Uncovering the Differences among Displaced Workers: Evidence from Canadian Job Separation Records

Serdar Birinci
St. Louis Fed

Youngmin Park
Bank of Canada

Thomas Pugh
Bank of Canada

Kurt See
Bank of Canada

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Background and Motivation

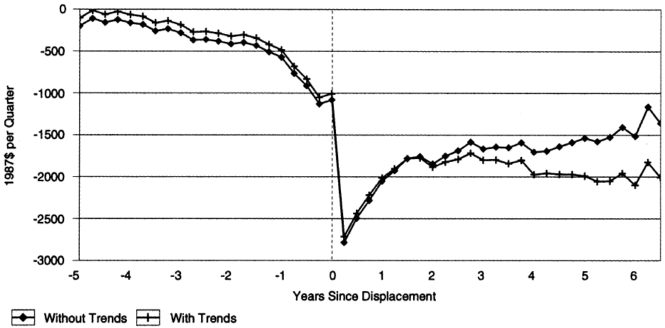

FIGURE 2. EARNINGS LOSSES FOR SEPARATORS IN MASS-LAYOFF SAMPLE

Source: Jacobson, LaLonde, and Sullivan (1993; AER)

- Large micro-labor literature on consequences of job displacement
- Estimates used to discipline quantitative macro models

Background and Motivation

Person ID	Employer ID	Time
1	A	t_1
1	B	t_2
...	...	
2	A	t_1
2	C	t_2
...	...	
3	A	t_1
3	D	t_2
...	...	

- Assumption 1: Separation is an employer ID change; all mass-layoff separations involuntary
- Assumption 2: Workers and employers do not react to upcoming mass layoff (no selection)

Background and Motivation

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- Admin data do not contain info on reason and exact timing (day/month) of separation
- Survey data are not employer-matched and small in sample size

Background and Motivation

Person ID	Employer ID	Time	Reason	Date
1	A	t_1	Layoff	03/01/2008
1	B	t_2		
...	...			
2	A	t_1	Quit	01/15/2008
2	C	t_2		
...	...			
3	A	t_1	Retirement	03/01/2008
3	D	t_2		
...	...			

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Introduction

- This paper:
  - Revisit sources and consequences of job loss using Canadian job separation records
  - Utilize Record of Employment (ROE) with detailed info on separations (reason and exact date)

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  - Revisit sources and consequences of job loss using Canadian job separation records
  - Utilize Record of Employment (ROE) with detailed info on separations (reason and exact date)
- Questions:
  1. Does existing strategy correctly identify involuntary separations?
  2. How do consequences of job separations differ depending on reason for a worker's separation?
  3. Do characteristics and outcomes of workers differ systematically by timing of separation?

What We Find

1. **Existing mass layoff (ML) identification strategy has shortcomings**
   - 45% of ML separations are spurious (e.g., changes in business name/ID, reorganization)
   - Only 25% of ML separations are involuntary separations (actual layoffs)

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   - All ML separations: 28% loss in Canada vs. 18% – 46% across countries in literature
   - ML layoffs: 54% loss

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3. **Large heterogeneity in sources and consequences upon separations by reason**
   - Larger earnings and employer premium (AKM) losses for laid-off vs. those who quit
   - AKM model better explains earnings dynamics for laid-off vs. those who quit

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   - AKM model better explains earnings dynamics for laid-off vs. those who quit
4. **Protracted mass layoffs and heterogeneity in outcomes by timing**
   - Around 50% of quits and 25% of layoffs occur before mass-layoff month
   - Employers layoff less-productive workers early (before mass-layoff month)
   - No evidence on more-productive workers quitting early (“leaving the sinking ship”)

Contributions

Roadmap

1. Data and Empirical Methodology
2. Uncovering Differences by Reason for Separation
3. Uncovering Differences by Timing of Separation
4. Conclusion

Canadian Employer-Employee Dynamics Database (CEEDD)

- Linkable environment based on various administrative records from 2001 to 2016 annually
- CEEDD links
  - individual-level information from T1 returns (similar to 1040 form)
  - employer-level information for corporations and unincorporated businesses (T2, T4, PD7 forms)
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- We use the following information:
  - individuals: demographics (age, gender, marital status), labor earnings, and main employer
  - employers: size, industry, legal status, income statement and balance sheet variables
  - jobs: reason for and exact date of separation (ROE)

