ONLINE APPENDIX FOR "UNDERSTANDING THE SCARRING EFFECT OF RECESSIONS"

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Date: November 2, 2021.
Webpage: `https://christopher-huckfeldt.github.io/`.

Appendix A. Empirical appendix

A.1. **Data construction.** I follow Farber (2015) closely in construction of the DWS sample. The CPS reports weekly, not hourly, earnings for workers in the DWS. To minimize variation in earnings losses due to hours variation across jobs, I restrict my sample to workers who are employed full-time on their pre and post-displacement jobs. I drop workers whose weekly earnings are top coded, or whose full-time status and earnings imply they earn less than the minimum wage. I exclude self-employed workers. Earnings on the lost job are deflated using the average CPI the year of job loss. Earnings on the new job are deflated using the CPI the month and year of the interview. Survey respondents were asked about displacement events in the previous five years for the 1984-1992; subsequently, they were asked only about displacement events in the previous three years. To maintain comparability across surveys, I drop observations where the displacement event occurred more than three years before the survey date.

To create the occupation wage ranking for use with the CPS, I use the Autor and Dorn (2013) occupation codes to link the CPS to the Census and American Community Survey. I then use average occupation wages computed by Autor and Dorn (2013) from the 2000 Census. No two occupations have exactly the same average wage. Hence, the union of the upwards and downwards occupation switchers in the sample exactly comprise the set of occupation switchers.

The PSID is a longitudinal dataset with a long panel dimension that has been a workhorse for studying earnings and hours dynamics, e.g. Altonji et al. (2013). While the PSID lacks an instrument to identify exogenous separations similar to that offered by the DWS, it offers a sufficiently long panel for tracking the long-term effects of job displacement: see Topel (1990), Ruhm (1991), and Stevens (1997) for similar studies that use the PSID.

The construction of the PSID sample follows Stevens (1997) closely, but with several slight differences. Relative to Stevens (1997), I use an expanded sample with data from 1968 to 1997. Stevens drops individuals who were not present for the entirety of her sample. Given the longer duration of my sample, such a selection criterion would effectively constrain my analysis to a single cohort. Hence, I follow much of the other papers studying displacement and do not use a balanced panel. The rest of the sample construction is similar. I limit the analysis to household heads (for whom the most income data is available), restricting the sample to be predominantly male. I generate variables for involuntary job displacement using a survey question that is asked of respondents who are either without a job or have been employed in their current job for less than a year. Following Stevens (1997), I define an involuntary job loss as a separation due to company closing, layoff, or firing. The

1968 survey identifies workers who have been laid off or fired within the past ten years. Since it is not possible to determine when in the past ten years they were displaced, I drop these individuals from the sample.

A.2. **Relationship to the literature: Additional Remarks.** The main paper offers substantial detail about the relation of my empirical findings to the vast literature on displaced workers. However, I offer some additional remarks here.

A.2.1. *Relation to Robinson (2018).* As stated in the main text, this paper is not the first to consider the role of occupation switching in accounting for the cost of job loss. However, this paper is the first to document that the explanatory power of occupation switching for the cyclical cost of job loss is encoded along the vertical direction of the switch, as defined by average wages.

Robinson (2018) establishes a compatible but distinct finding on occupational sorting among displaced workers: Robinson situates occupations within a four-dimensional task space and then develops a notion by which to evaluate the distance and direction of occupation changes within this task space. Robinson finds that displaced workers suffer greater earnings losses if they make "negative" changes in occupation within the task space.

The findings of Section 1.3 and those of Robinson (2018) are distinct: neither finding implies the other. The measures of distance and direction over the four-dimensional task space of Robinson (2018) do not perfectly correlate with the ranking of occupations by average wages. Moreover, the empirical framework of Robinson (2018) emphasizes the importance of "skill portfolios," which highlights the importance of multi-dimensional sorting. In contrast, the findings of Section 1.3 are consistent with models of vertical sorting under absolute advantage along a single dimension of worker skill, à la Groes et al. (2015).

A.2.2. *How important are firm effects?* Four prominent papers in the literature consider the explanatory power of firm effects for the earnings cost of job loss: Moore and Scott-Clayton (2019), who use data for Ohio; Raposo et al. (2019), who use data from Portugal; Lachowska et al. (2020), who use data from Washington State for the period around the Great Recession; and Schmieder et al. (2020), who use data from Germany. Two of these papers, Raposo et al. (2019) and Schmieder et al. (2020), also have information on either occupation or job-title.

Firm effects only appear to play a strong explanatory role in the German context. Although Schmieder et al. (2020) document that occupations have explanatory power over earnings losses, this goes away once controls for firm effects are introduced to the regression. In contrast, Raposo et al. (2019) find that job titles have greater explanatory power than firm effects.

Moore and Scott-Clayton (2019) and Lachowska et al. (2020) find only a modest role for firm effects in the United States context. However, neither study is able to control for occupation. Thus, Lachowska et al. (2020) conclude that "match-specific factors are the main mechanism behind displaced worker's long-term wage losses" (pg. 3234). The channel emphasized here offers one such match-specific factor, as occupation is not a fixed characteristic of either an establishment or an individual.

