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

Andreas Gulyas[†] Krzysztof Pytka[‡]

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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: (i) young workers displaced from employers with high wage premia in areas with relatively low firm rents and (ii) older workers with long job tenure.

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

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[†]University of Mannheim; andreas.gulyas@uni-mannheim.de

[‡]University of Mannheim; pytka@uni-mannheim.de

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.

Early evidence indicates that the Pandemic Recession affects very different labor-market segments compared to previous experiences (Alon *et al.*, 2020; Adams-Prassl *et al.*, 2020). 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.

We draw upon the universe of all new UI claims up until May 31st 2020 to study which segments of the labor market were more affected by layoffs, 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,

[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.

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 of layoffs 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.

First, 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, 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.

With the random forest at hand 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 190-209% of their pre-displacement annual income, during the Covid-19 episode total losses are expected to be only 138%. 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

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

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 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 more than a quarter of individuals can expected wage gains after reemployment, many individuals face significant long-lasting declines in income. 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 92.44% of individuals with positive wage losses correctly. Our policy recommendation suggests targeting: (i) young workers displaced from employers with high wage premia in areas with relatively fewer well-paying jobs and (ii) older workers with long job tenure. Not only does the policy tree detect workers who are actually facing wage losses, but its structure also provides guidelines about which type of program should be implemented. The policy rule shows that while for older workers the lost job tenure is the most important factor explaining wage losses, losses in firms' rents play a larger role for younger workers. Consequently, while all workers would benefit from UI extensions giving more time to find similarly well-paying jobs, bailouts or short-time work schemes should be targeted to preserving jobs at well-paying firms and of older workers.

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 build on generalized random forests (Athey *et al.*, 2019) to estimate the long-term consequences of the the COVID-19-related layoffs. Moreover, we undertake the systematic study of heterogeneity of earnings losses. This is done by deconstructing the losses into losses in employment days and wages

[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.

and looking into how they are associated with other observables.

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]

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 June 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. 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:

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

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

[5] We deflate all earnings to 2017 level using the CPI index provided by the Austrian Statistical Agency.

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]

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 . The left panel plots the change in UI claimants from March to May 2020 compared to the average during same time period of 2018 and 2019. The right panel plots 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 increased by 120 percent during the COVID-19 epidemics compared to pre-recession levels, whereas the same increase was only 33 percent during the Great Recession. 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. Similarly to other countries, Austria enacted a strict lock-down in March 2020 with mandatory closures of all hotels, restaurants,

[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 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.

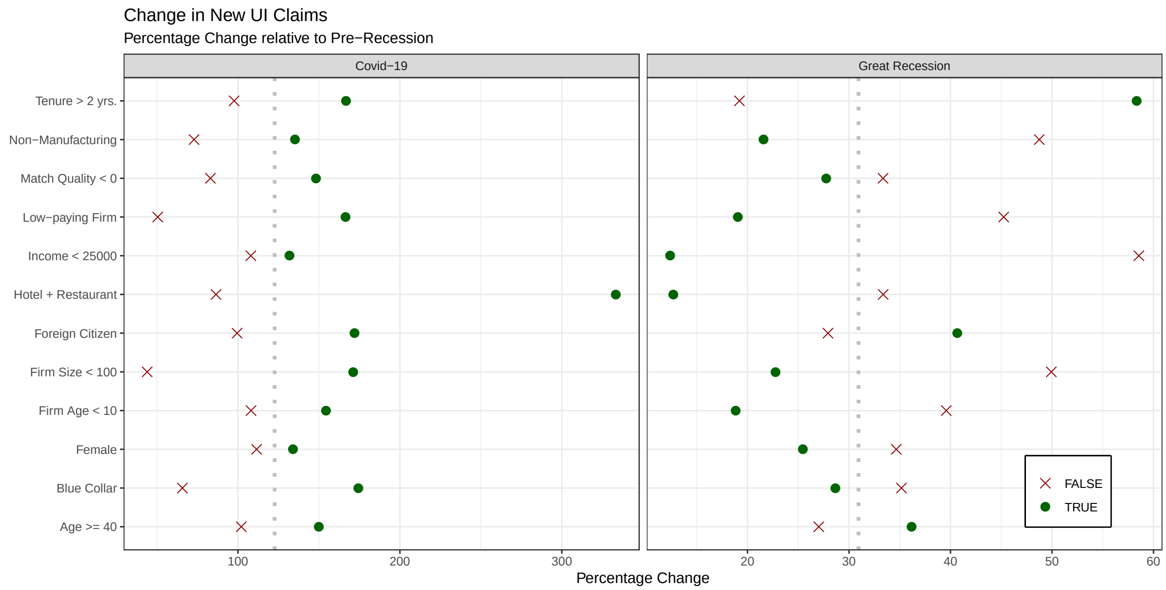

Figure 1: The figure shows the percentage change in the number of new UI claims March 2020 - May 2020 relative to the same period in 2019 (Covid-19) and 2009 compared to 2007 (Great Recession). The grey dotted line represents the overall change in UI take-ups. Subgroups indicated by green dots experienced larger increases in UI claims, 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.

and non-essential shops. Therefore, perhaps unsurprisingly, job separations in the hotel and restaurant industry increased much more than in other industries, whereas in the Great Recession, this industry was more resilient. This is in contrast to manufacturing, which was less affected 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, UI claims with prior yearly income above €25,000 increased almost 10 times more for workers earning *above* €25,000 compared to workers earning below this threshold.[10] 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

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

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).

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. 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 characteristics 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.[11] 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.[12] 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 earnings losses caused by 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

[11] 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).

[12] 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.

Pytka, 2020). The implemented algorithm is able to identify the conditional average causal cost of job loss at a worker's 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.[13] To have a meaningful measure of firm growth, we only consider establishment with at least 30 employees.

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:[14]

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

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.[15] 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–

[13]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 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.

