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The costs of job loss and task usage: Do social tasks soften the drop?

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Abstract
Do different tasks shield differently from the scarring effects of job loss? This study examines how the effects of job loss depend on task usage. We use Finnish linked employer–employee data from 2001 to 2016, representative survey data on task usage, and plant closures to identify individuals who involuntarily lose their jobs. We find that heterogeneity in the cost of job loss is linked to task usage. Workers in more social task-intensive origin jobs have smaller employment and earnings losses, whereas workers in routine jobs face larger wage losses. The probability of being employed is 8.3 pp higher (3.9 pp lower) per one standard deviation higher than mean social (routine) task usage 1 year after the job loss event. We also find that workers with longer tenure face larger losses and that task usage contributes more to their losses. The results show that the costs of job loss depend on task usage in the origin job. Public policy measures should be targeted at employees in routine-intensive jobs, since they face the largest losses.

Keywords Job loss · Earnings loss · Linked employer–employee data · Specific human capital · Task usage

JEL Classification J62 · J65 · J31 · J24

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1 Introduction

Several studies find persistent earnings losses for displaced workers.[1] A large body of literature has shown that the cost of job loss depends on the similarity of pre- and post-displacement jobs in terms of occupation, industry, and region (e.g., Addison and Portugal 1989; Jacobson et al. 1993; Couch and Placzek 2010). Recent literature has paid attention to the task content of jobs as an explanation for wage losses following displacement. Kambourov and Manovskii (2009) are among the first to show that the cost of job loss results from the loss of occupation-specific human capital. More recently, Blien et al. (2021) have studied whether the cost of job loss is larger for employees in more routine-intensive occupations than for those in less routine-intensive occupations.

The growing interest in task content as an explanation for the heterogeneity in the costs of job loss is linked to the research showing that technological change affects the task structures of the economy (e.g., Acemoglu and Autor 2011; Goos et al. 2014; Atalay et al. 2018). There is less demand for routine tasks (see, e.g.,Cortes et al. 2017; Atalay et al. 2020), and the occupational wage premia for routine occupations has decreased (Cortes 2016).[2] The demand for social tasks has, in turn, increased, and their labor market return has risen during the past decades (Deming 2017). Weidmann and Deming (2021) also show that social skills are an important asset and improve team performance as much as does IQ.

The cost of job loss is likely to be dependent on the task composition of the origin job. On the one hand, workers who lose routine-intensive jobs may experience exceptionally large losses from displacement, since the demand for such skills has decreased in the labor market due to automation, for example. On the other hand, workers who lose social task-intensive jobs may experience smaller losses, as such skills are increasingly in demand in the labor market. Understanding the factors determining earnings losses helps in targeting public policy measures to the persons most likely to suffer from job loss.

In this paper, we study how initial task usage affects the size of the shock displaced workers face. The keys to our analysis are Finnish administrative linked employer–employee data and representative survey data on task usage for occupation–industry cells. We use plant closures to identify those who have lost their jobs involuntarily due to exogenous shocks, and we follow them for 5 years before and 10 years after job displacement.

Our main question is whether the cost of job loss varies by task usage. We estimate the effect of job loss and task usage in each pre- and post-displacement year by comparing the outcomes of workers who were displaced to two groups of workers: (i) similar workers with similar task usage who were not displaced and (ii) otherwise similar displaced workers who differ by task usage. The task measures we use are similar to those used in the job polarization literature.

[1] See, e.g., Jacobson et al. (1993), Stevens (1997), Eliason and Storrie (2006), Couch and Placzek (2010), Hijzen et al. (2010), Huttunen et al. (2011, 2018).

[2] Vainiomäki (2018) shows similar results for Finland for the years 1995–2013. The wage ratio for routine occupations compared to abstract occupations has decreased. However, the routine/service wage ratio has increased.

To preview our main results, we find that the cost of job loss depends on initial task usage. Above mean social task usage is associated with both a higher probability of being employed and higher earnings, while the reverse is the case for routine task usage. In contrast, we do not find equally large and precise effects for manual and abstract task usage.

The magnitudes of the effects are large. The probability of being employed is 8.3 pp higher per one standard deviation higher than mean social task usage 1 year after the job loss event. This is a substantial magnitude since the effect of job loss on employment 1 year after is 13.6 pp. As a back of the envelope calculation, a 1.64 (13.6/8.3) standard deviations higher than average social task usage would eliminate the employment loss, which is the case for roughly one in every ten workers in our sample. The employment losses are larger for employees in routine-intensive occupations: one standard deviation higher routine task usage implies a 3.9 pp lower probability of being employed 1 year after job loss. Moreover, we find that social task usage is associated with a higher probability of remaining in the same occupation, industry, and region, which might explain at least partly why we also find a positive association with relative earnings.

A natural question to ask is whether the results reflect the impact of task usage on the cost of job loss or merely the impact of both observable and unobservable worker attributes. After all, workers have selected themselves into jobs that use a particular combination and level of tasks, which might be correlated with future labor market outcomes. Hence, it is not clear to what extent task usage explains the costs of job loss and what part is explained by both observed and unobserved skills. We address this issue in four ways.

First, we let the cost of job loss vary according to observable characteristics such as tenure, experience, education, gender, age, region, and occupation. Hence, we compare observationally similar workers who were displaced from similar jobs and differ only with regard to task usage. We use this identification strategy to examine whether workers with higher levels of, for example, social tasks adjust differently than their colleagues who use lower levels of social tasks or whether, for example, education or gender explain these differences. Second, we look at the dynamic responses of task usage by different sub-groups (for example, by gender or education) and show that they are similar. For instance, the cost of job loss for employees in routine-intensive jobs does not depend on their level of education. Third, we compare displaced workers to other displaced workers working in the same plant (and consequently the same region and industry) with similar observed characteristics but different occupations and hence who differ in terms of task usage. Fourth, we show that the pre-displacement employment and earnings trends 5 years prior to the job loss event are similar for different task usages; hence, it is highly likely that they would have followed similar patterns in the absence of plant closure.

Our paper is related to papers studying the cost of job loss and the heterogeneity behind it. The closest to our work is the paper by Blien et al. (2021) who have studied whether the cost of job loss is larger for employees in more routine-intensive occupations than for those in less routine-intensive occupations. They find that employees in more routine-intensive occupations face larger and more persistent earnings losses than do those in less routine-intensive occupations. We extend their investigation to other task usage categories, most importantly to social tasks, and to a longer time period of 10 years. Also related to our work is Goos et al. (2020), who find that re-employment probabilities 1.5 years after a car plant's closure are substantially higher for workers with non-routine task competencies and digital skills.

