Adjusters and Casualties:
Anatomy of labor market distress

Eric Hanushek, Simon Janssen, Jacob Light, Lisa Simon

Introduction

- Large literature on worker displacement
- Heterogeneity of effects – age, education, gender, firm characteristics, industry, occupation, regulations, business cycle
- **Key analytical question**: what would have occurred without displacement?
- **Standard approach**: event study/DID with nondisplaced workers
    - Average losses by heterogeneous circumstances
- **Our approach**: matching/synthetic controls to trace full distribution of losses

Representative existing literature

- **Overall closures:** Jacobson et al. (1993), Couch and Placzek (2010), Schmieder et al. (2010), Gulyas and Pytka (2022)
- **Education:** Schwerdt et al. (2010), Hanushek et al. (2017), Farber, 2017)
- **Gender**: Illing et al. (2021)
- **Tenure**: Chan and Stevens (1999), Chan and Huff Stevens (2001)
- **Worker-firm match**: Moore and Scott-Clayton (2019) Fackler et al. (2021), Graham et al. (2023), Lachowska et al. (2020)
- **Firm characteristics**: Fackler et al. (2021)

- **Country-specific institutions**: Bertheau et al. (2022), Janssen (2018)
- **Business cycles**: Davis and von Wachter (2011), Schmieder et al. (2023)

Summary of results

- Loss distributions are **bi-modal**
  - Outliers drive average losses
  - 20 percent experience no loss
- Observed characteristics explain little
  - Education, age, gender explain < 2 percent
  - Firms have some, but limited impact
- **Adjusters** and **casualties** respond very differently

Data and empirical strategy

Data

- Integrated Employment Biographies (IEB) [Germany]

- Firm closures
  - West Germany
  - 2000-2005
  - Firms with >50 workers

- Workers
  - Age 21-55
  - 2 years firm tenure
  - 5 years pre-displacement earnings
  - Nonemployment (out of labor force, self-employed, government) – retained with 0

Synthetic control approach

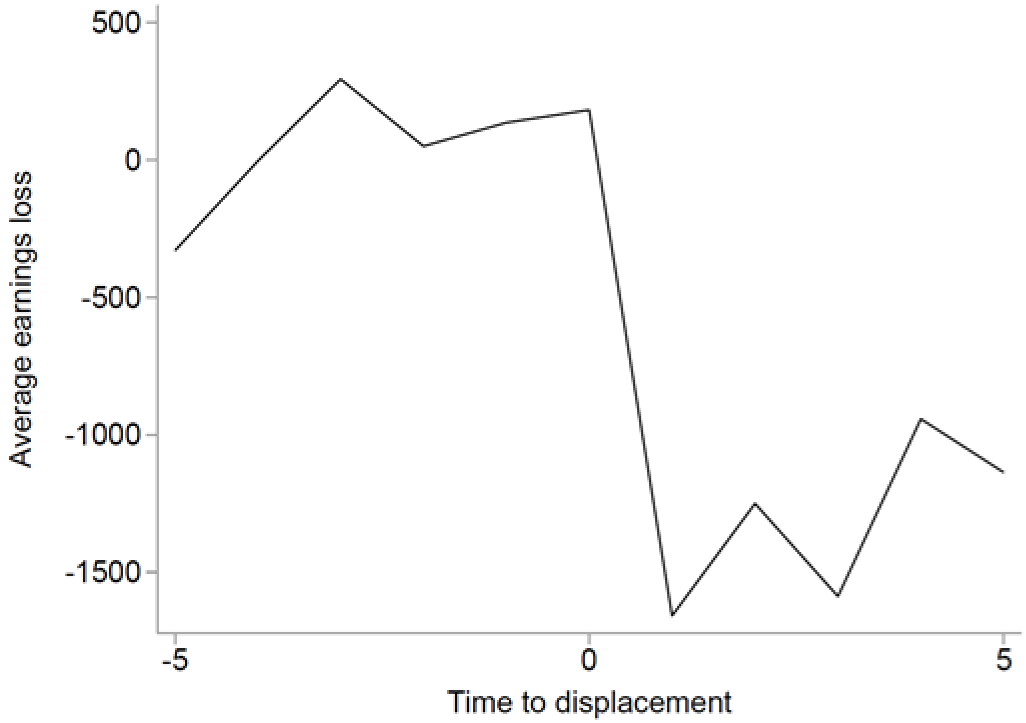
1. Identify displaced workers
2. Establish donor pool for each worker
    - Group nondisplaced by gender-education-occupation-industry
    - Select 20 workers with lowest RMSQ error in pre-closure income
3. Create synthetic control based on four-year pre-closure income
4. Calculate earnings losses for five years post-closure
5. Repeat #2 to #4 for each displaced worker (≈16,000)

Results

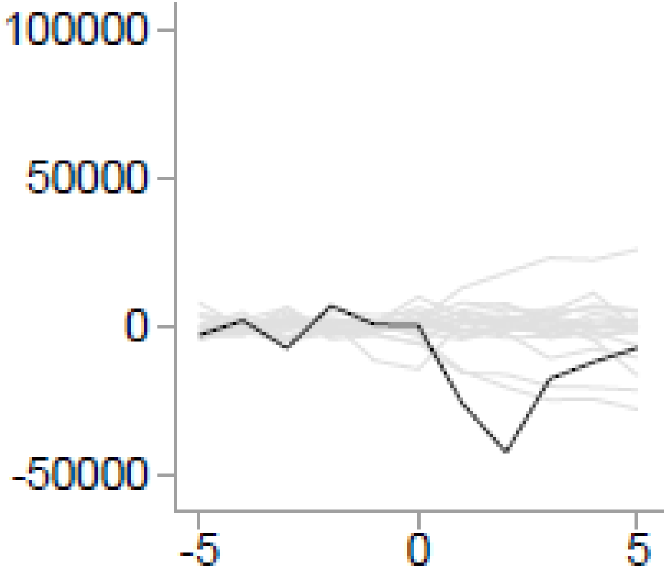
Example: estimating SCs for a small manufacturing firm

