The Heterogeneous Effects of COVID-19 on Labor Market Flows: Evidence from Administrative Data*

Alessandra Casarico
Bocconi University, CESifo, Dondena

Salvatore Lattanzio
University of Cambridge

January 15, 2021

Abstract

We investigate the short-term effects of COVID-19 on labor market flows and how they are mediated by labor market policy. Using Italian administrative data on a sample of active contracts between 2009 and the second quarter of 2020, we show that, before the pandemic, workers employed in non-essential activities are in majority men, young, located in the North and with low education. When we look at the change in hirings and separations, from the 9th week of 2020, we find a pronounced drop in hirings and endings of fixed-term contracts. Layoffs and quits increase after the 9th week, and then decline significantly, reflecting the effects of government intervention. The lifting of the lockdown triggers a slow recovery of labor market flows. Young, temporary, low-educated workers suffer from a lower probability of job creation and a higher risk of separating. Also, gender is a significant predictor of separation.

Keywords: COVID-19, hirings, separations, flows, gender

***JEL* codes**: J21, J63, J68

*We would like to thank Bruno Anastasia, Giulia Bovini, Francesco D'Amuri, Andrea Garnero and Christopher Rauh for useful comments and discussion. Salvatore Lattanzio gratefully acknowledges ESRC DTP Studentship (nr. ES/J500033/1) and Cambridge Commonwealth European and International Trust for financial support for PhD studies. Contacts: Casarico, alessandra.casarico@unibocconi.it; Lattanzio, sl828@cam.ac.uk.

1 Introduction

The COVID-19 pandemic is having dramatic consequences on society. In order to contain the spread of the virus, many governments around the world adopted unprecedented interventions that in most cases resulted in lockdowns of entire regions or countries. The suspension of economic activities had severe repercussions on employment and earnings of individuals and on profits of firms. As a consequence, global GDP growth is projected at -4.4 percent (IMF, 2020), with considerable heterogeneity between advanced (-5.8 percent) and emerging economies (-3.3 percent). Governments responded to the economic downturn with encompassing packages of fiscal measures, ranging from transfers, loans, postponements of tax dues, to facilitating liquidity and access to credit for firms. Preventing or reducing the disruption of the labor market was among the main goals of government intervention, and the specific instruments adopted varied across countries, also in light of pre-existing labor market institutions. The implemented policy measures and pre-existing labor market conditions and institutions mediate the impact of the pandemic on jobs. For example, Adams-Prassl et al. (2020) compare the United Kingdom, the United States and Germany and show that the job losses were higher in the first two countries, which are characterized by more flexible labor markets.

Using administrative data on a large sample of contracts active in the first and second quarters of 2020, this paper investigates the short term effects of COVID-19 on labor market flows and study how they were mediated by policy put in place by the government to shield workers from the disruption of economic activity. Italy was the first country in Europe to be hit by COVID-19 and the first to implement a national lockdown, which involved the definition of essential and non-essential economic activities, the former to be continued, the latter to be shut down. The lockdown was shortly after followed by two further policy measures relevant for labor market dynamics: a ban on layoffs and an ease of the requirements to access short-time work (STW) compensation schemes. While the former is unique to Italy for its breadth, the latter is common to most European countries (see OECD, 2020, for details on government policy responses across OECD countries).

First, we provide descriptive evidence on the personal and job characteristics of workers employed as of January 2020, distinguishing across essential and non-essential activities. The latter were mainly concentrated in services, such as restaurants, bars, hotels, and some categories of wholesale and retail shops, in line with government decisions in other countries. We show that workers employed in non-essential activities were in majority women, younger than 35 years old, located in the South of the country and with low level of education. Second, we analyze the change in net hirings, computed as hirings net of separations, and

in hirings, layoffs, endings of fixed-term contracts and quits – all as separate flows –, in each week of the first two quarters of 2020 relative to the average in the same weeks of 2017-19. For each labor market flow, we provide graphical evidence of the cumulative weekly change for all workers and for different subgroups based on age, gender, region, type of contract (open-ended, apprenticeship or fixed-term/temporary), education level, and sector (essential vs non-essential activities). The descriptive evidence shows that, before the pandemic, the trend in cumulative labor market flows was in line with the average in the previous three years. When COVID-19 spread quickly around the country, starting from the 9th week of the year, there was a pronounced drop in net hirings, which halted only after the lockdown was lifted. We find a very similar pattern for hirings. As to separations, we find that endings of fixed-term contracts declined monotonically except for a sudden increase at the end of the 13th week of the year, which corresponds to the end of March, when many contracts were not renewed given the tighter labor market conditions. Layoffs and quits increased right after the 9th week, and then dropped significantly. The evolution of layoffs reflects the policy introduced on 17 March, that explicitly forbids firms from laying off workers and, at the same time, eases the requirements to have access to STW compensation schemes. Absent the policy, layoffs were rising with respect to the past. Moreover, the ban on layoffs may also have contributed to the decreasing dynamics of hirings, as the higher employment protection for workers may have decreased turnover. Third, we further explore hirings and separations by examining which factors are associated with the change in the probability of being hired or separating from a job between 2019 and 2020. We find that a younger age, being on a fixed-term contract, working in the Centre or the South relative to the North, having lower or upper secondary education are all significant predictors of the change in the hiring probability: in other words, those workers that were already suffering the consequences of the previous recession (young, temporary, low-skill workers) are those at higher risk of facing a tighter labor market after the pandemic. On the other hand, when examining the separation probability, we generally find that government policy guaranteed protection to the most vulnerable groups in the labor market. In particular, relative to 2019, fixed-term contracts, workers in the South and low educated workers are less likely to separate between April and June. However, we find significant heterogeneity between essential and non-essential activities, i.e. between continuing and shutdown businesses. Fixed-term and younger workers are more likely to separate in March in non-essential activities relative to the past, indicating that these categories suffered from the contraction of economic activity, which was obviously more severe in shutdown sectors. We also find that female workers have higher separation probability in non-essential activities in April and May. The result that gender is correlated with the separation probability is in line with evidence shown

for example in Adams-Prassl et al. (2020). Given the higher concentration of women in temporary contracts and part-time positions, coupled with the nation-wide school closures, one could expect a harsher impact of the crisis on women, as highlighted by Alon et al. (2020). We do indeed find that not only women suffered a more pronounced drop in net hirings with respect to men, but also that they are characterized by a higher separation probability relative to men in non-essential activities. Note that the effect of gender in the aggregate may even be stronger than the one we find, since we can only discuss the extensive margin of adjustment – whether a worker separates from her job or not. Clearly, the adjustment may happen also on the intensive margin, if women had to adjust their work hours in response to the pandemic. This is an important element we cannot directly address with the data at hand.

Our analysis contributes to the recent and growing literature on the effects of the pandemic recession on economic activity (e.g. Carvalho et al., 2020; Chetty et al., 2020; Baker et al., 2020) and, specifically, on the labor market and the policy responses put in place by governments. Evidence using real-time survey data (Bick and Blandin, 2020; Adams-Prassl et al., 2020; von Gaudecker et al., 2020), administrative data (Cajner et al., 2020) and a combination of both (Forsythe et al., 2020) highlights the severe and unequal consequences of the pandemic recession on the labor market. A strand of this literature specifically focuses on how different categories of workers were affected by the pandemic (Blundell et al., 2020; Crossley et al., 2021; Bonacini et al., 2021), with particular focus on age (Belot et al., 2020) and gender (Alon et al., 2020; Hupkau and Petrongolo, 2020; Farré et al., 2020). We provide new evidence based on detailed administrative data on a sample of active, new and terminated contracts, coming from the *Comunicazioni Obbligatorie*, i.e. the compulsory information firms need to provide on their workforce. These data are highly reliable and less subject to measurement errors with respect to survey data. We can explore many dimensions of heterogeneity and provide an exhaustive picture of the unequal impact of COVID-19. We also assess the short run impact of a government policy that explicitly forbids layoffs and extends the generosity of STW compensation schemes. We show it was successful in taming layoffs – as expected –, but may also have reduced hirings. This lays the groundwork for a long term assessment of their impact on labor market dynamics. Finally, by showing how workers on different types of contracts and different degrees of employment protection are affected by the pandemic recession, we contribute to the literature that analyzes the margins of adjustment in the labor market in the presence of negative shocks (Izquierdo et al., 2017; Garin and Silvério, 2019; Adamopoulou et al., 2020).

The remainder of the paper is organized as follows. Section 2 describes the data and gives details about the evolution of the pandemic in Italy and the policy response by the

government. Section 3 shows the distribution of workers in essential and non-essential activities before the pandemic. Section 4 analyzes the changes in hirings and separations between 2020 and previous years, whereas section 5 focuses on a formal analysis of the determinants of the hiring and separation probability. Finally, section 6 concludes.

2 Data and Institutional Context

2.1 Data and Descriptive Statistics

We use data from a random sample of mandatory notifications (*Campione Integrato delle Comunicazioni Obbligatorie*, CICO) that firms submit to relevant public agencies in Italy and to the Ministry of Labor and Social Policy. The data collects information on a sample of contracts activated and terminated between 2009 and the second quarter of 2020 for public- and private-sector workers, farming and domestic workers.[1] For each contract, we have information on the exact start date and, if the contract ends, on the end date and the reason for its ending (mainly, layoffs, expiry of temporary contracts, voluntary quits).[2] Furthermore, we have information on the type of contract (open-ended, apprenticeship or temporary/fixed-term, full-time or part-time), detailed occupational and sectoral codes (4-digit Isco and 6-digit Ateco 2007, respectively) and individual characteristics of workers, such as gender, the year of birth, the region of domicile and work, and the education level. We keep only workers in the private sector in our analysis and we further exclude workers in agriculture and domestic workers, as information on these workers is less reliable. Table 1 reports descriptive statistics on the contracts – and on the individual characteristics of the workers holding them – and compares them with the population of workers from aggregate data provided by the Italian Social Security Administration (INPS) as of 2019 (when the latest information on the labor market before the pandemic is available). Our data over-samples contracts held by workers in the age group 15-34 and under-samples contracts of workers on open-ended and full-time positions and contracts of workers in manufacturing. The bottom part of the table, column (1), reports the sample size of CICO, distinguishing total contracts and total workers

[1] The sampling strategy is based on the day of birth: workers born on the 1st, 9th, 10th and 11th day of each month and year in the full administrative records are included in the sample. CICO contains information on contracts that have been activated, transformed or ended starting from 2009. Hence, the data contains information on new contracts from 2009 and on contracts that have been established before 2009 but that were either terminated or transformed in subsequent years. Therefore, the data do not contain information on contracts that have been stipulated before 2009 and that have not been modified since then.

