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

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# Motivation

- Job loss has long lasting and persistent detrimental effects on workers' earnings
- Many policy interventions depend on severity of earnings losses
  - Unemployment insurance
  - Firm bail-outs
  - Short-time work subsidy schemes
- $\Rightarrow$ Important to predict long-term earnings losses at the onset of recessions

  & identify high loss individuals

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**This paper**

- Document changing composition of Covid-19 job losses in Austria
- Use machine-learning to predict earnings losses for Covid-19 job losses
- Contrast results to Great Recession

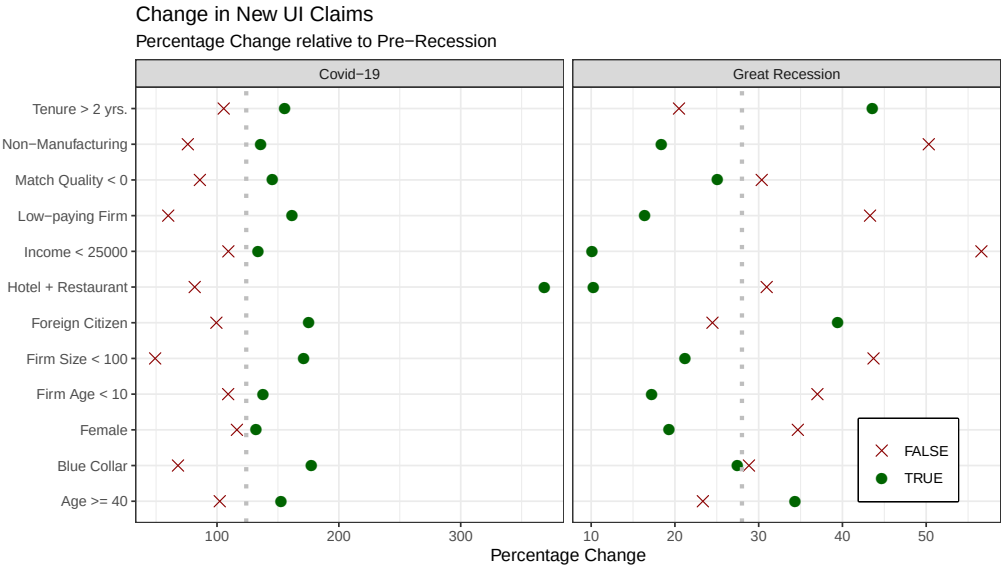
# Main Results

- Implement a **machine-learning algorithm** (Athey et. al. 2019) to **DiD setting**:
  $\Rightarrow$ Estimate causal cost of job loss as a function of worker and job characteristics
- Train machine-learning algorithm on universe of Austrian social security records from 1984-2019
- Composition of UI claimants during Covid-19 (until August 2020) compared to Great Recession is:
  1. worse paid, more female
  2. from younger, smaller, and lower paying firms
- Predicted labor market outcomes compared to Great Recession:
  1. Similar employment losses
  2. Lower earnings & wage losses

# Related Literature

- Effects of job loss:
  Jacobson et al. (1993), Davis and Von Wachter (2011), many more
- Composition of Covid-19 job losses
  (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), many more
- Machine-Learning in economics:
  Gulyas and Pytka (2020), Athey et al. (2019), and many others

# Composition of UI claimants



# Composition of UI claimants

- Gulyas and Pytka (2020) show substantial heterogeneity in earnings losses across individuals
- Covid-19 UI pool: more low paid workers in bad matches, more female, more hotel& restaurant, younger, smaller, worse paying firms
- UI pool very different compared to past recessions
  $\Rightarrow$ Will job-loss still have persistent long-term negative effects?
- Use machine-learning, i.e. random-forest for DiD estimate (Gulyas and Pytka, 2020)
- Trained on Austrian social security data 1984-2019
- Machine-learning algorithm takes into account worker & job characeristics + business cycle conditions

# Long-Term Consequences of Job Losses

| | Prior to Great Recession | Great Recession | Prior to COVID-19 | COVID-19 |
|---|---|---|---|---|
| Pre-displ. Income (Euros) | 33,281 | 35,229 | 33,255 | 26,600 |

