Reconsidering the Consequences of Worker Displacements: Firm versus Worker Perspective

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B Appendix: Matching Procedure, Properties of the Match and Variables

B.1 Separators

We match jobs in the SIPP to those in the LEHD in the following manner.

In the SIPP, we start with the universe of jobs with 12 months or more of tenure based on question TSJDATE: "When did ... start this job?". We assign the separations, which are monthly, to the relevant quarter. Row 1 of Table B2 shows the relevant counts. Starting with these jobs (which we refer to as SIPP-quarters) we then find jobs in the LEHD in the following order:

- Whether the worker in the SIPP ever had earnings in the LEHD (row (1) in Table B2);
- Whether the worker in the SIPP ever has earnings in the LEHD (row (2) in Table B2);
- We impose the requirement that the earnings in the LEHD be in the same quarter as the worker appears in the SIPP (row (3) in Table B2);
- We impose a tenure requirement by restricting attention to jobs with positive earnings in quarter t for which the worker also had positive earnings in quarter $t-3$, $t-2$ and $t-1$; (row (4) in Table B2)
- We impose a "full-time" earnings requirement by restricting attention to quarters with earnings that exceed 70% of 480 hours of work at $4.25 (in 1991 dollars, the Federal minimum wage) (row (5) in Table B2);
- We then match if the job actually ends in the relevant quarter (row (6) in Table B2).

Table B2 provides details on the counts at each step. We start with 22,700 separations in the SIPP (row 1 in Table B2) and are able to match 10,100 of them to the LEHD (row (6) in Table B2).

B.2 Non-separators

For the sample of non-separators, we match the SIPP to the LEHD by looking in in the quarter occupying the majority of the relevant SIPP interview frame, and then follow that job in the LEHD. If we dont find positive earnings in that quarter, we then look on either side of that quarter for positive earnings. We impose a tenure requirement in an identical manner to the separators. Of course, we do not impose a separation requirement.

Table B2 provides further details. We start with 525,900 job-quarters in the SIPP and are able to match 348,100 of them to the LEHD.

B.3 Other Variables

B.3.1 Worker-Level Variables

Among the set of workers that we match, we construct the following variables in the LEHD:

- Total earnings in quarter t: we take the sum across all jobs in the LEHD (not just those passing the earnings test). We winsorize (topcode) at the 99th percentile of earnings in that quarter.[1]
- For workers who separate, we keep track of whether they have any earnings from their pre-separation employer in every quarter following the separation. We also record whether their pre-separation employer is their source of maximum earnings in a particular quarter.

B.3.2 Establishment-Level Variables

We restrict attention to workers earnings at least 35% of 480 hours at the 1991 minimum wage. We then create the following variables at the SEIN quarter level:

- Employment counts in quarter t: the number of workers with earnings above our threshold.

Table B1: Illustration of Methodology using Fictional Earnings Record

(1) Earnings	(2) Employer ID	(3) Calendar Time	(4) Event Time 1	(5) Event Time 2	(6) Event Time 3
10000	3653	2000:I	-3		
10000	3653	2000:II	-2	-3	
10000	3653	2000:III	-1	-2	
10000	3653	2000:IV	0	-1	
9500	3653	2001:I	1	0	
0	NA	2001:II	2	1	
8000	4511	2001:III	3	2	
9000	5205	2001:IV	4	3	-3
9000	5205	2002:I	5	4	-2
9000	5205	2002:II	6	5	-1
9000	5205	2002:III	7	6	0
9000	5205	2002:IV	8	7	1
Event			Continue	Sep.	Continue

[1] Couch and Placzek (2010, Web appendix A) topcode at $155,000 in 2000 dollars.

