Quantile Regression Estimates of the Earnings Losses of Displaced Workers

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Abstract

We study the earnings losses of Finnish private sector workers who lost their jobs at two very different points in a business cycle. The first group was displaced in 1992 (depression period) and the second one in 1997 (recovery period). The focal point of the analysis is the quantile displacement effect, the change in the earnings distribution due to involuntary job separation. We use mass layoffs to identify a group of workers who were displaced from exogenous causes. The effect of displacement is strongest at the lower end of the earnings distribution, and small or negligible at the upper end. Workers displaced during the depression period experienced the largest earnings losses.

Keywords: Displacement, earnings losses, unemployment, quantile regression.

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1 Introduction

As a result of downsizing or firm exit, a large number of workers is forced to leave their jobs every year in all labor markets. Some of these displaced workers are able to find equally good employment elsewhere, whereas others experience unemployment spells and/or have to accept a significant reduction in earnings to get a new job. The costs of job loss have been a focus of intensive study in recent years.

A typical finding in US studies has been that the wage losses are large and persistent. They have been estimated to be in the neighborhood of 10-25 percent still several years after the displacement had taken place (see Ruhm, 1991; Jacobson et al., 1993; Schoeni and Dardia, 1996; and Stevens, 1997). On the other hand, the reduction in employment that followed displacement has been found to be relatively short-lived in the US labor market. The picture that emerges from recent European literature is less clear. Some studies, like the ones by Couch (2001), Burda and Mertens (2001), and Bender et al. (2002) for Germany, Huttunen et al. (2005) for Norway, and Hijzen (2006) for the UK, seem to indicate that the long-term costs of job loss are small or non-existent. On the other hand, studies by Boreland et al. (2002) for the UK, Margolis (1999) for France, and Carneiro and Portugal (2003) for Portugal find the long-term losses to be much larger and more similar with the earlier studies from the US. While there seems to be significant variation in the outcomes of displaced workers in different countries, it is worth emphasizing that the results from these studies are not directly comparable due to large discrepancies in the underlying data and research design.

Starting from Ruhm (1991) and Jacobson et al. (1993), practically all of the recent studies on the cost of job loss have employed a methodology that involves a comparison of displaced workers with a control group of similar workers who did not experience displacement during a given reference period.[1] Worker displacement is typically defined as permanent and involuntary separation of workers with established work histories initiated by economic factors unrelated to job performance. Because of the limitations of available data, many authors have take separations associated with a mass layoff or a plant/firm closure to be displacements in empirical work, since they are likely to be exogenous from the worker's standpoint.

In this study, we investigate the cost of job displacement in Finland. A linked employer-employee panel data, which has been constructed from administrative records by Statistics Finland, is used to construct groups of private sector work-

[1] While Huttunen et al. (2005) and Hijzen et al. (2006), for example, use control groups in which separations at later periods were allowed, many other studies require that individuals in the control group remain employed over the whole observation period.

ers who were at risk of displacement in 1992 and 1997. We identify workers who were displaced from exogenous reasons using mass layoffs. These groups of workers and the associated comparison groups are followed over a nine-year period beginning three years before and ending five years after the displacement took place: from 1989 until 1997 and from 1994 until 2002, respectively.

The years chosen for this study reflect markedly different macroeconomic conditions in Finland. In the beginning of 1990s, Finland suffered a severe depression, and the employees who were displaced in 1992 faced an exceptionally difficult labor market situation.[2] However, given the fast recovery from the depression, the Finnish macroeconomic climate was dramatically changed by the end of 1990s. Consequently, the workers displaced in 1997 encountered an entirely different situation. The first case, in which the job loss took place in 1992, is an extreme case that highlights the severe consequences that may follow from a displacement during a deep depression. It should be seen as an interesting, albeit nearly unique, special case while keeping in mind just how atypical the Finnish labor market conditions were in 1992. In many ways, the latter case is more typical and hence more in line with the research on displacement conducted elsewhere.[3]

With an exception of Carneiro and Portugal (2003), the existing analysis of earnings losses associated with displacements has employed classical least-squares regression methods. Although the resulting effect on the conditional mean of earnings is of considerable interest, it is not indicative about the size and nature of the effect of displacement on the lower and upper tails of the earnings distribution. For a given mean loss it does make a difference whether the losses are distributed equally or whether they are concentrated in some particular groups of workers. If there is evidence of a moderate mean effect with large losses within a small group of displaced workers, it may or may not imply a need for directed supportive measures. The need may be obvious if this group includes low skilled workers who are located at the lower end of the earnings distribution in any case and who tend to suffer from large earnings losses after job loss due to long periods out of work. By contrast, this may not be viewed as a problem if the largest losses are experienced by high skill workers who are able to return to work with earnings that are low compared to their earnings without displacement but relatively high compared to the mean level.