[2] We exclude from the sample contracts ending due to retirement and death, or contracts whose end date is modified, as there is no further information on whether the end date is anticipated or postponed.

Table 1: Descriptive statistics

	(1) CICO	(2) Inps
Female	0.39	0.38
Age 15-34	0.34	0.29
Age 35-54	0.53	0.55
Age 55+	0.14	0.17
North	0.56	0.58
Centre	0.22	0.21
South	0.22	0.21
Open-ended contract	0.65	0.83
Full-time contract	0.64	0.72
Manufacturing	0.22	0.29
Total contracts	1,561,611	-
Total workers	1,363,010	12,192,608

Notes. The table reports the share of contracts in each group from the sample of *Comunicazioni Obbligatorie* (CICO) as of January 2020 and the share of workers from official statistics provided by the Social Security Administration (INPS) at the end of 2019 in the non-agricultural private sector. The last two rows of the table report the total number of contracts and workers (as a worker may hold multiple contracts) present in CICO and the total number of workers in INPS.

(as workers can hold multiple contracts) by the end of the sample period.[3] Column (2) reports the number of private sector workers from INPS (excluding agriculture and domestic workers). Overall, our sample represents approximately 11.2% of the population of workers in Italy. The fact that younger workers are over-represented, whereas more stable contractual arrangements – such as, open-ended and full-time contracts – are under-represented comes as no surprise given the sample selection described above. The data over-samples contracts stipulated in the last decade, which capture the first contract of new workers, who are therefore more likely to be young and on temporary positions. However, although not fully representative of the population of workers at a given point in time, the data allows us to compare flows between different years (e.g., the change in hirings or separations over time) and to contrast the distribution of workers in the subgroups of essential and non-essential activities, as one can believe the sampling bias would be orthogonal with respect to the allocation of workers across essential and non-essential activities.

[3]The sample statistics reported in the top part of the table are computed using the contract as unit of observation. This choice does not affect the composition of our sample: if we use the worker as unit of analysis and keep only the primary contract per each worker, we get almost identical sample shares.

2.2 COVID-19 in Italy and Public Policy

The first cases of COVID-19 in Italy date back to 31 January 2020, but the disease began to spread exponentially in the second half of February. At the beginning, the virus spread predominantly in Northern regions and the first COVID-related death was registered in Veneto on 21 February. Following the diffusion of the virus in the North, two "red zones" were implemented, involving 11 municipalities in Lombardy and Veneto, that were effectively in lockdown. At the same time, many Northern regions opted to close schools, a measure that extended to the whole nation on 4 March. On 10 March the whole country went into lockdown. The decree establishing the nationwide lockdown also specified the activities that were deemed as essential and could continue to operate and those that were classified as non-essential and were forced to shut down: the former mainly include agriculture, some manufacturing, energy and water supply, transports and logistics, ICT, banking and insurance, professional and scientific activities, public administration, education, healthcare and some service activities; shutdown sectors include most of manufacturing activities, wholesale and retail trade, hotels, restaurants and bars, entertainment and sport activities. In light of these closures, the government adopted on 17 March a Decree Law that considerably increased worker's employment protection. Two main labor market policies were adopted:

(1) A special COVID-related STW compensation scheme of the duration of 9 weeks, that applied retroactively starting from 23 February. This measure aimed at preserving employment relationships and allowing firms to cut labor costs during the lockdown period, by reducing hours of work thanks to a wage subsidy granted by the government. The measure extended the regular STW by allowing firms with less than 15 employees and firms that were already using the extra-ordinary STW (one of the sub-species of STW granted by the Italian employment protection legislation) to use it. Moreover, firms using the COVID-related STW could renew temporary contracts, waiving to the norms of the standard regulation.

(2) A ban on layoffs that forbade them for 60 days, starting from 17 March and that could be applied retroactively to pending layoffs (i.e. those that were yet to be validated) from 23 February.

Two later decrees extended the validity of these measures until the end of the year. Thus, the COVID-related STW compensation scheme and the ban on layoffs were valid throughout the whole period we consider for our analysis.

3 Before the Pandemic: the Distribution of Workers in Essential and Non-Essential Activities

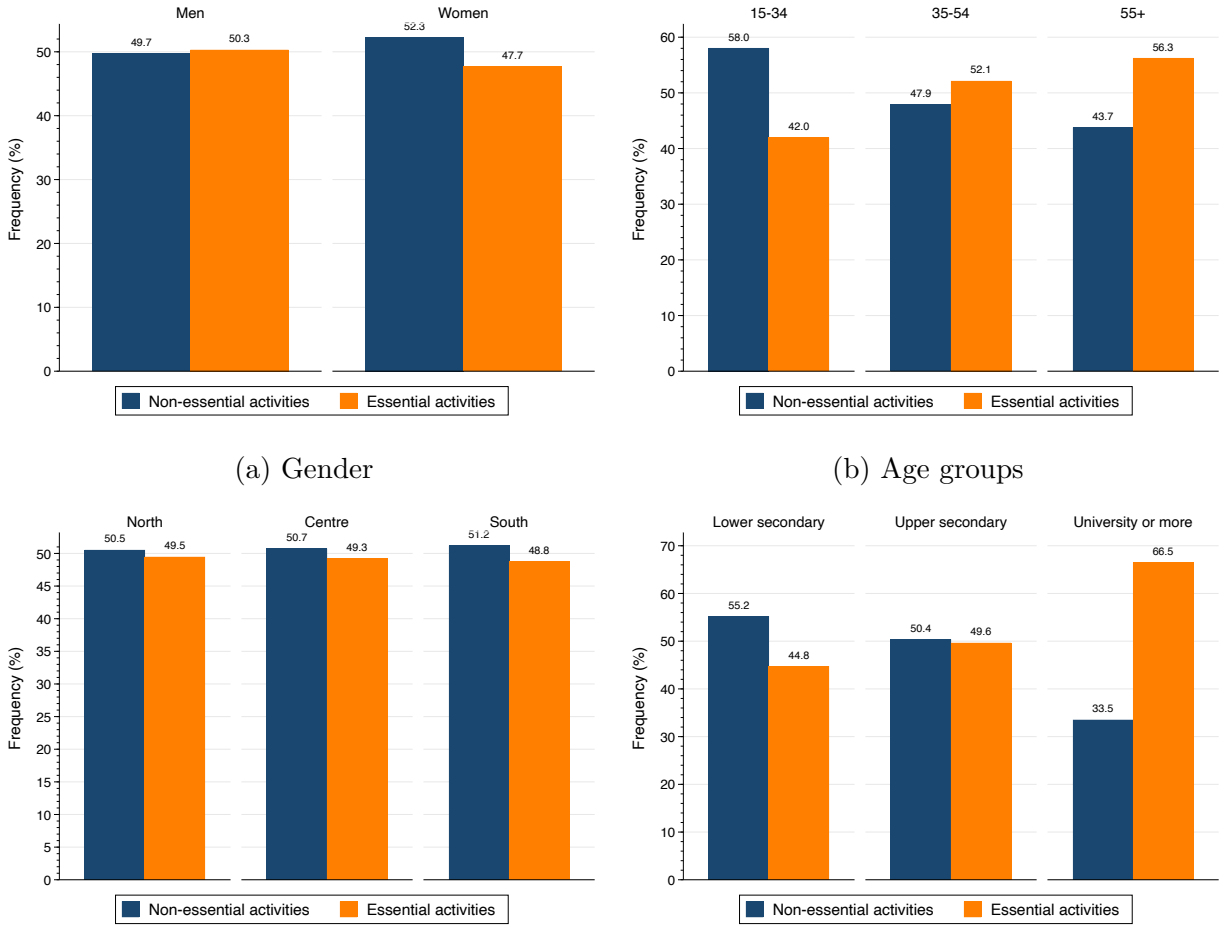
Using data from CICO up to January 2020, we show the distribution of workers in essential and non-essential activities (i.e. between open and shutdown sectors, as defined by the Prime Minister's decree of 11 March based on sectoral codes) at the onset of the pandemic. Figure 1, panels (a)-(d), shows the distribution of workers by gender, age, region of work and education level. Panel (a) shows that women are over-represented in non-essential activities (52.3%) relative to men (49.7%): this result is in line with the evidence provided, for example, by Blundell et al. (2020) for the UK.

Panel (b) shows the distribution by age, distinguishing workers in age groups 15-34, 35-54 and 55 or older. The figure shows that, while young workers are over-represented in non-essential activities, middle-aged and older workers are more present in essential activities. Hence, the closure of non-essential sectors has a stronger impact on young workers, 58% of whom are employed in shutdown sectors.

Panel (c) reports the distribution by region of work. Differences between the North, the Centre and the South are small and, if anything, slightly more workers are employed in shutdown sectors in the South, relative to the rest of the country, but differences are hardly economically significant. This may seem counter-intuitive, considering that tourism and connected services are some of the strengths of Southern Italy, were one could expect a stronger concentration of non-essential activities. This distribution may be correlated with the presence of the informal economy, which is higher in the South, as documented, for example, in Boeri et al. (2019), and particularly relevant for workers in accommodation, tourism and restaurants—sectors belonging to non-essential activities.

Panel (d) shows the distribution by education level. While 55.2% and 50.4% of workers with lower and upper secondary education are in shutdown sectors, only 33.5% of individuals with university degree work in non-essential activities, suggesting a disproportionate impact of the pandemic on workers with lower levels of education.

This analysis takes a snapshot of the Italian labor market at the onset of the pandemic. We now turn to the inspection of the impact of the crisis on hirings and separations in the first two quarters of 2020.



