A Appendix tables

Table A.1: Impact of sample restrictions on sample composition in the ACS

	Public data			Public data, full-time			Public data, full-time, wage $\leq$ \$15			Public data, full-time, wage $\in$ (\$15,\$30]		
	Mean	S.D.	p50	Mean	S.D.	p50	Mean	S.D.	p50	Mean	S.D.	p50
Demographics												
Male	0.53			0.60			0.52			0.57		
White	0.77			0.78			0.72			0.78		
Age	37.19	(8.26)	38	37.75	(8.00)	38	35.43	(8.64)	35	37.36	(7.97)	38
Some college	0.65			0.66			0.44			0.64		
Bachelors degree	0.34			0.34			0.13			0.28		
Income and employment												
Household earnings	107,395	(83,288)	88,512	113,949	(82,223)	94,960	68,259	(50,387)	57,189	96,501	(52,132)	87,004
Total individual income	56,998	(53,846)	43,647	67,205	(54,325)	52,594	26,811	(14,351)	25,742	51,737	(16,802)	49,677
Wage and salary earnings	51,364	(48,180)	40,869	64,607	(49,102)	51,311	25,203	(8,240)	25,242	50,220	(12,740)	48,746
Weeks worked last year	48.12	(9.47)	52	51.95	(0.13)	52	51.95	(0.14)	52	51.95	(0.13)	52
Usual hours worked	41.32	(10.93)	40	44.79	(7.73)	40	44.93	(8.87)	40	44.40	(7.32)	40
Hourly wage	26.68	(196.52)	20.06	27.60	(19.55)	22.50	10.85	(2.95)	11.42	21.77	(4.20)	21.43
Industry (NAICS)												
Manufacturing (31-33)	0.13			0.16			0.15			0.16		
Retail trade (44-45)	0.10			0.09			0.13			0.09		
Health care / social assistance (62)	0.12			0.10			0.12			0.10		
Education (61)	0.09			0.06			0.05			0.08		
Accommodation / food (72)	0.05			0.04			0.09			0.03		
All others	0.52			0.54			0.46			0.53		
Census region												
Midwest	0.30			0.31			0.29			0.34		
South	0.31			0.32			0.35			0.32		
West	0.38			0.36			0.34			0.34		
Total observations	2,104,801			1,276,139			308,282			570,322		

Notes: This table presents summary statistics for three samples. All the estimates are based on authors' calculations from the public use files of the American Community Survey from 2001 to 2008 maintained by IPUMS. All dollar values are adjusted to reflect 2020 dollars. Columns 1 to 3 include all employed workers without any restrictions on hours, weeks of work, or hourly wages. Columns 4 to 6 include workers who worked for at least 51 weeks in the last year and whose usual hours work are at least 40 and no restrictions on hourly wages. Columns 7 to 9 includes full-time workers who earn an hourly wage of no more than \$15 . The difference between the sample in Columns 7 to 9 and our primary analysis sample (Table 1 Columns 1 to 3) stems from the sample restrictions based on matching to the LEHD data. Finally, Columns 10 to 12 include full-time workers who earn an hourly wages between \$15 to \$30.

Table A.2: Occupational distribution of full-time low-wage workers in the ACS

	Among workers with wage ≤ \$15	
Occupation	Percent	Cumulative percent
First-Line Supervisors of Sales Workers	3.74%	3.74%
Secretaries and Administrative Assistants	3.33%	7.07%
Driver/Sales Workers and Truck Drivers	3.19%	10.25%
Chefs and Cooks	2.90%	13.15%
Janitors and Building Cleaners	2.69%	15.84%
Laborers and Freight, Stock, and Material Movers, Hand	2.22%	18.06%
Nursing, Psychiatric, and Home Health Aides	2.16%	20.23%
Retail Salespersons	2.09%	22.32%
Cashiers	2.00%	24.32%
Customer Service Representatives	1.92%	26.23%
Agricultural workers	1.90%	28.14%
Construction Laborers	1.65%	29.78%
Stock Clerks and Order Fillers	1.62%	31.40%
Other production workers	1.57%	32.97%
Assemblers and Fabricators	1.54%	34.51%
Grounds Maintenance Workers	1.45%	35.95%
Maids and Housekeeping Cleaners	1.42%	37.37%
Bookkeeping, Accounting, and Auditing Clerks	1.29%	38.66%
Receptionists and Information Clerks	1.21%	39.87%
Waiters and Waitresses	1.20%	41.07%

Notes: This table shows estimated occupational distribution of workers based on authors' calculations from the public use files of the 2001-2008 American Community Survey maintained by IPUMS. This table presents the top 20 most common occupations among full-time workers in the last year who earn an hourly wage of no more than $15 (see Columns 7 to 9 of Table A.1 for summary statistics of this sample). Full-time is defined as working for at least 51 weeks in the last year and having usual hours worked of at least 40. Although occupation codes changed several times (link), IPUMS provides harmonized occupation codes based on 2010 occupation classification. We used the harmonized 2010 occupation code for the calculations reported in the table.

Table A.3: Instrument balance

	(1) Outcome mean	(2) Left job	(3) Left job	(4) Instrument
Labor market activity				
Average prior employment	0.89	-0.045	-0.014	-0.0001
		(0.0010)	(0.0009)	(0.0023)
Average prior earnings	6,997	-983	-390	-4.52
		(18.49)	(16.44)	(42.13)
Prior quarters employed	12.9	-5.78	-1.38	-0.053
		(0.06)	(0.03)	(0.09)
Prior emp to non-emp transitions	0.02	0.009	0.002	-0.0005
		(0.0002)	(0.0002)	(0.0005)
Prior continuous employment	0.70	-0.092	-0.028	-0.0018
		(0.0011)	(0.0009)	(0.0024)
Prior employer changes	0.08	0.0313	0.0089	0.0023
		(0.0005)	(0.0005)	(0.0012)
Demographics				
Age	35.6	-2.43	-1.62	-0.67
		(0.04)	(0.05)	(0.11)
Male	0.44	0.0377	0.027	0.0023
		(0.002)	(0.002)	(0.006)
White	0.82	-0.0185	-0.012	0.0071
		(0.002)	(0.002)	(0.005)
Some college	0.47	0.005	0.0076	0.010
		(0.00)	(0.002)	(0.01)
Bachelors degree	0.15	0.004	0.0034	0.004
		(0.002)	(0.002)	(0.004)
Summary index				
Predicted earnings	8,302	-656.3	-237.2	31.81
State-by-NAICS2-by-time FE		✓	✓	✓
Firm characteristics			✓	✓
Total observations	234,000			
Total individuals	233,000			
Total firms	96,000			

Notes: This table shows the association between various worker characteristics and an indicator for separating from workers' $t = 0$ employer within one year (Columns 2 and 3) and the leave-out-mean instrument (Column 4). The mean of the outcome variable is shown for reference in Column 1. The final outcome is a summary covariate index formed using a regression of earnings on all available covariates. All regressions use the baseline set of fixed effects, including state-by-industry-by-year-by-quarter fixed effects. Columns 3 and 4 also include controls for firm characteristics interacted with tenure. "Average prior employment" is the share of periods employed in the four years prior to $t = 0$ and "Prior quarters employed" is the number of quarters employed prior to $t = 0$.

Table A.4: Effects of placebo shocks

	(1) Commuting zone	(2) NAICS 3	(3) Commuting zone-by-NAICS 3
Dependent variable			
Instrument	0.0023	0.0060	0.0059
	(0.0044)	(0.0041)	(0.0052)
Job separation by $t = 4$	-0.0028	-0.0039	-0.0072
	(0.0095)	(0.0087)	(0.0109)
Earnings at $t = 24$	54.0	9.5	48.6
	(137.2)	(122.4)	(155.1)

Notes: This table reports the results of regressing a "placebo" shock on key outcomes. The first row uses the firm's realized shock as the outcome (i.e., the instrument used in the main analysis). The second row uses job separation by $t = 4$ (i.e., the endogenous variable used in the main analysis). The third row uses quarterly earnings at $t = 24$ for workers in the firm at $t = 0$ (i.e., a key long-run outcome). The placebo shock is defined by randomly assigning each firm the shock of another firm in the same local labor market. We examine three definitions of a local labor market, each of which is more granular than the fixed effects used in our primary specification. Column 1 uses commuting zone (rather than state)-by-2 digit NAICS-by-year and quarter of initial ACS response. Column 2 uses state-by-3 (rather than 2) digit NAICS-by-year and quarter of initial ACS response. Column 3 uses commuting zone (rather than state)-by-3 (rather than 2) digit NAICS-by-year and quarter of initial ACS response. Each permutation assigns each firm a placebo shock and then regress the outcome listed in the row on the placebo shock and our baseline set of fixed effects and firm-level controls from Equation 1. Each cell reports the average value of the regression coefficient on the placebo shock and the average standard error across 1,000 permutations. Appendix C provides further details on the procedure.

Table A.5: Robustness of job loss effects to local labor market shocks

	(1)	(2)	(3)	(4)	(5)
Reduced-form estimate	491.9	491.2	489.5	512.0	543.9
	(80.5)	(80.5)	(86.7)	(105.2)	(132.4)
R^2	0.18	0.18	0.26	0.36	0.49
Outcome mean	7654	7654	7654	7654	7654
Controls					
Base	✓	✓	✓	✓	✓
County level unemployment rate at $t = 0$		✓			
State-by-NAICS3-by-year-quarter FEs			✓		
Commuting zone-by-NAICS2-by-year-quarter FEs				✓	
Commuting zone-by-NAICS3-by-year-quarter FEs					✓

Notes: This table examines the robustness of the reduced-form effect of firm-specific shocks on total quarterly earnings six years after initial ACS response. Column 1, indicated with "Base," corresponds to our primary specification. The remaining columns add additional controls or increase the granularity of the fixed effects, as indicated by the check marks at the bottom of the table. The scale of the instrument implies the coefficients can be interpreted as the impact of 100% leave-out-mean decrease in employment. Total quarterly earnings is the sum of quarterly earnings from all employers in the 21 LEHD states included in the study, inflated to constant 2020 dollars using the CPI. Standard errors are clustered by employer at $t = 0$.

Table A.6: Model estimates of initial conditions

	(1)	(2)	(3)	(4)
	Untreated		Treated	
	Initial share	Share active	Initial share	Share active
Unemployed	0.000	-	0.348	0.601
$1,333	0.042	0.739	0.000	0.813
$1,666	0.038	0.739	0.044	0.813
$2,000	0.091	0.739	0.081	0.813
$2,333	0.123	0.739	0.096	0.813
$2,666	0.137	0.739	0.102	0.813
$3,333	0.228	0.739	0.150	0.813
$4,000	0.137	0.739	0.078	0.813
$4,751	0.203	0.739	0.100	0.813

Notes: This table shows estimates of initial conditions from model described in Section 9. Columns 1 and 3 report the initial shares of each group by state as of $t = 4$, where a state is either unemployment or employment at one of the eight discrete wage levels. Columns 2 and 4 report the estimated share of workers in each state who are active. As discussed in the main text, initial active shares are constrained to be equal employed workers.

Table A.7: Model estimates allowing for different search productivity on and off the job

	(1) Estimates	(2) Exact rents
Parameter		
λ_u	0.27	
	(0.02)	
λ_e	0.03	
	(0.01)	
δ	0.017	
	(0.001)	
π	0.75	
	(0.01)	
Monthly earnings CDF / rents		
\$1,333	0.231	0%
	(0.023)	
\$1,666	0.329	488%
	(0.030)	
\$2,000	0.453	840%
	(0.035)	
\$2,333	0.572	1125%
	(0.036)	
\$2,666	0.677	1373%
	(0.033)	
\$3,333	0.813	1777%
	(0.023)	
\$4,000	0.886	2122%
	(0.015)	
Top earnings	\$4,712	2428%
	(4.31)	
Min. dist. criterion	280.476	
Number of moments	378	

Notes: This table shows estimates of parameters from the model described in Appendix D.2 that allows for different job arrival rates on and off the job. Column 1 shows estimates of the core parameters of the model, including monthly job arrival rates in unemployment (λ_u) and while employed (λ_e), job destruction rates (δ), the population share of active workers (π), and the CMF of the discrete wage distribution. The final row shows the estimated earnings level for the top mass point in the earnings distribution. Column 2 shows exact proportional rent estimates implied by the discrete earnings distribution and assuming a 5% annual interest rate. Rents are the flow utility difference relative to unemployment as a fraction of earnings, with b set to the implied value when \$1,333 is the reservation earnings level. Standard errors reported assume a diagonal variance-covariance matrix for the targeted moments.