Record of Employment (ROE)

- By law, employers are required to issue ROE whenever there is "interruption in earnings"
  - seven consecutive days of no earnings (e.g., layoff, quit)
  - salary falls by at least 60% of regular weekly earnings (e.g., leave of absence)

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- Contains information on
  - separation reason (layoff, quit, illness, parental leave, retirement, training, other, etc) Details
  - exact hiring and separation dates

Sample Selection and Estimation

- Select long-tenure workers with strong labor market attachment at medium/large employers
  - same main employer in 2002–2007
  - main employer with at least 50 employees in any years 2002–2007
  - positive earnings in 2002–2014

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- Create groups based on job separation: **Existing ML separator identification**
  - **ML separator**: changed employer ID in 2008–10 (focus GR separations) when main employer
    1. employment contracted $> 30\%$ relative to 2007 employment
    2. 2007 employment $< 130\%$ of 2006 employment
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- Estimate earnings losses (JLS); uncover employer (AKM or BLM), match, and direct effects

Estimation | Employer effects | Match effects | Summary statistics

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Utilizing ROE Data: ML Separators by Reason

ROE reasons	Share (%)	Share (%) of ROE	Average fraction (%) Outflow	Average fraction (%) Inflow
Layoff	25.3	45.5	5.8	8.3
Quit	11.9	21.4	2.0	4.7
Other	18.4	33.1	18.1	17.4
Missing	44.3	-	53.9	49.8

1. 44% of ML separations are spurious: concentrated flows; no earnings loss; no EI More More

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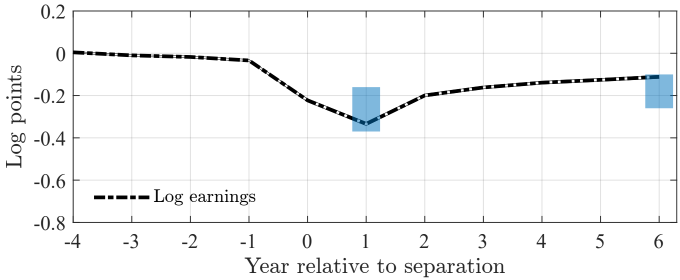
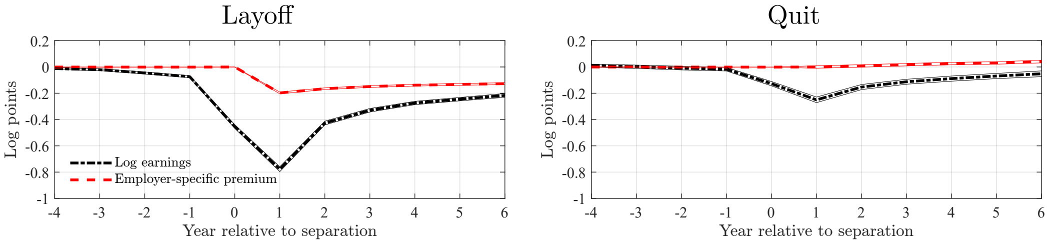
Henceforth, focus on layoffs and quits

Benchmarking Estimates: All ML Separations



Estimates on average earnings loss for all ML separations are comparable to existing estimates

Uncovering Differences in Outcomes among Layoffs vs Quits



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2. Employer effects are important in explaining earnings loss for layoffs but not for quits
   - Layoffs: 26% (20/78) in short term and 59% (13/22) in long term
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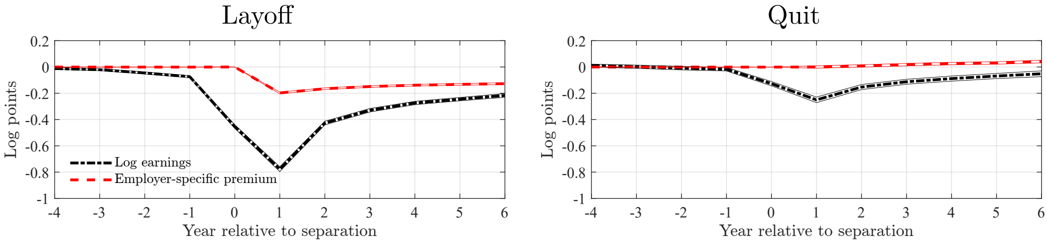

