Reconsidering the Consequences of Worker Displacement: Survey versus Administrative Measurements

by Flaaen, Shapiro and Sorkin

Discussion: Luigi Pistaferri (Stanford)

Background

- There is a huge labor literature on the effects of job displacement (mass layoff) on worker outcomes
  - Wages
  - Employment opportunities
  - Other outcomes (health, children human capital investment, consumption, etc.)

- Effects are large and persistent
  - In this paper, it takes 16 quarters for wages to go back to pre-displacement levels
  - Other papers have emphasized that the recovery (size and duration) depends on *when* the job was lost
    - Larger shock and slower recovery if job was lost in downturn

What this paper does

- Revisits the issue arguing that administrative measures of displacement ("mass layoff", or a 30%+ decline in employment) may be measured with error
  - Some of the separations would have occurred anyway
  - Stylized decomposition: $S_{jt} = N_{jt} + Q_{jt} + L_{jt}$
    - S are <u>all</u> separations
      - N are "natural" separations (retirement, seasonals, etc.)
      - Q are voluntary quits
      - L are actual layoffs motivated by economic distress/firm contraction
  - The authors want to isolate the economic impact of the L_{jt} separations

Why do we care?

- Presumably: We want to have a better idea of the welfare losses associated with an unanticipated shock
- In the US, several programs are designed to at least partially insure against such shocks
  - Unemployment Insurance
  - Trade Adjustment Assistance
- However: a broad discussion of the welfare costs of job displacement should include an evaluation of workers' ability to self-insure
  - Saving/borrowing (but note that shocks are persistent, so not ideal)
  - Added worker effects
- Most papers in the literature lack this perspective, and focus exclusively on the measurement of wage losses

Idea (1)

- When the firm is contracting we naturally expect all types of separation to change (relative to a "normal" state)
- In the example above (under a normalization $L_{jt} = \epsilon_{jt}$):

$$S_{jt}(\epsilon_{jt}) = N_{jt}(\epsilon_{jt}) + Q_{jt}(\epsilon_{jt}) + \epsilon_{jt}$$

- So we're trying to identify how many of the separations are direct and how many are indirect
  - Some people are fired due to distress (ϵ)
  - Some people accelerate their transition to retirement ($N(\epsilon)$)
  - Some rats leave the ship before it sinks ($Q(\epsilon)$)

- Workers at "stationary firms" give us estimates of what N and Q would have looked like in the absence of a "contraction shock"

Idea (2)

- While the “mass-layoff” indicator comes from administrative sources (firm is shrinking 30%+ in LEHD data), they can match LEHD data with worker data from the SIPP

- In the SIPP, people who lost their job are asked why
  - Firm was in economic distress
  - Quit
  - Other reasons

Do reports agree?

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	55%	45%
No mass layoff in admin data ($d^A = 0$)	18%	82%

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	28%	7%
No mass layoff in admin data ($d^A = 0$)	72%	93%

Do reports agree?

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	55%	45%
No mass layoff in admin data ($d^A = 0$)	18%	82%

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	28%	7%
No mass layoff in admin data ($d^A = 0$)	72%	93%

These are guys who may have moved in anticipation of the firm's distress

Do reports agree?

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	55%	45%
No mass layoff in admin data ($d^A = 0$)	18%	82%

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	28%	7%
No mass layoff in admin data ($d^A = 0$)	72%	93%

These are guys who are trying to rationalize a “firing with cause” with firm doing badly

Do reports agree?

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	55%	45%
No mass layoff in admin data ($d^A = 0$)	18%	82%

	Firm in distress in survey ($d^S = 1$)	No firm distress in survey ($d^S = 0$)
Mass layoff in admin data ($d^A = 1$)	28%	7%
No mass layoff in admin data ($d^A = 0$)	72%	93%

The firm fires an entire unit (i.e., an R&D lab), or closes a plant without crossing the 30% threshold

Measurement error interpretation

- The paper naturally offers a measurement error interpretation:

$$d^A = d^* + v^A$$
$$d^S = d^* + v^S$$

- Where d^A=1 if we record a mass layoff in admin data, and $d^S = 1$ if we record a separation due to the firm's economic distress in the survey data
- Both variables are error-ridden measures of some true, unobservable "firm contraction" indicator d^*
  - v^A reflects other separation that would have happened anyway, or arbitrary threshold issues
  - v^S reflects ex-post rationalization, or information issues
- Note: given that d is binary → non-classical measurement error
- The paper dances around this idea, but never fully exploits it