- Manufacturing of refractory ceramic material and goods
- 30 employees
  - All men
  - 10 w/o degree; 20 w/ apprenticeship degree
- Mixed occupations
  - 24 in occupation for industrial process and plant engineering for ceramic materials
  - 5 machine builders
  - 1 accountant

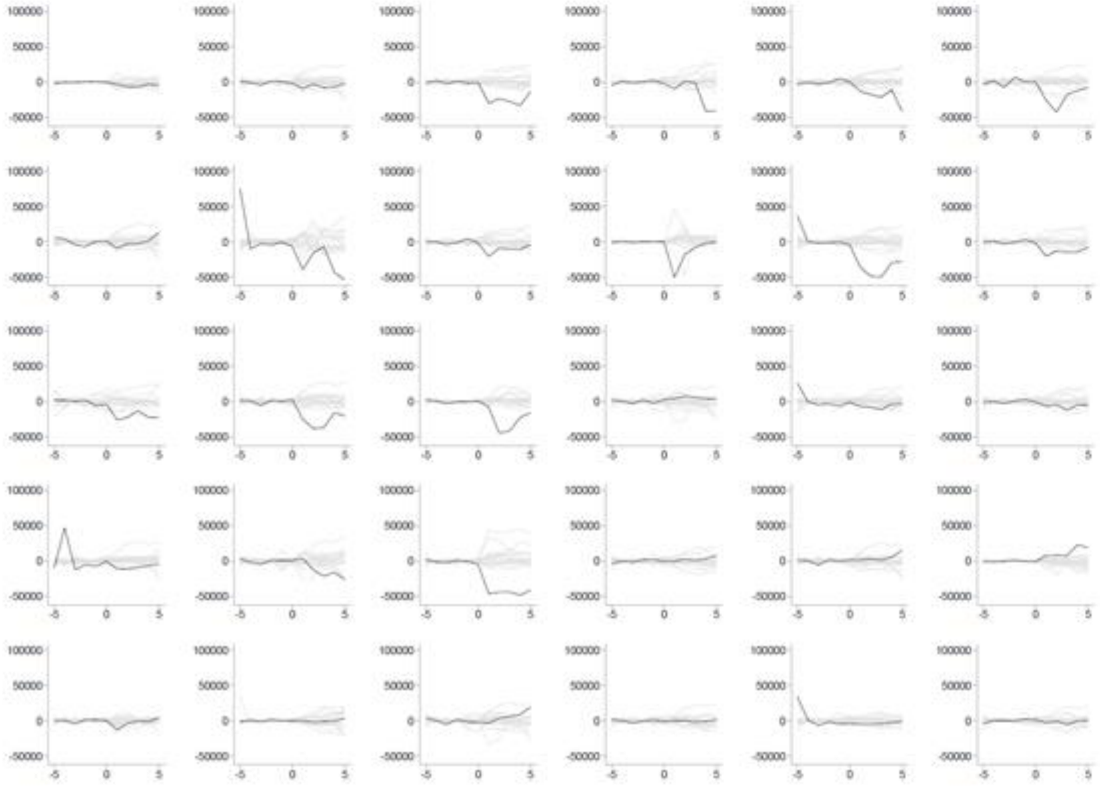
Average earnings losses in small manufacturing firm



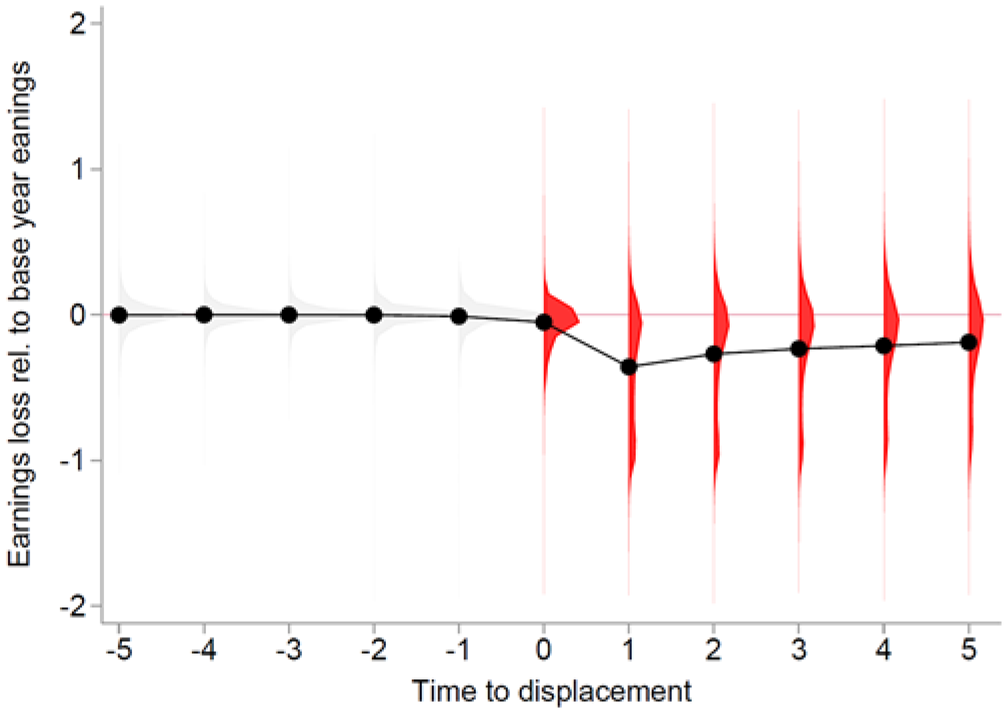
Estimates of earnings losses for an individual worker



