Red Nacional de
Investigadores
en Economía

Job Displacement Costs of Phasing out Coal

Juan-Pablo Rud (University of London)

Michael Simmons (Umeå University)

Gerhard Toews (Orléans University)

Fernando Aragon (Simon Fraser University)

DOCUMENTO DE TRABAJO N° 184

Octubre de 2022

Citar como:
Rud, Juan-Pablo, Michael Simmons, Gerhard Toews y Fernando Aragon (2022). Job Displacement Costs of Phasing out Coal. *Documento de trabajo RedNIE N°184.*

Job displacement costs of phasing out coal*

Juan-Pablo Rud Michael Simmons Gerhard Toews
Fernando Aragon

Abstract

The reduction of carbon emissions will require a rapid phasing out of coal and the displacement of millions of coal miners. How much could this energy transition cost mining workers? We use the dramatic collapse of the UK coal industry to estimate the long-term impact on displaced miners. We find evidence of substantial losses: wages fell by 40% and earnings fell by 80% to 90% one year after job loss. These losses are persistent and remain significantly depressed fifteen years later, amounting to present discounted value earnings losses of between four and six times the miners pre-displacement earnings. (JEL J30, J63, J64, O4)

> We intend to support communities and regions that are particularly vulnerable to the economic, employment and social effects of a global transition away from carbon-intensive activity
>
> *Just Transition Declaration, 04.11.2021*
>
> *U.N. climate change conference COP26*

A well-established literature finds that displaced workers suffer substantive earning losses that persist several years after losing their job (Jacobson et al., 1993; Stevens, 1997; Couch and Placzek, 2010; Davis and von Wachter, 2012; Bertheau et al., 2022).[1] These findings raise concerns regarding

*Rud: Department of Economics, Royal Holloway, University of London, IZA and Institute for Fiscal Studies (juan.rud@rhul.ac.uk); Simmons: Umeå University (michael.simmons@umu.se); Toews: New Economics School and LEO, Orléans University. (gerhardtoews@gmail.com); Aragón: Department of Economics, Simon Fraser University (faragons@sfu.ca). We thank Antoine Bertheau, Irina Denisova, Ruben Enikolopov, Kate Koppy, Olga Kuzmina, Anastasiya Nebolsina, Marta Troya-Martinez, Carsten Sprenger, Jonathan Wadsworth and Hosny Zoabi, and different audiences for useful comments and suggestions. Simmons thanks Handelsbankens forskningsstiftelser for financial support.

[1]Displacements also have been shown to impact health (Sullivan and von Wachter, 2009; Lindo, 2011; Schaller and Stevens, 2015), schooling (Rege et al., 2011), fertility (Huttenen and Kellokumpu, 2016), divorce (Charles and

the future of millions of coal miners who will likely be displaced and forced to switch sectors if plans to reduce carbon emissions by phasing out coal are implemented due to climate change concerns (United Nations, 2022; Ruppert Bulmer et al., 2021).[2] How much will this energy transition cost mining workers? Answering this question is important to account for the economic losses of phasing out coal and to inform policies aimed at honoring the Just Transition Declaration quoted in the epigraph.

The existing evidence on job displacement costs is, however, unsuitable to quantitatively answer this question. The majority of the existing studies rely on mass layoff events using samples representative of the whole workforce to estimate the costs of job displacement. These estimates of average earnings losses are likely to be well below the costs of job loss for a coal miner who faces the complete phase-out of an industry. The collapse of an entire sector will force sector reallocation. Since coal mining is a highly specialized occupation (Samuel, 2016), this specificity of human capital may reduce miners' ability to transfer their skills, in particular as they are forced to switch occupations.[3] Moreover, most coal miners are employed in remote and rural areas where mining is often the main employer. This feature reduces local economies capacity to absorb workers after a mine closure and, due to the need to emigrate, may increase workers' job search costs and lengthy periods of unemployment.

The contribution of this paper is to provide estimates of job displacement costs during a well known episode of sector collapse specific to coal miners. We study the dissolution of the UK coal industry that accelerated in the mid-1980s under Margaret Thatcher. This dissolution was comprehensive and fast: in just over a decade, the majority of coal mines in the UK closed and more than 200,000 miners (almost 90 percent of the industry's workforce) lost their jobs (Glyn and Machin, 1997; Aragon et al., 2018) (see Figure 1). This setting is one of the few documented experiences of a large and systematic displacement of miners, and thus offers an opportunity to learn about the possible long-term impact of coal phase-out.

Stephens, 2012; Eliason, 2012) and retirement decisions (Chan and Stevens, 1999, 2001; Merkurieva, 2019). Losses also vary with the business cycle (Davis and von Wachter, 2012; Gulyas and Pytka, 2020; Schmieder et al., 2022). A related literature also studies the underlying causes of the losses in earnings (Krolikowski, 2017b; Jung and Kuhn, 2018; Burdett et al., 2020; Lachowska et al., 2020; Gulyas and Pytka, 2020; Raposo et al., 2021; Jarosch, 2021; Simmons, 2021; Huckfeldt, 2022; Braxton and Taska, 2022; Leenders, 2022).

[2] See the Online Appendix for our back-of-the-envelope calculation of the aggregate number of active coal miners adding up to around 5.4 million.

[3] Neal (1995), Huckfeldt (2022) and Braxton and Taska (2022) find that those who switch sectors and occupations following job loss fare worse than those who do not. See

Our empirical analysis uses data from the UK New Earnings Panel Survey, which collects earnings information from a representative sample of individuals from 1975 to the present. The richness of the data allows us to construct a longitudinal dataset tracking more than 2,000 displaced coal miners many years before and after job separation. We estimate the impact of the average mine worker's final displacement from a mine on wages and earnings using a panel data model with time and individual fixed effects that is commonly used in the literature. This estimator compares the evolution of earnings of displaced workers relative to a group of observationally similar, non-displaced workers. This control group is constructed by matching coal miners to blue-collar manufacturing workers with similar pre-displacement characteristics. We provide several variations to the definition of the treatment and control groups and show that our results remain robust and quantitatively very similar.

We find evidence of large and persistent earnings losses. Wages for those who found a new job after displacement drop by around 40% during the first years after job loss, and remain around 20% below the wages of the control group fifteen years later. Overall earnings fall by 80% to 90% in the year after displacement and remain depressed by 20% to 30% fifteen years later. Over the fifteen year period, present discounted earnings losses amount to between 4 and 6 times the miners pre-displacement earnings.

Our findings are qualitatively similar to other studies on job displacement. However, the magnitudes are substantially larger. For instance, Couch and Placzek (2010) document more moderate earnings losses of 32-33% in the first year and 13-15% after six years, while Davis and von Wachter (2012) estimate cumulative losses over a twenty year period of around 1.7 times pre-displacement earnings. The large and persistent earning losses in our findings are consistent with coal miners being particularly vulnerable to job displacement, perhaps due to the low transferability of occupation-specific skills or lower labor mobility. Assuming that these conditions apply to coal miners in other settings today, our results suggest that the phasing out of coal could bring substantial disruptions to miners, their families and mining communities. Active labor market policies (Card et al., 2018; Van Den Berg and Vikström, 2022) are likely to be particularly important in this context.

The remainder of the paper proceeds as follows. In Section I we briefly discuss the dissolution of the UK coal industry. In Section II we discuss our empirical strategy and Section III presents the results. We conclude in Section IV.

I BACKGROUND

Coal played a key role fuelling UK's industrialization process and was an important source of well-paid, manual jobs. By the early 1980s, however, the industry had experienced a long, albeit gradual, decline and was reliant on government subsidies (NUM, 2021; Glyn, 1988). In 1985, after a year-long strike, the government started withdrawing its support and the mine closures accelerated.

The dissolution of the industry was comprehensive and fast (Glyn, 1988; Glyn and Machin, 1997; Aragon et al., 2018). In just two years, 1985 to 1986, one-third of coal mines closed. By 1994, when the industry was privatized, only 26 mines were operational out of more than 200 at the beginning of 1980s. By the early 2000s, only a handful of mines remained. The closure of mines was mirrored by a massive displacement of coal miners. Between 1980 and 1994, more than 200,000 miners lost their jobs (see Figure 1). This amount represented a reduction of approximately 90 percent of the industry's workforce.

The socioeconomic impact of coal mine closures, especially at the community level, has been widely studied. These studies document severe and persistent negative impacts on employment and labor force participation rates, population and living conditions in the affected mining communities (Beatty and Fothergill, 1996; Bennett et al., 2000; Beatty et al., 2007; Aragon et al., 2018).