Table B2: Properties of the SIPP-LEHD Match

		Continuers	Separators
(1)	SIPP	525,900	22,700
(2)	Positive LEHD earnings ever	499,800	22,000
(3)	Positive LEHD earnings in the relevant quarter	466,100	18,900
(4)	4 quarters of earnings before match	418,600	14,700
(5)	Pass an earnings test	374,000	10,500
(6)	Matched	348,100	10,100
(7)	Number of quarters	27	27

Note: This table shows the properties of the match. Row (1) shows the number person-quarters in the SIPP, where quarter is defined as the quarter in which the person appears in the SIPP. Row (2) shows the number of those person-quarters that have positive earnings in the LEHD. Row (3) shows the number that have positive earnings in the LEHD in the same quarter as in the SIPP. Row (4) shows the number that have 4 quarters of LEHD earnings before the match (i.e., that satisfy our tenure requirement). Row (5) shows the number of observations that also pass an earnings test. Finally, row (6) shows the final sample once we have dropped duplicates and the timing of the separation aligns with the SIPP.

C Appendix: Cleaning Employer IDs

We might record a mass layoff when an employer shuts down, when in fact the employer identification number has just changed. Following Schoeni and Dardia (1996) and Benedetto et al. (2007), we use worker flows across establishments to correct longitudinal linkages.[2]

Table C1 presents a simplified version of Table 3 in Benedetto et al. (2007), which summarizes how we use worker flows to edit longitudinal linkages. The basic idea is that if most workers from an employer move to the same employer and then make up the majority of the new employer then this probably reflects an ID change. If most workers from an employer move to the same employer but make up a smaller share of the new employer, then this is more plausibly an acquisition/merger in which the new ID number swallowed the old ID number. The only difference from Benedetto et al. (2007) is that we use a 70% threshold rather than an 80%. The reason to do this is to be more conservative. It also aligns with Jacobson, LaLonde, and Sullivan (1993) definition of a displacement more tightly so that we know that the JLS mass layoffs are never associated with large flows of workers to a common employer.

When we observe an ID change or a merger/acquisition we go back and change the ID so that we have a consistent ID series. This correction allows us to compute employer-level outcomes.

Table C1: Successor/predeccessor flow and firm birth/death combinations

Link description	70% of successor comes from predecessor	less than 70% of successor from predecessor
70% of predecessor moves to successor and predecessor exits	ID Change	Acquisition/merger
70% of predecessor moves to successor and predecessor lives on	ID Change	Acquisition/merger

Note: this table is based on Table 3 in Benedetto et al. (2007).

[2] Davis and von Wachter (2011) use an alternative strategy to mitigate concerns about measurement error in employer IDS: they alter their definition of displacement to exclude all cases where the ID disappears.

D Appendix: Standard Errors

There are several issues concerning computing standard errors for the pooled specification in equation (2). First, insofar as there is heterogeneity in the displaced worker earnings losses, then we expect there to be serial correlation in the standard errors at the individual level. This concern arises even in specification (1). We address this concern by clustering at the person level. Second, a given person-quarter observation might appear several times. For example, if a person continues in a job for several quarters and then loses their job in a mass displacement, then a particular calendar quarter of earnings would show up in two different calendar times. This specification with a given observation potentially appearing multiple times is formally identical to the preferred specification in Dube, Lester, and Reich (2010), and we adopt their solution of clustering at the level of aggregation at which a given observation might appear multiple times.[3]

To summarize, our standard errors have the following structure: $E[u_{ik}^{y} u_{i'k'}^{y'}] \neq 0$ if $i = i'$ or $k + y = k' + y'$. As a result, we use the Cameron, Gelbach, and Miller (2011) two-way clustered standard errors where we cluster at the person level and calendar time level. They show that the variance matrix is then $V^{IT} = V^{I} + V^{T} - V^{I \cap T}$ where the right-hand side are variance matrices from one-way clustering and I is the set of individuals and T is the set of calendar time periods.[4]

[3]Davis and von Wachter (2011) implicitly have this issue in that their year-by-year estimates are not independent samples.

[4]In our application, we have over 30 clusters in the time dimension and over 30,000 dimensions in the person dimension.

E Appendix: Propensity Score Reweighting

The basic idea of propensity score reweighting is to make the control group "look like" the treatment group. That is, we are interested in estimating the average treatment on the treated (ATT). To operationalize this reweighting, we estimate a propensity score, $\hat{p}$, to be in the treated group including all of the covariates in Table 3. We use a logit functional form. We construct a weight, $\frac{\hat{p}}{1-\hat{p}}$, to be in the control group. We then re-estimate equation (2) using these weights.