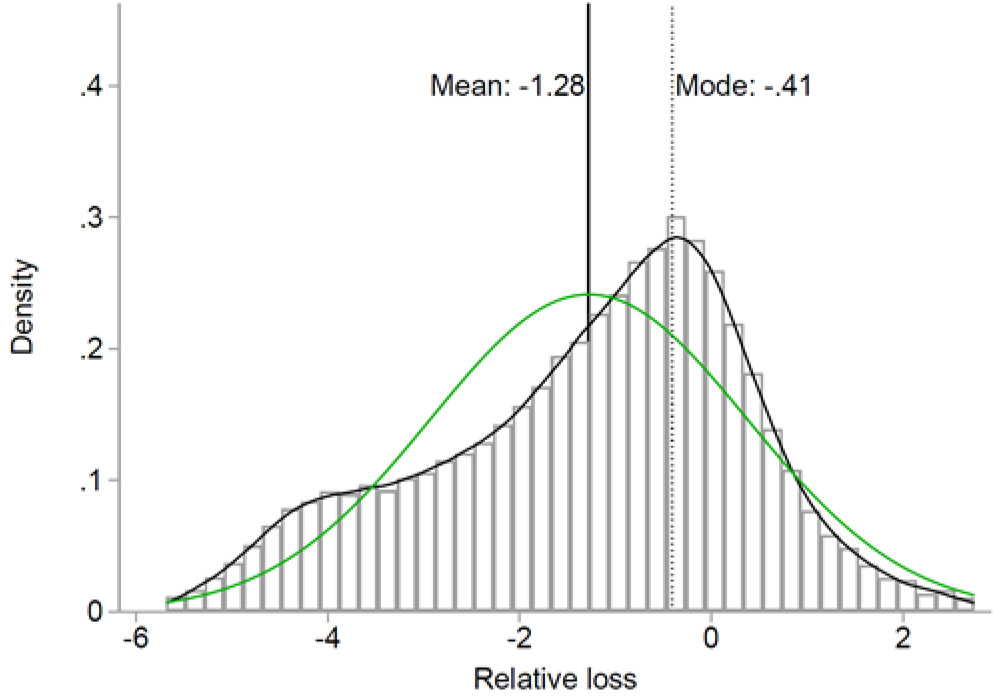
Substantial heterogeneity in earnings losses estimates for workers at sample firm



Main result: large variance in estimated earnings losses following firm closure



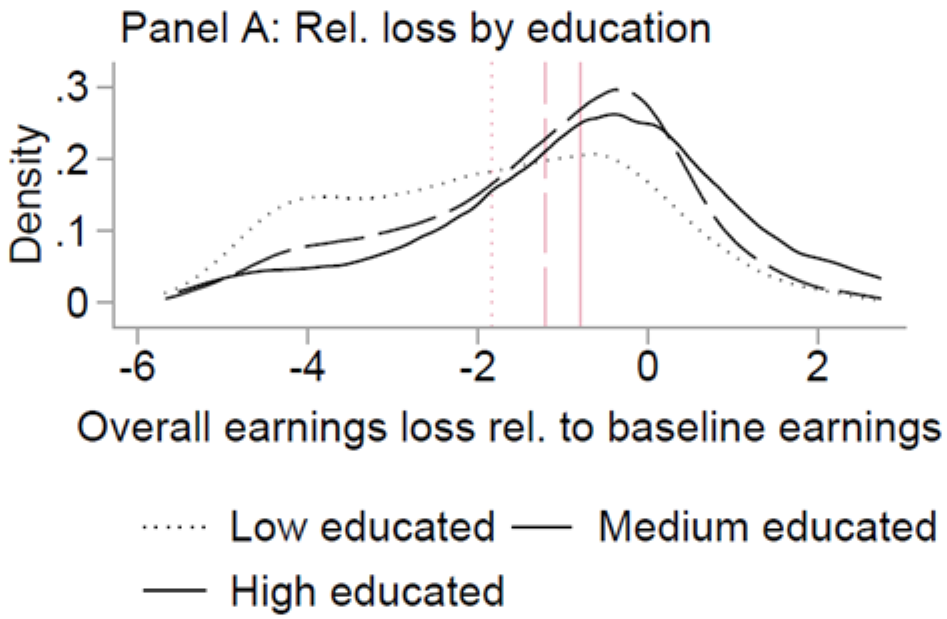
The distribution of cumulative earnings in the five years post-layoff is not normal



Note: relative loss measured as earnings losses normalized by the worker's earnings in the year before firm closure.

