

Online Appendix for “The Heterogeneous Earnings Impact of Job Loss Across Workers, Establishments, and Markets”

Susan Athey* Lisa K. Simon[†] Oskar N. Skans[‡] Johan Vikström[§]
Yaroslav Yakymovych[¶]

May 25, 2026

*Stanford University, GSB

[†]Revelio Labs, New York

[‡]Dep. of Economics, Uppsala University oskar.nordstrom_skans@nek.uu.se

[§]IFAU; Dep. of Economics, Uppsala University

[¶]Institute for Housing and Urban Research, Uppsala University

A Online Appendix: Data Details

Below, we explain the variables used in the GRF model and when matching displaced workers to non-displaced controls. The micro-level data on individuals, establishments and firms that we use come from the Register-Based Labour Market Statistics ([Statistics Sweden, 2019b](#)), Longitudinal Integrated Database for Health Insurance and Labour Market Studies (LISA) ([Statistics Sweden, 2019a](#)) and the Wage Structure Statistics ([Swedish National Mediation Office and Statistics Sweden, 2019](#)).

A.1 Demographics

Data on basic demographics are drawn from the administrative population register Louise produced by Statistics Sweden. Data in Louise is collected in November of each year. *Age* is measured in years. We include a *Female* dummy. A categorical *Native-immigrant* variable takes the value zero for natives, one for those with two foreign-born parents, and two for those born abroad (unless both parents are born in Sweden).

A.2 Family

Civil status is coded using two dummies. *Married* workers are either formally married, or cohabit with a partner with whom they have a common child. This definition is well in line with Swedish perceptions of “marriages” and is used in most research on Swedish data. *Divorced* is a dummy for workers whose marriage has ended and who are not currently defined as married according to *Married*.

To quantify the economic value of the partnership and degree of dependence, our *Share of household income* variable measures the subject’s labor earnings as a share of total household labor earnings.

We measure the number of children in the household using two different variables. *Children* contains the number of all children under the age of 18 in the household, whereas *School-aged children* counts children aged 7 to 17. We make this distinction to allow the second variable to measure the additional impediments to mobility that may arise when children start school at age 7.

Social ties to the current location are measured by two variables. First, we define a dummy for being *Born outside of the current county*. This variable naturally takes the value 1 for all foreign-born.¹ We also measure *Past mobility* as the number of moves

¹The register information is based on the county of birth and cannot be disaggregated further.

across local labor market boundaries during the past 10 years. This variable is a lagged counterpart of our key indicator for geographical mobility after the event.

A.3 General Human Capital

Years of schooling are based on the highest achieved level of education. *Labor market experience* is measured as the number of years employed during the 10 years prior to displacement. Because of the tenure restriction, all displaced and control workers must have been employed for at least three years prior to the year $t = 0$ and the variable therefore has a range from 3 to 10.

In this category, we also include pre-displacement earnings. We measure these by *Earnings* as the rank among the full population of displaced and controls in year $t = -1$, as well as two variables capturing *Earnings growth* from $t = -3$ and $t = -2$ respectively to $t = -1$. The rank form of the *Earnings* variable has been chosen to ensure orthogonality to time trends.

A.4 Specific Human Capital

It is likely that workers differ in terms of how costly or difficult it is for them to switch firm and industry if hit by a negative shock. The ability to adjust along this margin is potentially determined by the degree to which the worker is tied to the closing firm or sector. In order to measure the empirical relevance of these aspects, we include variables capturing pre-closure establishment *Tenure* (truncated at 10), and the number of years spent in the same industry as the closing establishment (*Industry tenure*, also truncated at 10).

Furthermore, we characterize the *Education specificity* using data on the 1-digit level and 3-digit field of the highest achieved education (thus, high school programs and college majors). Our metric uses the fraction of workers, by education cell, that is employed in the ten main 3-digit industries. The strategy follows [Altonji et al. \(2012\)](#).² Examples of fields with high levels of specificity are pharmacists and nurses.

We further include an indicator for *STEM* education beyond high school. We also provide a dummy for *Education in a licensed field*, that is a field that caters to the health or education sector.

²An alternative is provided by [Leighton and Speer \(2020\)](#) but their approach requires a full matrix where all types of education are present in all industries and is therefore less well suited to our granular data.

A.5 Lost Job Characteristics

The causal impact of job loss for displaced workers does not only depend on their outside opportunities, but also on aspects of the job that they have lost. We therefore define a number of variables which capture key characteristics of the lost job.

We first characterize the lost job by *Plant size* in terms of employment in $t = -1$, and *Plant size trend* between $t = -3$ and $t = -1$, measured as the difference in $\log(\text{Plant size})$.

Additionally, we measure the *Plant wage* premium at the closing establishment. This feature is shown to be particularly important in the case of Austria by [Gulyas and Pytka \(forthcoming\)](#). They study mass layoffs and characterize the affected firms by firm wage effects as estimated conditional on person-fixed effects in the tradition of the AKM model ([Abowd et al., 1999](#)). Indeed, there is a large literature discussing the origins of firm-specific rents, and how they should be estimated and interpreted (see, e.g., [Card et al., 2018](#); [Bonhomme et al., 2019](#); [Lachowska et al., 2020](#), in the context of plant closures). A drawback of the AKM model is that it requires structural assumptions that we do not want to impose, and is likely to result in biased premium estimates for dying firms. We therefore take a slightly different route. As a reduced form measure of the pay level of the closing firm at the time of displacement, we use the leave-one-out mean of residual earnings in year $t = -1$ as in [Card et al. \(2013\)](#). For each displaced worker and potential control, we characterize the closing establishment environment by the average Mincer residual earnings of all co-workers at the same establishment. Residual earnings are computed using year-specific regressions of log earnings on 3-digit industry indicators, years of schooling, field of education (2 digits), gender, immigration status and a full set of age dummies.³

We measure the *Routine* task component of the lost job. To this end, we use data on routine intensity by occupation from [Autor and Dorn \(2013\)](#) and [Goos et al. \(2014\)](#). We translate the occupational codes into the Swedish nomenclature. We have data on occupations for about half of our workers. We impute routine intensity for each worker based on the average routine score for those in the same detailed education-industry

³The R^2 in a regression of labor earnings on the plant wage premium measure among the displaced is around 22 percent.

combination.^{4,5}

We further construct a *Manager* dummy for workers who are employed as managers. This information is drawn from the occupational codes, which we do not have for all workers, and therefore contains false negatives. To mitigate the problem, we impute manager status based on data from the previous three years if the information is missing in $t = -1$.

We calculate the *Relative size of the displacement event* as the share of total employment by 3-digit industry and local labor market combination. This is motivated by previous studies, e.g. Cederlöf (2019) and Gathmann et al. (2020), that have found that the impact of being displaced in a large event is particularly severe. One possible explanation for this finding is that workers from the same event may compete with each other for the same job openings, and this type of competition might be particularly problematic if the displacement event is large relative to the industry-specific local labor market.

Finally, we generate a variable for *Industry being matched to education*. This indicator takes on the value 1 for workers who were employed in one of the 10 main 3-digit industries for their 1-digit level and 3-digit field before displacement.

A.6 Industry Characteristics

There is ample evidence that, on average, workers have comparative advantage in their industry of employment and that shocks to this industry have an impact on their overall earnings prospects. Examples include Carlsson et al. (2016) for Sweden, who show that that technology shocks have a larger impact on workers' wages if the shocks are shared with other firms in the same industry and that this distinction is entirely driven by workers with fields of education where most job-to-job mobility is within the industry. Similar arguments are made in Lamadon et al. (2022). It is also likely that displacement has more lasting negative effects in industries with low labor turnover such as manufacturing than in fluid sectors such as restaurants. Overall, this suggests that workers who lose their jobs in declining low-turnover sectors will suffer more adverse consequences,

⁴We define the combinations using 1-digit education level, 2-digit education field, and three-digit industry. For cells where we have fewer than 100 workers we use data on the 1-digit industry and education (field+level) instead. The leave-out correlation between our education-industry-based measure of routineness and routineness as measured directly based on occupation is 0.7. The reason for not using occupation-level routineness directly is the large number of missing values this would imply.

⁵Robustness analyses indicate that our results are robust to imputing routine intensity for half of the sample. Our results are robust using only data where information on occupations is available. Moreover, broad occupational categories do not appear to predict displacement effects beyond job routineness and the other covariates, suggesting that detailed occupational data for all workers may not be crucial for predicting heterogeneous job-loss effects.

in particular if much of their human capital is industry-specific.

In order to quantify the conditions in each industry, we first construct time-consistent industry indicators at the 3-digit level. This is a non-trivial endeavour as the codes changed three times during our sample period. We start from the SNI2002 codes that our raw data provide for the period 2002 to 2010. Next, we rely on the SNI2002 code reported in 2010 and use it for all later years for those establishments that continue to exist beyond 2010, and conversely use the data from 2002 for establishments that existed prior to that. We refer to these overlapping establishments as stayers. We then use the modal overlap between SNI2002 (as imputed for stayers) and the current codes (SNI69, SNI92 and SNI2007) to fill in SNI2002 codes for non-stayers. This works particularly well for the years and sample we study, as almost all closing establishments existed in 2010 (due to the 3-year tenure requirement) and since most codes remained unchanged between SNI92 and SNI2002.

We measure *Industry wage* premia in each 3-digit industry as average earnings in the industry, residual on years of schooling, 2-digit education field, gender, immigrant background and a full set of age dummies. Furthermore, we also include average *Churn* and *Reallocation* rates for each industry. We follow conventions from Burgess et al. (2000), and define establishment-level churning as the number of workers who are hired or separated beyond what was needed for the actual change in employment between two adjacent years. The churning rate is measured as churning relative to the average employment during the two years.⁶ Similarly, we calculate excess reallocation in each industry as the excess creation and destruction of jobs over what was needed to adjust industry employment. The reallocation rate is measured relative to the average employment in the two years.⁷ We then aggregate the establishment-year churning rates and the industry-year reallocation rates to industry-level averages which are constant over time. When computing these numbers, we take care to exclude workers that satisfy the conditions for false closures as discussed above. Note also that the scale of the measures (relative to average employment in the two years) is in approximate percentages, but with a maximum of 2 and a minimum of -2.

We also follow the conventions from this literature when computing *Employment growth over the past 10 years* in each industry. Thus, for displacement events in the year $t = -1$, we define $Trend_{Ind,t} = (Emp_{Ind,t-1} - Emp_{Ind,t-10}) / (Emp_{Ind,t-1}/2 + Emp_{Ind,t-10}/2)$ which takes the value 2 for newly emerging industries and the value -2 for disappear-

⁶Thus, churning is $[(Hires+Separations)-abs(Emp(t)-Emp(t-1))]/[Emp(t)/2+Emp(t-1)/2]$ at the establishment-year level.

