Understanding the Heterogeneity of Earnings Losses After Job Displacement: A Machine-Learning Approach

Andreas Gulyas and Krzysztof Pytka (U Mannheim)

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Motivation

- Job loss has long lasting and persistent detrimental effects on workers
- To design effective policy responses, we need to understand:
    1. How do earnings losses differ across individuals?
    2. What are the sources of large and persistent earnings losses?
    3. Why do earnings losses vary over the business cycle?

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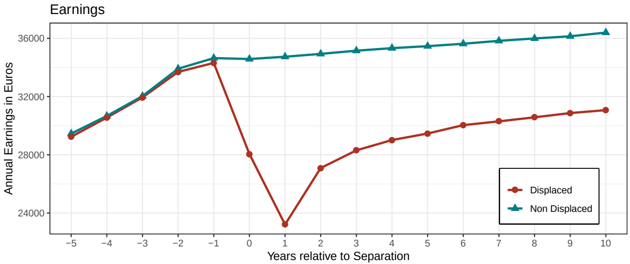
Big Data: Universe of Austrian social security records from 1984-2019



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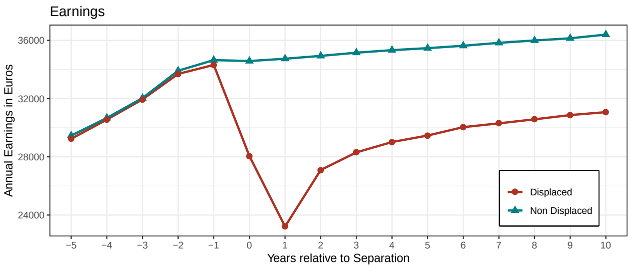

This paper

We use machine learning to answer all these & more questions

Methodology

Typical approaches for studying heterogeneity:

Structural models	➔	losses driven by *assumed* theories.
Reduced-form models	➔	cut by variables motivated by *assumed* theories.

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- Adapt a **machine-learning algorithm** (Athey et al. 2019) to **difference-in-difference setting**:

  $\Rightarrow$ Estimate causal cost of job loss as a function of worker and job characteristics + SE

Methodology

- How do earnings/employment/wage/firm wage losses vary across individuals?
- Conceptually, we estimate

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

Sample construction

- Goal: Estimate how causal cost of job loss varies with explanatory (partitioning variables) z, i.e. $\tau(z)$
- Explanatory variables: Firm wage premia (AKM), firm separation rate, job tenure, recession indicator, regional factors, firm characteristics, match effect (residual), socio-demographics

Contribution to the Literature

- Estimate large and persistent earnings losses for Austria

  Jacobson et al. (1993), Davis and Von Wachter (2011), Halla et al. (2018)

- Comprehensive study of channels behind losses

  Lachowska et al. (2020), Schmieder et al. (2020)

- Provide guidance for structural models

  Burdett, Carrillo-Tudela, and Coles (2020); Jarosch (2021); Gregory, Menzio, and Wiczer (2021)

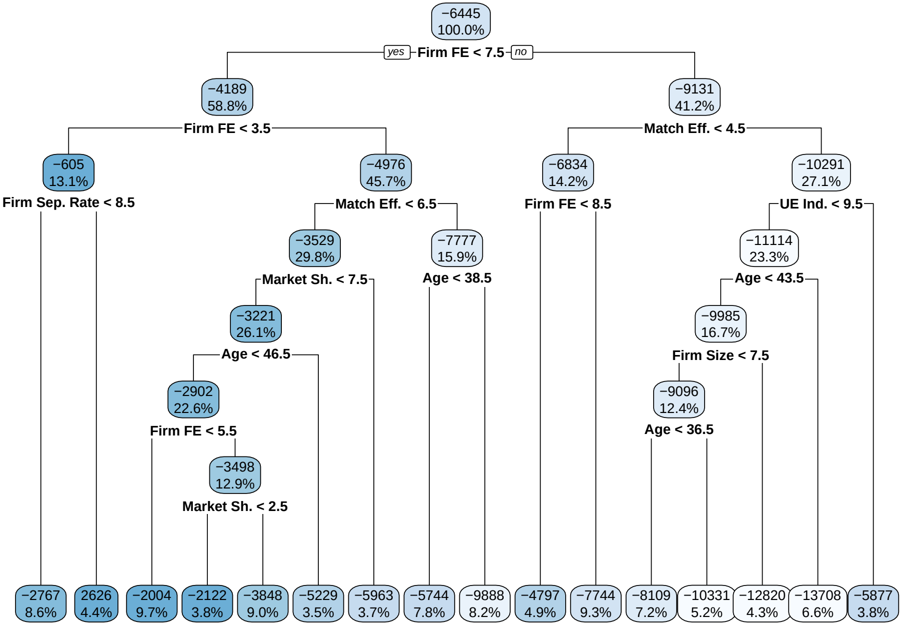
- Machine-Learning in economics:

  Athey et al. (2019); Athey and Imbens (2016)

Preview of the Main Results

- Large differences in earnings losses across individuals:
    1. A quarter of workers lose 30% on average in terms of wages
    2. A quarter of workers gain on average
- Jointly estimate how losses vary with 18 variables ⇒ **Horse-race** between theories
- Most important factor: **Firm wage premia** (AKM)
    - Explains **42%** of **variation** in log-wage losses
- Earnings losses are cyclical:
    1. 90% explained by **Composition Effect**: Different workers lose jobs in booms/recessions
    2. 10% explained by **Pure Recession Effect**: Identical workers face higher losses in recessions
- Gender differences fully explained by composition
- Implications: Labor market policies aiming to mitigate cost of job loss should be **targeted** and rather **time-invariant**

Causal Tree



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Match Eff. < 4.5
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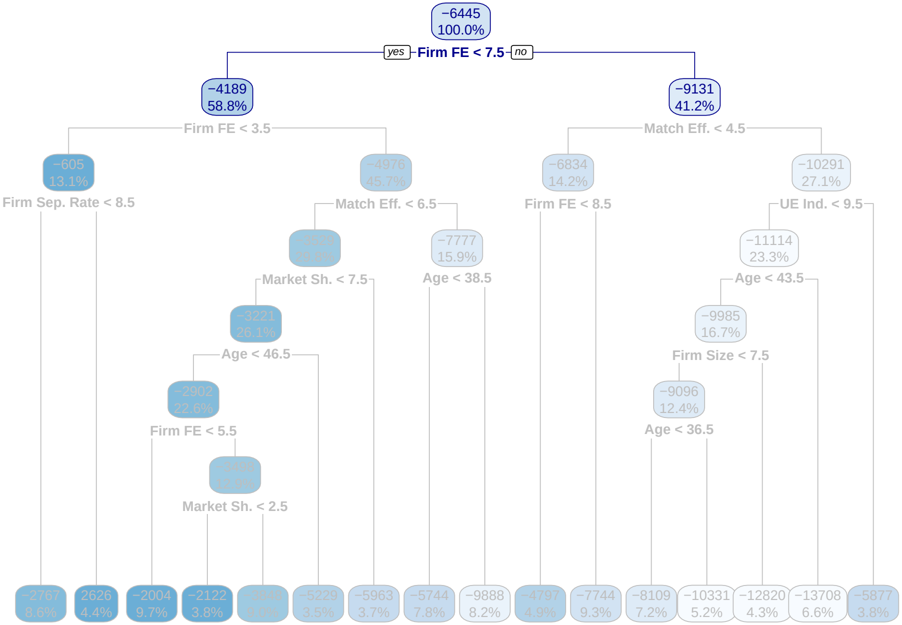