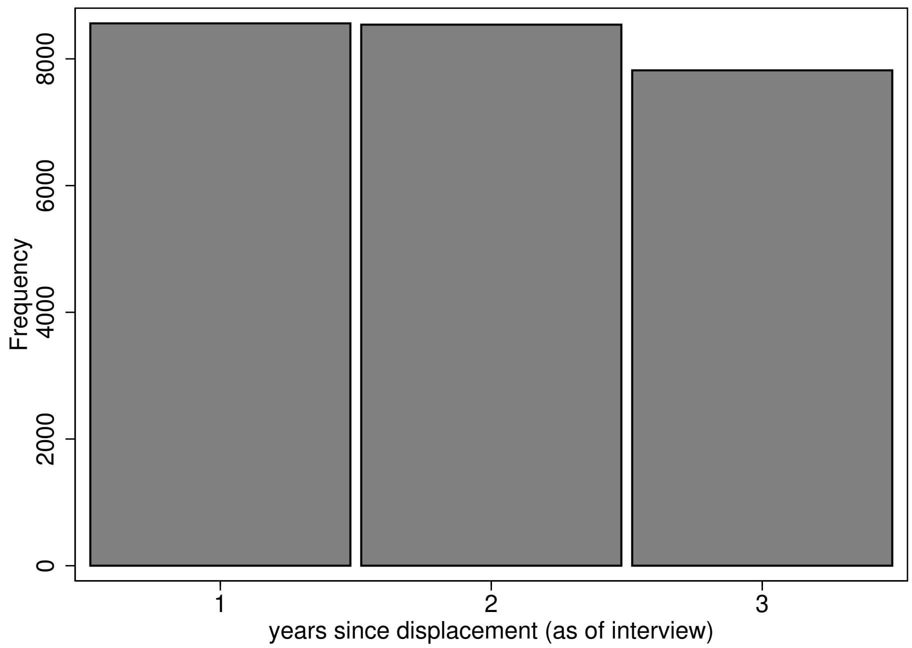
A.2.3. *Hours losses.* This paper focuses on lost wages as the determinant factor for earnings losses. This focus is supported by findings from earlier papers using the PSID to study long-run earnings and wage losses from displacement. Most notably, Stevens (1997) finds that earnings losses and wage losses converge within three to four years of displacement. Similarly, Altonji et al. (2013, pg. 1438) estimate that hours recover within two years of an "unemployment shock" (see Figure 3, bottom pane) even as wage losses persist.

Although the paper by Stevens (1997) focuses on the role of repeated displacement, the paper has been cited by other author for documenting a relatively quick hours recovery. For example, in assessing the relatively slow employment rates of college graduates entering the labor market during a recession, Altonji et al. (2016, pg. S379) write, "One might have expected a more persistent effect on wages than earnings in view of the evidence on the consequences of layoffs, which shows that employment and work hours recover fairly quickly following a layoff but wage losses persist. See, e.g., Stevens (1997) and Altonji, Smith, and Vidangos (2013)."

Recent work using administrative data documents similarly quick hours recoveries. For example, Lachowska et al. (2020) find a quantitative small role for hours losses in explaining the earnings cost of job loss; and they argue that these hours losses are likely due to increased part-time work rather than reduced attachment to employment. In describing their findings, Lachowska et al. (2020, pg. 3248) conclude, "Qualitatively, these estimates are similar to work by Topel (1990) and Stevens (1997) using the Panel Study of Income Dynamics, which showed that reduced work time plays a relatively minor role in explaining the long-term losses of displaced workers."

How does one reconcile the coexistence of multiple displacements à la Stevens (1997) with a quantitatively small role for hours losses à la Stevens (1997)? If displaced workers are willing to take easy-to-find but insecure "stop-gap" employment subsequent to job loss, such stop-gap work may well reduce the total amount of time a worker spends non-employed. This is an empirical question, however, that goes beyond the scope of this paper.

FIGURE A.1. CPS DWS: Histogram of years since displacement, estimation sample



A.3. **Histograms of DWS samples.**

Figure A.2. CPS DWS: Histogram of displacement year, estimation sample

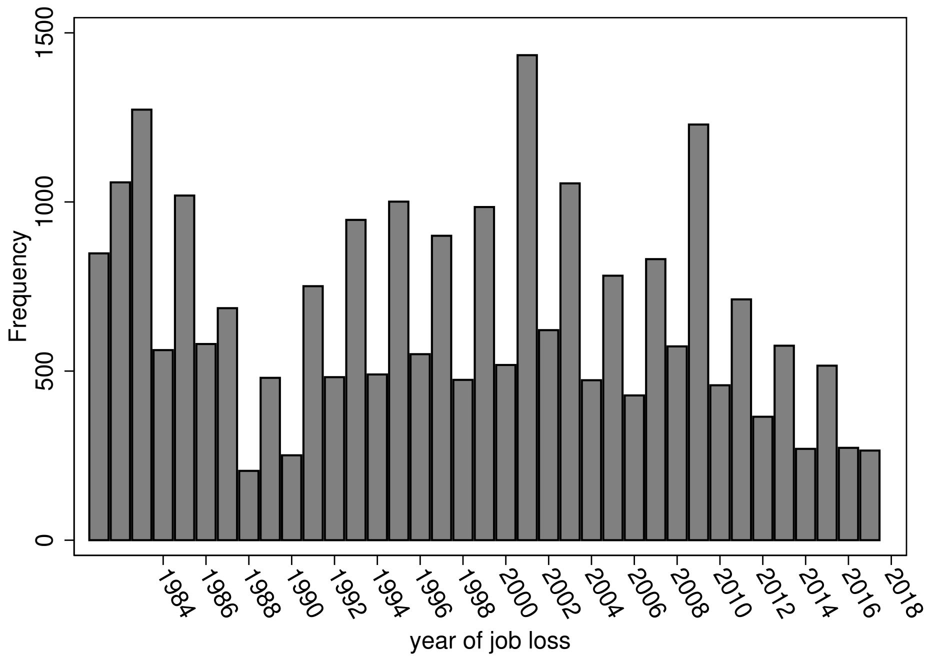


FIGURE A.3. CPS DWS: Histogram of displacement year, estimation sample, interviewed within two years of displacement

