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The Consequences of the COVID-19 Job Losses: Who Will Suffer Most and by How Much?

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The Consequences of the Covid-19 Job Losses: Who Will Suffer Most and by How Much?*

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Abstract

Using the universe of Austrian unemployment insurance records until May 2020, we document that the composition of UI claimants during the Covid-19 outbreak is substantially different compared to past times. Using a machine-learning algorithm from Gulyas and Pytka (2020), we identify individual earnings losses conditional on worker and job characteristics. Covid-19-related job terminations are associated with lower losses in earnings and wages compared to the Great Recession, but similar employment losses. We further derive an accurate but simple policy rule targeting individuals vulnerable to long-term wage losses.

Keywords: Covid-19 , Job displacement, Earnings losses, Causal machine learning

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I. Introduction

The Covid-19 epidemics have seen an unprecedented number of job losses around the world. A large economic literature documents that workers displaced during mass layoffs experience significant and long-lasting income losses, which are even larger during recessions.[1] The question naturally arises whether the millions of layoffs during the Covid-19 epidemics will have similar detrimental long-term consequences. Understanding this is not only important for predicting the shape of the recovery from the current downturn. Many policy interventions aimed at avoiding job losses such as firm bail-outs and short-time work subsidy schemes, or policies aimed at insuring workers through unemployment insurance extensions and top-ups should optimally depend on the severity of earnings losses. Therefore it is key to provide an accurate estimation of the long-term consequences of the job losses incurred during the Covid-19 outbreak.

In this paper, we comprehensively document which segments of the labor market were more affected by Covid-19 layoffs and we use a machine-learning approach to predict their long-term consequences. We draw upon the universe of all new UI claims up until May 31st 2020 and contrast the recent experience with the Great Recession of 2008/2009. The administrative nature of our data allows us to document the compositional pool without any measurement errors and small sample issues, and allows us to study worker and firm dimensions which cannot be measured in surveys, such as layoffs along the firm wage premium distribution. Similarly to other countries, Austria experienced an unprecedented scale of layoffs during the pandemic. New UI claims reached an all-time high in March 2020, more than three times the caseload during the peak of the financial crisis. The unemployment rate exceeded 12 percent in April 2020, the highest level recorded in the last 65 years.

We document that the current downturn in the labor market is not only unprecedented in its magnitude, but also unusual in terms of the segments of the labor market that are affected. Typically, during recessions the composition of UI claimants shifts towards worker and job characteristics that are associated with better labor market outcomes. During the Great Recession, UI claims increased more for well earning and male workers, and in larger, older and better-paying firms. The pattern of layoffs during Covid-19 is completely the opposite to the experience during the Great Recession. During the first three months of this downturn, UI claims increased more for workers earning below €25,000, for foreign citizens,

[1] Jacobson *et al.* (1993), Neal (1995), Couch and Placzek (2010), Davis and Von Wachter (2011), Farber (2011), Farber (2017), Davis and Von Wachter (2011), Schmieder *et al.* (2020), and Gulyas and Pytka (2020), among many others.

and for workers earning less than what would be expected according to their characteristics. In addition, UI claims are more concentrated among smaller, younger and lower-paying firms.

Given the worker and job characteristics of unemployment insurance (henceforth UI) claimants are so different during the COVID-19 epidemics, it is unclear whether the long-term consequences of an average job loser documented in the literature so far will be representative for the Pandemic Recession. To answer this question, we build on the machine-learning approach developed in Gulyas and Pytka (2020). This methodology allows us to estimate the long-term consequences of layoffs conditional on high dimensional worker and job characteristics. The machine-learning algorithm is trained on Austrian social security data from 1984 to 2019. This recession might be different in dimensions our machine learning algorithm does not capture. Nevertheless, we believe it is an important exercise since our approach enables us to explicitly take into account the different compositional pool of laid off workers during the COVID-19 epidemics.

Using the machine-learning algorithm we predict the long-term consequences of job losses for UI claimants from mass layoffs from March to May 2020 and compare these to the ones from the financial crises in 2009, as well as to the boom years just before these two recessions. While before the Pandemic Recession the average 11-year cumulative earnings losses of workers displaced in mass layoffs oscillated between 191-206% of their pre-displacement annual income, during the COVID-19 episode total losses are expected to be only 143%. This decrease is highly unusual because typically job terminations in downturns are associated with higher losses.[2] For our understanding of the labor-market recovery from the downturn, it is important to study whether those lower earnings losses stem from people finding jobs quicker or from lower long-term declines in wages. Although UI claimants exhibit very different characteristics, we predict employment losses to be as severe as during the financial crises. Over the next 11 years, we predict displaced workers to forgo 1.3 years of employment. Based on these findings, the danger of another jobless recovery looms.

The expected wage losses are of particular interest as they provide a forecast whether the wage growth will be as sluggish as after the financial crisis, which caused a lot of concerns among policy makers. In addition, wage losses provide the measure of human-capital destruction of job terminations. Here our findings provide a silver lining. The group of workers affected by the COVID-19 job losses is expected to have much lower wage losses upon re-employment compared to previous experiences. We show that this is due to the different composition of displaced workers during the Pandemic Recession. Almost all of the worker

[2]See e.g. Davis and Von Wachter (2011).

and job characteristics which are more heavily affected by job losses during the Covid-19 recessions are associated with lower wage declines. In particular, relying on our previous findings from (Gulyas and Pytka, 2020), the lower firm wage premia of displaced workers during the pandemic is able to explain the observed differences in estimated earnings losses. This observation is consistent with a simple job search model in the spirit of McCall (1970).[3]

Furthermore, we show that the low average wage losses of the Covid-19 job losses mask a lot of heterogeneity. While many individuals face significant long-lasting declines in income, 30% of individuals can expected wage gains after reemployment. Therefore, targeting policy interventions such as firm bail-outs, short-time work subsidy schemes, or UI extensions towards high-loss individuals would likely yield welfare gains. In order to guide policy makers, we use an algorithmic approach to derive a decision rule to identify individuals with positive wage losses. Despite its simplicity, the tree classifies 86.82% of individuals with positive wage losses correctly. Our policy recommendation suggests targeting (i) workers displaced from employers paying above the median and (ii) workers with a relatively long job tenure displaced from low paying firms in regions with fewer good jobs on the market.

Literature review. Our paper contributes to an emerging literature that documents that the Covid-19 downturn affected very different labor market segments compared to previous recessions (Dingel and Neiman, 2020; Mongey *et al.*, 2020; Alstadsæter *et al.*, 2020; Alon *et al.*, 2020; Adams-Prassl *et al.*, 2020; Cajner *et al.*, 2020; Kahn *et al.*, 2020; Coibion *et al.*, 2020). What distinguishes our study from the other papers is that we estimate the long-term consequences of the the Covid-19-related layoffs. To this end, we build on generalized random forests (Athey *et al.*, 2019) and undertake the systematic study of heterogeneity of earnings losses.

II. Layoffs during Covid-19

The Covid-19 crisis had similar devastating effects on the Austrian labor market as in other countries. The number of new monthly unemployment claims reached an unprecedented record high of 175,000 workers in April 2020, more than 3 times the peak during the Great Recession of 2009. The number of unemployed workers exceeded half a million for the first time since World War II, which implied an unprecedented unemployment rate of 12.7 percent in April 2020, nearly doubling compared to the previous year.[4] This increase in

[3] Workers employed at low paying firms expect higher wages in their new jobs whereas workers with in above average paying firms are much more likely to suffer more from a job displacement.

[4] Figure 5 in the Appendix plots the evolution of unemployment and UI claims over time.

unemployment occurred despite a generous short time work (STW) subsidy scheme, which covered at its peak almost a quarter of the Austrian workforce.

We start by documenting which segments of the labor market are comparably more affected during the Covid-19 epidemics and how the experience differs from the Great Recession. We use administrative employment and unemployment records from the social security administration in Austria until May 2020 for unemployment records and beginning of August 2020 for the employment records. This data comprises day-to-day information on all employment and unemployment spells covered by social security in Austria (Zweimüller *et al.*, 2009). It contains information on yearly earnings for each worker-establishment pair, in addition to basic socio-demographic information at the worker level such as age, gender, occupation, and citizenship.[5] Each establishment (we use firm and establishment exchangeably from here on) has a unique identifier, which allows us to study how unemployed workers differ in employer specific characteristics. At the establishment level we have data on the geographic location and a 4-digit industry classifier.

From the social security records we select all separations that are followed by a UI claim within 90 days. In order to focus on workers with some prior labor market attachment, we impose that workers need to have had positive earnings in the year prior to the UI claim and had at least 180 days of job tenure. We construct a number of variables in addition to the ones readily available in the social security dataset to provide a comprehensive picture of the worker and job characteristics of newly unemployed workers. These include job tenure, number of previous employers, firm size, regional and industry unemployment rates and the firm pay premium as job characteristics. The firm pay premium is computed using the seminal two-way fixed effect model of Abowd *et al.* (1999). We estimate:

$$\ln(w_{it}) = \psi_{J(i,t)} + \alpha_i + \theta_t + x_{it}\beta + \epsilon_{it}, \tag{1}$$

where $\ln(w_{it})$ is the log daily wage of the dominant employer in period t[6], α_i the worker fixed effect, θ_t the year fixed effect, x_{it} are time varying observables, comprising of a cubic polynomial of age, and $\psi_{J(i,t)}$ represents the establishment fixed effect of the employer of worker i at period t, which measure the pay premium relative to a baseline firm.[7] Using these firm wage premium estimates, we in addition compute the average firm wage premium in the region.[8]

[5]We deflate all earnings to 2017 level using the CPI index provided by the Austrian Statistical Agency.
[6]The dominant employer is selected based on the total earnings in calendar year t.
[7]We use data from 1984-2019 to estimate the firm pay premia.
[8]We compute the average firm wage premia of all jobs in a given region leaving out all jobs of

We are also interested how workers with different match qualities are affected during recessions. We estimate the match effect of worker i employed at firm $J(i,t)$ as the residual term ϵ_{it} from the following regression:

$$\ln(w_{it}) = \alpha_i + \hat{\psi}_{J(i,t)} + \theta_t + f(age_{it}) + f(tenure_{it}) + \epsilon_{it}, \tag{2}$$

where $f(age_{it})$ and $f(tenure_{it})$ are cubic polynomials and $\hat{\psi}_{J(i,t)}$ is the estimated firm fixed effect from regression (1).