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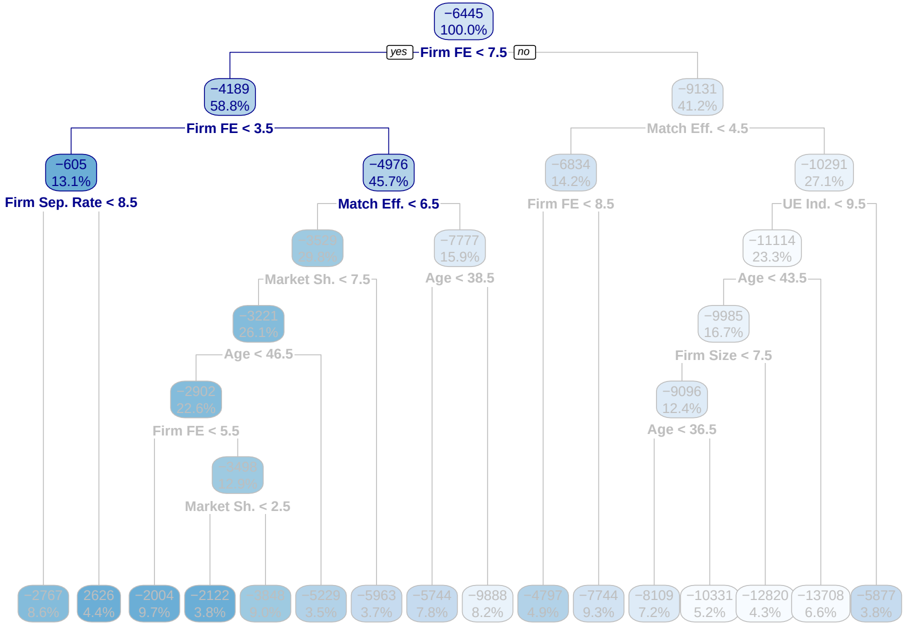
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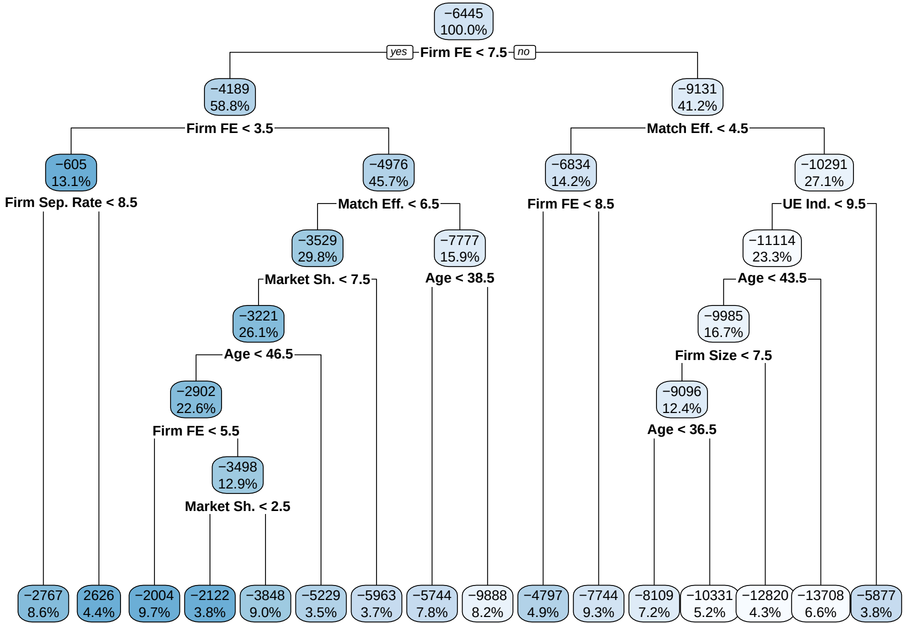
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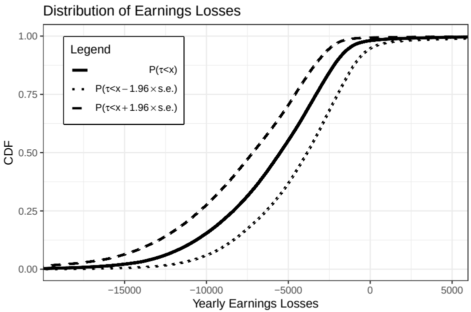
Random Forest

- One single tree has high variance, might be subject to overfitting
- $\Rightarrow$ Random Forest as ensemble of many (10,000) trees
    1. Sample 50 % of observations from dataset
    2. "Honest" estimation (Athey et al., 2019)
    3. Sample $\approx$1/3 of partitioning variables
    4. Grow tree as described before