Table A.8: Parameter and rents for model estimated on higher-wage job losers

	(1) Est	(2) Weak bound	(3) Better bound	(4) Exact rents
Parameter				
λ	0.31			
	(0.02)			
δ	0.007			
	(0.000)			
π	0.66			
	(0.01)			
Monthly earnings CDF / rents				
\$1,333	0.608	0%	0%	0%
	(0.028)			
\$1,666	0.692	62%	94%	151%
	(0.021)			
\$2,000	0.761	104%	164%	283%
	(0.016)			
\$2,333	0.807	134%	219%	410%
	(0.013)			
\$2,666	0.846	156%	264%	534%
	(0.010)			
\$3,333	0.931	187%	340%	767%
	(0.005)			
\$4,000	0.960	208%	388%	1151%
	(0.003)			
Top earnings	\$6,026	243%	470%	2192%
	(0.16)			
Min. dist. criterion	1306			
Number of moments	378			

Notes: This table shows estimates of parameters from the model described in Section 9 when fit to the post-job loss earnings dynamics of workers initially earning \$15-30 per hour. Column 1 shows estimates of the core parameters of the model, including monthly job arrival (λ) and destruction rates (δ), the population share of active workers (π), and the CMF of the discrete wage distribution. The final row shows the estimated earnings level for the top mass point in the earnings distribution. Columns 2 through 4 present bounds on proportional rents for holding a job at each point in the wage distribution, as well as exact computation of rents using the discrete distribution of job offers. Rents are differences in the present value of utility relative to unemployment as a fraction of earnings. All rent calculations assume a 5% annual interest rate and set b equal to the lowest earnings mass point, \$1,333 per month, since the model implies reservation earnings levels equal b. Standard errors reported assume a diagonal variance-covariance matrix for the targeted moments.

Table A.9: Estimates of the surplus and rents from employment when workers have non-linear utility from earnings

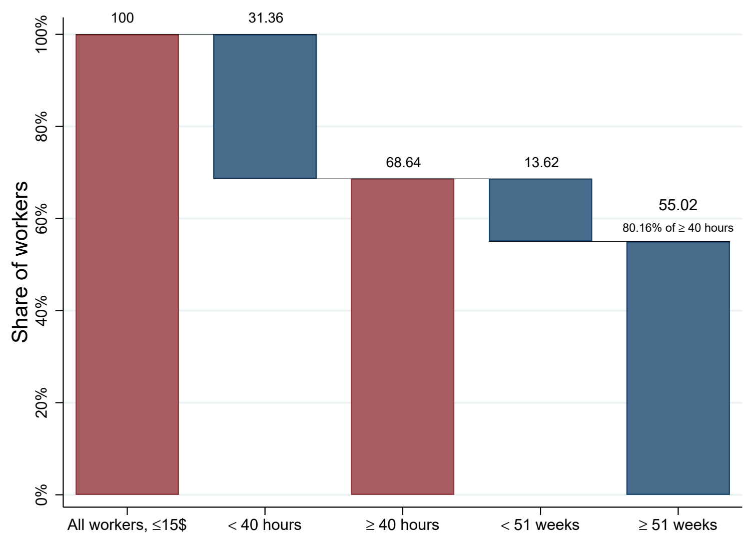
Earnings level	(1) Wage	(2) Hours	(3) MVT	(4) AVT	(5) Rents
\$1,333	27.71	5.47	652.31	7.97	0%
\$1,666	30.79	5.72	757.83	7.97	225%
\$2,000	33.25	7.20	1029.18	14.68	288%
\$2,333	35.27	7.63	1156.39	14.68	533%
\$2,666	36.95	7.80	1239.96	12.00	829%
\$3,333	39.59	8.08	1376.14	12.00	1350%
\$4,000	41.57	8.64	1544.84	21.89	1793%
\$4,752	43.28	9.17	1705.97	21.89	2224%

Notes: This table shows estimates of the surplus and rents from employment at different levels of earnings when workers have non-linear utility from earnings due to disutility from labor or diminishing utility from consumption. The search model parameters are the same as in Table 8 but the utility from earnings is non-linear as described in Section E. Columns 1 and 2 report the hourly wage and weekly working hours associated with each monthly earning level. We calibrate the hourly wage and work hours associated with each earning level according to the following procedure. We first set the hourly wage at the lowest earning job to be the median hourly wage at $t = 0$, $w_{min} = \$11.19$. The bottom rung of the earnings ladder is a job that pays \$1,333 per month, which thus involves $h_{min} = 1333/11.19$ hours per month (roughly 30 hours per week). Let γ be the share of the increase in earnings (above \$1,333) that can be explained by a higher hourly wage, with the remainder attributed to longer work hours, therefore, the hourly wage for earnings e is $w(e) = w_{min} + \frac{\gamma \cdot (e-1333)}{h_{min}}$ and $h(e) = h_{min} + \frac{(1-\gamma)\cdot(e-1333)}{w(e)}$. We use $\gamma = 0.5$. Columns 3 and 4 report the Marginal Value of Time (MVT) and the Average Value of Time (AVT) associated with each earning level based on estimates from Mas and Pallais (2019). Columns 5 reports rents $\left(\frac{(V(e)-V_u)}{e}\right)$ from employment at each earning level relative to unemployment. All rent calculations assume a 5% annual interest rate and set b such that $V_u = V(1,333)$, the implied reservation earnings level.

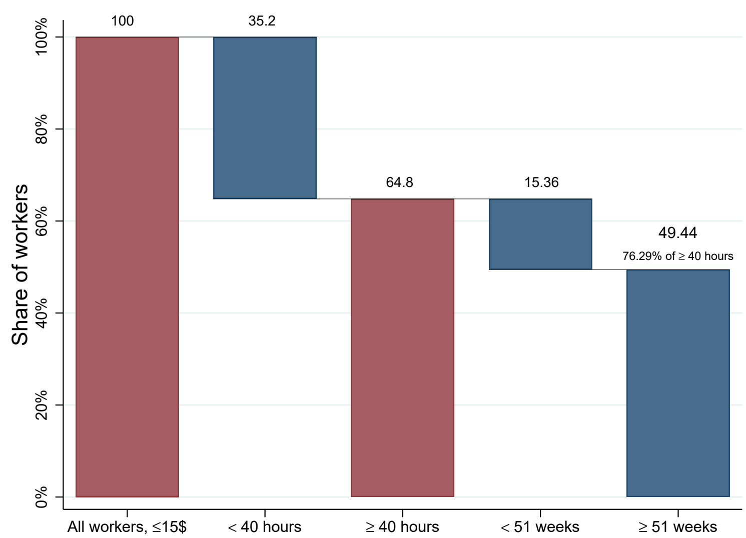
B Appendix figures

Figure B.1: Hours and weeks worked for workers with wage ≤ \$15

A) American Community Survey

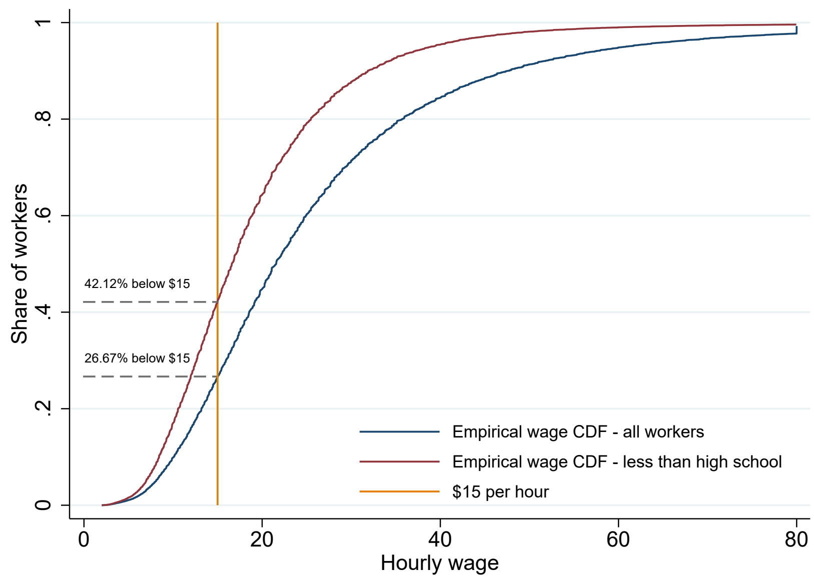


B) Current Population Survey



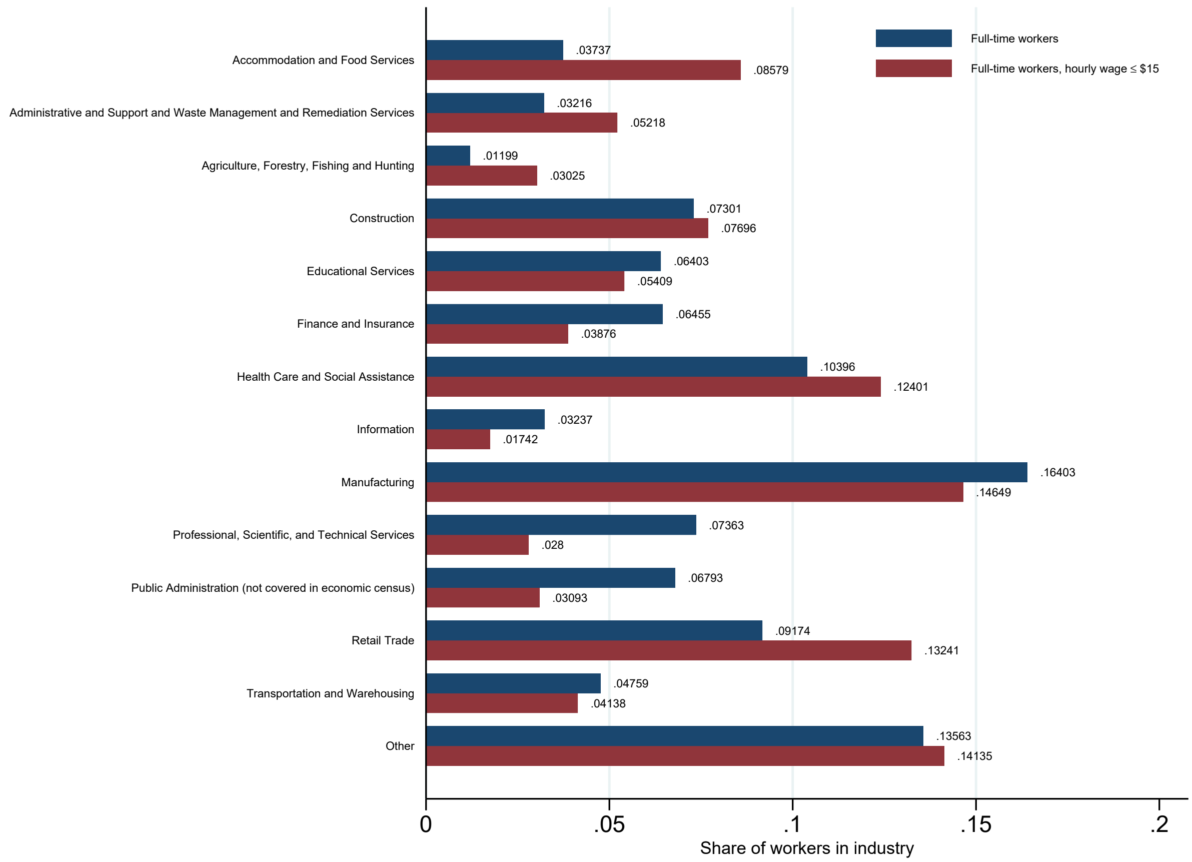
Notes: This figure shows the distribution of usual hours and weeks worked last year among low-wage workers. Panel A shows the results from American Community Survey data, while Panel B uses Current Population Survey data, restricting to participants in the Annual Social and Economical Supplement within either wave 4 or 8 (the Outgoing Rotation Groups, or "Earners study"). The samples cover 2001-2014 and respondents between the ages of 22 to 50, employed in a hourly job, and in one of our LEHD approving states. Both samples include only workers reporting hourly wages below \$15 and above \$2. For the ACS data, we impute hourly wages as total annual income from wages divided by number of weeks worked times usual hours worked per week, while for CPS data we used the reported hourly wage last week.