From the policy point of view, the distributional aspects of earnings losses of

[2] The Finnish real GDP dropped approximately 14 percent between 1990 and 1993 causing the unemployment levels to reach 20 percent. For a discussion of the Finnish depression, see, e.g., Honkapohja and Koskela (1999).

[3] Similar analysis was conducted for all displacements taking place between 1991 and 2000 to make sure that different base years do not produce erratically changing results; more on this topic in Section 5.

displaced workers are of great importance. Most evaluations of displacement costs have focused exclusively on mean impacts. A more complete picture of consequences of displacement can be obtained by estimating a family of conditional quantile functions. This approach is taken in this study. It allows us to study the effect of displacement over the entire distribution of earnings. We find evidence of considerable heterogeneity in the displacement effect. The effect of job loss is highest at the lower end of the distribution, being rather moderate or even negligible at the upper end. We find that the effect of displacement on the mean earnings differ substantially from its effect at the median. Moreover, the earnings losses are find to be especially large if job loss takes place in the depression period.

In the next section we define the quantile displacement effect, the effect of involuntary job loss over the distribution of potential earnings, and discuss its estimation by the method of quantile regression of Koenker and Batesse (1978). In Section 3 we describe our data and the technique used for identifying displaced workers. The estimation results are presented and discussed in Section 4. The final section concludes.

2 Quantile displacement effect

We are interested in the effect of job displacement in period t on annual earnings in period $s > t$. When involuntary job loss is viewed as a "treatment", we can derive its effect on the earnings distribution along the lines of quantile treatment literature, which history goes back to Lehmann (1974) and Doksum (1974). Let W_s be the annual earnings in the absence of displacement in period t, which is a random variable distributed according to F_s. Suppose that the annual earnings would be $W_s + \Delta_s(W_s)$ had the individual be displaced from his or her job in period t, and denote the distribution function of this random variable with G_s. Following Doksum (1974), we define $\Delta_s(w_s)$ as

$$F_s(w_s) = G_s(w_s + \Delta_s(w_s)). \tag{1}$$

By denoting $\tau = F_s(w_s)$, so that $w_s = F_s^{-1}(\tau)$, we can rewrite this as

$$\delta_s(\tau) = G_s^{-1}(\tau) - F_s^{-1}(\tau), \tag{2}$$

where $\delta_s(\tau) \equiv \Delta_s\left(F_s^{-1}(\tau)\right)$, and $\tau \in [0, 1]$ denotes the τ-th quantile. We refer to $\delta_s(\tau)$ as the *quantile displacement effect* (QDE). It equals the horizontal distance between the distribution functions of potential earnings with and without displacement at given τ. A family of $\delta_s(\tau)$ over τ is able to capture potential heterogeneity in the effect of displacement over the distribution of potential earnings in period s.

In the absence of covariates, the natural and simple estimator of the QDE is obtained by replacing $G_s^{-1}(\tau)$ and $F_s^{-1}(\tau)$ in (2) with their empirical counterparts. This requires two *randomized* samples of individuals: those who were displaced in period t and those who were not. Then, for example, the difference in median earnings in period s between the displaced and control groups would give an estimate of the QDE at $\tau = 1/2$. Alternatively, we can estimate the effect of displacement at the τ-th quantile from the quantile regression model

$$Q_{W_{is}}(\tau \,|D_i) = \alpha_s(\tau) + \delta_s(\tau)D_i, \tag{3}$$

where $D_i = 1$ if worker i was displaced in period t, and $D_i = 0$ otherwise. The parameters of the model (3) can be estimated by solving a linear programming problem as suggested by Koenker and Batesse (1978). It is crucial for valid statistical inference that the displacement status is exogenous in the analyzed data. Displacements are certainly not randomly assigned in general but dismissed workers are selected in a complicated procedure which takes into accounts also individual characteristics that are not observable for the researcher. To deal with this selection problem, we use mass layoffs to identify workers who lost their jobs from exogenous reasons, which justifies the exogeneity assumption in our application.[4]

If $\delta_s(\tau) < 0$ for all $\tau \in [0, 1]$, that is, $\Delta_s(w_s) < 0$ for all w_s, the displacement in period t has an unambiguous negative effect on earnings in period s, so that the earnings distribution without displacement stochastically dominates the earnings distribution under displacement. In a special case where the quantile displacement effect $\delta_s(\tau)$ does not vary with τ it equals the mean displacement effect δ_s^* in the model:

$$E(W_{is}\,|D_i) = \alpha_s^* + \delta_s^* D_i. \tag{4}$$

In the general case, the mean effect equals the quantile effect integrated over τ; that is, $\int_0^1 \delta_s(z)dz = \delta_s^*$, see Koenker (2005, p. 27).

In the quantile regression model (3) the effect of displacement is allowed to vary over the quantiles of the earnings distribution.[5] When the QDE is defined at the individual level, heterogeneity in the displacement effect can be interpreted to arise from the interaction between some latent characteristic and displacement (Doksum, 1974; and Koenker, 2005). To see this, suppose that workers differ in

[4] Otherwise we could apply instrumental variables quantile regression techniques (references...).