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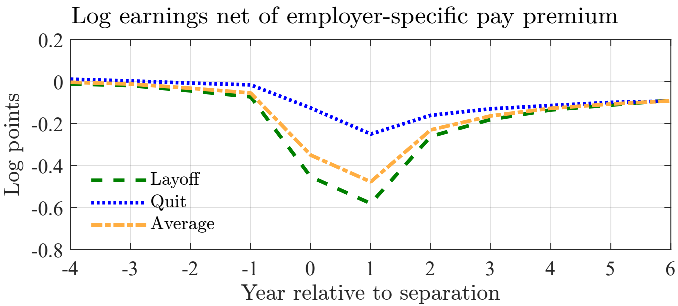
Composition of layoffs and quits might reconcile divergent results in

Lachowska, Mas, and Woodbury (2020; AER) **vs** Schmieder, von Wachter, Heining (2023; AER)

Underlying Sources behind Earnings Loss Gap bet. Layoffs and Quits



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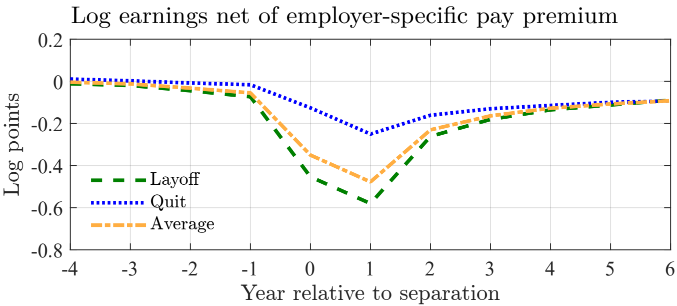

1. Difference in long-term earnings losses is entirely driven by differences in employer effects
2. 38% (20/53) of short-term earnings loss gap is due to differences in employer effects
3. Direct effects matter for short-term gap, match effects small but widen gap

Direct & Match Effects | All Sources

Cross-sectional Earnings Loss Differences between Layoffs vs Quits

	Below diagonal	On diagonal	Above diagonal
(a) Layoff			
Share of separators	0.468	0.370	0.164
Average change in log earnings	-0.332	-0.017	0.159
Average change in employer effect	-0.414	-0.002	0.303
Average change in match effect	0.037	-0.050	-0.167
Average direct effect	0.046	0.034	0.023
(b) Quit			
Share of separators	0.288	0.380	0.335
Average change in log earnings	-0.097	0.139	0.277
Average change in employer effect	-0.360	0.017	0.365
Average change in match effect	0.191	0.048	-0.130
Average direct effect	0.073	0.074	0.042

Separator dist Transition prob Interquintile changes

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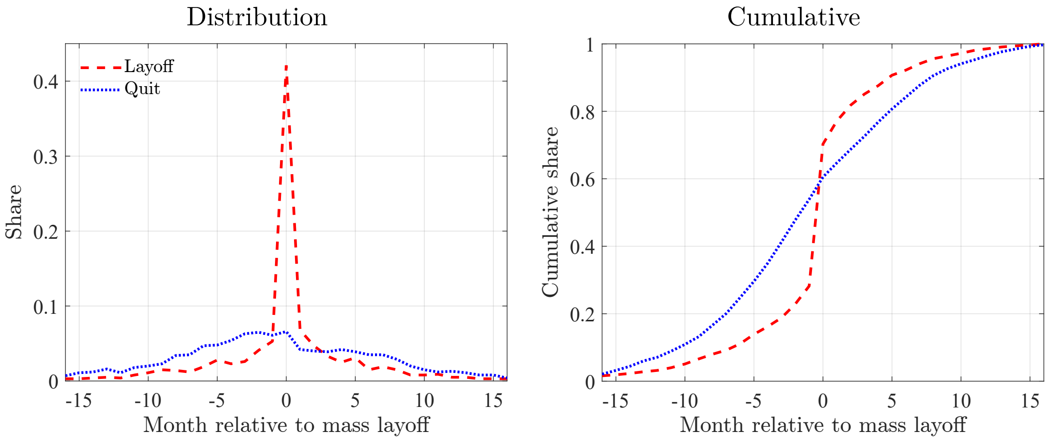
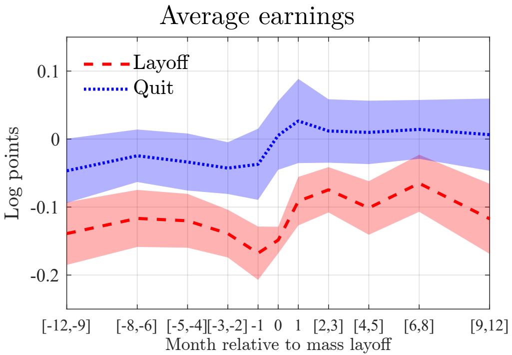
Roadmap

