How Many Jobs Can Be Done at Home?" In *Working Paper Series 26948*. National Bureau of Economic Research. Also available at http://www.nber.org/papers/w26948.

European Commission. 2018. *European Semester: Country Specific Recommendation/Commission Recommendation — Portugal*. Also available at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52018DC0421.

Farré, L., Y. Fawaz, L. Gonzalez, and J. Graves. 2020. "How the COVID-19 Lockdown Affected Gender Inequality in Paid and UnpaidWork in Spain." In *IZA Discussion Papers, No. 13434*. Institute of Labor Economics.

Ferreira, P., J. Cerejeira, and M. Portela. 2020. *IZA COVID-19 Crisis Response Monitoring - Portugal (November 2020)*. Bonn: Institute of Labor Economics.

Forsythe, E., L. B. Kahn, F. Lange, and D. G. Wiczer. 2020. "Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims." *Journal of Public Economics* 189: 104238.

Gabe, T., and R. Florida. 2021. "Impacts of Jobs Requiring Close Physical Proximity and High Interaction with the Public on US Industry Employment Change during the Early Stages of the COVID-19 Pandemic." *The B.E. Journal of Economic Analysis & Policy* 21 (3): 1163–72.

Giupponi, G., C. Landais, and A. Lapeyre. 2022. "Should We Insure Workers or Jobs during Recessions?" *The Journal of Economic Perspectives* 36 (2): 29–54.

Grabner, S. M., and A. Tsvetkova. 2022. "Urban Labour Market Resilience during the Covid-19 Pandemic: What Is the Promise of Teleworking?" *Regional Studies* 1–16. https://doi.org/10.1080/00343404.2022.2042470.

Graeber, D., A. S. Kritikos, and J. Seebauer. 2021. "COVID-19: A Crisis of the Female Self-Employed." *Journal of Population Economics* 34 (4): 1141–87.

Hensvik, L., T. Le Barbanchon, and R. Rathelot. 2020. "Job Search during the COVID-19 Crisis." *Journal of Public Economics* 194: 104349.

Herzog-Stein, A., P. Nüß, L. Peede, and U. Stein. 2022. "Germany and the United States in Coronavirus Distress: Internal versus External Labour Market Flexibility." *Journal for Labour Market Research* 56 (11).

Hupkau, C., and B. Petrongolo. 2020. "Work, Care and Gender during the Covid-19 Crisis." *Fiscal Studies* 41 (3): 623–51.

ILO. 2017. "The Covid-19 Response: Getting Gender Equality Right for a Better Future for Women at Work." In *ILO Brief*. International Labour Organization.

INE. 2020. *Trabalho a partir de casa — Módulo ad hoc do Inquérito ao Emprego (2.° trimestre de 2020)*. Lisbon: Instituto Nacional de Estatística.

Jones, S. R. G., F. Lange, W. C. Riddell, and C. Warman. 2020. "Waiting for Recovery: The Canadian Labour Market in June 2020." *Canadian Public Policy* 46 (S2): S102–18.

Kalenkoski, C. M., and P. S. Wulff. 2020. "Initial Impact of the COVID-19 Pandemic on the Employment and Hours of Self- Employed Coupled and Single Workers by Gender and Parental Status." In *IZA Discussion Papers, No. 13443*. Institute of Labor Economics.

Kikuchi, S., S. Kitao, and M. Mikoshiba. 2021. "Who Suffers from the COVID-19 Shocks? Labor Market Heterogeneity and Welfare Consequences in Japan." *Journal of the Japanese and International Economies* 59: 101117.

Lafuente, C., R. Santaeulália-Llopis, and L. Visschers. 2022. "Temping Fates in Spain: Hours and Employment in a Dual Labor Market during the Great Recession and COVID-19." *SERIEs* 13: 101–45.

Lemieux, T., K. Milligan, T. Schirle, and M. Skuterud. 2020. "Initial Impacts of the COVID-19 Pandemic on the Canadian Labour Market." *Canadian Public Policy* 46 (S1): S55–65.

Martins, F., and P. Portugal. 2019. "De que forma a rigidez á baixa dos salários afetou o desemprego durante a crise económica?" In *O Crescimento Económico Português: uma visão sobre questões estruturais, bloqueios e reformas*, vol. 97–106. Banco de Portugal.

Mayhew, K., and P. Anand. 2020. "COVID-19 and the UK Labour Market." *Oxford Review of Economic Policy* 36 (Supplement1): S215–24.

Meekes, J., W. Hassink, and G. Kalb. 2020. "Essential Work and Emergency Childcare: Identifying Gender Differences in COVID-19 Effects on Labour Demand and Supply." In *IZA Discussion Papers, No. 13843*. Institute of Labor Economics.

Midões, C. 2020. *Social Distancing: Did Individuals Act before Governments?* Also available at https://www.bruegel.org/2020/04/social-distancing-did-individuals-act-before-governments/ (Accessed December 29, 2020).

Mitman, K., and S. Rabinovich. 2021. "Whether, When and How to Extend Unemployment Benefits: Theory and Application to COVID-19." *Journal of Public Economics*, 200: 104447.

Montenovo, L., X. Jiang, F. L. Rojas, I. M. Schmutte, K. I. Simon, B. A. Weinberg, and C. Wing. 2020. "Determinants of Disparities in Covid- 19 Job Losses." In *Working Paper Series, No. 27132*. National Bureau of Economic Research.

OECD. 2017. *Labour Market Reforms in Portugal 2011–15: A Preliminary Assessment*. OECD Publishing.

OECD. 2020. "Job Retention Schemes during the COVID-19 Lockdown and beyond." In *OECD Policy Responses to Coronavirus (COVID-19)*.

Peralta, S., B. P. Carvalho, and M. Esteves. 2021. "Portugal, Balanço Social 2020: Um retrato Do país e dos efeitos da pandemia." In *Social Equity Initiative*. Lisbon: Nova School of Business and Economics.

Portugal, P., and H. Vilares. 2013. "Labor Unions, Union Density and the Union Wage Premium." In *Economic Bulletin*, 61–71. Lisbon: Banco de Portugal.

Weel, B. 2018. "The Rise of Temporary Work in Europe." *De Economist* 166.