Another closely related study is Robinson (2018), who creates measures of task distance and direction between different occupations and shows that wage losses within 3 years of displacement are strongly related to the distance and direction of task usage.[3] Related to these studies is Edin et al. (2023) who find that, compared to similar workers, those facing occupational decline lost approximately 2–5% of mean cumulative earnings from 1986 to 2013 in Sweden.

Several studies have also focused on the reasons for the magnitude and persistence of earnings losses. Davis and Von Wachter (2011) show how leading labor market models, including that of Mortensen and Pissarides (1994) and its variants, fail to explain the extent of the losses observed in the data. One reason for this is that basic models contain no heterogeneity in productivity, match surplus values, or wages, which all seem to be important factors in generating large earnings losses due to job loss. Our paper is also related to the literature on the portability of skills in the labor market. Gathmann and Schönberg (2010) study the degree to which skills accumulated in the labor market are portable. They find that individuals move to occupations with similar task usage and that the distance decreases with experience. They also show that it is an important source of individual wage growth. Cortes and Gallipoli (2018) estimate the costs of occupational mobility and find that task-specific costs account for no more than 15% of the total transition costs. Our aim is to study whether some tasks, particularly social tasks, are associated with smaller losses after job loss than others.

The remainder of the paper proceeds as follows. Sect. 2 presents the data and the task usage variables and categories and explains how we define plant closures. Sect. 3 presents our empirical strategy. Sect. 4 presents the results and Sect. 5 the robustness checks. Finally, Sect. 6 concludes.

2 Data and task usage

2.1 EWCS data on task usage

We use European Working Conditions Survey (EWCS) data for the year 2005 for Finland and Sweden to define the task content of each job.[4] A job is defined as a

[3] Robinson (2018) finds that the overall negative effect of task distance on wages is mostly due to the negative effect of mobility in a negative direction. He compares displaced workers to each other and studies the distance between the origin and destination jobs, which both pose potential selection issues. Our data on detailed task usage and plant closures allow us to study whether a particular task usage category, such as social task usage, matters and to compare displaced workers to non-displaced workers also in the long term.

[4] The European Working Conditions Survey (EWCS) is a survey conducted by the European Foundation for the Improvement of Living and Working Conditions (Eurofound). It aims to assess the working conditions and job quality of workers in European countries, identify relationships between different indicators of working conditions and job quality, and study how working conditions and job quality evolve over time. The survey samples in each participating country are representative of the population of employed individuals

one-digit occupation in a one-digit industry due to the nature of the data.[5] Examples of jobs include clerical support workers in real estate activities, or plant and machine operators in mining, quarrying, and manufacturing.

The tasks are divided into four different categories: (1) manual (i.e., non-routine manual), (2) routine (i.e., routine manual and routine cognitive), (3) abstract (i.e., non-routine cognitive), and (4) social tasks (i.e., team work and dealing with people). We closely follow the approach taken in Eurofound (2016) (see Fernández-Macías et al. 2016) in creating the task variables. We use data for both Finland and Sweden to obtain more data and more precise measures of task usage for each job. Finland and Sweden are very similar countries, and the analyses in Fernández-Macías et al. (2016) show that the task measures vary little by country.

We use 22 different subcomponents, or survey items, to construct the four task usage categories. A complete list of these subcomponents (i.e., the survey items and possible answers to them) can be found in Online Appendix Table A1. Manual tasks are measured with three items that measure (1) vibrations from handtools, machinery, etc.; (2) tiring positions; and (3) carrying or moving heavy loads. This measure of manual tasks is quite similar to the one used by Autor and Handel (2013). Routine tasks are defined by nine items, which measure repetitive movements, repetitive tasks, constraints on the pace of work, and monotonous tasks. These measures are similar to those used in the previous literature (e.g.,Acemoglu and Autor 2011; Autor and Handel 2013). Abstract tasks are measured with five items that cover (1) assessing the quality of one's own work; (2) problem solving; (3) complex tasks; (4) learning new things; and (5) applying one's own ideas. This measure captures complex problem solving and creative thinking and thus captures tasks similar to the abstract task measure used in Acemoglu and Autor (2011) and Autor and Handel (2013). Social tasks are measured by (1) the amount of interaction with people and (2) four measures capturing the autonomy of team work. There are few papers in the literature measuring social tasks, and measures of working with others are sometimes included in the measure of routine tasks (e.g., Autor and Handel 2013). Our measure is cruder than the measure in Deming (2017); however, by including measures of team work, it captures tasks that are similar to his measure (see footnote 20 Deming 2017). We modify the answers to the survey items to give them values of 0 or 1, or between 0 and 1, depending on the question, as shown in Online Appendix Table A1. We then take the average of these modified variables as a measure of task intensity.

In Table 1, we summarize task usage for different occupations in our sample to compare our classification to prior literature. Here, an occupation includes all the existing one-digit level occupation–industry pairs that we refer to as jobs. We have

aged 15 and older who live in private households and had done at least one hour of paid work during the week preceding the interview.

[5] Unfortunately, a problem with the EWCS data is that the country-level and EU15-level survey weights have been computed only so that the employment shares of ISCO-88 1-digit occupations would be close to their true shares. Therefore, there is no guarantee that the ISCO-88 2-digit occupational employment shares computed from the data are accurate. A further problem is that the number of observations in some"2-digit ISCO $\times$ 1-digit NACE" cells becomes rather small even at the EU15-level. Therefore, the task intensity
Footnote 5 continued
measures for these occupation–industry groups become very noisy. Hence, we use the data at the 1-digit occupation and 1-digit industry levels.