[5] The model (4) can account for heterogeneity as well if the effect of displacement for individual i is $\delta_s^* + \varphi_i$, with $E(\varphi_i\,|D_i) = 0$. That is, δ_s^* is the average displacement effect in the population, which is consistently estimated by OLS. In the random coefficient model, the displacement shifts the location of the earnings distribtion in an individual-specific way but does not affect the *shape* of the distribution, the assumption that is rather restriction.

terms of "ability", which is not observed by the econometrician but is rewarded in the labor market. As a consequence, low ability workers are characterized by a higher incidence of unemployment and lower pay when employed. This unobserved characteristic is implicitly indexed by τ and reflected in $\alpha_s(\tau)$; that is, low ability individuals are located at the lower end of the earnings distribution without displacement. In this setting, the QDE equals the change in earnings that is needed to hold individual's relative position in the earnings distribution unchanged in case of involuntary job loss. Thus, the worker is assumed to maintain his or her rank in the earnings distribution if displaced. This interpretation is motivated by the definition (1). Since we do not observe same individuals in both states (i.e. with and without displacement), we cannot be sure that the effect of displacement actually works in this way (Koenker, 2005, p. 31).

Alternatively, we can interpreted the QDE's simply to measure differences in the two marginal distributions of potential outcomes. For example, $\delta_s(.5)$ describes the difference in the median earnings with and without displacement, not the effect of displacement on the worker located at the middle of the earnings distribution in the absence of displacement. In this setting the estimates may reveal, for example, that job displacement is associated with the average earnings losses (the distribution shifts left) and an increase in uncertainty (dispersion increases). The focus on the difference in the marginal distributions seems natural as it is all we can identify from the observed data.

In the empirical application we estimate the effect of displacement over the distribution of log earnings conditional on observed characteristics. Namely, we apply the following model to the τ-th quantile of the distribution of log earnings:

$$Q_{\ln W_{is}}(\tau \,|\mathbf{X}_{is}, D_i) = \alpha_s(\tau) + \delta_s(\tau)D_i + \boldsymbol{\beta}_s(\tau)\mathbf{X}_{is}, \tag{5}$$

where $\mathbf{X}_{is}$ is a vector of control variables. It should be noted that the logarithmic transformation of the dependent variable is completely transparent in the quantile regression setting (which is not the case in the conditional mean setting). By taking the exponent of the right-hand side of (5), we obtain the τ-th quantile of the annual earnings distribution. The model outlined above is estimated separately for post-displacement periods $s = t+1, ..., t+5$. To test the validity of the selection of displacement and control groups, we also estimate the model for three pre-displacement period.

One additional advantage of quantile regression over mean regression in our setting should be pointed out. Our data contain a number of observations with zero earnings for the long-term unemployed and those who withdrew from the labor market. This makes the least-squares estimation of mean earnings problematic.

Technically, we can deal with zero observations by transforming the dependent variable as $\ln(W_{is}+\theta)$ for some $\theta > 0$. While the coefficients of quantile regression are unaffected by such a transformation, the least-squares estimates are generally not. Whatever transformation adopted, (outlier) observations with zero earnings have potentially a great influence on the least-square results. In the displacement literature, the analysis has been often restricted to a subset of observations with positive earnings, which of course raises an issue of selection bias. In the quantile regression setting, the inclusion of observations with zero earnings (subject to a transformation allowing us to take logarithms) does not cause any problems.

3 Data and descriptive statistics

3.1 FLEED database

Our empirical analysis has been conducted using the Finnish Longitudinal Employer-Employee Data (FLEED). The FLEED is a linked employer-employee database that has been constructed by Statistics Finland for research purposes. It combines data from several administrative registers and includes detailed information regarding employment and earnings for all Finnish permanent residents between ages 16 and 70. The data is collected at the individual level using a unique social security number to identify different statistical units.

In addition to earnings data, the FLEED includes information on various relevant background factors like education, marital status, age, location of residence etc. Furthermore, it includes unique identification codes for all of the firms and plants operating in Finland. The information on plants and individuals has been linked in a manner that makes it possible to identify all the workers that worked for some plant at the end of any given year.

One main advantage of the FLEED used in our study is that it includes all Finnish residents, not just those who are currently working or part of the labor force. This is important because the losses following displacement may come in the form of unemployment spells or changes in labor force participation rather than lower wages. If all costs of job loss are to be included, we should not exclude people who are not working or even looking for work from our calculations. There is no reason to think that the members of the displacement group initially have less desire to work.

3.2 Sample construction

An ideal situation would allow us to first observe a group of people over a period of time without the treatment. Later, the same people would be observed over the same period while this time including the treatment. The displacement effect would be the difference between the two cases. Obviously, this is not possible, since an individual cannot both belong to the displacement group and the control group at the same time. The best we can do is to construct the two groups in such a way that makes it plausible that they are reasonably similar in relevant respects.