There is also some evidence of the direct impact on miners. These studies confirm the deterioration of labor outcomes, albeit they do not estimate long-term earning losses due to job displacements. Moreover, they highlight the limited use of migration or changes in occupation as a response to job loss. Instead, many miners seem to have retired earlier or been declared sick or permanently disabled, a phenomenon called "hidden unemployment". For instance, Fieldhouse and Hollywood (1999) find that in 1991, the employment rate of individuals identified as miners in 1981 was around 30%, much lower than the average rate of 50%. They also find that, consistent with hidden unemployment, a large fraction of former miners (around 50%) reported being

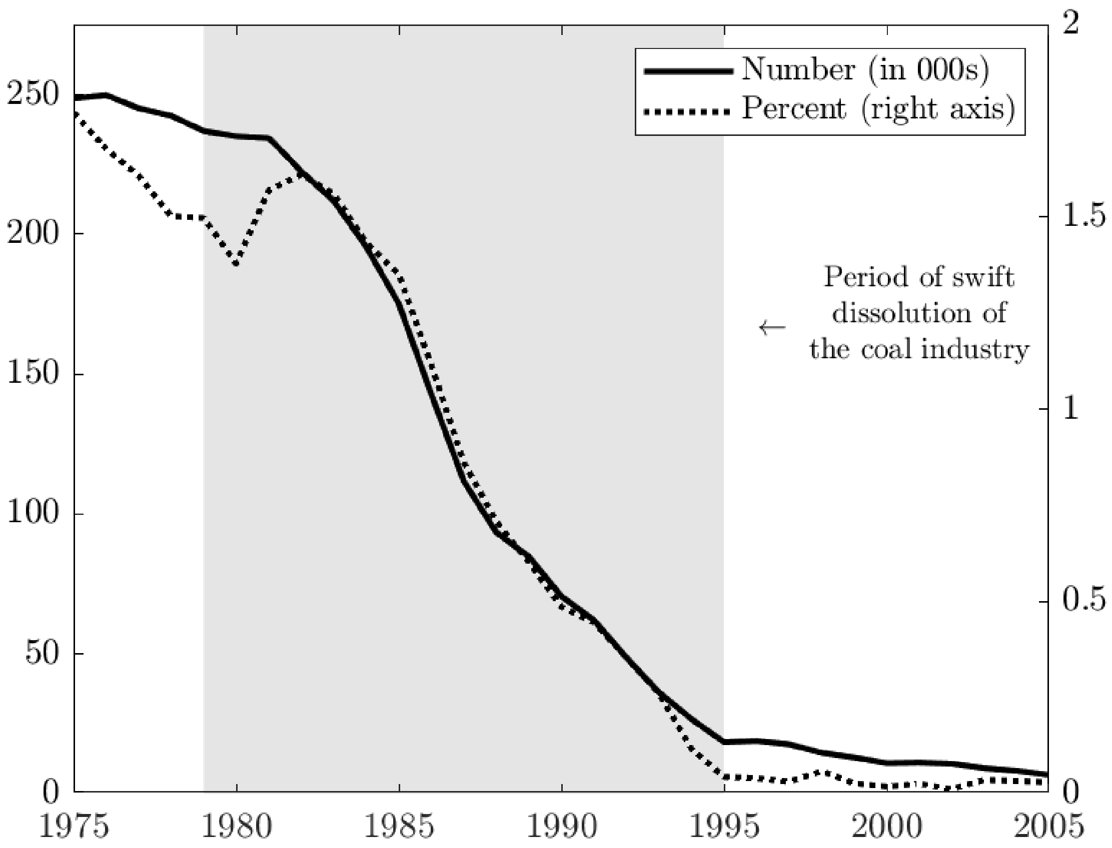


FIGURE 1: Coal mining employment in the UK 1975-2005

Note: The grey area denotes the period where we will entertain separations from in the empirical analysis. Source: The number employed is collected from National Coal Board (1970-1993) and used in Aragon et al. (2018). The percent shown on the right axis was calculated from the New Earnings Survey.

permanently sick or retired early. Hollywood (2002) documents that miners, especially the older and less educated, have been less likely to migrate relative to workers in other highly-specialized occupations, such as metal manufacturing. In general, most studies on the socioeconomic impact of the coal mine closures on the displaced miners conclude that there are few, *if any*, more striking examples of chronic job loss in Western Europe, with nearly all the burden carried by a few local areas and a specific segment of the workforce – male, manual workers, as first documented in Beatty and Fothergill (1996).

There have been several policies aimed at fostering the economic recovery of former mining. These regeneration policies have included re-training of local workers, promotion of small and medium-sized business, and construction of local infrastructure, among others. However, their success has been limited and former mining communities remain among the poorest in the UK (Guy, 1994; Beatty et al., 2007).

II METHODS

II.A DATA

Data: We use data from the 2017 New Earnings Panel Survey (Office for National Statistics, 2017).[4] This is a longitudinal survey that tracks cohorts of individuals from 1975 to the present and provides annual information on weekly earnings and hours worked. Throughout, we deflate earnings to 2000 prices. Information is also provided on occupation, industry, gender, age, geographical administrative unit, and whether the wage was determined through a collective agreement. Individuals are tracked using their National Insurance number, a unique tax identifier which does not change over the lifetime of a worker. This feature allows us to track individuals even after unemployment spells, and across different employers and locations.

Treatment: Studies focusing on the identification of job displacements, typically rely on mass layoffs in situations in which a firm's employment permanently declines by thirty or more percent over a short period of time such as for example in Davis and von Wachter (2012), Flaaen et al.

[4]This data set has been used to study the effect of minimum wages on wage dispersion and employment (Machin and Manning, 1994), the distribution of top earnings in the UK since WWII (Atkinson and Voitchovsky, 2011), as well as spatial differences in earnings and unemployment (Blackaby and Manning, 1990).

(2019) and Bertheau et al. (2022). As discussed in the background section, the dissolution of the coal industry proceeded fairly quickly and was plausibly exogenous to the individual coal miner, implying selection is less of a concern. This allows us to study all separations during this period, which is distinguishing us from the previous literature focusing only on the proportion of layoffs during mass layoffs. Moreover, sectoral dissolution allows us to be confident that reemployment as a coal miner was not an option and so sectoral reallocation was a requirement for future employment.[5] The dissolution of the coal sector was determined on the national level and brought to a conclusion 30 years later, even though 80% of the task was accomplished within a period of 10 years, by 1995.

Displaced miners: We follow the literature and choose for each year t all workers that work full time at a coal mine. From this group of miners we keep those who are between 25 and 55 years old, and those who were employed by the same firm for at least 2 consecutive years, in t and $t-1$, before being laid-off between t and $t+1$. We focus on the periods during which the coal industry collapses, and analyse displacements in the years between, and inclusive of, 1979 and 1995. Since we are interested in displacements associated with being subsequently unable to work in coal mining, we focus on a worker's final separation from a mine. This leaves us with 17 year-specific cohorts and a total of 2,152 displaced miners. Each cohort contains 20 years, 4 prior to displacement and 15 after. Let $k = \{-4, 15\}$ represent these years where a displacement occurs between $k = 0$ and $k = 1$. In alternative specifications, we adjust the sample and analyse (i) miners working underground only (excluding white-collar workers) and (ii) displacements that occurred along with the closure of a mine at the county level (standard geographical administrative unit). Focusing on displacements that occurred along with the closure of a mine at the county level, as in (ii), allows us to test whether closures are driving our results.

The New Earnings Survey is based on a 1% random sample of workers enrolled in the pay-as-you-earn (PAYE) scheme. The PAYE is a payroll-deduction system in which employers collect taxes and insurance payments from their employees' wages. The data is collected through a questionnaire that firms are required by law to complete with reference to payrolls. This system, however, does not include the self-employed, a data limitation which is shared by many other studies in the literature such as for example Jacobson et al. (1993), Schmieder et al. (2022) and Bertheau

[5] Note that the complete dissolution of the sector also allows us not to worry about mergers, takeovers, or changes in the identification number of firms.

et al. (2022).[6] These papers deal with this limitation in two distinct ways. On the one hand, periods without any observed labor earnings in the data are interpreted as zero individual earnings, such as in Schmieder et al. (2022) and Bertheau et al. (2022). Using the British Household Panel Survey and studying the costs of job loss in the UK, Upward and Wright (2017) find that reassigning earnings during periods of self-employment as zero makes very little difference to the estimated earnings losses. Bertheau et al. (2022) also find that a similar exercise using Swedish data results in only minor differences. While these studies find the issue to be negligible, we are unable to say whether it is indeed negligible in our case. Thus, we complement our results with a similar approach to Jacobson et al. (1993), and only keep those individuals who report positive earnings within four years of displacement. This latter approach provides a more conservative estimate of displacement costs by focusing on individuals who eventually return to work within a certain time frame.

Control group: To obtain a causal estimate of being displaced, we require a comparable control group of workers who did not experience job loss during the same years as each cohort of miners but followed the same pre-displacement employment and earnings path. Choosing a control group in this setting is a particular challenge by the very nature of the exercise – a group of miners who did not lose their job does not exist.

Our baseline approach is to match miners to blue collar manufacturing workers with the same two-digit occupation code using propensity score matching. In practice, this involves estimating a probit or logit model with the dependent variable taking the value of 1 if they are in the treated group and 0 otherwise, and then matching treated and control workers with the closest predicted value without replacement.[7] We match on an array of observable characteristics: age, gender[8], hours worked, full-time status, geographical administrative unit (county), whether the wage was determined by a collective agreement, as well as the worker's pre-layoff weekly earnings and hours worked between $k = -4$ and $k = -1$ and employment levels between $k = -4$ and $k = -2$. We do not require the comparison group to be employed during any year after displacement including the

[6] Similarly, a very small amount of low paying jobs are also not included in PAYE. This may result in understating the wage losses and overstating the employment losses after displacement. However, as has been found in recent work and discussed in the next few sentences, ignoring the self employed which likely provides a bigger source of bias makes very little difference to results from the literature.

[7] We use the psmatch2 function within STATA to perform the propensity score matching (Leuven, 2003).