Observable characteristics explain little of the variation in earnings losses following firm closure

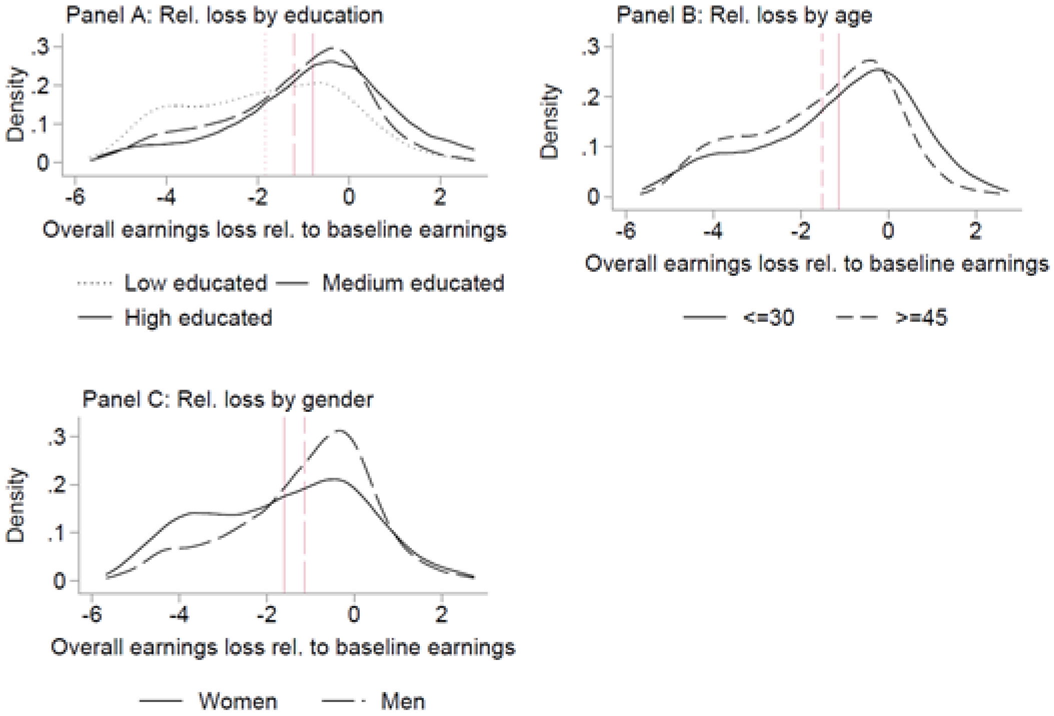
Average losses are heterogeneous across groups, but distributions overlap substantially



- Average cumulative earnings losses greater for less-educated workers
  - Low educated: 1.9 years
  - Medium educated: 1.2 years
  - High educated: 0.8 years

- Substantial overlap in *distributions* of losses

Average losses are heterogeneous across groups, but distributions overlap substantially



- By age:
  - Older: 1.5 years
  - Younger: 1.14 years
- By gender:
  - Female: 1.6 years
  - Male: 1.15 years

Fixed worker characteristics cannot explain variation in earnings losses

- Variance decomposition to disentangle portion of cumulative five-year earnings losses explained by fixed worker and firm characteristics:

Pre-closure firm

Municipality

$$Y_i = X'_{i(-1)}\beta + \theta_{i(-1)} + \vartheta_{i(-1)} + r_{i(-1)} + u_{i(-1)}$$

Worker characteristics

Pre-closure occupation

$$\begin{aligned} Var(Y_i) = & Var(X'_{i(-1)}\hat{\beta}) + Var(\hat{\theta}_{i(-1)}) + Var(\hat{\vartheta}_{i(-1)}) + Var(\hat{r}_{i(-1)}) + \\ & 2Cov(X'_{i(-1)}\hat{\beta}, \hat{\theta}_{i(-1)}) + ... + 2Cov(X'_{i(-1)}\hat{\beta}, \hat{r}_{i(-1)}) + Var(\hat{u}_{i(-1)}) \end{aligned}$$

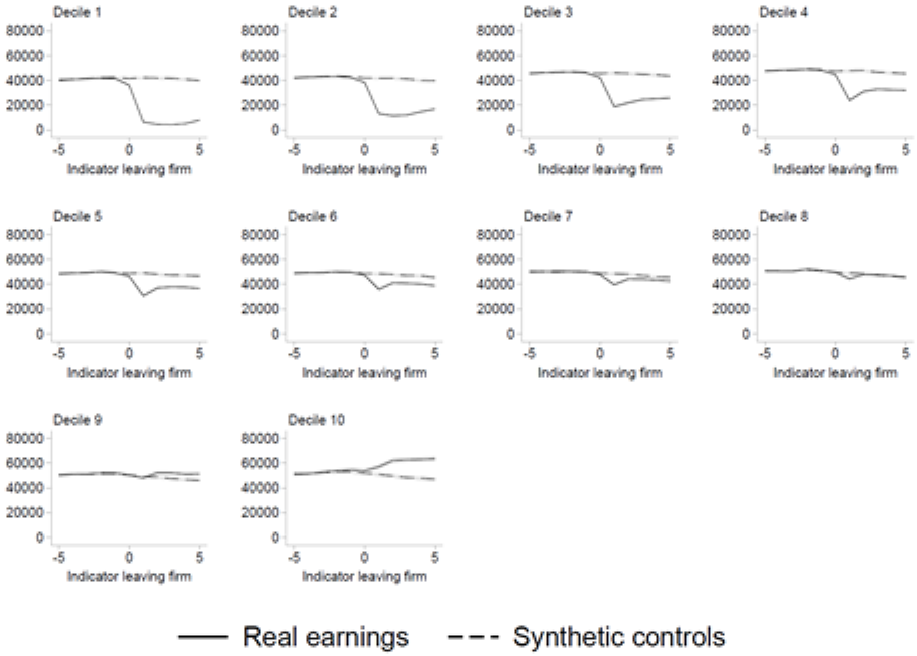
Fixed worker characteristics cannot explain variation in earnings losses