The best way to construct the groups would be to randomly divide all of the workers into two groups. Again, it is clear that such experiments are not possible in practice. Instead, we use mass-layoffs to simulate an experiment in which the membership in the treatment group is based on random assignment. This way the displacements are to a large extent exogenous and the selection bias is minimized.

For the purposes our study, we construct two separate samples using the years 1992 and 1997 as base years. The sample construction procedure is identical in both cases. For both years, we identify a group of displaced workers as well as a group of workers who were not displaced at that time. The first group is the displacement group and the second the control group. Both displacement groups and the corresponding control groups are then followed over a nine-year period beginning three years before and ending five years after the displacement took place: from 1989 until 1997 and from 1994 until 2002, respectively.

Our analysis focuses on workers who initially all have a fairly strong labor market attachment. Specifically, we require that everyone included in the sample has three or more years of tenure with the same private sector employer before the possible event of displacement. We also require that during these three years everyone included in the sample had exactly one employer and did not have any unemployment spells. The employers are identified using plant codes and we only include workers from plants that employ at least ten workers during the base year.

In addition, we require that during the base year, 1992 or 1997, the age of everyone included in the sample was between 21 and 52. The age restriction has been placed to make sure that everyone in the sample is potentially suitable for being in the labor force during the whole period. Furthermore, by excluding individuals over 52 years of age, we rule out the possibility of early retirement via the so-called unemployment tunnel that could potentially influence our results.[6] Finally, we only

[6] In Finland, displaced elderly workers are allowed to collect earnings-related unemployment benefits until the age of 60 which is the time when they become eligible for the unemployment pension benefit. This system is known as the "unemployment tunnel". There is good reason to think that it increases unemployment among elderly workers who have been displaced (see, e.g.,

include individuals who are present every year in our data and were not self-employed at any point during our time-frame.[7]

We do not require continuous employment from workers in the control group after the base year. In other words, it is possible that also the members of the control group are displaced at later dates. We follow Huttunen et al. (2005) and Hijzen et al. (2006) in this respect. Similarly, we do not keep tract of future displacements that the members of the displacement group may encounter. These displacements are interpreted either as independent events that could have happened to workers in the control group as well, or as consequences of the initial displacement. In the latter case, it is correct to include in the original estimates the additional costs that follow from later displacements.[8]

Since the workers who have been displaced are not directly identified in the data, an indirect process of inference must be used to form the displacement and control groups. The process is essentially the same as the one that was initially used by Jacobson et al. (1993) and that has later been applied in similar studies that use data from administrative records. The same procedure is applied to both years 1992 and 1997 and the corresponding samples are constructed separately.

Using the years 1992 and 1997 as base years, we divide the sample into stayers and separators. Stayers are workers who still have at the end of the base year the same plant identification code they did previously, i.e., workers who still work for the same employer for whom they have been working for, at least, the past three years. The rest of the workers are separators, i.e., workers who, in the end of the base year, do not work at the same plant at which they worked previously.

All separations are potential cases of displacement. However, we only count as displacements those separations in which workers were separated from plants from which at least 50 percent of their employees left during the base year. Other separations are classified as being unclear and are excluded from the sample.[9] Also

Kyyrä and Wilke, 2007). The age criterion for the eligibility for these benefits used to be 53 but it was raised to 55 in 1997. In any case, displaced workers in our study cannot directly enter the unemployment tunnel in either of the samples, since we require that the displaced workers are at most 52 years old during the base year.

[7] Self-employed are left out because we are interested in the effects of displacement on labor income. Self-employed individuals form a special group in this respect. Typically, self-employed have little labor income, whereas they may have other significant sources of income. Our sample construction procedure leaves out a potentially interesting, albeit surely quite small, group of workers who are pushed to becoming self-employed as a consequence of being displaced.

[8] There is some evidence to indicate that later displacements may significantly increase the costs from job loss (see Stevens 1997).

[9] The chosen threshold value for a mass layoff is essentially arbitrary. To check the robustness of the results, we applied different criteria for defining the displacement group, ranging from X to Y percent. Our results...

displaced workers who are re-employed by their original employer are excluded. At end of the sample construction procedure, we are left with two nine-year-long balanced panels. The first one has 2,400,921 observations (266,769 individuals) and the second one 2,519,550 observations (279,950 individuals).

The intuitive definition given for "displaced worker" in Section 1 characterizes displacements as involuntary and permanent separations of workers with established job histories that happen for reasons unrelated to job performance. The definition is too vague to exactly specify which separations are displacements. However, many of the criteria used in our sample construction procedure can be seen as giving specific empirical content to the intuitive definition. For instance, we have required that at least 50 percent of the workers leave at the same time, which makes it plausible to assume that the separation was involuntary and unrelated to job performance. We have also excluded displaced workers who were re-employed by the same plant to make sure that the separation was permanent. In addition, we have placed several criteria for previous tenure. This was done mostly to guarantee that the workers had established job histories, but also partly to strengthen the case for the inference that the separation was involuntary.