Table 1 Task usage in different occupations

	Manual task usage	Routine task usage	Abstract task usage	Social task usage
Managers	10.46	31.49	92.29	63.33
Professionals	7.56	34.96	86.53	58.48
Technicians and associate professionals	11.27	31.22	82.76	62.31
Clerical support workers	14.24	38.63	76.15	63.26
Service and sales workers	20.18	37.63	77.06	83.10
Craft and related trade workers	38.83	46.51	82.07	60.33
Plant and machine operators and assemblers	29.28	52.27	66.52	57.09
Elementary occupations	27.72	53.25	59.43	62.68

Sample consists of workers who were 20–50 years old at time in base years 2004–2006) and who were working in private sector plants with 10–500 workers and had a tenure of at least 3 years. Task usage measures have been multiplied by 100 and weighted by the share of workers in industry

defined the task usage at the job level. Hence, an occupation's task usage differs by industry. As shown in Table 1, occupations differ in both the level and the combination of the various tasks used. The ranking of occupations in terms of routine intensity is similar to that of Goos et al. (2014) and Autor and Dorn (2013). For example, managers and professionals are both occupations that have fewer routine tasks than average across all occupations, whereas plant and machine operators have more routine tasks. Concerning manual task usage and abstract task usage, we find a ranking of occupations that is similar to that given in Autor and Dorn (2013). Managers and professionals have many abstract tasks and few manual tasks, whereas plant and machine operators, for instance, have many manual tasks but few abstract tasks. Comparing social tasks is more difficult because the use of social skills has not been reported by occupation in the prior literature. However, in Table 2 of Autor and Handel (2013), sales and service workers score highly on their measure of having a lot of face-to-face contact, which is similar to our measure.

2.2 Plant closures

Our primary dataset is the Finnish linked employer–employee data (FLEED) set, which covers all Finnish residents between the ages of 16 and 70 years in the period 1988–2016. We use the years 2001–2016 because occupational codes are not available for all years before 2004.[6] The unique person identification codes allow us to follow individuals over time. Likewise, unique firm and plant codes allow us to identify each worker's employer and to examine whether their plant is closing down. Our approach closely follows the approach taken in, for example, Huttunen et al. (2018) and Huttunen and Riukula (2019). We focus on individuals who were working in private sector plants

[6] In some cases, we do not have pre-base-year occupational codes. The missing occupational codes are replaced with occupational codes of the following year.

in 2004–2006. We label these years "base years" b. We construct separate samples for each base year b by including observations for each worker 5 years prior to the base year b and 10 years after. In the analyses we pool these three base year samples to a panel spanning the years 2001–2016.

In the original data, which cover all private sector plants from 1988 to 2016, we first define plant closures and downsizing plants. Here a plant is a production unit (for goods or services) that is owned by one firm (or enterprise), is located on one site and operates within one industry. A plant is defined as an exiting plant if it is in the data in year t but is no longer in year $t+1$ or in any of the years after $t+1$. We also check whether these are real plant closures. Those exiting plants for which more than 70% of the workforce is working in a single new plant in the following year are not considered real closures. Then, we merge the plant exit data with the individual-level data.

We label workers "displaced" if their plant closed down during b and $b+1$. We also include so called early levers as is common in the literature (e.g., Huttunen and Kellokumpu 2016).[7] A plant closure can be thought to be an exogenous shock to a worker's career, since it results in separation of all the plant's workers and is not related to the worker's own job performance. The comparison group consists of all workers who were not displaced due to plant closures between years b and $b+1$. Importantly, we allow workers in the control group to separate for reasons other than displacement, including voluntary job changes and sickness (Krolikowski 2018). To ensure that the treatment and control groups are as similar as possible, we restrict the plant size to more than 10 but fewer than 500 workers and require the workers to be 20–50 years old in base year b. We also conduct a robustness check using mass-layoff events, where a mass-layoff is defined as an employment drop of at least 30% in plants with 50–2000 workers and where no more than 30% of the workforce is allowed to be re-employed together.

3 Empirical strategy and descriptive statistics

3.1 Empirical strategy

To estimate the labor market and task usage effects of job loss, we use a standard approach in the job displacement literature and estimate an event-study style fixed effect regression in which the outcome is relative earnings[8] or employment[9]

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[7] Early leavers are persons who separated from a plant during b and $tb+1$ that closed down the next year between $b+1$ and $b+2$ and which reduced their workforce by more than 30% between b and $b+1$. We also restrict the sample to individuals for whom we can find a plant code for years $b+t$, where $t=[-3,-1]$ and we drop workers who were displaced earlier in $b-2$ or $b-1$. We restrict the analysis to those with at least 3 years of tenure. The results are robust to including all private sector workers without restrictions on prior displacement or having a plant code before base year b (not reported). If the worker is displaced and appears more than once in the data, we keep the first base year when (s)he was displaced. If the worker is not displaced, (s)he can appear in the data up to three times, as there are three base years that we pool together.

[8] Relative to earnings in years $b-3$ to $b-1$

[9] Employment refers to employment status in the last week of the year.

$$Y_{ibt} = \alpha_{ib} + \beta' \mathbf{X}_{ibt} + \sum_{j=-5}^{10} \delta_j D_{it,b+j} + \left(\sum_{j=-5}^{10} \theta_j D_{it,b+j} \mathbf{G}_{ib} \right) + \tau_{bt} + \epsilon_{ibt} \quad (1)$$

In Eq. 1, Y_{ibt} is the outcome variable for worker i in base year sample b at time t. The variables $D_{it,b+j}$ are the variables of main interest. These are dummy variables indicating whether a displacement occurred in year $b + j$, where t is the observation year. The associated parameters measure, for example, the earnings differentials of displaced workers relative to the non-displaced workers in pre- and post-displacement years $j \in [-5, \ldots, 10]$. We use the period $b - 1$ as the baseline and thus drop the displacement dummy for this year. Our estimation strategy relies on the assumption that a job displacement event is exogenous to a worker's career. The model has a full set of time dummy $\times$ base year dummy interactions, τ_{bt}. We also include base year-specific individual fixed effects, α_{ib}, to control for permanent differences in earnings between displaced and non-displaced workers (in a given base year b). When including worker-base-year fixed effects, we cannot include any time-invariant base-year controls, but X_{ibt} includes current year age and age squared. We cluster standard errors by individual i to allow for the correlation of the error terms, ϵ_{ibt}, across different time periods t and base years b for individual i.

We use the propensity score matching procedure adapted from Schmieder et al. (2023) and Bertheau et al. (2023) to construct the control group and estimate matched difference-in-differences. We match them with the following pre-displacement characteristics from the base year b: age, tenure, industry, occupation, and plant size, and both annual earnings and employment status from years $b - 5$ to $b - 1$.

To study how task usage affects labor market outcomes, we extend the analysis by including (standardized)[10] base year task usage variables interacted with the displacement dummy $\times$ time dummy interactions $\sum_{j=-5}^{10} \theta_j D_{it,b+j} \mathbf{G}_{ib}$. The variables in $\mathbf{G_{ib}}$ include standardized base year task usage variables (i.e., manual, social, abstract and routine) and other base year worker and plant characteristics (i.e., tenure, experience, female dummy, tertiary and secondary education dummies, indicators for one-digit occupation and plant size,[11] and capital region dummy). The base year characteristics provide a better understanding of the heterogeneity of the cost of job loss and allow us to compare observationally similar displaced workers. The worker-base-year fixed effects should also account for a large part of the unobservable characteristics.