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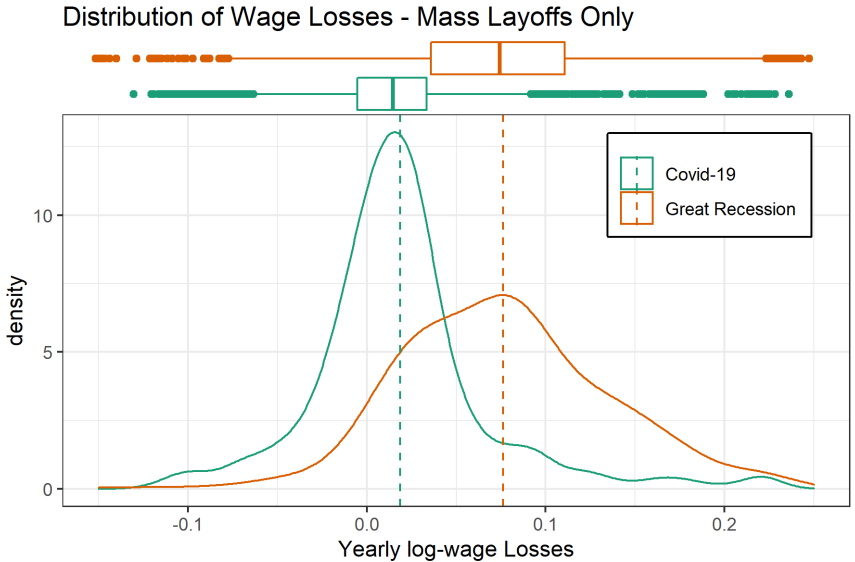
| 11-Year Earnings Losses (% of Pre-displ. Income) | 191% | 206% | 183% | 143% |
| 11-Year Emp. Losses (Days) | 439 | 476 | 494 | 478 |
| Log Wage Losses | 0.061 | 0.076 | 0.055 | 0.019 |

# Why Lower Earnings Losses?


⇒ All Covid-19 characteristics are associated with lower losses

# Distribution of Losses

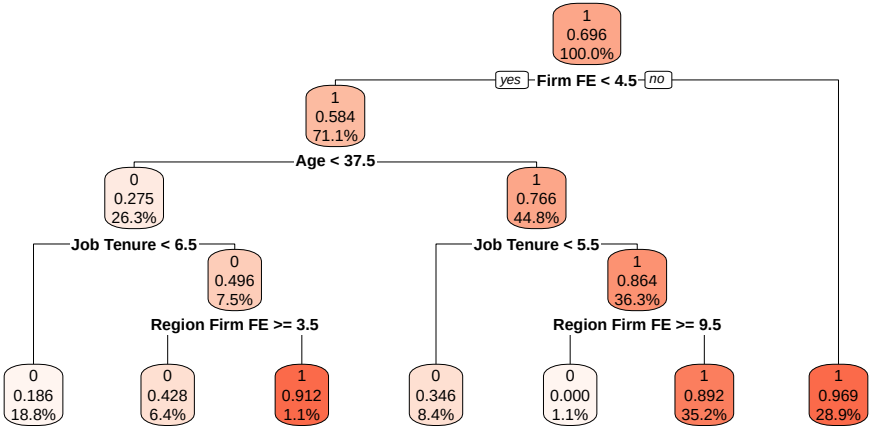


# Policy Tree

- Average long-term wage losses lower compare to "normal" times
- But many workers still are facing high losses
- Can we target high loss workers?

  (E.g. short-time work subsidies, firm bailouts, UI top-ups)
- $\Rightarrow$ Derive algorithmic policy tree targeting workers with long-term wage losses

# Policy Tree


1
0.696
100.0%
yes
Firm FE < 4.5
no
1
0.584
71.1%
Age < 37.5
0
0.275
26.3%
1
0.766
44.8%
Job Tenure < 6.5
0
0.496
7.5%
Job Tenure < 5.5
1
0.864
36.3%
Region Firm FE >= 3.5
Region Firm FE >= 9.5
0
0.186
18.8%
0
0.428
6.4%
1
0.912
1.1%
0
0.346
8.4%
0
0.000
1.1%
1
0.892
35.2%
1
0.969
28.9%

# Conclusions

- Document changing composition of UI claimants during Covid-19
- Use machine-learning to predict long-term losses
- Lower expected wage losses
- Derive policy tree to target high loss workers

**Estimate your own earnings losses:**

Link: `https://gulyas-pytka.shinyapps.io/general_audience/`

# References

Abi Adams-Prassl, Teodora Boneva, Marta Golin, and Christopher Rauh. Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, page 104245, 2020. ISSN 0047-2727. doi: https://doi.org/10.1016/j.jpubeco.2020.104245. URL http://www.sciencedirect.com/science/article/pii/S0047272720301092.

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