Graduate Labor Economics

Lecture 14: Displaced Workers

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 Email: brendan.m.price@frb.gov. These notes are adapted from UC Davis course ECN 250A, which I taught in Winter 2018 and Spring 2019. Any views or opinions expressed here are my own and do not necessarily represent the views or policies of the Board of Governors of the Federal Reserve System or its staff. This version: March 21, 2020.

Today's lecture

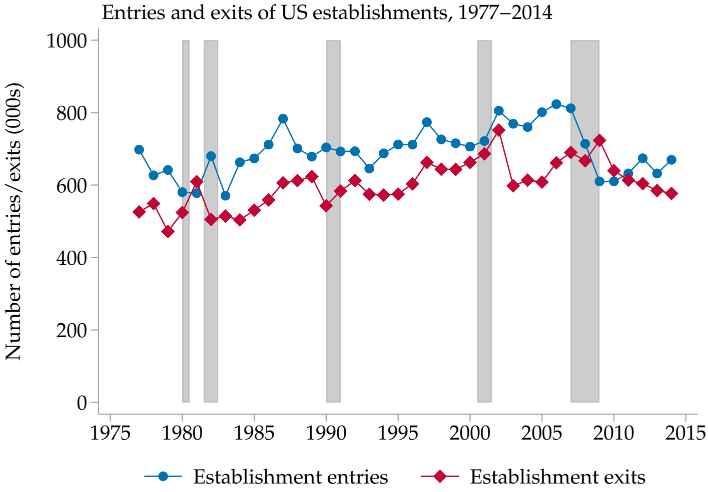
- Job loss in context
  - Causes of job loss
  - Descriptive stats on job creation/destruction
- The displaced workers literature
  - Jacobson, Lalonde, and Sullivan (1993)
  - Subsequent contributions

The big picture: job loss in context

- Why do workers lose their jobs?
  - Changes in firm-level demand
    - Structural shifts
    - Cyclical declines
    - Baseline churn ("creative destruction")
  - Changes in (perceived) worker productivity
    - Learning about ability/match quality
    - Detection of shirking
    - Declining health, skill depreciation
  - Idiosyncratic factors
- Literature focuses on adverse demand shocks
  - Mass layoffs (Jacobson, Lalonde, and Sullivan 1993)
  - Declining industries (Walker 2013; Autor et al. 2014)

600,000 US establishments shut down every year

Data: US Census Bureau, Business Dynamics Statistics



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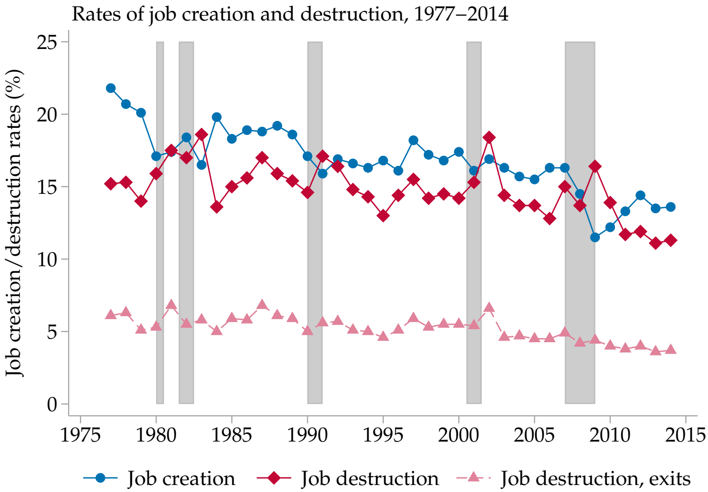
High (though falling) rates of job creation and destruction