We estimate the effect of job loss and task usage in each pre- and post-displacement year by comparing the outcomes of workers who were displaced to (i) similar workers with similar task usage who were not displaced and (ii) to otherwise similar displaced workers who differ by task usage. If we observe similar trends for earnings and employment prior to the job loss event for different levels of task usage, it is plausible that they would have evolved along similar trajectories in the absence of plant closure.

[10] Standardization means that the mean is standardized to zero and the variance is standardized to one.

[11] Plant size is divided into five categories: less than 21 workers (but more than 10 due to sample restrictions), 21–50 workers, 51–100 workers, 101–200 workers, and 201–500 workers.

Table 2 Pre-displacement characteristics

	Displaced Mean	Non-displaced Mean	*P*-value for difference *p*
Age	38.56	38.69	0.18
Female	0.38	0.35	0.00
Children under 18	0.96	0.99	0.06
Tenure	6.04	6.04	0.84
Plant size	122.54	122.83	0.87
Primary education	0.16	0.16	0.52
Secondary education	0.50	0.48	0.00
Tertiary education	0.34	0.36	0.01
Experience	16.78	16.92	0.25
Married	0.50	0.51	0.02
Annual earnings	40118.10	39963.65	0.70
Annual income	41537.18	41171.39	0.41
Manual task usage	21.08	21.25	0.31
Routine task usage	42.84	42.48	0.02
Abstract task usage	76.68	76.80	0.40
Social task usage	59.58	60.36	0.00
Observations	10,637	10,489	21,126

Annual income and earnings deflated to year 2013 euros. Non-displaced workers were matched to displaced workers using propensity score matching and following, e.g., Schmieder et al. (2023) See Table 1 for additional table notes

3.2 Descriptive statistics

Table 2 describes the background characteristics of the displaced workers and their matched non-displaced counterparts in our sample. On most characteristics the workers who experienced a plant closure look very similar to their matched counterparts who did not experience a job loss during the period. Their age, education, work experience, marital status, number of children and earnings look similar. Earnings are measured as annual taxable labor income and deflated to 2013 euros using the national consumer price index. Annual income includes components such as regular labor income, income from self-employment, and taxable benefits received while on sick leave, being unemployed or on parental leave. We also summarize task usage in the pre-displacement year, b, by displacement status. The displaced workers work in jobs that are somewhat more routine-intensive and less social-intensive. However, the differences are small.

A large proportion of the displaced workers, 38%, work in the manufacturing sector, while 37% of the non-displaced workers also work in that industry, as shown in Online Appendix Table A2.[12] Real estate activities come second with 19% of dis-

[12] The manufacturing sector also includes mining.

Table 3 Occupation by displacement status

	All	Displaced	Non-displaced
Managers	5.43	5.46	5.40
Professionals	14.50	14.98	14.02
Technicians and associate professionals	18.93	18.87	18.99
Clerical support workers	8.16	8.09	8.23
Service and sales workers	8.23	8.23	8.24
Craft and related trades workers	13.58	13.30	13.85
Plant and machine operators and assemblers	22.47	22.38	22.55
Elementary occupations	8.70	8.69	8.72
Total (%)	100.00	100.00	100.00

See Table 2 for table notes

placed workers working there. Over 30% of the workers work either as professionals or technicians and associate professionals, as shown in Table 3.

In Online Appendix Fig. A1, we plot selected labor market statistics by time and displacement status. As shown in the figure, the displaced workers are similar to their non-displaced counterparts in terms of their earnings and employment before the job loss. After the job loss occurs, a persistent gap opens in employment and earnings.

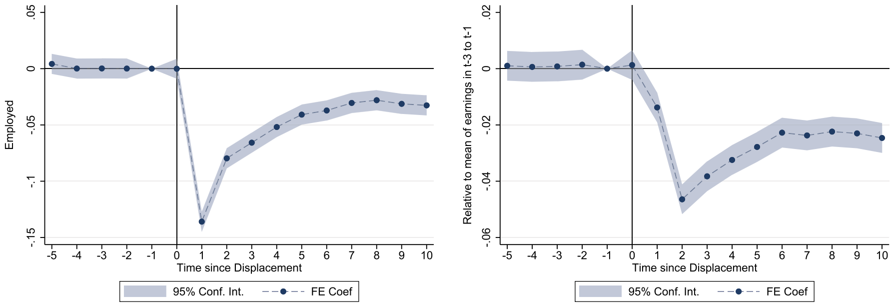
4 Results

4.1 The costs of job loss

We first show how job displacement affects employment and earnings. In Fig. 1, we plot the estimates of δ_j and the 95% confidence intervals from equation 1. [13] The job displacement occurs between b and $b + 1$. Panel a) in Fig. 1 shows that displaced workers suffer a long-lasting drop in employment. Initially, employment drops by approximately 13.6 pp, but over time the gap shrinks to approximately 3 pp, which corresponds to a 3.5% reduction as the employment rate for the non-displaced workers is 86% 10 years after the job loss.

The displaced workers also experience a drop in earnings as shown in panel b) in Fig. 1, where we plot the results for relative earnings. After 5 years following the job loss event, their relative earnings have decreased by 3.0%. Their earnings do not converge to the non-displaced levels even after 10 years. In the long term, relative earnings drop by around 2.5%. These results are qualitatively similar to the results reported in, for example, Huttunen et al. (2011). The results indicate that job loss results in a long-lasting drop in earnings and employment. Moreover, we show that the pre-displacement trends with respect to labor market outcomes are similar for 5

[13] As a reminder, we exclude worker (including task usage) and plant base year variable interactions with the displacement dummy $\times$ time dummy interactions from the specification at this point.