With all the worker and job characteristics defined, we now turn to the analysis of which parts of the labor market were more affected by the Covid-19 recession, and how the recent experience differs from the Great Recession. Figure 1 displays the change in the number of UI take-ups during the last two recessions compared to pre-recession periods by different worker and job characteristics, broken down by the type of layoff. We distinguish between temporary layoffs (bottom panels), which we define as a UI claimant who is recalled within two months to her previous employer, and permanent layoffs (top panels). The left panels plot the change in UI claimants from March to May 2020 compared to the average during same time period of 2018 and 2019. The right panels plot the change from the Great Recession (2009) compared to 2007.[9]

First of all, the plot highlights the unprecedented magnitude of the Covid-19 shock on the labor market. As shown by the grey dotted lines, the overall number of UI claimants with a permanent layoff increased by 124 percent during the Covid-19 epidemics compared to pre-recession levels and temporary layoffs increased by a staggering 600 percent, albeit from a very low base.[10] During the Great Recession, UI claims from permanent and temporary layoffs increased by 28 and 35 percent in comparison. Especially the stark increase in furloughs is noteworthy, because Austria had a generous STW subsidy scheme in place, which covered at its peak almost a quarter of all employed workers. During the Corona Pandemic, firms were allowed to cut back hours and thus the wage bill by up to 90 percent, with the government replacing 80-90 percent of the workers' forgone income. The significant spike in temporary layoffs points towards many firms shunning STW, perhaps because

the worker's current employer. Formally for every worker i employed at firm $J(i,t)$ we compute $\sum_{k \notin J(i,t) \wedge k \in r(i)} \hat{\psi}_{J(k,t)} / \#(k \notin J(i,t) \wedge k \in r(i))$, where $r(i)$ is the region of the worker i.

[9] For the Great Recession, it is harder to pin down the exact starting and end point of the recession. In Austria, UI take-ups peaked in 2009, therefore we choose 2009 as the recession year. Throughout 2007, the number of unemployed was still falling and thus we choose it as the pre-recession comparison. See Figure 5 in the Appendix for the evolution of the number of unemployed and UI-take ups.

[10] In March-May 2018 and 2019, only 8 percent of UI claimants were temporarily laid off.

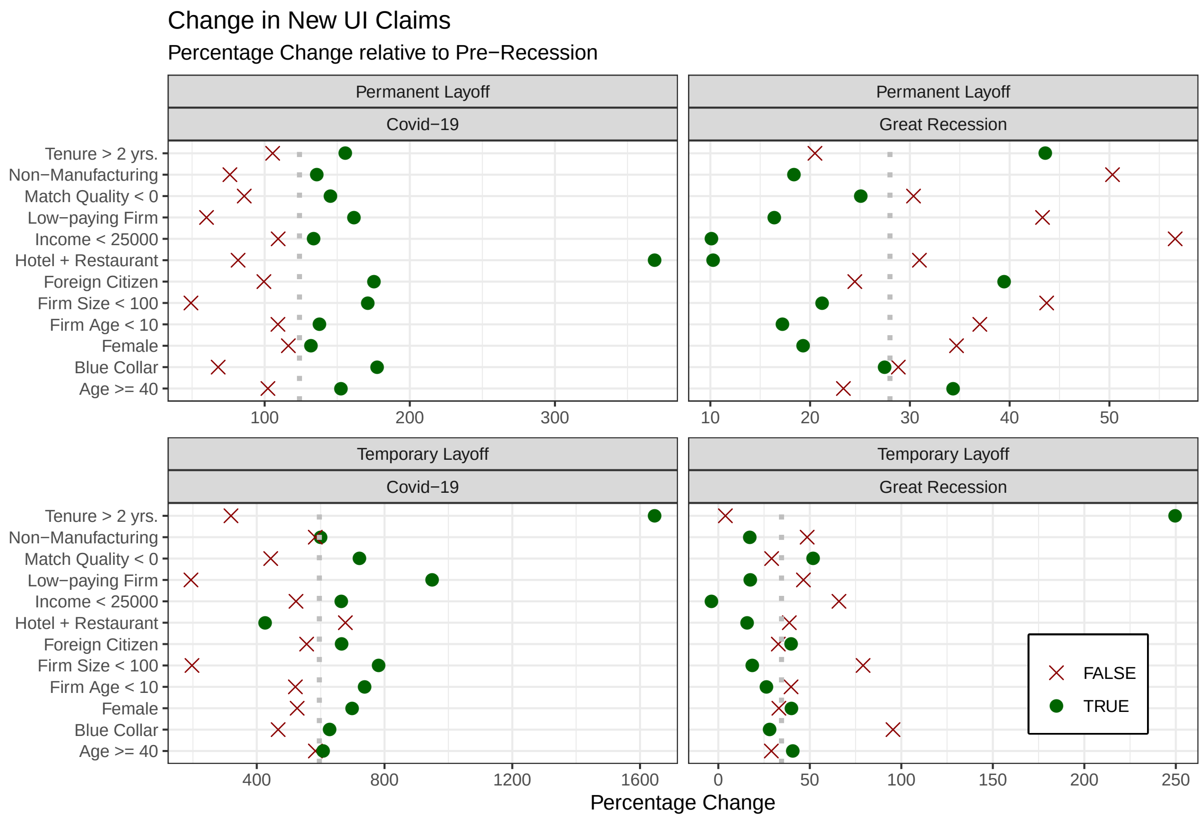

Figure 1: The figure shows the percentage change in the number of new UI claims March 2020 - May 2020 relative to the same period in 2019 and 2018 (Covid-19) and 2009 compared to 2007 (Great Recession), for temporary and permanent layoffs. Temporary layoff is defined as a recall within 2 months. The grey dotted line represents the overall change in UI take-ups. Sample consists of all UI claimants with positive earnings in the prior year and more than 180 days of job tenure. Source: Authors calculations using the AMDB data.

the restrictions on firing were perceived as too restrictive, or because of the administrative burden.[11]

The other striking feature of the Covid-19 recession is that very different parts of the labor market were affected compared to the previous recession. This is especially true for permanent layoffs, which constitute the overwhelming majority of UI claimants. Similarly to other countries, Austria enacted a strict lock-down in March 2020 with mandatory closures of all hotels, restaurants, and non-essential shops. Therefore, perhaps unsurprisingly, permanent layoffs in the hotel and restaurant industry increased much more than in other industries, whereas in the Great Recession, this industry was more resilient. The hotel and

[11]Firms are not allowed to downsize or lay off workers during the STW scheme, although exceptions are allowed with the permission of the work council.

restaurant industry seems also more pessimistic about a potential quick recovery. Not only did furloughs increase more than in other industries, but it is the only group in this figure where permanent layoffs increased more than temporary ones. In contrast, manufacturing was less affected by layoffs compared to the Great Recession.

Typically, during recessions the pool of unemployed shifts towards worker and job characteristics that are associated with better labor market outcomes. For example, in the Great Recession, permanent layoffs with prior yearly income *above* €25,000 increased six times more than for workers earning below this threshold.[12] In contrast, the COVID-19 recession affected workers earning *below* €25,000 relatively more than higher paid individuals. In addition, UI claims increased more for workers earning less than what would be expected based on their characteristics, again the opposite pattern to the Great Recession. UI claims from blue collar occupations, which are harder to perform via remote working, increased more than in white collar occupations, a pattern documented as well in (Mongey *et al.*, 2020). This is again in contrast to the Great Recession, where UI take-ups increased less for blue collar occupations. In the COVID-19 recession, job losses are more severe for females, which is very atypical for recessions (Alon *et al.*, 2020). This is likely due to an over-representation of females in the most affected sectors in addition to schools and daycare closures forcing more mothers to leave their jobs (Fuchs-Schündeln *et al.*, 2020).[13]

The administrative nature of our dataset also allows us to study a number of firm characteristics which are not readily available in other datasets. During the Great Recession, the composition of UI-claimants shifted towards larger, older and better paying firms. Here again the experience during the COVID-19 epidemics stands out. Layoffs were more concentrated in smaller, younger, and lower paying firms.

To summarize, contrary to the Great Recession, the composition of UI claimants shifted towards workers and job characteristics that are associated with worse labor market outcomes. As a result, as Table 2 in the Appendix shows, the composition of UI claimants is much more female, less Austrian, and consists of more workers from smaller, younger and lower paying firms and lower quality matches. A worker displaced from a bad quality match at a firm that pays well below market wage is likely facing different wage losses than a worker separating from a region's flagship company. These large compositional differences of the COVID-19 layoffs in comparison to the previous recession highlights the need for a method of estimating long-term consequences of job losses that takes the different worker and job char-

[12]For the United States, Mueller (2017) documents a similar pattern during previous recessions.

[13]55 percent of all workers in the hotel and restaurant industry are female, whereas only 25 percent of manufacturing workers are female.

acteristics of UI claimants into account. The methodological details of the machine-learning algorithm are presented in the next section.

III. Employed Methodology

The ultimate goal of our exercise is to predict the long-term cost of job termination occurred on the eve of the Pandemic Recession borne by displaced workers. In the earnings-loss literature the cost of job loss has been studied typically in a quasi-experimental setup using mass layoffs as a proxy for random treatments.[14] Consequently, by employing an event-study analysis the average long-term cost of job displacement can be estimated for workers separating during a mass-layoff event.[15] Nonetheless, given the fact that there is very strong heterogeneity in earnings losses across individuals as documented in Gulyas and Pytka (2020) and that the composition of workers displaced during the Covid-19 episode is substantially different from past events as we presented in the previous section, the identified average cost may not be a good representation for the current pandemic event. For this reason, we adapt the generalized random forest methodology (Athey *et al.*, 2019) to a difference-in-difference setting in a similar way to our companion paper (Gulyas and Pytka, 2020). The implemented algorithm is able to identify the conditional average cost of job loss at the worker level as a function of individual characteristics. Equipped with a random forest grown to detect heterogeneity in treatment effects, we are in a position to provide a prediction of earnings losses for each individual separately. Then, we can recover the average cost of job termination during the beginning of the Pandemic Recession simply by computing the average of individual predictions for the recently displaced employees.

For the definition of mass layoff displacement events, we follow the typically applied definitions and sample restrictions as much as possible. A worker is considered displaced if she separated from her employer that experienced a mass layoff in the given year. We define a mass-layoff event at the firm level in year t if it declined by more then 30 percent in size during year t.[16] To have a meaningful measure of firm growth, we only consider

[14] Just to cite but a few seminal examples: Jacobson *et al.* (1993), Neal (1995), Couch and Placzek (2010), Davis and Von Wachter (2011), Farber (2011), Farber (2017).