Figure B.2: Distribution of hourly wages among employed workers in the American Community Survey



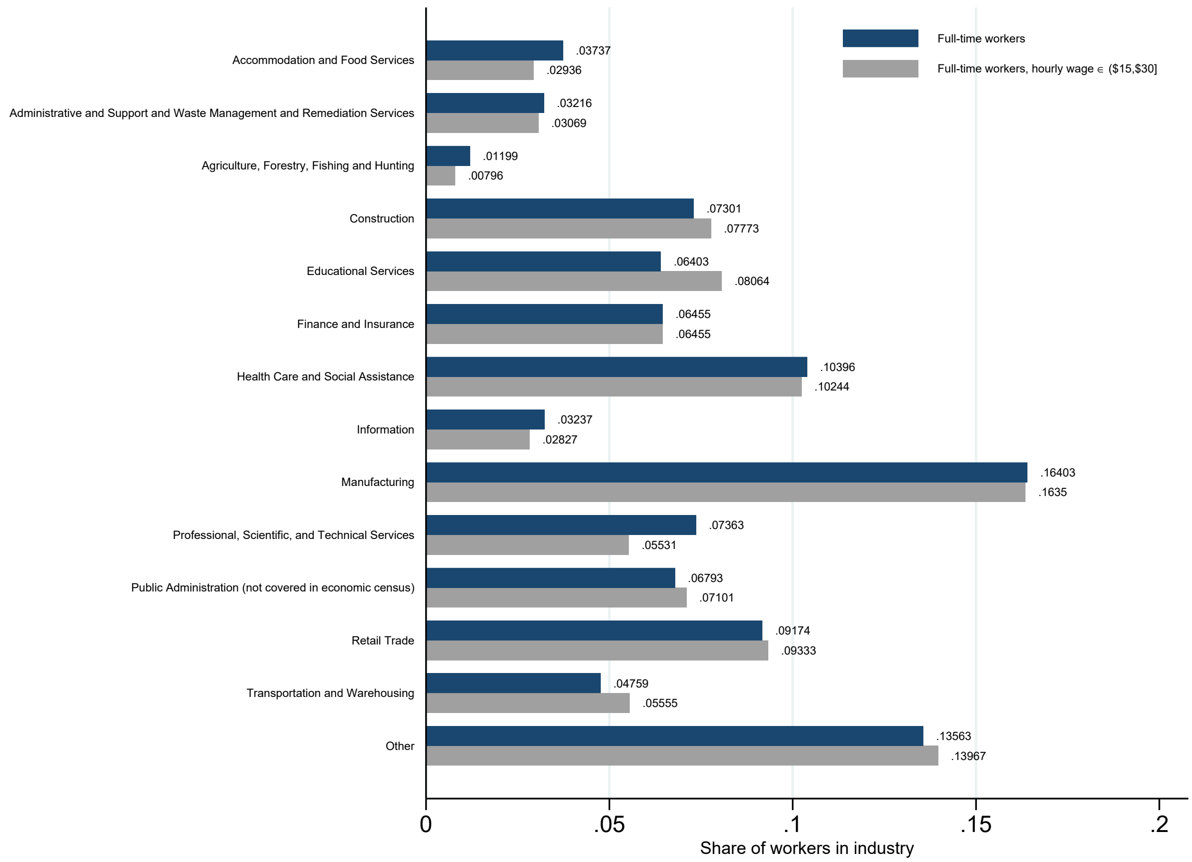
Notes: This figure shows the distribution of hourly wages among employed workers. The figure is based on the authors' calculations using the publicly available American Community Survey, 2001-2008. We restrict attention to ACS respondents between the ages of 22 to 50 who are civilian employees, at work, who report usually working at least 40 or more hours per week and 51 weeks in the last year. To be consistent with the sample restrictions imposed in the analysis and to reduce measurement error, we also drop observations with implausibly low hourly wages (below $2 per hour). The plots contains two data series. The first is for all workers satisfying the above restrictions. The second is for workers with a high-school diploma or less (i.e., no more than 12 years of education).

Figure B.3: Distribution of all full-time workers and low-wage workers across industries



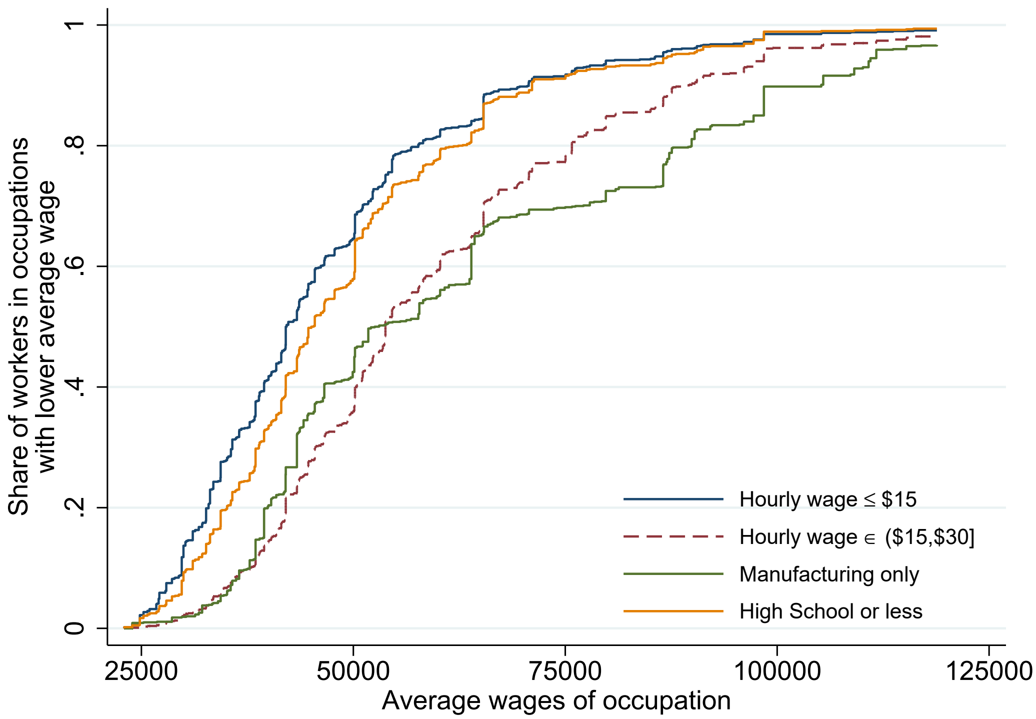
Notes: This figure shows the distribution of employed workers across industries based on 2-digit North American Industry Classification System (NAICS) codes. The figure includes two samples. All workers who are employed full-time in the last year are defined as individuals who worked for at least 51 weeks with usual hours of at least 40. The second sample further imposes that the hourly wage rate is no more than \$15 inflation adjusted to 2020 values. The figure is based on the authors' calculations using the publicly available American Community Survey, 2001-2008. We further restrict attention to ACS respondents between the ages of 22 to 50 who are civilian employees, at work. The "Other" category includes the following industry codes: "Management of Companies and Enterprises", "Utilities", "Mining, Quarrying, and Oil and Gas Extraction", "Real Estate and Rental and Leasing", "Wholesale Trade", "Arts, Entertainment, and Recreation", "Other Services (except Public Administration)."

Figure B.4: Distribution of all full-time workers and workers earnings wages of $15 to $30 across industries in the ACS



Notes: This figure shows the distribution of employed workers across industries based on 2-digit North American Industry Classification System (NAICS) codes. The figure includes two samples. All workers who are employed full-time in the last year are defined as individuals who worked for at least 51 weeks with usual hours of at least 40. The second sample further imposes that the hourly wage rate is between $15 to $30 inflation adjusted to 2020 values. The figure is based on the authors' calculations using the publicly available American Community Survey, 2001-2008. We further restrict attention to ACS respondents between the ages of 22 to 50 who are civilian employees, at work. The "Other" category includes the following industry codes: "Management of Companies and Enterprises", "Utilities", "Mining, Quarrying, and Oil and Gas Extraction", "Real Estate and Rental and Leasing", "Wholesale Trade", "Arts, Entertainment, and Recreation", "Other Services (except Public Administration)."

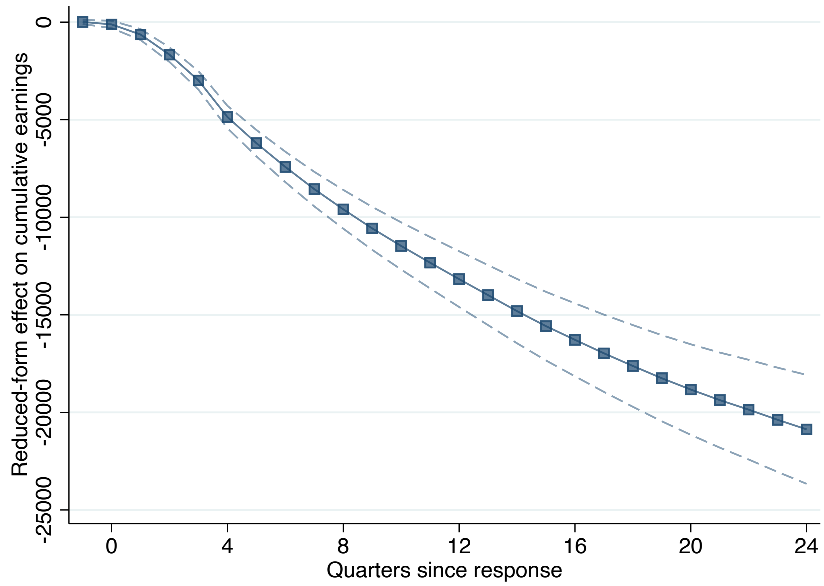
Figure B.5: Distribution of full-time workers by occupation average wage



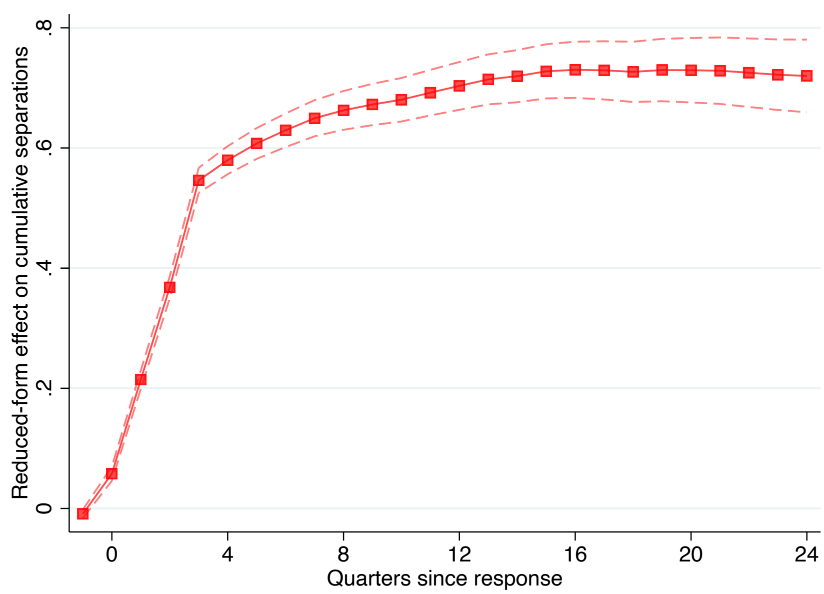
Notes: This figure shows the distribution of full-time employed workers across occupations (based on 2010 occupation codes). The x-axis reports the average wage of full-time workers in each occupation using ACS surveys from 2001 to 2020. The y-axis reports the share of workers working in occupations with average wages of equal or less the value on the x-axis (i.e., the cumulative distribution function). The figure includes four samples of workers who are employed full-time in the last year defined as individuals who worked for at least 51 weeks with usual hours of at least 40. The blue line represent low-wage workers defined as individuals earning an hourly wage of $15 or less, the dashed red line higher-wage workers defined as earning hourly wages between $15 to $30, the green line includes only workers in manufacturing industries, and the dashed yellow line workers with 12 or less years of education (i.e., high-school graduates or less). We also further restrict attention to ACS respondents between the ages of 22 to 50 who are civilian employees, at work, and work in one of our 21 LEHD approving states.