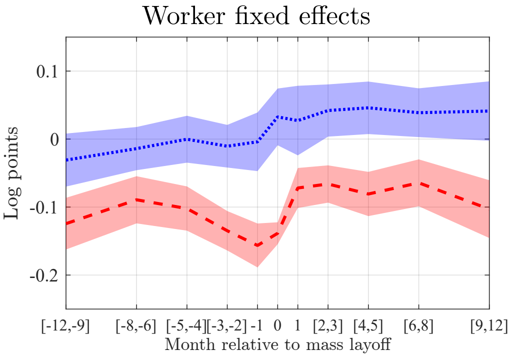
Timing of Separations around a Mass Layoff



1. Quits are gradual around mass-layoff month, while layoffs spike
2. Employers face substantial emp. loss before ML: 53% of quits 27% of layoffs occur before ML

Worker Characteristics by Timing of Separation





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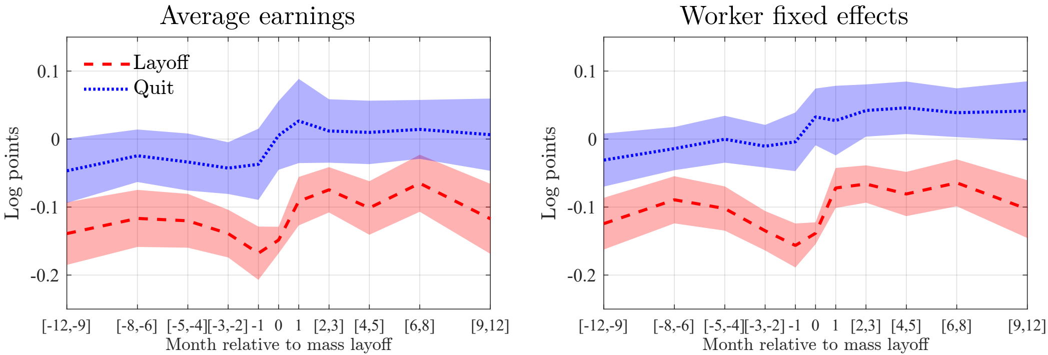

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Employers layoff less-productive workers first

No evidence on more-productive workers quitting early ("leaving the sinking ship")

Earnings: SR Earnings: LR

Roadmap

Conclusion

- Findings reveal substantial heterogeneity in outcomes among ML separators by
  - reason for separation
  - timing of separation
- Implications for quantitative macroeconomic models:
  1. Models should consider layoffs and quits separately
  2. Models should account for selection mechanisms around large employment contractions

EXTRA SLIDES

Contributions

1. Consequences of job separation
   - Admin data: Jacobson, LaLonde, and Sullivan (1993); Davis and von Wachter (2011); Lachowska, Mas, and Woodbury (2020); Schmieder, von Wachter, and Heining (2023); Bertheau et al. (2023)
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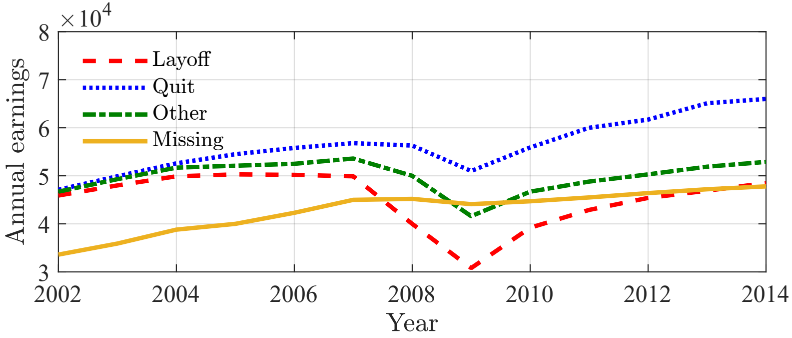
   This paper: Link employer-employee data for *all* sep.; provide results for employer effects
3. Timing of job separation
   - Schwerdt (2011): Early leavers vs displaced workers during plant closures in Austria