[15] In our study our treatment group is selected from mass-layoffs event that happened from 1989 through 2009. The control group is generated using propensity score matching.

[16] For the training of our machine learning procedure, we additionally apply the following sample restrictions. To avoid selecting volatile firms, we exclude firms that either grew rapidly the years before the mass layoff, or rebounded in size 3 years after the mass layoff event. That is, we exclude firms that grew by more than 30 percent in either $t-1$, or $t-2$, as well as firms that are larger 3 years after the event than before. In addition, to avoid mis-specifying mergers, outsourcing or firm restructures as mass layoffs, we compute a

establishment with at least 30 employees. We also exclude temporary layoffs by excluding anyone who is recalled to their previous employer.

Average cost of job displacement. In our study we are interested in the cumulative 11-year losses. Those losses can be identified by estimating a difference-in-difference setup:[17]

$$y_{it} = \tau \mathbb{1}(t \geq t^*) \times D_i + \theta D_i + \gamma_t + \epsilon_{it}, \tag{3}$$

where D_i is an indicator for displaced persons, t^* the displacement year and t the current year, period fixed effects γ_t control for the evolution of the control group's outcomes, and τ measures the average change of the variable of the interest in the horizon of 10 years after the displacement.[18] On the left-hand side as y_{it}, we use consider three specifications with different dependent variables: total annual labor earnings, employment days, and log average daily wages. An important concern is that the average cost from Equation (3) estimated with events from 1989 through 2009 may be not representative for the recent COVID-19–related job terminations. The reason for this is that heterogeneity in individual losses and different composition of displaced workers between the past and the presence might shape the average cost in a completely different way.

Conditional average cost of job displacement. One way to address the different composition of individuals displaced during the COVID-19 crisis is to identify the cost of job displacement, $\tau(\mathbf{z})$, as a function of some observables $\mathbf{z}$. In theory, this could be identified by running a modified version of (3) for all values of $\mathbf{z}$. Then the average cost $\mathbb{E}_{covid}\tau(\mathbf{z})$ related to the pandemic job layoffs could be computed simply by reweighing $\mathbf{z}$ according to the distribution $F^{covid}(\mathbf{z})$. That being said, estimation of $\tau(\mathbf{z})$ would require many observations for *each* combination of values in $\mathbf{z}$ and such a procedure would be extremely inefficient or, in practice, even infeasible. For this reason we employ a machine-learning technique, which is our adaptation of generalized random forests by Athey *et al.* (2019) in the difference-in-difference setup as in (Gulyas and Pytka, 2020), to detect individuals with similar values of

cross flow matrix for all firms in each year. We exclude all firms where more than 30 percent of its workforce ends up working for the same employer in $t + 1$. Thereby we exclude mass layoff firms with large worker flows to other firms.

[17] A more general specification with event-study coefficients is relegated to Appendix B.

[18] Table 4 in the Appendix shows the estimates from this regression for different specifications for the mass layoffs events that occurred events between 1989 and 2009. Column (1) reports the estimates for Equation (3) without any controls, column (2) and (3) a polynomial in age and worker fixed effects are added. In all specifications, the yearly earnings losses amount to close to €5,900 per year, or close to €65,000 over 11 years.

the treatment effect. The general idea relies on building trees which maximize heterogeneity in the estimated losses across different groups of workers. Growing a single tree consists in partitioning the dataset into smaller subsamples with different displacement costs, τ. The algorithm decides upon which variables and their cutoff values the dataset is split into two subsets. The splitting criteria maximizes the (adjusted) between-group heterogeneity in displacements costs. Having divided the dataset, the procedure is recursively repeated for two newly created subsets. The process continues until no new satisfactory splits can be obtained or the maximum depth of the tree is achieved. More formally, the procedure is presented in Algorithm 1.

Algorithm 1 Tree Algorithm of Recursive Partitioning

i. Start with the whole dataset and consider it as one large data partition, $\mathcal{P}$.

ii. For each explanatory variable z_k and its every occurring value $\overline{z}$, split partition $\mathcal{P}$ into two complementary sets of individuals i such that $\mathcal{P}_l = \{i \in \mathcal{P} : z_{ki} \leq \overline{z}\}$ and $\mathcal{P}_r = \mathcal{P} \setminus \mathcal{P}_l$ and estimate cumulative earnings losses τ_l and τ_r for both partitions by running two separate regressions of form (3) on $\mathcal{P}_l$ and $\mathcal{P}_r$.

iii. Choose the variable z_k and value $\overline{z}$ that maximizes:

$$(\tau_l - \tau_r)^2 \frac{n_l \cdot n_r}{N^2}, \tag{4}$$

where n_l and n_r are sizes of $\mathcal{P}_l$ and $\mathcal{P}_r$ and N is the sample size of $\mathcal{P}$.

iv. If (4) is smaller than a tolerance improvement threshold, then stop. Otherwise, go to step (ii) and repeat the splitting procedure for $\mathcal{P}_l$ and $\mathcal{P}_r$ separately, where $\mathcal{P}_l$ and $\mathcal{P}_r$ are new partitions subject to the splitting procedure, $\mathcal{P}$.

In the literature (e.g., Efron and Hastie, 2016; Hastie *et al.*, 2017) the shortcomings of a single tree such as high variance, overfitness and low stability are well known. To address those issues, a random forest, which is an ensemble of many trees trained on random subsamples with a random subset of explanatory variables, is recommended. In our application we built the random forest with 2,000 trees. Then, the displacement cost $\tau(\mathbf{z}_i)$ of individual i is identified by weighted-least squares estimation of Equation 3. The weight of each observation relevant in estimating $\tau(\mathbf{z}_i)$ is recovered from the random forest. Intuitively, those weights capture the frequency with which other observations fall into the same final node as the observation of our interest. We present the algorithm of building those weights more formally in Appendix C.

Explanatory variables. In our analysis we consider 16 different explanatory variables **z** for estimating the cost of job loss, which cover the most prominent theories from the earnings loss literature. We include worker characteristics such as age, gender, the number of previous employers, job tenure at the last job, and indicators for Blue-collar job and Austrian citizenship. In addition we include firm wage premia obtained from Equation (1), the match quality measured by the residual of Equation (2). Apart from the firm FE, other firm-related variables are: firm size, a manufacturing dummy, and the firm separation rate. The current state of the economy is reflected by five additional variables, *i.e.* regional and industry-specific unemployment rates and its year-to-year changes, Herfindahl-Hirschman index of labor market concentration, the regional average of the firm FE and a dummy accounting for recession years according to the OECD definition.

The Covid-19 outbreak was an unprecedented event in the modern history and thus the looming recession may be different in many dimensions. That being said, our machine-learning procedure takes into account some of the differences through our choice of explanatory variables. More specifically, we use multiple business cycle indicators at the national, regional, and industry level to account for any geographic- or industry-specific shocks of the Covid-19 recession. In addition, because of the rapid increase in unemployment during the Pandemic Recession, we not only use unemployment levels but also their year-to-year changes.

IV. Long-Term Consequences of Covid-19 Layoffs

Equipped with our random forest, we can predict the long-term cost for each displaced worker. In our main analysis, we focus on workers with at least two years of tenure separating from their employers in a mass-layoff. These are the same restriction that are typically applied in the literature and that were used to train the random forest. As mentioned before, we are aware that the Pandemic Recession might be different from previous recessions. Our machine-learning algorithm is trained on past mass-layoff events, which implies that in our prediction exercise it is implicitly assumed that the impact of all included channels has not changed. At the moment of writing this paper we do not know whether we will observe some structural changes. Nonetheless, as we show further, abstracting from plausible structural breaks and focusing only on changes in pools of displaced workers is sufficient to document that the Covid-19-related earnings losses are very different from the past ones. This difference might be amplified even more if some new and currently unknown properties

Table 1: Consequences of job loss - mass layoffs only

	Prior to Great Recession	Great Recession	Prior to Covid-19	Covid-19
All				
Pre-displ. Income	33,281.620	35,229.560	33,255.900	26,600.030
Earnings Losses (Euros)	63,600.580	72,700.760	60,947.730	38,062.180
Earnings Losses (% of Pre-displ. Income)	191%	206%	183%	143%
Emp. Losses (Days)	439.552	476.516	494.559	478.354
Log Wage Losses	0.061	0.076	0.055	0.019
Cor(Emp. Loss , Earn. Loss)	0.547	0.464	0.537	0.589
Female				
Pre-displ. Income	25,897.740	26,882.620	26,618.460	22,325.920
Earnings Losses (Euros)	52,380.900	58,560.430	53,396.870	30,714.660
Earnings Losses (% of Pre-displ. Income)	202%	218%	201%	138%
Emp. Losses (Days)	447.578	501.669	515.076	471.180
Log Wage Losses	0.057	0.071	0.054	0.017
Cor(Emp. Loss , Earn. Loss)	0.570	0.480	0.534	0.642
Male				
Pre-displ. Income	39,585.170	39,223.190	38,829.210	29,646.810
Earnings Losses (Euros)	73,178.720	79,466.260	67,288.020	43,299.820
Earnings Losses (% of Pre-displ. Income)	185%	203%	173%	146%
Emp. Losses (Days)	432.701	464.481	477.331	483.468
Log Wage Losses	0.064	0.079	0.056	0.020
Cor(Emp. Loss , Earn. Loss)	0.574	0.512	0.576	0.585

Earnings, employment and log-wage losses of all masslayoff UI claimants with 2+ years of job tenure, see text for definition of mass layoff. Covid-19 refers to March-May 2020, Pre Covid-19 to March-May 2018 and 2019, Great Recession to 2009 and Pre Great Recession to 2007. Earnings and employment losses are cumulative over 11 year, while log-wage losses are average declines. Results from a generalized random forest. Positive number imply losses, while negative numbers imply gains.

of the Pandemic Recession emerge in the near future.