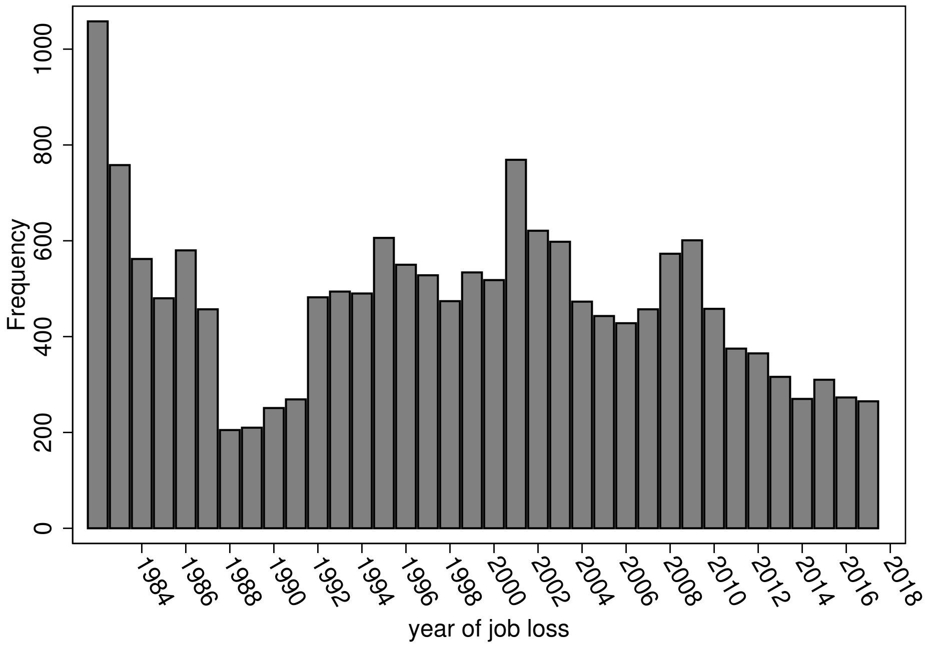
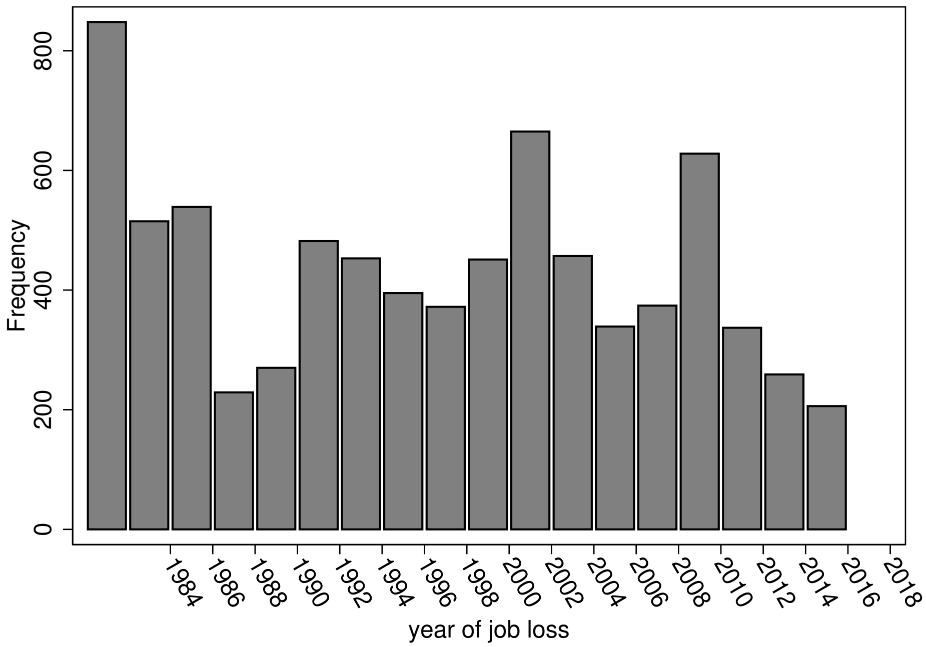


Figure A.4. CPS DWS: Histogram of displacement year, estimation sample, interviewed more than two years past displacement



A.4. **Cost of job loss from CPS DWS.** Write the regression equations for Tables 5 and 6 as

$$\mathbb{I}\left\{\mathrm{AD}{\downarrow}_{it}\right\} = \alpha_0 + x_{it}'\alpha_x + \alpha_{rec}\cdot\mathbb{I}\left\{\mathrm{Rec}_{it}\right\} + \varepsilon_{it} \tag{1}$$

$$\begin{aligned}\Delta\log w_{it} &= \beta_0 + x_{it}'\beta_x + \beta_{rec}\cdot\mathbb{I}\left\{\mathrm{Rec}_{it}\right\} + \beta_{sw}\cdot\mathbb{I}\left\{\mathrm{AD}{\downarrow}_{it}\right\} \\ &\quad + \beta_{sw,rec}\cdot\mathbb{I}\left\{\mathrm{AD}{\downarrow}_{it}\right\}\cdot\mathbb{I}\left\{\mathrm{Rec}_{it}\right\} + \epsilon_{it}\end{aligned} \tag{2}$$

The implied average cost of job loss during expansions can be expressed as

$$c_{exp} = \beta_0 + \alpha_0\cdot\beta_{sw}, \tag{3}$$

where β_0 is the average earnings losses of non-switchers, β_{sw} is the average earnings losses of switchers, and α_0 is the fraction of switchers. Similarly, the average cost of job loss during recessions can be expressed as

$$c_{rec} = \beta_0 + \beta_{rec} + \left(\alpha_0 + \alpha_{rec}\right)\left(\beta_{sw} + \beta_{sw,rec}\right), \tag{4}$$

where $\beta_0 + \beta_{rec}$ is the average earnings losses of non-switchers, $\beta_{sw} + \beta_{rec} + \beta_{sw} + \beta_{sw,rec}$ is the average earnings losses of switchers, and $\alpha_0 + \alpha_{rec}$ is the fraction of switchers.