The literature has emphasized three implementation issues in propensity score reweighting: normalization, common support and "large weights." Busso, DiNardo, and McCrary (2014) emphasize in their finite-sample Monte Carlo results that it is important to normalize the weights. We normalize the weights so that the number of units in the control group is the same as before reweighting (i.e., the average weight is 1). Common support refers to whether there is overlap in the propensity score distributions between the treatment and control groups. Conceptually, if there is not overlap then the control group is very different from the treated group, and it is harder to imagine that these are randomly assigned. For each comparison, we verify that there is common support. Heuristically, this means that there are not (near) perfect predictors of being displaced. Finally, a concern emphasized by Crump et al. (2014) is that for propensity scores close to 1, the weights blow-up and in the bias-variance tradeoff, a researcher is better off dropping some observations.[5] In practice, the events that we study are relatively rare and so we do not have estimated propensity scores close to 1.

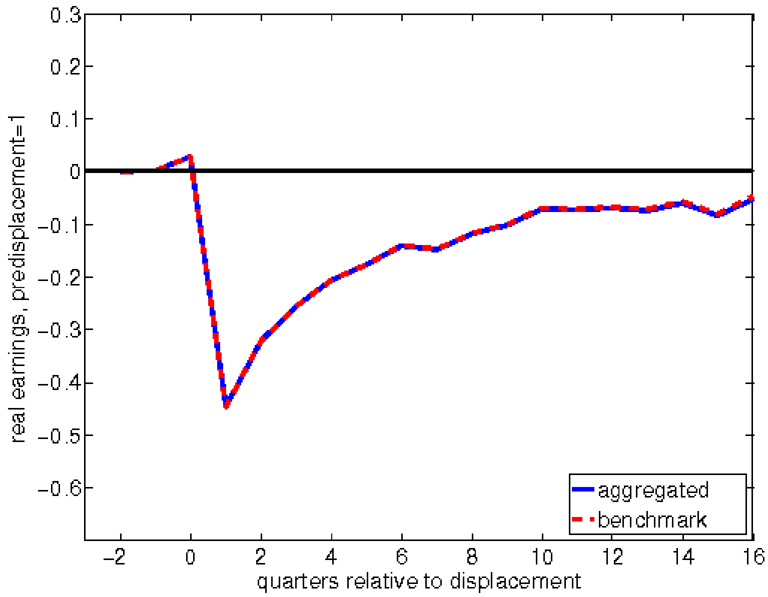
Table E1: Latent Firm Contribution to Survey Reports (unweighted)

	Survey reason (s)		
	Distress	Quit	Other
Pr(Separation$_s$ — ML)	0.055	0.021	0.026
Pr(Separation$_s$ — No growth)	0.001	0.006	0.006
$\Pr(\text{ML}_s^*\|\text{ML}_s) = \pi_s$	0.974	0.726	0.767
$\omega_s = \text{Share}_s\|\text{ML}$	0.54	0.20	0.25
$\omega_s^* = \text{Share}_s\|\text{ML}^*$	0.61	0.17	0.22

Source: SIPP-LEHD as explained in text.
This table reports the unweighted version of Table 4.