[8] Female miners make up about 6% of the mining workers in our treatment group. We chose to keep the women in our preferred specification, but the results do not change by removing all female miners. See Table 5 in Online Appendix.

displacement year, i.e. for $k > 0$. Such a requirement could lead to systematic differences between displaced and control groups, and possible overestimation of the earnings losses (Krolikowski, 2017a).

In Table 1 we provide basic statistics for the main observable characteristics on which we match before displacement for $k = -4$ and $k = -1$. In columns we show mean and standard deviations for three distinct groups: the treated, the individuals from our baseline matching as well as the individuals from the non-matched control group (blue collar manufacturing workers). In comparison to the non-matched sample, we see that the displaced coal miners are special since they are more likely to be male, a bit older and have higher earnings. As expected, the matching greatly reduces these differences.

Despite being able to match on an array of observable characteristics, we complement our results by providing an alternative control group for comparison. We restrict the pool of workers from which we match to workers who are involved in the creation of primary metal products consisting of iron, aluminum and copper as well as their alloys.[9] Primary metal manufacturing plants traditionally employ male manual workers with sector-specific skills which are difficult to reemploy anywhere else and which, due to the nature of their activity, are operating in spatially remote locations. To produce primary metal products, heat from a variety of fuels, most commonly coal, is used for smelting such that metal production plants are often located next to coal deposits to keep transportation costs of coal at a minimum (Michielsen, 2013). Since this control group is chosen from a subset of blue collar manufacturing workers, we are implicitly leaning less heavily on the propensity score matching routine relative to the baseline. The advantage to the approach is that this control group may be better suited to capture the dynamics of unobserved characteristics of the displaced miners, such as long-run trends in technological progress and structural transformation.

II.B EMPIRICAL MODEL

Using the 17 stacked treatment and control cohorts, we run a similar regression model as other studies in the job displacement literature (Jacobson et al., 1993; Couch and Placzek, 2010). In

[9]The associated standard industrial classification codes that we chose are 311, 312, 313, 321, 322, 333 (before 1984), 2210, 2220, 2234, 2235, 2245, 2246, 2247 (after 1984).

	(1)	(2)	(3)
	Treated	Main control	No matching
	$k = -4$		
Weekly earnings (£)	321.86	317.12	252.50
	(160.12)	(207.92)	(190.60)
Employment	.921	.907	.806
	(.270)	(.291)	(.395)
Age	39.35	39.26	38.11
	(8.07)	(7.91)	(7.67)
Weekly hours	37.21	37.88	37.63
	(2.20)	(3.82)	(4.66)
Male	.947	.913	.764
	(.225)	(.288)	(.425)
Overtime pay	25.10	24.89	14.82
	(43.45)	(41.48)	(31.87)
	$k = -1$		
Weekly earnings (£)	355.29	353.12	328.35
	(148.93)	(199.20)	(31.87)
Employment	1.00	1.00	1.00
	(0)	(0)	(0)
Age	40.73	40.75	39.67
	(9.10)	(8.91)	(8.54)
Weekly hours	37.11	37.37	37.55
	(2.45)	(4.16)	(4.47)
Male	.942	.913	.764
	(.236)	(.288)	(.426)
Overtime pay	32.02	27.29	18.28
	(54.96)	(48.68)	(39.01)
N	2,152	2,152	379,904

TABLE 1: Observables of the treated group, matched control group and non-matched control group

Note: Standard deviations are shown in parentheses. Weekly earnings are in 2000 prices.

particular, we estimate the following panel data model with distributed lags:

$$y_{ik} = a_i + \gamma_k + \mathbf{x}_{ik}'\beta + \sum_{k=-3}^{15} \delta_k D_{ik} + u_{ik}, \tag{1}$$

where y_{ik} is the outcome for individual i at time k, such as earnings, wages, or employment status. a_i and γ_k are person and time fixed effects, respectively. $\mathbf{x}_{ik}$ is a vector of observables (quartic in age). D_{ik} are dummies for year k and u_{ik} is the error term, which we cluster at the individual level.

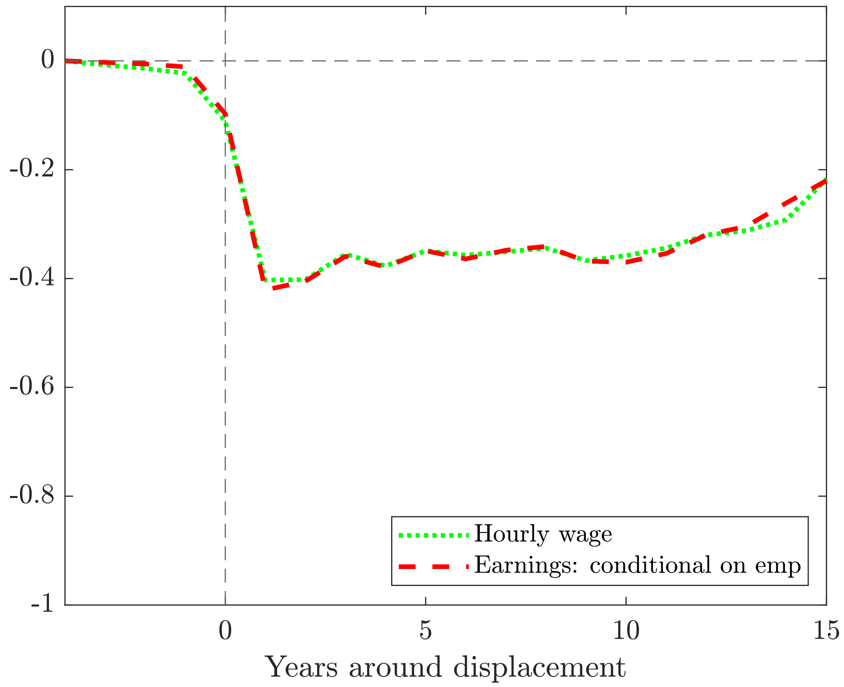
The coefficients of interest are δ_k. These coefficients provide an estimate of the impact of displacement, k years after separation. We normalize the continuous outcome variables (such as earnings and wages) by dividing them by the individual's pre-displacement average, i.e. for $k < 0$. Thus, we can interpret δ_k as the percentage change relative to pre-displacement values. Similar to previous work, the identification assumption is that, conditional on the control variables, the evolution of the displaced miners' outcomes would have follow a similar path as the comparison group's, have they not been displaced.

III RESULTS

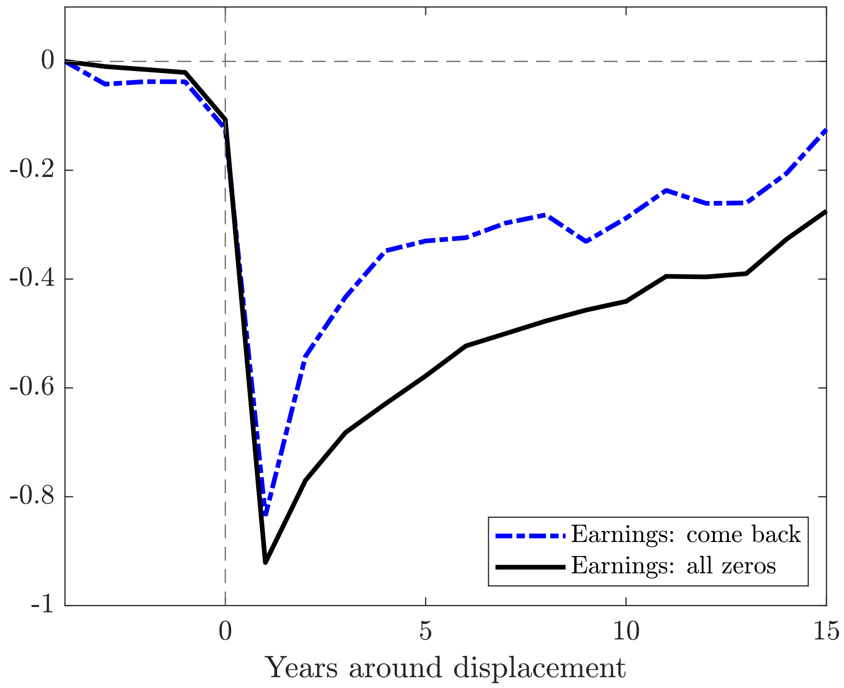
Figure 2 shows our main results. Using the baseline control group we include regression results where the dependent variable in (1) takes on hourly wages; weekly earnings conditional on employment; weekly earnings unconditional on employment (including zeros), but where we include only miners who have positive earnings within four years after job loss (similar to Jacobson et al. (1993)); and weekly earnings unconditional on employment including all zeros (Davis and von Wachter, 2012; Schmieder et al., 2022; Bertheau et al., 2022).

Our estimates show devastating losses for the miners. In the year following job loss, the miners earnings conditional on employment falls by 40% and remains depressed by 20% fifteen years later. These losses are not driven by a reduction in hours worked since the losses in hourly wages (dotted line) and weekly earnings conditional on employment (dashed line) are close to identical.

Unconditional earning losses (solid line) are 90% in the first year, and remain 30% below the earnings of the control group fifteen years later. Even if we focus on the the more conservative earnings losses, where we only include individuals who return to work within four



(a) Wages and earnings conditional on employment



(b) Earnings including zeros

FIGURE 2: The estimated proportional changes in wages and earnings following job loss

Note: "Earnings: come back" refers to the treatment group where we only include those who have positive earnings at some point four years after job loss, while replacing their earnings with a zero if the miner is not observed for any $k > 0$. "Earnings: all zeros" refers to the treatment in which we replace the earning of any miners with a zero if the miner is not observed for any $k > 0$, without any restrictions. We report point estimates and standard errors of all coefficients in Table 1 and 2 of the Online Appendix.

years (dashed-dotted line), the losses are still substantial, at 80% in the first year and 10-20% fifteen years later. Note that we observe these losses despite the existence of regeneration policies, targeting the laid-off miners and the affected communities.