⁷Thus, reallocation is $[(Job\ Creation+Job\ Destruction)-abs(Emp(t)-Emp(t-1))]/[Emp(t)/2+Emp(t-1)/2]$ at the industry-year level.

ing industries. This metric bounds cases where some very small industries experience extreme changes (including exits and entries) during the sample period. Similarly, we calculate the *Industry-specific business cycle* as the change in employment between year $t = -1$ and $t = 0$ using the same metric.

We also add dummy variables for closures in the *Manufacturing industry*, as this industry has been a focus of the job displacement literature since [Jacobson et al. \(1993\)](#). Furthermore, we add a dummy for closures within *Education, health and public administration*, as the labor markets in these (mostly public sector) industries tend to experience a constant shortage of workers.

A.7 Location Characteristics

As with industries, there is ample evidence suggesting that local labor market conditions have causal effects on workers' outcomes. This is also the case in Sweden, where wages seem to react to local labor market shocks ([Carlsson et al., 2019](#)).

Our local variables are measured at the level of local labor markets, which are an aggregation of municipalities. These are constructed by Statistics Sweden based on commuting patterns.

For each local labor market, we measure the *Local unemployment* rate as the number of residents who are registered with the public employment service (a prerequisite for receiving benefits from either the unemployment insurance system or from the municipal welfare system) divided by the size of the local labor force (sum of the registered unemployed and the number of employed as described above). *Population density* is also measured at the local labor market level. The *Concentration of local employment across 3-digit industries* is measured using an HHI index.

In addition, we measure local exposure to the industry characteristics discussed above. These shift-share/Bartik-style variables are calculated by multiplying each industry's employment share in the local labor market (by year) with the characteristics of that industry and then summing over the industries within the local labor market. In this way, we define the *Manufacturing employment share*, *Average long-term industry trend*, *Average industry business cycle*, *Average industry churn* and *Average industry reallocation*.

It is important to note the fundamental difference between these variables and their industry-level counterparts. Whereas the industry-level variables measure characteristics in the industry from which the worker was displaced (and is potentially tied to, if changing industry is costly), the local labor market counterpart measure how exposed the worker is to these attributes if searching at random at the local labor market (which

should be more pertinent for workers who are restricted in their mobility).

A.8 Aggregate Conditions

To capture aggregate conditions in the economy, which may both impact the average size of earnings losses, as well as have heterogeneous effects on different worker groups, we include the calendar *Year* ($t = 0$) and the *National unemployment rate* in the year $t = 1$. The national unemployment rate captures the aggregate business cycle conditions displaced workers experience after job loss. These have been shown to be an important correlate of earnings losses by [Davis and von Wachter \(2011\)](#).

B Online Appendix: Additional Results

Table B.1: Sample statistics for displaced and non-displaced workers

	Controls (unmatched) (1)	Controls (matched) (2)	Displaced (unmatched) (3)
N workers	28,914,261	556,824	185,627
N establishments	231,958	120,597	22,005
Covariates			
<i>Demographics</i>			
Age	44.113	42.146	42.157
Female	0.478	0.346	0.347
Born abroad	0.097	0.129	0.131
Two foreign born parents	0.028	0.032	0.032
Native, not birth county	0.274	0.249	0.249
<i>Family</i>			
Married	0.645	0.589	0.588
Divorced	0.101	0.099	0.099
Children (# living at home)	0.780	0.749	0.746
School-aged children	0.524	0.470	0.467
Share household inc.	0.714	0.754	0.754
Past mobility (# location moves in last 10 years)	0.164	0.212	0.211
<i>Human capital</i>			
Schooling (years of education)	12.160	11.466	11.470
Exp. (years employed in last 10)	9.229	8.913	8.908
Tenure	6.624	5.896	5.890
Industry tenure	7.927	7.137	7.138
Earnings(rank)	0.500	0.497	0.497
Earnings in t-2	0.994	1.013	1.014
Earnings in t-3	0.951	0.961	0.962
STEM education	0.097	0.108	0.109
Education in licensed field	0.238	0.070	0.071
Education specificity	0.565	0.470	0.470
<i>Lost job characteristics</i>			
Establishment size	520.493	177.714	185.309
Establishment size trend	0.025	-0.020	-0.022
Establishment wage premium	0.001	-0.032	-0.033

Job routineness	0.515	0.557	0.557
Industry matched to education	0.560	0.377	0.376
Size of displacement	0.170	0.157	0.158
Manager	0.033	0.026	0.027
<i>Industry characteristics</i>			
Employment trend	0.052	0.079	0.081
Employment cycle	0.005	-0.001	-0.001
Industry wage premium	0.006	0.028	0.027
Churning	0.223	0.209	0.209
Reallocation rate	0.131	0.140	0.140
Manufacturing	0.230	0.363	0.366
Education, health, admin	0.383	0.078	0.079
<i>Location characteristics</i>			
Population density	82.472	86.275	86.295
Unemployment	0.086	0.086	0.086
Concentration (HHI industries)	0.031	0.031	0.031
Manufacturing (share of local emp.).	0.189	0.186	0.186
Average industry trends	0.081	0.079	0.079
Average industry cycle	0.007	0.007	0.007
Average industry churning	0.224	0.226	0.226
Average industry reallocation	0.147	0.148	0.148
Year	2,005.881	2,005.580	2,005.580
National unemployment	7.451	7.432	7.432

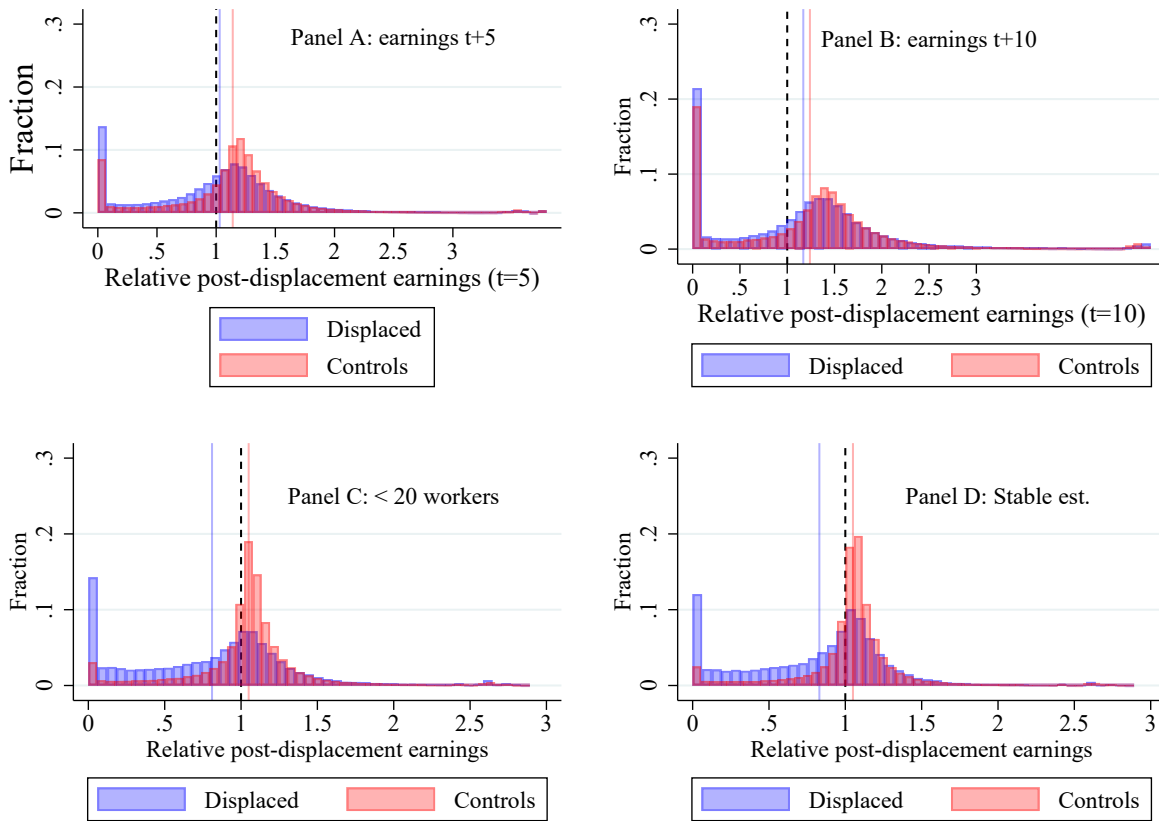
Note: Statistics for the non-displaced (controls) before matching (Column 1) and after matching (column 2), and for the displaced workers (Column 3). Mean values of all covariates used in the analyses. Details for all covariates are in Appendix A.

Table B.2: RATE estimates of GRF model and different simple targeting rules on the test set

	Qini coefficient (x100)	SE(x100)
GRF	-3.56	.2
Age	-1.74	.2
Schooling	-1.47	.2
Manufacturing	-1.52	.3
Population density	-1.08	.3
Manufacturing & age	-2.43	.3
Manufacturing & schooling	-2.16	.3

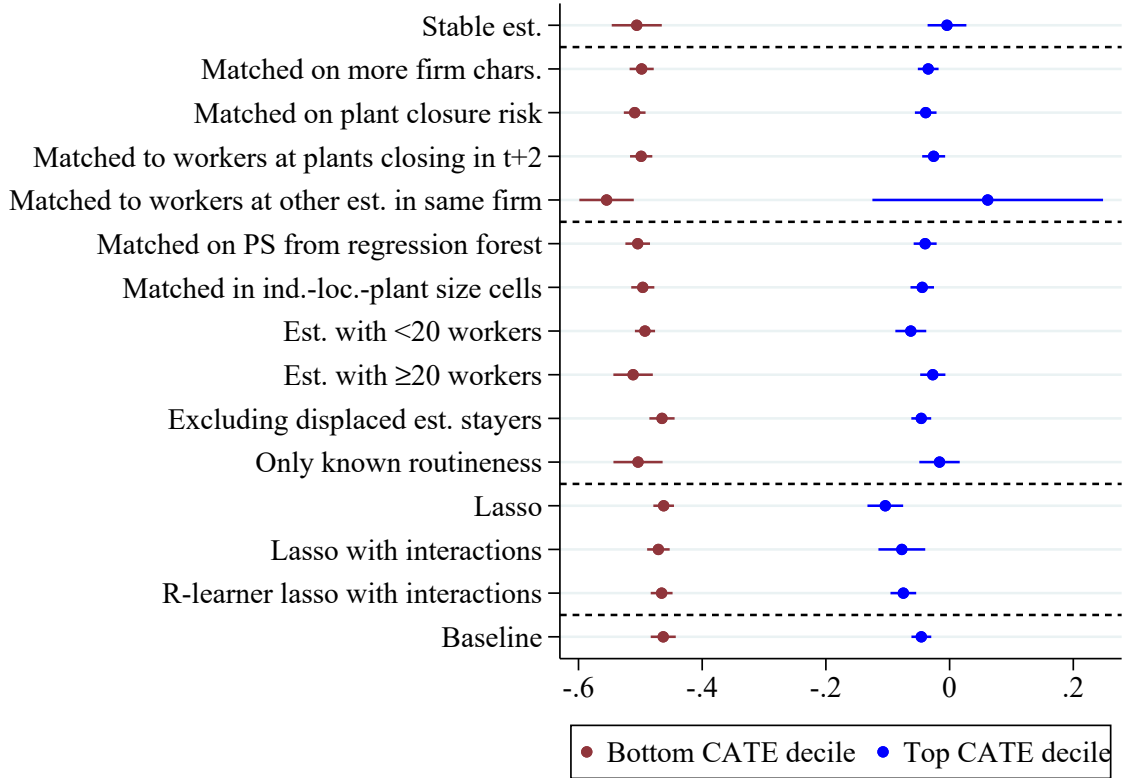
Note: GRF: workers with the lowest estimated CATEs; Age: oldest workers; Schooling: least educated workers; Manufacturing: manufacturing workers at random and then other workers; Population density: least dense locations; Manufacturing and age: oldest manufacturing workers; Manufacturing and schooling: least educated manufacturing workers.