Denote the component of the cost of job loss in recessions over expansions shared to both switchers and non-switchers to be

$$\frac{c_{rec}^{sh}}{c_{exp}^{sh}} = \frac{\beta_0 + \beta_{rec}}{\beta_0}$$

Denote the contribution of switchers to the cost of job loss in recessions over expansions as

$$\frac{c_{rec}^{sw}}{c_{exp}^{sw}} = \frac{\left(\alpha_0 + \alpha_{rec}\right)\left(\beta_{sw} + \beta_{sw,rec}\right)}{\alpha_0\beta_{sw}}$$

Then, we can write the average cost of job loss in recession over expansions as

$$\frac{c_{exp}}{c_{rec}} = \omega\cdot\left(\frac{c_{rec}^{sh}}{c_{exp}^{sh}}\right) + (1-\omega)\cdot\left(\frac{c_{rec}^{sw}}{c_{exp}^{sw}}\right)$$

where $\omega = \frac{\beta_0}{\beta_0 + \alpha_0\cdot\beta_{sw}}$.

A.5. **Occupational wage changes.** The empirical results document that earnings losses are greater for displaced workers who find reemployment in a lower-paying occupation. Here, I offer a brief discussion on the extent to which the distance of pre- and post-displacement occupations, as measured by difference in log average occupational wages, influences earnings losses.

Table A.1 shows the estimates from a regression of the log difference of average wages of pre- and post-displacement occupation on a set of controls, including an indicator for whether job-displacement occurred during a recession year. The regression is repeated across several sub-samples of the full sample. Here, we see that workers who lose their job during a recession make larger downward moves in occupation, as measured by the average hourly wage of the pre- and post-displacement occupation. It is interesting to compare the coefficient on the indicator variable for "Recession" reported in Table A.1 with similar coefficients from Tables 1 and 4. In all instances, the earnings losses associated with switching occupation exceeds the associated change in average wages across the pre- and post-displacement occupations. Combined, these results suggest that workers switch from particularly good jobs of their previous occupation, and/or switch to particularly bad jobs of their current occupation. Simply put, whether or not a displaced worker switches to a lower-paying occupation has explanatory power for earnings outcomes that goes beyond the "extent" of the occupation changes.

This issue receives further consideration in Table A.2. Here, I consider the simultaneous impact of occupation downgrading and the extent of occupation changes (again measured by log differences in average hourly wages across occupations) on earnings losses. Several patterns emerge: in the full sample, the effect of the extent of occupation changes appears to be attenuated when the regression also controls for the occurrence of occupation downgrading: e.g., compare columns one and two. This is not the case, however, for workers observed more than two years subsequent to job displacement: e.g., compare columns five and six.[1]

Figure A.5 offers kernel densities for changes in occupation switching distances among occupation switchers, as measured by the log difference in average wages of pre- and post-displacement occupation. At short horizons, there is no particular pattern in occupation distances for recessions versus expansions. For longer horizons, however, we see that occupation-switching workers displaced during a recession are uniformly less likely to be observed at higher-paying occupations; and there is a substantially higher mass of workers observed making occupation switches associated with particularly large reductions in log average hourly occupational wages.

[1]Of course, the regressors are highly correlated, and hence the results should be interpreted with caution.

Table A.1. Occupational wage changes among occupation switchers

Dependent variable: log difference of average wages of pre-displacement and current occupation

	All workers		Displaced more than two years prior to survey	
	(1)	(2)	(3)	(4)
Recession	−0.021**	−0.018**	−0.034***	−0.028**
	(0.0081)	(0.0079)	(0.0085)	(0.0130)
Constant	−0.047***	−0.039***	−0.008	−0.011
	(0.0119)	(0.0106)	(0.0175)	(0.0140)
N	9,757	16,372	2,799	5,342
R^2	0.006	0.005	0.010	0.012
First jobs only?	Yes	No	Yes	No

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses.

TABLE A.2. Earnings losses and mean occupational wage changes

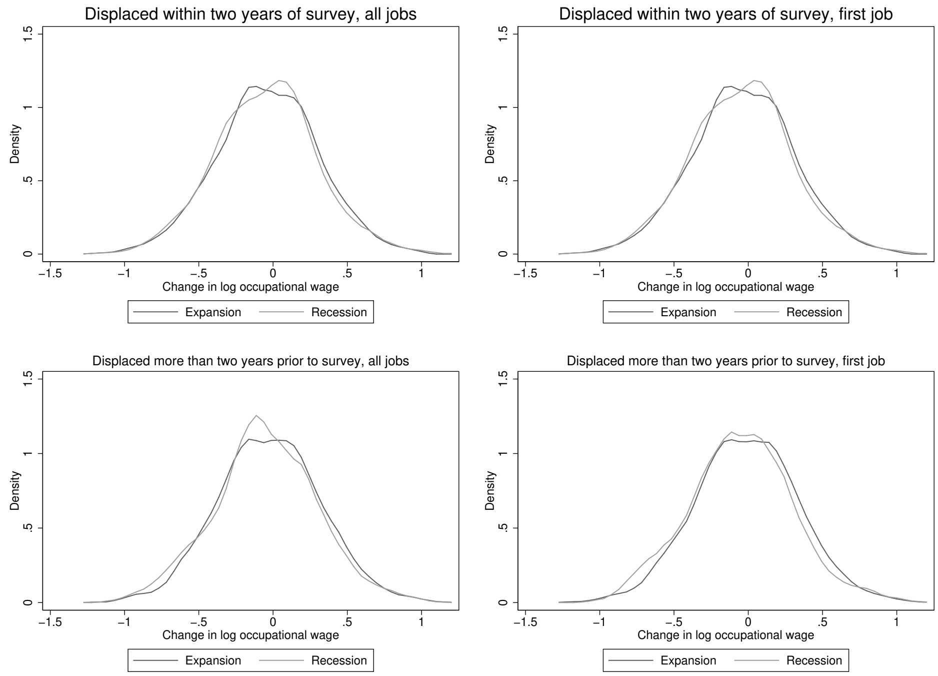
Dependent variable: log difference of pre-displacement and current real weekly earnings