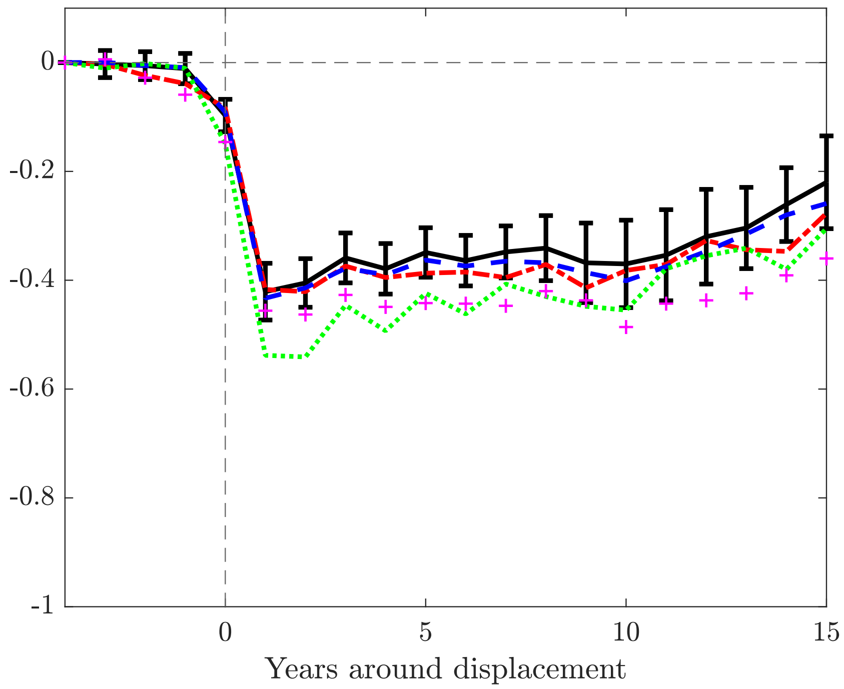
Figure 3 replicates the losses in earnings conditional on employment in the top panel and earnings losses including all zeroes in the bottom panel. We include 95% confidence intervals allowing for a statistical comparison of the additional results, determined by varying definitions of treatment and control groups. Neither the change in our treated group, by focusing on the underground miners (dotted line), nor the changes in the definition of the treatment, by focusing on the last separation in locations with coal mine closures (dashed line) lead to significant difference in the results. On the other hand, our more conservative choice of the control group (dashed-dotted line), in which we focus on blue collar manufacturing workers in primary metal production as well as the matching on age and pre-displacement earnings only (line of crosses), lead to if anything higher estimates of the displacement cost.[10]

In Table 2 we use our baseline specification to estimate the associated losses in present discounted value (PDV) caused by the layoff.[11] We use a 5% discount rate to remain comparable to Davis and von Wachter (2012). We estimate present discounted losses in: earnings conditional on employment, earnings conditional on having positive earnings within four years of displacement, and earnings losses including all zeros. In column (1) our estimates range from 3.8 to 6 years of pre-displacement earnings. 6 years of pre-displacement earnings represent our upper bound estimate and is equivalent to around $\$140,000$ or £100,000 in 2000 prices. Column (2) shows the present discounted earnings of the miners relative to the control.[12] Including all miners who have been displaced, and assuming that they have zero earnings if they do not reappear in our data set, the miners present discounted earnings were 40% of the counterfactual. This number increases to 60% when we exclude miners who do not reappear in the data after displacement and if we focus on those who remain employed. The final two columns split the losses into those due to losses in earnings conditional on employment and those due to losses in employment. By construction,

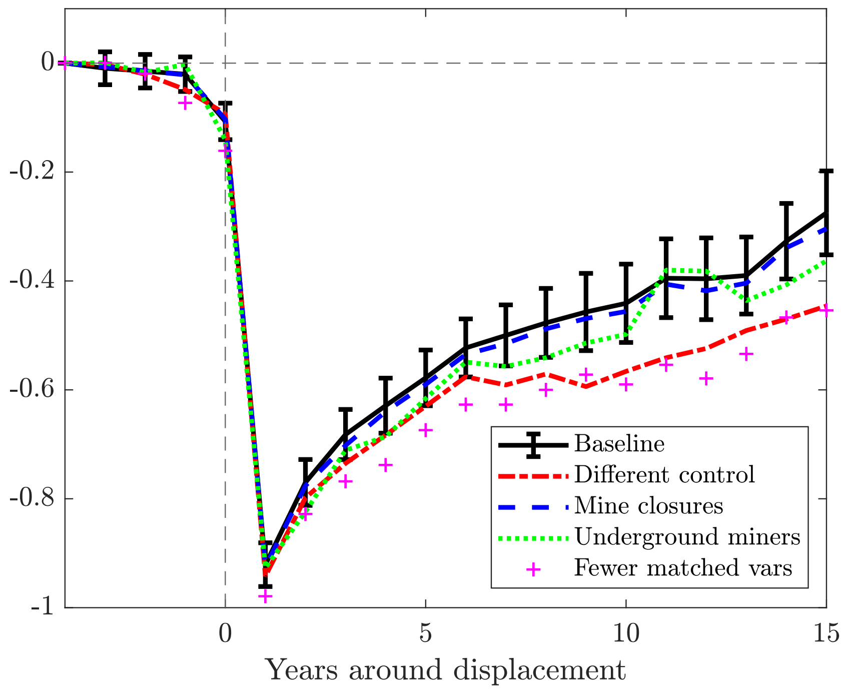
[10] In Table 6 of the Online Appendix we also document the results in which we do not employ the matching procedure prior the estimation and the results are robust.

[11] The present discounted value of the displacement costs is equal to $\sum_{k=1}^{15} \frac{\hat{\delta}_k}{(1.05)^{k-1}}$.

[12] The present discounted earnings for the miners relative to the control is equal to $\sum_{k=1}^{15} \frac{\hat{y}_k^T}{1.05^{k-1}} / \sum_{k=1}^{15} \frac{\hat{y}_k^C}{1.05^{k-1}}$, where $\hat{y}^T$ and $\hat{y}^C$ indicate the estimated earnings from (1) for the treated and control groups, respectively.



(a) Earnings conditional on employment



(b) Earnings including all zeros

FIGURE 3: The estimated proportional changes in earnings following job loss including all zeros over different treatments and controls

Note: "Baseline" shows the estimated costs as well as the 95% confidence interval of job loss using the baseline control group described in Section II. “Different control” shows the estimated costs of job loss in comparison to a more restricted control group, focusing blue collar manufacturing workers who are involved in the creation of primary metal products consisting of iron, aluminum and copper as well as their alloys. We report point estimates and standard errors of all coefficients in Table 3 of the Online Appendix. “Mine closure” reports the costs of job loss using the baseline control group where we only include those miners who experienced job loss when a mine also closed in the county. We report point estimates and standard errors of all coefficients in Table 4 of the Online Appendix. “Underground miners” reports the costs of job loss using the baseline control group, where we only include those miners who were working underground. Finally, “Fewer matched vars” reports the costs of job loss where we only match the miners to a control group using the variables age and pre-displacement earnings.

losses in wages were particularly important for the results in the first two rows. However, even if we take into account individuals who never return to work, two-thirds of the losses are still explained by the drop in wages while only a third of the losses are explained by a drop in employment.

	(1) PDV losses as a multiple of predisplacement annual earnings	(2) Miners' PDV earnings relative to counterfactual	(3) Due to the losses in wages	(4) Due to the losses in employment
Conditional on employment	3.85	63.9%	100%	0%
Come back	4.02	60.2%	93.8%	6.2%
All zeros	6.01	40.8%	64.0%	36.0%

TABLE 2: The estimated present discounted wage and earnings losses

Note: Column (1) shows the present discounted earnings losses relative to our baseline counterfactual, with the earnings being standardised by the average individual pre-displacement earnings from period $t-1$ to $t-4$ and displacement taking place between t and $t+1$: $\sum_{k=1}^{15} \frac{\hat{\delta}_k}{1.05^{k-1}}$. Column (2) shows the estimated present discounted earnings of the miners as a proportion of the estimated present discounted earnings of the control group: $\sum_{k=1}^{15} \frac{\hat{y}_k^T}{1.05^{k-1}} / \sum_{k=1}^{15} \frac{\hat{y}_k^C}{1.05^{k-1}}$, where T is the treatment and C is the control. Columns (3) and (4) split the losses shown in column (1) into those attributable to losses in wages and those due to losses in employment.