Figure B.1: Distribution of relative earnings five and ten years after displacement



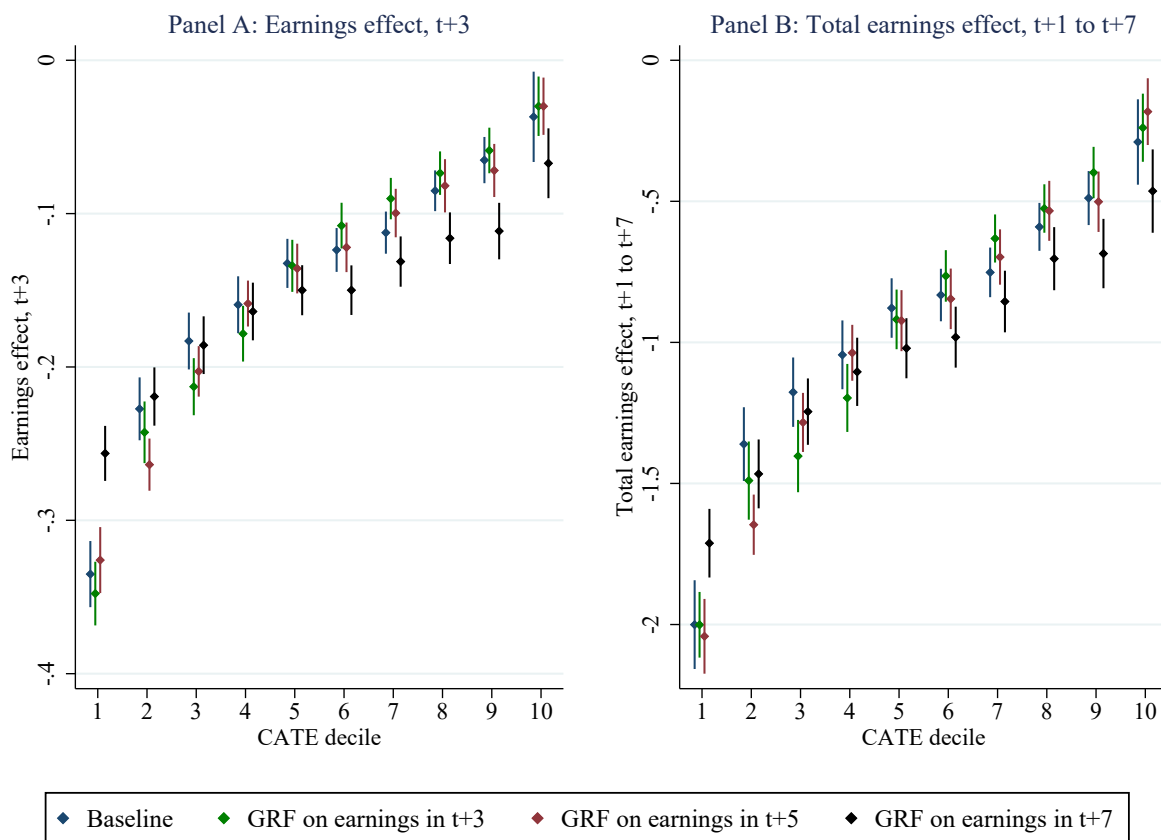
Note: Panels A and B show the distributions of relative earnings between one year before displacement and five years after displacement (Panel A) and ten years after displacement (Panel B). Panels C and D show distributions of relative earnings in $t = 1$ for displaced and matched controls in sub-samples with less than 20 workers (Panel C) and with less than 10 percent change in employment between $t-3$ and $t-1$ (Panel D), similar to Figure 1B in the main paper. Solid lines indicate group means, the dashed lines indicate unchanged nominal earnings.

Figure B.2: Robustness of ATE estimates for the top and bottom CATE deciles for subgroups, alternative control groups, and alternative estimation methods



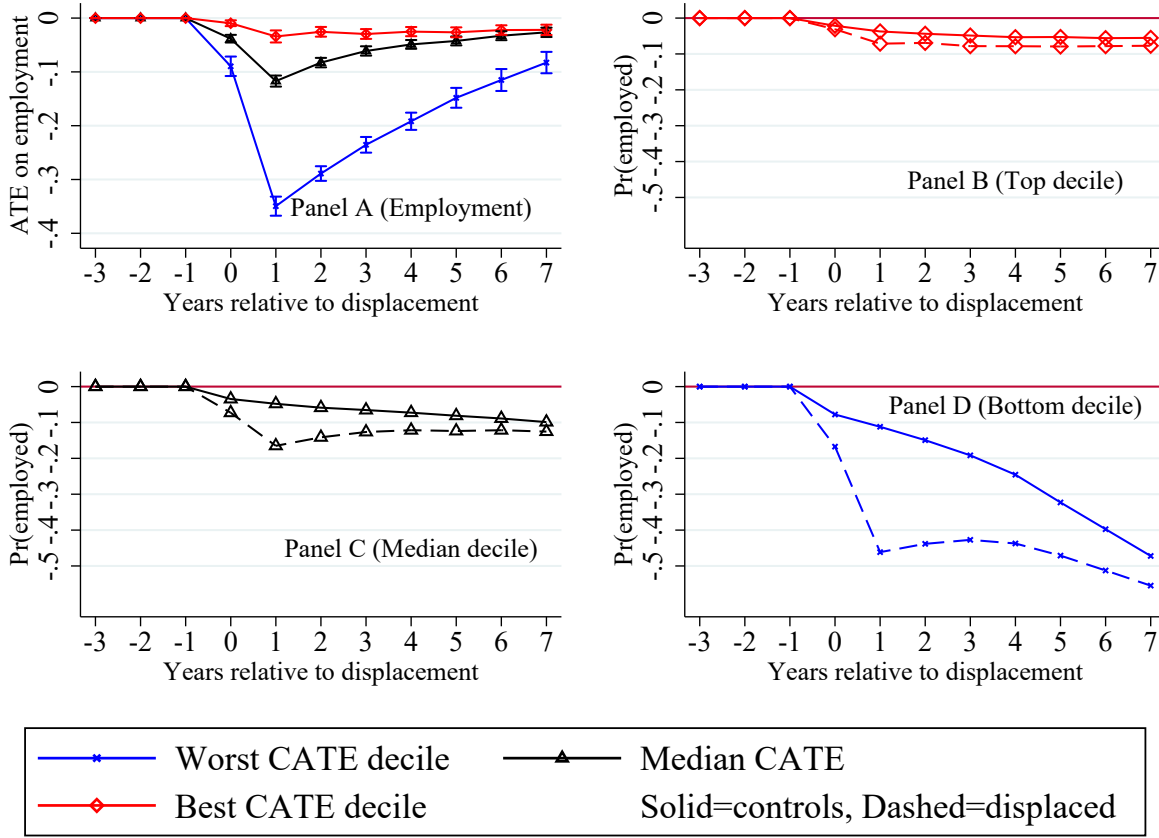
Note: ATE estimates for individuals in the top and bottom deciles of CATEs for different subgroups, using different matching approaches or different estimation methods. In the case of subgroups, displaced from that subgroup are re-matched to controls to ensure that all matched controls satisfy the subgroup restrictions. *Stable est.:* establishments with absolute employment growth $< 10\%$ from $t = -3$ to $t = -1$. *Matched on more firm chars.:* in addition to all variables used for matching in the baseline, matched on the wage quantile, hire share and leaver share in the firm the establishment belongs to (measured as the firm's average in the years $t = -5$ through $t = -1$). *Matched on plant-closure risk:* matching based on predicted plant-closure risk, using all industry and location variables, establishment size, trend in establishment size, plant wage level, plant share of location-industry, firm wage quantile, hire share and leaver share to predict the risk. *Matched to workers at plants closing in t+2:* control group consists of workers employed in $t = -1$ at plants which close in $t = 2$. *Matched on PS from regression forest:* propensity scores for matching estimated using regression forest instead of logit. *Matched in ind.-loc.-plant size cells:* matching within cells defined by combinations of metropolitan/non-metropolitan local labor markets, manufacturing/education, health, public administration/other non-manufacturing industries, establishments with 5-20/21-100/100+ employees. *Est. with < 20 workers:* establishments with < 20 workers in $t = -1$. *Est. with ≥ 20 workers:* establishments with ≥ 20 workers in $t = -1$. *Excluding displaced est. stayers:* excluding individuals who are still employed at a closing establishment in $t = 1$. *Only known routineness:* only individuals whose occupations are known and hence routineness is non-imputed. *Lasso:* lasso using displacement interacted with the variables. *Lasso with interactions:* lasso using displacement interacted with the variables, their squares and within-block interactions. *R-learner lasso with interactions:* R-learner lasso based on the variables, their squares and within-block interactions.