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

[15]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.

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 conditional cost of job displacement, $\tau(\mathbf{z})$. 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, to detect individuals with similar values of the treatment effect. The general idea consists in choosing cutoff values in $\mathbf{z}$ for recursive splitting the dataset into smaller subsamples in which individuals exhibit similar losses. This procedure is repeated many times (in our case 2,000 times) on random subsamples with a random subset of variables according to which the data is partitioned. Finally, for each individual the algorithm provides similarity measures of other individuals in terms of their cost of job loss. Next, those measures are used as weights in weighted least-square estimation of Equation (3) for each observation of interest. We present the whole algorithm in greater detail in Appendix C.

Explanatory variables. In our analysis we consider 16 different explanatory variables $\mathbf{z}$ 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 rate, 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.

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	32,864	36,046	32,342	26,539
Earnings Losses (Euros)	63,903	75,228	61,586	36,556
Earnings Losses (% of Pre-displ. Income)	194%	209%	190%	138%
Emp. Losses (Days)	441.84	467.78	486.79	474.99
Log Wage Losses	0.062	0.079	0.058	0.021
Female				
Pre-displ. Income	25,520	26,719	25,773	22,239
Earnings Losses (Euros)	52,438	60,334	53,148	31,167
Earnings Losses (% of Pre-displ. Income)	205%	226%	206%	140%
Emp. Losses (Days)	447.03	499.40	499.27	493.04
Log Wage Losses	0.060	0.075	0.057	0.020
Male				
Pre-displ. Income	38,616	39,497	37,872	30,234
Earnings Losses (Euros)	72,883	80,740	68,689	41,188
Earnings Losses (% of Pre-displ. Income)	189%	204%	181%	136%
Emp. Losses (Days)	437.77	456.07	476.29	459.47
Log Wage Losses	0.064	0.080	0.059	0.021

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.

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. Although mass-layoffs constitute a small fraction of total job losses, we show in the Appendix (section G) that all our results are qualitatively unchanged for the full sample of UI claimants.[16]

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 138%. What is quite interesting is the dynamics of losses. Typically, job terminations in downturns are associated with higher losses.[17] 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, wage losses decreased for job losses during the pandemic in comparison to the pre-Covid-19 levels, whereas employment losses are of a similar magnitude. 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

[16] Even though our algorithm was not trained on short tenured workers at smaller firms, we nevertheless believe that these predictions are accurate. In Gulyas and Pytka (2020) we show that earnings losses do not change much with tenure and firm size. Thus, as long as there is no strong non-monotonicity just below the conditioning thresholds, the results should still be accurate.

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

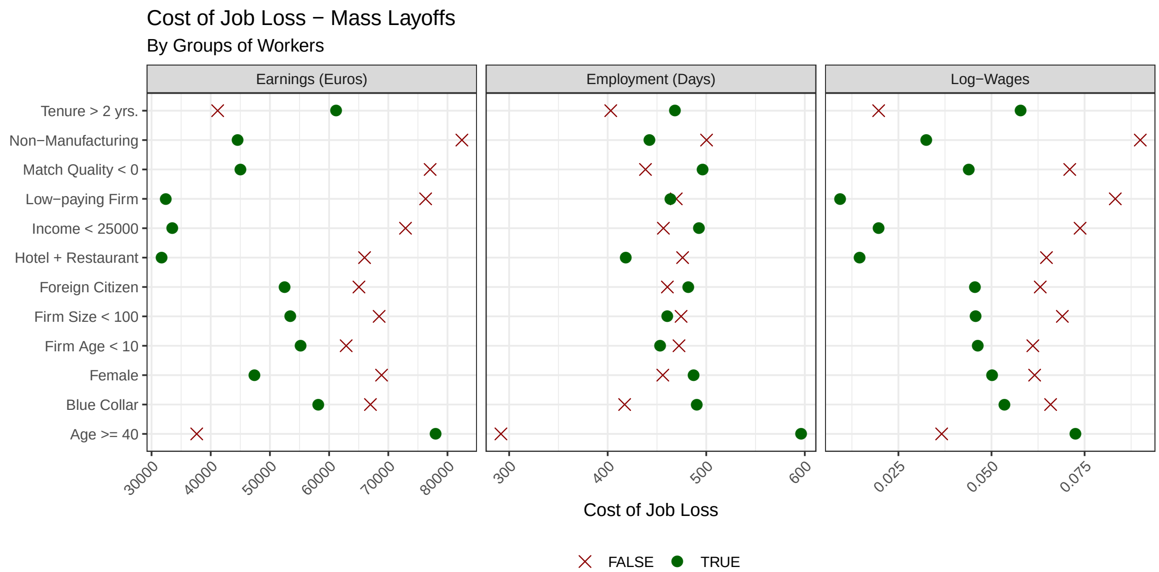

Figure 2: The figure shows the estimated cost of job losses for different groups of workers. Subgroups indicated by green dots experienced larger increases in UI claims, see Figure 1. Sample consists of UI claimants pooled over all samples conditional on mass-layoff, see text for definition. Estimated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

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 4 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 suggests less human capital being destroyed and 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 at the beginning of the COVID-19 crisis 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 workers. 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.[18] 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. 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. In addition, as shown in Gulyas and Pytka (2020), firm wage premia is the most important factor in explaining earnings losses in general. Furthermore, recent layoffs were more common for smaller and younger firms, which are typically financially less stable companies.[19] 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. 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

[18]See e.g. Krueger and Summers (1988).
[19]A similar finding was made by Alstadsæter *et al.* (2020) for Norway.

another quarter suffered permanent wage declines 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 at the same time their heterogeneity across different workers stayed almost the same. The smaller dispersion in wage losses is likely a reflection from the fact that 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, 27% 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). In general, depending on the welfare criteria of the policy maker and budgetary generosity of the intervention optimal trees might