(a) Gender

(b) Age groups

(c) Region

(d) Education level

Figure 1: Distribution of workers in essential and non-essential activities as of January 2020

4 After the Pandemic: the Impact of the Recession on Labor Market Flows

4.1 Measurement

In this section, we analyze the dynamics of net hirings (N) – computed as the difference between hirings[4] and separations –, hirings (H) and separations – distinguished in layoffs (F), endings of fixed-term contracts (E) and quits (Q) – in the first two quarters of 2020. Specifically, we compute the cumulative weekly change in each flow between 2020 and the average of 2017-19, with respect to the total stock of workers (L_{pre}) in our sample, as of January 2020 – before the pandemic started. In other words, for each week t, we compute

[4]Our definition of hirings is broad, since we use this term to indicate the activation of new contracts, which can be new hirings or transformations of fixed-term contracts into permanent contracts.

the per-capita cumulative change in total flows $Y_t = \{N_t, H_t, L_t, E_t, Q_t\}$ as:

$$\triangle Y_t = 100 \times \frac{Y_{t,2020} - \overline{Y}_{t,2017-19}}{L_{pre}}, \tag{1}$$

where $\triangle Y_t$ is the cumulative change in net hirings, hirings and separations up to week t, with $t = \{1, ..., 26\}$. $Y_{t,2020}$ are the cumulative flows in 2020 until week t. $\overline{Y}_{t,2017-19}$ are the average cumulative flows in 2017-2019 until week t. L_{pre} is the stock of workers in the sample at the onset of the pandemic, i.e. January 2020. Hence, we compute a change in each flow per 100 workers. We normalize the change to be 0 in week 8 of the year, that is, the one between 19 and 25 February – before the onset of the pandemic – and compare changes relative to that week.[5]

We also compute changes in flows for subgroup $g \in G$, with G including age, gender, region of work, type of contract (permanent, fixed-term or apprenticeship), education level and group of activity (essential or non-essential). Specifically, for each week t, we compute the per-capita cumulative change in $Y_t^g = \{N_t^g, H_t^g, L_t^g, E_t^g, Q_t^g\}$ as:

$$\triangle Y_t^g = 100 \times \frac{Y_{t,2020}^g - \overline{Y}_{t,2017-19}^g}{L_{pre}^g},$$

where $\triangle Y_t^g$ is the cumulative change in flows for subgroup g. $Y_{t,2020}^g$ and $\overline{Y}_{t,2017-19}^g$ are, respectively, the cumulative flows in 2020 and 2017-19 for each g, and L_{pre}^g is the stock of workers in subgroup g in January 2020.

4.2 Total change

Figure 2 reports the cumulative change in net hirings, hirings, layoffs, endings of fixed terms contracts, quits and total separations for each week in the first two quarters of 2020 relative to the average of 2017-19 and for all workers, as from equation (1). Total separations are computed as an aggregate of layoffs, endings of fixed-term contracts and quits, while net hirings are the difference between the curves of hirings and total separations. The figure shows that net hirings were on a parallel trend before the onset of the pandemic, but after the 9th week (i.e. after the first cases and deaths were recorded), there is a marked contraction, which is determined especially by a decline in hirings and an increase in separations. Starting from week 12-13, separations begin to decline, too, as a consequence of the layoff ban, the COVID-related STW compensation scheme and the contraction in economic activity, which lowers job turnover. We observe that the decline is particularly marked for endings of fixed-term contracts. Until week 18 (i.e. the end of the strict lockdown) the slope of the decline

[5]This choice is innocuous and results would almost be unchanged if we do not use this normalization.

in hirings is steeper than the decline in separations, therefore producing a continuing drop in net hirings. After week 18, when businesses began to return to a new normal, there is a change in the slope of net hirings as activations of new contracts started to recover, and separations continued to be below their levels in the past (as the ban on layoff and STW were still in place). Overall, by the end of our observation period, we find a net change of -6, determined by a change in hirings of -12.8 and in separations of -6.8 per 100 workers, with respect to the average of 2017-19 and relative to week 8 of the year.[6] The large decline in job creation is naturally a consequence of the pandemic recession and the subsequent lockdown of economic activities. It is possible that the ban on layoffs had a negative effect, too.[7] However, the graph shows that when restrictions on mobility were lifted from week 18, the slope of the curves change and net hirings start to converge back to their levels in the past, even in the presence of the layoff ban, mainly through a recovery of hirings. Although this is only suggestive evidence, as it is impossible to clearly and separately identify the effect of the lockdown from that of the policy, it seems that the recession induced by the pandemic (and the non-pharmaceutical intervention to contain its spread) contributes more to the drop in net hirings than the layoff ban.

4.3 Changes by subgroups

Net Hirings Figure 3, panels (a)-(f), shows the cumulative change in net hirings per 100 workers with the same characteristics between 2020 and the average 2017-19. Panel (a) reports the changes for different age groups and shows that the impact of the pandemic recession was harsher for young workers (age group 15-34) relative to middle-aged (35-54) and old workers (over 55). At the end of the second quarter, net hirings were 10 units lower for young workers, relative to week 8, compared to 3.9 for both middle aged and old workers. Panel (b) reports results by gender and shows that the pandemic had a stronger impact on female net hirings, which dropped by 7 units as opposed to 5.3 for men. Panel (c) reports the cumulative changes by region, and shows that the impact was slightly larger for workers in the South and Centre (-6.7 and -6.4, respectively) than for workers in the North (-5.5): hence, although the health effects of the pandemic were more severe in the North during the first wave, the negative economic consequences were distributed across the whole country. Panel (d) shows the disproportionate impact of the pandemic on fixed-term contracts, with a cumulative change in net hirings equal to -17 units per 100 workers, as opposed to an

[6] Without the normalization in the 8th week, we have a net change of -5.6, determined by a change in hirings of -11.5 and a change in separations of -5.9 per 100 workers.

[7] See, e.g., Kugler and Pica (2008) for evidence on the impact of increased employment protection legislation on worker flows.

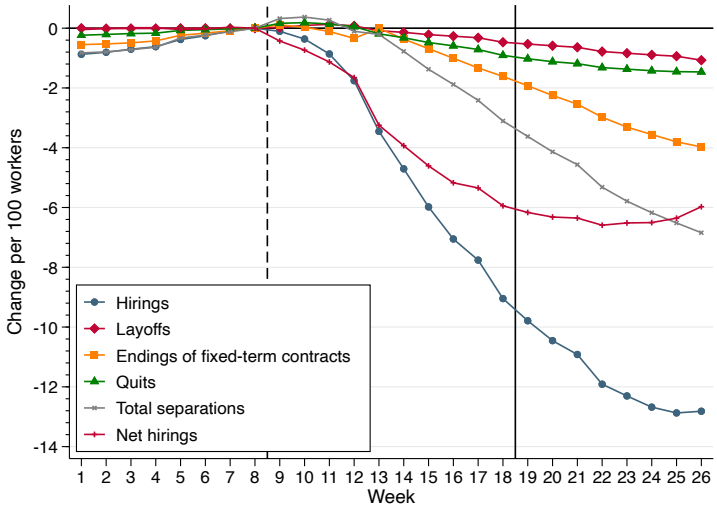
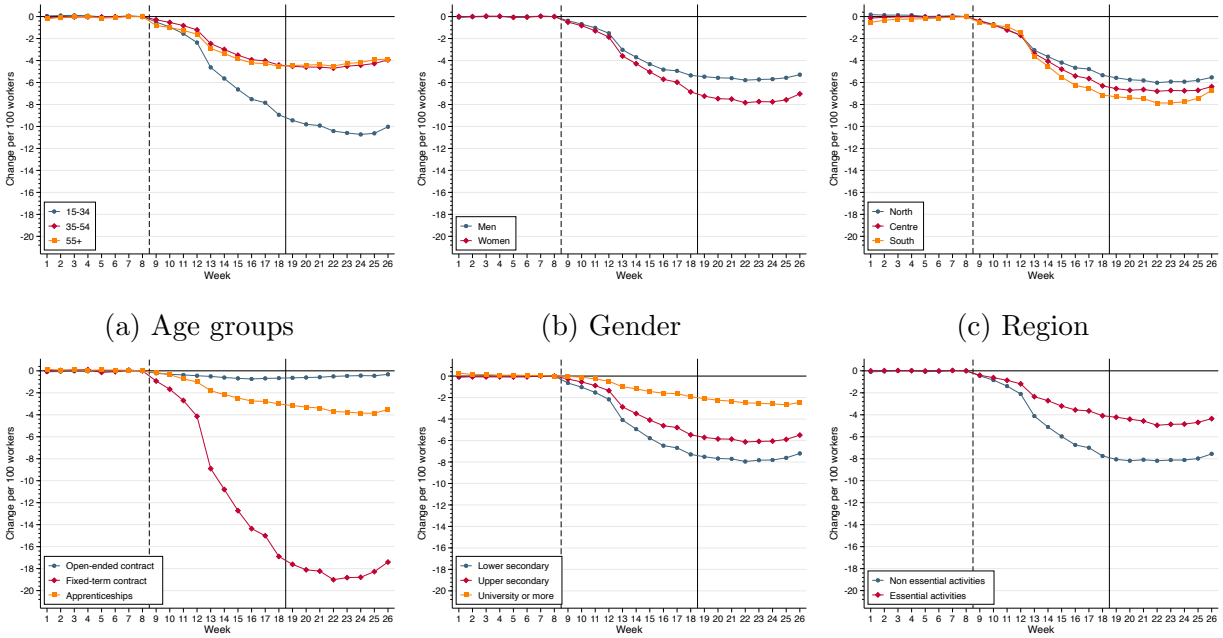


Figure 2: Cumulative change in net hirings, hirings and separations

Notes. The figure shows the cumulative change in net hirings (activations of new contracts minus separations), hirings and separations up until each week in the first two quarters of 2020 with respect to the average of 2017-19 over the same period of the year and relative to the week before the pandemic (week 8). Values are expressed per 100 workers. The dashed vertical line indicates the onset of the pandemic. The solid vertical line indicates the end of the lockdown.

almost unchanged trend for open-ended contracts, for which net hirings declined by only 0.3 units, and a lower decline for apprenticeships (−3.5). Panel (e) reports the impact across different education groups, and shows that low educated workers are suffering more the negative consequences of the recession: workers with lower secondary and upper secondary education experience a change in net hirings of −7.2 and −5.5, respectively, relative to −2.5 for university graduates. Finally, panel (f) reports the change for essential and non-essential activities, i.e. for open and shutdown sectors, showing that the latter had a larger decrease in net hirings (−7.6) than the former (−4.3). The impact on non-essential activities is a consequence of the business closures, as those sectors were not operating. The impact on essential activities reflects the general contraction in economic activity and demand.