	All workers				Displaced more than two years prior to survey			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log \bar{w}^{\text{occ}}$	0.256***	0.180***	0.279***	0.205***	0.268***	0.238***	0.269***	0.226***
	(0.0184)	(0.0276)	(0.0160)	(0.0214)	(0.0364)	(0.0500)	(0.0274)	(0.0386)
$\Delta \log \bar{w}^{\text{occ}} \times$ Recession	−0.068**	−0.068**	−0.004	0.004	−0.116**	−0.067	−0.088*	−0.020
	(0.0289)	(0.0308)	(0.0386)	(0.0349)	(0.0479)	(0.0746)	(0.0455)	(0.0524)
Switch ↓	—	−0.063***	—	−0.062***	—	−0.026	—	−0.037*
		(0.0115)		(0.0078)		(0.0236)		(0.0190)
Switch ↓ × Recession	—	0.000	—	−0.007	—	−0.042	—	−0.058***
		(0.0282)		(0.0183)		(0.0309)		(0.0200)
Recession	−0.057***	−0.056***	−0.056***	−0.053***	−0.091***	−0.077***	−0.070***	−0.048***
	(0.0083)	(0.0103)	(0.0091)	(0.0087)	(0.0126)	(0.0122)	(0.0154)	(0.0141)
Constant	−0.079***	−0.064***	−0.078***	−0.063***	−0.025	−0.018	−0.065***	−0.055***
	(0.0144)	(0.0140)	(0.0102)	(0.0100)	(0.0179)	(0.0155)	(0.0157)	(0.0149)
N	15,245	15,245	24,809	24,809	4,256	4,256	7,792	7,792
R^2	0.062	0.065	0.061	0.064	0.093	0.094	0.077	0.080
First jobs only?	Yes	Yes	No	No	Yes	Yes	No	No

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

FIGURE A.5. Kernel density for changes in average occupation wages



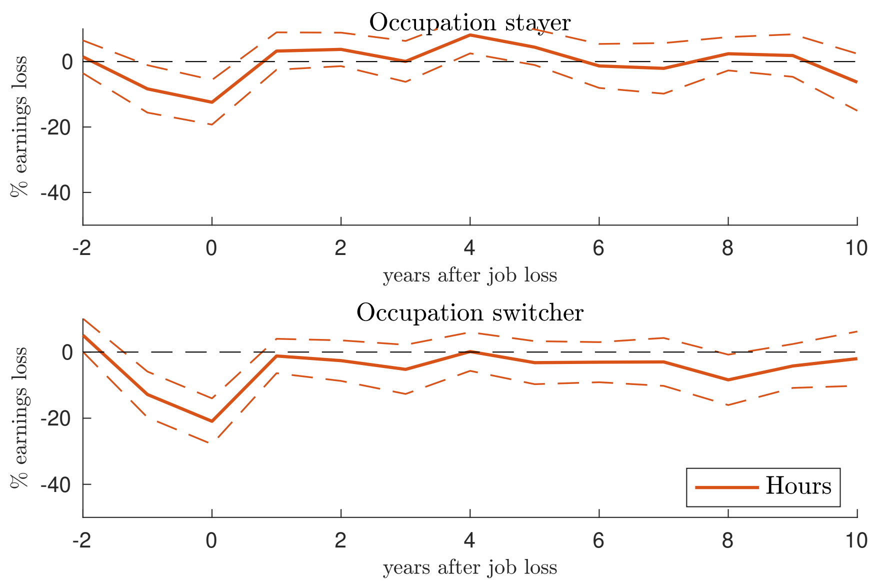
A.6. **Cost of job loss for workers displaced due to firm shutdown.** In Section 1.5 of the main paper, I identify displaced workers from the PSID as workers who lose their job either because they are fired, or because their firm went out-of-business, following Stevens (1997). However, one might be curious whether these findings hold for only for workers who lose their job due to firm shutdown.

Figures A.6 and A.7 are analogous to figures 1 and 2 of the main text, but only include workers who lose their job due to firm shutdown. Although the smaller number of displaced workers makes the confidence bands wider, one can see that the same pattern arises: earnings and wage losses in the long-run are only severe for workers who lose their job and find reemployment in a job of a different occupation. Hours losses are mild in the long-run, both for occupation-stayers and switchers and stayers; but occupation switchers have larger employment losses immediately following job loss.

Figure A.6. Earnings and wage losses are more persistent for occupation switchers: shutdowns only

Estimates come from PSID. The figure only includes workers who lose their job due to firm shutdown as displaced workers. Dashed lines represent 95% confidence intervals around estimates.

FIGURE A.7. Longer hours recoveries for occupation switchers: shutdowns only



Estimates come from PSID. The figure only includes workers who lose their job due to firm shutdown as displaced workers. Dashed lines represent 95% confidence intervals around estimates.