Heterogeneity in Earnings Losses



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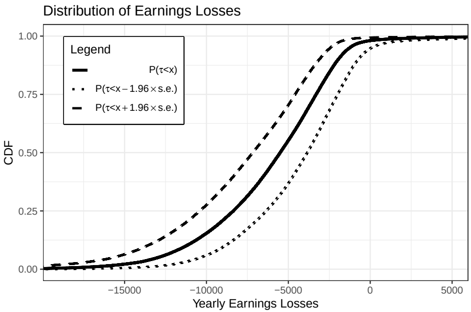
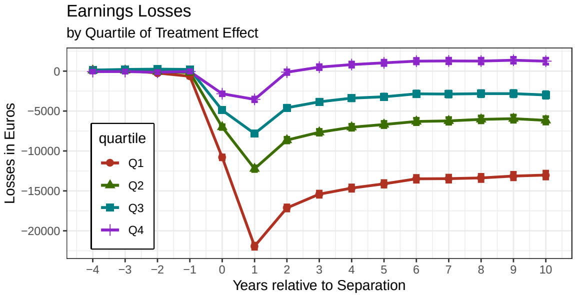
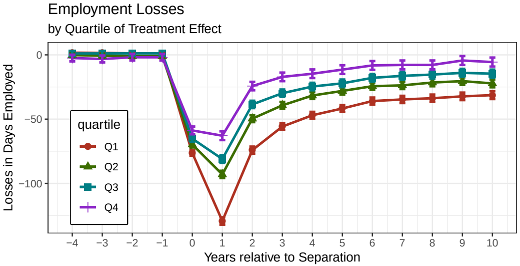
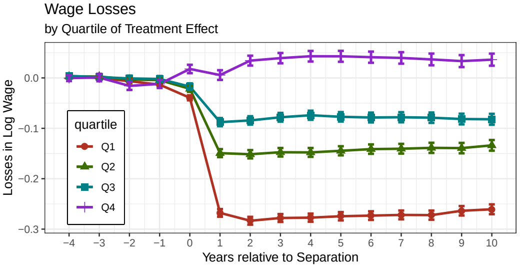




Heterogeneity in Earnings Losses: Wages and Employment

Individuals stacked by *quartiles of identified earnings losses.*





Comparative statics

- Now we know that indeed there is heterogeneity in earnings losses.

  But can we say anything about the drivers of those losses?
- Varying one channel at a time. All other variables fixed at their median.

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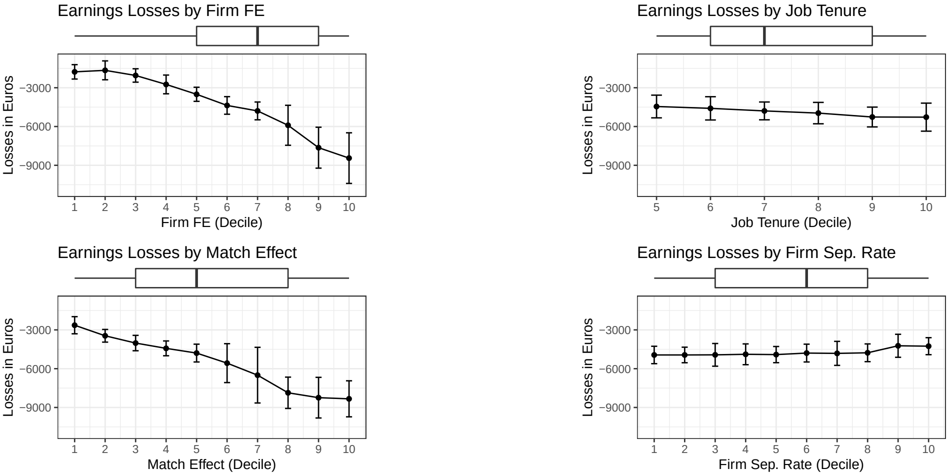
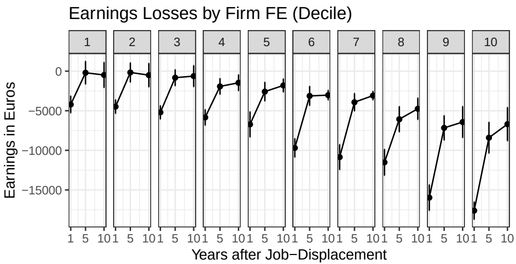