Cases of interest

	$\boldsymbol{d^* = 1}$	$\boldsymbol{d^* = 0}$
$\boldsymbol{d^A = 1}$	✓	Retirements, quits, etc.
$\boldsymbol{d^A = 0}$	Threshold issues	✓

	$\boldsymbol{d^* = 1}$	$\boldsymbol{d^* = 0}$
$\boldsymbol{d^S = 1}$	✓	Ex-post rationalization, stigma
$\boldsymbol{d^S = 0}$	Information issues	✓

Speaking of which…

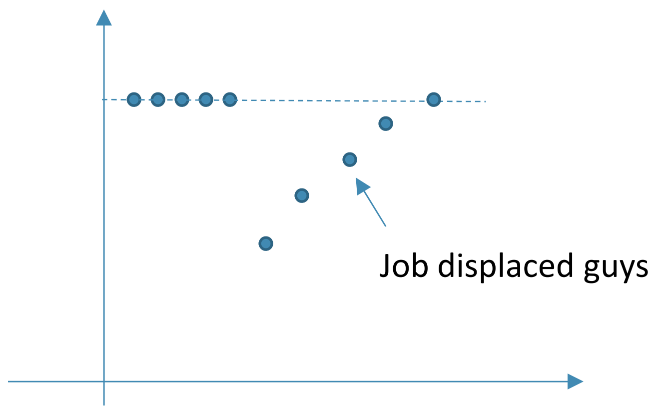
- Why the obsession of the literature with *discrete* indicators?
- In general, I can think of earnings being related to some measure of the firm's fortune (value added, profits, etc., Guiso, Pistaferri and Schivardi, 2005):

$$\Delta y_{ijt} = X'_{ijt}\beta + \phi\epsilon_{jt} + u_{ijt}$$

- With some extreme events (e.g., job displacement) happening when value added falls below a certain threshold (censoring, etc.)
- This is important for the construction of the counterfactual:
  - Separating workers lose job
  - Continuing workers at the same firm (those who didn't go on the chopping block) also suffer: their wages are renegotiated down, etc.

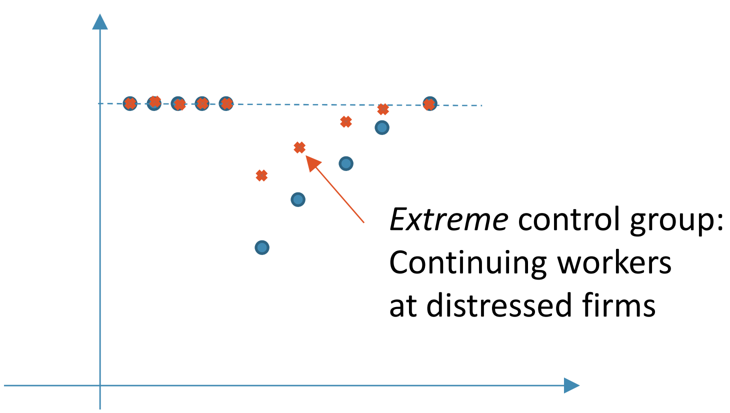
But their control group is different

- Presumably in the attempt of cleaning for "naturally occurring" separations, their control group is not the traditional "continuing workers" (at distressed and non-distressed firms), but "workers at stationary firms"