A. Average cost of job displacement

Table 1 presents the average cost in terms of earnings, employment, and log-wage losses of job terminations during mass-layoff events. The reported statistics are broken down by gender for layoffs that occurred in four different periods: prior to the Great Recession, the Great Recession, prior to the COVID-19 crisis, and the COVID-19 crisis. First, in comparison to years prior to the COVID-19 outbreak, the predicted earnings losses in 2020 are substantially lower. While in the previous episodes the average long-term losses of job termination were estimated at the level of almost 200% of the pre-displacement annual income, recently displaced workers can expect much lower losses amounting to 143%. The dynamics of losses is quite interesting. Typically, job terminations in downturns are associated with higher losses.[19] In fact, this was observed during the Great Recession, when both employment and wage losses increased, which lead to an overall rise in earnings losses. In contrast, both wage and employment losses decreased for job terminations during the pandemic in comparison to the pre-COVID-19 levels. Recent job losers can expect yearly wages to decline by 2 percent on average for the next 11 years, compared to the control group who kept their jobs. This number is strikingly low in comparison to the previous years, where wage losses are three to four times as high.

The dynamics of losses by gender are the same as for the whole population. For all periods the predicted employment losses for women were higher than for men, likely a result of the lower labor market attachment of women. The log-wage losses are nearly the same for both gender for all periods. For all episodes except the Pandemic Recession, women's average costs exceeded 200% and was much higher than for males. Only during the current COVID-19 crisis the gender gap in the relative earnings losses reduced to a one-digit number equal to 8 percentage points.

Our findings can help to understand the shape of the recovery from the Pandemic Recession. Because we expect workers to incur employment losses of a similar magnitude as in the Great Recession, we predict a similar sluggish employment recovery as after the Great Recession. Another well documented fact of the Great Recession was the extremely slow wage growth during the recovery (Pinheiro and Yang, 2017). Here our findings provide a silver lining. The group of workers affected by the COVID-19 job losses is expected to have much lower wage losses upon re-employment compared to previous experiences. This sug-

[19] See e.g. Davis and Von Wachter (2011).

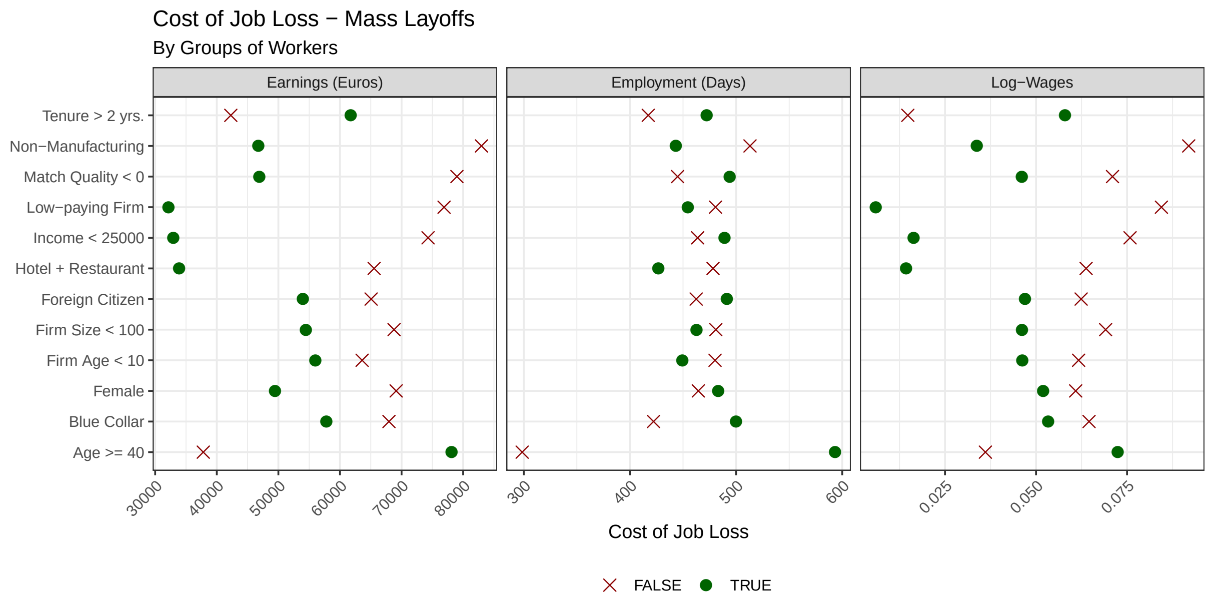

Figure 2: The figure shows the estimated cost of job losses for different groups of workers. Subgroups indicated by green dots experienced larger increases in UI claims, see Figure 1. Sample consists of UI claimants pooled over all samples conditional on mass-layoff, see text for definition. Estimated earnings losses from a generalized random forest.

gests that purely from the different composition of UI claimants we can expect less human capital being destroyed which points towards a quicker recovery in wages after the end of the Pandemic Recession.

B. Who losses more?

To understand why the predicted losses decreased for Covid-19 job losses and increased during the Great Recession we take a closer look on losses across displaced employees. Figure 2 shows average losses in earnings, employment, and wages for different groups of workers. This also allows us to judge the plausibility of our predictions. As mentioned before, usually during recessions the pool of unemployed shifts towards worker and job characteristics that are associated with better labor market outcomes. In Gulyas and Pytka (2020) we show that this compositional change almost entirely explains why workers displaced during recessions face higher earnings losses. During the Covid-19 episode we observed something completely different. Almost all groups whose UI take-ups increased proportionally more during the Pandemic Recession (green dots) are also associated with *lower* earnings and wage losses. The Covid-19 layoffs disproportionately affected the hotel and restaurant industry and other non-manufacturing sectors which employ many low income workers and in addition typically have the lowest firm wage premia.[20] UI claimants during the first three months of the Pandemic recession not only earned 25 percent less than the average UI claimant during the Great Recession, but also lost jobs with a whopping 24 percent lower employer-specific wage component (see table 3 in the appendix). Interpreted through a job-ladder model, it will be easier for workers to find a similarly paying job if they were not very high up on the firm quality ladder. This is consistent with the pattern seen in the right panel in Figure 2, where the workers with prior lower firm wage premia experience lower log-wage losses. This is also confirmed by Gulyas and Pytka (2020) and Schmieder *et al.* (2020), who show that firm wage premia is an important factor in explaining earnings losses. Given this information, it is not surprising that our machine-learning procedure predicts lower wage losses for the Covid-19 UI claimants.

Furthermore, recent layoffs were more common for smaller and younger firms, which are typically financially less stable companies.[21] As Figure 2 shows, job losses at these companies are associated with lower earnings losses. This potentially can be explained by the future earnings dynamics of workers from the control group. The employees who kept their jobs at such firms can be fired in future events or their future wage promotion can be slower than in other firms. Consequently, this can explain why the displacement cost from such employers is relatively lower.

Overall, almost all groups that are relatively more affected by layoffs during Covid-19 are also groups that experience lower earnings losses in general. The lower predicted wage losses are a reflection of the fact that the Pandemic recession hit groups of workers that were already disadvantaged in terms of income, firm wage premia, and match quality. This pattern is not observed for employment losses, which explains why we predict a similar employment losses compared to the Great Recession.

C. Heterogenous costs of job displacement

Documenting the differences in average cost of job loss is important to our understanding of the recovery from the current Pandemic Recession. But as Figure 3 shows, the averages mask a lot of individual heterogeneity in the long-term consequences of job losses. First, we can see that heterogeneity is substantial for all periods. For example, before the Covid-19 shock, almost a quarter of workers were experiencing wage gains after mass layoffs, whereas

[20] See e.g. Krueger and Summers (1988).

[21] A similar finding was made by Alstadsæter *et al.* (2020) for Norway.

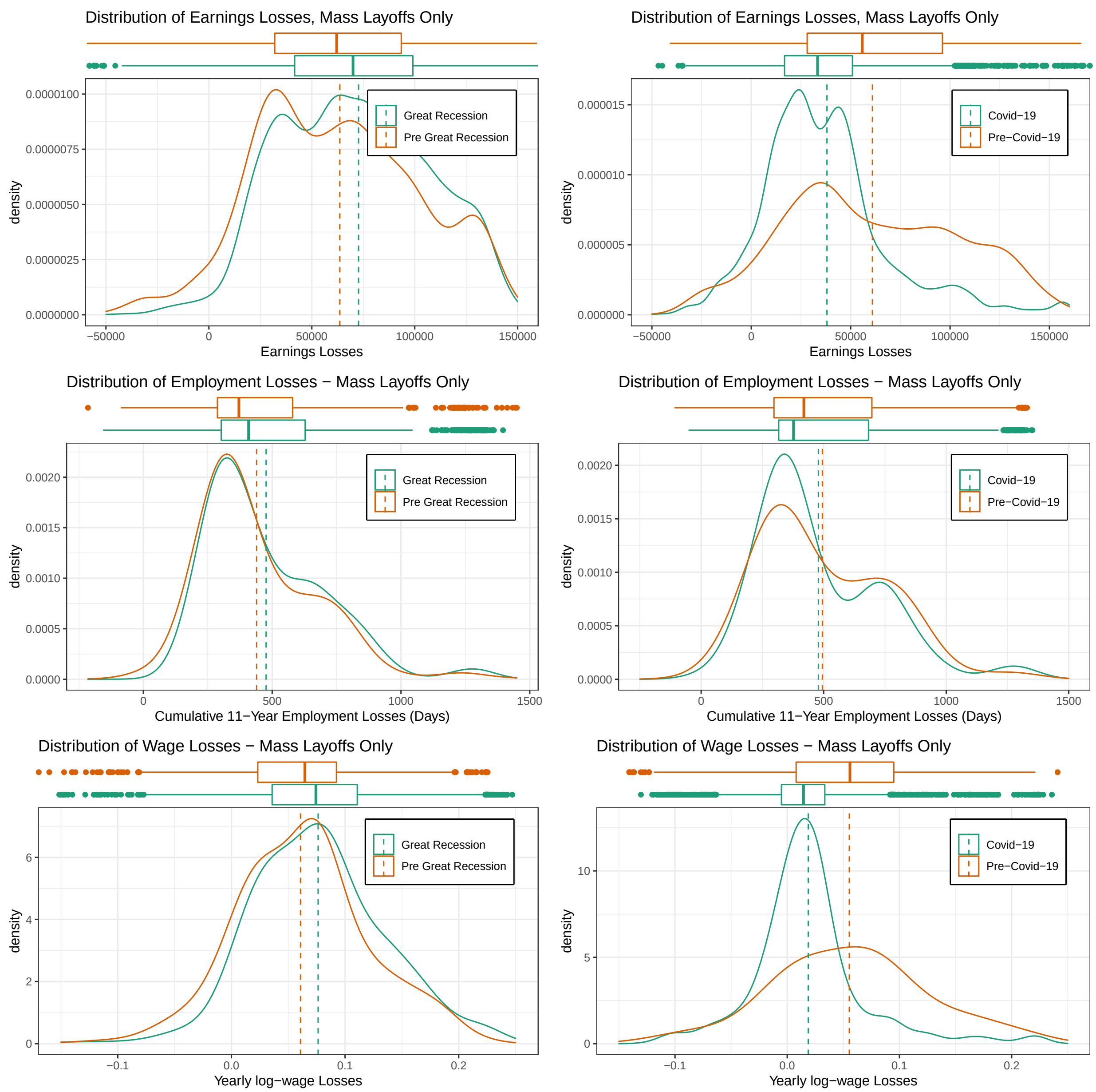

Figure 3: The figure shows the distribution of predicted earnings losses for every mass-layoff UI claimant with 180+ days of job tenure and positive earnings in the year prior to the separation. Covid-19 refers to March-May 2019, Pre Covid-19 to March-May 2018 and 2019, Great Recession to 2009 and Pre Great Recession to 2007. Predicted earnings losses from a generalized random forest. Earnings and employment losses are cumulative over 11 years, while log-wage losses are average declines. Positive numbers imply losses, while negative numbers imply gains. On the top of each panel there is a boxplot with quartiles and outliers. Dashed lines show means.

another quarter suffered permanent wage declines by more than 10 percent.