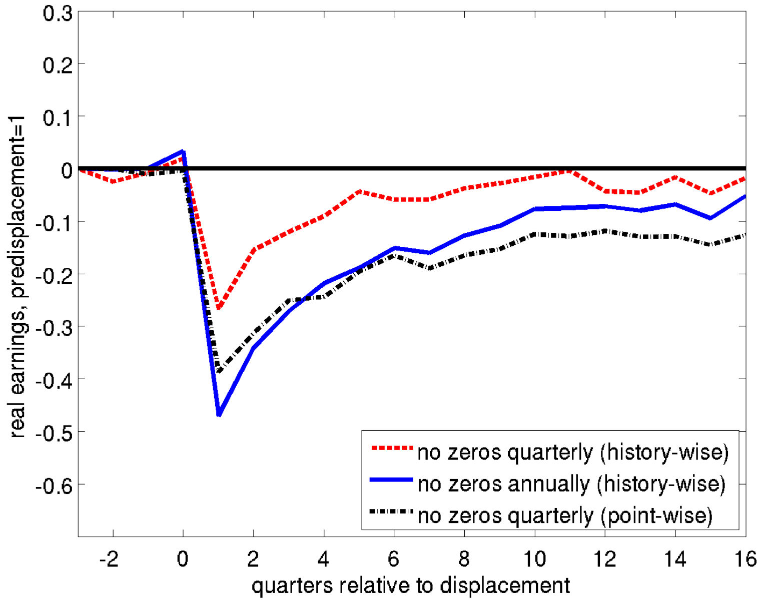
[5] They are interested in the average treatment effect (ATE), and so have weights that look like $\frac{p}{1-p}$ and $\frac{1-p}{p}$ and so they recommend trimming weights both at the top and the bottom. We are interested in the average treatment on the treated (ATT) and so only have weights that look like $\frac{p}{1-p}$ and so their approach would only suggest trimming at the top.

Figure E1: Mass layoff: benchmark and aggregated



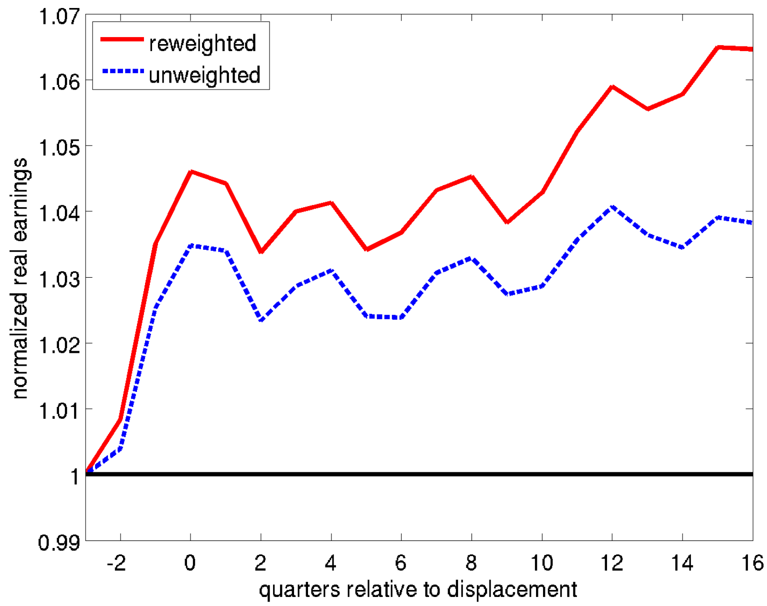
Source: SIPP-LEHD as explained in text.
This figure plots earnings changes from administrative mass layoffs computed in two different ways. The first way is from equation (2), which is also plotted in Panel A of Figure 2. The second way is from equation (4) in section 4, where we have estimated the earnings changes associated with each of the survey responses separately. This line is also plotted in Figure 5. Confidence intervals are suppressed for the sake of clarity. See equation (2) in the text.

Figure E2: Latent earnings losses: Alternative treatment of zeros



Source: SIPP-LEHD as explained in text.
This figure plots the latent notion of earnings losses in a mass layoff calculated using the method in section 4 and given by equation (8) based on three different treatments of observations with zero earnings. The annual no zeros (history-wise) line is our benchmark filter of dropping earnings histories that have a calendar year of zero earnings. The "no zeros quarterly (history-wise)" drops all earnings histories that have a quarter of zeros. The "no zeros (point-wise)" drops all quarterly earnings observations that are zero (but retains the rest of the history). The units on the y-axis are fraction of pre-displacement earnings, where the pre-displacement earnings are normalized to 0.

Figure E3: Control group mean earnings: weighted and unweighted



Source: SIPP-LEHD as explained in text.
This figure plots the mean earnings of the control group period-by-period with and without reweighting. The units on the y-axis are fraction of predisplacement earnings, where the predisplacement earnings are normalized to 0.

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