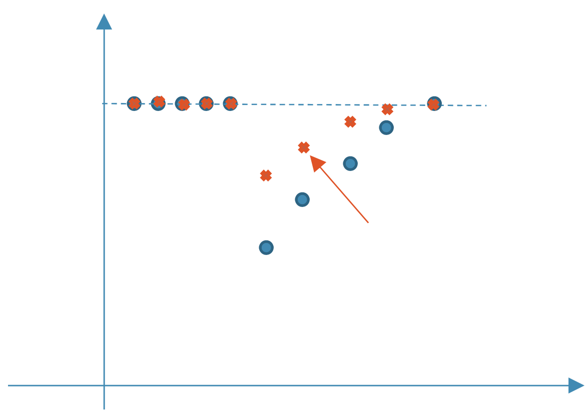
But their control group is different

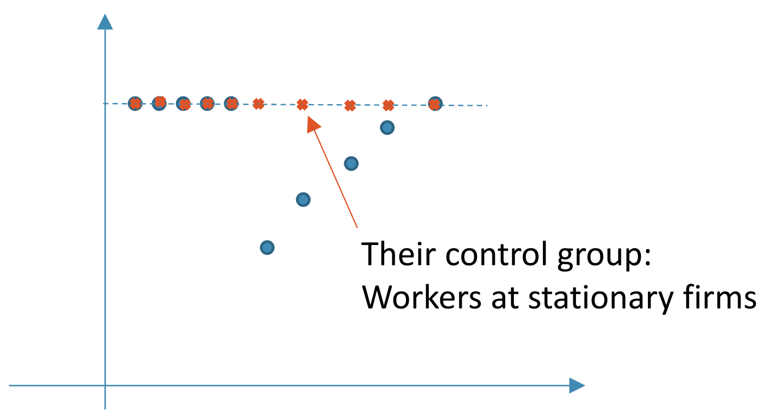
- Presumably in the attempt of cleaning for "naturally occurring" separations, their control group is not the traditional "continuing workers" (at distressed and non-distressed firms), but "workers at stationary firms"



But their control group is different

- Presumably in the attempt of cleaning for "naturally occurring" separations, their control group is not the traditional "continuing workers" (at distressed and non-distressed firms), but "workers at stationary firms"





What’s the right control group?

- Typically: *continuing* workers (at mass-layoff and non-mass-layoff firms)
- Less frequently: *surviving* workers at mass-layoff firms
- All have advantages and disadvantages
    - When conditioning on mass-layoff firms, kills all “sorting into firms” etc.
        - Their control firms are very different from treatment on the basis of observables
        - Propensity score adjusts via reweighting, but doesn’t eliminate sorting onto unobservables (i.e., risk averse people choose stable firms and self-insure more – so value insurance very differently)
    - But of course need to make strong assumption that workers go randomly on the chopping block

- They don’t explain (well) why they choose a different control group, and what it implies
    - First - How is it formally defined?
    - Overstating losses?
- At a minimum, would present results using traditional approach (or justify why the new one is superior)

An alternative empirical approach?

- What they do is pretty involved…
- Consider as an alternative the following IV procedure.
- Regress (more complicated case has various lags and leads):

$$\Delta y_{it} = \cdots + \delta d_{i0}^{A} + u_{it}$$

- and instrument d_{i0}^{A} with d_{i0}^{S}
- As long as measurement error in the two indicators are uncorrelated, it should work
  - We already know the instrument has power
- Maybe they're doing something similar, but I don't know.

- True relationship is:

$$\Delta y_{it} = \alpha + \delta d_{i0}^{*} + u_{it}$$

- But we regress:

$$\Delta y_{it} = \alpha + \delta d_{i0}^{A} + (u_{it} - \delta v_{it}^{A})$$

- With the usual attenuation bias:

$$plim\hat{\delta}_{\text{OLS}} = \delta - \delta \frac{\sigma_{v^A}^2}{\sigma_{d^*}^2 + \sigma_{v^A}^2}$$

- But IV is

$$plim\hat{\delta}_{IV} = \frac{plim\ cov(\Delta y_{it}, d_{i0}^{S})}{plim\ cov(d_{i0}^{A}, d_{i0}^{S})} = \frac{plim\ cov(\alpha + \delta d_{i0}^{*} + u_{it}, d_{i0}^{*} + v_{i0}^{A})}{plim\ cov(d_{i0}^{*} + v_{i0}^{A}, d_{i0}^{*} + v_{i0}^{S})} = \delta$$

- Caveat: Non-classical measurement error
  - But IV biased upwards, so OLS+IV provide bounds

Other issues

- In papers using only admin data, wage and employment losses are overstated if some of those who disappear from sample move into self-employment
  - SIPP match should give you a sense of the extent of overstatement?

- Seam effects?

- Measurement error in separations?

- I find the empirical methodology useful, but also tricky
  - For example what prevents $\pi_s = \frac{\Pr(ML_s) - \Pr(no\ growth)}{\Pr(ML_s)}$ from (occasionally) being negative?
    - Need $\Pr(ML_s) \geq \Pr(no\ growth)$, so control group can never be too large

Conclusion

- This is a very nice paper doing an important decomposition exercise, and I enjoyed reading it

- Maybe try to make something out of the measurement error interpretation?

- Also clarify who the stationary firms are