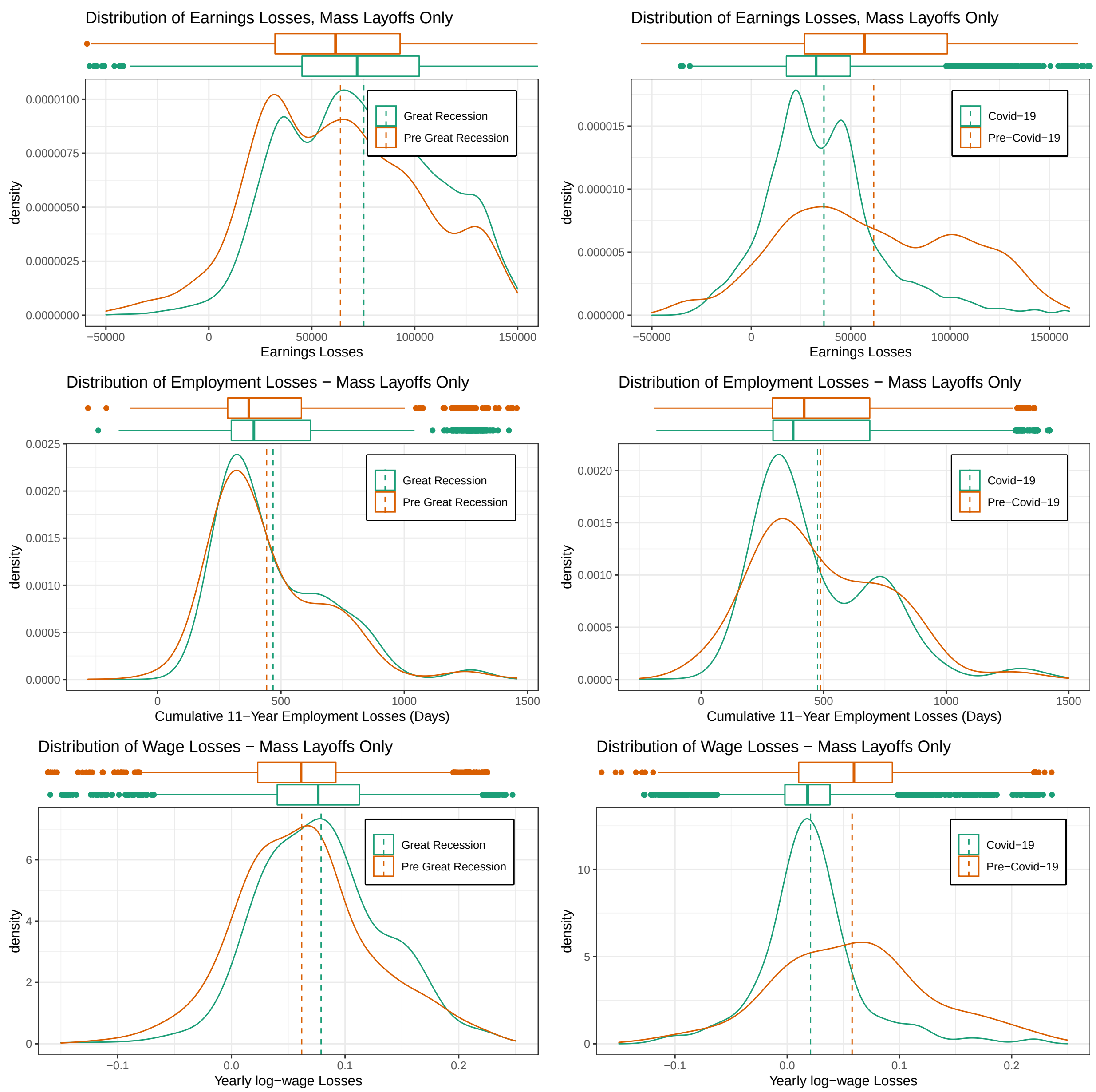

Figure 3: The figure shows the distribution of predicted earnings losses for UI claimants between March and May 2020 and 2019. Only UI claims from mass layoffs, see text for definition. Predicted earnings losses from a generalized random forest. On the top of each panel there is a boxplot with quartiles and outliers. Dashed lines show means.

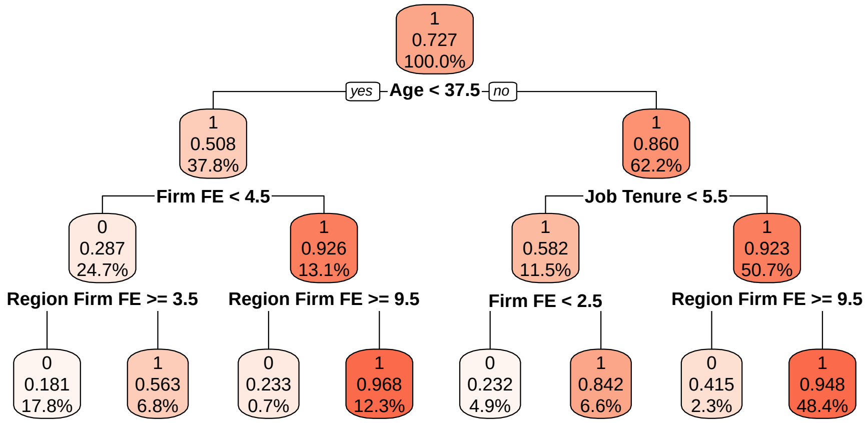

Figure 4: Classification tree classifying individuals with wage losses. On the top there is the most common value. A fraction of observations with wage losses in a node is reported in the middle. A fraction of observations in the global sample is shown in the bottom there.

look different. That being said, we decided to focus on wage loss due to its persistency.[20]

In the considered time window of the Pandemic Recession, 5,801 workers were displaced in mass-layoff events. Using our methodology we identified 4,219 individuals with losses in log wages and 1,582 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 3.[21] Figure 4 shows the generated classification tree. 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 87.55% is very good. 92.44% of individuals with positive wage losses are detected correctly.[22] Workers who are classified by our tree for targeting are expected to suffer a wage declines by 3.52 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 decision tree further also reveals more about the underlying channels of

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

[21] This also rules out problems of overfitting.