Naturally, the mechanism used to construct the displacement and control groups is not 100 percent accurate. Since the data does not directly identify the workers who were displaced, it can never be known for sure which separations were actual displacements and which ones voluntary separations, endings of temporary contracts, or firings for cause. It is, for example, possible that some workers who end up being classified as displaced actually voluntarily left their jobs at that very moment for a reason that did not have anything to do with the reduction in employment at that particular plant. However, it does not seem likely that this kind of classification error seriously jeopardizes the relevance of our study: if over half of the workforce leave from a plant during a period of one year, it is probable that most of them were forced to leave due to plant closure or downsizing. This is particularly likely given our sample construction criteria that make it probable that many of the workers in our sample have a fairly strong attachment to their current employer in the beginning of the base year.[10]

In any case, the analysis of our results should be made with all these caveats in mind. It is also possible to interpret the sample construction procedure as a definition of displacement given for the purposes of this study. In this case, it remains unclear how well our specific technical definition corresponds to some other intuitive definition people may have about displacement. When interpreting the

[10] Even if some of the workers did actually leave "quasi-voluntarily" in anticipation of future layoffs, it seems that counting them as displaced is appropriate.

Groups	N		%	
	Year 1992	Year 1997	Year 1992	Year 1997
Non-displaced	255 617	275 895	90.60%	95.70%
Displaced	26 677	12 267	9.50%	4.30%
• Plant closure	10 942	5 637	3.90%	2.00%
• Downsizing	15 735	6 630	5.60%	2.30%
TOTAL	282 294	288 162	100%	100%

Table 1: Displacement status

Variable	Non-Displaced		Displaced	
	Year 1992	Year 1997	Year 1992	Year 1997
General				
• age (average)	38.7 years	40.0 years	38.1 years	39.3 years
• tenure (average)	12.3 years	12.6 years	10.8 years	10.7 years
Sex				
• men	58.80%	61.00%	58.00%	57.30%
• women	41.20%	39%	42.00%	42.70%
Education				
• secondary/higher	20.50%	24.40%	20.50%	29.90%
• master's/higher	4.40%	5.20%	3.80%	6.50%
Industry				
• manufacturing	50.20%	51.40%	46.80%	33.00%
• construction	4.00%	2.70%	10.90%	2.00%
• sales	15.90%	15.70%	16.60%	19.10%
• service	6.80%	9.40%	2.80%	19.00%
• transportation	13.30%	11.30%	19.10%	19.00%

Table 2: Some general characteristics of workers in different groups

results, it should also be kept in mind that our sample is by no means a random sample from the whole Finnish population, nor is it intended as one. The effects of involuntary separation for some other type of group could obviously differ.

3.3 Descriptive statistics

Tables 1 and 2 present summary statistics on different groups formed with the procedures described above. Table 1 contains information on the relative sizes of displacement groups and control groups formed in both base years. Table 2 includes data on some variables that characterize workers belonging to different groups.

By and large, the displacement and non-displacement groups seem similar. But there are certain differences. For example, the members of both displacement groups seem to be slightly younger on average and to have shorter pre-displacement tenures.