Figure B.3: ATE:s on earnings in $t+3$ and on cumulative earnings in $t+1$ to $t+7$



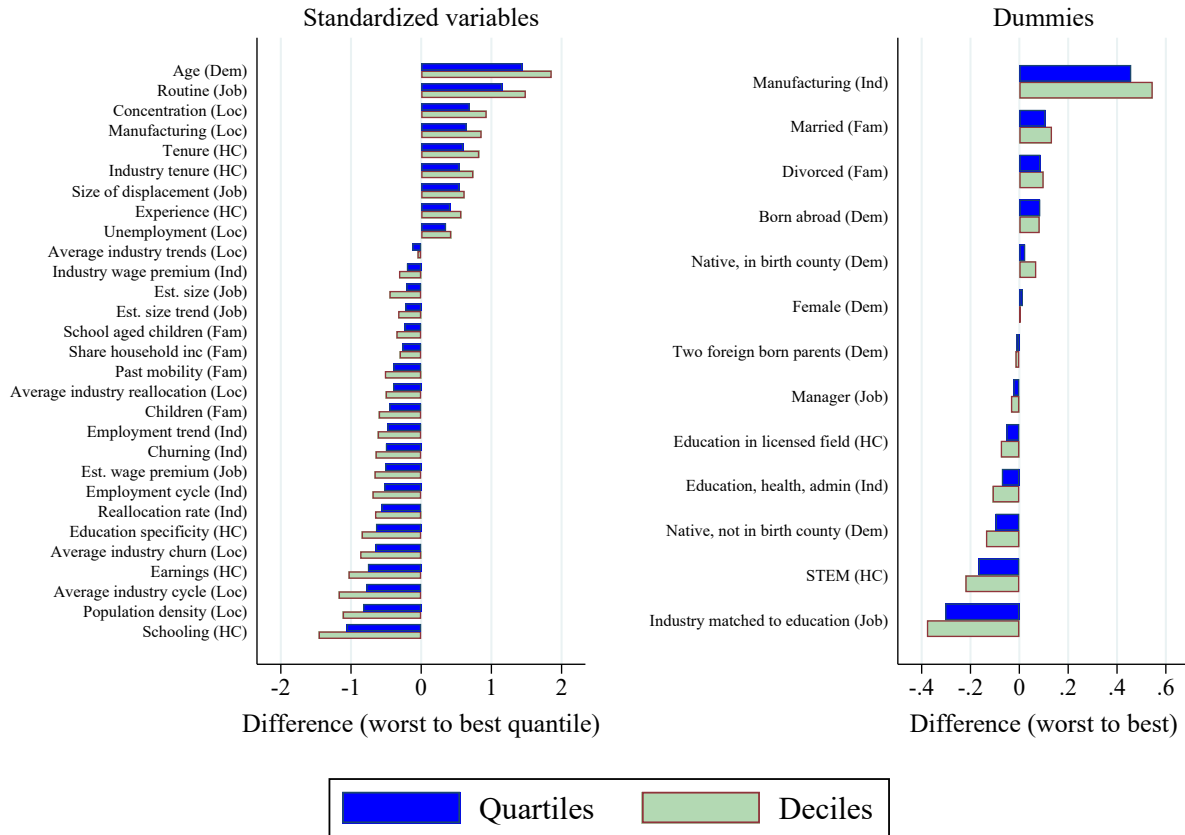
Note: Panel A: ATE:s (differences between displaced and control workers) in terms of earnings three years after displacement. Panel B: ATE:s (differences between displaced and control workers) in terms of cumulative earnings from one to seven years after displacement. Workers sorted into deciles of CATE:s based on GRF models estimated on earnings in $t+1$ (baseline), $t+3$, $t+5$ and $t+7$ respectively. 95 percent confidence intervals.

Figure B.4: Effects of displacement on employment over time



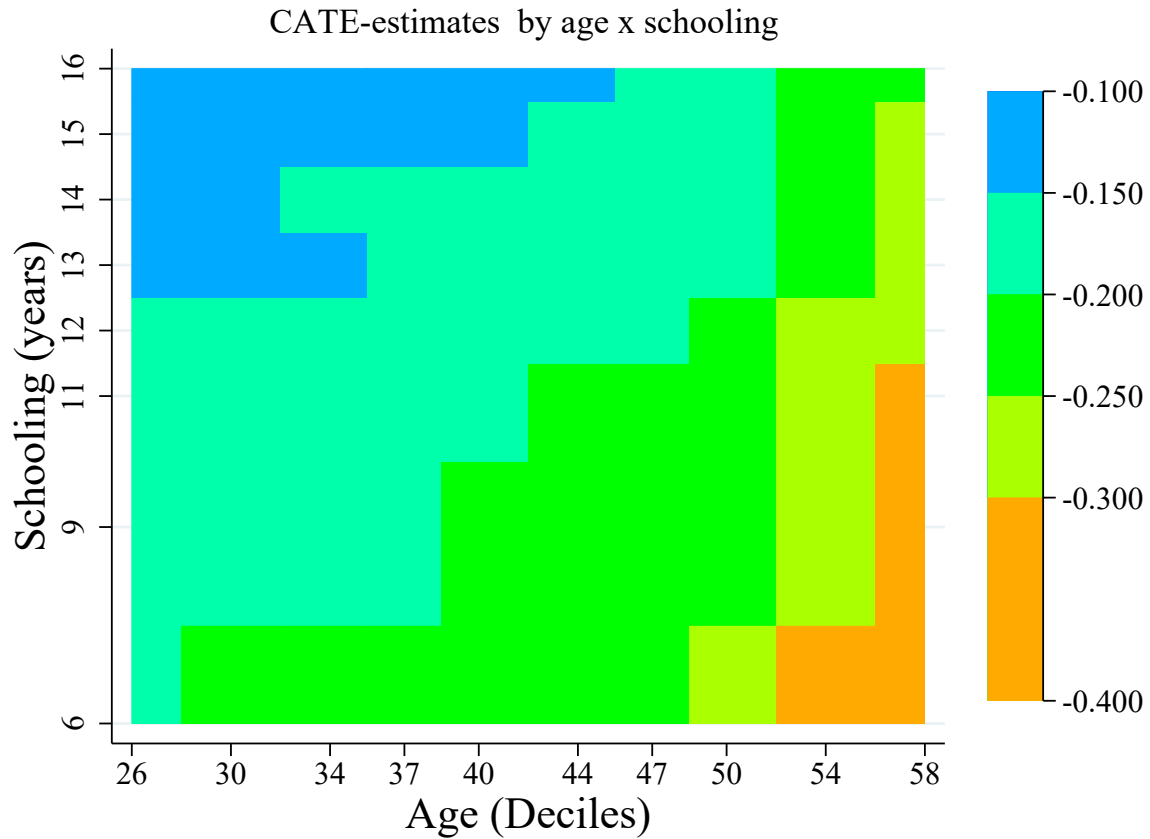
Note: The figure replicates Figure 4 in the paper, but with employment as the outcome instead of earnings. It shows statistics for three decile groups of the CATE distribution. The “median” group straddles the median (i.e. it contains the 10th and 11th ventile). Panel A shows the ATE over time, similar to Figure 1 of the main paper, but separately for the decile groups. Point estimates and 95 percent confidence interval with standard errors clustered at the establishment in $t = -1$. Panels B–D show the underlying employment trajectories for displaced and matched controls within each decile group for the top, bottom and median deciles respectively. Only workers observed in each of the periods $t = -3$ to $t = 7$ are included (this entails excluding the years 2011–2014). Sample restrictions ensure that employment is equal to 1 for all until $t = -1$.

Figure B.5: Differences in characteristics across CATE quartiles and deciles



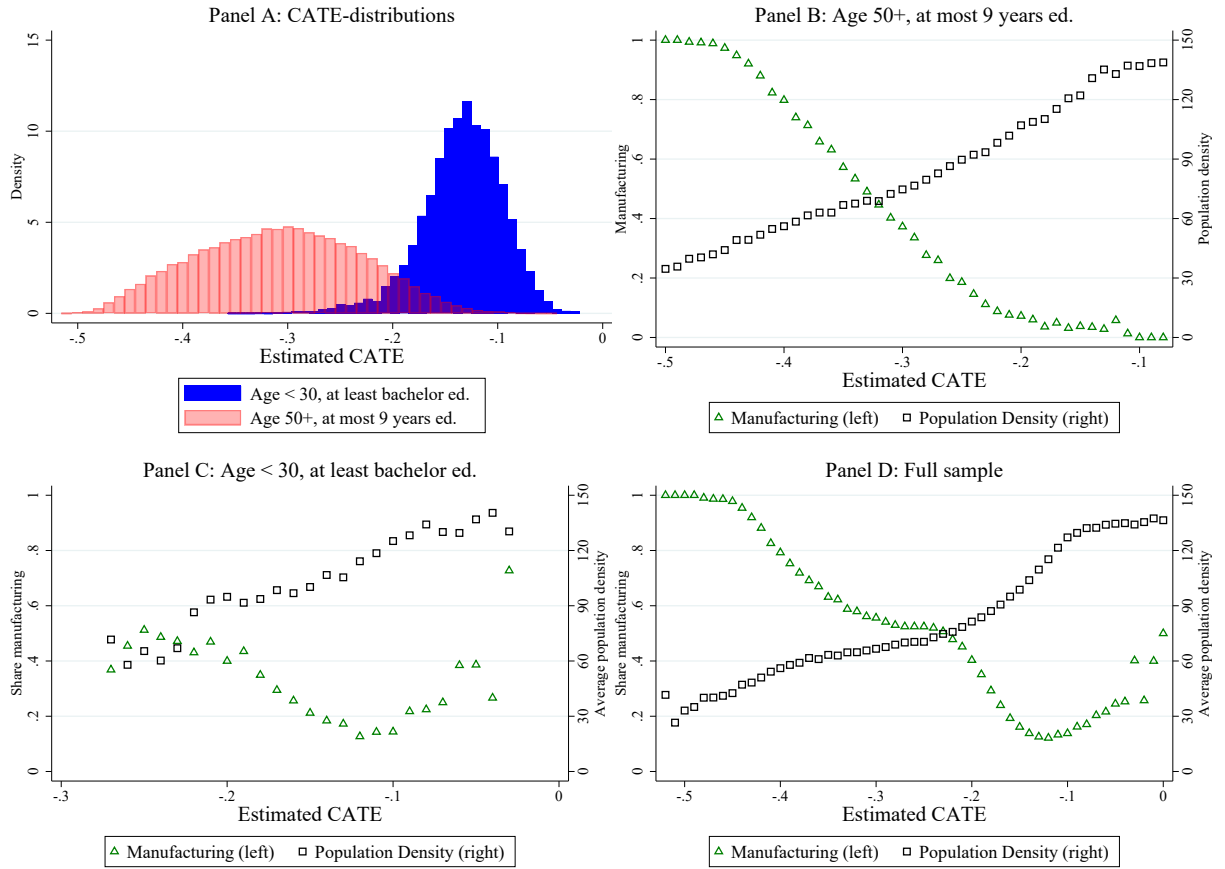
Note: The figure shows differences in characteristics between individuals in the lowest and highest quartiles and deciles of CATE:s, using the training data set. CATE:s estimated using 5-fold estimation and ranking done within each fold. The left-hand panel contains standardized (mean 0 and standard deviation 1) continuous variables and the right-hand panel contains dummy variables. Blue bars indicate quartiles and green bars indicate deciles.