[22] 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.

earnings losses. The first split that improves the prediction power the most goes according to workers' age. We can see that 86% of people older than 37 incur positive wage losses and for younger people it is only 50.8%. This shows that wage losses are more common among older workers. Amongst younger workers what really matters is the interaction of the rank on the job ladder of the displacing firm and the regional average of firm rents at other employers. Most of young people ($100\% - 28.7\% = 71.3\%$) fired from firms with below median firm wage premia will find better paying jobs. On other hand, young displaced people who used to work at firms with firm FE equal or greater than the median value will have bigger problems with finding better or equally paid jobs. Only people living in regions with particularly high firm wage premia (the top decile) can expect a higher new wage. By and large, the observed wage losses dynamics of young workers follows mean reversion in firm rents and can be understood by a simple job-ladder search model rather than by human-accumulation models.

Most workers aged above 38 face wage declines after displacement. It can improve their wage situation under two scenarios. First, older workers with relatively short job tenure at low-paying firms can expect wage increases. In this group of people, only 23.2% will suffer wage losses, which is very different than the initial 86% of the all older workers. Alternatively, older workers with a longer job tenure employed in the best paying regions can find jobs with better wages. That being said, the improvement is more modest than in the former scenario.

Our application shows that not only does the policy tree detect workers who are actually facing wage losses, but its structure also provides guidelines about which type of programs should be implemented. Firm wage premia (both firm- and region-level) appear in splits for both younger and older workers, which points toward falling of the firm-quality ladder as an important factor for earnings losses. Recent research shows that extended unemployment duration support workers to find better paying jobs (Nekoei and Weber, 2017; Farooq *et al.*, 2020). Thus, extending UI benefits, perhaps especially in regions with lower average firm wage premia would be beneficial. Moreover, job tenure matters more strongly for older workers, as it does not appear in the decision rule for younger workers. This suggests that younger workers are better at recouping lost job-specific human capital than older workers. Therefore, policies that focus on avoiding the destruction of job specific human capital could be targeted rather at older workers. This could be achieved by, *e.g.*, increasing severance pay for older workers with above-median job tenure tenure, bailing out firms for keeping those jobs, or introducing targeted short-time work schemes. Nonetheless, given that job losses are more concentrated at smaller and younger firms which are likely financially more vulnerable, creating an additional burden through severance pay might be counterproductive.

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 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.

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) young workers displaced from employers with high wage premia in areas with relatively low firm rents and (ii) older workers with long job tenure. Consequently, while all workers would benefit from UI extension giving more time to find similarly well-paying jobs, bailouts or short-time work schemes should be targeted rather at preserving jobs at well-paying firms and of older workers.

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A. Appendix

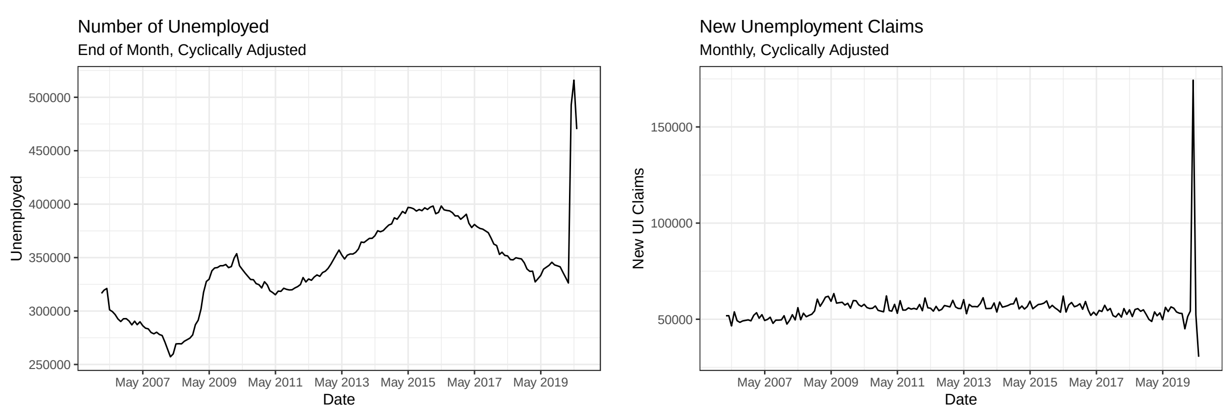


Figure 5: Evolution of number of unemployed and number of UI claiments in Austria. Authors calculation using AMDB data.

Table 2

	2007	2009	2018 & 2019	Covid-19
New UI Claims	224,525	293,987	103,160	114,852
Mass Layoffs (Share)	0.014	0.031	0.017	0.051
Austrian (Share)	0.764	0.746	0.680	0.609
Blue-Collar (Share)	0.651	0.640	0.524	0.646
Female (Share)	0.405	0.388	0.496	0.521
Age (yrs)	37.270	37.646	38.187	39.580
Manufacturing (Share)	0.133	0.211	0.128	0.096
Hotel & Restaurants (Share)	0.118	0.101	0.144	0.281
Firm-Tenure (yrs)	2.382	2.889	2.784	3.108
Income t-1 (Euros)	22,901.310	25,393.100	23,124.120	22,699.300
Firm Size	304.478	335.102	481.374	273.374
Firm Wage Premium	-0.065	-0.039	-0.094	-0.202
Match Quality	0.018	0.022	-0.101	-0.165
Regional Firm Wage Premium	0.004	0.003	0.013	0.007

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 June 10th.