How do our estimates compare to the previous literature on mass layoffs? Couch and Placzek (2010) reconsider the earnings losses estimated in the seminal work of Jacobson et al. (1993), and also review the literature on mass layoffs. The initial loss tends to be in the range of 25 to 50%, with the largest fall in earnings that they report in the first year after displacement being 66%. In a more recent study, Huckfeldt (2022) finds that workers laid-off during a recession and who switched occupation experienced a first year reduction of 42% in earnings and that the relative losses remain around 10-15% a decade later. This is in line with Lachowska et al. (2020) who document first year losses of 45-49% that decline to 15-25% after 5 years. Upward and Wright (2017) use data from the British Household Panel Survey and also find the losses to be below 50% in the year after separation. We, on the other hand, find the initial earning losses to be between 80 and 90%, with the initial losses being around 40% only for the sample of those miners who manage to find another job, abstracting from those miners who fail to find alternative employment. Davis and von Wachter (2012) find for the US that the cumulative losses over a period of 20 years are close to 1.7 times the displaced workers' pre-displacement earnings, while we find that the miners' losses add up to between 4 and 6 times the pre-displacement earning for a shorter period of 15 years.

IV FINAL REMARKS

We examine the impact of job displacement on coal miners' earnings. Our analysis exploits individual panel data from the UK and the dramatic collapse of the coal industry that accelerated in mid-1980s. We find evidence of a substantial reduction in earnings of displaced miners that persists in the long-term. As far as we know, our estimates are the largest in the literature.

While specific to the UK context, these findings suggest that the phase out of the coal industry, a policy which has been repeatedly proposed as one way to reduce carbon emissions, could impose large costs on coal miners, their families and mining communities that may persist in the long term. The external validity of our results may hinge on location, job and worker characteristics at existing coal mines. Overall, the phasing out of coal around the world will displace more than 5 million workers, most of them in China (around 3 million). Just as in the case of the UK in the 1980s, coal mining remains an important employer of male workers with low educational attainment in many remote locations of China, the United States, Poland, India, Indonesia, Russia and South Africa (Ruppert Bulmer et al., 2021). In these remote locations, the sector pays relatively higher wages than alternative occupations available, while the capacity of the local labor markets to absorb the displaced miners is limited. All this suggests that the UK experience, given the characteristics of workers and communities in coal mining areas and the speed with which the dissolution of the coal industry took place, makes it similar to the one that coal miners around the world may experience during the upcoming energy transition.

While our analysis can identify the size of the earning losses, we are unable to pin down a possible cause. Previous work suggests that earning loses reflect the loss of occupation of specific human capital. While this could certainly be the case for coal miners, we cannot rule out other possible factors specific to coal mining in the UK such as compensating differentials (due to the higher risk of mining jobs), union wage premiums, or lower labor mobility. Examining these issues warrants further research.

References

Aragon, F., J. P. Rud, and G. Toews. 2018. "Resource shocks, employment, and gender: Evidence from the collapse of the UK coal industry." *Labour Economics*, 52 54–67.

Atkinson, A. B., and S. Voitchovsky. 2011. "The distribution of top earnings in the uk since the second world war." *Economica*, 78(311): 440–459.

Beatty, C., and S. Fothergill. 1996. "Labour market adjustment in areas of chronic industrial decline: the case of the uk coalfields." *Regional studies*, 30(7): 627–640.

Beatty, C., S. Fothergill, and R. Powell. 2007. "Twenty years on: has the economy of the uk coalfields recovered?" *Environment and Planning A*, 39(7): , p. 1654.

Bennett, K., H. Beynon, and R. Hudson. 2000. *Coalfields regeneration: Dealing with the consequences of industrial decline*. The Policy Press.

Bertheau, A., E. Maria Acabbi, C. Barceló, A. Gulyas, S. Lombardi, and R. Saggio. 2022. "The unequal consequences of job loss across countries." *American Economic Review: Insights*, Forthcoming.

Blackaby, D. H., and D. Manning. 1990. "Earnings, unemployment and the regional employment structure in britain." *Regional Studies*, 24(6): 529–535.

Braxton, J. C., and B. Taska. 2022. "Technological Change and the Consequences of Job Loss." *mimeo*.

Burdett, K., C. Carrillo-Tudela, and M. Coles. 2020. "The cost of job loss." *Review of Economic Studies*, 87(4): 1757–1798.

Card, D., J. Kluve, and A. Weber. 2018. "What works? A meta analysis of active labor market program evaluations." *Journal of the European Economic Association*, 16(3): 894–931.

Chan, S., and A. H. Stevens. 1999. "Employment and retirement following a late-career job loss." *American Economic Review*, 89(2): 211–216.

Chan, S., and A. H. Stevens. 2001. “Job loss and employment patterns of older workers.” *Journal of Labor Economics*, 19(2): 484–521.

Charles, K. K., and M. Stephens. 2012. “Disability, job displacement, and divorce.” *Journal of Labor Economics*, 22(2): 489–522.

Couch, K., and D. Placzek. 2010. “Earnings losses of displaced workers revisited.” *American Economic Review*, 100(1): 572–589.

Davis, S., and T. von Wachter. 2012. “Recessions and the cost of job loss.” *Brookings Papers on Economic Activity*.

Eliason, M. 2012. “Lost jobs, broken marriages.” *Journal of Population Economics*, 24(4): 831–856.

Fieldhouse, E., and E. Hollywood. 1999. “Life after mining: hidden unemployment and changing patterns of economic activity amongst miners in england and wales, 1981–1991.” *Work, employment and society*, 13(3): 483–502.

Flaaen, A., M. D. Shapiro, and I. Sorkin. 2019. “Reconsidering the consequences of worker displacement: Firm versus worker perspective.” *American Economic Journal: Macroeconomics*, 11(2): , p. 193–227.

Glyn, A. 1988. “Colliery results and closures after the 1984–85 coal dispute.” *Oxford Bulletin of Economics and Statistics*, 50(2): 161–173.

Glyn, A., and S. Machin. 1997. “Colliery closures and the decline of the uk coal industry.” *British Journal of Industrial Relations*, 35(2): 197–214.

Gulyas, A., and K. Pytka. 2020. “Recessions and the cost of job loss.” *mimeo*.

Guy, N. 1994. *Dole Not Coal: The Labour Market Experience of Redundant Miners Since October 1992*. Coalfield Communities Campaign Barnsley.

Hollywood, E. 2002. “Mining, migration and immobility: towards an understanding of the relationship between migration and occupation in the context of the uk mining industry.” *International Journal of Population Geography*, 8(4): 297–314.

Huckfeldt, C. 2022. "Understanding the scarring effects of recessions." *American Economic Review*, 112(4): 1273–1310.

Huttenen, K., and J. Kellokumpu. 2016. "The effect of job displacement on couples' fertility decisions." *Journal of Labor Economics*, 34(2): 403–442.

Jacobson, L., R. Lalonde, and D. Sullivan. 1993. "Earnings losses of displaced workers." *American Economic Review*, 83(4): 685–709.

Jarosch, G. 2021. "Searching for Job Security and the Consequences of Job Loss."Technical Report 28481.

Jung, P., and M. Kuhn. 2018. "Earnings losses and labor mobility over the life cycle." *Journal of the European Economic Association*, 17(3): 678–724.

Krolikowski, P. 2017a. "Choosing a control group of displaced workers." *Industrial and Labor Relations Review*, 71(5): 1232–1254.

Krolikowski, P. 2017b. "Job ladders and earnings of displaced workers." *American Economic Journal: Macroeconomics*, 9(2): 1–31.

Lachowska, M., A. Mas, and S. A. Woodbury. 2020. "Sources of displaced workers' long-term earnings losses." *American Economic Review*, 110(10): 3231–3266.

Leenders, F. 2022. "Recall and the scaring effects of job displacement." *mimeo*.

Leuven, E. 2003. "Psmatch2: Stata module to perform full mahalanobis and propensity score score matching, common support graphing, and covariate imbalancing testing." *Stata Journal*.

Lindo, J. 2011. "Parental job loss and infant health." *Journal of Health Economics*, 30(5): 869–879.

Machin, S., and A. Manning. 1994. "The effects of minimum wages on wage dispersion and employment: Evidence from the uk wages councils." *ILR Review*, 47(2): 319–329.

Merkurieva, I. 2019. "Late career job loss and the decision to retire." *International Economic Review*, 60(1): 259–282.

Michielsen, T. O. 2013. "The distribution of energy-intensive sectors in the usa." *Journal of Economic Geography*, 13(5): 871–888.

National Coal Board. 1970-1993. *Guide to the coalfields*. Colliery Guardian Co..

Neal, D. 1995. "Industry specific human capital: Evidence from displaced workers." *Journal of Labor Economics*, 13(4): 653–677.

NUM. 2021. "NUM History." http://num.org.uk/archives/, Accessed: 2021-08-01.

Office for National Statistics. 2017. "New Earnings Survey Panel Dataset, 1975-2016: Secure Access.7th Edition. UK Data Service.." https://beta.ukdataservice.ac.uk/datacatalogue/doi/?id=6706#!#7, Accessed: 2017-07-01.

Raposo, P., P. Portugal, and A. Carneiro. 2021. "The Sources of the Wage Losses of Displaced Workers The Role of the Reallocation of Workers into Firms, Matches, and Job Titles." *Journal of Human Resources*, 56(3): 786–820.

Rege, M., K. Telle, and M. Votruba. 2011. "Parental job loss and children's school performance." *The Review of Economic Studies*, 78(4): 1462–1489.

Ruppert Bulmer, E., K. Pela, A. Eberhard-Ruiz, and J. Montoya. 2021. "Global Perspective on Coal Jobs and Managing Labor Transition out of Coal : Key Issues and Policy Responses." https://openknowledge.worldbank.org/handle/10986/37118, Accessed: 2022-07-28.

Samuel, R. 2016. *Miners, quarrymen and saltworkers*. Routledge.