Figure B.6: Reduced-form effects on cumulative earnings and job separations

A) Cumulative earnings

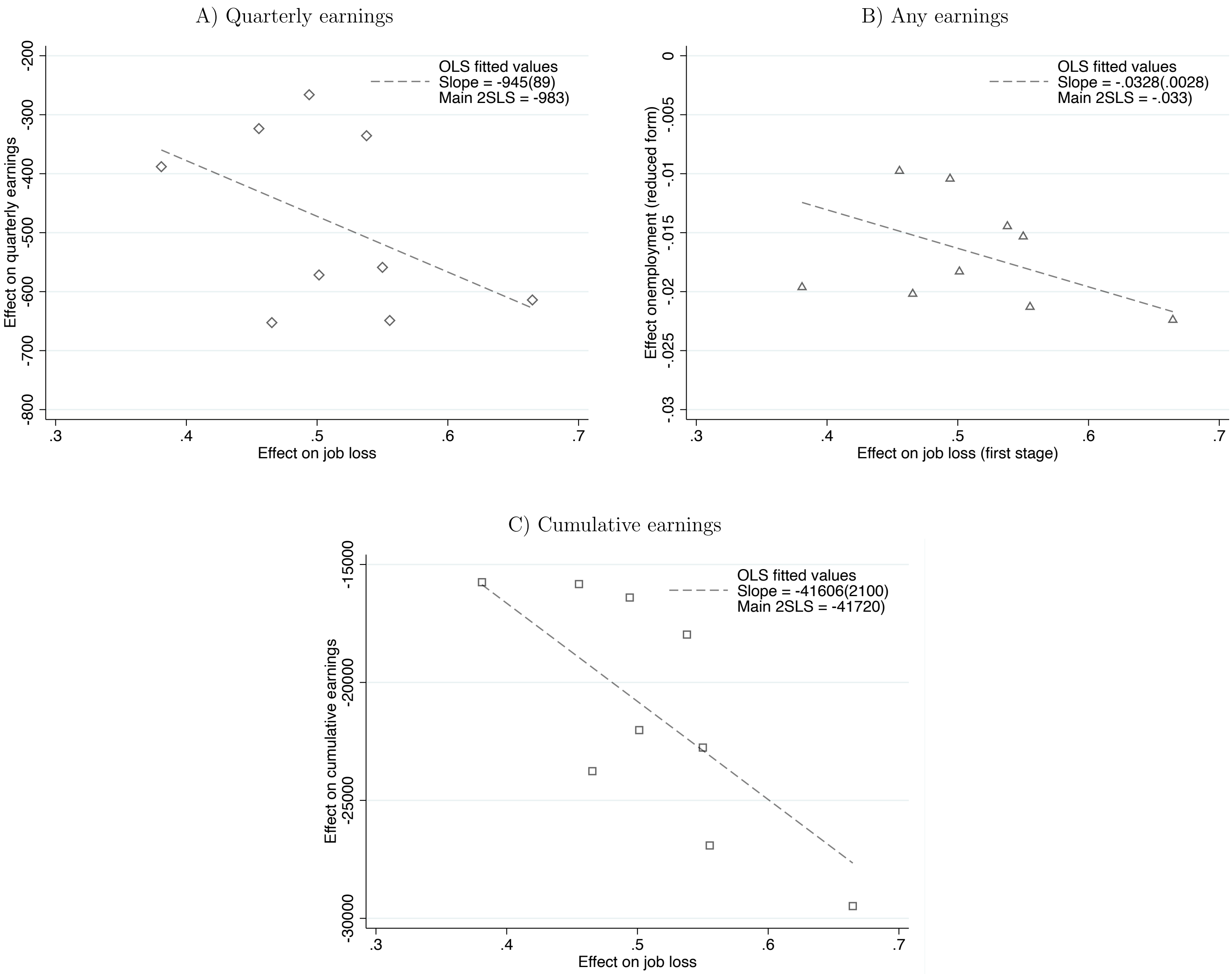


B) Cumulative separations



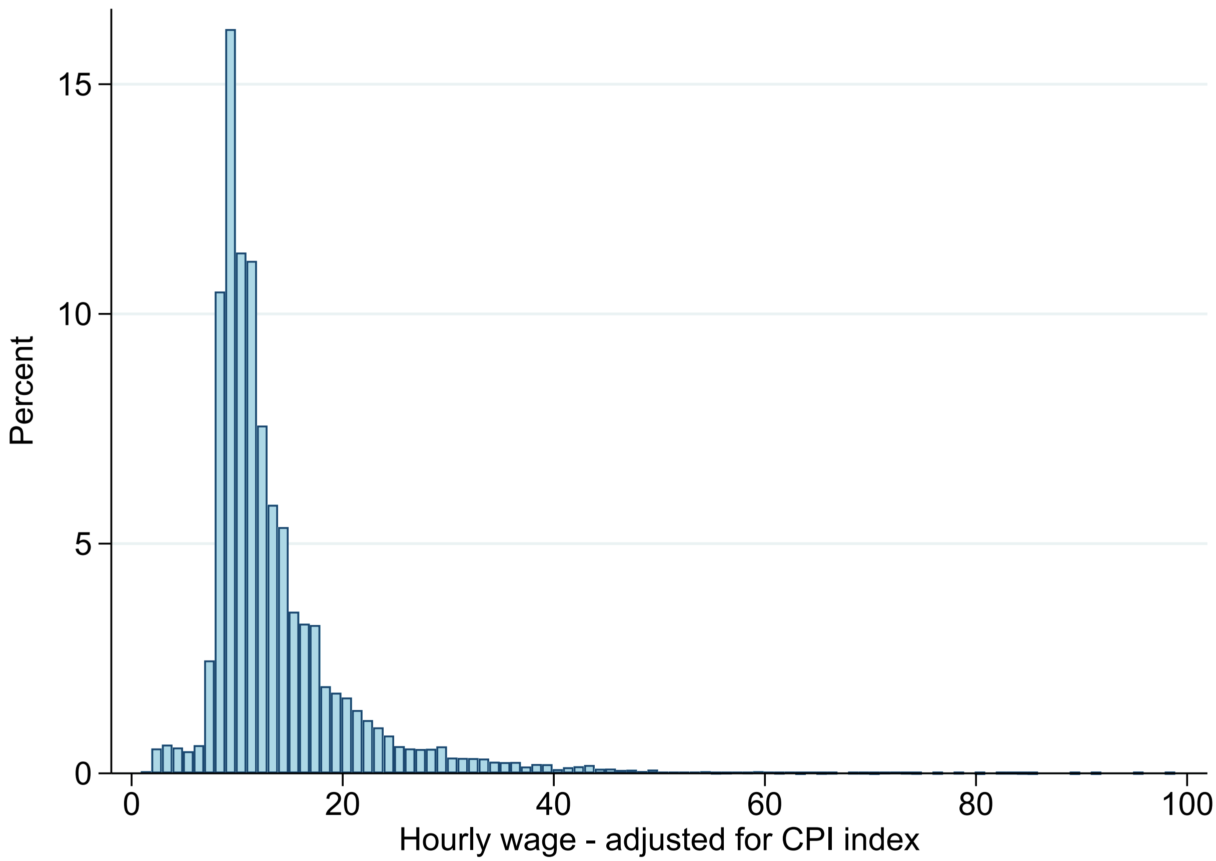
Notes: This figure shows estimates of reduced-form effects of firm-level labor demand shocks on cumulative earnings (Panel A) and cumulative job separations (Panel B) in the six years after initial ACS response. Each coefficient and standard error comes from a separate regression using outcomes measured in the quarter indicated on the x-axis. The scale of the instrument implies the coefficients can be interpreted as the impact of 100% firm-level decrease in employment. Cumulative earnings is the sum of quarterly earnings until period t from all employers in the 21 LEHD states included in the study, inflated to constant 2020 dollars using the CPI. Separation is an indicator for having zero earnings from your top-paying employer in the prior quarter. Cumulative separations is sum of total separations until perod t. Standard errors are clustered by employer at $t = 0$.

Figure B.7: Effects on job loss vs. earnings and employment across demographic groups



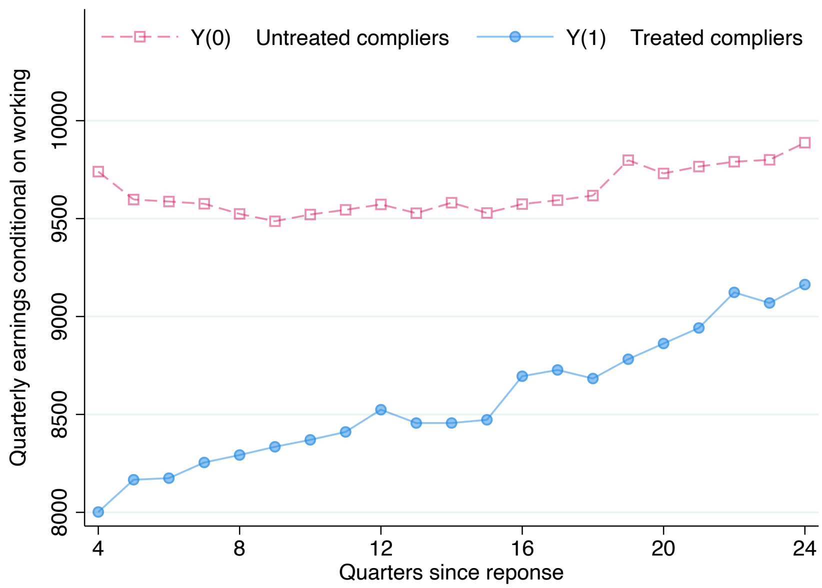
Notes: This figure plots first-stage effects on job loss and reduced-form effects on long-run quarterly earnings (Panel A), employment (Panel B), and cumulative earnings (Panel C). Each point corresponds to the estimated effect on job loss (x-axis) and the estimated effect on a long-run outcome (y-axis) in a different sample split by race, sex, or age. Any earnings is an indicator for any earnings in the LEHD nationally. Total earnings is the sum of quarterly earnings from all employers in the 21 LEHD states included in the study, inflated to constant 2020 dollars using the CPI. Standard errors are clustered by employer at $t = 0$. The line represents the OLS fit and the slope and standard error are reported in the top corner. The regression specification does not include an intercept. The intercept is not statistically significant when it is included. The 2SLS estimates reported at the top-right corner are from Table 2.

Figure B.8: Share of involuntarily part-time workers by wage in the CPS



Notes: This figure shows incidence of involuntarily part-time employment by wage. Each bar reports the share of workers in a \$1 wage bin whose employment status is part-time for involuntary reasons, coded using the standard Bureau of Labor Statistics definitions. The sample includes the Outgoing Rotation Groups of the Current Population Survey. The sample cover years 2001-2014 and respondents between the ages of 22 to 50, and in one of our LEHD approving states. We inflation adjust hourly wages to constant 2020 dollars using the CPI. We restrict the graph to individuals with wages below \$100.

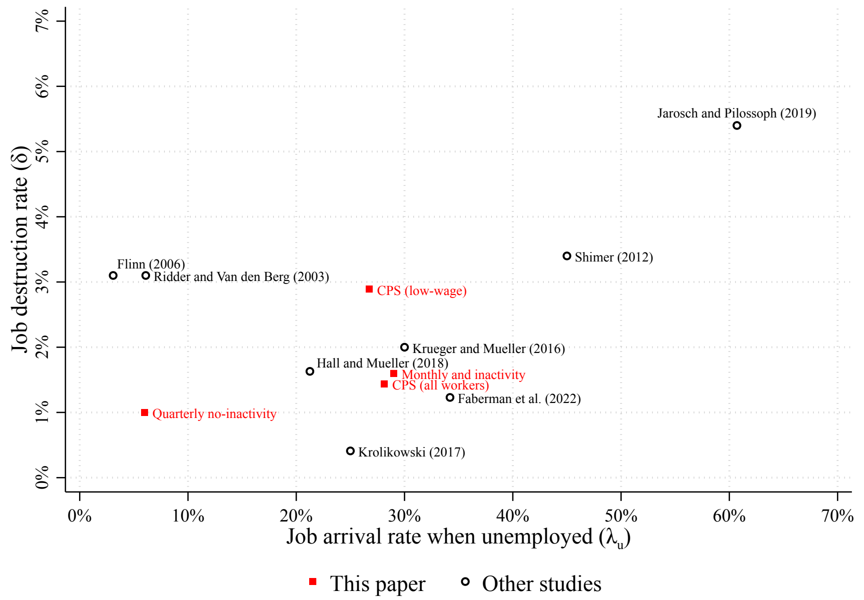
Figure B.9: Average earnings among working treated and untreated compliers



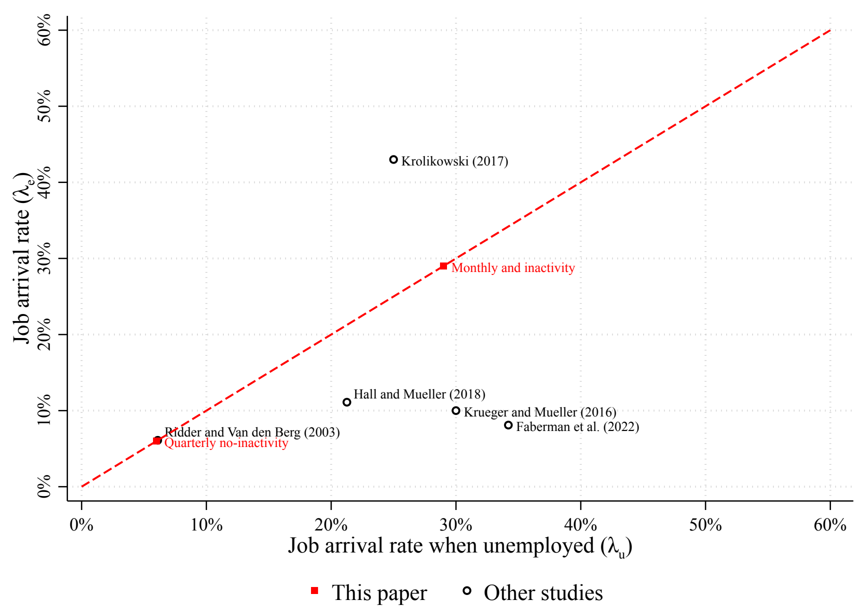
Notes: This figure shows estimates of average quarterly earnings in the LEHD data among the treated ($Y(1)$) and untreated ($Y(0)$) compliers conditional on working (i.e., observing some positive earnings in the LEHD data) using the standard formulas from Imbens and Rubin (1997) and Abadie (2002). Each coefficient comes from a separate regression using outcomes measured in the quarter indicated on the x-axis. Quarterly earnings are measured using all employers in the 21 LEHD states included in the study, inflated to constant 2020 dollars using the CPI.