Table 3

	2007	2009	2018 & 2019	Covid-19
Mass Layoffs	3,110	9,170	1,768	5,801
Austrian (Share)	0.751	0.750	0.745	0.486
Blue-Collar (Share)	0.526	0.690	0.446	0.844
Female (Share)	0.439	0.270	0.457	0.462
Age (yrs)	40.819	41.404	42.380	42.001
Manufacturing (Share)	0.293	0.586	0.323	0.091
Hotel & Restaurants (Share)	0.037	0.023	0.036	0.437
Firm-Tenure (yrs)	6.773	7.211	7.056	5.311
Income t-1 (Euros)	32,864.000	36,045.530	32,342.460	26,539.360
Firm Size	385.386	203.966	388.734	208.087
Firm Wage Premium	0.065	0.108	0.006	-0.130
Match Quality	0.021	0.081	-0.048	-0.193
Regional Firm Wage Premium	0.015	-0.005	0.013	0.010

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 June 30th.

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:

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

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.[23] 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.

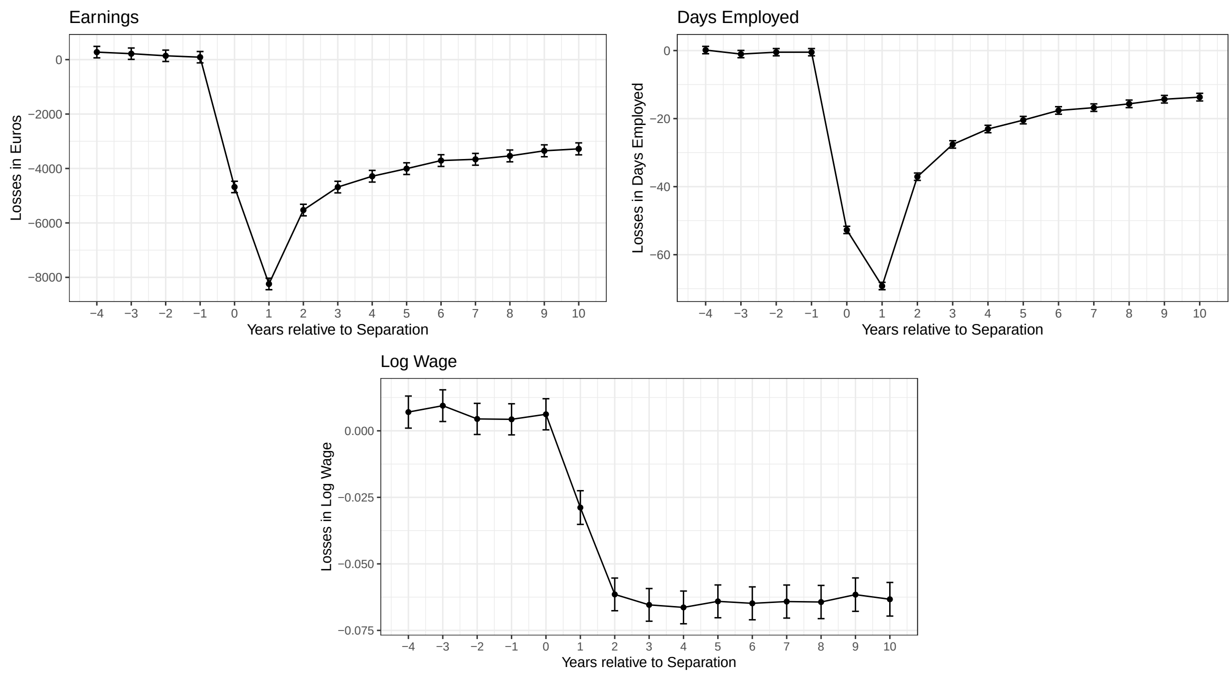


Figure 6: Earnings Losses of displaced workers - Eventstudy regression estimates of Equation (4). Period 0 corresponds to the separation year. Earnings and days employed are computed for the whole year, log wages are computed as the log average daily wage from the employer on 1st January. Control group is selected via propensity score matching.

[23] 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. Causal Random Forest: Machine-Learning Algorithm

We reinforce our estimation procedure with a machine-learning algorithm. The purpose of the algorithm is to detect underlying heterogeneity of displacement costs as a function of some observables. To this end we adapt a generalized random forest proposed by Athey *et al.* (2019) to a difference-in-difference setup. While the whole algorithm is explained in Gulyas and Pytka (2020) including all technical details, here we focus on presenting a general intuition. This allows the reader to understand the reason for implementing the employed technique and to interpret the presented results in the main body of the article. The presentation of the method is carried out in three steps. First, we show how a single tree is grown. Next, we extend the analysis to a generalized random forest. Eventually, we discuss how weights used in estimation of Equation (3) are derived from the structure of the grown forest.

Building a single tree consists in partitioning the dataset into smaller subsamples in which individuals exhibit similar earnings losses and at the same time the differences in earnings losses between subsamples are maximized. The data fragmentation is carried out using a sequence of complementary restrictions on explanatory variables. Due to the computational complexity, a top-down, greedy approach is traditionally used. The procedure of building a tree can be characterized in the recursive way by Algorithm (1). In each data partition (called also a node or a leaf) the scarring effect is estimated from Equation (3) separately.

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:

$$(\tau_l - \tau_r)^2 \frac{n_l \cdot n_r}{N^2}, \tag{5}$$

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 (5) 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, $\mathcal{P}$.

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.

Finally, 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.[24] 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 8.4 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 6.5 and 10 log points) and prior to the Covid-19 episode firing firms were paying at the market average (0.6 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.[25]

[24] 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.

[25] 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.

