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 all 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 ($\epsilon$)
  • 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?

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These are guys who may have moved in anticipation of the firm’s distress.
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These are guys who are trying to rationalize a “firing with cause” with firm doing badly.
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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:

\[ d^A = d^* + \nu^A \]
\[ d^S = d^* + \nu^S \]

• 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 \( d^* \)
  • \( \nu^A \) reflects other separation that would have happened anyway, or arbitrary threshold issues
  • \( \nu^S \) reflects ex-post rationalization, or information issues

• Note: given that \( d \) is binary \( \rightarrow \) non-classical measurement error

• The paper dances around this idea, but never fully exploits it
## Cases of interest

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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”
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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:
\[ \text{plim} \hat{\delta}_{\text{OLS}} = \delta - \delta \frac{\sigma_{vA}^2}{\sigma_{d*}^2 + \sigma_{vA}^2} \]

• But IV is
\[ \text{plim} \hat{\delta}_{\text{IV}} = \frac{\text{plim} \text{cov}(\Delta y_{it}, d_{i0}^S)}{\text{plim} \text{cov}(d_{i0}^A, d_{i0}^S)} = \frac{\text{plim} \text{cov}(\alpha + \delta d_{i0}^* + u_{it}, d_{i0}^* + v_{i0}^A)}{\text{plim} \text{cov}(d_{i0}^* + v_{i0}^A, d_{i0}^* + v_{i0}^S)} = \delta \]

• 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