Second, while the distribution of employment losses during the Pandemic Recession is comparable to before, the distributions of log-wage and earnings losses stand out. Not only did the whole distributions of log-wage and earnings losses shift towards lower losses, but the distribution shows much lower dispersion. The interquartile range prior to the Pandemic Recession was equal to 8.4 log points and it decreased by over 50 percent to 4 log points. This is something new in comparison to previous experiences. During the previous crisis the wage losses were characterized with a higher average but similar dispersion. This is likely because the Covid-19 recession hit a much narrower segment of the labor market, compared to the Great Recession, which saw job losses across the board.

We also documented the distribution of earnings, employment and log-wages for the Covid-19 job losses separately by gender (Figure 10 in the Appendix). The distribution of employment and wage losses look surprisingly similar for men and women. The only noteworthy difference between men and women is perhaps that earnings losses for men are somewhat more dispersed, which is due to the higher dispersion in earnings for men.

Given the large amount of heterogeneity in earnings losses across workers, where a considerable fraction of workers even experience wage gains, any government intervention should likely be target. The next section presents how our algorithm can be used to identify high loss individuals.

V. Targeting Policies

Even though we expect lower earnings losses from the Pandemic Recession compared to the past, the average worker affected by a mass layoff still faces significant declines in income. Thus, policy interventions such as avoiding costly job losses through firm bail-outs and short-time work subsidy schemes, or policies aimed at insuring workers from the income losses through unemployment insurance extensions and top-ups are likely warranted. Moreover, we showed in the previous section that there is substantial heterogeneity in losses across different workers. For instance, 30% of workers can expect higher wages after re-employment. Thus, targeting policy interventions towards individuals that can expect wage losses would likely result in welfare gains. To detect workers with positive log wage losses we build a simple policy tree in the spirit of Athey and Wager (2017).[22] In general, depending on the welfare

[22] A certain caveat needs to be applied here. The reported losses are identified with our random forest, which was grown using pre-Covid-19 mass-layoff events. Our machine-learning technique allows us to predict individual earnings losses. As discussed before, the Covid-19 episode may be quantitatively different also

criteria of the policy maker and budgetary generosity of the intervention optimal trees might look different. That being said, we decided to focus on wage losses due to its persistency.[23]

In the considered time window of the Pandemic Recession, 3,227 workers were displaced in mass-layoff events and have not been recalled by their previous employer. Using our methodology we identified 2,104 individuals with losses in log wages and 1,123 people that are predicted to benefit from a job termination in terms of their reemployment wages. The tree forecasts whether estimated wage losses of each individual is positive ($y = 1$ if so, $y = 0$ otherwise). To provide an accurate but simple decision rule, we keep the max depth of the tree to 4.[24] Figure 4 illustrates the generated classification tree. Each node is characterized with three numbers. The dominant category in each node is reported on the top. The fraction of observations with positive wage losses in the node and the fraction of overall observations that fall in the node are shown in the middle and the bottom, respectively. Table 7 in the Appendix presents its confusion matrix computed on the set of people displaced in Covid-19 mass layoffs. Despite its simplicity, the prediction performance with an overall accuracy 86.02% is very good. 86.82% of individuals with positive wage losses are detected correctly.[25] Workers who are classified by our tree for targeting are expected to suffer a wage declines by 3.96 log points on average. Those workers who would not be selected in contrast are expected to see wage gains of more than two percent. This highlights the potential usefulness of the algorithmic decision tree for policy targeting.

Inspecting the policy tree further also reveals more about the underlying channels of wage losses. The first split chosen by the algorithm is associated with firm wage premia, which only reconfirms the importance of this variable for explaining the losses. It is quite striking that 97% of workers displaced from employers paying above the median face wage losses which amount to close to six percent on average.

On the other hand, for workers fired from low-paying firms it is much easier to find jobs with better pays. An interaction of a job-specific accumulated human capital, firm rents at other employers in a region, and a worker's age determines how likely it will be. Most of those employees who in addition have a relatively shorter job tenure will find better paying

in how observations with certain worker, job, and business-cycle characteristics are affected by a job loss. Our analysis does not include this effect.

[23] In Appendix F, we present an alternative tree grown to detect heterogeneity in the overall earnings losses.

[24] This also rules out potential problems of overfitting.

[25] In designing targeting policies the latter statistics can be even more important than the accuracy. Given budgetary constraints policy makers might want to sacrifice the accuracy and be less stringent in classifying somebody as needing help so as to reduce the false negative error rate, which in our case is equal to the fraction of people with actual wage losses predicted to have no losses.

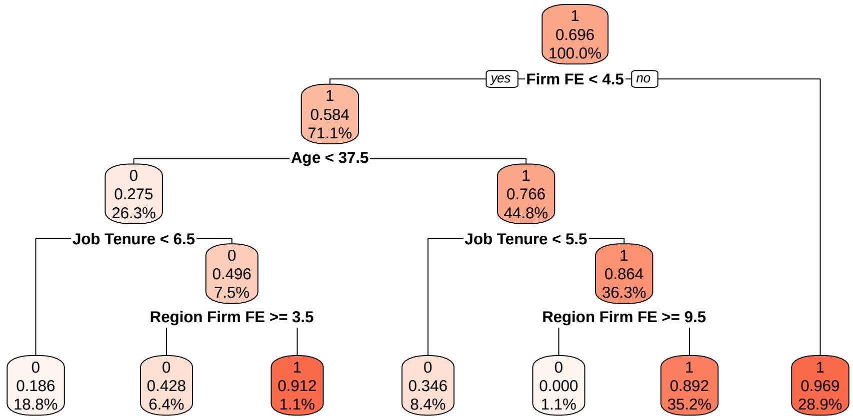

Figure 4: Classification tree classifying individuals with wage losses. On the top there is the most common value. The fraction of observations with wage losses in a node is reported in the middle. The fraction of observations in the global sample is shown in the bottom.

jobs. Depending on age it varies between $(100\% - 18.6\% =)81.4\%$ for younger workers and $(100\% - 34.6\% =)65.4\%$ for older workers. This difference might suggest that younger people are better skilled in looking for jobs (*e.g.*, due to better computer literacy) or that prospective employers discriminate older workers with similar characteristics. Next, lost job-specific human capital accumulated at a previous employer can be offset with availability of good jobs on the market. Again, it will be easier for younger workers. For them even slightly below-median regional firm premia are enough. Older workers are able to compensate wage losses implied by destructed job-specific human capital only if they will look for jobs in regions with the best paying firms.

We fully acknowledge that our decision tree does not provide a comprehensive welfare analysis of these policy recommendations. But we believe that by revealing which factors are more important drivers of earnings losses, our decision rule provides important insights for policy makers.

VI. Conclusions

Using the universe of Austrian unemployment insurance records, we document that the composition of UI claimants during the pandemic crisis was substantially different compared to previous experiences. In contrast to a typical recession, the pool of Covid-19 UI claimants shifted towards worker and job characteristics that are associated with worse labor market outcomes. During the first three months of the Pandemic Recession, UI claims increased relatively more for females, low paid workers, as well as for younger, smaller and worse-paying firms. Using a machine-learning algorithm developed in Gulyas and Pytka (2020) we predict the individual cost of job loss for Covid-19 job losers conditional on their worker and job characteristics. As we show, those job terminations are associated with much lower losses in earnings and wages compared to the Great Recession, but similar employment losses.

The Covid-19 layoffs disproportionately affected the hotel and restaurant industry and other non-manufacturing sectors which employ many low income workers and typically have the lowest firm wage premia. In general, our study reconfirms our previous finding from Gulyas and Pytka (2020) stressing that firm wage premia is the most important factor in explaining earnings losses. Interpreted through a job-ladder model, it will be easier for workers to find a similarly paying job if they were not very high up on the ladder. Moreover, we document that recent layoffs were more common for smaller and younger firms, where job terminations are associated with lower earnings losses. Therefore, it is very important to take compositional changes of UI claimants into account for estimating earnings losses.

Given this significant heterogeneity in earnings losses across individuals, any policy intervention aimed at avoiding job losses such as firm bail-outs and short-time subsidy schemes should likely be targeted. We present a simple but accurate decision rule for policy makers to target individuals with high wage losses: (i) workers displaced from employers paying above the median and (ii) workers with a relatively long job tenure displaced from low paying firms in regions with fewer well-paying jobs on the market.