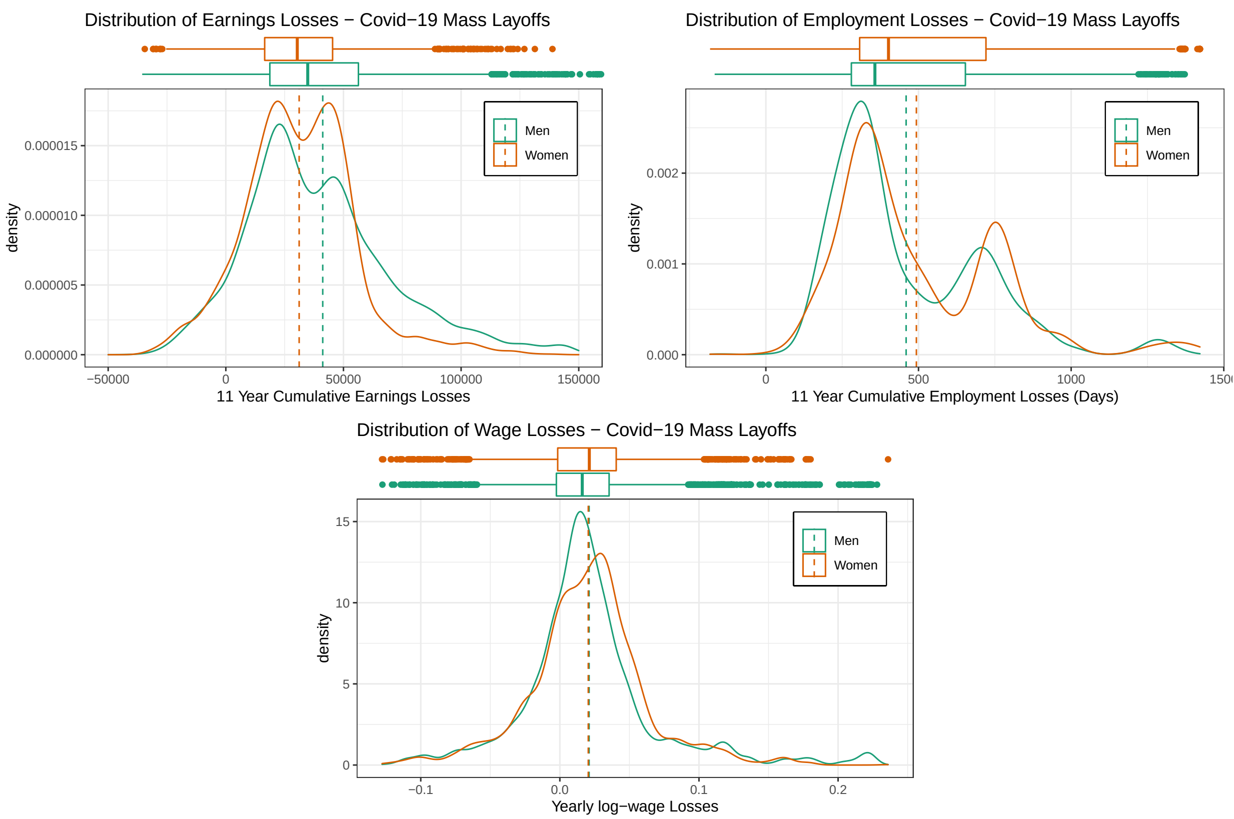
Table 5: Worker and Job Characteristics by Earnings Losses - Mass Layoffs Only

	Tercile 1	Tercile 2	Tercile 3
Earn. Losses	8,129.881	32,945.980	68,609.880
Empl. Losses	292.391	440.510	692.165
Wage Losses	-0.014	0.020	0.057
Blue Collar	0.825	0.879	0.827
Austrian	0.441	0.431	0.586
Manufacturing	0.036	0.082	0.213
Female	0.499	0.523	0.364
Age	32.185	42.476	51.346
Job Tenure	3.777	4.502	7.655
Number of Employers	4.208	5.759	7.506
Firm Size	220.122	207.957	196.176
Match Quality	-0.261	-0.285	-0.032
Firm Wage Premium	-0.187	-0.120	-0.084
Avg. F. Wage Premia	0.021	0.009	0.001
Herfindahl Index	0.014	0.019	0.025
Industry UE-Rate	0.163	0.176	0.149
Regional UE-Rate	0.098	0.098	0.103

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	20.32%	6.95%	27.27%
Positive	5.5%	67.23%	72.73%
Sum	25.82%	74.18%	100.00%

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

Table 6

	Male	Female
Mass Layoffs	3,120	2,681
Austrian (Share)	0.463	0.512
Blue-Collar (Share)	0.897	0.781
Age (yrs)	41.948	42.062
Manufacturing (Share)	0.094	0.087
Hotel & Restaurants (Share)	0.432	0.443
Firm-Tenure (yrs)	5.579	4.999
Income t-1 (Euros)	30,234.960	22,238.620
Firm Size	211.877	203.677
Firm Wage Premium	-0.108	-0.157
Firm Age	19.402	19.586
Match Quality	-0.076	-0.328
Regional Firm Wage Premium	0.016	0.003

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 June 30th.

F. Targeting Individuals with High Earnings Losses

Figure 8 depicts the generated tree. As can be seen, there are two groups with above-median earnings losses. The first group consists of workers older than 44 years located in all regions except those ones with the highest firm wage premia. In this group of people accounting for 41.6% of displaced workers, the overwhelming majority of 94.4% exhibit losses above the median. The second group consists of workers not older than 44 who were displaced from

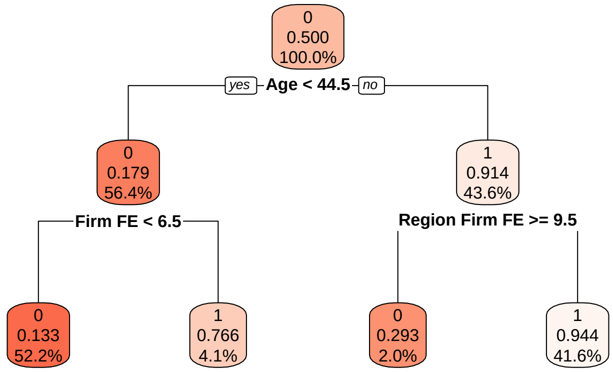


Figure 8: Classification tree predicting earnings losses above the median level. On the top there is the most common value. In the middle there is a fraction of observations with earnings losses above the median. In the bottom there is a fraction of observations in the global sample.

well-paying firms. This group is much smaller though. This very simple criteria allows us to classify 89% of displaced individuals correctly and to identify 85% of workers with high earnings losses.