Losses in Earnings & Employment by Firm FE



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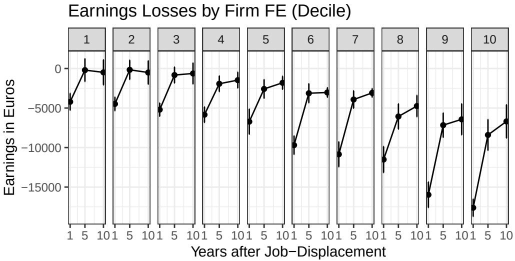
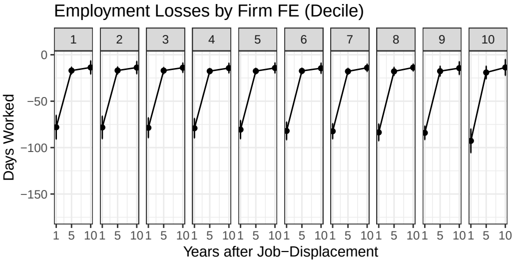
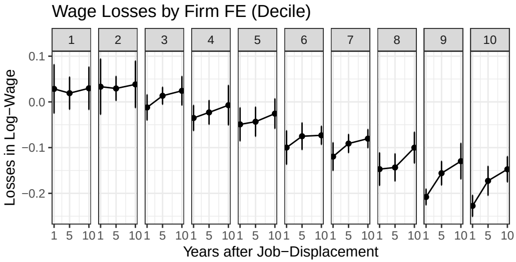




- Steep slope in earnings losses by Firm FE
- No variation in employment losses

Losses in Wages & Firm FE by Firm FE



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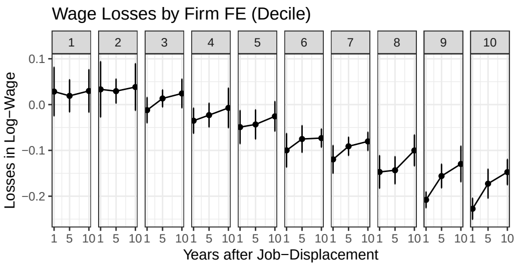
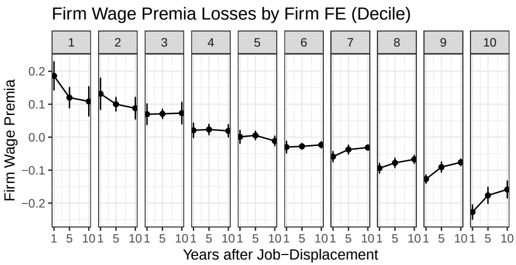
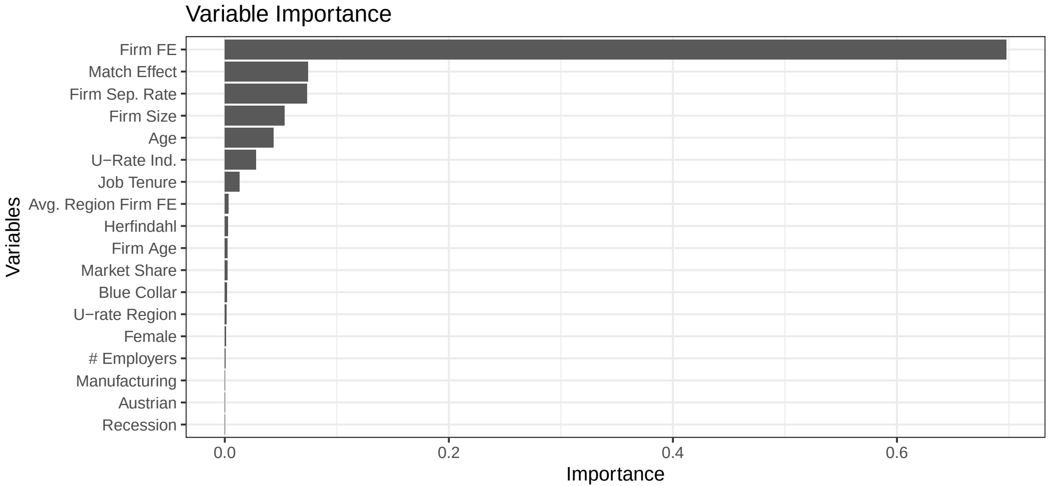