Schaller, J., and A. Stevens. 2015. "Short-run effects of job loss on health conditions, health insurance, and health care utilization.." *Journal of Health Economics*, 43 190–203.

Schmieder, J., T. von Wachter, and J. Heining. 2022. "The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany." *mimeo*.

Simmons, M. 2021. "Pre-layoff search." *mimeo*.

Stevens, A. H. 1997. "Persistent effects of job displacement: The importance of multiple job losses." *Journal of Labor Economics*, 15(1): 165–188.

Sullivan, D., and T. von Wachter. 2009. "Job displacement and mortality: An analysis using administrative data." *The Quarterly Journal of Economics*, 124(3): 1265–1306.

United Nations. 2022. "UN Chief: Phase Out of Coal Is Key Climate Priority." https://unfccc.int/news/un-chief-phase-out-of-coal-is-key-climate-priority, Accessed: 2022-07-01.

Upward, R., and P. Wright. 2017. "Don't look down: The consequences of job loss in a flexible labour market." *Economica*, 2019(86): 166–200.

Van Den Berg, G. J., and J. Vikström. 2022. "Long-run effects of dynamically assigned treatments: a new methodology and an evaluation of training effects on earnings." *Econometrica*, 90(3): 1337–1354.

Online appendix for "The job displacement costs of phasing out coal"*

Juan-Pablo Rud   Michael Simmons   Gerhard Toews
Fernando Aragon

*Rud: Department of Economics, Royal Holloway, University of London and Institute for Fiscal Studies (juan.rud@rhul.ac.uk); Simmons: Umeå University (michael.simmons@umu.se); Toews: New Economics School and LEO, Orléans University. (gerhardtoews@gmail.com); Aragón: Department of Economics, Simon Fraser University (faragons@sfu.ca). We thank Antoine Bertheau, Irina Denisova, Ruben Enikolopov, Kate Koppy, Olga Kuzmina, Anastasiya Nebolsina, Marta Troya-Martinez, Carsten Sprenger, Jonathan Wadsworth and Hosny Zoabi, and different audiences for useful comments and suggestions. Simmons thanks Handelsbankens forskningsstiftelser for financial support.

1 BACK-OF-THE-ENVELOPE CALCULATION

We use national statistics on formal employment in the mining industry for the seven biggest exporters and producers to construct the time series in Figure 1. China is by far the largest employer of coal miners in the world, followed by Indonesia, India, Russia, South Africa, United States and Australia. Also, China and India consume most of the extracted coal, such that Russia and South Africa replace these two on the top 5 list of global exporters. In Figure 2, we present the location of industrial mines. As is apparent from the Figure, many of the mines are located in remote parts of the world. Thus, miners are often displaced in remote locations during the closures of coal mines.

To estimate the global number of active coal miners we proceed as follows. First, we use the last available country level information on active coal miners from Figure 1: 43,250 in Australia (2020), 2,750,460 in China (2021), 274,445 in India (2020), 1,381,180 in Indonesia (2017), 137,819 in Russia (2016), 86,919 in South Africa (2018) as well as 42,583 in the US (2021). Combining this information with country level statistics on the total number of industrial mines we can calculate the average number of miners per mine for these countries. Applying this estimate to other countries, for which we did not collect national statistics on the number of active coal miners, we get to a total of approximately 5.4 million active coal miners. Note that this is likely to be lower bound, since we do not account for individuals involved in the informal mining of coal.

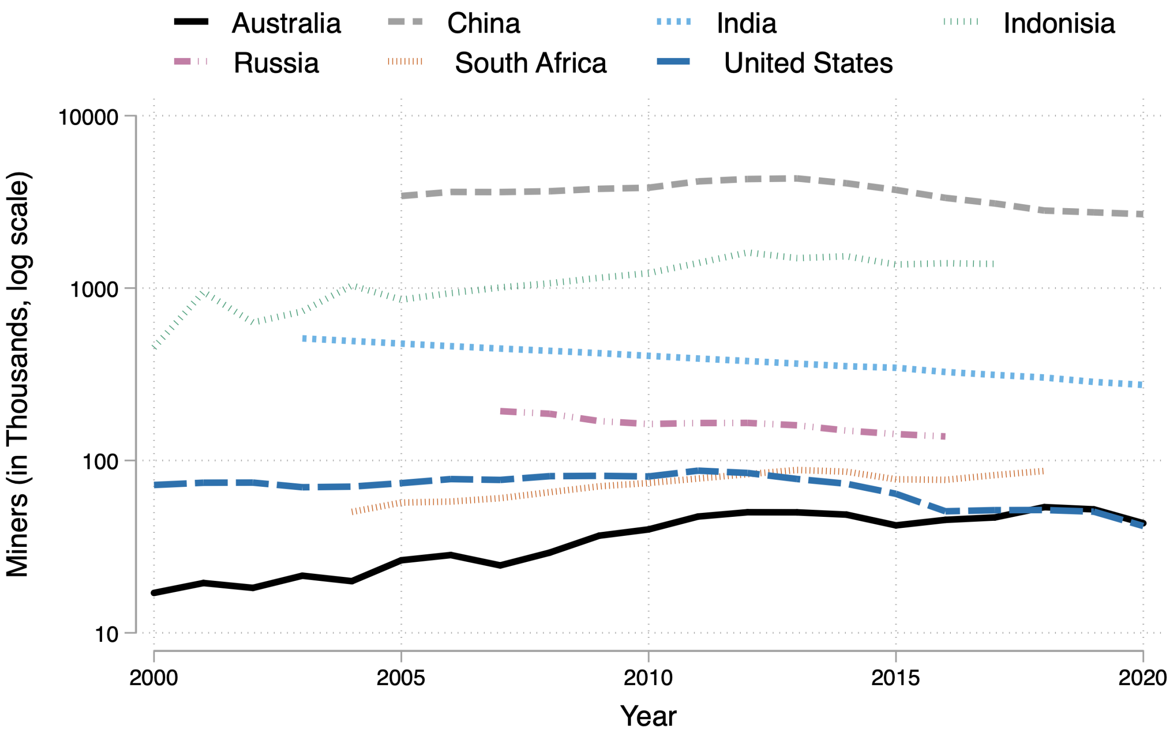


Figure 1: Total number of coal miners by country for the top seven producing and exporting countries

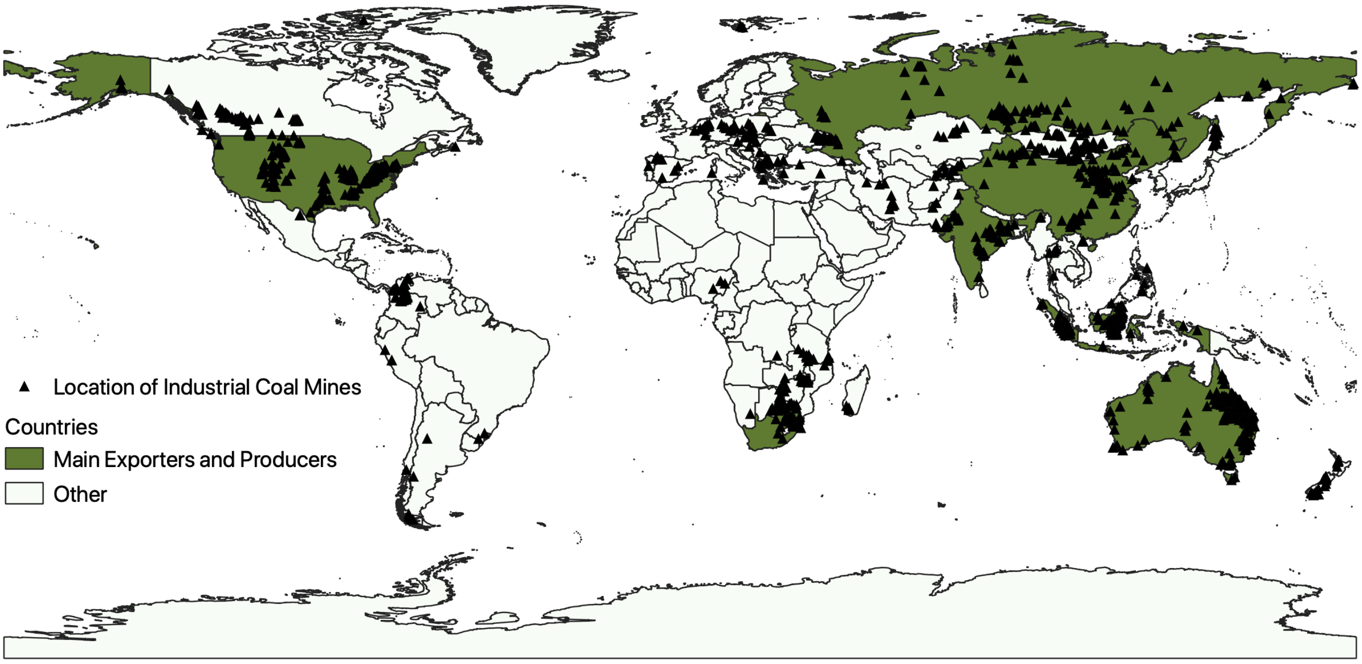


Figure 2: Employment by the top 7 producing and exporting countries

Note: Main exporters and producers are marked in green. The location of coal mines is taken from the SNL Energy Data Set produced by S&P Global a publicly traded corporation whose primary areas of business are financial information and analytics.