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.

G. Analysis for all UI-claimants

Table 8: Consequences of job loss

	Pre Great Recession	Great Recession	Pre Covid-19	Covid-19
All				
Pre-displ Income	27,406.360	31,539.790	26,021.040	23,096.300
Earnings Losses (Euros)	52,472.090	61,604.280	46,831.620	30,430.350
Employment Losses (Days)	397.940	421.645	441.448	424.475
Log Wage Losses	0.042	0.058	0.029	0.003
Cor(Emp. Loss,Earn. Loss)	0.568	0.523	0.555	0.586
Female				
Pre-displ Income	21,541.330	23,293.290	21,209.190	19,733.050
Earnings Losses (Euros)	41,664.190	48,260.550	40,719.940	27,026.670
Employment Losses (Days)	407.914	444.923	447.935	446.302
Log Wage Losses	0.035	0.050	0.026	0.003
Cor(Emp. Loss,Earn. Loss)	0.549	0.497	0.569	0.614
Male				
Pre-displ. Income	31,024.620	34,542.240	29,585.510	26,020.150
Earnings Losses (Euros)	59,139.720	66,462.560	51,358.950	33,389.350
Employment Losses (Days)	391.786	413.169	436.643	405.499
Log Wage Losses	0.046	0.061	0.031	0.004
Cor(Emp. Loss,Earn. Loss)	0.617	0.570	0.560	0.606

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. Earnings and employment losses are cumulative over 11 year, while log-wage losses are average declines. Positive number imply losses, while negative numbers imply gains.

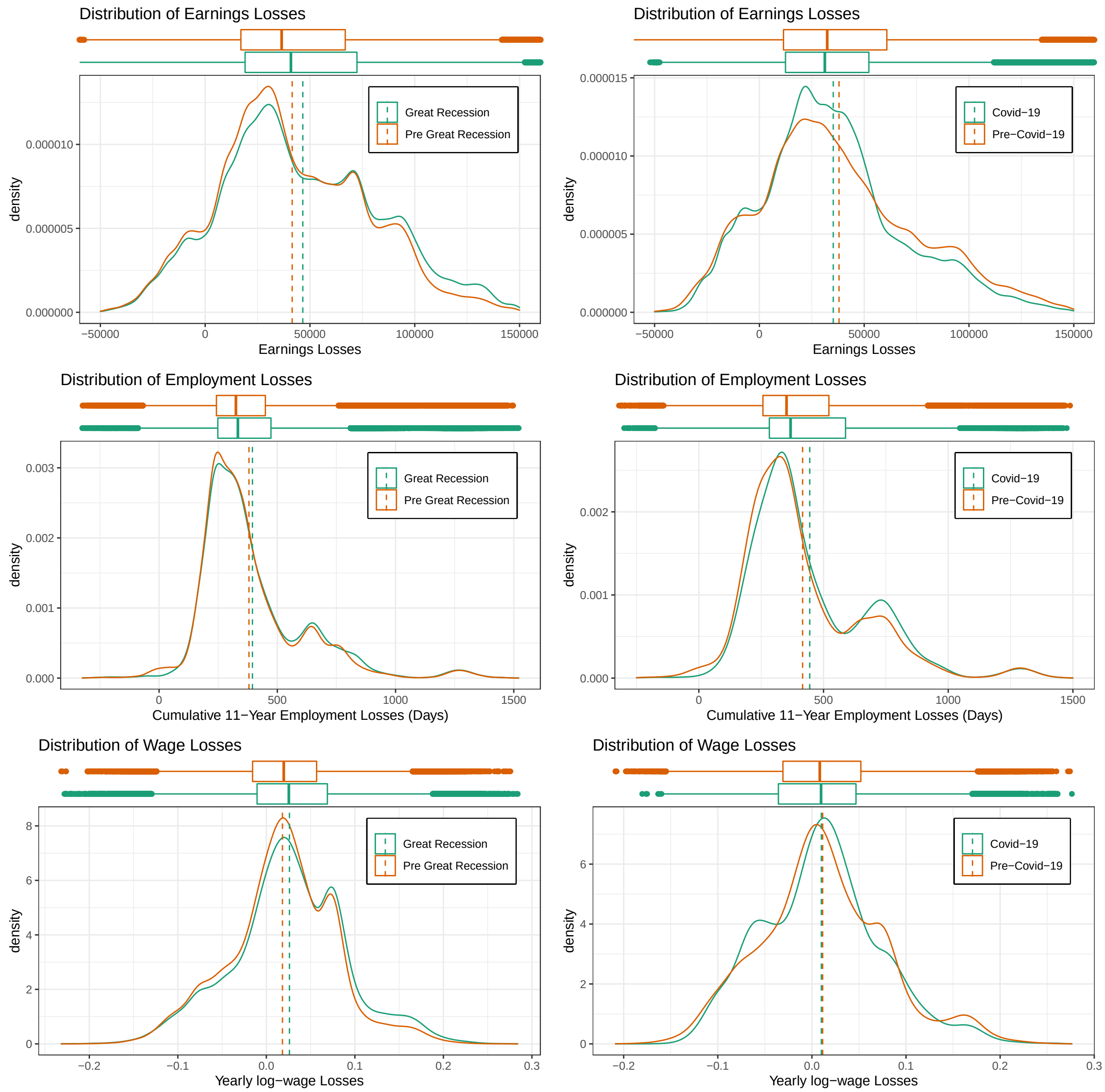


Figure 9: The figure shows the the distribution of predicted earnings losses for every UI claimant between March and May 2020 and 2019. Predicted earnings losses from a generalized random forest.