   This paper: Do not rely on ML identification but use ROE; compare early vs late separators; document worker characteristics by timing

Back

Average Annual Earnings of ML Separators by ROE Reasons



1. Average earnings drop for layoffs, quits, and other
2. Average earnings remain nearly unchanged for separators with missing ROE

Back

Statistics on EI Benefits

	Stayers	Mass layoff separators			
		Layoff	Quit	Other	Missing
Fraction received EI benefit	0.164	0.789	0.316	0.450	0.093
Average amount of total EI benefit received (among those received positive amount)	8,600	13,800	8,600	10,900	10,600

1. Less than 10% of ML separators with missing ROE receive EI
2. 32% quitters receive EI; they are eligible when they had a just cause (e.g., significant change in work duties, discrimination, harassment)
3. 16% of stayers receive EI; part-time workers are eligible

Back

Institutional Details

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- EI program in Canada does not feature experience rating, unlike the U.S. program
- Employers still carefully reports separation reason as it affects severance and other transfers
- CEEDD + ROE + Inst. details $\Longrightarrow$ Ideal setup to study differences among ML separators

ROE

Reasons for Separation in ROE

- Shortage of work (layoff)
- Quit
- Other:
    - other: 80% of separations grouped “other” are coded under this category (code “K”), which is primarily used when an ROE is issued without an interruption of earnings
    - maternity leave: 6%
    - illness or injury: 5%
    - return to school: 3%
    - retirement: 2%
    - strike or lockout, work-sharing, apprentice training, dismissal or suspension, leave of absence, parental, compassionate care/family caregiver: 4%

Estimating Consequences of Job Separations

- Jacobson, LaLonde, and Sullivan (1993; AER):

$$y_{i,t} = \alpha_i + \zeta_t + \beta x_{i,t} + \sum_{s \in S} \sum_{k=-4}^{6} d^s_{i,t,k} \times \gamma^s_k + \varepsilon_{i,t}$$

  - γ^s_k: estimated differences in annual earnings between ML separators and stayers
  - allow for heterogeneity in γ_k for separation type s (reasons and timing of separation)
- Controls include
  - quadratic on age, interactions between gender and age
  - year dummies interacted with average earnings (2005–2007), employer size, one-digit NAICS
- Decompose losses into **employer (AKM)**, **match**, and **direct** effects
- Alternative: Bonhomme, Lamadon and Manresa (2019; ECMA): BLM to fix endogenous mobility bias

Back

Estimating Employer Effects

- Estimate AKM effects using the following regression:

$$y_{i,t} = \kappa_i + \psi_{j(i,t)} + \lambda_t + v_{i,t}$$

- Use estimated $\widehat{\psi}_j$ on LHS of distributed-lag regression to estimate employer premium losses:

$$\widehat{\psi}_{j(i,t)} = \alpha_i + \zeta_t + \beta x_{i,t} + \sum_{s \in S} \sum_{k=-4}^{6} d^s_{i,t,k} \times \gamma^s_k + \varepsilon_{i,t}$$

Back

Estimating Match Effects

- Match effects are time-invariant worker-employer fixed effects
- These can be interpreted as changes in a worker's productivity when worker is employed by different employers due to differences in work arrangements that affect worker's productivity
- Calculate average log of earnings $\overline{y_{ij}}$ for each pair (i, j) over the duration of the match
- Regress average earnings on worker θ_i and employer $\xi_{j(i,t)}$ fixed effects

$$\overline{y_{ij}} = \theta_i + \xi_{j(i,t)} + \mu_{ij}$$

- Residuals $\widehat{\mu}_{ij}$ represent component of earnings accounted for by time-invariant worker-employer match effects after accounting for worker and employer effects

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Sample Descriptive Statistics