Data: US Census Bureau, Business Dynamics Statistics



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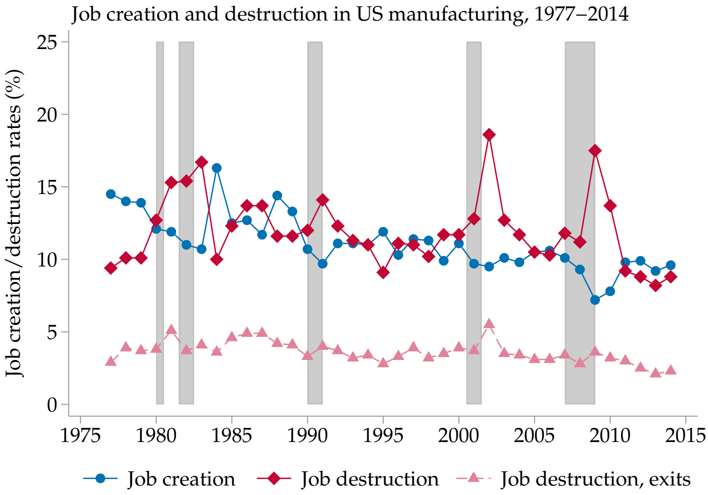
Job creation/destruction in US manufacturing

Data: US Census Bureau, Business Dynamics Statistics



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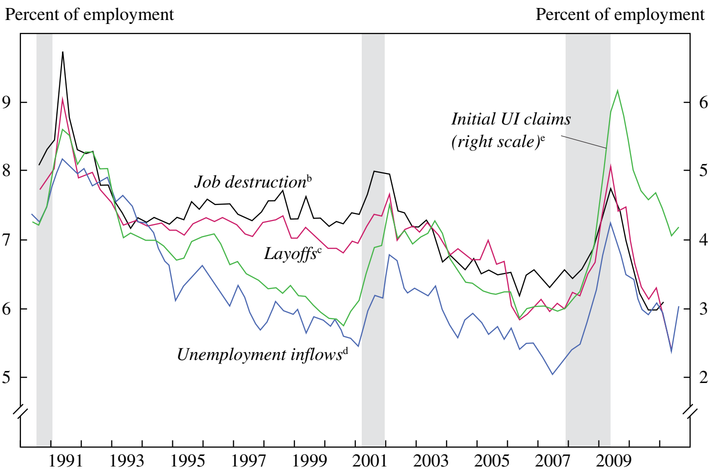
Job flows $\Longrightarrow$ worker flows



(Davis and von Wachter, 2011, Figure 1)

JLS 1993 in one slide: key takeaways

- Question:
  - How does job loss affect earnings among high-tenure workers . . .
  - . . . beforehand, in the short run, and in the long run?
- Data:
  - Administrative data on 5% sample of Pennsylvania workers
  - 1974–1986 at quarterly frequency
- Methodology:
  - Event studies around time of job loss
  - Compare displaced to non-displaced workers
- Results:
  - 3 years before job loss: earnings start to decline
  - At job loss: earnings drop sharply, start to rebound
  - 5 years later: earnings 25 percent below counterfactual

Why is job loss costly?

- Frictionless benchmark: instantly find an equally good job
- Real world: costly adjustment
  - Initial period of unemployment
  - Loss of firm-specific human capital
  - Loss of "match capital" (Jovanovic 1979)
  - Loss of firm-specific wage premiums
  - Loss of deferred compensation (Lazear 1981)
  - Effects on physical and mental health
- Likely to be greater for high-tenure workers . . . but how big?

The state of knowledge before JLS

- Prior work: CPS Displaced Worker Survey
  - Imperfect recall
  - No comparison group
  - Limited info on pre-displacement earnings
- Ruhm (1991): used the PSID
  - 800 displaced and 3000 non-displaced
    (JLS: 9500 displaced, 13,700 non-displaced)
  - Earnings still down 10–13% four years after job loss