Figure B.6: CATE across combinations of age and schooling



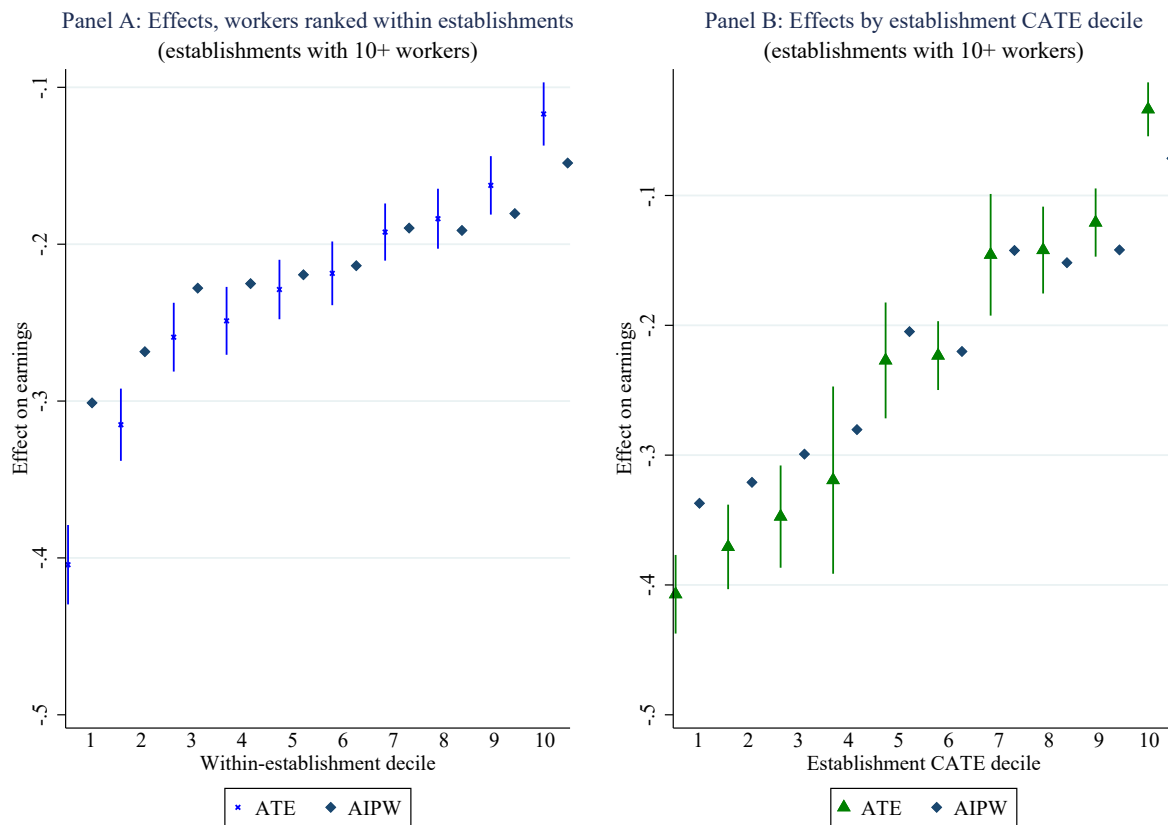
Note: The figure replicates Figure 6A (and B) in the paper, but using CATE instead of ATE (or AIPW). It divides training set workers into cells by age and schooling. Schooling has been aggregated to 8 groups by pooling the few with 10 years of schooling together with those with 9 years of schooling, and by letting the top group include all with 16 or more years of schooling. Age is defined in deciles among the displaced and the x-axis shows the median in each age group. Colors indicate the size of point estimates. It shows estimated CATE:s by combinations of age and schooling.

Figure B.7: Heterogeneity within extreme combinations of age and schooling



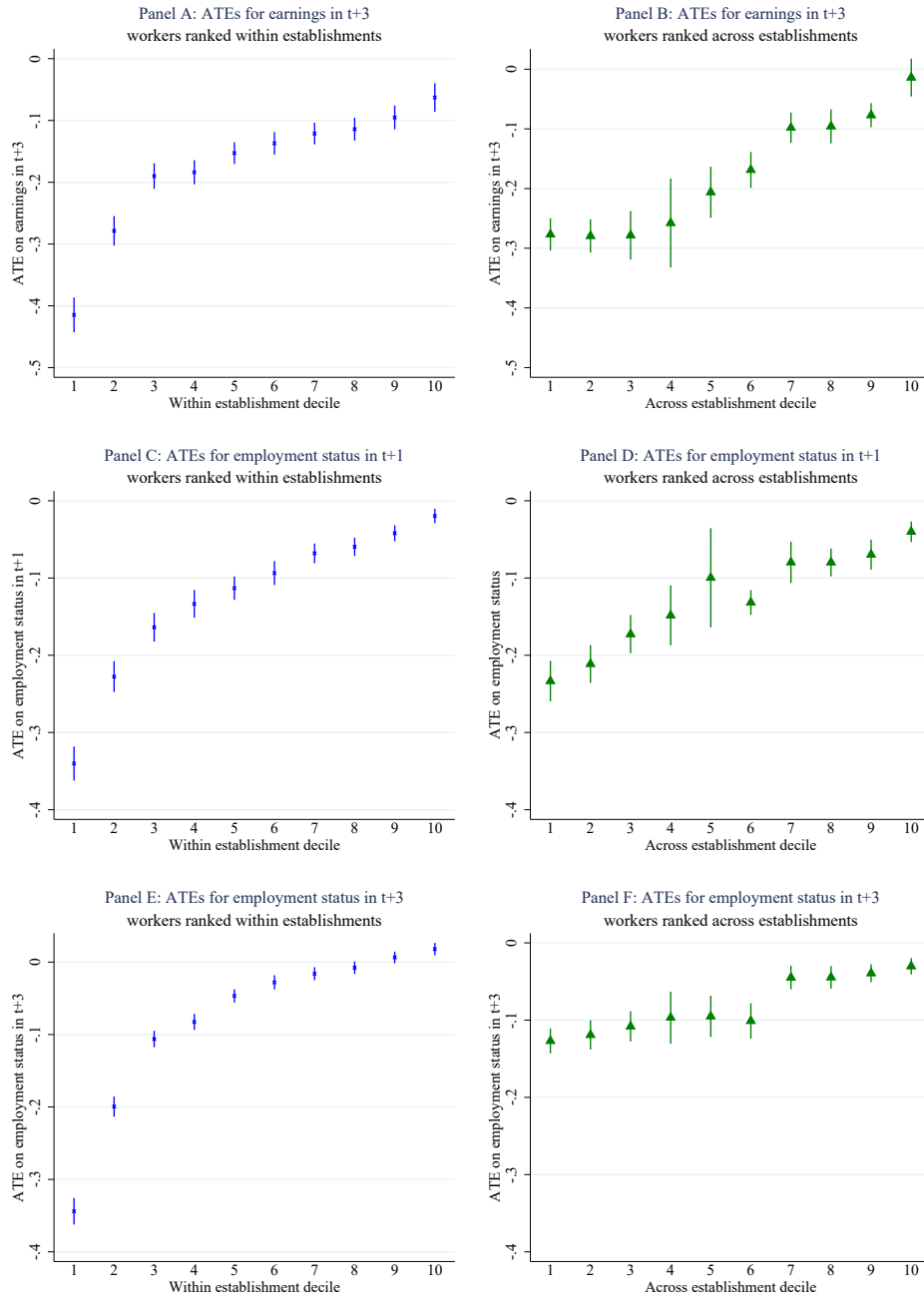
Note: Training set workers who are (a) younger than 30 and have at least 15 years of education or (b) older than 50 and have at most 10 years of education. Panel A: Histograms of 5-folds GRF CATEs within these groups. Panels B-C: Share of manufacturing workers and average population density within each CATE cell for the two groups. Panel D repeats this for the full sample. Cells defined as CATE bins of one percentage point. Bins containing fewer than ten workers are dropped.

Figure B.8: Robustness analyses: Displacement effects across and within establishments using AIPW



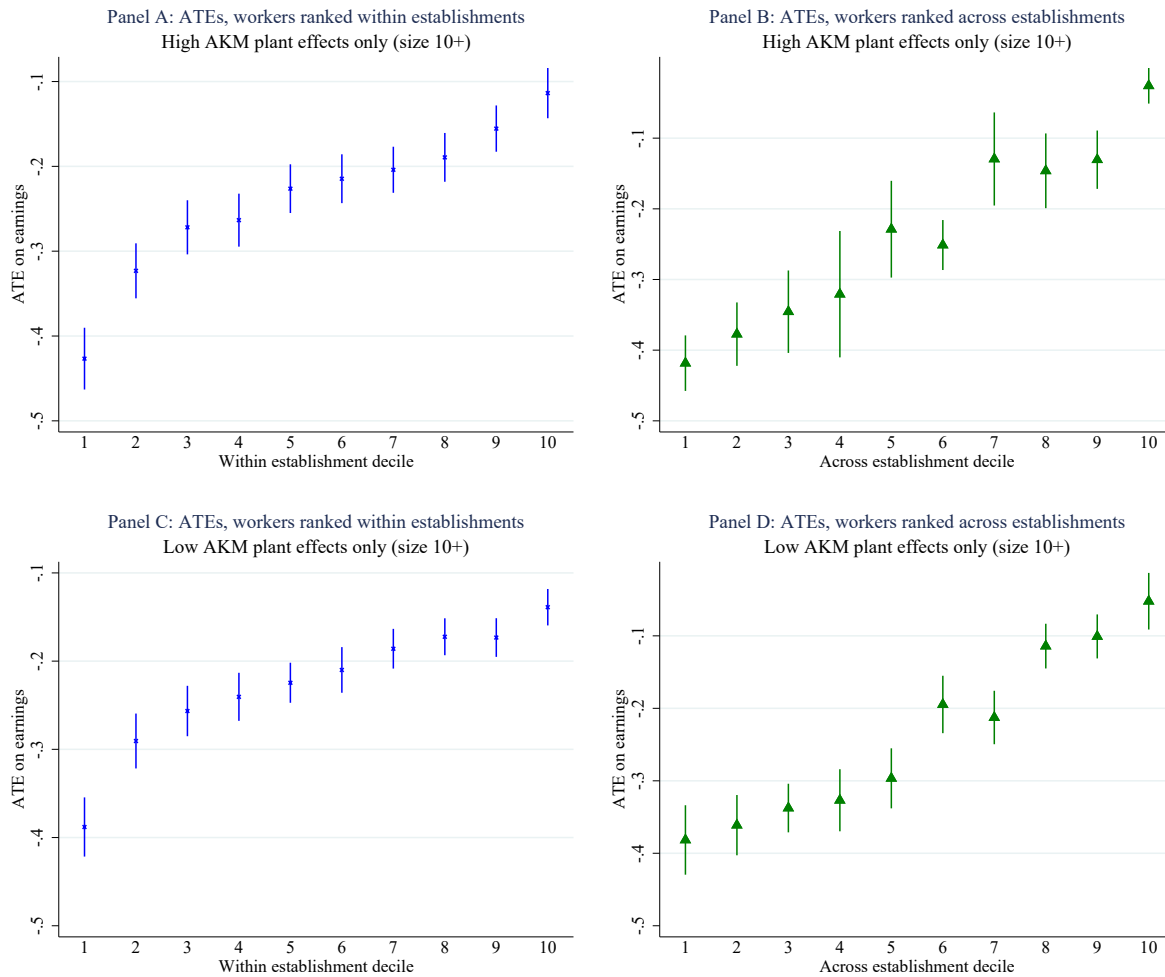
Note: The figure shows robustness analyses using both ATE:s and average AIPW scores in the respective CATE deciles. Panel A shows ATE/AIPW estimates when displaced workers are ranked based on their within-establishment CATE. Panel B shows ATE/AIPW estimates when displaced workers are ranked based on the CATE of their co-workers (defined as the leave-out mean for the workers at the establishment and then averaging over the individuals in the CATE decile.) This analysis excludes establishments with fewer than 10 displaced workers. Controls are allocated to the same decile sample as the treated workers they were matched to.