TABLE A.3. Immediate earnings losses are higher for occupation switchers: with occupation/industry/year fixed-effects for displacement job

Dependent variable: log difference of pre-displacement and current real weekly earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Switcher	-0.067^{***}	-0.075^{***}	-0.071^{***}	-0.140^{***}	-0.129^{***}	-0.154^{***}
	(0.0073)	(0.0055)	(0.0058)	(0.0064)	(0.0075)	(0.0087)
Recession	-0.024^{***}	-0.025^{***}	-0.025^{***}	-0.024^{***}	-0.025^{***}	-0.025^{***}
	(0.0088)	(0.0088)	(0.0087)	(0.0084)	(0.0086)	(0.0088)
Constant	0.045	0.079	0.075	0.095^{**}	0.044	0.052
	(0.0610)	(0.0582)	(0.0582)	(0.0420)	(0.0592)	(0.0594)
N	24,822	24,822	24,822	24,822	24,822	24,822
Occ. def.	CPS/Broad	CPS/Fine	AD	AD↓	AD6↓	AD3↓

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

A.7. **Robustness of empirical results.**

- Tables A.3 and A.4 establish that the results of Table 1 are robust to the inclusion of occupation/industry/year fixed-effects.
- Table A.5 establishes that the pattern of countercyclical occupation displacement is due to aggregate conditions the year of displacement, not the year that the worker is observed.
- The theory predicts a stronger relationship of occupation displacement to aggregate conditions at the time of displacement for the worker's first job from unemployment. Tables A.6, A.7, A.8, and A.9 offer the same results as Tables 1, 2, 3, and 4 of the main text, but for workers who report being on their first job since job displacement.
- Tables A.10, A.11, A.13, A.12, A.14, and A.15 replicate the analysis of Tables 1, 2, 3, 4, 5, and 6, but use a variable measuring the fraction of the displacement year classified as an NBER recession rather than a simple indicator variable for NBER recession.

Table A.4. Immediate earnings losses are higher for occupation switchers: with occupation/industry/year fixed-effects for post-displacement job

Dependent variable: log difference of pre-displacement and current real weekly earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Switcher	-0.051^{***}	-0.065^{***}	-0.061^{***}	-0.127^{***}	-0.103^{***}	-0.117^{***}
	(0.0067)	(0.0058)	(0.0060)	(0.0079)	(0.0094)	(0.0099)
Recession	-0.036^{***}	-0.036^{***}	-0.036^{***}	-0.035^{***}	-0.037^{***}	-0.038^{***}
	(0.0090)	(0.0090)	(0.0089)	(0.0086)	(0.0089)	(0.0089)
Constant	0.040	0.079	0.075	0.096	0.042	0.014
	(0.0739)	(0.0772)	(0.0767)	(0.0685)	(0.0778)	(0.0732)
N	24,920	24,920	24,920	24,920	24,920	24,920
Occ. def.	CPS/Broad	CPS/Fine	AD	AD↓	AD6↓	AD3↓

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.5. Countercyclical occupation switching of displaced workers: the role of contemporary conditions

	(1)	(2)	(3)	(4)	(5)	(6)
Recession at displacement	0.034***	0.032***	0.033***	0.030***	0.016**	0.020***
	(0.0111)	(0.0089)	(0.0088)	(0.0091)	(0.0070)	(0.0050)
Recession at survey year	−0.041***	0.006	0.002	0.002	−0.020	−0.009
	(0.0129)	(0.0067)	(0.0074)	(0.0090)	(0.0135)	(0.0073)
Constant	0.341***	0.555***	0.525***	0.280***	0.120***	0.096***
	(0.0181)	(0.0187)	(0.0182)	(0.0129)	(0.0100)	(0.0090)
N	15,325	15,325	15,325	15,325	15,325	15,325
R^2	0.016	0.011	0.013	0.006	0.009	0.006
Occ. def.	CPS/Broad	CPS/Fine	AD	AD↓	AD6↓	JS3↓

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. “AD” occupation coding adopted from “occ1990dd” codes from Autor and Dorn (2013). First job sample. Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.6. Immediate earnings losses are higher for occupation switchers: first job sample

Dependent variable: log difference of pre-displacement and current real weekly earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Switcher	-0.058^{***}	-0.066^{***}	-0.061^{***}	-0.065^{***}	-0.073^{***}	-0.068^{***}
	(0.0073)	(0.0057)	(0.0062)	(0.0070)	(0.0053)	(0.0056)
Recession	-0.060^{***}	-0.060^{***}	-0.060^{***}	-0.059^{***}	-0.059^{***}	-0.059^{***}
	(0.0094)	(0.0094)	(0.0094)	(0.0091)	(0.0090)	(0.0090)
Constant	-0.040^{***}	-0.023^{***}	-0.027^{***}	-0.065^{***}	-0.047^{***}	-0.052^{***}
	(0.0078)	(0.0079)	(0.0078)	(0.0152)	(0.0149)	(0.0147)
N	15,325	15,325	15,325	15,325	15,325	15,325
Occ. def.	CPS/Broad	CPS/Fine	AD	CPS/Broad	CPS/Fine	AD
Controls?	No	No	No	Yes	Yes	Yes
Predicted loss: Switcher/Stayer	2.43	3.89	3.24	2.00	2.57	2.33

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.7. Occupation switching is countercyclical for displaced workers: first job sample