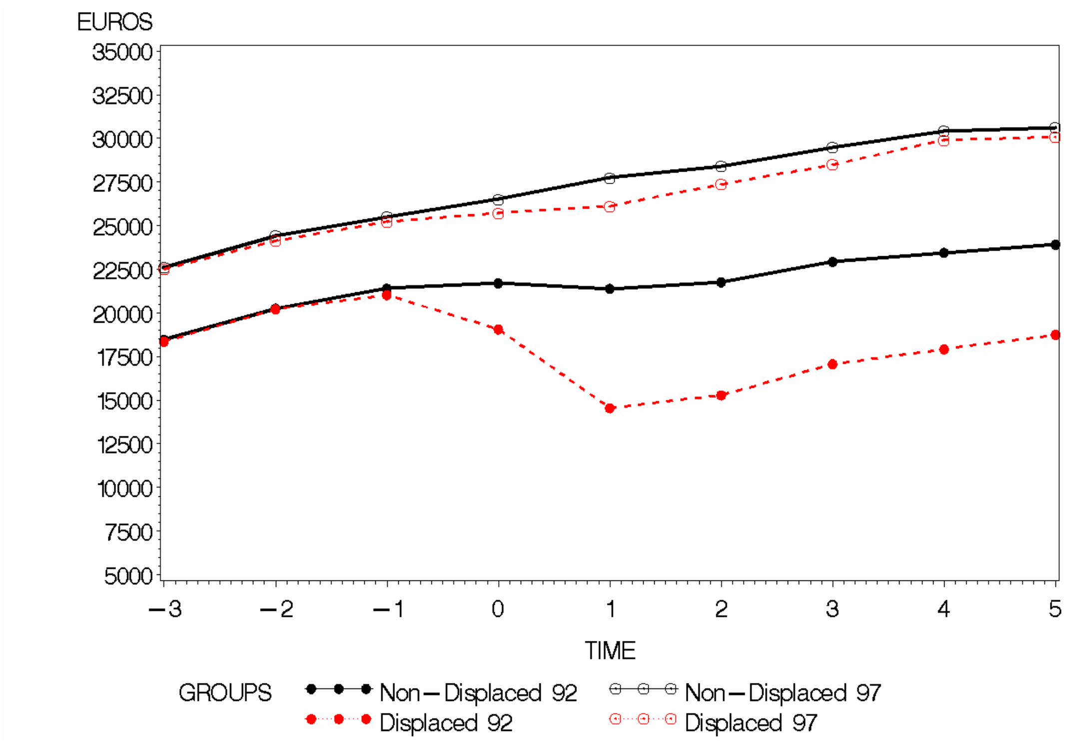

Figure 1: Annual earnings over time

Also the share of women seems to be slightly higher among displaced workers. In addition, the incidence of displacement seems to differ between industries. The share of workers employed in manufacturing is larger in both control groups, whereas the share of service and transportation sectors seems to be higher in both displacement groups. Finally, the relative share of displaced workers is considerably higher in 1992 compared to 1997: 9.5 percent vs. 4.3 percent. This is natural given that 1992 is the year when Finland was in the middle of an exceptionally severe depression.

Figure 1 shows the average annual earnings, and Figure 2 the average employment levels for different groups. Time is measured relative to the base year $t = 0$, which is the year when the displacements happen (either 1992 or 1997). Figure 1 shows that on average displaced workers earn less after the displacement. The difference is much larger for the first displacement group. Figure 2 shows how many months the individuals in different groups worked on average during each year. The first displacement group clearly stands out: the employment levels drop dramatically in 1992–1993 and the following recovery is slow. A similar but smaller drop is evident in the second displacement group as well. It can also be seen that the average number of months worked decreases slowly in both of the control groups. This is natural, since both voluntary and involuntary separations were allowed for

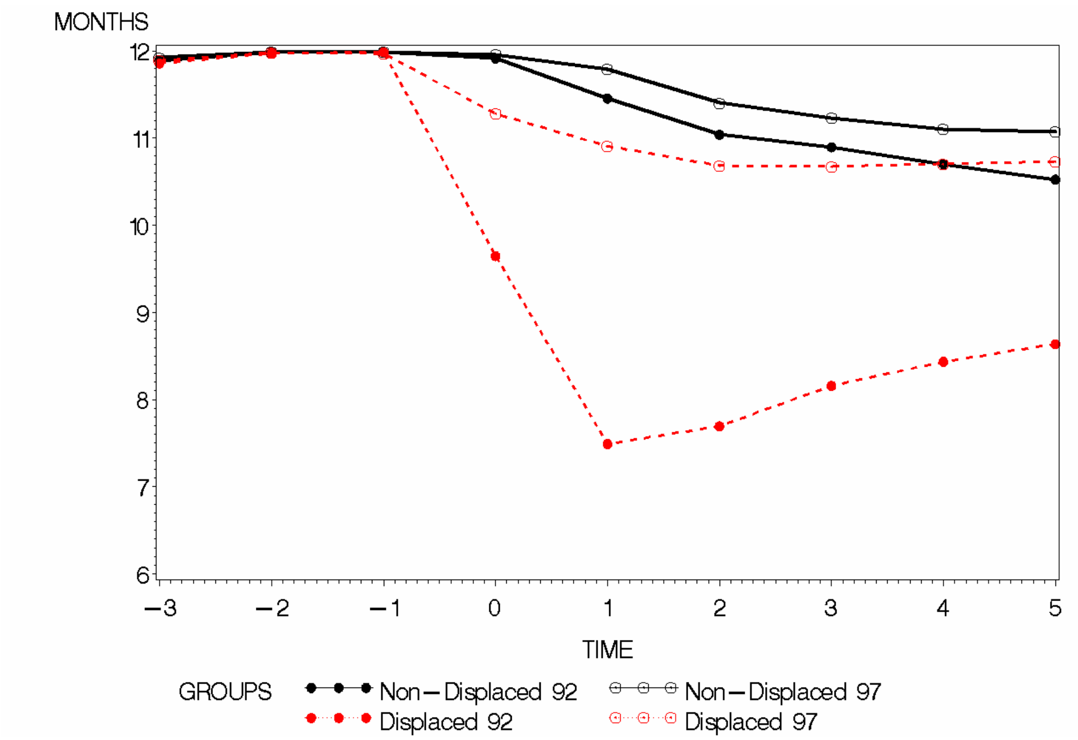

Figure 2: Employment levels over time

the members of the control groups after the base year.