Figure B.9: Robustness analyses: Displacement effects across and within establishments for additional outcomes



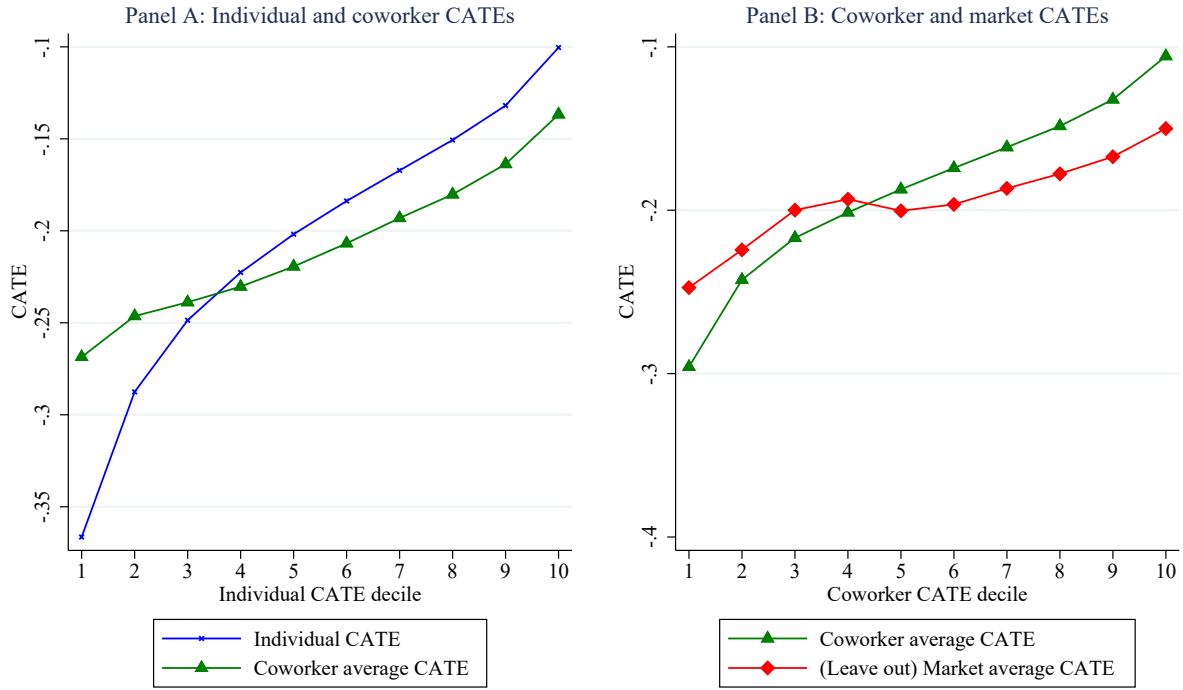
Note: The figure shows robustness analyses using employment status in $t + 1$, earnings in $t + 3$ and employment status in $t + 3$ as outcomes. Panels A, C and E show ATE estimates when displaced workers are ranked based on their within-establishment CATE. Panels B, D and F show ATE estimates when displaced workers are ranked based on the CATE of their co-workers (defined as the leave-out mean for the workers at the establishment and then averaging over the individuals in the CATE decile.) Panels A and B exclude establishments with fewer than 10 displaced workers. Controls are allocated to the same decile sample as the treated workers they were matched to.

Figure B.10: Robustness analyses: Displacement effects across and within establishments by AKM plant estimates



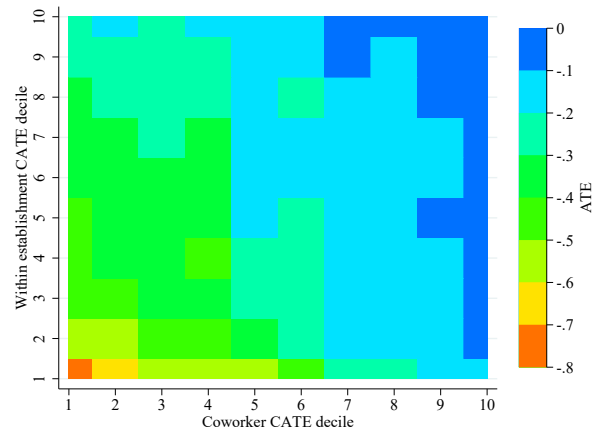
Note: Panel A (high AKM-plant effects) and C (low AKM-plant effects) shows ATE estimates when displaced workers are ranked based on their within-establishment CATE. Panel B (high AKM-plant effects) and D (low AKM-plant effects) shows ATE estimates when displaced workers are ranked based on the CATE of their co-workers (defined as the leave-out mean for the workers at the establishment and then averaging over the individuals in the CATE decile.) All panels exclude establishments with fewer than 10 displaced workers. Controls are allocated to the same decile sample as the treated workers they were matched to. AKM-estimates (Abowd et al., 1999) are derived from estimates on rolling 5-year samples ending in the year prior to the event ($t = -1$). Models have fixed establishment ("plants") effects, fixed person effects, year dummies, and third order polynomial in age (in deviation from 45), separately for three education groups (less than high school, high school, more than high school). The outcome is log earnings conditional on employment. Sample is split into high vs. low plant-effects samples by the median plant effect within each displacement cohort.

Figure B.11: CATE across and within establishments



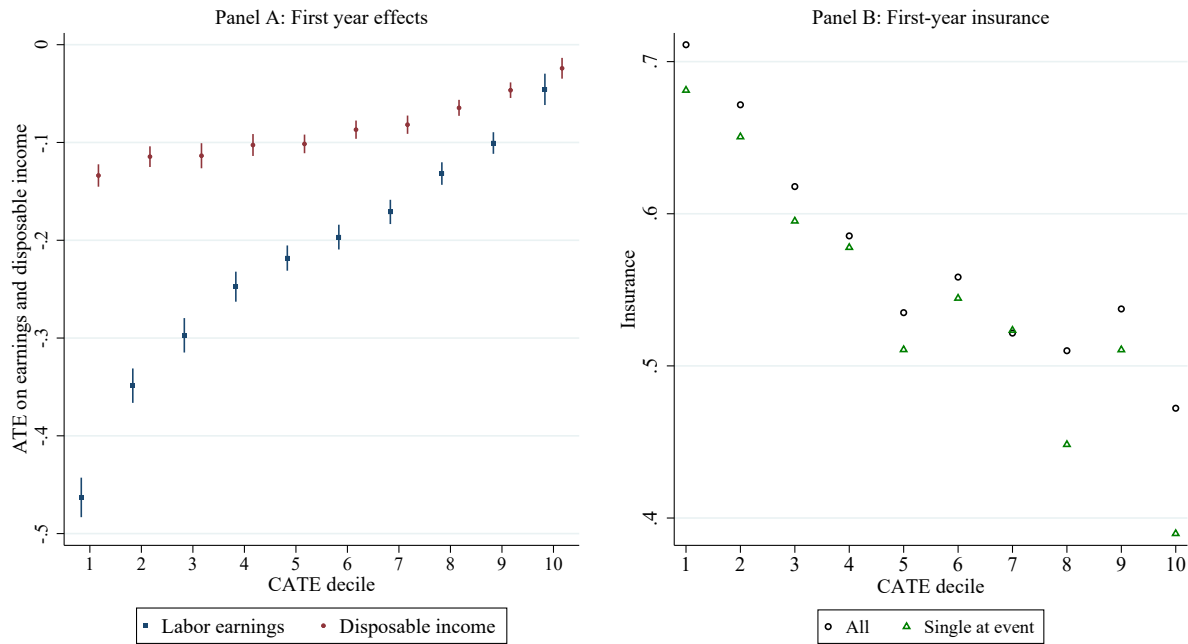
Note: Panel A shows statistics for displaced workers in the main (training) set by CATE decile (5-fold estimation and ranking done within each fold). It reports average individual CATE and the average CATE for the coworkers of the individuals in each CATE decile taken as a leave-out mean across the workers at the establishment and then averaging over the individuals in the CATE decile. Panel B shows average coworker CATE and the average CATE for other closures in the same industry, location and year by coworker CATE decile. Establishments with less than 10 displaced workers are discarded in Panel A. Workers from markets with only one event are discarded in Panel B.