- Long-term earnings losses due to wage losses
- Workers from low paying firms see wage *gains*
- Mean reversion in firm pay

Variable Importance for Earnings Losses

Firm Wage Premia first order



Cyclicality of Losses

- Many labor market policies are enacted/extended in recessions:
  - Extended UI benefits in US
  - Firm bail-outs
  - Short time work subsidies
- Motivation: job loss has been shown to be more costly in recessions

  Davis and Von Wachter (2011), Schmieder et al. (2020)
- Is it the effect of recessions, or is it compositional differences of displaced workers?

Recession effect vs. compositional difference

Cyclicality of losses, $\int \tau(z|rec = 1)\mathrm{d}F(z|rec = 1) - \int \tau(z|rec = 0)\mathrm{d}F(z|rec = 0)$, can be decomposed in two ways:

1. recession distr.:

$$\underbrace{\int [\tau(z|rec = 1) - \tau(z|rec = 0)]\, \mathrm{d}F(z|rec = 1)}_{\text{Recession effect}}$$
$$+$$
$$\underbrace{\int \tau(z|rec = 0)\mathrm{d}F(z|rec = 1) - \int \tau(z|rec = 0)\mathrm{d}F(z|rec = 0)}_{\text{Compositional difference}}$$

2. expansion distr.:

$$\underbrace{\int \tau(z|rec = 1)\mathrm{d}F(z|rec = 1) - \int \tau(z|rec = 1)\mathrm{d}F(z|rec = 0)}_{\text{Compositional difference}}$$
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$$\underbrace{\int [\tau(z|rec = 1) - \tau(z|rec = 0)]\, \mathrm{d}F(z|rec = 0)}_{\text{Recession effect}}$$

		Recession Effect		Composition	
	Difference	Level	Share	Level	Share
Recession dist.	-513.35	-60.00	0.12	-453.34	0.88
Expansion dist.	-513.35	-54.66	0.11	-458.69	0.89

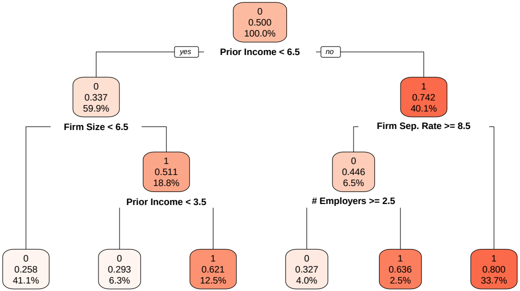
Policy Targeting

- Suppose the govt. wants to detect displaced individuals with relative wage losses above the median level.
- According to GDPR (2016/679), all people have the right to explanation, *i.e.* "meaningful information about the logic involved" in automated decisions. For this reason:
    - we project the identified log-wage losses through our forest on a single policy tree;
    - we exclude four partitioning variables *that may be difficult to understand by most people*:
        i. firm wage premia,
        ii. regional average firm wage premia,
        iii. concentration of the labor market,
        iv. and workers' match effect.

Policy Targeting (cont'd)

The algorithm detects 3 groups of individuals with high relative losses:

- Middle-income individuals displaced from larger firms.
- High-income individuals displaced from not the riskiest firms.
- High-income individuals with low job-mobility displaced from the riskiest firms.