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A. Appendix

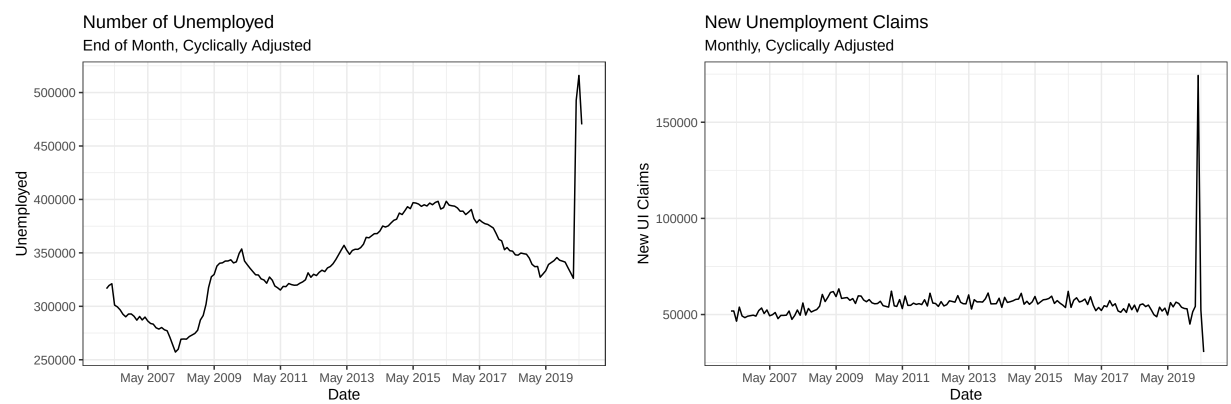


Figure 5: Evolution of number of unemployed and number of UI claiments in Austria. Authors calculation using AMDB data.

Table 2

	2007	2009	2018 & 2019	COVID-19
New UI Claims	215,894	278,482	94,462	124,178
Mass Layoffs (Share)	0.013	0.023	0.017	0.026
Temporary Layoff (Share)	0.151	0.157	0.082	0.218
Austrian (Share)	0.763	0.744	0.674	0.603
Blue-Collar (Share)	0.658	0.651	0.535	0.678
Female (Share)	0.400	0.375	0.482	0.497
Age (yrs)	37.351	37.795	38.308	39.798
Manufacturing (Share)	0.131	0.213	0.129	0.092
Hotel & Restaurants (Share)	0.113	0.098	0.147	0.269
Firm-Tenure (yrs)	2.355	2.881	2.748	3.167
Income t-1 (Euros)	23,177.290	25,938.530	23,963.470	23,475.610
Firm Size	300.111	328.436	469.929	239.738
Firm Wage Premium	-0.064	-0.037	-0.092	-0.203
Firm Age	16.976	17.797	19.754	17.728
Match Quality	0.026	0.031	-0.088	-0.152
Regional Firm Wage Premium	0.003	0.003	0.013	0.005

Notes: Sample statistics of all new UI claimants conditional on positive earnings in the last year and more than 180 days of job tenure. COVID-19 column refers to new UI claims from March 2020-May 2020, who have not returned to work as of beginning of August.

Table 3

	2007	2009	2018 & 2019	Covid-19
Mass Layoffs	2,762	6,313	1,595	3,227
Austrian (Share)	0.756	0.729	0.752	0.477
Blue-Collar (Share)	0.504	0.631	0.445	0.850
Female (Share)	0.461	0.324	0.456	0.416
Age (yrs)	40.919	41.940	42.488	41.866
Manufacturing (Share)	0.301	0.522	0.340	0.084
Hotel & Restaurants (Share)	0.040	0.031	0.031	0.440
Firm-Tenure (yrs)	6.929	7.016	7.153	5.424
Income t-1 (Euros)	33,281.620	35,229.560	33,255.900	26,600.030
Firm Size	393.981	188.450	391.951	218.830
Firm Wage Premium	0.066	0.098	0.003	-0.139
Firm Age	19.979	20.963	24.357	19.112
Match Quality	0.008	0.033	-0.076	-0.189
Regional Firm Wage Premium	0.018	0.002	0.012	0.021

Notes: Sample statistics of all UI claimants originating from mass layoffs, conditional on more than 2 years of job tenure. Covid-19 column refers to new UI claims from March 2020-May 2020, who have not returned to their previous employer as of August 10th.

B. Average cost of job displacement

The average causal cost of job termination of workers displaced in the past mass layoffs can be estimated from the following regression model:

$$y_{it} = \sum_{j=-4}^{10} \delta_j \mathbb{1}(t = t^* + j) \times D_i + \theta D_i + \gamma_t + \epsilon_{it}, \tag{5}$$

where D_i is an indicator for displaced persons, t^* the displacement year and t the current year. To control for the evolution of the control group's earning and initial differences in earnings year fixed effects γ_t and a displacement dummy D_i have been included. On the left-hand side as y_{it}, we use consider three specifications with different dependent variables: total annual labor earnings, employment days, and log average daily wages. Then $\{\delta_j\}_{j=-4}^{10}$

measure the change in the variable of the interest relative to the baseline year $t^* - 5$, after controlling for differences in initial earnings between the two groups.[26] One year after job displacement, earnings losses amount to approximately €8,000, which on average is the result of employment losses of approximately 70 days and wages decline by about 3 log points. In the following years earnings increase, but the recovery fades out after 5-6 year, after which the losses still amount to €5,000 yearly and log wage losses increase to 6-7.5 log points. The log-wages do not recover.

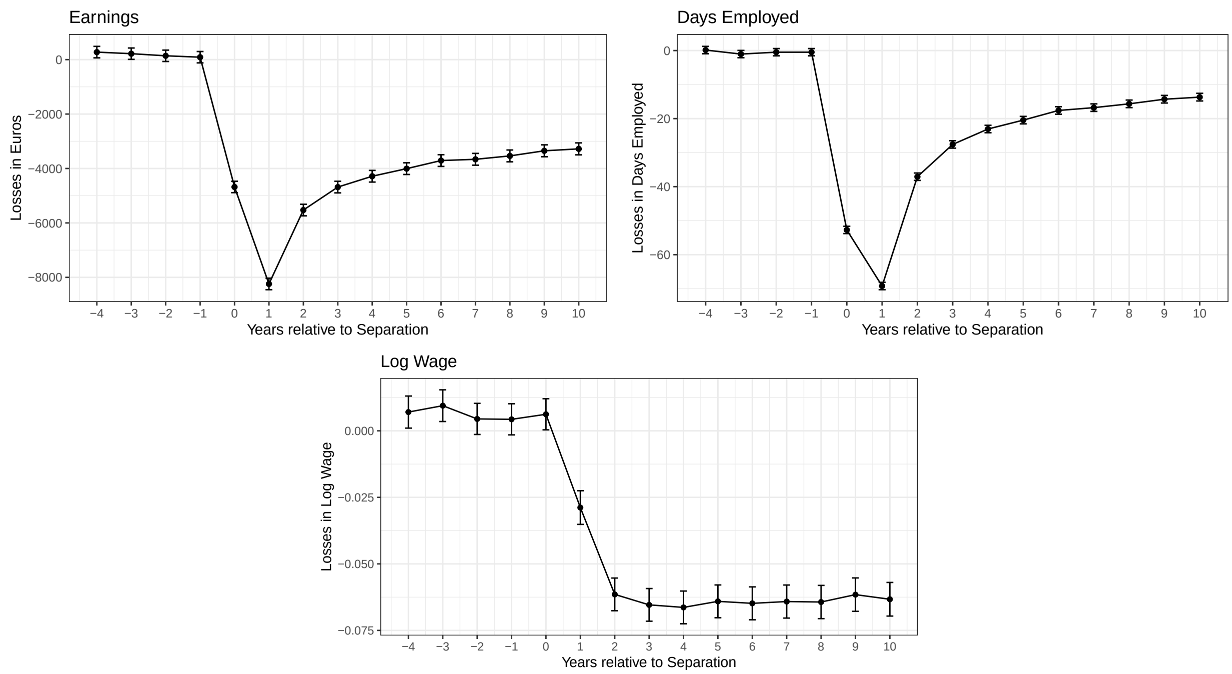


Figure 6: Earnings Losses of displaced workers - Eventstudy regression estimates of Equation (5). Period 0 corresponds to the separation year. Earnings and days employed are computed for the whole year, log wages are computed as the log average daily wage from the employer on 1st January. Control group is selected via propensity score matching.

[26] Figure 6 in the Appendix of this paper depicts event study coefficients δ_t for all periods (before and after displacement), for three variables of the interest. Because of the fact we analyzed mass-layoffs events from 1989 through 2009, the event-study coefficients are estimated using observations from 1984 through 2019.

	Dependent variable:		
	Yearly Income		
	(1)	(2)	(3)
$\hat{\tau}$	−5,850.6	−5,981.3	−5,952.0
	(55.2)	(33.0)	(32.1)
Worker FE		✓	✓
f(age)			✓
Observations	1,365,468	1,365,468	1,365,468
R^2	0.04	0.7	0.7
Adjusted R^2	0.04	0.7	0.7

Table 4: DiD Regression. Estimation results of Equation (3) for different sets of controls

C. Similarity Weights: Machine-Learning Algorithm

It is well known that a single tree tends to exhibit high prediction variance (e.g., Efron and Hastie, 2016; Hastie *et al.*, 2017). For this reason, just as in Athey *et al.* (2019), we have extended our procedure to a random forest in the spirit of Breiman (2001). The idea of this refinement is to grow many trees with bootstrapped datasets and sampling a subset of considered variables for each generated split. Thanks to this procedure, the prediction variance is very often reduced considerably and the impact of variables is smoother.

Equipped with the structure of the random forest, we are in a position to build weights used for estimating (3). Those weights capture the frequency with which other observations fall into the same leaf as the observation of our interest. Note that this means that for each individual the displacement cost is estimated separately using a different set of implied weights. Suppose that there is a forest with B trees indexed by b. Then weight $\alpha_{it}^{b}(\mathbf{z})$ measures the similarity of observation (i,t) with $\mathbf{z}$ and is defined as:

$$\alpha_{it}^{b}(\mathbf{z}) := \begin{cases} \frac{1}{|L_b(\mathbf{z})|}, & \mathbf{z}_{it} \in L_b(\mathbf{z}) \\ 0, & \text{otherwise}, \end{cases} \tag{6}$$

where $L_b(\mathbf{z})$ is the set of all observations, which share the same terminal node ("leaf") with an individual with characteristics $\mathbf{z}$ in tree b and $|L_b(\mathbf{z})|$ is the size of this set. The weight $\alpha_i(\mathbf{z})$ is the average across all trees: $\alpha_i(\mathbf{z}) := \frac{1}{B}\sum_{b=1}^{B}\alpha_{it}^{b}(\mathbf{z})$.