Administrative data: familiar pros and cons

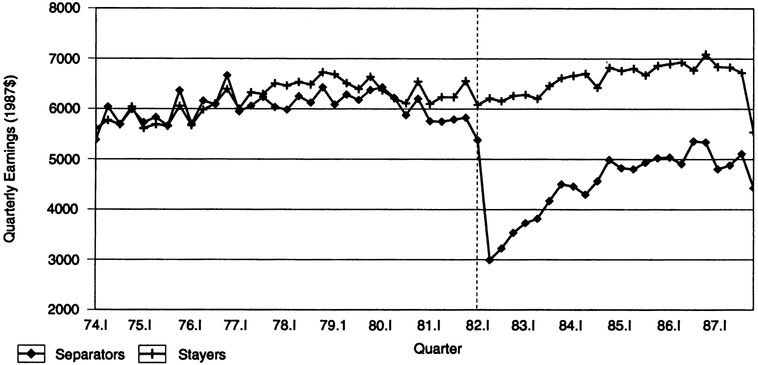
- Administrative data on Pennsylvania workers/firms
  - Minimal measurement error
  - Big samples (precise estimates, subsample analyses)
- Limitations
  - Exits from universe (out-of-state moves, self-employment)
  - Limited demographics (sex, age)
  - No info on hours worked
  - Can't distinguish quits from layoffs
- Sample construction
  - Born 1930–1959, 6+ years of tenure by beginning of 1980
  - Condition on positive earnings in every year

Sample statistics: what stands out?

Workers	Observations	Mean	Standard deviation	Median	10th percentile	90th percentile
A. *Age in 1979:*						
Separators:						
All	9,507	37.0	7.4	37	27	47
Males	7,092	36.9	7.2	37	27	47
Females	2,415	37.3	7.8	38	27	48
Nonmanufacturing	2,870	36.9	7.3	37	27	47
Manufacturing	6,637	37.1	7.4	37	27	47
Western Pennsylvania	3,804	36.8	7.4	37	27	47
Eastern Pennsylvania	5,703	37.1	7.3	37	27	47
Non-mass layoffs	3,072	36.9	7.3	37	27	47
Mass layoffs	6,435	37.1	7.4	37	27	47
Stayers	13,704	37.7	7.0	38	28	47
B. *1979 Earnings:*						
Separators:						
All	9,507	$24,196	$12,287	$22,904	$11,525	$36,798
Males	7,092	27,363	12,161	25,942	16,326	38,557
Females	2,415	14,897	6,641	14,275	7,595	22,928
Nonmanufacturing	2,870	24,648	15,547	22,363	10,029	39,358
Manufacturing	6,637	24,001	10,566	23,096	12,070	35,963
Western Pennsylvania	3,804	25,147	12,449	24,292	12,359	37,561
Eastern Pennsylvania	5,703	23,561	12,138	22,176	11,005	36,140
Non-mass layoffs	3,072	23,640	14,415	21,665	10,585	36,726
Mass layoffs	6,435	24,461	11,120	23,593	12,037	36,805
Stayers	13,704	26,322	12,980	24,867	13,644	38,880

(Jacobson et al., 1993, Table 1)

A first look: job losses in 1982Q1



(Jacobson et al., 1993, Figure 1)

Towards a research design

- Naïve approach: compare earnings pre/post job loss
  - Ignores macroeconomic shocks
  - Ignores counterfactual wage growth
  - Ignores pre-displacement wage losses
- Potential comparison groups
  - Workers who never separate
  - Non-separators within same firm
  - Future separators (in Ruhm 1991; not in JLS)

Defining the treatment effect

- Notation:
  - y_{it}: worker i's earnings at date t
  - D_{is}: indicator for being displaced at date s
  - $\mathbf{I}_{i,s-p}$; information set at date $s-p$
- Suppose $s-p$ predates any effects of displacement event
- Average treatment effect:

$$\mathbb{E}(y_{it} \mid D_{is} = 1, \mathbf{I}_{i,s-p}) - \mathbb{E}(y_{it} \mid D_{i\nu} = 0 \text{ for all } \nu, \mathbf{I}_{i,s-p})$$

Specifications

- Let D_{it}^k denote displacement k periods ago
- Base specification:

$$y_{it} = \alpha_i + \gamma_t + x_{it}\beta + \sum_{k \geq -m} D_{it}^k \delta_k + \varepsilon_{it}$$

- Add worker-specific trends:

$$y_{it} = \alpha_i + \omega_i t + \gamma_t + x_{it}\beta + \sum_{k \geq -m} D_{it}^k \delta_k + \varepsilon_{it}$$

- Add firm-time FEs for each firm j:

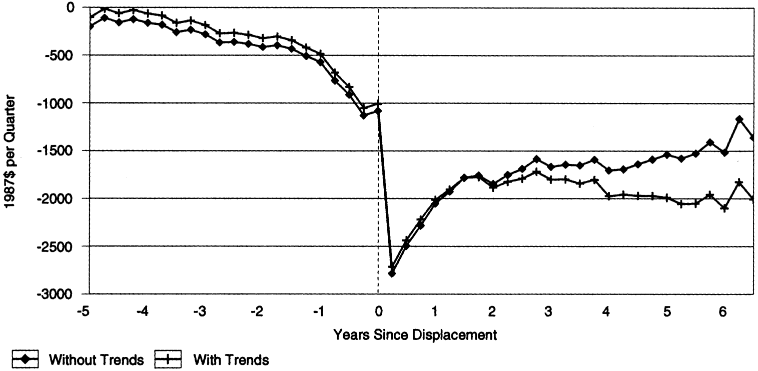
$$y_{it} = \alpha_i + \gamma_{j(i),t} + x_{it}\beta + \sum_{k \geq -m} D_{it}^k \delta_k + \varepsilon_{it}$$

Some things we'd do differently today

- "the error term, ε_{it}, is assumed to have constant variance and to be uncorrelated across individuals and time"
    - Should allow for heteroskedastic errors
    - Should definitely cluster by individual, or arguably by firm (standard practice since Bertrand, Duflo, Mullainathan 2004)
- Earnings are specified in levels
    - Probably right not to use log earnings here (why?)
    - What I'd do: normalize by pre-displacement earnings

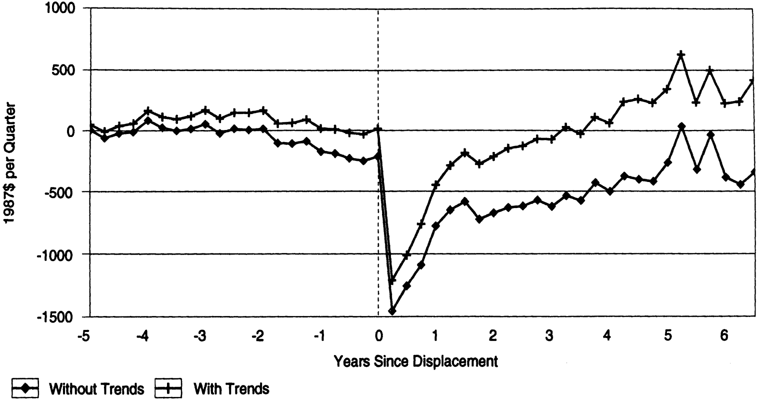
Results using mass-layoff sample

(Mass layoff = firm emp falls by at least 30% relative to late-1970s levels)



(Jacobson et al., 1993, Figure 2)

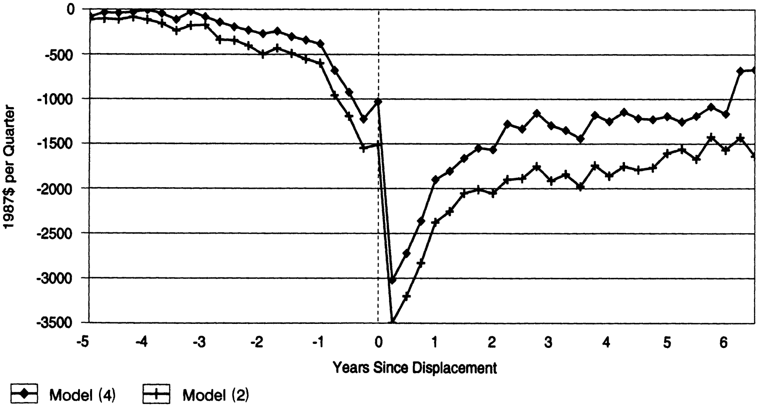
v. different earnings dynamics for non-mass-layoff sample



(Jacobson et al., 1993, Figure 3)

Comparing mass-layoff job-losers to stayers in same firm

Model 2: base specification, model 4: add firm FEs



(Jacobson et al., 1993, Figure 4)

Interpreting these results

- Earnings decline pre-displacement
  - Temporary layoffs
  - Below-average wage growth
  - Highlights importance of having adequate pre-loss data
- Immediate drop: unemployment
- Long-term drop: earnings while employed

Plausible magnitudes?