Hirings Figure 4, panels (a)-(f), shows the cumulative change in hirings in 2020 relative to 2017-19. The patterns are very similar to those reported for net hirings in Figure 3. Hirings had a sharp decline for young workers (−19.5 per 100 workers in the same age group) relative to middle-age (−9.9) and old workers (−7.6), as shown in panel (a). In panel (b) we see that they were slightly lower for women compared to men (−13.9 and −12.1, respectively). Panel (c) shows that the pandemic hampered hirings especially in Southern and Centre regions (−16.3 and −15.7, respectively), with differences that are more marked than those observed in net hirings with respect to Northern regions (−10.3). Again, we see how the pandemic had



(a) Age groups (b) Gender (c) Region

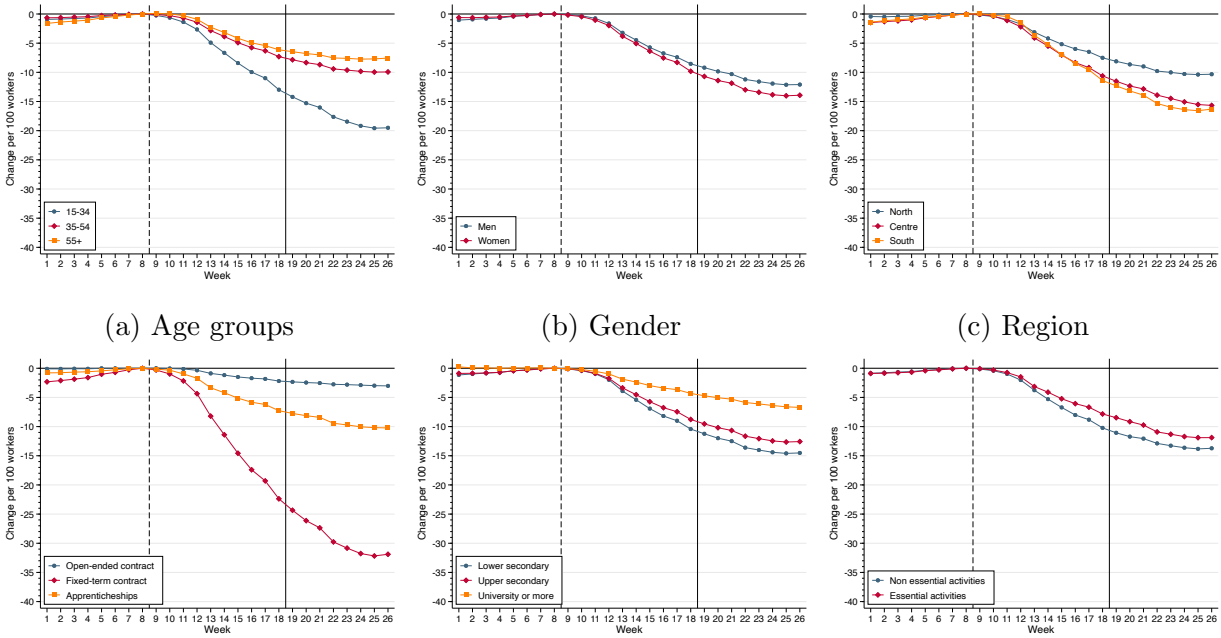
(d) Type of contract (e) Education level (f) Groups of activities

Figure 3: Cumulative change in net hirings (hirings minus separations) between 2020 and average 2017-2019

Notes. The figure shows the cumulative change in net hirings (activations of new contracts minus separations) up until each week in the first two quarters of 2020 with respect to the average of 2017-19 over the same period of the year and relative to the week before the pandemic (week 8). Values are expressed for 100 workers in the same subgroup. The dashed vertical line indicates the onset of the pandemic. The solid vertical line indicates the end of the lockdown.

a disproportionate impact on fixed-term contracts: hirings of workers with such contracts declined by 31.9 units, as opposed to smaller declines of 10.2 for apprenticeships and 3 units of permanent contracts. Low educated individuals experienced larger declines in hirings than high-educated workers (panel e), as well as workers in non-essential activities (panel f).

Layoffs Figure 5 reports the cumulative weekly change in layoffs for different subgroups. Until the beginning of the pandemic recession, layoffs were on the same trend as those registered in the past. After the onset of the pandemic, we observe an increase in layoffs, which was particularly evident between weeks 9 and 12 and especially for workers on fixed-term contracts (panel d) and low educated individuals (panel e). In week 12, the ban on layoffs together with the COVID-related STW compensation scheme came into force and we observe a steady decline in cumulative layoffs, until the end of our period of analysis (as both the ban and STW were in place throughout the whole period). Overall, this evidence suggests that, absent the policy, firms would have resorted to layoffs to cut labor costs, although it is difficult to separate the impact of the layoff ban from that of STW compensation scheme.



(a) Age groups (b) Gender (c) Region

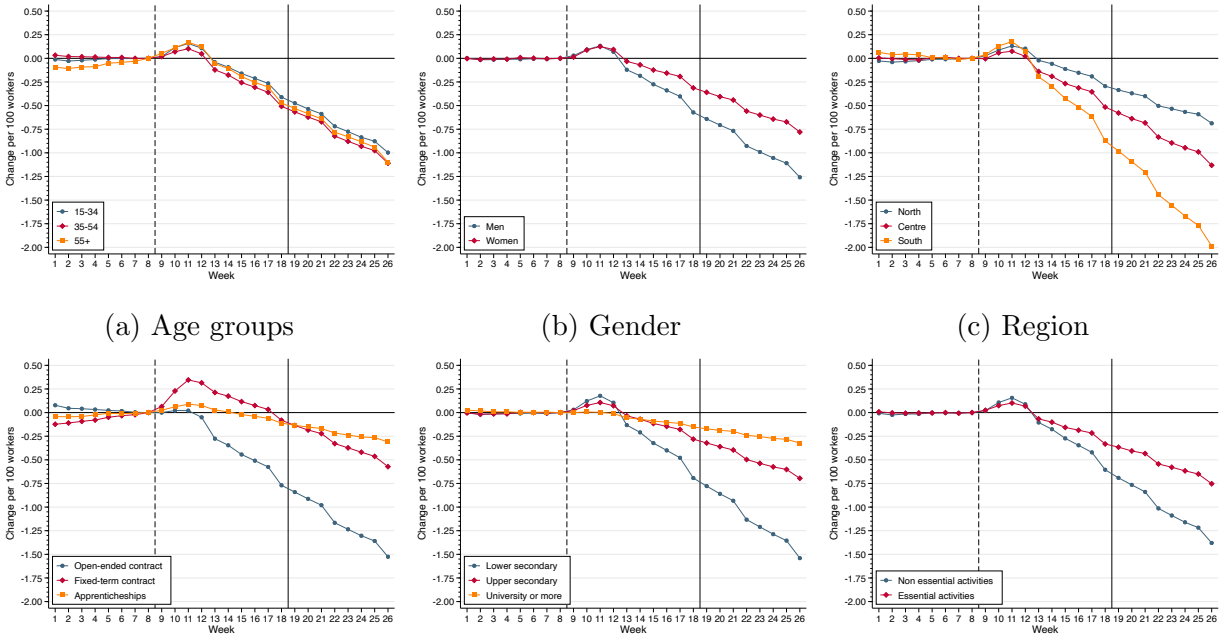
(d) Type of contract (e) Education level (f) Groups of activities

Figure 4: Cumulative change in hirings between 2020 and average 2017-2019

Notes. The figure shows the cumulative change in hirings up until each week in the first two quarters of 2020 with respect to the average of 2017-19 over the same period of the year and relative to the week before the pandemic (week 8). Values are expressed for 100 workers in the same subgroup. The dashed vertical line indicates the onset of the pandemic. The solid vertical line indicates the end of the lockdown.

Which categories benefited the most from the ban? Panel (a) suggests that, if anything, younger workers experience a slight lower reduction in layoffs with respect to middle-age and old workers, but differences are small. Panel (b) displays differences by gender. The rise in layoffs hit both genders equally, but at the end of the observation period the cumulative decline in layoffs is higher for men (-1.3, as opposed to -0.8 women). Geographic differences are more evident (panel c), with workers in the South benefiting from the increased employment protection legislation: 2 workers less are being laid off with respect to the past, as compared to -1.1 in the Centre and -0.7 in the North. We also observe a different cumulative change for workers with open-ended contracts (-1.5) relative to fixed-term contracts (-0.6) and apprenticeships (-0.3) in panel (d). A more pronounced decline is also observed for low-educated workers and workers employed in non-essential activities, indicating that the policies aimed at preserving employment relationship partially helped more vulnerable categories and more exposed sectors in coping with the consequences of the recession.

Endings of fixed-term contracts Figure 6 reports the evolution of endings of fixed-term contracts. For all subgroups, we observe similar patterns: the trend in the cumulative



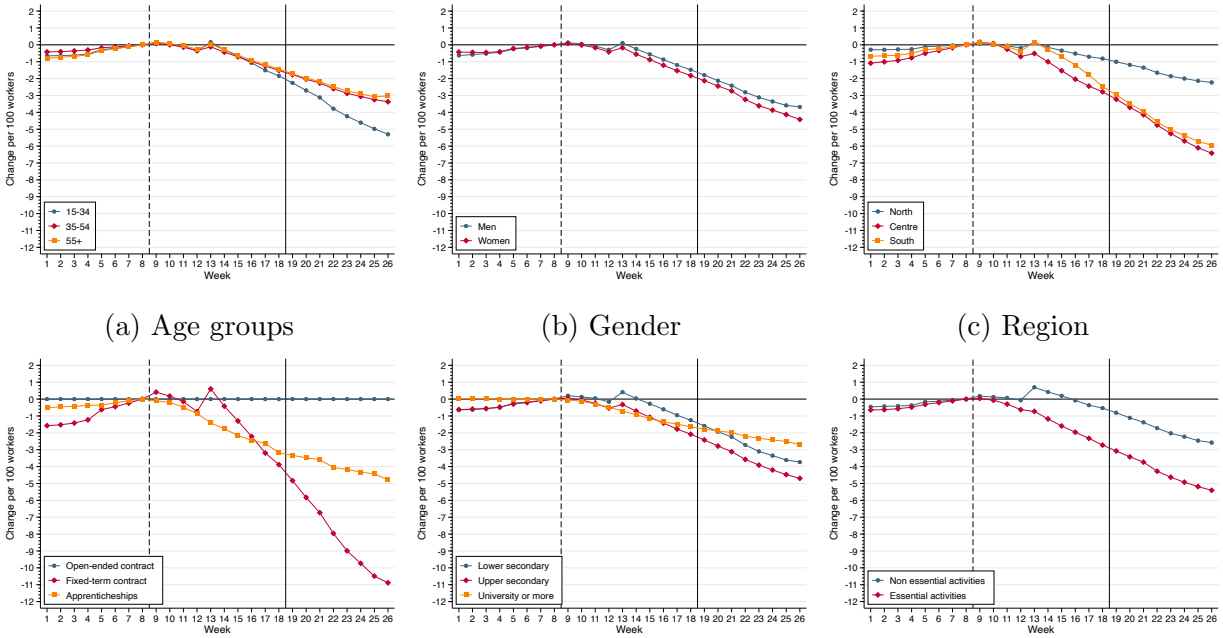
(a) Age groups (b) Gender (c) Region

(d) Type of contract (e) Education level (f) Groups of activities

Figure 5: Cumulative change in layoffs between 2020 and average 2017-2019

Notes. The figure shows the cumulative change in layoffs up until each week in the first two quarters of 2020 with respect to the average of 2017-19 over the same period of the year and relative to the week before the pandemic (week 8). Values are expressed for 100 workers in the same subgroup. The dashed vertical line indicates the onset of the pandemic. The solid vertical line indicates the end of the lockdown.

change in endings is similar in the first 8 weeks of the year to that observed right before the pandemic, but for few exceptions. After the start of the pandemic there is a decline in the number of endings with respect to the past three years, except for a spike in week 13, which corresponds to the last week of March. This spike is probably due to employers choosing not to renew temporary contracts, which were expiring in that week: the end of quarters is a frequent date for the ending of fixed-term contracts and, in fact, if we plot the weekly instead of the cumulative change in endings of fixed-term contracts, we would observe similar spikes at the end of each month, but less pronounced than the one at the end of the first quarter. The general decline observed at the end of the observation window is very likely to reflect the general decline in economic activities: the drop in aggregate demand generates a decrease in the demand for labor, and therefore in the activation of new fixed-terms contracts (as highlighted in both Figure 3 and 4), which then calls for a lower number of expirations. Overall, at the end of the second quarter of 2020, endings of fixed-term contracts are lower relative to the past in particular for young workers (panel a), women (panel b), workers in the Centre and South of the country (panel c), low educated workers (panel e) and workers in essential activities (panel f).