2 TABLES

In the following tables we present point estimates of the earnings, wages, employment and hourly wage consequences of displacement. The estimates in the Tables 1-4 are used for the construction of Figure 2 and Figure 3 in the main body of the paper. We also provide results for different samples. In Table 5 we show the results for male miners only. These are close to identical to those including female miners. We also provide the results for a sample in which we include all manufacturing workers as controls, without any matching. The results are presented in Table 6. Note that the consequences of displacement on earning are larger in the long run when not conducting matching prior to estimation.

VARIABLES	(1) Earnings	(2) Wages	(3) Employment	(4) Hourly wage
δ_{-3}	-0.00941	-0.00273	-0.00691	-0.00745
	(0.0154)	(0.0127)	(0.0106)	(0.0121)
δ_{-2}	-0.0148	-0.00565	-0.00905	-0.0138
	(0.0157)	(0.0131)	(0.0102)	(0.0125)
δ_{-1}	-0.0203	-0.0110	-0.0184*	-0.0229*
	(0.0162)	(0.0142)	(0.00946)	(0.0135)
δ_{0}	-0.107***	-0.0973***	-0.0182*	-0.111***
	(0.0171)	(0.0152)	(0.00950)	(0.0145)
δ_{1}	-0.921***	-0.421***	-0.752***	-0.403***
	(0.0205)	(0.0266)	(0.0142)	(0.0258)
δ_{2}	-0.770***	-0.405***	-0.585***	-0.402***
	(0.0215)	(0.0228)	(0.0159)	(0.0224)
δ_{3}	-0.682***	-0.359***	-0.495***	-0.355***
	(0.0235)	(0.0234)	(0.0168)	(0.0221)
δ_{4}	-0.629***	-0.379***	-0.428***	-0.377***
	(0.0258)	(0.0237)	(0.0175)	(0.0216)
δ_{5}	-0.578***	-0.349***	-0.390***	-0.349***
	(0.0261)	(0.0232)	(0.0180)	(0.0217)
δ_{6}	-0.523***	-0.364***	-0.329***	-0.357***
	(0.0272)	(0.0237)	(0.0188)	(0.0218)
δ_{7}	-0.500***	-0.348***	-0.321***	-0.351***
	(0.0286)	(0.0244)	(0.0195)	(0.0232)
δ_{8}	-0.477***	-0.341***	-0.289***	-0.344***
	(0.0323)	(0.0305)	(0.0199)	(0.0290)
δ_{9}	-0.457***	-0.368***	-0.272***	-0.367***
	(0.0362)	(0.0373)	(0.0206)	(0.0343)
δ_{10}	-0.441***	-0.370***	-0.254***	-0.358***
	(0.0367)	(0.0410)	(0.0211)	(0.0364)
δ_{11}	-0.395***	-0.354***	-0.227***	-0.344***
	(0.0369)	(0.0427)	(0.0215)	(0.0379)
δ_{12}	-0.396***	-0.320***	-0.239***	-0.320***
	(0.0383)	(0.0444)	(0.0221)	(0.0425)
δ_{13}	-0.390***	-0.304***	-0.233***	-0.312***
	(0.0361)	(0.0381)	(0.0225)	(0.0412)
δ_{14}	-0.327***	-0.261***	-0.207***	-0.292***
	(0.0354)	(0.0346)	(0.0234)	(0.0336)
δ_{15}	-0.275***	-0.220***	-0.192***	-0.217***
	(0.0393)	(0.0435)	(0.0238)	(0.0593)
R-squared	0.180	0.054	0.324	0.057

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: The costs of job loss including all zeros for earnings

Note: Used to plot Figure 2.

VARIABLES	(1) Earnings	(2) Wages	(3) Employment	(4) Hourly wage
δ_{-3}	-0.0418*	-0.00803	-0.0256*	-0.00800
	(0.0243)	(0.0210)	(0.0152)	(0.0196)
δ_{-2}	-0.0372	-0.0134	-0.0192	-0.0161
	(0.0244)	(0.0210)	(0.0147)	(0.0198)
δ_{-1}	-0.0374	-0.0157	-0.0260*	-0.0215
	(0.0256)	(0.0226)	(0.0143)	(0.0214)
δ_0	-0.124***	-0.0997***	-0.0292**	-0.107***
	(0.0284)	(0.0254)	(0.0144)	(0.0242)
δ_1	-0.835***	-0.411***	-0.602***	-0.394***
	(0.0347)	(0.0319)	(0.0237)	(0.0305)
δ_2	-0.542***	-0.381***	-0.282***	-0.379***
	(0.0333)	(0.0300)	(0.0248)	(0.0288)
δ_3	-0.433***	-0.362***	-0.162***	-0.358***
	(0.0377)	(0.0305)	(0.0251)	(0.0294)
δ_4	-0.348***	-0.363***	-0.0702***	-0.365***
	(0.0425)	(0.0321)	(0.0254)	(0.0299)
δ_5	-0.330***	-0.348***	-0.0815***	-0.349***
	(0.0422)	(0.0309)	(0.0263)	(0.0291)
δ_6	-0.324***	-0.359***	-0.0727***	-0.353***
	(0.0436)	(0.0322)	(0.0273)	(0.0297)
δ_7	-0.297***	-0.328***	-0.0898***	-0.334***
	(0.0445)	(0.0329)	(0.0282)	(0.0325)
δ_8	-0.282***	-0.308***	-0.0668**	-0.317***
	(0.0541)	(0.0480)	(0.0284)	(0.0460)
δ_9	-0.331***	-0.384***	-0.0988***	-0.378***
	(0.0622)	(0.0635)	(0.0293)	(0.0589)
δ_{10}	-0.288***	-0.335***	-0.0960***	-0.333***
	(0.0475)	(0.0429)	(0.0298)	(0.0412)
δ_{11}	-0.237***	-0.306***	-0.0729**	-0.300***
	(0.0479)	(0.0458)	(0.0303)	(0.0443)
δ_{12}	-0.261***	-0.355***	-0.0682**	-0.355***
	(0.0600)	(0.0710)	(0.0315)	(0.0681)
δ_{13}	-0.260***	-0.317***	-0.0758**	-0.315***
	(0.0556)	(0.0571)	(0.0322)	(0.0601)
δ_{14}	-0.206***	-0.282***	-0.0591*	-0.299***
	(0.0533)	(0.0492)	(0.0337)	(0.0478)
δ_{15}	-0.125**	-0.241***	-0.0326	-0.252***
	(0.0566)	(0.0543)	(0.0342)	(0.0523)
R-squared	0.097	0.068	0.186	0.069

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: The costs of job loss including all only those who have one year of positive earnings during the four years after job loss

Note: Used to plot Figure 2.

VARIABLES	(1) Earnings	(2) Wages	(3) Employment	(4) Hourly wage
δ_{-3}	-0.00265	-0.00343	-0.00401	-0.00322
	(0.0147)	(0.0115)	(0.0107)	(0.0115)
δ_{-2}	-0.0204	-0.0235*	-0.00882	-0.0200
	(0.0156)	(0.0125)	(0.0107)	(0.0124)
δ_{-1}	-0.0485***	-0.0386***	-0.0255***	-0.0335**
	(0.0156)	(0.0136)	(0.00961)	(0.0131)
δ_{0}	-0.0928***	-0.0838***	-0.0246**	-0.0818***
	(0.0161)	(0.0141)	(0.00967)	(0.0137)
δ_{1}	-0.942***	-0.417***	-0.762***	-0.379***
	(0.0193)	(0.0263)	(0.0143)	(0.0260)
δ_{2}	-0.798***	-0.421***	-0.581***	-0.414***
	(0.0210)	(0.0219)	(0.0161)	(0.0218)
δ_{3}	-0.735***	-0.374***	-0.511***	-0.369***
	(0.0221)	(0.0227)	(0.0167)	(0.0217)
δ_{4}	-0.683***	-0.395***	-0.440***	-0.402***
	(0.0234)	(0.0223)	(0.0174)	(0.0209)
δ_{5}	-0.630***	-0.387***	-0.389***	-0.391***
	(0.0244)	(0.0225)	(0.0180)	(0.0218)
δ_{6}	-0.576***	-0.385***	-0.343***	-0.380***
	(0.0263)	(0.0239)	(0.0187)	(0.0232)
δ_{7}	-0.591***	-0.395***	-0.338***	-0.398***
	(0.0279)	(0.0255)	(0.0192)	(0.0246)
δ_{8}	-0.571***	-0.371***	-0.327***	-0.377***
	(0.0292)	(0.0279)	(0.0196)	(0.0273)
δ_{9}	-0.594***	-0.414***	-0.327***	-0.399***
	(0.0329)	(0.0329)	(0.0202)	(0.0312)
δ_{10}	-0.566***	-0.382***	-0.320***	-0.371***
	(0.0344)	(0.0358)	(0.0204)	(0.0336)
δ_{11}	-0.541***	-0.371***	-0.304***	-0.362***
	(0.0320)	(0.0297)	(0.0211)	(0.0295)
δ_{12}	-0.524***	-0.327***	-0.302***	-0.308***
	(0.0351)	(0.0356)	(0.0218)	(0.0360)
δ_{13}	-0.491***	-0.344***	-0.272***	-0.330***
	(0.0364)	(0.0356)	(0.0225)	(0.0399)
δ_{14}	-0.470***	-0.347***	-0.248***	-0.342***
	(0.0406)	(0.0431)	(0.0233)	(0.0418)
δ_{15}	-0.446***	-0.277***	-0.258***	-0.240***
	(0.0392)	(0.0412)	(0.0238)	(0.0577)
R-squared	0.205	0.072	0.322	0.069

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: The costs of job loss including all zeros for earnings for a different control group

Used to plot Figure 3.