- These effects are large
  - Big impact on permanent income
  - Even bigger if we include people who never earn again
- Always ask: are they too large?
  - Depends on your audience's priors
  - Depends on what previous work has found
- Researcher's job: rationalize the effect size
  - Are past estimates likely to be biased?
  - Are present estimates for a different population?

Subsample analyses

- JLS next look at how costs of job loss vary across groups
  - Big samples make this possible
- Practical problem: how much flexibility?
  - Most flexible: estimate spec separately by subgroup
  - Next most: interact event-time dummies w/group dummies
  - Parsimonious: interact event-time *splines* w/group dummies
- JLS impose a “dip, drop, recovery” structure
  - Linear decline in 12 quarters preceding job loss
  - Discrete drop at job loss
  - Linear recovery starting 6 quarters after job loss

One key heterogeneity: bigger losses at bigger firms

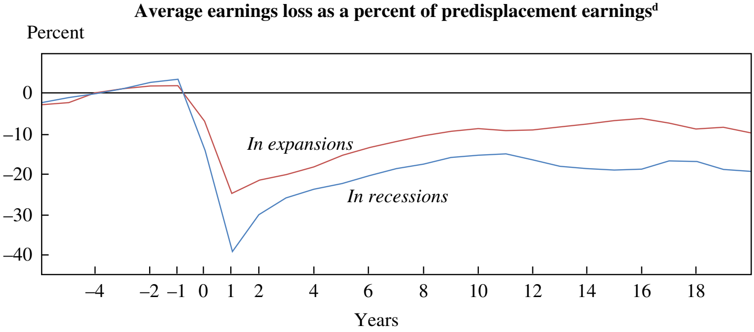
Group	Number	Dip[c]	Drop[d]	Recovery[e]	Fifth-year loss dif	Fifth-year loss
Overall	6,435					
Sex:						
Male	4,972	−10.8	−217	6.5	−545	−7,143
		(0.7)	(7)	(0.9)	(40)	(132)
Female	1,463	36.7	738	−22.0	1,853	−4,744
		(2.2)	(24)	(3.0)	(136)	(184)
Firm size:						
50–500	1,704	7.9	351	0.6	1,434	−5,403
		(1.9)	(20)	(2.6)	(113)	(163)
501–2,000	1,497	33.5	501	−14.1	1,298	−5,540
		(2.0)	(22)	(2.9)	(127)	(176)
2,001–5,000	1,381	40.9	720	−32.3	1,267	−5,570
		(2.2)	(23)	(3.1)	(134)	(179)
Greater than 5,000	1,853	−64.8	−1,265	34.9	−3,312	−10.150
		(1.8)	(19)	(2.9)	(125)	(190)

(Jacobson et al., 1993, Table 2)

More questions: the post-JLS agenda

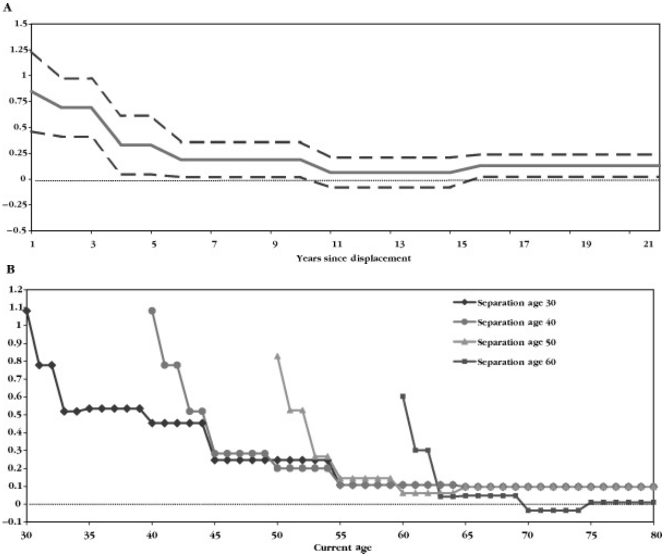
- How does job loss affect . . .
  - future job security? (Stevens 1997, Jarosch 2015)
  - the next generation? (Oreopoulos, Page, Stevens 2008)
  - health/mortality? (Sullivan and von Wachter, 2009)
- How do the costs of job loss . . .
  - differ in recessions/expansions? (Davis & von Wachter 2011)
  - decompose into reduced hours vs. reduced wages? (Lachowska, Mas, Woodbury 2018)
- How do mass layoffs affect local economies? (Gathmann, Helm, and Schönberg 2018)