- Fixed individual and closing firm characteristics explain only **17%** of variance in earnings losses
  - Closing firm FEs explain the majority of this variation
- Observables explain **70%** of variance in counterfactual earnings → treated worker earnings losses not purely driven by noise in SC estimates

	Treated earnings losses
Individual char.	0.016
Education	0.001
Pre-displacement firm f.e.	0.125
Pre-displacement occupation f.e.	0.030
Pre-displacement region f.e.	0.006
Citizenship	0.006
Residuals	0.830
Covariances	-0.014
Total variance of loss	1.000

Adjusters and Casualties

Firm closure leads to winners and losers



- Split workers into deciles of accumulated five-year losses
- Parallel trends for all deciles of losses
- Workers in bottom 60% of losses never fully recover
- Top 20% come out ahead

Zoom in on **adjusters** and **casualties** based on cumulative earnings losses

- Split workers by quartile of cumulative five-year earnings losses (relative to SC)

- Focus on:
  - **Adjusters**: workers in the lowest quartile of earnings losses
  - **Casualties**: workers in the highest quartile of earnings losses

- Will show (not casual):
  - How these losses accumulate
  - How ex post margins of adjustment differ in these groups

Adjusters recover quickly, many earn higher wages

	Adjusters				
Years after closure	1	2	3	4	5
No wage					
Unemployed full year	1.1	0.2	0.2	0.2	0.4
Partial year employed	5.9	1.4	0.6	0.6	0.4
Wage loss > 50%					
Partial year employed	0.5	0.1	0.1	0.0	0.1
Full year employed	0.5	0.3	0.1	0.2	0.2
Wage loss 10-50%					
Partial year employed	2.4	0.4	0.2	0.3	0.4
Full year employed	8.2	5.7	3.8	4.5	4.7
Wage loss 0-10%					
Partial year employed	4.5	0.6	0.3	0.3	0.6
Full year employed	15.6	15.1	12.5	10.7	11.7
Wage gain					
Partial year employed	11.2	4.3	2.6	2.2	3.0
Full year employed	50.2	71.8	79.6	81.1	78.7

- One year after the firm closure, 75% are working full time and 61% earn a higher wage
- After 5 years, most adjusters are *better off* than would have been predicted absent the firm closure

Casualties struggle for years after layoff

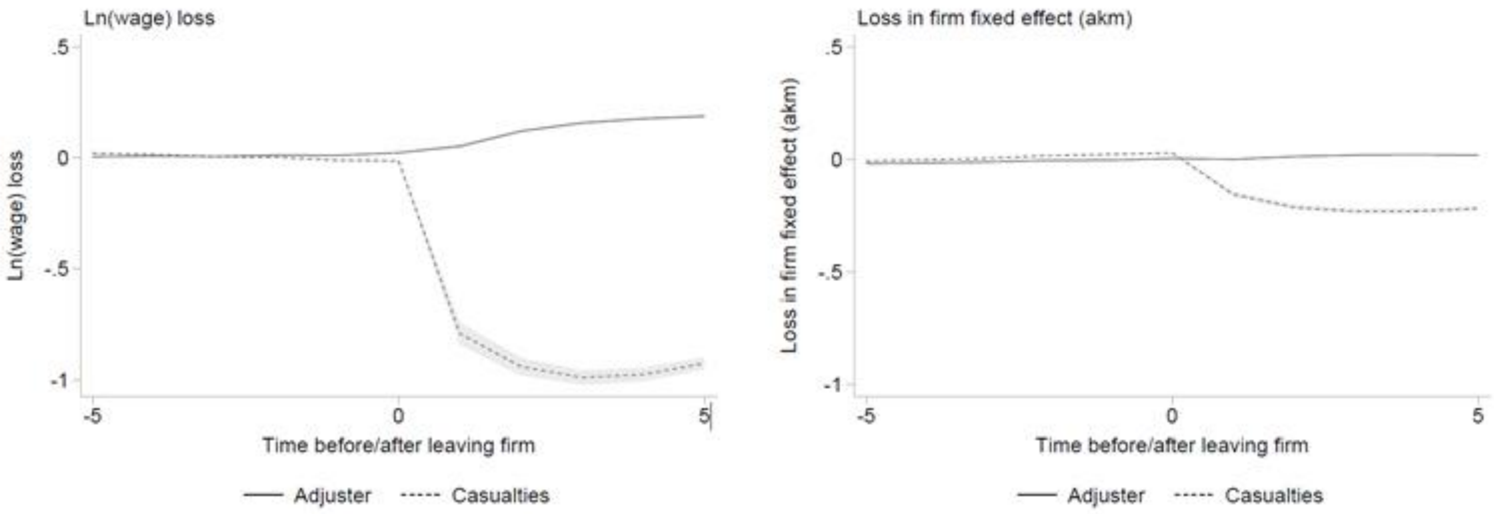
	Casualties				
Years after closure	1	2	3	4	5
No wage					
Unemployed full year	35.3	39.9	37.4	31.9	23.4
Partial year employed	31.6	15.4	9.2	7.1	5.6
Wage loss > 50%					
Partial year employed	5.8	8.6	8.4	8.1	8.2
Full year employed	4.4	10.3	17.0	21.1	23.7
Wage loss 10-50%					
Partial year employed	7.2	10.3	9.2	8.2	8.6
Full year employed	5.9	9.1	14.9	19.3	23.5
Wage loss 0-10%					
Partial year employed	2.3	1.9	1.4	0.9	0.6
Full year employed	1.9	1.1	0.9	1.0	2.1
Wage gain					
Partial year employed	3.1	2.0	1.2	1.0	1.1
Full year employed	2.5	1.4	0.5	1.3	3.2

- Initially: high rates of unemployment
- Over time: persistently depressed wages, partial employment
- Not just an unemployment story: 75% of casualties are in the lowest quartile of year 5 earnings

Are casualties systematically sorting to worse firms?