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)	(4)	(5)	(6)
Recession	0.027***	0.029***	0.028***	0.038***	0.031***	0.033***
	(0.0096)	(0.0082)	(0.0081)	(0.0114)	(0.0084)	(0.0084)
Constant	0.445***	0.655***	0.636***	0.338***	0.555***	0.525***
	(0.0067)	(0.0053)	(0.0056)	(0.0186)	(0.0187)	(0.0182)
N	15,325	15,325	15,325	15,325	15,325	15,325
Occ. def.	CPS/Broad	CPS/Fine	AD	CPS/Broad	CPS/Fine	AD
Controls?	No	No	No	Yes	Yes	Yes

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.8. The verticality of countercyclical occupation displacement: first job sample

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)	(4)	(5)	(6)
Recession	0.029***	0.004	0.018***	0.008	0.021***	−0.001
	(0.0088)	(0.0121)	(0.0070)	(0.0101)	(0.0051)	(0.0071)
Constant	0.280***	0.245***	0.119***	0.075***	0.096***	0.061***
	(0.0129)	(0.0139)	(0.0100)	(0.0094)	(0.0091)	(0.0085)
N	15,325	15,325	15,325	15,325	15,325	15,325
Occ. def.	AD↓	AD↑	AD6↓	AD6↑	JS3↓	JS3↑

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. “AD” occupation coding adopted from “occ1990dd” codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.9. Vertical displacement and re-employment earnings losses: first job sample

Dependent variable: log difference of pre-displacement and current real weekly earnings

	(1)	(2)	(3)
Switch ↑	0.009	0.015	0.028**
	(0.0081)	(0.0125)	(0.0129)
Switch ↓	−0.134***	−0.116***	−0.125***
	(0.0071)	(0.0101)	(0.0102)
Recession	−0.058***	−0.060***	−0.059***
	(0.0089)	(0.0088)	(0.0088)
Constant	−0.052***	−0.075***	−0.077***
	(0.0148)	(0.0146)	(0.0147)
N	15,325	15,325	15,325
Occ. def.	AD	AD6	JS3
Predicted loss: Switcher/Stayer	3.59	2.55	2.62

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.10. Immediate earnings losses are higher for occupation switchers: fraction of year in recession

Dependent variable: log difference of pre-displacement and current real weekly earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Switcher	-0.057^{***}	-0.069^{***}	-0.064^{***}	-0.065^{***}	-0.077^{***}	-0.072^{***}
	(0.0064)	(0.0055)	(0.0057)	(0.0064)	(0.0052)	(0.0053)
Recession Frac.	-0.074^{***}	-0.074^{***}	-0.074^{***}	-0.078^{***}	-0.078^{***}	-0.078^{***}
	(0.0234)	(0.0234)	(0.0234)	(0.0207)	(0.0211)	(0.0210)
Constant	-0.056^{***}	-0.036^{***}	-0.041^{***}	-0.062^{***}	-0.042^{***}	-0.046^{***}
	(0.0071)	(0.0074)	(0.0070)	(0.0111)	(0.0109)	(0.0108)
N	24,920	24,920	24,920	24,920	24,920	24,920
Occ. def.	CPS/Broad	CPS/Fine	AD	CPS/Broad	CPS/Fine	AD
Controls?	No	No	No	Yes	Yes	Yes
Predicted loss: Switcher/Stayer	2.01	2.90	2.56	2.05	2.86	2.56

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.11. Occupation switching is countercyclical for displaced workers: fraction of year in recession

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)	(4)	(5)	(6)
Recession frac.	0.057***	0.040***	0.043***	0.042***	0.030***	0.032***
	(0.0178)	(0.0142)	(0.0148)	(0.0072)	(0.0102)	(0.0083)
Constant	0.461***	0.671***	0.654***	0.332***	0.546***	0.519***
	(0.0048)	(0.0043)	(0.0045)	(0.0145)	(0.0149)	(0.0144)
N	24,920	24,920	24,920	24,920	24,920	24,920
Occ. def.	CPS/Broad	CPS/Fine	AD	CPS/Broad	CPS/Fine	AD
Controls?	No	No	No	Yes	Yes	Yes

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.12. Vertical displacement and re-employment earnings losses: fraction of year in recession

Dependent variable: log difference of pre-displacement and current real weekly earnings

	(1)	(2)	(3)
Switch ↑	0.010	0.017*	0.038***
	(0.0069)	(0.0094)	(0.0111)
Switch ↓	−0.140***	−0.119***	−0.135***
	(0.0067)	(0.0082)	(0.0087)
Recession frac.	−0.074***	−0.077***	−0.078***
	(0.0204)	(0.0208)	(0.0206)
Constant	−0.049***	−0.072***	−0.074***
	(0.0105)	(0.0107)	(0.0108)
N	24,920	24,920	24,920
Occ. def.	AD	AD6	AD3
Predicted loss: Switcher/Stayer	3.88	2.64	2.81

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.13. The verticality of countercyclical occupation displacement: fraction of year in recession

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)	(4)	(5)	(6)
Recession	0.045***	−0.012	0.031***	0.012	0.023***	0.004
	(0.0134)	(0.0104)	(0.0073)	(0.0074)	(0.0089)	(0.0092)
Constant	0.269***	0.250***	0.110***	0.081***	0.089***	0.067***
	(0.0117)	(0.0112)	(0.0069)	(0.0073)	(0.0072)	(0.0072)
N	24,920	24,920	24,920	24,920	24,920	24,920
Occ. def.	AD↓	AD↑	AD6↓	AD6↑	AD3↓	AD3↑

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.14. Vertical occupation displacement in the short- and medium-run: fraction of year in recession

Dependent variable: indicator for AD↓ occupation switcher

	Displaced within two years of survey		Displaced more than two years prior to survey	
	(1)	(2)	(3)	(4)
Recession	0.032***	0.032***	0.094***	0.086***
	(0.0120)	(0.0117)	(0.0220)	(0.0208)
Constant	0.286***	0.278***	0.302***	0.282***
	(0.0095)	(0.0106)	(0.0133)	(0.0114)
N	17,101	11,052	7,819	4,273
R^2	0.007	0.006	0.007	0.009
First jobs only?	No	Yes	No	Yes