(a) Employment (b) Relative Earnings

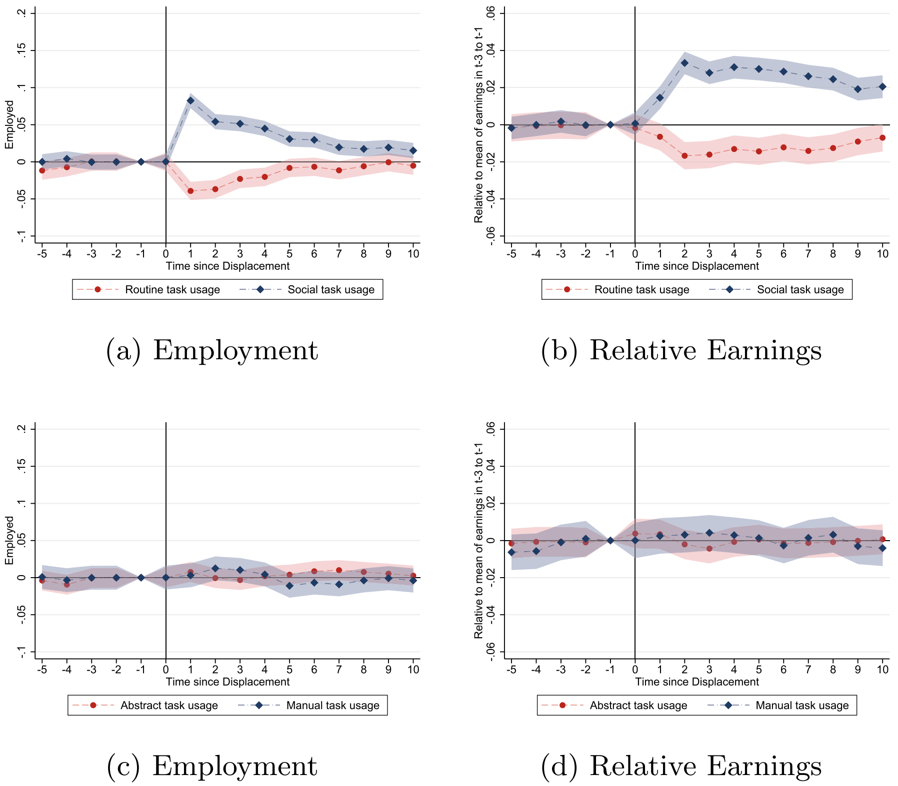
Fig. 1 Job loss and labor market outcomes. The figure plots the estimates of δ_j and 95% confidence intervals obtained using Eq. 1 (including only displacement $\times$ time dummy interactions) for employment and earnings

years before the job loss event. Next, we turn our focus to the heterogeneity of job loss and the role of task usage.

4.2 Task usage and the costs of job loss

We explore the role of task usage by interacting base year task usage variables and other base year characteristics with the displacement dummy $\times$ time dummy interactions. Adding base year characteristics for the worker and plant allows us to compare observationally similar workers who work in similar plants to workers whose plant was closed down and to otherwise similar displaced workers who differ in their task usage. We report the results in Fig. 2, where we plot the estimates of θ_j from Eq. 1. We use standardized values of task usage; hence, the point estimates correspond to having a one standard deviation higher task usage than on average. The full results, including results for other worker and plant base year characteristics, are reported in Online Appendix Tables A3, A4 and A5 for employment and in Online Appendix Tables A6, A7 and A8 for relative earnings.

The results suggest that the cost of job loss is linked to task usage and especially to routine and social task usage. Figure 2 panel a) shows that the probability of being employed is 8.3 pp higher per one standard deviation higher than mean social task usage 1 year after the job loss event. This is a substantial magnitude since the effect of job loss on employment 1 year after is 13.6 pp (see Online Appendix Table A3). As a back of the envelope calculation, a 1.64 (13.6/8.3) standard deviations higher than average social task usage would eliminate the employment loss, which is the case for roughly one tenth of the workers in the sample. Concerning the longer-term impact, it is seen that the employment loss converges to approximately 1.5 pp after 10 years. For routine task usage, the story is the opposite. There is a 3.9 pp lower probability of being employed 1 year after job loss for one standard deviation higher routine task usage.



(a) Employment (b) Relative Earnings

(c) Employment (d) Relative Earnings

Fig. 2 Task usage and labor market outcomes. The figure plots the estimates of θ_j and 95% confidence intervals obtained using Eq. 1 for employment and earnings

The story is similar for relative earnings as shown in panel b). We can see a positive (negative) and persistent effect of social (routine) task usage on relative earnings. The earnings loss after 5 years would be eliminated with a 1.37 standard deviations (4.1/3.0) higher than average social task usage, which is the case for roughly one tenth of the workers in the sample. For abstract and manual tasks and for both employment and earnings, the coefficients are close to zero and quite imprecisely estimated as shown in panels c) and d). Hence, they do not contribute to the loss as much as routine tasks or shield as much as social tasks. Importantly, Fig. 2 shows no differences between different levels of task usage prior to job loss. Hence, it is likely that they would have followed similar employment and earnings patterns in the absence of plant closure.

4.3 Heterogeneity: education, gender, and tenure

Both as a heterogeneity analysis and a robustness check, we study how the effects of task usage vary by education and gender. Workers using different levels of different tasks also differ in terms of, for example, education. However, controlling for these characteristics is insufficient as the dynamic responses might also differ. Hence, the