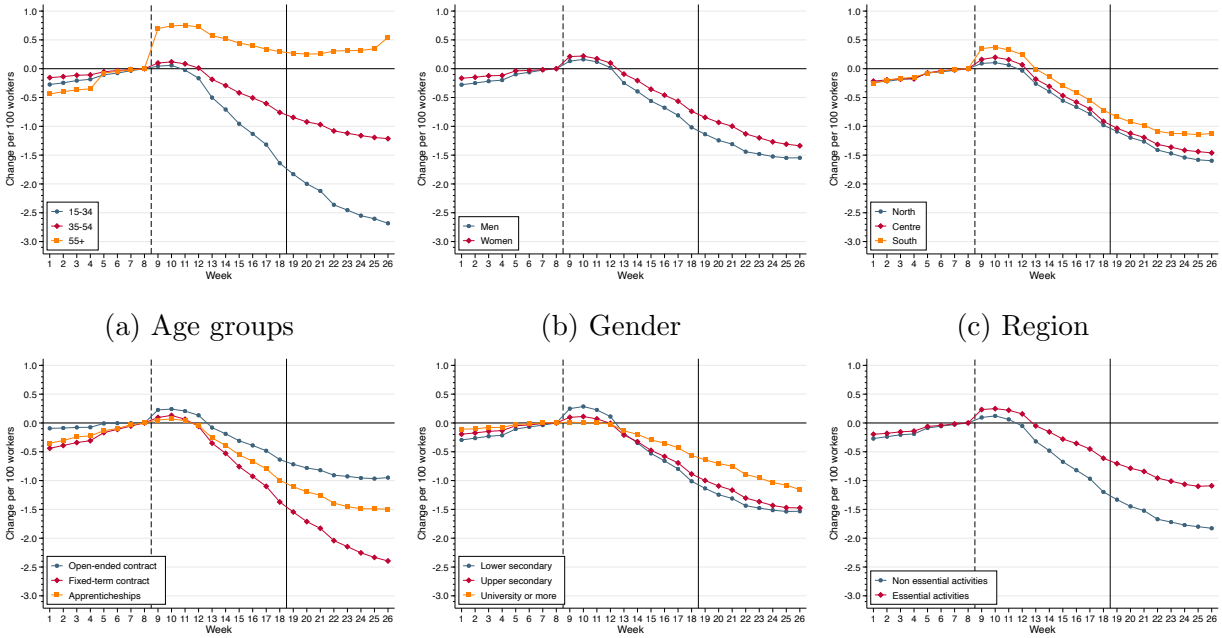
(a) Age groups (b) Gender (c) Region

(d) Type of contract (e) Education level (f) Groups of activities

Figure 6: Cumulative change in endings of fixed-term contracts between 2020 and average 2017-2019

Notes. The figure shows the cumulative change in endings of fixed-term contracts up until each week in the first two quarters of 2020 with respect to the average of 2017-19 over the same period of the year and relative to the week before the pandemic (week 8). Values are expressed for 100 workers in the same subgroup. The dashed vertical line indicates the onset of the pandemic. The solid vertical line indicates the end of the lockdown.

Quits Figure 7 reports the evolution of quits. Voluntary quits display an increasing trend between weeks 9 and 12, right after the pandemic started, similarly to layoffs. Panel (a) shows striking differences by age groups: for older workers the difference between quits in 2020 and in the past is positive, meaning that, by the end of second quarter of 2020, the quit rate of employees older than 55 increased. Overall, by the end of the observation window, we find that there have been 0.5 quits more per 100 workers older than 55. Older workers may have increased their quit rate as a consequence of school closures to help their families with child care activities or firms may have used quits as a way to anticipate retirement for some workers, in the absence of alternative ways to cut labor costs given the layoff ban. We do not observe higher quit rates for other age groups (although there is a slight increase in weeks 9-12 for workers aged 35-54, which can be again related to the impossibility of balancing work and family duties after school closures). Panel (b) shows that quits increased more for women right after the beginning of the pandemic and this translated into a less pronounced cumulative drop by the end of the second quarter. Quits were also higher in the South



(a) Age groups (b) Gender (c) Region

(d) Type of contract (e) Education level (f) Groups of activities

Figure 7: Cumulative change in quits between 2020 and average 2017-2019

Notes. The figure shows the cumulative change in quits up until each week in the first two quarters of 2020 with respect to the average of 2017-19 over the same period of the year and relative to the week before the pandemic (week 8). Values are expressed for 100 workers in the same subgroup. The dashed vertical line indicates the onset of the pandemic. The solid vertical line indicates the end of the lockdown.

in weeks 9-12 (panel c) and by the end of the second quarter. Panel (d) shows that the decline in quits is less pronounced for open-ended contracts and apprenticeships compared to temporary contracts: this comes as no surprise as most open-ended contracts are held by workers older than 35. The decline in quits is similar for workers with lower secondary or upper secondary education, but higher in magnitude than that of university graduates (panel e): it is likely that university graduates are employed in jobs that are more easily done from home, easing the work-life balance after the lockdown. Moreover, in weeks 9-12, low educated workers significantly increased their quitting rate. Finally, panel (f) shows that the increase in quits right after the pandemic was higher in essential activities than in non-essential ones. Since business was continuing in essential activities, some workers may have been forced to quit their jobs because of school closures or firms may have used quits as an alternative to layoffs, either by bargaining with the worker in order to reduce labor costs or by forcing workers to blank resignations.[8]

[8]The latter possibility is however much more difficult to materialize, as the Jobs Act (Legislative Decree 151/2015) changed the procedure to communicate quits – which have to be done online through specific online forms provided by the Ministry of Labor – and explicitly forbid employers to make any changes to those forms.

5 Changes in Hiring and Separation Probabilities

5.1 Empirical Strategy

We focus on the hiring and separation probabilities, by jointly analyzing what categories of workers are more likely to get or separate from a job during the recession. To this end, exploiting the start and end date of each contract, we convert our cross-sectional data at the contract (or spell) level into a panel at the monthly level, using the worker as unit of observation. We keep workers between January and June 2019 and January and June 2020 and, separately for each month m, we estimate the following linear probability model:

$$y_{it}^m = \alpha^m + \beta^m X_{it}^m + \gamma^m Post_t + \delta^m X_{it}^m \cdot Post_t + \psi_{s(i)}^m + \phi_{o(i)}^m + \epsilon_{it}^m, \tag{2}$$

where y_{it}^m is a dummy equal to one if worker i is hired or separates from her job (depending on whether we focus on the hiring or separation probability) in month m, with $m = \{\text{January, February, March, April, May, June}\}$, and year t, with $t = \{2019,2020\}$. α^m is a constant. X_{it}^m is a vector of observables that includes a dummy for female workers, a dummy for the type of contract (fixed-term or apprentices, open-ended excluded), the geographical area of work (Centre or South, North excluded), the level of education (lower or upper secondary, university excluded) and age groups (15-34 or 35-54, 55+ excluded). $Post_t$ is a dummy equal to 1 for 2020. Finally, $\psi_{s(i)}^m$ and $\phi_{o(i)}^m$ are sector and occupation fixed effects (both at a 3-digit level).[9] We are interested in the vector of coefficients δ^m, which measures the correlation between the covariates X_{it}^m and the change in the hiring or separation probability between 2019 and 2020 in each month, relative to the excluded category (for example, we can interpret the coefficient for workers on fixed-term contracts as the change in the hiring/separation probability between 2020 and 2019 with respect to workers on open-ended contracts, keeping fixed the other covariates included in the regression). We estimate this regression separately for each month between January and June, and plot the related coefficients for each variable in X_{it}^m.

5.2 Change in Hiring Probability

Figure 8 reports the results of the estimation of equation (2), where the dependent variable is a dummy equal to 1 if the worker is hired in that month[10] (Table A.1 in the Appendix

[9] Although we have more granular information on both occupations and sectors (respectively, at 4- and 6-digit level), we include fixed effects at 3-digit level in order not to have clusters with too few observations (which, in the extreme case of singletons, would be dropped from the sample).

[10] The dummy equals one in the month of the start date of the contract held by the worker.