Figure B.10: Search model parameters in the literature

A) Job arrival rates from unemployment (λ_u) and destruction rates (δ)

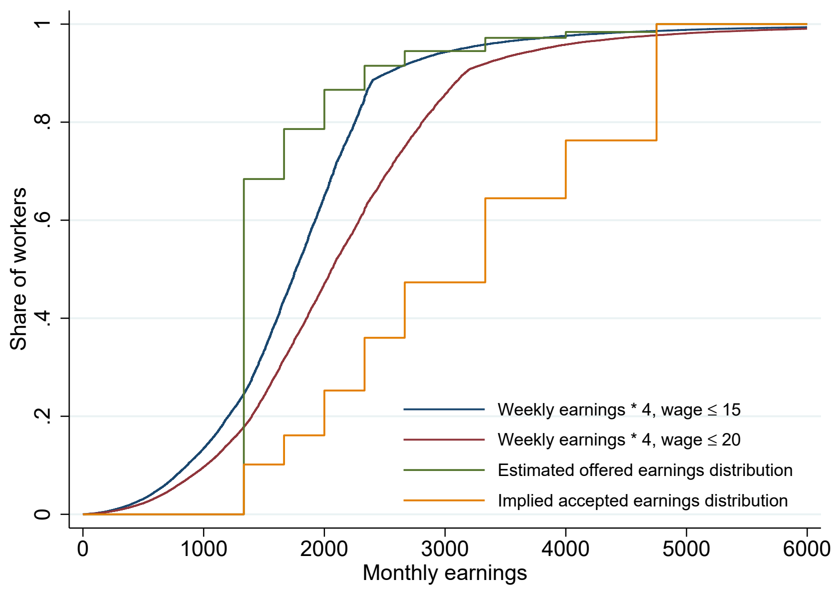


B) Job arrival rates from unemployment (λ_u) and employment (λ_e)



Notes: This figure shows estimates of key parameters of job search models in other studies. Panel A reports the job arrival rate among unemployed workers (λ_u) and the job destruction rate (δ) in other studies as well as the CPS data described in Appendix F. The CPS estimates are based on the transition probabilities in Appendix Table F.1. The job arrival rate among unemployed workers (λ_u) is defined as the likelihood of moving from a state of unemployment to full-time work or part-time work due to economic reasons. The job destruction rate (δ) is defined as the likelihood of moving from full-time employment to unemployment or part-time work due to economic reasons. Panel B reports the job arrival rate among unemployed workers (λ_u) and employed workers (λ_e). All rates are normalized to the monthly level.

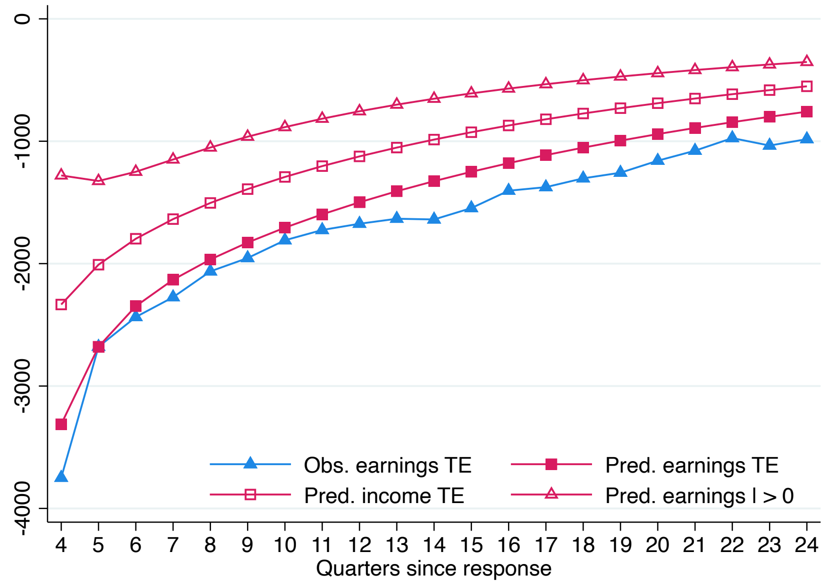
Figure B.11: Offered and accepted wage distribution vs. the CPS



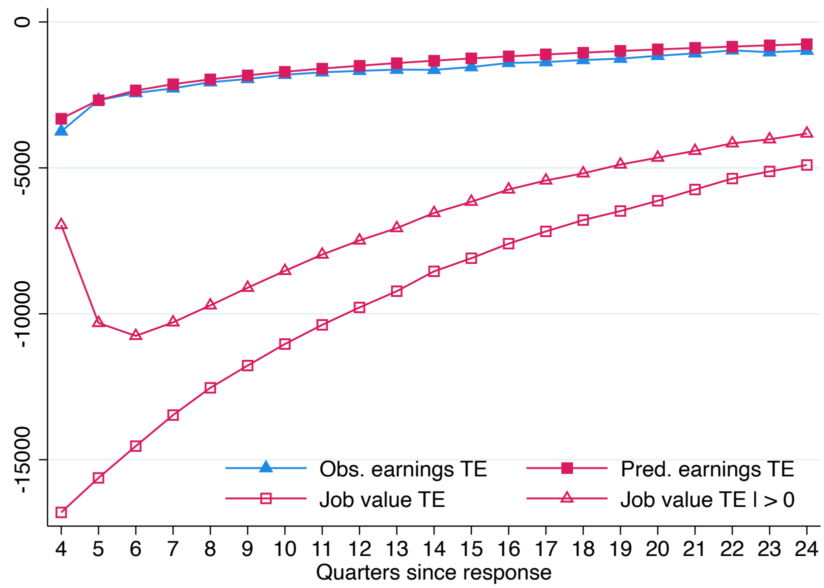
Notes: This figure plots offered and accepted wages from the estimated offer distribution described in Section 9. The figure also plots two benchmarks from the CPS outgoing rotation groups. The blue line plots the cumulative distribution of implied monthly earnings for all workers with wage last week of ≤ 15 per hour. The red line does the same for workers with a wage last week of ≤ 20 per hour. CPS sample restrictions are described in Appendix F.

Figure B.12: Model-based treatment effects

A) Earnings and income effects



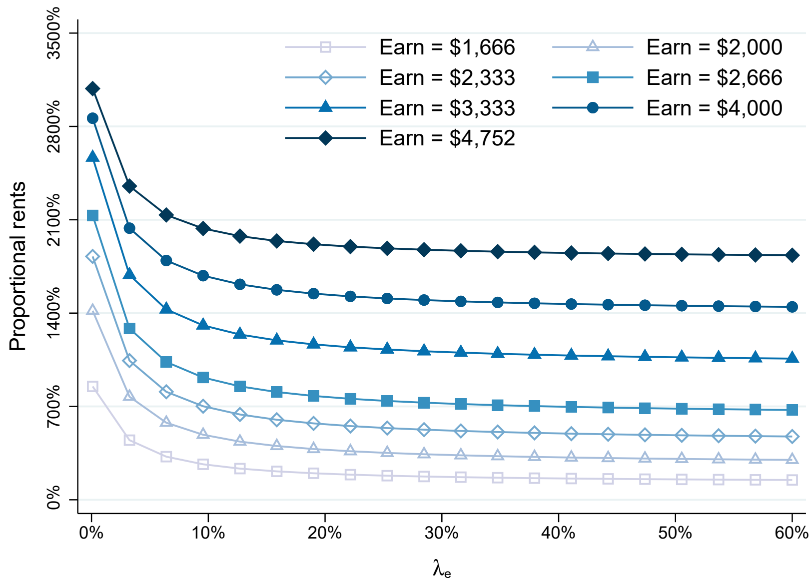
B) Job value functions



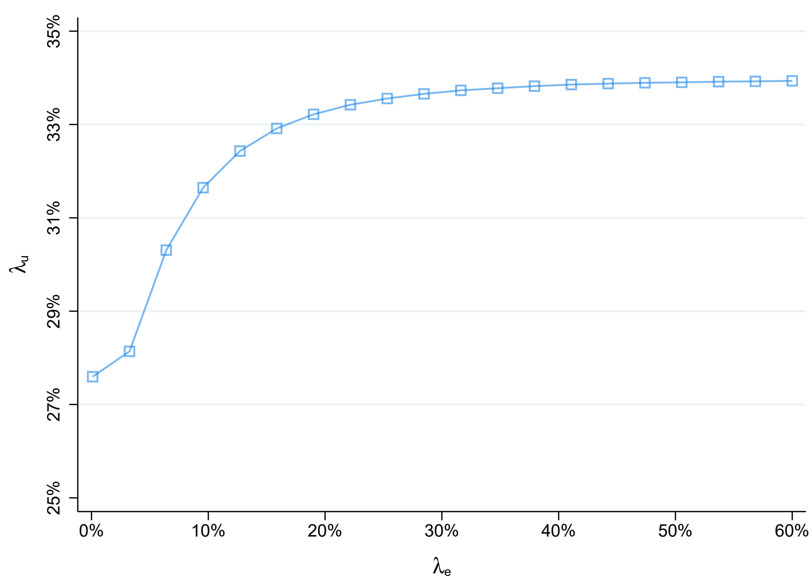
Notes: This figure presents decompositions of the earnings and income effects of job loss using estimates from the job-ladder model described in Section 9. Panel A show effects on total wage earnings and income (including unemployment benefits b), as well as earnings conditional on holding any job. Panel B shows observed and predicted estimates on total earnings, as well as estimated effects on average job values $V(e)$. Unemployed workers (including inactive workers) are assigned V_u.

Figure B.13: Rents and job arrival rates fixing on-the-job search productivit

A) Exact rent estimates



B) Job arrival rates in unemployment (λ_u)



Notes: This figure shows estimates of rents (Panel A) and job arrival rates in unemployment (Panel B) from the model described in Appendix D.2, which allows for different job arrival rates on and off the job. Panel A plots exact proportional rent estimates implied by the discrete earnings distribution and assuming a 5% annual interest rate for each level of earnings. Rents are the present value utility difference relative to unemployment as a fraction of earnings, with b set to the implied value when $1,333 is the reservation earnings level. Panel B reports estimates of λ_u. Each estimate in both panels fixes the value of λ_e at the value listed on the x-axis.

C Within-labor market placebo shocks

This appendix describes the permutation procedure employed to construct the estimates presented in Table A.4. We are interested in testing whether our instrument is correlated across firms in the same local labor market and therefore may capture local labor market shocks as opposed to idiosyncratic, firm-specific shocks.

Since our main specification includes state-by-NAICS2-by-year and quarter fixed effects, any common shocks to firms at this level would be absorbed. To explore whether shocks may be correlated within more narrowly defined markets, we construct "placebo" shocks by randomly permuting the instrument among firms in the same cell. Cells are defined as more granular variations on the groups defined by our baseline fixed effects. In one option, we replace states with commuting zones. Another option replaces NAICS 2 with NAICS 3 codes. A final option replaces both state and NAICS 2 codes with commuting zones and NAICS 3 codes, respectively.

To implement the test, we use the following procedure:

1. We begin by collapsing the data to the firm-by-cell level. Denote by Y_{jc} the average outcome for firm j in cell c.

2. To account for mechanical correlations explained in the next sub-section, we use a split sample technique when permuting shocks. Within a cell c, we randomly split the firms into two equally sized groups. We then assign each firm in the first group the shock of a random firm in the second group (without replacement). Denote each firm's assigned placebo shock $Z_{jc}^{placebo}$.

3. Using only the first group,[40] we then regress Y_{jc} on $Z_{jc}^{placebo}$ and the same controls as in our primary specification, Equation 1:

$$Y_{jc} = X'_{jc}\alpha^0 + \gamma Z_{jc}^{placebo} + \psi_{n(j,c),s(j,c),q(j,c)} + e_{jc} \tag{C.1}$$

   where $\psi_{n(j,c),s(j,c),q(j,c)}$ are our primary set of fixed effects for 2-digit NAICS ($n(j,c)$) by state ($s(j,c)$) by year and quarter ($q(j,c)$), and X_{jc} are the firm-level controls in Equation 1.

We repeat the above permutation procedure for 1,000 times and record estimates of γ and a standard error. Each cell in Table A.4 reports the average value of $\hat{\gamma}$ across these simulations and the average standard error. We conduct the procedure using as outcomes: the

[40] Cells with only one firm are excluded.

instrument—i.e., the firm's own shock, Z_{jc}; job separation by $t = 4$—i.e., the endogenous variable; and average earnings at $t = 24$ for the firm's $t = 0$ workers—i.e., a long-run outcome. The results show no significant correlation between placebo shocks and these outcomes.