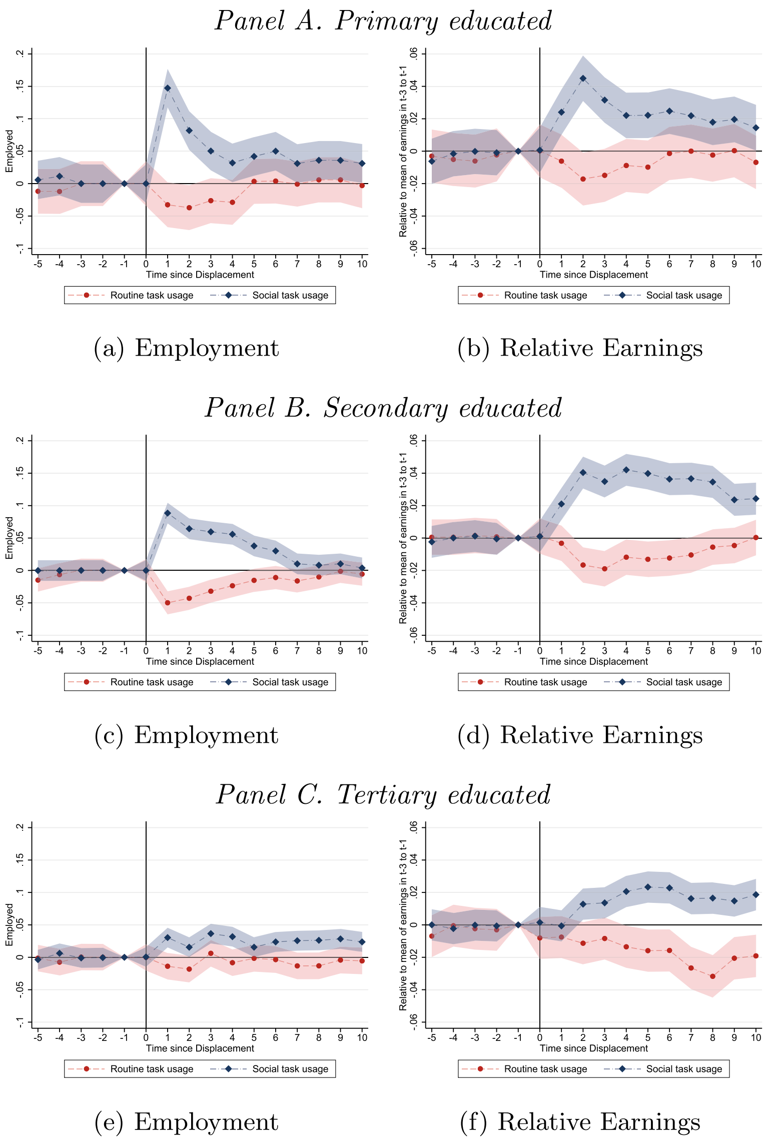


Fig. 3 Task usage and labor market outcomes by education

results might be driven by, for example, education and not by task usage. To determine whether gender or education drives our results, we divide workers by educational level and gender into five groups: primary, secondary and tertiary educated workers and into females and males. If we see different effects on employment and earnings for different groups, it might suggest that our results are driven by that characteristic.

In Fig. 3, we plot the results for employment and relative earnings for all three education groups. We include interactions with the displacement dummy × time dummy interactions and various other base year characteristics as previously. A one standard

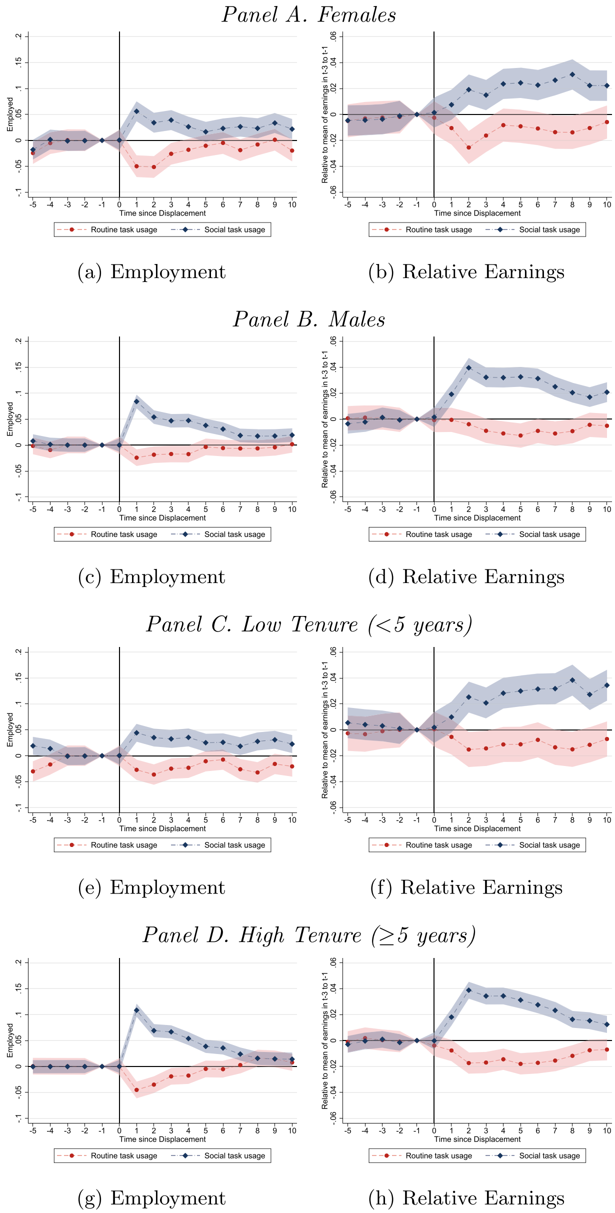


Fig. 4 Task usage and labor market outcomes by gender and tenure

deviation increase in social task usage is associated with a higher probability of being employed for all education groups, the effect being largest for workers with a primary education. For the primary educated, the probability of being employed is 14.7 pp higher per one standard deviation higher than average social task usage. The story is similar with respect to relative earnings, but not as precisely estimated. For routine task usage, displacement is associated with a smaller probability of being employed for all education groups. However, for the tertiary educated group, the coefficients are very close to zero. The point estimates for relative earnings are mostly negative, but they are imprecisely estimated for the primary educated group. Taken together, these results suggest that routine task usage is associated with employment and earnings losses regardless of the education group.

Figure 4 panels a)–d) show the results separately for men and women. The results are similar for men and women for both routine and social task usage; social task usage is associated with better labor market outcomes whereas routine task usage is associated with worse labor market outcomes. However, the results concerning routine task usage are not as precise and large in magnitude for males as they are for females and the whole sample.

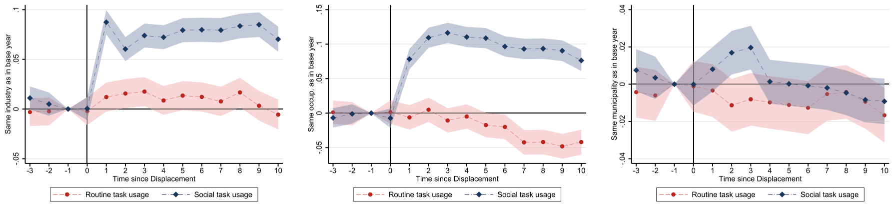
In Fig. 4 panels e)–h), we plot the estimates for employment and earnings for high- and low-tenure workers. For those with a tenure of less than 5 years, one standard deviation higher social task usage than on average is associated with an increase in the probability of being employed 1 year after being displaced by 4.4 pp, while for those with five or more years of tenure, the figure is 10.8 pp. The results for relative earnings follow a similar pattern. For those with a tenure of less than 5 years, one standard deviation higher social task usage than on average is not associated with higher relative earnings 1 year after being displaced, while for those with five or more years of tenure, the coefficient is larger and more precise.