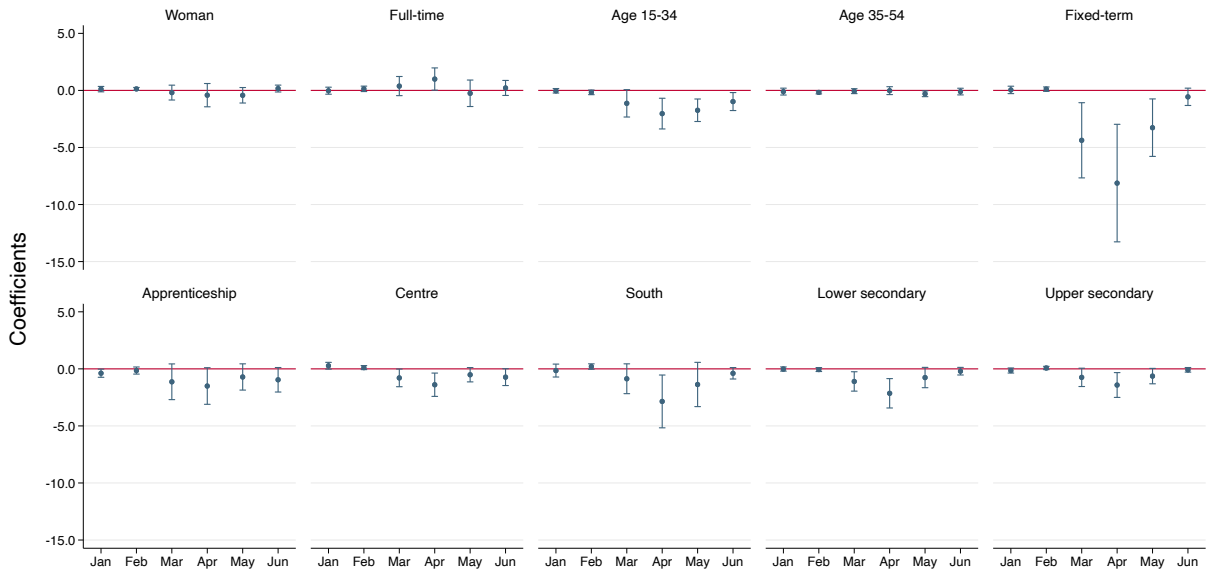


Figure 8: Change in hiring probability

Notes. The figure reports the vector of coefficients δ^m, estimated from equation (2) where the dependent variable is the hiring probability. Each panel reports the estimates for each coefficient in each month from January to June, where the estimates for each month come from separate regressions. Each regression includes occupation and sector fixed effects (both at 3-digit level). The figure also reports 95 percent confidence intervals, from cluster-robust standard errors at the sector-occupation level.

shows the coefficients behind the figure). Between January and February we observe small differences in the change of the hiring probability by subgroups between 2020 and 2019. After the pandemic started and the country went into lockdown, we find that being on a temporary contract is associated with a lower hiring probability of 4.4 p.p. in March, 8.1 p.p. in April and 3.3 p.p. in May. We also find that there is a significant penalty for younger workers from March to June (between 1 and 2 p.p.), for apprentices in April and June (-1.5 and -1 p.p.), for workers in the Centre and in the South (between -0.7 and -2.9 p.p.) and for workers with lower secondary and upper secondary education (between -0.6 and -2.1 p.p.). Therefore, we confirm that, even after controlling for all personal characteristics of workers (including detailed sector and occupation fixed effects) being on a temporary contract is associated with a remarkable penalty in terms of hiring probability, especially in April, when the country was in full lockdown. Moreover, even controlling for the contract type, young and low educated workers, in the Centre and South of the country, are those bearing the burden of the lower rate of job creation.

We also investigate heterogeneous effects between essential and non-essential activities, estimating model (2) separately for workers employed in sectors belonging to the two groups of activities. Figure 9 shows the results (Table A.2 reports the point estimates and standard

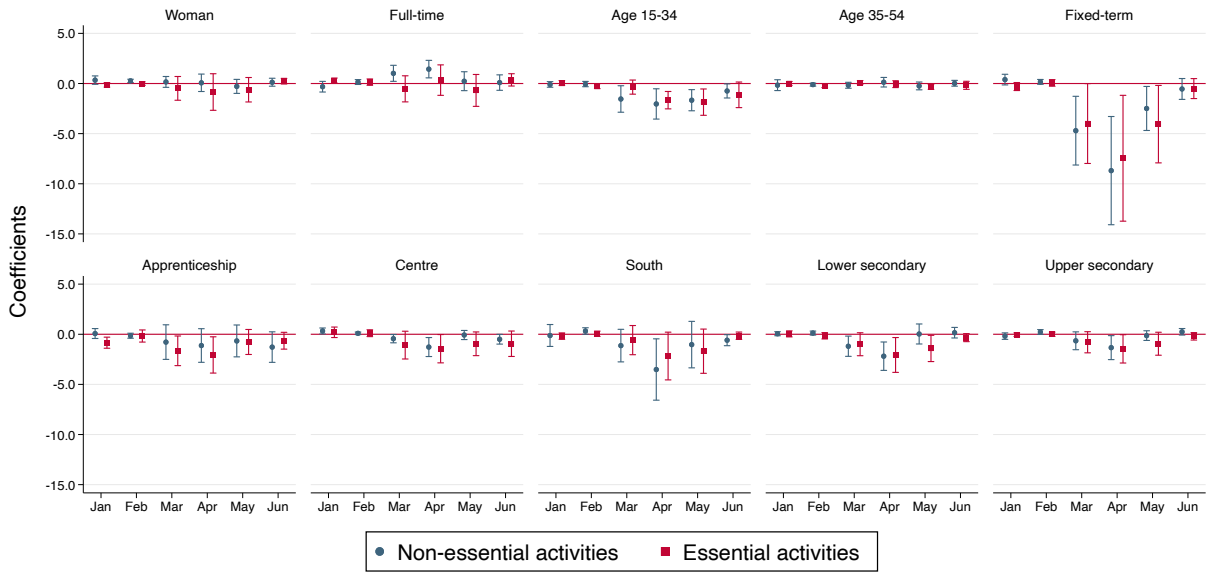


Figure 9: Change in hiring probability in essential and non-essential activities

Notes. The figure reports the vector of coefficients δ^m, estimated from equation (2) where the dependent variable is the hiring probability, separately for workers employed in essential and non-essential activities. Each panel reports the estimates for each coefficient in each month from January to June, where the estimates for each month come from separate regressions. Each regression includes occupation and sector fixed effects (both at 3-digit level). The figure also reports 95 percent confidence intervals, from cluster-robust standard errors at the sector-occupation level.

errors behind the figure). As highlighted already, we observe little differences in the hiring probability with respect to the past and across activities in January and February. In March we observe that the coefficient for young workers is significantly different from zero and negative in non-essential sectors only. Besides, in March and April we observe lower point estimates for workers in non-essential activities on fixed-term contracts and workers in the South, but the differences between sectors are not statistically significant. Hence, once controlling for all covariates at the same time, there is no evidence of a different evolution of the hiring probability for subgroups of workers in essential and non-essential activities, indicating that job creation came to a halt in the entire labor market.

5.3 Change in Separation Probability

Figure 10 reports the estimates of δ^m from equation (2), where the dependent variable is the separation probability. In January and February, before the onset of the pandemic, we see little differences between 2020 and 2019 in the propensity of different subgroups of workers to separate from their jobs. In March we observe a marginally significant increase in the separation probability for young (0.4 p.p.) and middle-aged (0.2 p.p.) workers relative to

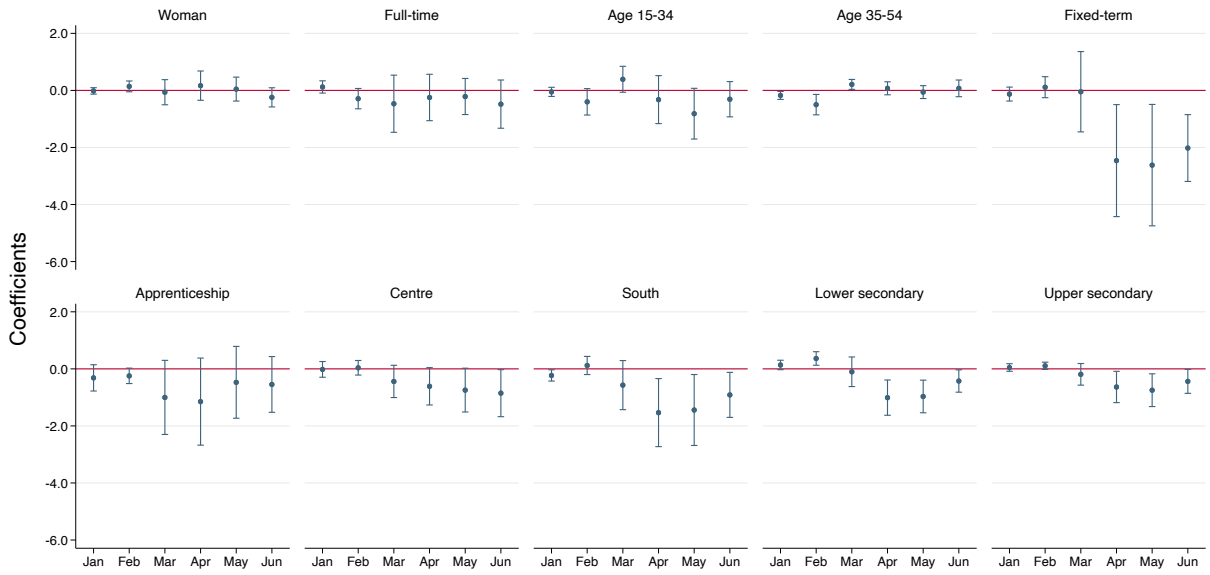


Figure 10: Change in separation probability

Notes. The figure reports the vector of coefficients δ^m, estimated from equation (2) where the dependent variable is the separation probability. Each panel reports the estimates for each coefficient in each month from January to June, where the estimates for each month come from separate regressions. Each regression includes occupation and sector fixed effects (both at 3-digit level). The figure also reports 95 percent confidence intervals, from cluster-robust standard errors at the sector-occupation level.

old workers: considering that the layoff ban and the COVID-related STW were introduced in the second half of the month, this increase signals that – absent the policies – the increase would have likely been larger. From April on, we observe significant and negative coefficients for workers on temporary contracts (between -2 and -2.5 p.p.), workers in the Centre and South (between -0.6 and -1.5) and those with lower or upper secondary education (between -0.4 and -1 p.p.). This result indicates, again, that policies were effective in limiting the number of separations with respect to the past, especially for more vulnerable categories of workers. Clearly, the decline in separations is also due to lower job turnover, which deflates both the creation and ending of fixed-term contracts in particular, as highlighted in section 4.