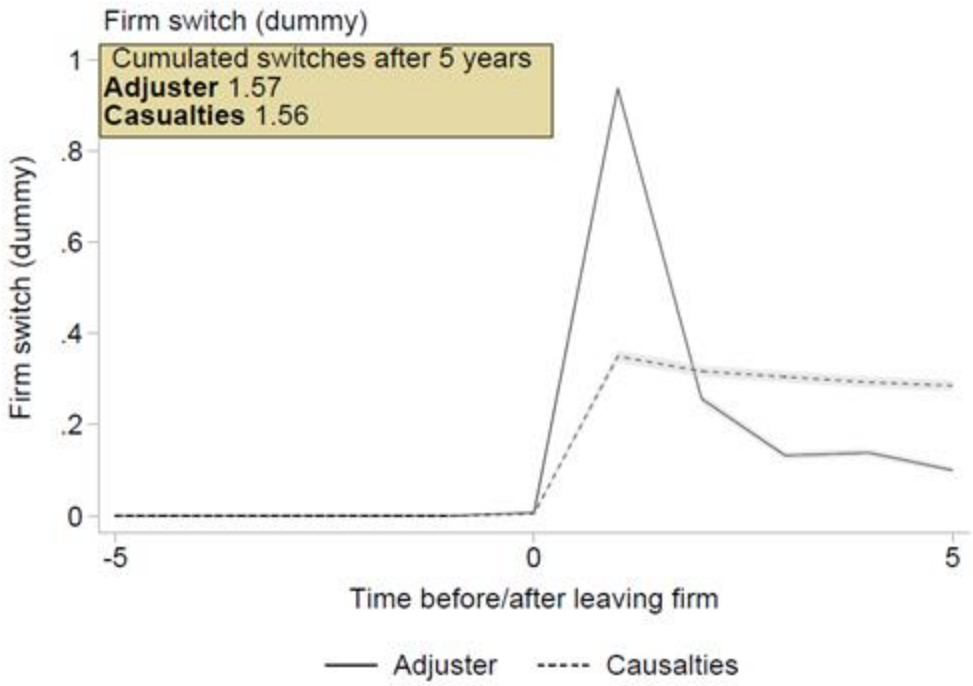
- Previous work: establishment effects account for a significant portion of wage losses (Schmieder et al. 2023)
- Goal: compare wage losses for adjusters/casualties to losses in firm AKM
    - Simulate counterfactual AKM path for each worker by applying synthetic control weights to donor AKM

Sorting across firms explains little of the wage differential between adjusters and casualties



- Casualties switch to lower-paying firms, on average
- Extreme wage losses cannot be explained by switching to lower-paying firms alone

Adjusters and casualties make adjustments at equal rates, but adjusters make adjustments immediately



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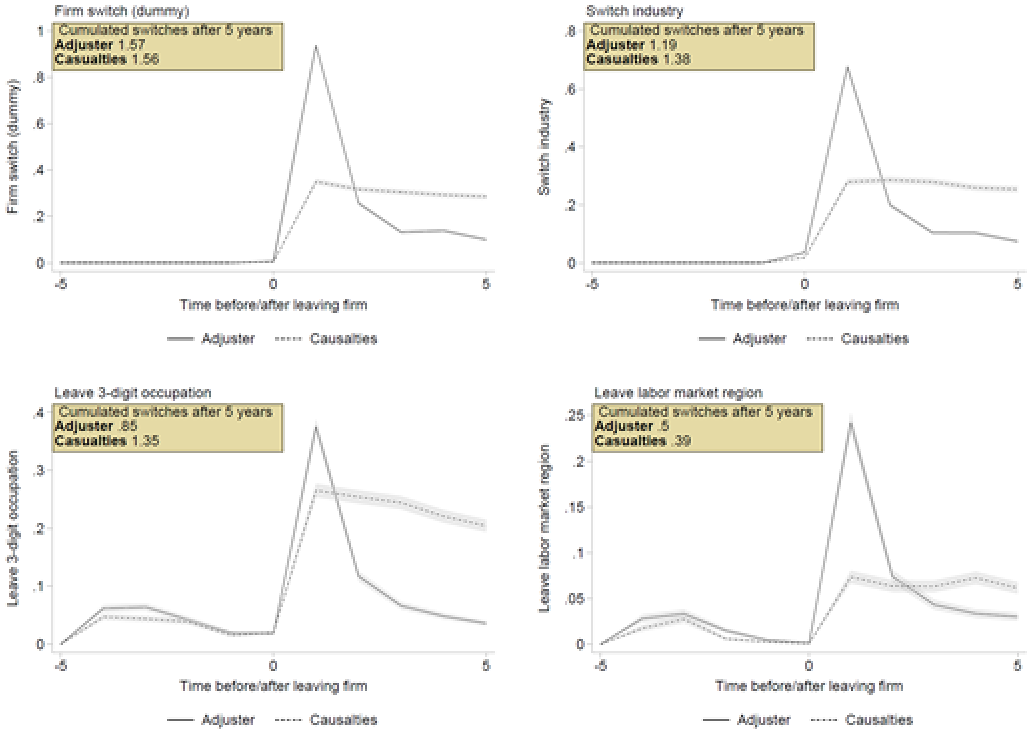

Additional analyses and robustness checks

- Adjuster/casualty results robust to comparing pairs of workers with identical characteristics who get laid off <u>from the same firm</u>

- **Education updating**: no effect

- **Trade exposure**: modest source of heterogeneous earnings losses

- **Early leavers**: are not systematically better off than workers who stay until the firm closes

Conclusion

- Recap: using a novel synthetic controls approach, we estimate the **distribution** of earnings losses following firm closures

- Large and persistent earnings losses *on average*, but considerable variation across individuals
    - 20% of workers come out ahead after 5 years

- Difference in outcomes is driven by post-layoff adaptability, not observable characteristics

- Future research: which margins of adjustment reduce impact of layoff?