C.1 Accounting for mechanical correlations

Care must be taken to ensure there is no mechanical correlation between $Z_{jc}^{placebo}$ and Y_{jc}. To understand the issue, consider the following simplified specification that omits the firm-level controls:

$$Y_{jc} = \gamma Z_{jc} + \psi_{n(j,c),s(j,c),q(j,c)} + e_{ic} \tag{C.2}$$

Assume that Z_{jc} is uncorrelated across all firms, so $Cov(Z_{jc}, Z_{j'c}) = 0\ \forall j \neq j'$. Then γ is given by:

$$\gamma = \frac{Cov(Y_{jc}, Z_{jc} - \bar{Z}_{j,c})}{Var(Z_{jc} - \bar{Z}_{j,c})} = \frac{Cov(Y_{jc}, Z_{jc}) - \frac{1}{N_{j,c}} Cov(Y_{jc}, Z_{jc})}{Var(Z_{jc} - \bar{Z}_{j,c})} \tag{C.3}$$

where $\bar{Z}_{j,c}$ is the mean of Z_{jc} within a state, NAICS 2 and time group $(n(j,c), s(j,c), q(j,c))$ and $N_{j,c}$ is the number of firms in this group. The second equality follows from the assumption that firm shocks are uncorrelated (both overall and within a fixed effect group).

If shocks are permuted within a cell c, then the specification becomes:

$$Y_{jc} = \gamma^p Z_{j'c} + \psi_{n(j,c),s(j,c),q(j,c)} + \zeta_{ic} \tag{C.4}$$

where $Z_{j'c}$ is the shock of another firm $j' \neq j$ in the same group c. Because these groups are nested by the groups that define the fixed effects $\psi_{n(j,c),s(j,c),q(j,c)}$, however, $\bar{Z}_{j,c}$ is unchanged. The coefficient γ^p will therefore be:

$$\gamma^p = \frac{Cov(Y_{jc}, Z_{j'c}) - \frac{1}{N_{j,c}} Cov(Y_{jc}, Z_{jc})}{Var(Z_{j'c} - \bar{Z}_{j,c})} = \frac{-\frac{1}{N_{j,c}} Cov(Y_{jc}, Z_{jc})}{Var(Z_{j'c} - \bar{Z}_{j,c})} \tag{C.5}$$

Thus, even if all shocks are completely uncorrelated, γ will not be equal to zero. Bias is larger when groups are small. The fundamental issue is that when shocks are permuted but all the data is retained, firm's own shock Z_{jc} contributes to the demeaning step. A simple solution, however, is to use a split sample technique so that Z_{jc} is excluded from $\bar{Z}_{j,c}$. We do so by drawing placebo shocks from half the observations within each cell, assigning them to the other half, and estimating γ^p using observations from the first half only.

D Derivation of earnings-ladder model

D.1 Baseline model

We begin with a simple transformation of the value functions that facilitates manipulation and builds a connection to continuous time versions of the same model. The value functions for unemployed and workers employed at earnings e can be written respectively as:

$$
\begin{aligned}
V_u &= b + \beta\left(\lambda \int_0^\infty max\{V(x), V_u\}dF(x) + (1-\lambda)V_u\right) \\
V(e) &= e + \beta\left(\lambda \int_0^\infty max\{V(x), V(e)\}dF(x) + \delta V_u + (1-\delta-\lambda)V(e)\right)
\end{aligned}
$$

Because search is equally productive on- and off-the-job by assumption, it can be shown that reservation earnings e^* are equal to b.

Re-arranging these expressions slightly yields:

$$
\begin{aligned}
(1-\beta)V_u &= b + \beta\left(\lambda \int_{e^*}^\infty [V(x) - V_u]dF(x)\right) \\
(1-\beta)V(e) &= e + \beta\left(\lambda \int_e^\infty [V(x) - V(e)]dF(x) + \delta(V(u) - V(e))\right)
\end{aligned}
$$

Letting $\frac{1}{1+r} = \beta$, $\bar{V}_u = V_u/(1+r)$, and $\bar{V}(e) = V(e)/(1+r)$ yields:

$$
\begin{aligned}
r\bar{V}_u &= b + \lambda \int_{e^*}^\infty [\bar{V}(x) - \bar{V}_u]dF(x) \\
r\bar{V}(e) &= e + \lambda \int_e^\infty [\bar{V}(x) - \bar{V}(e)]dF(x) + \delta(\bar{V}(u) - \bar{V}(e))
\end{aligned}
$$

Notice that these expressions also describe the flow utility from unemployment and employment at earnings e in an equivalent model set in continuous time (i.e., with instantaneous discount factor r and Poisson arrival rates λ). A similar argument appears in the supplemental material to Hornstein, Krusell and Violante (2011), Section 3.1.1.

In this transformed model, the "flow" difference in utility from holding a job at earnings level e relative to unemployment can be expressed as:

$$\begin{aligned}
r\bar{V}(e) - r\bar{V}_u &= \lambda \left[\int_e^\infty [\bar{V}(x) - \bar{V}(e)] dF(x) - \int_{e^*}^\infty [\bar{V}(x) - \bar{V}_u] dF(x) \right] \\
&\quad + e - b + \delta(\bar{V}_u - \bar{V}(e)) \\
&= \lambda \left[\bar{V}_u - \int_{e^*}^e \bar{V}(x) dF(x) - (1 - F(e))\bar{V}(e) \right] + e - b + \delta(\bar{V}_u - \bar{V}(e))
\end{aligned}$$

where the second line uses the assumption that $F(e^*) = 0$.

Some further simple algebra shows that these flow rents can be expressed as:

$$r\bar{V}(e) - r\bar{V}_u = \frac{r}{r + \delta + \lambda} \left[e - b + \lambda \int_{e^*}^e [\bar{V}(e) - \bar{V}(x)] dF(x) \right]$$

Because $\bar{V}'(e) = 1/(r + \delta + \lambda(1 - F(e))) > 0$, $\bar{V}(\cdot)$ is an increasing function of e. Thus $\int_{e^*}^e [\bar{V}(e) - \bar{V}(x)] dF(x)$ must be positive. It follows that:

$$\frac{r\bar{V}(e) - r\bar{V}_u}{e} \geq \frac{r}{r + \delta + \lambda}(1 - \rho_e)$$

where $\rho_e = b/e$. Moreover, because $F(e)$ is non-decreasing, $V(\cdot)$ must also be convex, which implies that:

$$\int_{e^*}^e [\bar{V}(e) - \bar{V}(x)] dF(x) \geq \frac{(F(e) - F(e^*))(\bar{V}(e) - \bar{V}(e^*))}{2}$$

which is the triangular approximation to this integral. Because $\bar{V}(e^*) = \bar{V}_u$ by definition, a tighter bound can obtained by substituting this inequality. After some algebraic rearrangement and using the assumption that $F(e^*) = 0$ again, the previous inequality can be written as:

$$\frac{r\bar{V}(e) - r\bar{V}_u}{e} \geq \frac{2r}{2(r + \delta) + \lambda(2 - F(e))}(1 - \rho_e)$$

In a continuous time version of the model, we therefore have that rents are bounded by:

$$\frac{\bar{V}(e) - \bar{V}_u}{e} \geq \frac{2}{2(r + \delta) + \lambda(2 - F(e))}(1 - \rho_e) \geq \frac{1}{r + \delta + \lambda}(1 - \rho_e)$$

Converting back to the original discrete time value functions produces the result in Proposition 1:

$$\frac{V(e) - V_u}{e} \geq \frac{2(1+r)}{2(r+\delta) + \lambda(2 - F(e))}(1 - \rho_e) \geq \frac{1+r}{r+\delta+\lambda}(1 - \rho_e)$$

Notice that as r becomes small the continuous time and discrete time version of the bounds converge, as one would expect taking the limit of the discrete time model as time periods shrink to zero.

D.2 Different search productivity on and off the job

If job offers arrive at different rates on and off the job, flow rents can be written as:

$$\begin{aligned} r\bar{V}_u &= b + \lambda_u \int_{e^*}^{\infty} [\bar{V}(x) - \bar{V}_u] dF(x) \\ rV(e) &= e + \lambda_e \int_{e}^{\infty} [\bar{V}(x) - \bar{V}(e)] dF(x) + \delta(\bar{V}_u - \bar{V}(e)) \end{aligned}$$

where λ_u and λ_e are the arrival rate of offers on and off the job, respectively.

Some algebraic manipulation shows that flow rents can be expressed in this case as:

$$r\bar{V}(e) - r\bar{V}_u = \frac{r}{r+\delta+\lambda_u}\left[e - b + \lambda_u \int_{e^*}^{e} [\bar{V}(e) - \bar{V}(x)] dF(x) + (\lambda_e - \lambda_u) \int_{e}^{\infty} [\bar{V}(x) - \bar{V}(e)] dF(x)\right]$$

which naturally collapses to the prior case when $\lambda_u = \lambda_e = \lambda$.

With differential search productivity on and off the job, rents involve an extra term capturing the added benefit (or costs) of being able to further climb the job ladder beyond earnings level e while employed vs. unemployed.

Because it remains the case that $\bar{V}'(e) = 1/(r + \delta + \lambda_e(1 - F(e))) > 0$, both the integral terms are positive. Thus whenever on-the-job search is at least as productive as off-the-job search, a similar bound to the case where $\lambda_u = \lambda_e = \lambda$ can be obtained by ignoring the second integral term:

$$\frac{V(e) - V_u}{e} \geq \frac{2(1+r)}{2(r+\delta) + \lambda_u(2 - F(e))}(1 - \rho_e)$$

When $\lambda_e < \lambda_u$, rents are lower because the second integral term decreases flow rents—holding a job is less valuable if you cannot continue to advance up the job ladder. In the extreme case where $\lambda_e = 0$, the value of employment can be expressed simply as:

$$V(e) - V_u = \frac{1+r}{r+\delta}(e - r\bar{V}_u)$$

Because it can be shown that when $\lambda_e = 0$ reservation earnings levels respect $e^* = b + \lambda_u \int_{e^*} \frac{1-F(x)}{r+\delta} dx$, we can express flow rents as a portion of earnings in this extreme case as:

$$\frac{V(e) - V_u}{e} = \frac{1+r}{r+\delta}\left(1 - \frac{b + \frac{\lambda_u}{r+\delta}\int_{e^*}(1-F(x))dx}{e}\right)$$

If F is known, this expression can also be evaluated exactly. If the value of F is known only at M points in the support of e, rents can be bounded using the fact that F is non-decreasing:

$$\frac{V(e) - V_u}{e} \geq \frac{1+r}{r+\delta}\left(1 - \frac{b + \frac{\lambda_u}{r+\delta}\left[\sum_{m=1}^{M}(1-F(e_{m-1}))(e_m - e_{m-1}) + (1-F(e_M))(\bar{e} - e_M)\right]}{e}\right)$$

where $\{e_1, \ldots, e_M\}$ are the points where the value of F is known, $\bar{e}$ is the highest level of earnings possible, e_0 can be assumed to be zero, and $F(e_0) = 0$. Note that this bound need not be positive, so a better bound can be found by taking the greater of its value and zero.

D.3 Discrete earnings distributions

When the earnings distribution is known, it is possible to compute rents exactly. We do so assuming a discrete distribution of earnings offers at M mass points $\{e_1, \ldots, e_M\}$. A discrete distribution of earnings offers implies that value functions can be written as the linear system:

$$r\bar{V}_u = b + \lambda \sum_{x=1}^{M}[\bar{V}_x - \bar{V}_u]f_x$$

$$r\bar{V}_m = e_m + \lambda \sum_{x=m}^{M}[\bar{V}_x - \bar{V}_m]f_x + \delta(\bar{V}_u - \bar{V}_m), \quad m \in \{1, ..., M\}$$

where $\bar{V}_m$ is the value of holding a job at earnings level e_m (divided by $1+r$) and f_m is the mass of job offers at e_m. Because we have assumed no job offers are made below the reservation earnings level, optimal search behavior requires that if e_1 is the reservation earnings level $\bar{V}_u = \bar{V}_1$. In the model with equally productive search on and off the job, this implies $b = e^* = e_1$. If search is not equally productive on and off the job, however, one can compute the value of b consistent with the model. The set of unknowns thus consists of $\{b, \bar{V}_1, \ldots, \bar{V}_m\}$ in the general case.

The entire system can be written in matrix form as:

$$\mathbf{e} = \mathbf{W}\mathbf{V}$$

where

$$\begin{aligned}
\mathbf{W} &= r\mathbf{I}_{M+1} - \lambda\mathbf{P} - \delta(\mathbf{I}_{1,M+1} - \mathbf{I}_{M+1}) \\
\mathbf{e} &= \{b, e_1, \ldots, e_M\}' \\
\mathbf{V} &= \{\bar{V}_u, \bar{V}_1, \ldots, \bar{V}_M\}' \\
\mathbf{P} &= \begin{pmatrix} -1 & f_1 & f_2 & \ldots & f_M \\ 0 & -\sum_{m=1}^{M} f_m & f_2 & \ldots & f_M \\ 0 & 0 & -\sum_{m=2}^{M} f_m & \ldots & f_M \\ 0 & 0 & 0 & \ldots & 0 \end{pmatrix}
\end{aligned}$$

and where $\mathbf{I}_n$ is the n-by-n identity matrix, and $\mathbf{I}_{1,n}$ is an n-by-n matrix with ones in the first column and zeros elsewhere.