We explore differences in separation probability by essential and non-essential activities in Figure 11. This heterogeneity analysis reveals that gender is a significant predictor of a higher separation probability in February in essential activities (by 0.3 p.p.). In March, April and May we observe positive point estimates for women employed in non-essential activities, instead. Although the overlap between confidence intervals is often wide, we can take this as evidence of the difficulty of balancing work and life for women at the onset of the pandemic recession. At the same time, we estimate a significant and positive change in

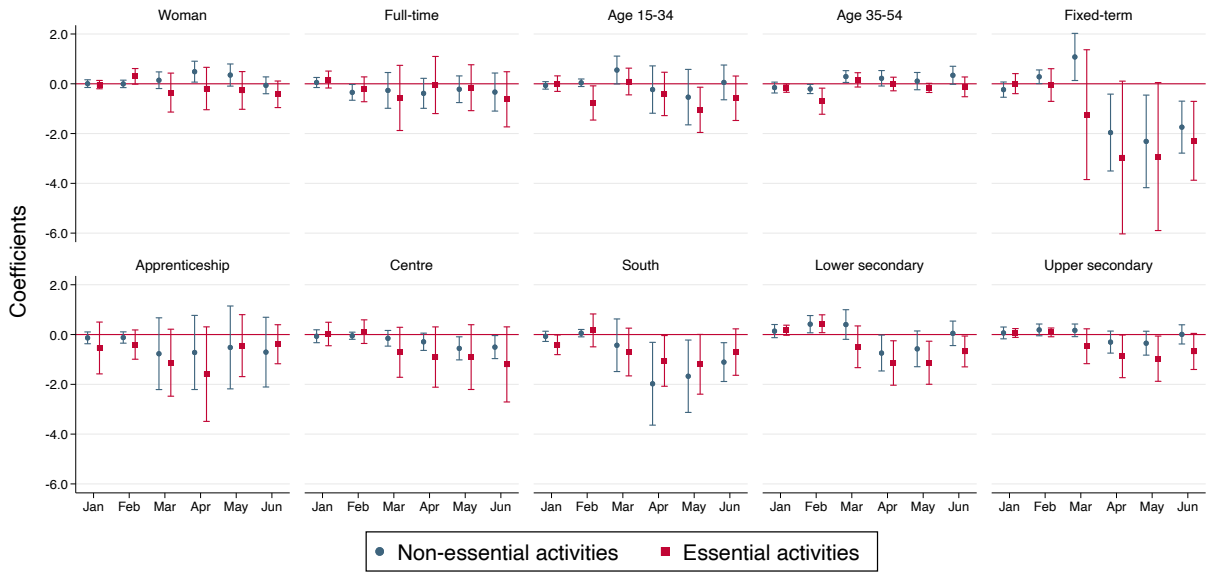


Figure 11: Change in separation probability in essential and non-essential activities

Notes. The figure reports the vector of coefficients δ^m, estimated from equation (2) where the dependent variable is the separation probability, separately for workers employed in essential and non-essential activities. Each panel reports the estimates for each coefficient in each month from January to June, where the estimates for each month come from separate regressions. Each regression includes occupation and sector fixed effects (both at 3-digit level). The figure also reports 95 percent confidence intervals, from cluster-robust standard errors at the sector-occupation level.

the separation probability for workers aged 15-34 and for workers with fixed-term contracts in March in non-essential activities only (although the precision of the estimate for essential activities is lower). From April onwards, we observe a similar decline in separations between the two groups of activities.

6 Conclusion

This paper explores the short-run heterogeneous effects of COVID-19 on labor market flows in Italy and how policy enacted to reduce the spread of the virus and the disruption of economic activity mediated them.

We show that, before the pandemic, workers employed in non-essential activities shut-down by the government were in majority men, younger than 35 years old, located in the North and with lower levels of education. When looking at the change in hirings and separations and decomposing it by age, gender, region, type of contract (open-ended or fixed-term), education level, and sector (essential vs non-essential activities), we find that from the 9th week of the year – when the virus started to spread exponentially across the country –, there

was a pronounced drop in hirings and endings of fixed-term contracts. On the contrary, layoffs and quits spiked right after the 9th week, and then dropped significantly, reflecting the effects of the ban on layoffs and the easing of access to STW compensation schemes. The ban on layoffs may also have contributed to the decreasing dynamics of hirings, as the higher employment protection for workers may have decreased turnover, but the fact that the drop in hirings halted by the end of second quarter of 2020 points to the dominant role of the lockdown in determining the decrease in the hiring margin observed during the pandemic. We further explore hirings and separations by examining which factors predict the hiring and separation probability. We find that workers already hit by the previous recession (young, temporary, low-educated workers) suffer from lower job creation and are at higher risk of losing their job because of COVID-19. Women have a higher separation probability, especially right after the pandemic kicks in. While we focus on short-term outcomes and cannot account for changes in hours worked, our evidence contributes to the understanding of labor market and policy responses in the wake of the pandemic. The use of detailed administrative data allows us to separately analyze how hirings and separations – distinguishing between layoffs, endings of fixed-terms contracts and quits – have evolved relative to normal times and how different categories of workers have been affected. Given the critical importance of the ban on layoffs and the special STW compensation scheme in affecting labor market flows, it is important to monitor the labor market transitions if these policies will be lifted, since they have protected vulnerable workers the most.

References

Adamopoulou, E., De Philippis, M., Sette, E., and Viviano, E. (2020). The Long Run Earnings Effects of a Credit Market Disruption. IZA Discussion Papers 13185, Institute of Labor Economics (IZA).

Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, 189:104245.

Alon, T., Doepke, M., Olmstead-Rumsey, J., and Tertilt, M. (2020). The Impact of COVID-19 on Gender Equality. *Covid Economics: Vetted and Real-Time Papers*, 4:62–85.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *Covid Economics: Vetted and Real-Time Papers*, 18:73–108.

Belot, M., Choi, S., Jamison, J. C., Papageorge, N. W., Tripodi, E., and Van den Broek-Altenburg, E. (2020). Unequal Consequences of Covid-19 across Age and Income: Representative Evidence from Six Countrie. *Covid Economics: Vetted and Real-Time Papers*, 38:196–217.

Bick, A. and Blandin, A. (2020). Real time labor market estimates during the 2020 coronavirus outbreak. *Unpublished Manuscript, Arizona State University.*

Blundell, R., Costa Dias, M., Joyce, R., and Xu, X. (2020). COVID-19 and Inequalities. *Fiscal Studies*, 41(2):291–319.

Boeri, T., Ichino, A., Moretti, E., and Posch, J. (2019). Wage Equalization and Regional Misallocation: Evidence from Italian and German Provinces. NBER Working Papers 25612, National Bureau of Economic Research, Inc.

Bonacini, L., Gallo, G., and Scicchitano, S. (2021). Working from home and income inequality: risks of a 'new normal' with COVID-19. *Journal of Population Economics*, 34(1):303–360.

Cajner, T., Crane, L. D., Decker, R. A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., and Yildirmaz, A. (2020). The US labor market during the beginning of the pandemic recession. Technical report, National Bureau of Economic Research.

Carvalho, V. M., Hansen, S., Ortiz, A., Ramón García, J., Rodrigo, T., Rodriguez Mora, S., and Ruiz, J. (2020). Tracking the COVID-19 Crisis with High-Resolution Transaction Data. CEPR Discussion Papers 14642, C.E.P.R. Discussion Papers.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., et al. (2020). How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data. Technical report, National Bureau of Economic Research.

Crossley, T. F., Fisher, P., and Low, H. (2021). The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data. *Journal of Public Economics*, 193:104334.

Farré, L., Fawaz, Y., Gonzalez, L., and Graves, J. (2020). How the COVID-19 Lockdown Affected Gender Inequality in Paid and Unpaid Work in Spain. IZA Discussion Papers 13434, Institute of Labor Economics (IZA).

Forsythe, E., Kahn, L. B., Lange, F., and Wiczer, D. (2020). Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims. *Journal of Public Economics*, 189:104238.

Garin, A. and Silvério, F. (2019). How Responsive are Wages to Demand within the Firm? Evidence from Idiosyncratic Export Demand Shocks. Technical report.

Hupkau, C. and Petrongolo, B. (2020). Work, care and gender during the Covid-19 crisis. CEP Covid-19 Briefings cepcovid-19-002, Centre for Economic Performance, LSE.

IMF (2020). World Economic Outlook, October 2020: A Long and Difficult Ascent. Report, Internation Monetary Fund.

Izquierdo, M., Jimeno, J. F., Kosma, T., Lamo, A., Millard, S., Rõõm, T., and Viviano, E. (2017). Labour market adjustment in Europe during the crisis: microeconomic evidence from the Wage Dynamics Network survey. *Banco de Espana Occasional Paper*, (1704).

Kugler, A. and Pica, G. (2008). Effects of employment protection on worker and job flows: Evidence from the 1990 Italian reform. *Labour Economics*, 15(1):78 – 95.

OECD (2020). *OECD Employment Outlook 2020*.

von Gaudecker, H.-M., Holler, R., Janys, L., Siflinger, B., and Zimpelmann, C. (2020). Labour Supply in the Early Stages of the Covid-19 Pandemic: Empirical Evidence on Hours, Home Office, and Expectations.

A Additional Tables

Table A.1: Determinants of hiring probability, change relative to 2019

	(1) Jan	(2) Feb	(3) Mar	(4) Apr	(5) May	(6) Jun
Woman	0.11	0.13**	-0.19	-0.41	-0.43	0.16
	(0.12)	(0.06)	(0.33)	(0.52)	(0.34)	(0.15)
Full-time	-0.02	0.14	0.38	1.00**	-0.25	0.22
	(0.16)	(0.12)	(0.42)	(0.49)	(0.59)	(0.33)
Age 15-34	-0.03	-0.17	-1.13*	-2.03***	-1.74***	-0.98**
	(0.10)	(0.10)	(0.61)	(0.68)	(0.50)	(0.40)
Age 35-54	-0.10	-0.17**	-0.07	-0.02	-0.29**	-0.10
	(0.15)	(0.07)	(0.11)	(0.17)	(0.13)	(0.15)
Fixed-term	0.04	0.11	-4.37***	-8.12***	-3.26**	-0.56
	(0.16)	(0.10)	(1.67)	(2.61)	(1.27)	(0.38)
Apprenticeship	-0.38**	-0.15	-1.13	-1.50*	-0.71	-0.96*
	(0.18)	(0.16)	(0.79)	(0.81)	(0.58)	(0.54)
Centre	0.27*	0.11	-0.79**	-1.39***	-0.51	-0.72*
	(0.15)	(0.09)	(0.39)	(0.52)	(0.32)	(0.37)
South	-0.15	0.20*	-0.87	-2.85**	-1.37	-0.39
	(0.29)	(0.12)	(0.66)	(1.17)	(0.98)	(0.25)
Lower secondary	-0.01	-0.06	-1.10**	-2.14***	-0.76*	-0.20
	(0.09)	(0.09)	(0.43)	(0.65)	(0.45)	(0.17)
Upper secondary	-0.14	0.08	-0.74*	-1.42**	-0.63*	-0.08
	(0.11)	(0.07)	(0.41)	(0.55)	(0.34)	(0.10)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.109	0.102	0.090	0.122	0.110	0.146
Observations	3,366,406	3,375,677	3,387,039	3,368,464	3,416,503	3,508,344

Notes. The table reports the estimates of δ^m from equation (2) where the dependent variable is the hiring probability. Standard errors, robust to clustering within 3-digit sectors and occupations, are reported in parentheses. Significance levels: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Determinants of hiring probability, change relative to 2019, by sector