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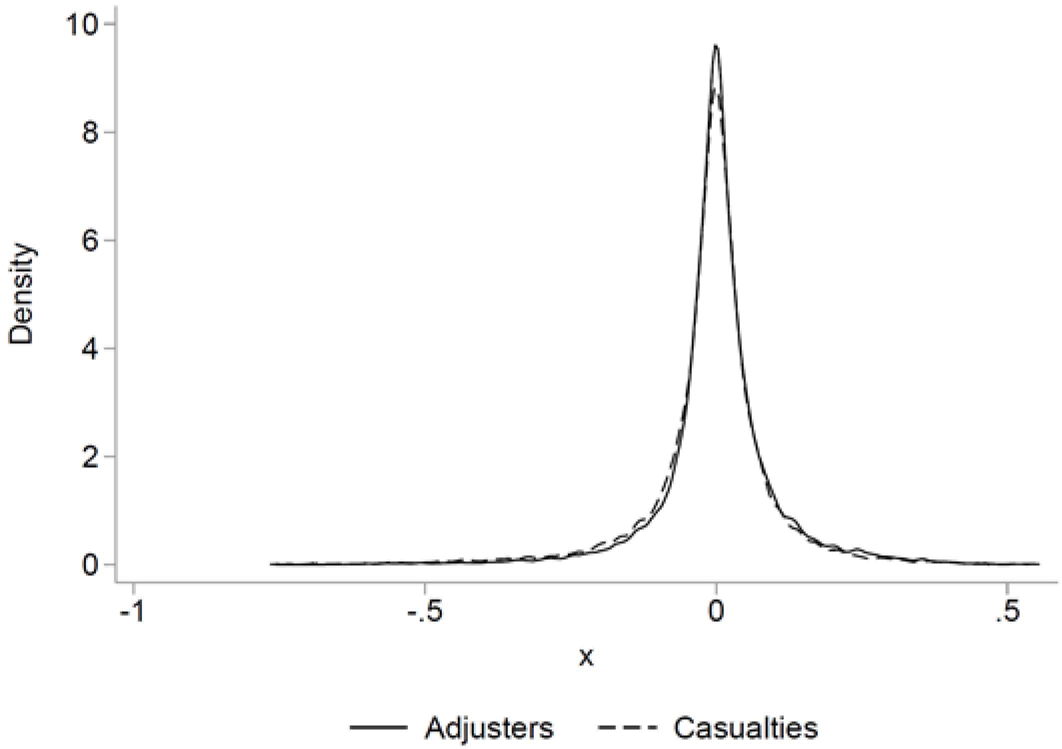
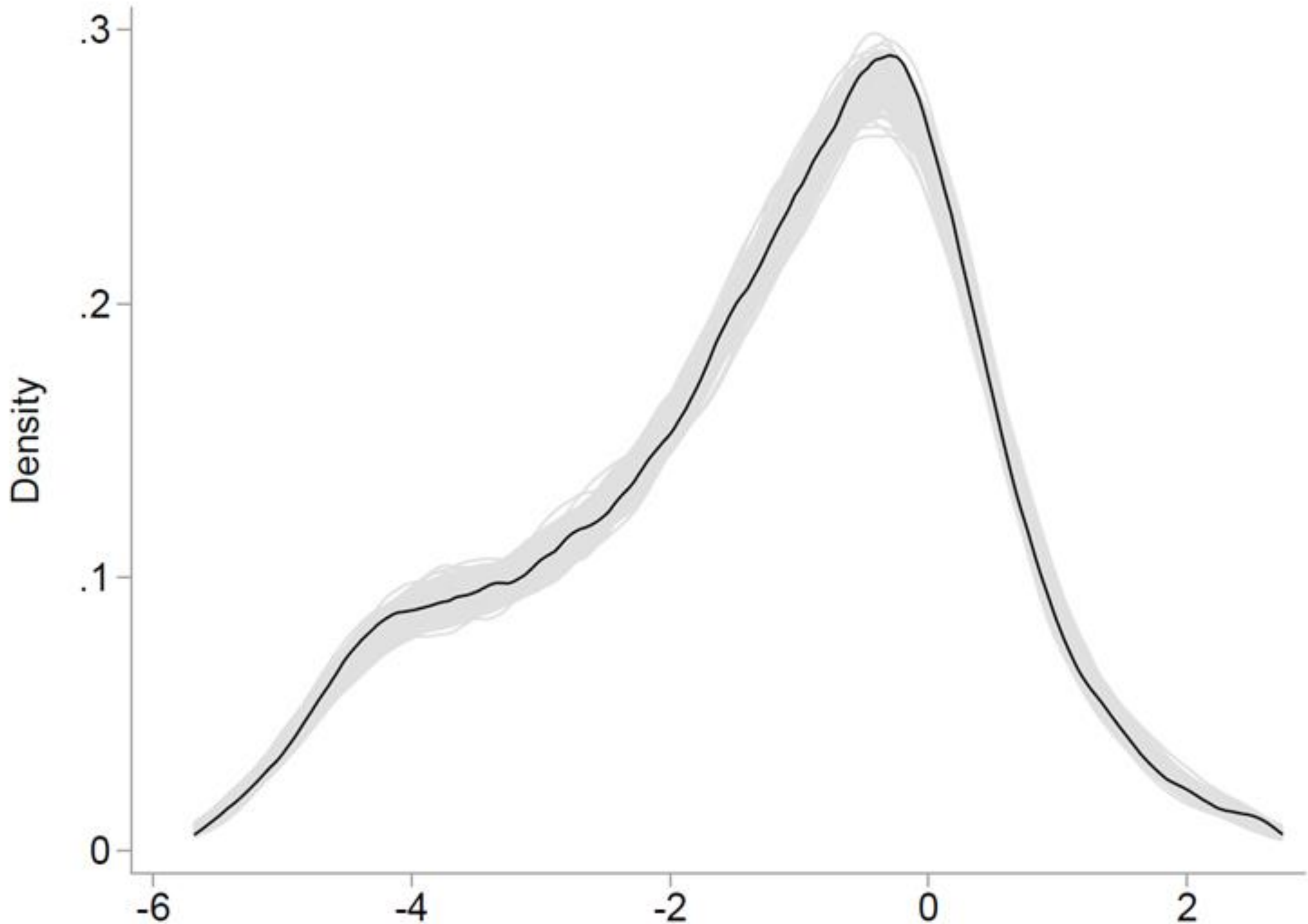
Overlapping pre-trend residual distributions for adjusters and casualties