4 Results

4.1 Main findings

We have estimated the earnings losses for workers displaced in 1992 and 1997 over the following six years. The former group was displaced in the middle of the deep depression, whereas workers in the latter group lost their jobs during the period of strong recovery. We also estimated the earnings differentials between the displacement and comparison groups for the displacement year and for the three years prior to job loss. The model outlined in (5) was estimated separately for each cross section over the nine deciles. We estimated also the corresponding mean effect by OLS. All models contain the same set of control variables, including age, gender, education, place of residence, and the size and industry of the firm in which the individual worked until the period of possible job loss.

A large number of displacement effect estimates are summarized in Figures 3 and 4. The OLS curve shows the effect of displacement on the mean earnings, measured by the ratio of the mean earnings of displaced workers to that of the comparison

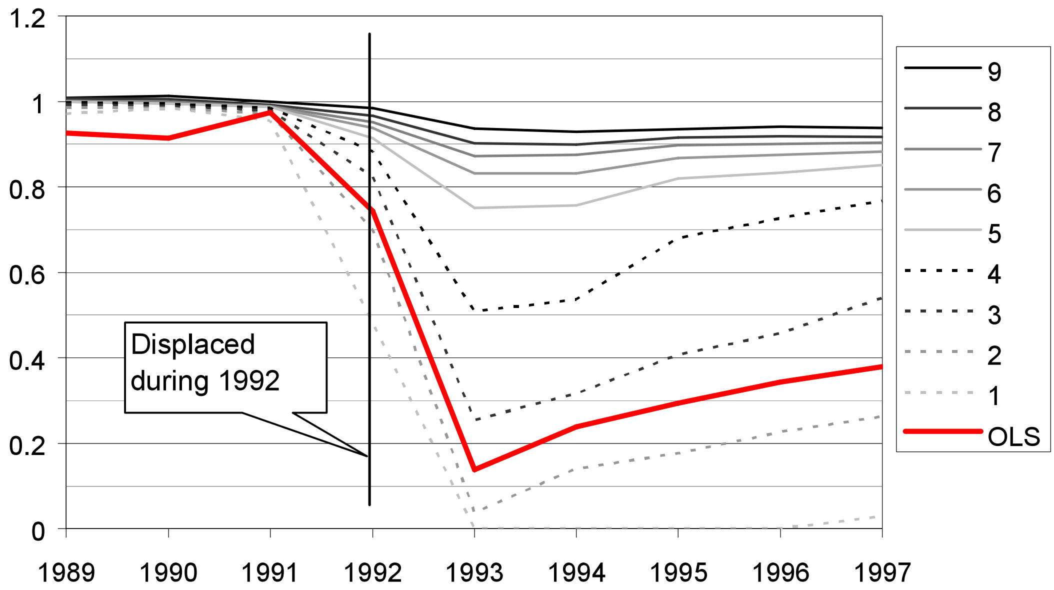

Figure 3: Earnings losses of workers displaced in 1992

group. The other curves describe the ratio of various earnings quantiles between the two groups. This ratio equals $e^{\delta_s(\tau)}$ at the τ-th quantile in period s. In a given cross section the family of the quantile displacement effects captures the heterogenous effect of job loss over the distribution of annual earnings.

The earnings distributions are almost identical prior to the displacement period. We find only a marginal decline at the lowest decile of the earnings distribution of the displacement group in one year preceding job loss. This may suggest that working hours of low paid workers have a tendency to decline prior to job displacement. Overall the estimates for the predisplacement periods do not show notable differences between the displacement and comparison groups. As a consequence, our approach to detect exogenous displacements using mass layoffs seems successful.

The estimates show that displacement has a sizeable negative effect on mean earnings of displaced workers in both groups. It can also be seen that the effect is considerably higher for the workers displaced in 1992 during the depression. For both groups, the largest loss occurs one year after displacement in 1993 or 1997. This was to be expected, since all of the workers were still employed in the beginning of the displacement period. The exact timing of job loss is unknown, but it may have happened at any point during that year. If a worker was displaced towards the end of the year, he or she probably had normal earnings up to that point.