D. Who losses more?

Table 5 presents the average characteristics of displaced workers broken down by the size of the cumulative earnings losses. As can be seen, workers with predicted higher losses are displaced from firms with higher wage premia. While one can also observe some relationships of other variables such as age in quartiles of the predicted costs, we know that the earnings losses by far are the most sensitive to changes in the firm wage premia.[27] Workers who bear the smallest losses (column Tercile 1 in Table 5) are relatively younger and are fired from firms paying substantially (almost 20 log points) below the average market wage. This group of workers is better off in terms of wages and they only suffer a lower number of employment days than the control group. On average the group of the recently displaced workers can expect higher wages than before (wage losses are negative). However, employments losses offset small wage increase, which leads to overall earnings losses. On the other extreme, there are workers with the highest losses (column Tercile 3 in Table 5). They are fired from firms paying only 7.9 log points below the market wage. Those employees are predicted to look for new jobs much longer and to find lower wages in comparison to the previous employers. A quite analogous picture can be drawn if we juxtapose the previous layoffs with the most current ones. As can be seen in Table 3, in 2007 and 2009 terminated jobs came from firms paying above the average market wage (between 6.6 and 9.8 log points) and prior to the Covid-19 episode firing firms were paying at the market average (0.3 log point above to be precise). As a result, on average workers who were recently laid off are predicted to weather the losses relatively well as they are fired from worse firms with worse match quality.[28]

[27] Here we rely on a finding from our previous paper (Gulyas and Pytka, 2020, section VI) where we are able to identify the impact of each variable on the losses separately while keeping all other confounding factors fixed. This result is extremely robust and we arrived at that conclusion through several complementary analyses.

[28] This can be illustrated quite easily in the vanilla labor-search model by McCall (1970). Workers paid below the market wage expect higher wages in their new jobs while workers with above average income are much more likely to suffer more from a job displacement.

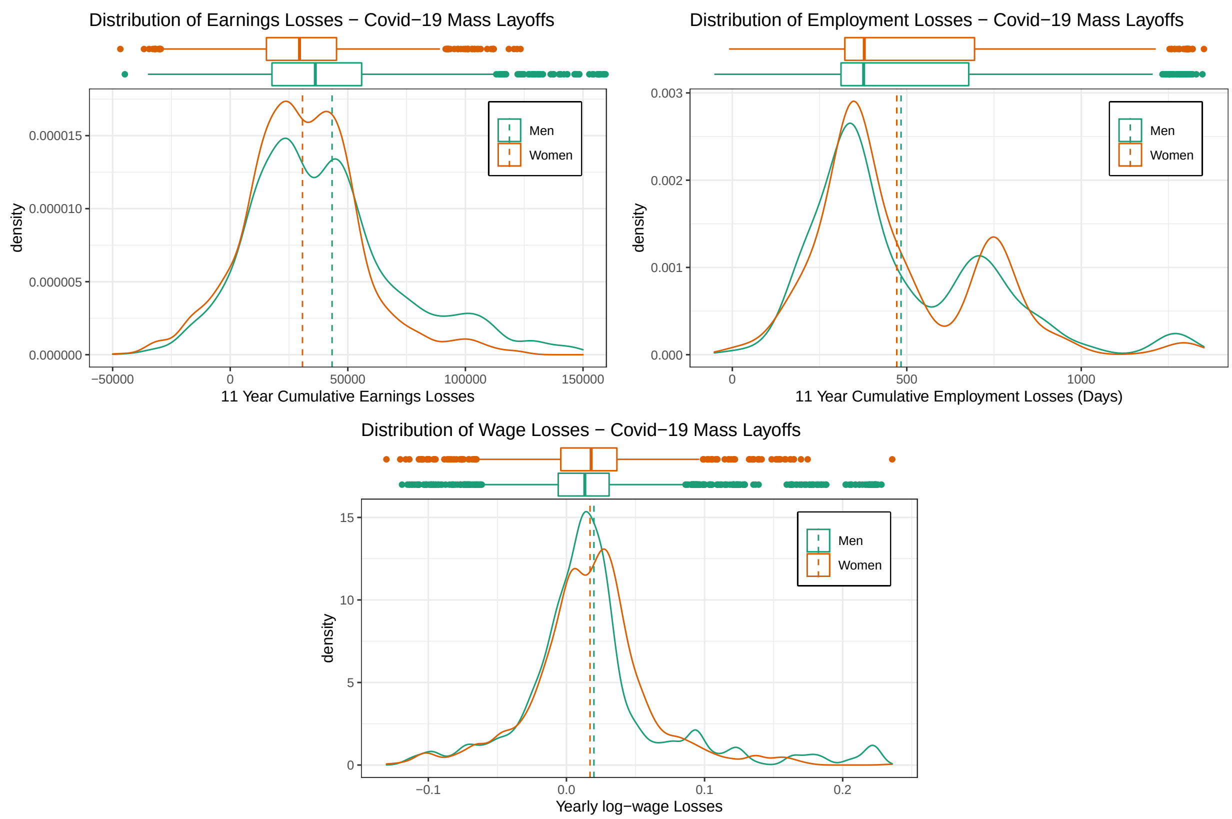
Table 5: Worker and Job Characteristics by Earnings Losses - Mass Layoffs Only

	Tercile 1	Tercile 2	Tercile 3
Earn. Losses	$7,231.448$	$33,406.200$	$73,581.900$
Empl. Losses	297.314	455.434	682.503
Wage Losses	-0.018	0.016	0.058
Blue Collar	0.825	0.878	0.847
Austrian	0.404	0.427	0.600
Manufacturing	0.017	0.046	0.211
Female	0.459	0.473	0.316
Age	32.288	42.231	51.086
Job Tenure	3.713	4.218	8.342
Number of Employers	4.230	6.189	7.720
Firm Size	150.664	294.629	211.188
Match Quality	-0.301	-0.261	-0.007
Firm Wage Premium	-0.203	-0.136	-0.079
Avg. F. Wage Premia	0.031	0.018	0.013
Herfindahl Index	0.015	0.021	0.027
Industry UE-Rate	0.373	0.326	0.281
Regional UE-Rate	0.137	0.139	0.139

Notes: Masslayoffs Only. Table shows mean baseline characteristics for each tercile of predicted treatment effects. Predictions from a causal forest

E. Long Term Consequences of Mass Layoffs by Gender

Figure 7



Actual wage losses	*Predicted wage losses* Negative	Positive	Sum
Negative	25.63%	4.8%	30.43%
Positive	9.17%	60.4%	69.6%
Sum	34.8%	65.2%	100.00%

Table 7: Confusion matrix for the classification tree from Figure 4.

Table 6

	Male	Female
Mass Layoffs	1,884	1,343
Austrian (Share)	0.473	0.482
Blue-Collar (Share)	0.901	0.779
Age (yrs)	42.153	41.462
Manufacturing (Share)	0.107	0.052
Hotel & Restaurants (Share)	0.436	0.445
Firm-Tenure (yrs)	5.781	4.922
Income t-1 (Euros)	29,646.810	22,325.920
Firm Size	209.313	232.180
Firm Wage Premium	-0.124	-0.161
Firm Age	19.107	19.121
Match Quality	-0.106	-0.307
Regional Firm Wage Premium	0.022	0.019

Notes: Sample statistics of all UI claimants originating from mass layoffs, conditional more than 2 years of job tenure. Covid-19 column refers to new UI claims from March 2020-May 2020, who have not returned to work as of beginning of August.

F. Targeting Individuals with High Earnings Losses

Figure 8 depicts the generated tree. The tree forecasts whether estimated earnings losses of each individual is above the median level ($y = 1$ if so, $y = 0$ otherwise). For simplicity the max depth of the tree was set to 2. As can be seen, there are two groups with above-median earnings losses. The first group consists of workers older than 45 years located in all regions except those ones with the highest firm wage premia. In this group of people accounting

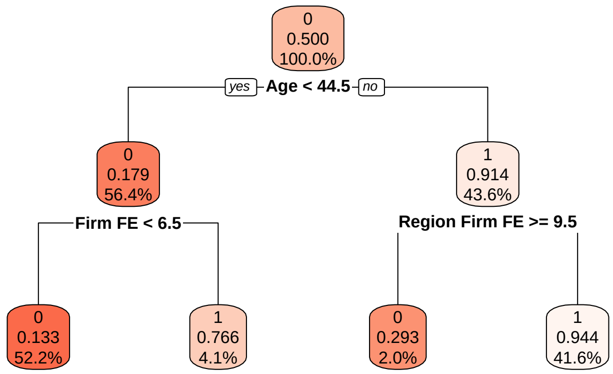


Figure 8: Classification tree predicting earnings losses above the median level. On the top there is the most common value. In the middle there is a fraction of observations with earnings losses above the median. In the bottom there is a fraction of observations in the global sample.

for 40.6% of displaced workers, the overwhelming majority of 94.2% exhibit losses above the median. The second group consists of workers not older than 45 who were displaced from well-paying firms. This group is much smaller though. This very simple criteria allows us to classify 89.96% of displaced individuals correctly and to identify 82.95% of workers with high earnings losses.

G. Analysis for all UI-claimants

This section presents the analysis without conditioning on mass layoffs. The only sample restrictions are that the UI claimant had positive earnings in the year prior to the UI claim, had more than 180 days of job tenure at their previous job, and was not recalled to their previous employer.

Table 8: Consequences of job loss

	Pre Great Recession	Great Recession	Pre COVID-19	COVID-19
All				
Pre-displ Inc.	23,261.010	25,569.370	24,140.740	23,456.840
Earnings Losses (Euros)	39,711.100	45,188.860	37,832.440	37,674.120
Employment Losses (Days)	369.153	387.481	413.143	447.939
Log Wage Losses	0.017	0.025	0.010	0.013
Cor(Emp. Loss , Earn. Loss)	0.488	0.488	0.487	0.489
Female				
Pre-displ Income	19,088.710	20,023.900	20,190.390	19,719.790
Earnings Losses (Euros)	31,346.670	34,833.750	31,961.990	32,865.590
Employment Losses (Days)	379.732	396.756	427.031	461.439
Log Wage Losses	0.007	0.013	0.003	0.012
Cor(Emp. Loss , Earn. Loss)	0.486	0.489	0.505	0.512
Male				
Pre-displ. Income	26,984.350	29,981.970	27,950.110	27,159.810
Earnings Losses (Euros)	47,175.500	53,428.540	43,493.390	42,438.790
Employment Losses (Days)	359.712	380.101	399.751	434.562
Log Wage Losses	0.025	0.035	0.017	0.014
Cor(Emp. Loss , Earn. Loss)	0.533	0.528	0.502	0.499

Earnings, employment and log-wage losses of all UI claimants with positive earnings in the last year and more than 180 days of job tenure. COVID-19 refers to March-May 2019, Pre COVID-19 to March-May 2018 and 2019, Great Recession to 2009 and Pre Great Recession to 2007. Predicted earnings losses from a generalized random forest. Earnings and employment losses are cumulative over 11 years, while log-wage losses are average declines. Positive numbers imply losses, while negative numbers imply gains.