If b is known, as in the case where $\lambda_u = \lambda_e$, an exact solution for $\mathbf{V}$ can be found as $\mathbf{V} = \mathbf{W}^{-1}\mathbf{e}$. Otherwise, one can solve for the values of b and $\{\bar{V}_1, \ldots, \bar{V}_m\}$ that solve this system exactly. Exact rents can then be computed substituting the integral for summation over the discrete distribution of earnings offers.

A similar approach can be used when allowing for different search productivity on and off the job by setting $\mathbf{W} = r\mathbf{I}_{M+1} - \tilde{\mathbf{P}} - \delta(\mathbf{I}_{1,M+1})$, where $\tilde{\mathbf{P}}$ is the matrix $\mathbf{P}$ with the first row multiplied by λ_u and all other rows multiplied by λ_e. When $\lambda_e > \lambda_u$, however, it no longer follows that $b = e^*$. Instead, reservation wages respect:

$$e^* = b + (\lambda_u - \lambda_e) \int_{e^*} \frac{1 - F(x)}{r + \delta + \lambda_e(1 - F(x))} dx$$

Setting $e^* = e_1$ implies an implied value for b that can be solved from the discrete wage distribution F.

D.4 Non-participation / inactivity

We assume that there are two types of workers: active and inactive. Active workers seek new jobs when they become unemployed. These jobs arrive at rate λ. Inactive workers do not seek new work after they become unemployed. While the population share of inactive workers is constant, over time inactive workers become increasingly concentrated in non-employment. Let π_{u_t} denote the share of active workers among the non-employed in period t. The average job-finding rate out of non-employment is given by $\lambda\pi_{u_t}$, and the evolution of employment stocks can be written as:

$$\triangle y_t^d = \lambda\pi_{u_t} - y_t^d(\delta + \lambda\pi_{u_t})$$

Likewise, the evolution of earnings distributions can be expressed as:

$$\triangle Q_t^d(e) = \delta - (1 - F(e))[\lambda\pi_{u_t} - \lambda](1 - y_t^d) - [\lambda(1 - F(e)) + \delta]Q_t^d(e)$$

Both expressions clearly collapse to the case discussed in the main text when $\pi_{u_t} = 1$. When some workers are inactive, however, job-finding rates out of non-employment may decay over time as inactive workers become increasingly concentrated among the non-employed. Likewise, $\pi_{u_t} < 1$ generates an implicit difference in the average productivity of search on-and-off the job. The evolution of earnings distributions measures this difference directly through the relative contributions of employment (y_t^d) and the earnings distribution ($Q_t^d(e)$) to its changes.

The evolution of π_{u_t} is also a deterministic function of the parameters of the model and π, the population share of active workers. To derive its law of motion, we need to account for both the likelihood that active workers remain non-employed and the impact of inflows of employed workers who lose their jobs. The first channel includes the $(1-y_t)\pi_{ut}(1-\lambda)$ active workers who do not find jobs. Because the population share of active workers is π, the share of active workers among the employed at time t can be written as: $\frac{\pi-(1-y_t)\pi_{ut}}{y_t}$. Thus the total inflows of active workers due to job loss amounts to $(\pi - (1 - y_t)\pi_{ut})\delta$.

We can therefore express the change in the share of active workers among the non-employed at time t as:

$$\Delta\pi_{ut} = \frac{(1 - y_t)\pi_{ut}(1 - \lambda) + (\pi - (1 - y_t)\pi_{ut})\delta}{1 - y_{t+1}} - \pi_{ut}$$

Taken together, these three equations make it possible to identify and estimate the parameters of this model. Although the dynamics of employment and earnings distributions are linear in the model parameters (or their combinations), the evolution of π_{u_t} is not. Rather than using regression-based approaches as above, we instead fit the model using minimum distance. First, however, we make an additional adjustment to account for the quarterly nature of our earnings data and allow for sub-quarterly job mobility, as discussed in the next subsection.

D.5 Sub-quarterly mobility

Our outcomes measure the probability of observing any earnings and the probability of earning less than particular levels over the course of a quarter, not employment itself or earnings levels in a particular job. These objects can be expressed as functions of model parameters as well with some additional structure. To see how, suppose there are K periods within a quarter. At the start of each period, employed workers collect earnings and unemployed workers collect benefits b. At the end of the period, workers receiving exogenous job offers and job destruction shocks, which determine their state (non-employed vs. employed at each earnings level) at start of the next period. The LEHD outcomes we measure report the sum of earnings from all states within a quarter.

Assume there are $G+1$ distinct states, including non-employment and G possible earnings levels. Let $g_t \in \{0, \ldots, G\}$ indicate the state occupied at time t, e_g denote earnings associated with occupying state g, and F_g denote the cumulative mass function of job offers evaluated at e_g (because there G earnings levels, F is discrete). Transition probabilities between states are functions of the model parameters and the worker's active/inactive status. Inactive workers never exit non-employment once they enter it, for example, while active workers exit at rate λ. The probability of moving from employment to non-employment is δ for all workers. And the probability of moving up the job ladder can be written as $\lambda(1 - F_g)$. Thus:

$$
\begin{aligned}
Pr(g_{t+1} = 0 | g_t = 0, active) &= (1 - \lambda) \\
Pr(g_{t+1} = 0 | g_t = 0, inactive) &= 1 \\
Pr(g_{t+1} > k | g_t = k) &= \lambda(1 - F_k) \ \forall \ k > 1 \\
Pr(g_{t+1} = 0 | g_t = k) &= \delta \ \forall \ k > 1
\end{aligned}
$$

The conditional likelihood of any K-length sequence of states beginning with g_t, which we denote as $\mathbf{g}_t = \{g_t, \ldots, g_{t+K-1}\}$ can thus be written separately for active and inactive workers as:

$$P^a(\mathbf{g}_t;\Theta) = \prod_{m=1}^{K-1} Pr(g_{t+m}|g_{t+m-1}, active)$$
$$P^i(\mathbf{g}_t;\Theta) = \prod_{m=1}^{K-1} Pr(g_{t+m}|g_{t+m-1}, inactive)$$

Given an initial share of workers in state g in period t, $P_t(g)$, of whom share π_{gt} are active, we can express the unconditional probability of the sequence $\mathbf{g}_t$ as:

$$P(\mathbf{g}_t;\Theta, P_t(g_t), \pi_{g_t t}) = P_t(g_t)\left[\pi_{g_t t} P^a(\mathbf{g}_t;\Theta) + (1-\pi_{g_t t})P^i(\mathbf{g}_t;\Theta)\right]$$

where $\Theta = \{\lambda, \delta, F\}$ collects the parameters of the search model.

Given state shares and active shares in an initial period, say $P_0 = \{P_0(0), \ldots, P_0(G)\}$ and $\pi_0 = \{\pi_{00}, \ldots, \pi_{0G}\}$, state and active shares in all subsequent periods are also determined model parameters. We write these objects as $P_t(g; P_0, \pi_0, \Theta)$ and $\pi_t(g; P_0, \pi_0, \Theta)$. For example, state shares and the distribution of active workers at the start of the second quarter, or $P_K(g)$ and π_{gK}, can be written as:

$$P_K(g) = \sum_{\{\mathbf{g}_0 \ | \ g_K = g\}} P(\mathbf{g}_0;\Theta, P_0(g_0), \pi_{g_1})$$
$$\pi_{g_K} = \frac{\sum_{\{\mathbf{g}_0 \ | \ g_K = g\}} P_0(g_0)\pi_{g_0 0} P^a(\mathbf{g}_0; g_0, \Theta)}{P_K(g)}$$

where with a slight abuse of notation we have extended the sequences $\mathbf{g}_0$ to be length $K+1$ and include the transition into the first period of the next quarter.

We can therefore express the likelihood of earning no more than m dollars over the course of the quarter beginning in period t as the sum of the likelihoods of all possible state sequences from periods t to $t+K-1$ that yield no more than m total earnings:

$$Pr(earn \leq m \ in \ q_t) = \sum_{\{\mathbf{g}_t \ | \ \sum_{g\in\mathbf{g}_t} e_g \leq m\}} P(\mathbf{g}_t;\Theta, P_t(g_t; P_0, \pi_0, \Theta), \pi_t(g_t; P_0, \pi_0, \Theta))$$

The full set of parameters thus consists of the search model parameters Θ, the set of initial conditions P_0 and π_0, and the population active share π. Conditional on these parameters, a full sequence of earnings probabilities, as well as average earnings, can be computed for all periods.

Initial conditions are also allowed to differ for treated and untreated compliers. This is critical, since at $t = 4$ a large share of treated compliers have zero earnings and all untreated compliers are employed by construction. Because job separation is exogenous, the distribution of active workers across initial employed states does not affect predicted earnings and employment. We therefore impose that $\pi_{0g} = \pi_{0g'}$ for all $g, g' > 0$ for both treated and untreated compliers.

E Further extensions to the job ladder model

On- vs. off-the-job search productivity: The model imposes that job offer arrival rates are the same on and off the job. In principle, it is straightforward to relax this assumption by allowing λ_u to capture offer arrival rates when unemployed and λ_e to capture arrival rates when employed. Appendix Section D.2 shows that in this version of the model, the rent bounds established above remain valid when substituting λ_u for λ if $\lambda_e \geq \lambda_u$. If $\lambda_e < \lambda_u$, rent calculations differ because part of the value of being unemployed includes increased access to potentially high-earning job offers. The appendix shows how rents can also be bounded in the extreme case where $\lambda_e = 0$ using partial knowledge of the distribution of job offers.[41]

Using the empirical approach from the previous subsection to estimate differences in λ_e and λ_u is more challenging. Intuitively, because we observe only quarterly totals of earnings, there is no information about the degree of job-to-job mobility within a quarter in our causal effect estimates. A worker who earns \$6,000 over the course of a quarter may have held a single job that pays \$2,000 per month for the entire quarter, or have climbed the earnings ladder from \$1,000 to \$2,000 to \$3,000 each month. In practice this means that differences in λ_e and λ_u combined with shifts in the CDF of the offer distributions provide similar fits to observed moments, with any identification coming from the assumed discrete-time nature of job transitions and the discretization of the offer distribution.

Nevertheless, to examine the sensitivity of rent calculations to different assumptions about on-the-job search, Appendix Figure B.13 presents rent estimates fixing λ_e over a range from 0.1 to 0.6. Rents are computed exactly using the assumed discrete distribution of job offers, as in Column 4 of Table 8. Because when $\lambda_e \neq \lambda_u$ reservation earnings levels need not be equal to b, we compute the level of b implied by reservation earnings being equal to \$1,333 per month, the lowest mass point in the discrete job offer distribution. We view this choice as conservative; it must be an upper bound on possible reservation earnings because workers also take jobs that pay less than this amount.

The results show that in general rents are larger when $\lambda_e < \lambda_u$. Intuitively, this is driven by the fact that low offer arrival rates on the job make unemployment relatively more attractive, since it offers better opportunities to advance into higher paying jobs. This means workers must have lower levels of b in order to rationalize taking jobs paying as low as \$1,333 per month when λ_e is small. Consistent with weak identification, the figure also shows that

[41] Panel B of Appendix Figure B.10 reports estimates of λ_u and λ_e in other studies using U.S. data. Generally, λ_e is smaller than λ_u. However, several recent studies estimate that $\lambda_e > \lambda_u$ in the U.S. and Germany (Krolikowski, 2017; Jarosch, 2021).

similar estimates of λ_u are obtained regardless of how λ_e is chosen.[42]

Non-linear utility over earnings: As noted in the main text, the baseline model features linear utility over earnings. This implies that the flow utility from a job that pays \$2,666 per month is exactly twice as much as that of a job that pays \$1,333 per month. In practice, flow utility from the former may be less than twice as high as from the latter if workers have any disutility from labor or diminishing utility from consumption. To introduce concavity into the utility function over earnings, we use estimates of the marginal value of time from Mas and Pallais (2019), who elicited preferences over hours and wage packages from a set of low-wage workers.