	Mass-layoff separators			Stayers
	Average	Layoff	Quit	
Worker characteristics				
Average earnings 2002–2005 (2010 CAD)	52,500	51,400	54,800	56,500
Female (proportions)	0.326	0.298	0.386	0.522
Age in 2007 (years)	39.14	40.02	37.29	40.74
	(6.78)	(6.58)	(6.83)	(6.17)
Fraction received EI	0.64	0.79	0.32	0.16
Average EI among recipients (2010 CAD)	12,132	13,800	8,600	8,600
Employer characteristics in 2007				
Employer size (number of workers)	3,755	1,805	7,899	9,575
	(10,744)	(4,219)	(17,253)	(22,469)
One-digit NAICS Industry (proportions)				
1 agriculture, forestry, fishing	0.021	0.027	0.009	0.003
2 mining, utilities, construction	0.041	0.041	0.040	0.040
3 manufacturing	0.620	0.712	0.425	0.189
4 trade, transportation	0.126	0.081	0.221	0.159
5 information, finance, prof. services	0.128	0.085	0.220	0.126
6 educational and health care services	0.015	0.012	0.021	0.364
7 arts, recreation, hospitality services	0.035	0.036	0.034	0.019
8 other services	0.005	0.004	0.008	0.015
9 public administration and unclassified	0.009	0.002	0.023	0.085
Number of employers (pre- and post-separation)	20,780	15,065	8,775	12,825
Number of workers	19,410	13,185	6,225	774,075

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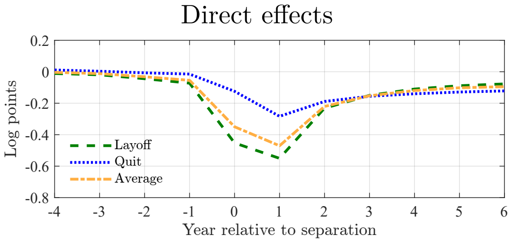

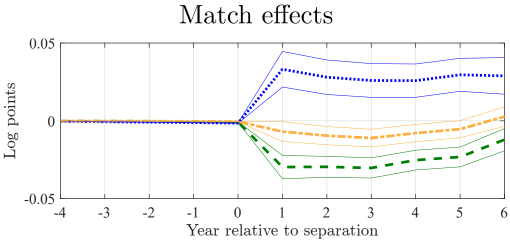

1. 51% of short-term earnings loss gap is due to direct effects; disappearing in long term
2. Match effects are small but positive for quits and negative for layoffs

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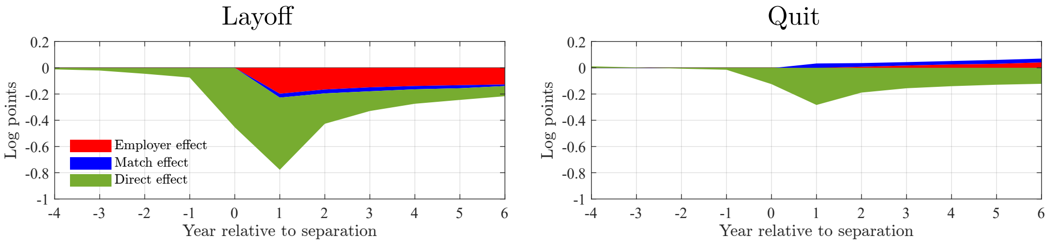
Sources of Earnings Losses upon Separations



1. Direct effects matter only for short-term earnings loss gap between layoffs and quits

2. Match effects small but are persistently negative (positive) for layoffs (quits)

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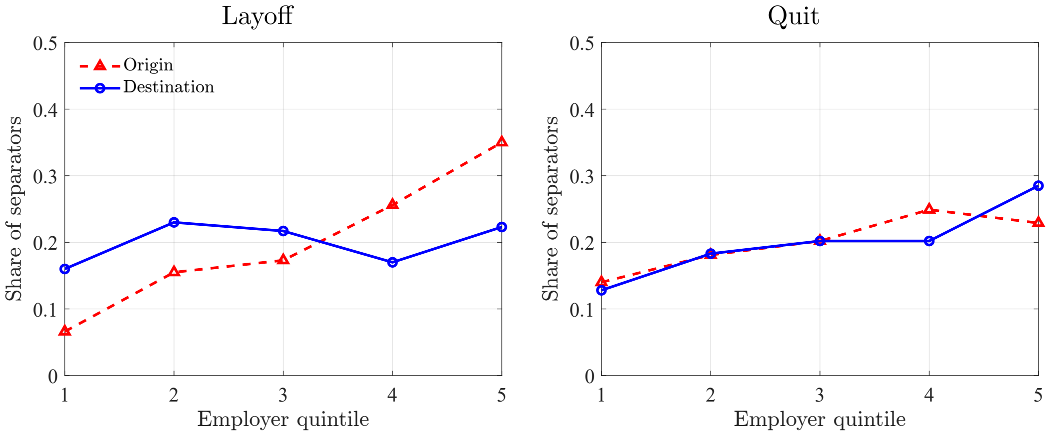
Distribution of Separators by Employer Effect Quintiles