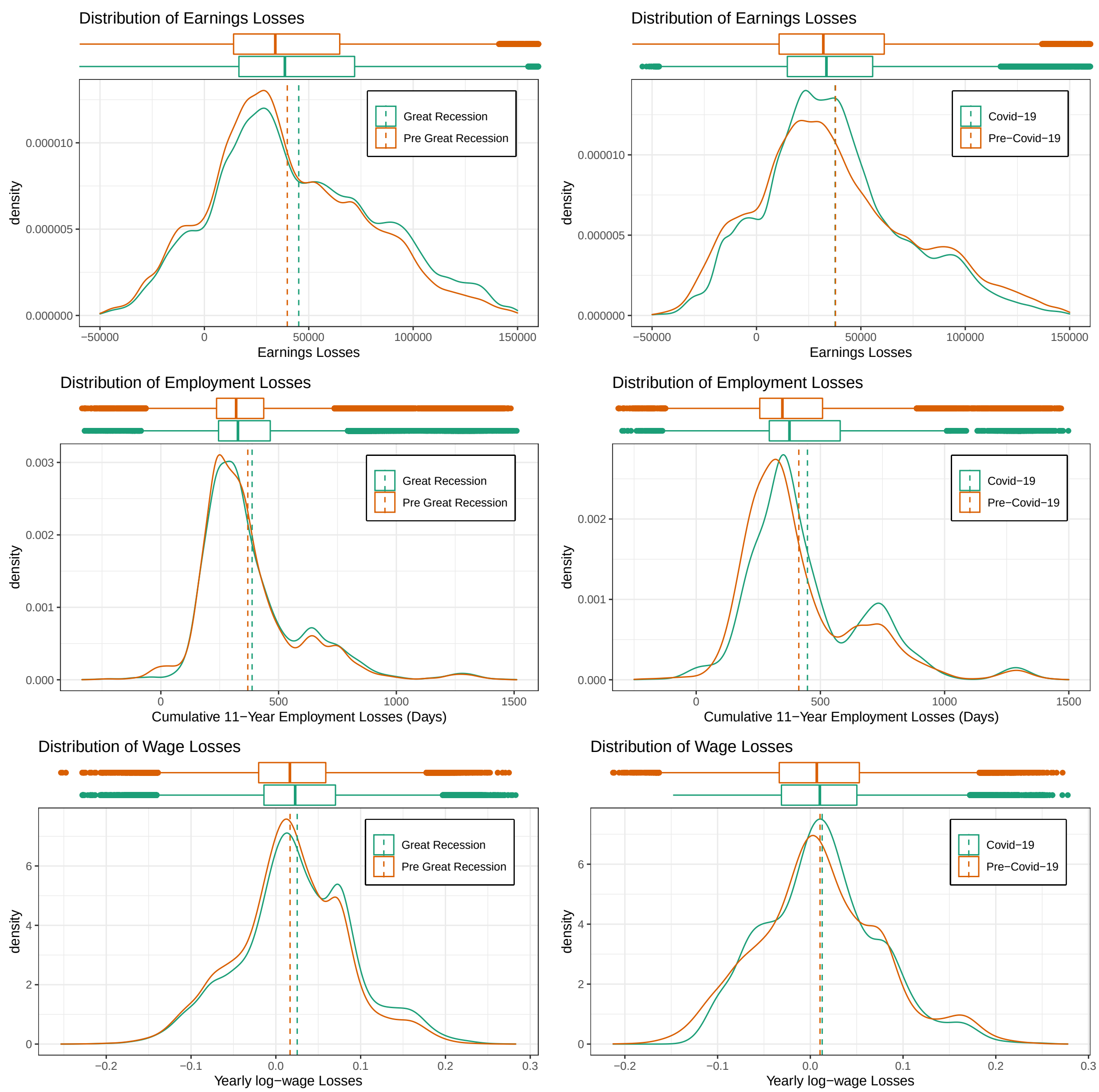
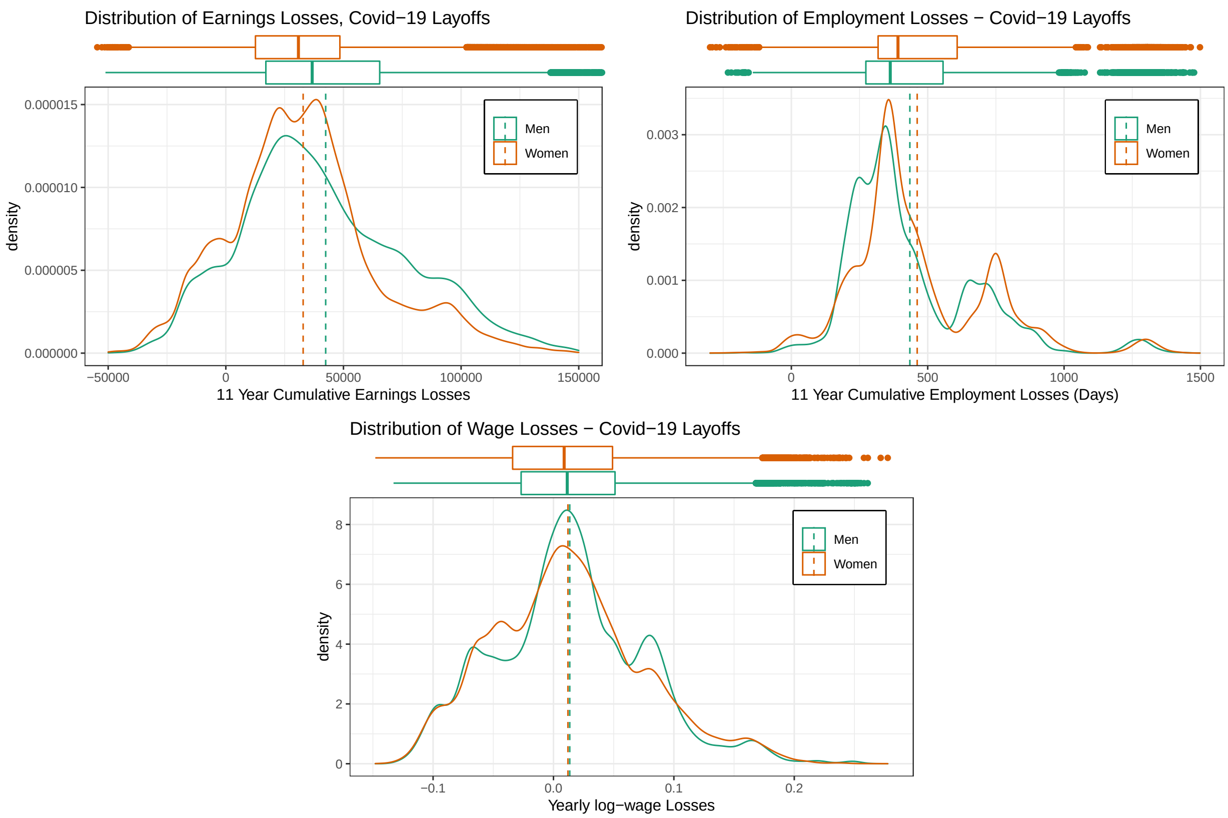


Figure 9: The figure shows the distribution of predicted earnings losses for every UI claimant with 180+ days of job tenure and positive earnings in the year prior to the separation. Covid-19 refers to March-May 2019, Pre Covid-19 to March-May 2018 and 2019, Great Recession to 2009 and Pre Great Recession to 2007. Predicted earnings losses from a generalized random forest. Earnings and employment losses are cumulative over 11 years, while log-wage losses are average declines. Positive numbers imply losses, while negative numbers imply gains.

Figure 10



Distribution of Earnings Losses, Covid−19 Layoffs
0.000015
0.000010
0.000005
0.000000
density
−50000
0
50000
100000
150000
11 Year Cumulative Earnings Losses
Men
Women
Distribution of Employment Losses − Covid−19 Layoffs
0.003
0.002
0.001
0.000
density
0
500
1000
1500
11 Year Cumulative Employment Losses (Days)
Men
Women
Distribution of Wage Losses − Covid−19 Layoffs
8
6
4
2
0
density
−0.1
0.0
0.1
0.2
Yearly log−wage Losses
Men
Women

Table 9

	Male	Female
UI Claimants	41,445	41,067
Austrian (Share)	0.578	0.644
Blue-Collar (Share)	0.709	0.506
Age (yrs)	39.073	39.803
Manufacturing (Share)	0.137	0.077
Hotel & Restaurants (Share)	0.201	0.245
Firm-Tenure (yrs)	2.942	3.011
Income t-1 (Euros)	27,159.810	19,719.790
Firm Size	287.514	356.109
Firm Wage Premium	-0.146	-0.216
Firm Age	17.809	18.661
Match Quality	-0.035	-0.284
Regional Firm Wage Premium	0.013	0.009

Notes: Sample statistics of all UI claimants, conditional on 180+ days of job tenure and positive earnings in the year before UI claim. Covid-19 column refers to new UI claims from March 2020-May 2020, who have not returned to work August 1st.

Table 10: Worker and Job Characteristics by Earnings Losses

	Tercile 1	Tercile 2	Tercile 3
Earn. Losses	$2,765.381$	$33,639.600$	$76,617.370$
Empl. Losses	287.359	477.507	578.951
Wage Losses	-0.036	0.009	0.065
Blue Collar	0.663	0.659	0.501
Austrian	0.545	0.585	0.704
Manufacturing	0.086	0.144	0.259
Female	0.544	0.543	0.407
Age	30.862	41.614	45.834
Job Tenure	1.971	2.621	4.337
Number of Employers	5.021	7.452	8.321
Firm Size	326.776	305.145	333.041
Match Quality	-0.261	-0.277	0.059
Firm Wage Premium	-0.285	-0.197	-0.061
Avg. F. Wage Premia	0.020	0.006	0.007
Herfindahl Index	0.023	0.027	0.030
Industry UE-Rate	0.260	0.231	0.169
Regional UE-Rate	0.133	0.135	0.134

Notes: Table shows mean baseline characteristics for each quartile of predicted treatment effects. Predictions from a causal forest