Doing so first requires calibrating the hours and wage combinations at each point on the earnings ladder. We set the hourly wage at the lowest earning job to be the median hourly wage at $t = 0$, $w_{min} = \$11.19$. The bottom rung of the earnings ladder is a job that pays \$1,333 per month, which thus involves $h_{min} = 1333/11.19$ hours per month (roughly 30 hours per week). Let γ be the share of the increase in earnings (above \$1,333) that can be explained by a higher hourly wage, with the remainder attributed to longer work hours.[43] The flow utility from each job on the ladder is given by the surplus over the relevant average value of time reported in Mas and Pallais (2019). That is, $u(e) = h(e)[w(e) - w^*(h(e)]$, where $h(e)$ and $w(e)$ are the hours worked and wages paid at earnings level e and $w^*(h(e))$ is the average value of time (the reservation wage) at hours h. We substitute these values for $u(e)$ into Equation 4 and recompute rents, allowing the value of b in Equation 3 to satisfy $V_u = V(e^*)$ as before.

The results are presented in Table A.9. The marginal value of time increases from less than \$8 per hour at the bottom of the ladder, where our calibration implies roughly 28 hours per week of work, to \$22 per hour at the top, where weekly hours surpass 43. Total utility remains higher for jobs further up the job ladder, however, consistent with the structure of the search model. A job that pays \$2,666 per month implies rents of 3.37 percent and a surplus ($\frac{V(2666)-V_u}{V_u}$) of 2.88 percent. At this earnings level, marginal and average value of time are \$14.7 and \$7.6 per hour, respectively. Rents are larger for higher earnings levels, reaching levels similar to those in Table 8. Incorporating non-linear utility over earnings into the model thus yields similar conclusions about the value of holding a full-time \$15 per hour job.

Higher-wage job losers: It is also possible to estimate the model using the post-job loss

[42] Appendix Table A.7 presents full model estimates for the value of λ_e that minimizes the diagonally-weighted distance between predicted and observed moments.

[43] Hence, the hourly wage for earnings e is $w(e) = w_{min} + \frac{\gamma \cdot (e-1333)}{h_{min}}$ and $h(e) = h_{min} + \frac{(1-\gamma)\cdot(e-1333)}{w(e)}$.

dynamics of workers initially earning between \$15 and \$30 per hour analyzed in Section 4. Appendix Table A.8 presents these estimates. The estimates we disclosed were chosen to cover the earnings activity of our primary sample of low-wage job losers and provide less information on the activity of higher-wage job losers. For example, more than half of higher-wage untreated compliers have $t = 24$ earnings above the top level we consider, \$12,000 per quarter, while only 16% of low-wage untreated compliers meet this benchmark. As a result, the discrete wage approximation used in the model provides a worse fit to higher-wage job losers' earnings activity, as evidenced by the minimum distance criterion reported at the bottom of the table.[44] Nevertheless, the results show that higher-wage job losers face higher monthly job-finding rates, lower job destruction rates, and a job offer distribution with substantially more mass at higher earnings levels. Rents are correspondingly lower.

Other measures of frictional inequality: Various other measures of frictional inequality have been studied in prior work. Hornstein, Krusell and Violante (2011), for example, propose summarizing levels of frictional inequality using the "mean-min ratio," or the ratio of the average wage accepted in a steady state to the reservation wage. In the case where $\lambda_e = \lambda_u$, the mean-min ratio collapses to $1/\rho_e$. If the average replacement rate is 0.5, then the mean-min would be 2. This metric is increasing in λ_e, so that allowing for $\lambda_e > \lambda_u$ would serve to increase frictional inequality. When $\lambda_e = 0$, on the other hand, mean-min ratios are generally small. As discussed above, however, rents in both cases can be non-negligible.

[44] The higher-wage sample is also significantly bigger, so the moments we match are estimated more precisely.

F CPS analysis

To compare our estimates to patterns in publicly available data, this section constructs estimates of employment dynamics using panel data from the Current Population Survey. We use CPS extracts covering 1996 to 2019 from IPUMS, which provides linked individual-level responses across survey waves. As in our main analysis, we restrict to individuals aged 22 to 50 and not in school. We also drop individuals not successfully linked across all eight survey waves. Recent research has found that CPS responses can be linked across waves with minimal error but some attrition due to cross-state migration and survey drop out. In 2009, linkage rates across survey waves one year apart was estimated to be 79% (Rivera Drew, Flood and Warren, 2014).

We then restrict to the sample of full-time hourly workers with a valid hourly wage observation recorded in the first outgoing rotation, or wave 4, and track their monthly transitions between waves five through eight. Employment states are classified using EMPSTAT, which defines whether the worker is consider employed, unemployed (U), or inactive (I) / out of the labor force. We further break down employment status using WRKSTAT as follows:

- **Full-Time (EF):** Full-time schedules (10); Full-time hours (35+), usually full-time (11) Part-time for non-economic reasons, usually full-time (12); Not at work, usually full-time (13).
- **Part-Time Economic Reasons (EPbus):** Full-time hours, usually part-time for economic reasons (14); Part-time for economic reasons (20); Part-time for economic reasons, usually full-time (21); Part-time hours, usually part-time for economic reasons (22).
- **Part-Time Non Economic (EPvol):** Full-time hours, usually part-time for non-economic reasons (15); Part-time for non-economic reasons, usually part-time (40); Part-time hours, usually part-time for non-economic reasons (41).

To construct standard errors, we estimate multinomial logistic regressions for appearing in each state in wave $t+1$ with indicators for each state at time t as covariates, with observations weighted by WTFNL. Standard errors are clustered by respondent.

Table F.1 reports transition rates splitting the sample by the observed hourly wage in wave 4.

Table F.1: Monthly transitions rates for CPS workers

A) All workers

	EF_{t+1}	$EPbus_{t+1}$	$EPvol_{t+1}$	U_{t+1}	I_{t+1}
EF_t	0.9679	0.0099	0.0096	0.0054	0.0071
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$EPbus_t$	0.5208	0.3144	0.0982	0.0463	0.0204
	(0.0035)	(0.0034)	(0.0019)	(0.0013)	(0.0009)
$EPvol_t$	0.3525	0.0661	0.5340	0.0139	0.0335
	(0.0027)	(0.0013)	(0.0029)	(0.0006)	(0.0009)
U_t	0.2330	0.0484	0.0224	0.5789	0.1173
	(0.0026)	(0.0013)	(0.0009)	(0.0032)	(0.0020)
I_t	0.2108	0.0149	0.0348	0.0850	0.6545
	(0.0023)	(0.0006)	(0.0009)	(0.0015)	(0.0028)
Observations	1,909,410				
N. of individuals	670,543				

B) Wage < \$15 / hour

	EF_{t+1}	$EPbus_{t+1}$	$EPvol_{t+1}$	U_{t+1}	I_{t+1}
EF_t	0.9410	0.0195	0.0179	0.0094	0.0121
	(0.0005)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
$EPbus_t$	0.4705	0.3472	0.1129	0.0472	0.0222
	(0.0057)	(0.0057)	(0.0034)	(0.0023)	(0.0015)
$EPvol_t$	0.3250	0.0872	0.5324	0.0177	0.0378
	(0.0046)	(0.0026)	(0.0051)	(0.0012)	(0.0017)
U_t	0.2082	0.0592	0.0303	0.5512	0.1511
	(0.0046)	(0.0026)	(0.0018)	(0.0059)	(0.0039)
I_t	0.1759	0.0185	0.0384	0.0930	0.6742
	(0.0036)	(0.0012)	(0.0017)	(0.0027)	(0.0046)
Observations	336,610				
N. of individuals	118,429				

C) Wage $\in [15, 30)$ / hour

	EF_{t+1}	$EPbus_{t+1}$	$EPvol_{t+1}$	U_{t+1}	I_{t+1}
EF_t	0.9703	0.0092	0.0074	0.0061	0.0069
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
$EPbus_t$	0.5429	0.3004	0.0867	0.0523	0.0176
	(0.0075)	(0.0073)	(0.0038)	(0.0030)	(0.0018)
$EPvol_t$	0.3410	0.0624	0.5529	0.0157	0.0279
	(0.0061)	(0.0030)	(0.0066)	(0.0015)	(0.0019)
U_t	0.2413	0.0442	0.0191	0.5934	0.1021
	(0.0051)	(0.0023)	(0.0015)	(0.0061)	(0.0035)
I_t	0.2235	0.0136	0.0248	0.0946	0.6435
	(0.0049)	(0.0013)	(0.0017)	(0.0033)	(0.0060)
Observations	465,274				
N. of individuals	163,190				

Notes: This table reports transition rates between employment states for a matched panel of CPS respondents over their fifth through eighth survey waves. EF stands for full-time employment, EPbus stands for part time for economic reasons, EPvol stands for part time for voluntary reasons, U stands for unemployed, and I stands for inactive / out of the labor force. Standard errors are clustered at the respondent level and are calculated by fitting a multinomial logistic regression with the employment state at $t + 1$ as the dependent variable and as independent variables indicators for the state at t. A separate regression was estimated for each wage level. The sample includes all individuals working full-time during wave four. Wages are adjusted to January 2020 equivalents using the CPI.

G Oaxaca-Blinder decomposition of job loss effects

The long-run effects of job loss on wage earnings for low-wage and higher-wage workers reported in Tables 3 and 5, respectively, can be decomposed to components attributed to any wages, weeks worked, usual weekly hours, and average hourly wage.

Let e_i denote wage earnings reported in the ACS. Let k_i^d, $\bar{h}_i^d$, $\bar{w}_i^d$ denote average weeks worked, usual weekly hours worked, and average hourly wages of $d \in [0,1]$ type compliers. The effect of job loss on long-run wage earnings reported in the ACS (i.e., the 2SLS estimates in Tables 3 and 5) can be written as:

$$
\begin{aligned}
&E[e_i^1] - E[e_i^0] = \\
&\Pr(e_i^1 > 0) \cdot Cov(k_i^1, \bar{h}_i^1 \cdot \bar{w}_i^1 | e_i^1 > 0) - \Pr(e_i^0 > 0) \cdot Cov(k_i^0, \bar{h}_i^0 \cdot \bar{w}_i^0 | e_i^0 > 0) \\
&+ \\
&\Pr(e_i^1 > 0) \cdot E[k_i^1 | e_i^1 > 0] \cdot Cov(\bar{h}_i^1, \bar{w}_i^1 | e_i^1 > 0) - \Pr(e_i^0 > 0) \cdot E[k_i^0 | e_i^0 > 0] \cdot Cov(\bar{h}_i^0, \bar{w}_i^0 | e_i^0 > 0) \\
&+ \\
&\left[Pr(e_i^1 > 0) \cdot E[k_i^1 | e_i^1 > 0] - Pr(e_i^0 > 0) \cdot E[k_i^0 | e_i^0 > 0]\right] \cdot E[\bar{h}_i^1 | e_i^1 > 0] E[\bar{w}_i^1 | e_i^1 > 0] \\
&+ \\
&\left[E[\bar{h}_i^1 | e_i^1 > 0] E[\bar{w}_i^1 | e_i^1 > 0] - E[\bar{h}_i^0 | e_i^0 > 0] E[\bar{w}_i^0 | e_i^0 > 0]\right] \cdot Pr(e_i^0 > 0) \cdot E[k_i^0 | e_i^0 > 0]
\end{aligned}
$$

The last two expressions can be further decomposed into two extensive margin components and two intensive margin components. And the last term can be decomposed to an hours and hourly wages component. Thus, the above last two terms can be decomposed further into:

$$
\begin{aligned}
&E[e_i^1] - E[e_i^0] = \\
&\text{Selection covariances terms} \\
&+ \\
&\big[Pr(e_i^1 > 0) - Pr(e_i^0 > 0)\big] \cdot E[k_i^1|e_i^1 > 0]E[\bar{h}_i^1|e_i^1 > 0]E[\bar{w}_i^1|e_i^1 > 0] \\
&+ \\
&\big[E[k_i^1|e_i^1 > 0] - E[k_i^0|e_i^0 > 0]\big] \cdot Pr(e_i^0 > 0)E[\bar{h}_i^1|e_i^1 > 0]E[\bar{w}_i^1|e_i^1 > 0] \\
&+ \\
&\big[E[\bar{h}_i^1|e_i^1 > 0] - E[\bar{h}_i^0|e_i^0 > 0]\big] \cdot E[\bar{w}_i^1|e_i^1 > 0]Pr(e_i^0 > 0) \cdot E[k_i^0|e_i^0 > 0] \\
&+ \\
&\big[E[\bar{w}_i^1|e_i^1 > 0] - E[\bar{w}_i^0|e_i^0 > 0]\big] \cdot E[\bar{h}_i^0|e_i^0 > 0]Pr(e_i^0 > 0) \cdot E[k_i^0|e_i^0 > 0]
\end{aligned}
$$

The estimate in the bottom line of Table 6 reports the share of the total effect of job loss that can be explained by reductions in the average hourly wage if working:

$$
\frac{[E[\bar{w}_i^1|e_i^1 > 0] - E[\bar{w}_i^0|e_i^0 > 0]] \cdot E[\bar{h}_i^0|e_i^0 > 0] \cdot E[k_i^0|e_i^0 > 0]Pr(e_i^0 > 0)}{E[e_i^1] - E[e_i^0]} \tag{G.1}
$$