1. Layoffs are more likely to originate from higher quintiles; quits are more evenly distributed
2. Distribution of employer effects shifts leftward upon layoffs (destination distribution is even)
3. Distribution of employer effects remains unchanged upon quits (slight rightward shift)

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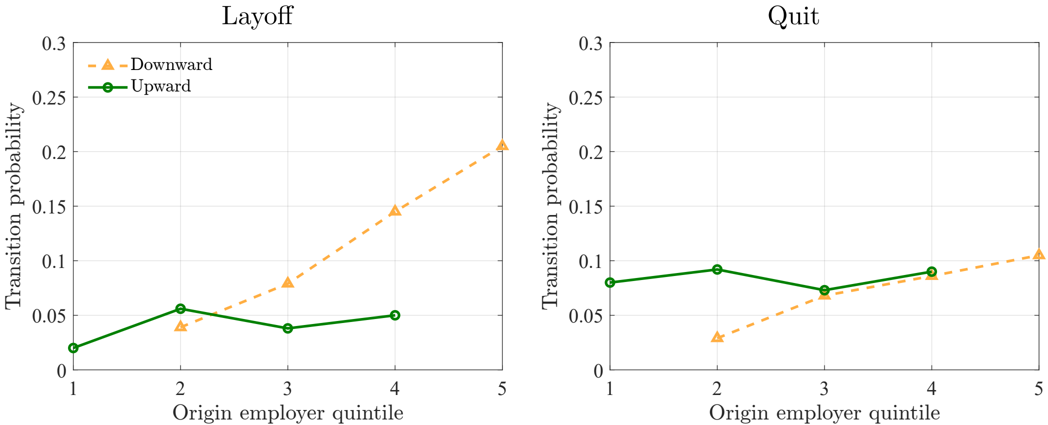
Transition Probabilities by Origin Employer Effect Quintiles



1. Downward transition probabilities are higher for layoffs, especially at high origin quintiles
2. Upward transition probabilities are twice as large for quits, regardless of origin quintile
3. Downward transition probabilities increase in origin quintile for layoffs, less so for quits

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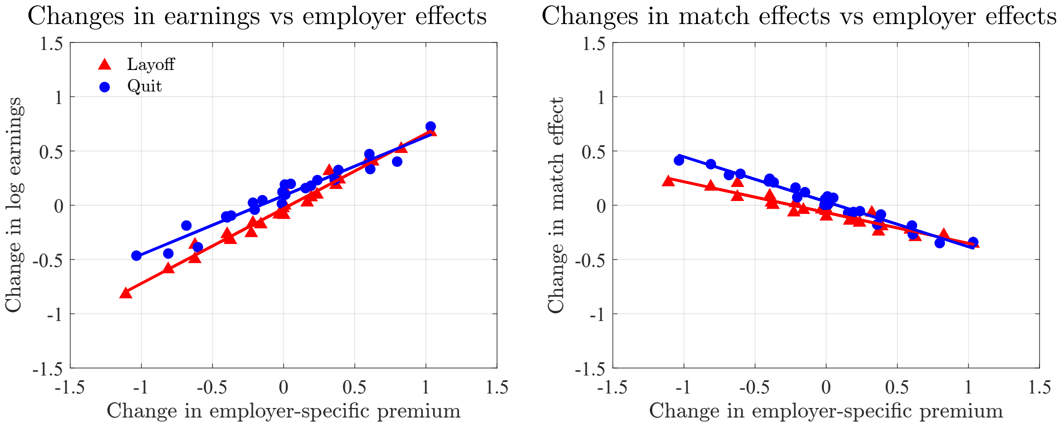
Interquintile Changes in Earnings, Match Effects vs Employer Effects



1. Larger earnings loss for layoffs than quits with same employer effect declines (esp. bottom)
2. For quits, rise in match effects mitigates a larger decline in earnings