Figure B.12: Heterogeneity within and across establishments, interactions



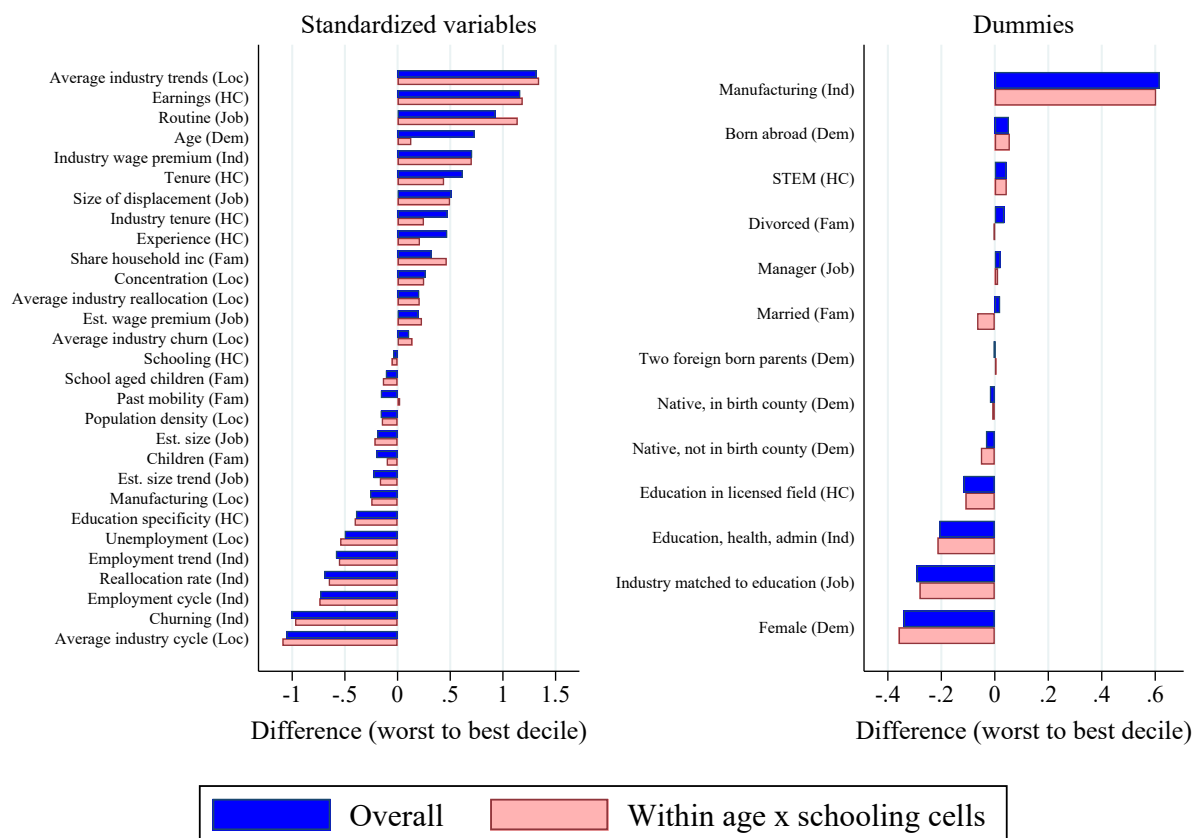
Note: The figure divides training set workers by combinations of coworker 5-fold CATE decile and within-establishment decile. Coworker CATE decile is determined by the ranking of the leave-out mean CATE at the establishment. For the within-establishment CATE, individuals are ranked by their CATE:s within the establishment. The figure restricts to establishments with at least 10 workers. Colors indicate the size of point estimates of the CATE within each cell.

Figure B.13: Insurance across the CATE distribution



Note: The figure shows outcomes when dividing the training data set into deciles based on CATE:s estimated with 5-fold estimation. Panel A shows ATE estimates on labor earnings (as in Figure 3) and corresponding ATE estimates for individualized disposable income. Point estimates and 95 percent confidence interval with standard errors clustered at the establishment level. Panel B shows the implied degree of insurance, defined as the difference between the ATE on disposable income the ATE on labor earnings, divided by the ATE on labor earnings. It provides separate estimates for the full population of displaced and for singles without children (in the year before displacement).

Figure B.14: Differences in characteristics across CATE quartiles for disposable income



Note: The figure divides the sample by the CATE estimates for disposable income. It shows differences in characteristics between individuals in the lowest and highest quartiles and deciles of CATE:s, using the training data set. CATE:s estimated using 5-fold estimation and ranking done within each fold. The left-hand panel contains standardized (mean 0 and standard deviation 1) continuous variables and the right-hand panel contains dummy variables. Blue bars are for the overall quartiles and red bars cover the highest and lowest quartiles of CATE within each combination of 8 schooling and 10 age categories

C Online Appendix: Partial Effects of Market Conditions

This appendix describes the most important industry and location variables in more detail. Isolating the importance of market-level factors is not trivial since workers are likely to be sorted across regions and industries. For that reason we use the GRF to estimate partial dependence functions, holding the individual characteristics at their empirical levels and sequentially rotating across all observed sets of market characteristics within the same year. This way, we capture the predicted role of aggregate conditions across the full distribution of displaced workers, making full use of the GRF's non-linear nature. Because market-level factors are correlated, we split locations and industries into groups, and then characterize effects and attributes for combinations of these groups.

Formally, we divide the vector of characteristics X into parts related to the location (X^L), the industry (X^S), or the displaced worker and lost job (X^I). Worker i was displaced from location $l(i)$ and industry $s(i)$, with $X_{l(i)}^L$ and $X_{s(i)}^S$ being the corresponding location and industry characteristics. Then we compute:

$$\tau_l^L = \frac{1}{N} \sum_{i=1}^N \text{CATE}(X^L = X_l^L, X_{s(i)}^S, X_i^I), \quad \tau_s^S = \frac{1}{N} \sum_{i=1}^N \text{CATE}(X_{l(i)}^L, X^S = X_s^S, X_i^I), \quad (1)$$

where N is the number workers in the sample. τ_l^L and τ_s^S are the average CATEs if all N workers experienced the conditions in location l /industry s . We use these predictions to rank industries and locations by τ^L and τ^S respectively.

We classify workers using a similar strategy. Here, we hold worker characteristics fixed and combine them with each observed combination of location and industry conditions. Then for each worker i we compute:

$$\tau_i^I = \frac{1}{N^L \times N^S} \sum_{l=1}^{N^L} \sum_{s=1}^{N^S} \text{CATE}(X_l^L, X_s^S, X_i^I), \quad (2)$$

where N^L and N^S are the number of locations and industries respectively. τ_i^I only reflects worker-level characteristics since we average over the same set of location and industry conditions for all workers (by year).

In the end, we compute how ATEs, and characteristics, vary with (combinations of) quartiles of τ^L , τ^S and τ^I . This strategy allows us to reduce the dimensionality of the heterogeneity and study how different types of heterogeneity interact.

C.1 ATE Estimates by Partial Market and Worker Quartiles

Table C.1 shows estimated ATEs for different cuts of the data, using combinations of τ_i^L , τ_s^S and τ_i^I . Panel A shows estimates for the lowest (Column 1) and highest (Column 2) quartile of worker-level effects (τ_i^I). Column 3 shows the inter-quartile differences, with standard errors in Column 4. The top row shows that workers in the lowest quartile of τ_i^I experience 26 pp larger losses than the top quartile.

In the rows below, we zoom in on workers exposed to different combinations of location and industry conditions. We see significant differences in ATEs across worker types within each set of market conditions (ranging from 0.30 to 0.16). Market conditions are particularly important predictors for workers with poor individual characteristics.⁸ The ATEs vary nearly as much when comparing across market (industry and location) conditions for the lowest worker quartile (25 pp difference, comparing across rows) as when comparing across worker quartiles within the worst market (industry and location) quartile setting (30 pp).

In Panels B and C, the columns instead represent location and industry (defined at the 3-digit level) quartiles, respectively. Here, the different rows represent worker types.⁹ Panel B shows that the location matters for the size of the displacement effect even when holding the worker quartile (τ_i^I) fixed (interquartile differences are 6 to 12 pp depending on type). Workers also suffer significantly larger effects if displaced from “bad” industries (Panel C), in particular if they belong to the bottom worker quartile. In this group, estimated losses are 19 pp larger if displaced in a low-quartile industry as compared to a high-quartile industry.

Market conditions should matter less (or not at all) if workers are mobile. We therefore estimate how displacement events affect mobility across locations and industries. Panel D shows that workers are more likely to change location if displaced under worse conditions. The estimated effects on location mobility are small, partly because location mobility overall is very low, but the results show that this is true even for workers displaced in very bad locations. The results also indicate that job loss leads to more mobility across locations among workers who are more resilient.

Panel E shows that workers are more likely to move away from their (1-digit) industry if they are displaced from an industry with large displacement effects. This analysis is performed on the endogenous subsample of workers who find new employment, which

⁸See Appendix Figure B.12 for similar results on the importance of establishment heterogeneity for low ranked workers.

⁹Standard errors for the cross-quartile differences are clustered at location (Panel B) and industry (Panel C) since the number of locations and industries is small relative to the sample.

warrants some caution. With this caveat in mind, the results suggest that cross-industry mobility due to job loss is more common among workers in industries where effects are larger; 33 (23) percent move because of displacement in industries in the worst (best) industry quartile. The magnitudes here are much more substantial than for location mobility throughout, which is natural since the old job disappears, but (other) ties to the location remain. Even though we find that industry mobility responds to displacement during distressful conditions, the fact that industry characteristics in general correlate so strongly with displacement effects suggests that the degree of industry mobility is insufficient to offset the negative effects of being displaced in a bad industry.

Table C.1: Earnings and mobility effects, by partial market and worker characteristics

	(1) Worst Quartile	(2) Best Quartile	(3) Interquartile Difference	(4) Standard Error of Difference
Earnings Estimates				
<i>Panel A: Worker Quartiles, earnings effects</i>				
All Market types	-0.374	-0.100	-0.274	0.008
Worst Market quartiles	-0.485	-0.141	-0.343	0.076
Median Markets	-0.360	-0.120	-0.240	0.027
Best Market quartiles	-0.234	-0.068	-0.166	0.021
<i>Panel B: Location Quartiles, earnings effects</i>				
All worker types	-0.296	-0.171	-0.125	0.015
Worst worker quartile	-0.424	-0.302	-0.122	0.013
Median workers	-0.257	-0.172	-0.085	0.014
Best worker quartile	-0.137	-0.086	-0.051	0.029
<i>Panel C: Industry Quartiles, earnings effects</i>				
All worker types	-0.323	-0.169	-0.154	0.022
Worst worker quartile	-0.453	-0.273	-0.180	0.028
Median workers	-0.282	-0.184	-0.098	0.019
Best worker quartile	-0.126	-0.088	-0.037	0.036
Mobility Estimates				
<i>Panel D: Location quartiles, effects on location mobility</i>				
All worker types	0.018	0.007	0.011	0.002
Worst worker quartile	0.012	0.011	0.001	0.002
Median workers	0.021	0.003	0.019	0.004
Best worker quartile	0.025	0.003	0.022	0.006
<i>Panel E: Industry quartiles, effects on industry mobility</i>				
All worker types	0.332	0.203	0.129	0.028
Worst worker quartile	0.416	0.246	0.170	0.034
Median workers	0.313	0.218	0.095	0.028
Best worker quartile	0.252	0.166	0.086	0.052

Note: Panels A–C display displacement effects on earnings on year after displacements (calculated as displaced-control differences, “ATEs”). Panel A shows earnings estimates for the worst quartile of workers (Column 1) and the best quartile (Column 2), using the worker resiliency measure described above. Results for workers in all markets (interaction between industry and location), for workers in the worst (best) market quartiles, and for median markets (workers in the 3d or 4th market quintiles). Column 3–4 show the difference between Columns (1) and (2), and the standard error for the difference (clustered at the level of the pre-displacement establishment). Panel B shows earnings estimates for the best and the worst quartiles of locations using the partial-effects procedure described above. Panel C shows similar earnings measures when dividing by the best and worst industries. Both Panel B and C report estimates for all workers and when dividing workers by worker resiliency using the worker resiliency measures described above. Median workers are those in the 3d or 4th worker quintiles. Panel D shows displacement effects on location mobility (mobility defined as moving to another local labor market between one year before and three years after the displacement), and Panel E displacement effects on industry mobility (mobility defined as switching 1-digit industry between one year before and three years after the displacement). Panels D–E show results for the full sample of workers and when dividing the sample by worker resilience as in Panels B–C. Standard errors in Panel B and D clustered at the location level, and standard errors in Panel C and E clustered at the industry level. All estimates use the main data set. Rankings of workers and reshuffling done using the k-folds procedure.