Conclusions

- Use machine learning to understand sources of earnings losses
- Document substantial heterogeneity
  (much more than linear interactions or quantile regression)
- Losses in firm wage premia most important channel
- Cyclicality of losses driven mainly by the compositional effect
- Labor market policies should be targeted, and time-invariant

Estimate your own earnings losses:

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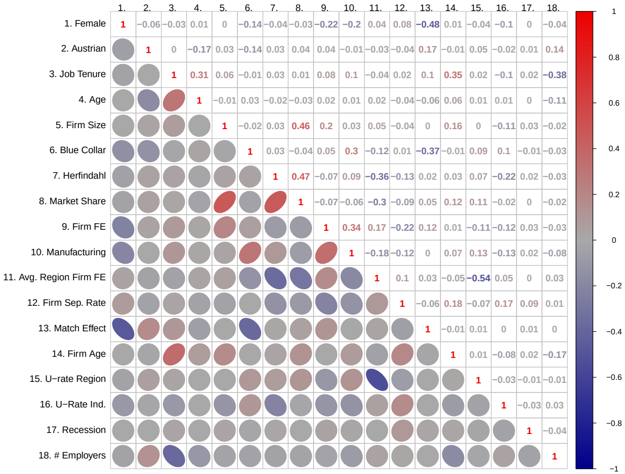
Thanks for your attention!

Sample Construction

- Universe of Austrian social security data 1984-2019
- Definition mass layoff event:
  1. Firm size declines by $\geq$ 30 %
  2. Firm size $\geq$ 30 employees
  3. Exclude fast growing firms before mass layoff, and firms that bounce back in size
- Sample Restrictions:
  1. Male & female workers
  2. Worker age: 25-50
  3. Job tenure $\geq$ 2 years
- Control group selected via propensity score matching

Correlogram of pre-displacement characteristics



Why to keep confounding factors fixed? (illustrative example)

- Imagine a simple economy with two sectors: *production* and *services*.
- There are equally numerous groups of workers: *high-school* educated and *college educated*.
- There is sectoral sorting:
  - 20% of the high-school educated work in services and 80% in production.
  - 80% of the college educated work in services and 20% in production.
- *Cognitive Booster Pills* increase cognitive productivy. Higher marginal effect for HS educated and services.

Table 1: Productivity increase after Pills

	Production	Services
High School	\$1.0	\$10
College degree	\$0.7	\$7

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This simple accounting ignores compositional differences!

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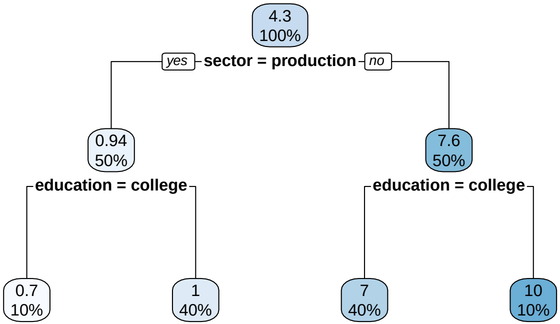

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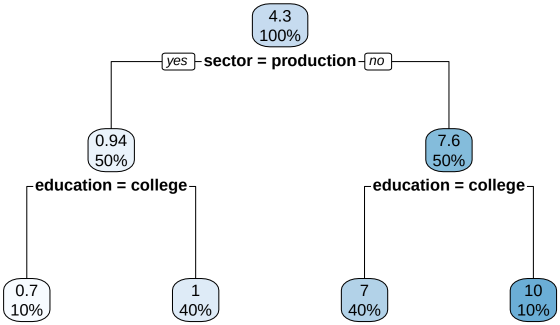

Case with two dummies is (intentionally) trivial. Real-world problems become more and more complicated if there are more variables. Which variables should be kept fixed and which can be ignored? ➔**task for the ML algorithm!**

Why do we need Machine Learning at all?

- Why not use interaction effects (or subsample estimations)?
- Which interaction effects to include?

  20.8 trillion! (20.8×10^{12}) possible interaction effects with our 18 variables
- Typical approach in the literature: Sample split, i.e. short vs long tenure

  Issue: tenure likely correlated with many other characteristics
- We estimate losses by varying one factor at a time, holding all other factors constant at the median.

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