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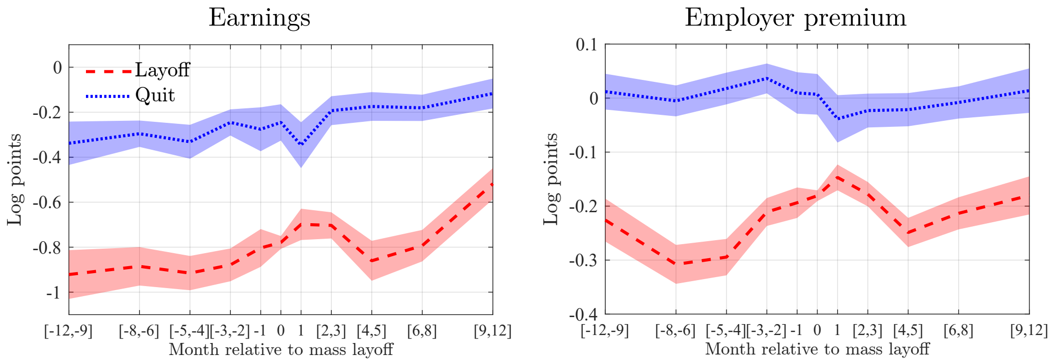
AKM better explains earnings dynamics for layoffs than quits (slopes: 0.69 vs 0.54)

Earnings Effects and Worker Characteristics by Timing of Separation



1. Earnings losses are larger among early separators, especially for layoffs
2. Employer premium losses are larger for early layoffs, similar for quits by timing of separation

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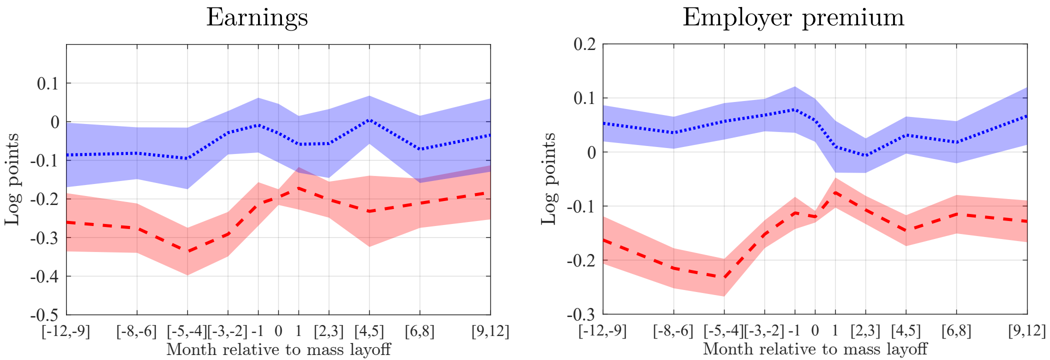
Earnings and Employer Effects by Timing of Separation: Long term



1. Earnings loss gap between early and late separators (both types) are smaller in long term
2. Other conclusion are identical in long term (six years after separation)

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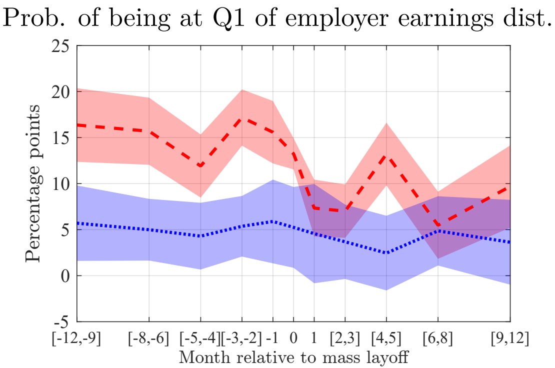
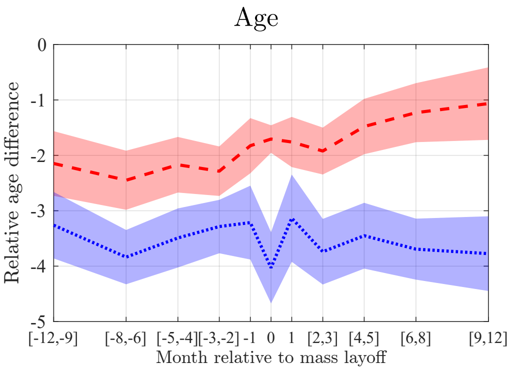
Worker Characteristics by Timing of Separation





1. Early layoffs are more likely to be at bottom; prob. does not change across time for quits
2. Early layoffs are slightly younger; age does not change for quits across timing of separation

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