For routine task usage, we can see a similar but mirror-wise pattern: routine task usage is more strongly associated with lower employment and earnings for those with longer tenure. For other task usage categories, we cannot see equally large differences with respect to tenure (not reported here).

Task usage seems to matter more for employment and earnings for those with longer tenure, especially in the case of routine and social tasks. When adding interactions with the displacement dummy $\times$ time dummy interactions and task usage variables, the coefficients of the displacement dummy $\times$ time dummy interactions become less precise and smaller for high-tenure workers, as shown in Online Appendix Tables A9 and A10, and in Online Appendix Fig. A2. We find similar results concerning experience (not reported here). These results suggest that task usage and demand for different types of tasks are important determinants of the costs of job loss. Experienced workers do not necessarily suffer from the cost of job loss if they are displaced from a job that is intensive in tasks that are in high demand.

4.4 Mechanism

Next, we turn our attention to mobility and, specifically, to how routine and social task usage are associated with different mobility measures following job loss. Our aim is to determine, whether, for example, social task usage is associated with less mobility in terms of occupation, industry, and region, which might explain why they experience smaller earnings losses. For example, Huckfeldt (2022) finds that the earnings cost of job loss is concentrated among workers who are re-employed in lower-skill occupations. We have three outcome variables to measure mobility: (1) a dummy for



(a) Same industry (b) Same occupation (c) Same municipality

Fig. 5 Task usage and mobility

having the same occupation as in the base year, (2) a dummy for working in the same industry as in the base year, and (3) a dummy for living in the same municipality as in the base year. As we do not have occupation codes yearly prior to 2004, we restrict the pre-years to $b-3$ to $b-1$. Moreover, the analysis is now restricted to individuals who are by definition working since we do not have occupation or industry codes for those who are not employed.

As shown in Fig. 5, social task usage is associated with decreased mobility, which might explain why it is also associated with smaller earnings losses following displacement. As shown in panels a)–c), the probability of working in the same industry, occupation and municipality as in the base year is higher for social task usage. Surprisingly, mobility is not positively associated with routine task usage. Hence, changing industries, occupations, or regions does not explain why we find a negative association between routine task usage and relative earnings.

5 Robustness checks

5.1 Grouping by task intensity

As an additional robustness check, we divide the sample into four distinct groups: employees in routine-, social-, abstract-, and manual-intensive jobs in the base year. We define a job as intensive in task if the task usage is in the top quartile in our sample. Hence, the group always includes approximately 25% of the sample. This setting is similar to that in Blien et al. (2021). Moreover, we divide these four groups into three subgroups depending on their level of education. Our aim is to determine whether, for example, routine-intensive workers with different levels of education respond differently to job loss. In the analysis we include only those who are intensive in one task category only to avoid having the same individual in two or more groups.[14]

Online Appendix Fig. A3 shows that the dynamic responses within task intensity groups for employment, panels a)–d), and relative earnings, panels e)–h), among workers with different educational levels, are very similar, suggesting that task usage rather than education drives the results. There is only a small drop or no drop for social-intensive workers with respect to employment and earnings, while the drop for

14 Dropping those in two or more groups leaves us with approximately 60% of the workers.

routine-intensive workers is remarkable. There is a 39.9 pp initial drop in employment for primary educated workers, a 37.2 pp drop for secondary educated workers, and a 35.7 pp drop for tertiary educated routine-intensive workers. As a reminder the drop for the whole sample is 13.6 pp. Hence, the drop in employment for routine-intensive workers is three times greater. The initial drop in relative earnings is also roughly threefold for routine-intensive workers compared to the whole sample 2 years after the job loss.

We cannot add plant fixed effects to our main specification to see whether the plant (which includes both region and industry) or task usage matters the most, as we would not be able to compare displaced and non-displaced workers (by definition, they work in different plants). Therefore, as a complementary approach, we take only displaced workers and extend Eq. 1 by including plant fixed effects and excluding worker-base-year fixed effects. In this way, we compare observationally similar displaced workers working in the same plant (and consequently in the same region and industry), but with different occupations and hence with different levels of task usage. These results are similar to our main results (Online Appendix Fig. A4).

5.2 Job displacement in years 2007–2011

We have focused on the base years 2004–2006 for three reasons. First, the data end in 2016, and we want to be able to follow workers for 10 years to grasp the long-term effects. Second, the occupation codes are not available yearly before 2004, and they are needed to match the workers to their task usage. Finally, and perhaps most importantly, the task usage data are from 2005. Hence, the further we move from this year, the less accurate it is. Next, we shorten the follow-up period by 5 years and examine the base years 2007–2011. Moreover, we split these base years into two periods: recession (years 2007–2008) and growth years (2009–2011). According to the results in the Online Appendix Fig. A5, social task usage is associated with better employment for both the recession and growth years in the period. In terms of relative earnings, social task usage is associated with higher relative earnings following job loss in recession years but not in the period of 2009–2011. For routine task usage, we find no association with employment following job loss and a negative association with earnings during the period of 2009–2011. A possible reason for this finding is that our task usage variable from 2005 might not well describe the actual task usage in these later years.

5.3 Mass-layoff events

In the analysis, we have followed, e.g., the work of Huttunen et al. (2011) in defining plant closures. Next, we follow Schmieder et al. (2023) and focus on mass-layoff events with an employment drop of at least 30% and where no more than 30% of the workforce is allowed to be re-employed together. Now, we restrict the plant size to 50–2000 workers. In terms of social task usage, the results are robust. Social task usage is associated with both a higher probability of being employed and higher relative earnings. Routine task usage is associated with a lower probability of being employed, while the association with relative earnings is negative in the years immediately after job loss and positive later on.

6 Conclusions

On average, job displacement leads to persistent earnings losses, even for those who are re-employed. The costs of job loss are heterogeneous, and recent literature has paid attention to the task content of jobs as an explanation for this heterogeneity. We study the heterogeneity of the cost of job loss by focusing on task usage in origin jobs. We measure task usage in terms of routine, social, abstract and manual tasks. Specifically, we study whether workers who involuntarily lose their jobs face different shocks depending on their initial task usage. Do routine-intensive workers, for example, pay a penalty in terms of lower wage levels? Do workers who use a lot of social tasks do better? We use plant closures to identify those who lose jobs involuntarily due to exogenous shocks and follow them for 5 years before and 10 years after job displacement.