For the 1992 group, the initial loss is extremely large: during 1993 the mean earnings of the displaced workers are nearly 86 percent lower than the mean earnings

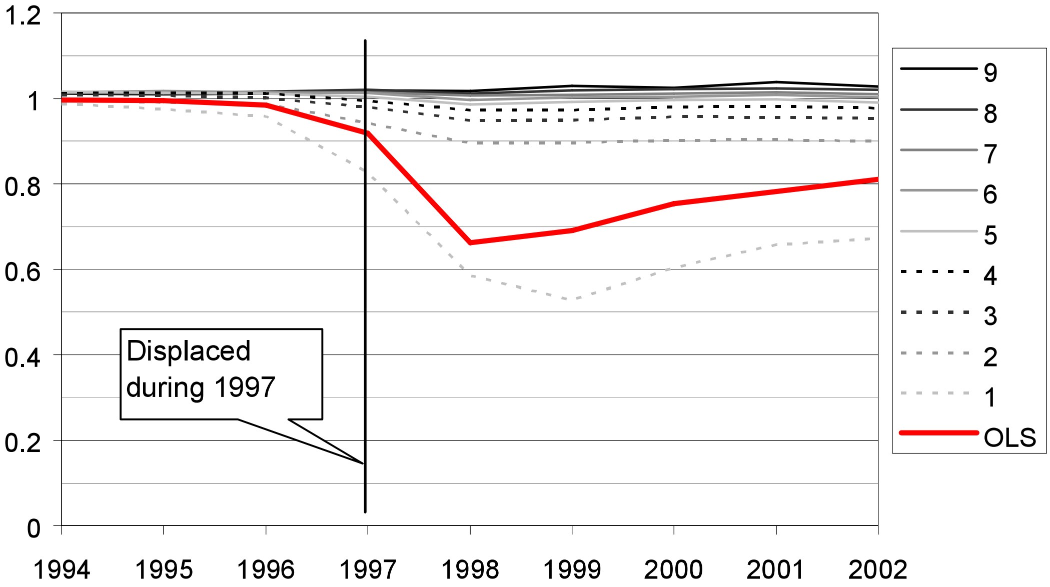

Figure 4: Earnings losses of workers displaced in 1997

in the comparison group. Similar estimate for the 1997 group is approximately 34 percent; still a large loss, but much more typical in the light of earlier research. Moreover, the losses for the 1992 group are very persistent. Still in 1997, after five years of job loss, the workers displaced in 1992 have approximately 63 percent lower mean earnings than the workers in the comparison group. Again, a similar estimate for the 1997 group is much lower: roughly 18-19 percent. This estimate is within the bounds of earlier estimates from similar studies.

The quantile displacement effects give us a more complete picture of consequences of job loss. The effect of displacement decreases monotonically over the quantiles of the earnings distribution, being much weaker at the upper end of the distribution. For example, the first quantile of the earnings distribution under displacement is zero until 1996 for the 1992 group, implying a notable risk of loosing all earnings for four years if displaced in the middle of the depression. By contrast, the displacement effect at the upper end of the distribution is quite moderate in the 1992 group and zero in the 1997 group. It is interesting to note that the effect of displacement at the median is a substantially lower than the mean effect. In fact, the median effect is close to zero in the 1997 group. These findings suggest that the large losses in the mean earnings associated with job loss are attributable to a relatively small fraction of displaced workers who had severe difficulties to return employment, and hence earning nothing.

4.2 Robustness of the results

A potential source of bias comes from the use of downsizing plants to assign membership in the treatment group. In our sample, some displaced workers were separated from downsizing plants, whereas others from plants that exited altogether. It seems that the latter situation might be closer to the random case in which the displacement is exogenous. If the displacement follows from downsizing, there might be some room for selection inside the plant. It is possible that firms attempt to get rid of their worst workers. If that is the case, then the group of displaced workers consists of workers who are less productive than the workers in the control group. Consequently, the estimated costs of job loss will be biased upwards. Again, it is likely that the rich set of control variables is able to take care of most of the bias that might otherwise result from this source.

Results to be added....

5 Concluding remarks

In this study, we have estimated the costs of involuntary job loss for Finnish workers using linked employer-employee data. Our main finding is that displaced worker suffer on average very substantial and persistent losses in annual earnings. The severity of losses is related to the time period during which the displacement took place. Workers who were displaced in 1992 had approximately 63 percent lower mean earnings five years after the displacement. The corresponding estimate for the workers who were displaced in 1997 is roughly 18-19 percent.

The big difference in the estimated mean losses for the two groups demonstrates the role played by the general labor market situation at the time when the displacements take place. In 1992, Finland was in the middle of a deep recession and the workers who lost their jobs at that time faced an exceptionally difficult labor market situation. Our study shows that displacement at that time led to extremely large earnings losses. By 1997, the labor market had moved back to a more typical state. Consequently, the mean losses from displacement were much smaller and hence our results for the latter displacement group are more typical in light of earlier research conducted elsewhere.

We found that the effect of displacement is very heterogenous, being much stronger at the lower quantiles. In the 1997 group job loss does not have a notable effect above the median but earnings losses occur only in the lower half of the distribution. This heterogeneity suggests that a large fraction of workers experience rather moderate earnings losses, if any, after job displacement. In other words, much of the decline in mean earnings is attributable to a relatively small group of displaced workers who experience extremely large earnings reductions due to difficulties to return to work. Our supplementary results from quantile regressions imply that the estimated mean effects alone give only a very incomplete picture of the consequences of job loss.

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