	Jan		Feb		Mar		Apr		May		Jun	
	(1) NE	(2) E	(3) NE	(4) E	(5) NE	(6) E	(7) NE	(8) E	(9) NE	(10) E	(11) NE	(12) E
Woman	0.34	-0.14	0.26***	-0.01	0.16	-0.49	0.07	-0.85	-0.29	-0.62	0.13	0.23
	(0.21)	(0.11)	(0.08)	(0.09)	(0.27)	(0.60)	(0.44)	(0.92)	(0.35)	(0.62)	(0.20)	(0.14)
Full-time	-0.32	0.29**	0.15	0.14	1.01**	-0.53	1.44***	0.34	0.23	-0.69	0.09	0.36
	(0.27)	(0.13)	(0.12)	(0.16)	(0.40)	(0.66)	(0.44)	(0.77)	(0.48)	(0.81)	(0.39)	(0.31)
Age 15-34	-0.09	0.04	-0.06	-0.26**	-1.54**	-0.36	-2.04***	-1.66***	-1.67***	-1.86***	-0.74**	-1.13*
	(0.14)	(0.12)	(0.13)	(0.13)	(0.67)	(0.36)	(0.76)	(0.44)	(0.53)	(0.66)	(0.36)	(0.65)
Age 35-54	-0.16	-0.00	-0.11	-0.21**	-0.18	0.09	0.13	-0.07	-0.24	-0.35***	0.02	-0.18
	(0.27)	(0.10)	(0.08)	(0.10)	(0.15)	(0.10)	(0.24)	(0.17)	(0.20)	(0.12)	(0.15)	(0.20)
Fixed-term	0.39	-0.30	0.16	0.06	-4.70***	-3.99**	-8.69***	-7.46**	-2.49**	-4.05**	-0.54	-0.51
	(0.27)	(0.20)	(0.12)	(0.17)	(1.73)	(2.02)	(2.73)	(3.18)	(1.11)	(1.95)	(0.53)	(0.50)
Apprenticeship	0.07	-0.84***	-0.15	-0.17	-0.78	-1.65**	-1.12	-2.06**	-0.67	-0.77	-1.28*	-0.64
	(0.25)	(0.28)	(0.13)	(0.31)	(0.87)	(0.75)	(0.85)	(0.91)	(0.80)	(0.63)	(0.77)	(0.42)
Centre	0.33**	0.20	0.09	0.11	-0.44**	-1.08	-1.27***	-1.44**	-0.07	-0.95	-0.50**	-0.95
	(0.15)	(0.26)	(0.07)	(0.17)	(0.21)	(0.70)	(0.48)	(0.71)	(0.23)	(0.60)	(0.25)	(0.64)
South	-0.12	-0.19	0.32*	0.05	-1.13	-0.58	-3.51**	-2.17*	-1.03	-1.69	-0.59**	-0.15
	(0.55)	(0.16)	(0.16)	(0.13)	(0.82)	(0.74)	(1.55)	(1.20)	(1.17)	(1.12)	(0.28)	(0.19)
Lower secondary	0.05	0.04	0.12	-0.15	-1.19**	-0.99*	-2.19***	-2.06**	0.03	-1.42**	0.16	-0.34
	(0.10)	(0.15)	(0.10)	(0.16)	(0.51)	(0.58)	(0.72)	(0.88)	(0.50)	(0.66)	(0.27)	(0.20)
Upper secondary	-0.18	-0.04	0.23*	0.01	-0.65	-0.80	-1.33**	-1.46**	-0.13	-0.94	0.25	-0.20
	(0.16)	(0.09)	(0.12)	(0.11)	(0.45)	(0.53)	(0.61)	(0.71)	(0.24)	(0.58)	(0.16)	(0.19)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.070	0.151	0.056	0.157	0.054	0.132	0.089	0.162	0.071	0.164	0.115	0.193
Observations	1,718,728	1,647,678	1,723,291	1,652,385	1,731,298	1,655,740	1,719,693	1,648,771	1,749,294	1,667,209	1,806,256	1,702,088

Notes. The table reports the estimates of δ^m from equation (2) where the dependent variable is the hiring probability, separately for workers employed in essential and non-essential activities. Standard errors, robust to clustering within 3-digit sectors and occupations, are reported in parentheses. Significance levels: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Determinants of separation probability, change relative to 2019

	(1) Jan	(2) Feb	(3) Mar	(4) Apr	(5) May	(6) Jun
Woman	-0.02	0.14	-0.06	0.17	0.05	-0.24
	(0.06)	(0.10)	(0.22)	(0.26)	(0.21)	(0.17)
Full-time	0.12	-0.29	-0.47	-0.25	-0.21	-0.48
	(0.11)	(0.18)	(0.51)	(0.41)	(0.32)	(0.43)
Age 15-34	-0.05	-0.40*	0.39*	-0.32	-0.82*	-0.31
	(0.08)	(0.23)	(0.23)	(0.43)	(0.45)	(0.31)
Age 35-54	-0.17**	-0.50***	0.21**	0.07	-0.06	0.07
	(0.07)	(0.18)	(0.09)	(0.12)	(0.11)	(0.15)
Fixed-term	-0.13	0.11	-0.05	-2.46**	-2.62**	-2.02***
	(0.12)	(0.19)	(0.71)	(0.99)	(1.08)	(0.59)
Apprenticeship	-0.32	-0.25*	-1.00	-1.15	-0.47	-0.55
	(0.23)	(0.14)	(0.66)	(0.77)	(0.64)	(0.49)
Centre	-0.02	0.04	-0.44	-0.61*	-0.74*	-0.85**
	(0.14)	(0.13)	(0.29)	(0.33)	(0.39)	(0.42)
South	-0.23**	0.12	-0.57	-1.53**	-1.44**	-0.91**
	(0.10)	(0.16)	(0.44)	(0.60)	(0.63)	(0.40)
Lower secondary	0.14	0.36***	-0.10	-1.01***	-0.97***	-0.43**
	(0.08)	(0.12)	(0.26)	(0.31)	(0.29)	(0.20)
Upper secondary	0.05	0.11	-0.19	-0.64**	-0.75**	-0.44**
	(0.07)	(0.06)	(0.19)	(0.28)	(0.29)	(0.21)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.105	0.108	0.094	0.089	0.102	0.107
Observations	3,366,406	3,375,677	3,387,039	3,368,464	3,416,503	3,508,344

Notes. The table reports the estimates of δ^m from equation (2) where the dependent variable is the separation probability. Standard errors, robust to clustering within 3-digit sectors and occupations, are reported in parentheses. Significance levels: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Determinants of separation probability, change relative to 2019, by sector

	Jan		Feb		Mar		Apr		May		Jun	
	(1) NE	(2) E	(3) NE	(4) E	(5) NE	(6) E	(7) NE	(8) E	(9) NE	(10) E	(11) NE	(12) E
Woman	0.01	-0.03	-0.00	0.30*	0.14	-0.35	0.49**	-0.19	0.35	-0.27	-0.06	-0.42
	(0.08)	(0.08)	(0.08)	(0.16)	(0.17)	(0.40)	(0.21)	(0.43)	(0.23)	(0.38)	(0.17)	(0.27)
Full-time	0.05	0.17	-0.34**	-0.22	-0.27	-0.57	-0.38	-0.05	-0.22	-0.16	-0.33	-0.62
	(0.10)	(0.17)	(0.16)	(0.25)	(0.36)	(0.66)	(0.30)	(0.58)	(0.27)	(0.47)	(0.39)	(0.56)
Age 15-34	-0.06	0.01	0.04	-0.77**	0.55*	0.09	-0.23	-0.41	-0.54	-1.05**	0.05	-0.58
	(0.08)	(0.16)	(0.08)	(0.35)	(0.28)	(0.27)	(0.48)	(0.44)	(0.56)	(0.46)	(0.35)	(0.45)
Age 35-54	-0.15	-0.18**	-0.21**	-0.70***	0.29**	0.16	0.22	-0.01	0.11	-0.17*	0.34*	-0.12
	(0.11)	(0.08)	(0.09)	(0.27)	(0.12)	(0.15)	(0.16)	(0.14)	(0.18)	(0.09)	(0.18)	(0.20)
Fixed-term	-0.23	0.01	0.28**	-0.05	1.08**	-1.24	-1.96**	-2.96*	-2.31**	-2.92*	-1.74***	-2.29***
	(0.16)	(0.20)	(0.14)	(0.33)	(0.48)	(1.32)	(0.78)	(1.55)	(0.94)	(1.50)	(0.53)	(0.80)
Apprenticeship	-0.13	-0.54	-0.12	-0.40	-0.77	-1.13*	-0.72	-1.59*	-0.52	-0.45	-0.71	-0.39
	(0.12)	(0.53)	(0.11)	(0.30)	(0.73)	(0.68)	(0.75)	(0.96)	(0.84)	(0.63)	(0.71)	(0.40)
Centre	-0.07	0.02	-0.05	0.12	-0.15	-0.71	-0.29*	-0.90	-0.55**	-0.91	-0.50**	-1.20
	(0.13)	(0.24)	(0.07)	(0.24)	(0.16)	(0.51)	(0.18)	(0.61)	(0.23)	(0.66)	(0.23)	(0.76)
South	-0.07	-0.41**	0.06	0.17	-0.43	-0.70	-1.98**	-1.06**	-1.67**	-1.20*	-1.11***	-0.70
	(0.10)	(0.20)	(0.07)	(0.33)	(0.53)	(0.48)	(0.84)	(0.52)	(0.74)	(0.61)	(0.39)	(0.47)
Lower secondary	0.14	0.17*	0.42**	0.43**	0.40	-0.49	-0.74**	-1.14**	-0.57	-1.13**	0.05	-0.68**
	(0.13)	(0.10)	(0.18)	(0.18)	(0.30)	(0.42)	(0.36)	(0.45)	(0.36)	(0.44)	(0.25)	(0.31)
Upper secondary	0.06	0.06	0.19	0.09	0.17	-0.47	-0.30	-0.88**	-0.35	-0.97**	0.01	-0.68*
	(0.12)	(0.09)	(0.12)	(0.09)	(0.13)	(0.35)	(0.22)	(0.43)	(0.24)	(0.46)	(0.20)	(0.37)
Occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.058	0.162	0.048	0.173	0.054	0.143	0.051	0.135	0.050	0.164	0.061	0.162
Observations	1,718,728	1,647,678	1,723,291	1,652,385	1,731,298	1,655,740	1,719,693	1,648,771	1,749,294	1,667,209	1,806,256	1,702,088

Notes. The table reports the estimates of δ^m from equation (2) where the dependent variable is the separation probability, separately for workers employed in essential and non-essential activities. Standard errors, robust to clustering within 3-digit sectors and occupations, are reported in parentheses. Significance levels: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$.