Job loss is much more costly during recessions



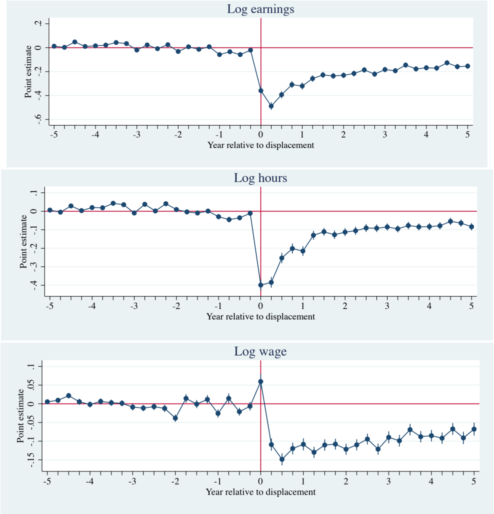
(Davis and von Wachter, 2011, Figure 4)

Job loss increases mortality rates (esp. in short run)



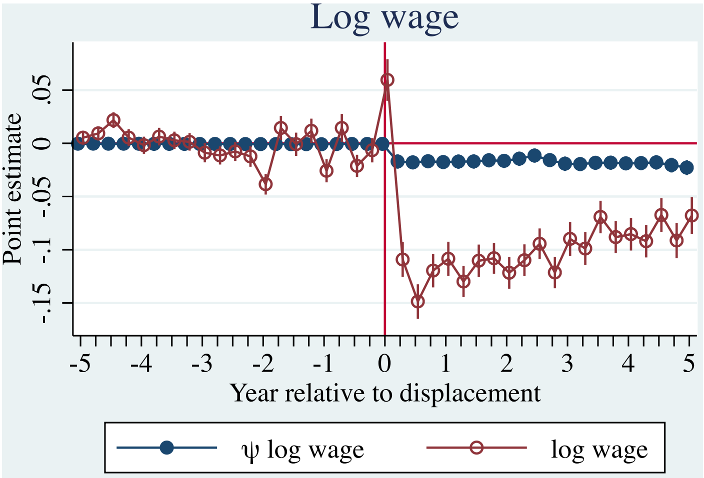
(Sullivan and von Wachter, 2009, Figure 2)

Hours vs. wages: Lachowska, Mas, and Woodbury (2018)



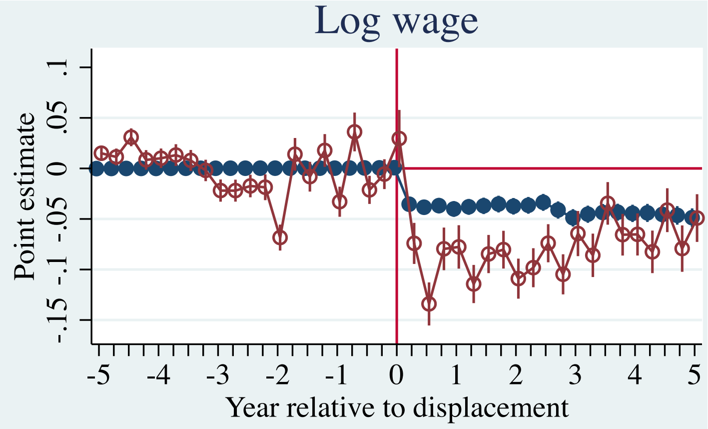
(Lachowska et al., 2018, Figures 2–3)

Loss of AKM wage premiums explains part of the wage loss



(Lachowska et al., 2018, Figure 8)

Bigger role for AKM FE for workers exiting top-decile firms



(Lachowska et al., 2018, Figure 9)