VARIABLES	(1) Earnings	(2) Wages	(3) Employment	(4) Hourly wage
δ_{-3}	-0.00656	0.000488	-0.00489	-0.00847
	(0.0160)	(0.0132)	(0.0108)	(0.0129)
δ_{-2}	-0.0141	-0.00558	-0.00591	-0.0138
	(0.0164)	(0.0136)	(0.0105)	(0.0128)
δ_{-1}	-0.0216	-0.00918	-0.0186*	-0.0258*
	(0.0170)	(0.0149)	(0.00982)	(0.0149)
δ_0	-0.103***	-0.0912***	-0.0182*	-0.138***
	(0.0180)	(0.0160)	(0.00987)	(0.0316)
δ_1	-0.925***	-0.433***	-0.758***	-0.435***
	(0.0212)	(0.0283)	(0.0147)	(0.0290)
δ_2	-0.776***	-0.414***	-0.588***	-0.359***
	(0.0223)	(0.0239)	(0.0166)	(0.0557)
δ_3	-0.702***	-0.378***	-0.507***	-0.367***
	(0.0244)	(0.0243)	(0.0175)	(0.0238)
δ_4	-0.640***	-0.390***	-0.429***	-0.382***
	(0.0270)	(0.0249)	(0.0183)	(0.0248)
δ_5	-0.590***	-0.363***	-0.396***	-0.358***
	(0.0273)	(0.0242)	(0.0187)	(0.0232)
δ_6	-0.535***	-0.374***	-0.333***	-0.369***
	(0.0283)	(0.0247)	(0.0197)	(0.0238)
δ_7	-0.515***	-0.365***	-0.326***	-0.374***
	(0.0297)	(0.0257)	(0.0203)	(0.0269)
δ_8	-0.488***	-0.368***	-0.287***	-0.370***
	(0.0339)	(0.0317)	(0.0208)	(0.0308)
δ_9	-0.469***	-0.386***	-0.275***	-0.384***
	(0.0382)	(0.0394)	(0.0215)	(0.0369)
δ_{10}	-0.456***	-0.401***	-0.249***	-0.386***
	(0.0377)	(0.0416)	(0.0220)	(0.0374)
δ_{11}	-0.406***	-0.375***	-0.228***	-0.369***
	(0.0388)	(0.0455)	(0.0225)	(0.0410)
δ_{12}	-0.418***	-0.347***	-0.243***	-0.350***
	(0.0396)	(0.0462)	(0.0231)	(0.0452)
δ_{13}	-0.404***	-0.315***	-0.240***	-0.330***
	(0.0378)	(0.0403)	(0.0236)	(0.0447)
δ_{14}	-0.339***	-0.280***	-0.208***	-0.310***
	(0.0368)	(0.0364)	(0.0245)	(0.0363)
δ_{15}	-0.304***	-0.259***	-0.198***	-0.226***
	(0.0391)	(0.0410)	(0.0250)	(0.0562)
R-squared	0.183	0.056	0.326	0.038

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: The costs of job loss including all zero earnings and where job loss coincides with the closure of a mine at the county level

Used to plot Figure 3.

VARIABLES	(1) Earnings	(2) Wages	(3) Employment	(4) Hourly wage
δ_{-3}	-0.00813	-0.00154	-0.00443	-0.00662
	(0.0158)	(0.0130)	(0.0108)	(0.0125)
δ_{-2}	-0.0135	-0.00441	-0.00601	-0.0124
	(0.0161)	(0.0134)	(0.0103)	(0.0128)
δ_{-1}	-0.0238	-0.0118	-0.0163*	-0.0235*
	(0.0166)	(0.0145)	(0.00933)	(0.0139)
δ_0	-0.111***	-0.0996***	-0.0159*	-0.112***
	(0.0175)	(0.0155)	(0.00938)	(0.0150)
δ_1	-0.910***	-0.421***	-0.758***	-0.410***
	(0.0208)	(0.0274)	(0.0143)	(0.0269)
δ_2	-0.764***	-0.399***	-0.591***	-0.404***
	(0.0219)	(0.0232)	(0.0161)	(0.0229)
δ_3	-0.676***	-0.347***	-0.503***	-0.354***
	(0.0240)	(0.0238)	(0.0171)	(0.0227)
δ_4	-0.628***	-0.371***	-0.442***	-0.380***
	(0.0265)	(0.0242)	(0.0178)	(0.0222)
δ_5	-0.575***	-0.344***	-0.399***	-0.353***
	(0.0266)	(0.0235)	(0.0183)	(0.0222)
δ_6	-0.523***	-0.366***	-0.335***	-0.367***
	(0.0278)	(0.0240)	(0.0192)	(0.0224)
δ_7	-0.500***	-0.345***	-0.333***	-0.355***
	(0.0293)	(0.0249)	(0.0200)	(0.0239)
δ_8	-0.483***	-0.342***	-0.303***	-0.348***
	(0.0333)	(0.0311)	(0.0204)	(0.0300)
δ_9	-0.456***	-0.374***	-0.276***	-0.378***
	(0.0374)	(0.0383)	(0.0212)	(0.0358)
δ_{10}	-0.441***	-0.369***	-0.262***	-0.364***
	(0.0379)	(0.0421)	(0.0217)	(0.0379)
δ_{11}	-0.397***	-0.358***	-0.235***	-0.358***
	(0.0381)	(0.0440)	(0.0222)	(0.0394)
δ_{12}	-0.394***	-0.326***	-0.242***	-0.337***
	(0.0395)	(0.0459)	(0.0227)	(0.0442)
δ_{13}	-0.393***	-0.306***	-0.245***	-0.320***
	(0.0370)	(0.0390)	(0.0231)	(0.0427)
δ_{14}	-0.323***	-0.258***	-0.213***	-0.295***
	(0.0363)	(0.0352)	(0.0240)	(0.0346)
δ_{15}	-0.263***	-0.219***	-0.187***	-0.230***
	(0.0404)	(0.0446)	(0.0246)	(0.0622)
R-squared	0.184	0.055	0.335	0.058

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The costs of job loss for men only including all zeros for earnings

Not plotted in the main body of the text.

VARIABLES	(1) Earnings	(2) Wages	(3) Employment	(4) Hours
δ_{-3}	-0.0150	-0.00588	-0.0185***	-0.00647
	(0.0102)	(0.00856)	(0.00690)	(0.00835)
δ_{-2}	-0.0430***	-0.0302***	-0.0306***	-0.0295***
	(0.0109)	(0.00937)	(0.00686)	(0.00907)
δ_{-1}	-0.136***	-0.0468***	-0.121***	-0.0455***
	(0.0111)	(0.00989)	(0.00651)	(0.00949)
δ_0	-0.190***	-0.102***	-0.120***	-0.0996***
	(0.0119)	(0.0107)	(0.00653)	(0.0102)
δ_1	-0.995***	-0.425***	-0.840***	-0.400***
	(0.0135)	(0.0238)	(0.0102)	(0.0233)
δ_2	-0.842***	-0.419***	-0.650***	-0.409***
	(0.0144)	(0.0188)	(0.0121)	(0.0188)
δ_3	-0.780***	-0.383***	-0.574***	-0.371***
	(0.0152)	(0.0190)	(0.0126)	(0.0180)
δ_4	-0.745***	-0.408***	-0.512***	-0.403***
	(0.0158)	(0.0182)	(0.0130)	(0.0164)
δ_5	-0.710***	-0.409***	-0.470***	-0.403***
	(0.0161)	(0.0177)	(0.0133)	(0.0167)
δ_6	-0.677***	-0.420***	-0.429***	-0.413***
	(0.0168)	(0.0177)	(0.0137)	(0.0164)
δ_7	-0.680***	-0.426***	-0.421***	-0.424***
	(0.0175)	(0.0182)	(0.0141)	(0.0170)
δ_8	-0.658***	-0.413***	-0.401***	-0.414***
	(0.0178)	(0.0196)	(0.0143)	(0.0189)
δ_9	-0.650***	-0.435***	-0.385***	-0.433***
	(0.0184)	(0.0199)	(0.0146)	(0.0187)
δ_{10}	-0.616***	-0.421***	-0.368***	-0.418***
	(0.0205)	(0.0241)	(0.0149)	(0.0227)
δ_{11}	-0.611***	-0.425***	-0.354***	-0.420***
	(0.0197)	(0.0218)	(0.0151)	(0.0222)
δ_{12}	-0.586***	-0.371***	-0.357***	-0.367***
	(0.0227)	(0.0279)	(0.0155)	(0.0292)
δ_{13}	-0.580***	-0.404***	-0.335***	-0.407***
	(0.0220)	(0.0247)	(0.0159)	(0.0311)
δ_{14}	-0.551***	-0.390***	-0.317***	-0.407***
	(0.0222)	(0.0234)	(0.0163)	(0.0240)
δ_{15}	-0.541***	-0.347***	-0.328***	-0.328***
	(0.0266)	(0.0339)	(0.0167)	(0.0535)
R-squared	0.490	0.703	0.345	0.702

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: The costs of job loss including all zeros for earnings where we do not perform a matching exercise prior to estimation

Not plotted in the main body of the text.