C.2 Characteristics of Markets with Large Partial Effects

Table 1 describes the best and worst locations and industries (top and bottom quartiles of τ_l^L and τ_s^S). Panel A shows location characteristics (X^L) for the “good” and “bad” locations as well as cross-quartile differences in X^L . Standard errors for differences are clustered at the location level. Locations with bottom-quartile partial effects (τ_l^L) are in particular characterized by much lower population density. These locations also have high unemployment rates and a more concentrated industry structure dominated by declining industries and manufacturing jobs.

Panel B shows similar results for industry characteristics. Industries with large predicted earnings losses for the average worker (τ_s^S) are exclusively found in manufacturing, while industries with small predicted losses are in non-manufacturing sectors. Industries with very negative τ_s^S -estimates also have higher wage premia, are less dynamic (lower churning and reallocation rates), and experience declining employment trends over both the short and the long run. All of these attributes are typical of manufacturing, but they are also related to effect heterogeneity if we only compare different manufacturing industries to each other, or if we only compare non-manufacturing industries to each other (see Table C.2).

Table C.2: Characteristics for the worst and best manufacturing and non-manufacturing industries

	Manufacturing			Non-manufacturing		
	Worst Quartile	Best Quartile	Interquartile Differ- ence	Worst Quartile	Best Quartile	Interquartile Differ- ence
	(1)	(2)	(3)	(4)	(5)	(6)
Employment trend	-0.284	0.062	0.346	-0.048	0.348	0.395
Employment cycle	-0.043	-0.006	0.037	-0.007	0.021	0.028
Industry wage	0.084	0.035	-0.050	0.051	-0.010	-0.061
Churning	0.165	0.164	-0.001	0.209	0.257	0.048
Reallocation	0.109	0.118	0.008	0.131	0.163	0.031
Manufacturing	1.000	1.000	0.000	0.000	0.000	0.000
Education, health, admin	0.000	0.000	0.000	0.031	0.233	0.202

Note: The table displays average industry characteristics for the best and the worst quartiles of manufacturing industries (Columns 1–3) and non-manufacturing industries (Columns 4–6). Both panels use the re-shuffling procedure described above. The industry characteristics are described in Section 3.2. Standard errors clustered at the industry level. All estimates use the main data set.

Table C.3 describes the characteristics of the top and bottom partial worker-level

quartiles (τ_i^I) and compare these to differences across raw CATE quartiles.¹⁰ Overall, the results show relatively small differences between the partial and overall quartiles. This suggests that a very small share of the differences in treatment effects associated with worker characteristics arises because of correlations with market factors. The table reaffirms the strong relationships with age, schooling, and specific human capital. The most striking difference is related to gender. Females are highly over-represented in the lowest *partial* quartile (τ_i^I), despite not being in the lowest *overall* CATE quartile. The (statistical) reason is that females are underrepresented in manufacturing where effects tend to be larger. There are also fewer immigrants in the best partial quartile than in the best overall CATE quartile, reflecting both an under-representation of immigrants in manufacturing and an over-representation of immigrants in metropolitan areas where effects tend to be more muted. Similarly, an over-representation of STEM graduates in the most resilient partial quartile reflects that many engineers work in manufacturing, but still suffer from relatively modest effects.

¹⁰In contrast to the related analysis in the paper’s main text, we use raw non-standardized numbers in this table.

Table C.3: Worker characteristics for resilient and non-resilient workers

	Workers ranked by <i>partial</i> CATE			Workers ranked by CATE		
	(1) Worst Worker Quartile	(2) Best Worker Quartile	(3) Difference [1]-[2]	(4) Worst Worker Quartile	(5) Best Worker Quartile	(6) Difference [1]-[2]
<i>Demographics</i>						
Age	52.331	35.626	16.705	50.736	36.136	14.600
Female	0.409	0.308	0.101	0.377	0.363	0.015
Born abroad	0.167	0.046	0.121	0.164	0.079	0.085
Two foreign born parents	0.025	0.033	-0.008	0.025	0.038	-0.013
Native, not in birth country	0.216	0.308	-0.093	0.202	0.299	-0.097
<i>Family</i>						
Married	0.641	0.542	0.099	0.634	0.527	0.107
Divorced	0.159	0.048	0.112	0.146	0.059	0.086
Children	0.330	0.918	-0.588	0.405	0.868	-0.463
School-aged children	0.240	0.506	-0.266	0.293	0.486	-0.194
Share household inc.	0.710	0.797	-0.087	0.718	0.788	-0.070
Past mobility	0.093	0.345	-0.252	0.104	0.330	-0.226
<i>Human capital</i>						
Schooling (years of education)	10.132	12.907	-2.776	10.145	12.648	-2.503
Experience	9.360	8.649	0.710	9.310	8.557	0.753
Tenure	6.702	5.278	1.423	6.771	5.189	1.583
Industry tenure	7.934	6.533	1.401	7.938	6.484	1.454
Earnings (rank)	0.364	0.654	-0.290	0.373	0.595	-0.222
STEM education	0.034	0.247	-0.214	0.035	0.202	-0.167
Education in licensed field	0.059	0.085	-0.026	0.049	0.102	-0.053
Education specificity	0.431	0.522	-0.092	0.423	0.523	-0.100

Note: The table shows average worker characteristics differ for the best and worst quartiles of workers. Columns 1–3 rank workers by CATE and Columns 4–6 by the partial worker resiliency measure described above. Columns 2–3 and 4–5 display averages within the respective quartiles. Column (3) shows differences between Columns (1) and (2). The worker characteristics are described in Section 3.2. All sample statistics are for the main data set. Rankings of workers and reshuffling done using the k-folds procedure.

References

- ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): "High wage workers and high wage firms," *Econometrica*, 67, 251–333.
- ALTONJI, J. G., E. BLOM, AND C. MEGHIR (2012): "Heterogeneity in human capital investments: High school curriculum, college major, and careers," *Annual Review of Economics*, 4, 185–223.
- AUTOR, D. H. AND D. DORN (2013): "The growth of low-skill service jobs and the polarization of the US labor market," *American Economic Review*, 103, 1553–97.
- BONHOMME, S., T. LAMADON, AND E. MANRESA (2019): "A Distributional Framework for Matched Employer-Employee Data," *Econometrica*, 81(3), 699–739.
- BURGESS, S., J. LANE, AND D. STEVENS (2000): "Job Flows, Worker Flows, and Churning," *Journal of Labor Economics*, 18(3), 473–502.
- CARD, D., A. R. CARDOSO, J. HEINING, AND P. KLINE (2018): "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, 36, S13–S70.
- CARD, D., J. HEINING, AND P. KLINE (2013): "Workplace heterogeneity and the rise of West German wage inequality," *The Quarterly journal of economics*, 128(3), 967–1015.
- CARLSSON, M., I. HÄKKINEN SKANS, AND O. N SKANS (2019): "Wage Flexibility in a Unionized Economy with Stable Wage Dispersion," Discussion Paper 12093, IZA.
- CARLSSON, M., J. MESSINA, AND O. N. SKANS (2016): "Wage adjustment and productivity shocks," *The Economic Journal*, 126, 1739–1773.
- CEDERLÖF, J. (2019): "Saved by Seniority? Effects of Displacement for Workers at the margin of Layoff," *Job market paper*.
- DAVIS, S. J. AND T. VON WACHTER (2011): "Recessions and the costs of job loss," *Brookings Papers on Economic Activity*.
- GATHMANN, C., I. HELM, AND U. SCHÖNBERG (2020): "Spillover effects of mass layoffs," *Journal of the European Economic Association*, 18, 427–468.
- GOOS, M., A. MANNING, AND A. SALOMONS (2014): "Explaining job polarization: Routine-biased technological change and offshoring," *American Economic Review*, 104, 2509–26.
- GULYAS, A. AND K. PYTKA (forthcoming): "Understanding the heterogeneity of earnings losses after job displacement: A machine-learning approach," *Journal of Labor Economics*.
- JACOBSON, L. S., R. LALONDE, AND D. SULLIVAN (1993): "Earnings Losses of Displaced Workers," *American Economic Review*, 83, 685–709.

- LACHOWSKA, M., A. MAS, AND S. WOODBURY (2020): "Sources of Displaced Workers' Long-Term Earnings Losses," *American Economic Review*, 110.
- LAMADON, T., M. MOGSTAD, AND B. SETZLER (2022): "Imperfect Competition, Compensating Differentials and Rent Sharing in the U.S. Labor Market," *American Economic Review*, 110, 169–212.
- LEIGHTON, M. AND J. D. SPEER (2020): "Labor market returns to college major specificity," *European Economic Review*, 128.
- STATISTICS SWEDEN (2019a): "LOUISE / Longitudinal Integrated Database for Health Insurance and Labour Market Studies (LISA), 1985-2017." Restricted-access microdata. Accessed 2019.
- (2019b): "Register-Based Labour Market Statistics (RAMS), 1985–2018." Restricted-access microdata. Accessed 2019.
- SWEDISH NATIONAL MEDIATION OFFICE AND STATISTICS SWEDEN (2019): "Wage Structure Statistics / Lönestrukturstatistiken, 1985-2018." Restricted-access microdata. Accessed 2019.