We find that workers who lose jobs due to plant closures suffer persistent earnings losses, which is in line with the findings of previous studies. Workers in origin jobs with high levels of social tasks have a higher probability of being re-employed, while routine task usage is associated with a lower probability of finding employment. Routine task usage is associated with large and persistent earnings losses, while social task usage shields workers from earnings losses. The results for routine-intensive workers are consistent with Blien et al. (2021). We find generally small effects on the costs of job loss for abstract and manual task usage.

We find evidence that workers with longer tenure suffer larger losses. We also find that task usage contributes more to their losses. This is as expected, as they have had time to accumulate their (firm-)specific human capital for a longer period. As above, the association between social task usage and employment and earnings is positive, while these findings for routine task usage are negative.

Taken together, the results show that the costs of job loss depend on task usage in the origin job. Public policy measures should be targeted at employees in routine-intensive jobs, since they face the largest losses. These individuals would likely benefit the most from, for example, government-sponsored training programs.

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Availability of data and materials The dataset generated during the current study is not publicly available as it contains proprietary information that the authors acquired through a license. Information on how to obtain it and reproduce the analysis is available from the corresponding author upon request.

Code availability The do-file used for analysis is collected in the electronic supplementary material of this article.

Declarations

Conflict of interest Krista Riukula and Antti Kauhanen declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by the author.

References

Acemoglu D, Autor D (2011) Skills, tasks and technologies: implications for employment and earnings, handbook of labor economics, volume 4. Elsevier, pp 1043–1171
Addison JT, Portugal P (1989) Job displacement, relative wage changes, and duration of unemployment. J Law Econ 7(3):281–302
Atalay E, Phongthiengtham P, Sotelo S, Tannenbaum D (2018) New technologies and the labor market. J Monet Econ 97:48–67
Atalay E, Phongthiengtham P, Sotelo S, Tannenbaum D (2020) The evolution of work in the united states. Am Econ J Appl 12(2):1–34
Autor D, Dorn D (2013) The growth of low-skill service jobs and the polarization of the us labor market. Am Econ Rev 103(5):1553–97
Autor DH, Handel MJ (2013) Putting tasks to the test: human capital, job tasks, and wages. J Law Econ 31(S1):S59–S96
Bertheau A, Acabbi EM, Barceló C, Gulyas A, Lombardi S, Saggio R (2023) The unequal consequences of job loss across countries. Am Econ Rev Insights 5(3):393–408
Blien U, Dauth W, Roth DH (2021) Occupational routine intensity and the costs of job loss: evidence from mass layoffs. Labour Econ 68:101953
Cortes GM (2016) Where have the middle-wage workers gone? A study of polarization using panel data. J Law Econ 34(1):63–105
Cortes GM, Gallipoli G (2018) The costs of occupational mobility: an aggregate analysis. J Eur Econ Assoc 16(2):275–315
Cortes GM, Jaimovich N, Siu HE (2017) Disappearing routine jobs: Who, how, and why? J Monet Econ 91:69–87
Couch KA, Placzek DW (2010) Earnings losses of displaced workers revisited. Am Econ Rev 100(1):572–89
Davis S.J, Von Wachter T.M (2011). Recessions and the cost of job loss. Brookings Papers on Economic Activity: 1–72
Deming DJ (2017) The growing importance of social skills in the labor market. Quart J Econ 132(4):1593–1640
Edin PA, Evans T, Graetz G, Hernnäs S, Michaels G (2023) Individual consequences of occupational decline. Econ J 133(654):2178–2209

Eliason M, Storrie D (2006) Lasting or latent scars? Swedish evidence on the long-term effects of job displacement. J Law Econ 24(4):831–856
Eurofound (2016) What do Europeans do at work? A task-based analysis: European jobs monitor 2016. https://policycommons.net/artifacts/1841077/what-do-europeans-do-at-work-atask-based-analysis/2584230/
Fernández-Macías, E. et al., 2016. What do Europeans do at work? A task-based analysis: European Jobs Monitor 2016, Eurofound. Ireland. Retrieved from https://policycommons.net/artifacts/1841077/what-do-europeans-do-at-work-atask-based-analysis/2584230/on25Apr2024.CID:20.500.12592/5xtszh
Gathmann C, Schönberg U (2010) How general is human capital? A task-based approach. J Law Econ 28(1):1–49
Goos M, Manning A, Salomons A (2014) Explaining job polarization: routine-biased technological change and offshoring. Am Econ Rev 104(8):2509–26
Goos M, Rademakers E, Röttger R (2020) Routine-biased technical change: individual-level evidence from a plant closure. Res Policy 50:104002
Hijzen A, Upward R, Wright PW (2010) The income losses of displaced workers. J Hum Resourc 45(1):243–269
Huckfeldt C (2022) Understanding the scarring effect of recessions. Am Econ Rev 112(4):1273–1310
Huttunen K, Kellokumpu J (2016) The effect of job displacement on couples' fertility decisions. J Law Econ 34(2):403–442
Huttunen K, Møen J, Salvanes KG (2011) How destructive is creative destruction? Effects of job loss on job mobility, withdrawal and income. J Eur Econ Assoc 9(5):840–870
Huttunen K, Møen J, Salvanes KG (2018) Job loss and regional mobility. J Law Econ 36(2):479–509
Huttunen K, Riukula K (2019) Parental job loss and children's careers. IZA Discussion Papers 12788
Jacobson LS, LaLonde RJ, Sullivan DG (1993) Earnings losses of displaced workers. Am Econ Rev pp 685–709. https://www.jstor.org/stable/2117574
Kambourov G, Manovskii I (2009) Occupational specificity of human capital. Int Econ Rev 50(1):63–115
Krolikowski P (2018) Choosing a control group for displaced workers. ILR Rev 71(5):1232–1254
Mortensen DT, Pissarides CA (1994) Job creation and job destruction in the theory of unemployment. Rev Econ Stud 61(3):397–415
Robinson C (2018) Occupational mobility, occupation distance, and specific human capital. J Hum Resour 53(2):513–551
Schmieder JF, Von Wachter T, Heining J (2023) The costs of job displacement over the business cycle and its sources: evidence from Germany. Am Econ Rev 113(5):1208–1254
Stevens AH (1997) Persistent effects of job displacement: the importance of multiple job losses. J Labor Econ 15(1, Part 1):165–188
Vainiomäki J (2018) Ketkä poistuvat rutiiniammateista ja kuinka se vaikuttaa tulevaan palkkakehitykseen? Yhteiskuntapolitiikka 3:272–286
Weidmann B, Deming DJ (2021) Team players: how social skills improve team performance. Econometrica 89(6):2637–2657