Figure 10

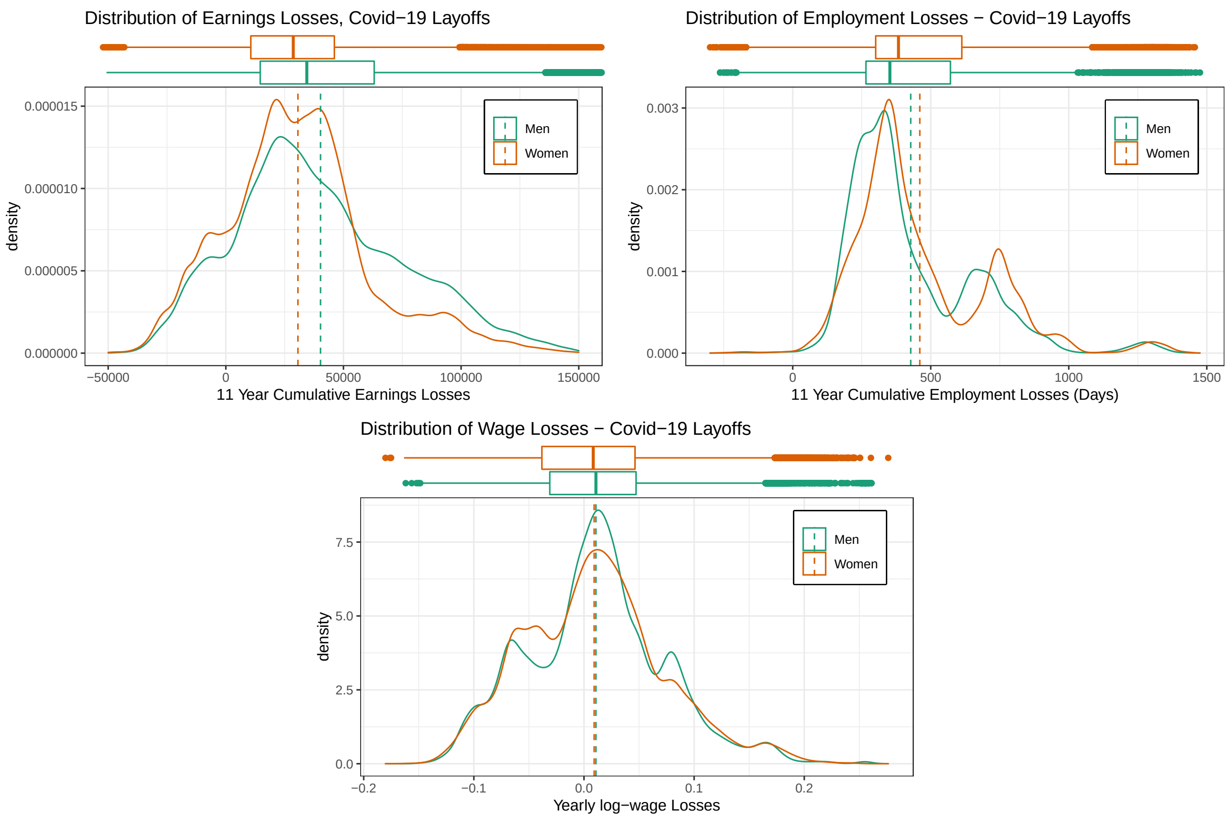

Distribution of Earnings Losses, Covid−19 Layoffs
Men
Women
density
0.000015
0.000010
0.000005
0.000000
−50000
0
50000
100000
150000
11 Year Cumulative Earnings Losses
Distribution of Employment Losses − Covid−19 Layoffs
Men
Women
density
0.003
0.002
0.001
0.000
0
500
1000
1500
11 Year Cumulative Employment Losses (Days)
Distribution of Wage Losses − Covid−19 Layoffs
Men
Women
density
7.5
5.0
2.5
0.0
−0.2
−0.1
0.0
0.1
0.2
Yearly log−wage Losses

Table 9

	Male	Female
UI Claimants	55,010	59,842
Austrian (Share)	0.564	0.651
Blue-Collar (Share)	0.736	0.563
Age (yrs)	39.262	39.873
Manufacturing (Share)	0.121	0.073
Hotel & Restaurants (Share)	0.256	0.305
Firm-Tenure (yrs)	2.996	3.211
Income t-1 (Euros)	26,651.690	19,066.060
Firm Size	251.529	293.453
Firm Wage Premium	-0.163	-0.237
Firm Age	17.125	18.115
Match Quality	-0.031	-0.289
Regional Firm Wage Premium	0.011	0.004

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 as of June 30th.

Table 10: Worker and Job Characteristics by Earnings Losses

	Tercile 1	Tercile 2	Tercile 3
Earn. Losses	647.539	$31,448.670$	$73,646.840$
Empl. Losses	287.036	447.208	599.715
Wage Losses	-0.041	0.008	0.063
Blue Collar	0.705	0.689	0.544
Austrian	0.551	0.576	0.701
Manufacturing	0.082	0.141	0.246
Female	0.563	0.573	0.427
Age	30.632	40.764	47.345
Job Tenure	2.048	2.740	4.537
Number of Employers	4.848	6.834	8.309
Firm Size	275.310	256.377	288.434
Match Quality	-0.240	-0.292	0.033
Firm Wage Premium	-0.311	-0.201	-0.094
Avg. F. Wage Premia	0.016	0.003	0.002
Herfindahl Index	0.020	0.023	0.028
Industry UE-Rate	0.133	0.139	0.118
Regional UE-Rate	0.100	0.103	0.104

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