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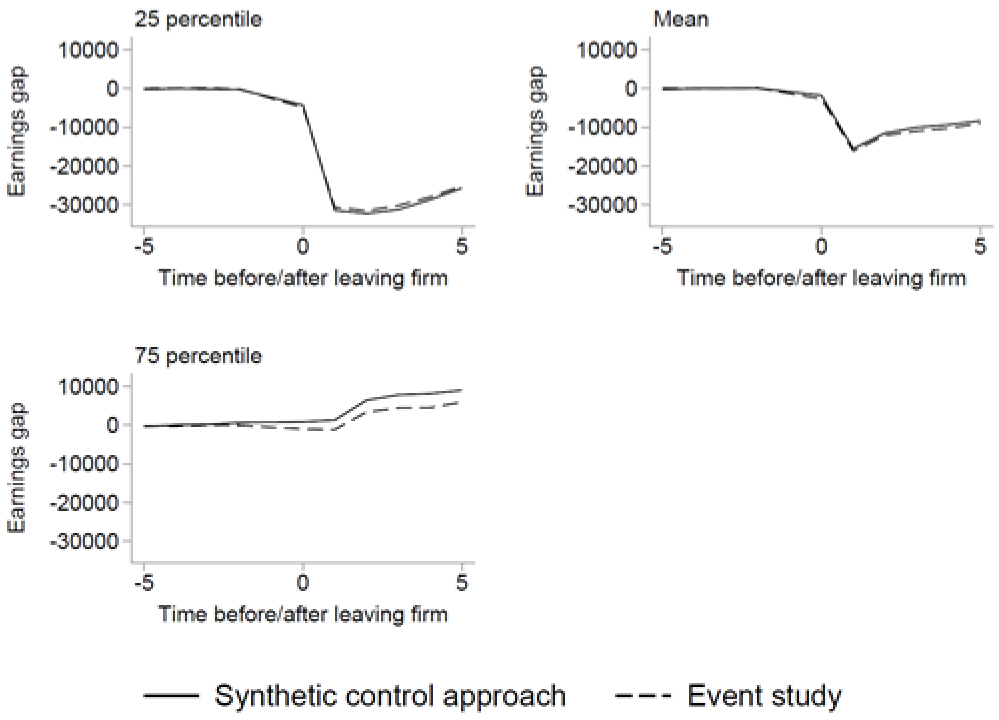

25 percentile
Mean
75 percentile
Earnings gap
10000
0
-10000
-20000
-30000
-5
0
5
Time before/after leaving firm
Synthetic control approach
Event study

	Non-displaced	Displaced	Difference	P-value
Total labor earnings per calendar year	48380.874	48525.941	-145.067	0.629
Gender	0.318	0.290	0.028	0.000
Real tenure	3.618	5.471	-1.853	0.000
Age (in years)	39.375	38.176	1.199	0.000
		Education:		
Low educated (no vocational degree)	0.190	0.139	0.051	0.000
Medium educated (apprenticeship degree)	0.746	0.837	-0.091	0.000
High educated (univerisity degree)	0.064	0.025	0.040	0.000
No. employees total	553.937	170.998	382.939	0.000
		Main industries of displaced workers:		
Manufacturing	0.457	0.449	0.008	0.042
Wholesale and retail	0.170	0.217	-0.047	0.000
Construction	0.093	0.165	-0.072	0.000
Individuals	567508	161,213		

	All	Education			Gender	
		Low	*Medium*	*High*	*Women*	*Men*
Mean	-1.275	-1.841	-1.196	-0.765	-1.612	-1.137
Mode	-0.489	-0.534	-0.482	-0.212	-0.520	-0.493
Skewness	-0.428	-0.037	-0.493	-0.476	-0.101	-0.551
P25	-2.354	-3.258	-2.188	-1.797	-3.105	-2.042
P75	-0.096	-0.486	-0.068	0.468	-0.208	-0.069
Loss $<$ 1 month	0.246	0.167	0.256	0.358	0.223	0.255
N	15960	2213	13364	383	4625	11335