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. “AD” occupation coding adopted from “occ1990dd” codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Table A.15. Short- and medium-run earnings losses of vertical displacement: fraction of year in recession

Dependent variable: log difference of pre-displacement and current real weekly earnings

	Displaced within two years of survey		Displaced more than two years prior to survey	
	(1)	(2)	(3)	(4)
AD↓	−0.152***	−0.141***	−0.125***	−0.118***
	(0.0079)	(0.0077)	(0.0150)	(0.0193)
AD↓ × Recession frac.	0.059***	0.033	−0.127***	−0.122***
	(0.0145)	(0.0281)	(0.0343)	(0.0441)
Recession frac.	−0.075***	−0.061***	−0.104***	−0.124***
	(0.0115)	(0.0133)	(0.0288)	(0.0248)
Constant	−0.054***	−0.029**	−0.023	0.015
	(0.0184)	(0.0131)	(0.0152)	(0.0173)
N	17,101	11,052	7,819	4,273
R^2	0.048	0.048	0.068	0.078
First jobs only?	No	Yes	No	Yes
Recessionary increase in predicted earnings losses, occ. switchers component	-32.2%	-14.2%	166.9%	162.2%

*** significant at 0.01, ** at 0.05, * at 0.10.

Controls include years since displacement, potential experience, potential experience squared, a linear time trend, indicator for female, indicator for non-white, and 4 eduction dummies. Potential experience, potential experience squared, and the linear time trend are normalized to mean zero. "AD" occupation coding adopted from "occ1990dd" codes from Autor and Dorn (2013). Robust standard errors clustered by year of job loss in parentheses. Data from CPS DWS, 1984-2018.

Appendix B. Derivation of wage equations

B.1. **Environment.** Workers and firms in a match of type-i bargain period-by-period over wages in a series of alternating offers. The firm makes the first offer. Should the worker accept the offer, production occurs, wages are paid, and the worker and firm enter as a match in the subsequent period, with the firm retaining the right-of-first-offer into the next period. Should the worker reject the offer, production is halted: workers enjoy utility from leisure $u_i^d(h)$, and firms incur delay cost $d_i(h)$. The matched pair are subject to a possibly higher exogenous separation probability ς in the next period, but otherwise, the matched pair enter the next period similar to as before: shocks to productivity, human capital, and mortality are realized, and workers in skill-insensitive matches choose whether or not to search on-the-job. However, the right-of-first-offer is transferred to the worker; thus, conditional on remaining matched in the production/bargaining sub-period of the subsequent period, the worker makes an offer. Should the firm accept the offer, production occurs, wages are paid, and the worker and firm enter as a match in the subsequent period, with the worker retaining the right-of-first-offer. The last party whose offer is accepted by the other retains the right-of-first-offer for the duration of the match, or until another offer is rejected. As in Hall and Milgrom (2008), the unique equilibrium is one in which the first offer from the firm is accepted by the worker. The equilibrium is supported by strategies in which firms and workers offer their counterparties wages that leave them indifferent between accepting and rejecting the wage offer, conditional on the wage meeting a participation constraint.

Let $\tilde{w}_L(\psi, Z)$ represent the wage offered by the worker in a skill-insensitive match, and let $\tilde{W}_L$ and $\tilde{J}_L$ denote the value functions of the worker and firm of such a match when the worker retains the right-of-first-offer. Then, the wage pair $\{w_L(\psi, Z), \tilde{w}_L(\psi, Z)\}$ satisfy

$$\begin{aligned} W_L(\psi, Z) = \max\Big\{ & u^d(\psi) + (1-\nu)\beta \mathbb{E}_{\psi,Z}\Big[p_{H_+}(\psi', Z')(1-\varsigma)W_H(\psi', Z') \\ & + \left(1 - p_{H_+}(\psi', Z')\right)(1-\varsigma)\tilde{W}_L(\psi', Z') + \varsigma U(\psi', Z')\Big], U(\psi, Z)\Big\} \end{aligned} \tag{5}$$

and

$$\tilde{J}_L(\psi, Z) = \max\Big\{-d(\psi, Z) + (1-\nu)\beta \mathbb{E}_{\psi,Z}\left[\left(1 - p_{H_+}(\psi, Z')\right)(1-\varsigma)J_L(\psi, Z')\right], 0\Big\} \tag{6}$$

where $S_i \equiv W_i - U$ and $\tilde{S}_i \equiv \tilde{W}_i - U$ denote the surplus of a type-i worker when the firm and worker retain the right-of-first-offer.

Similarly, let $\tilde{w}_H(\psi, Z)$ represent the wage proposed by the worker in a skill-sensitive match, and let $\tilde{W}_H$ and $\tilde{J}_H$ denote the value functions of the worker and firm when the worker retains the right-of-first-offer.[2] Then, the wage pair $\{w_H(\psi, Z), \tilde{w}_H(\psi, Z)\}$ satisfy

$$W_H(\psi, Z) = \max\left\{u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\left[(1-\varsigma)\tilde{W}_H(\psi', Z') + \varsigma U(\psi', Z')\right], U(\psi, Z)\right\} \tag{7}$$

and

$$\tilde{J}_H(\psi, Z) = \max\left\{-d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\left[(1-\varsigma)J_H(\psi', Z')\right], 0\right\}. \tag{8}$$

B.2. **Additional value functions.** In deriving the wage equations, we must generate expressions for the value of a worker and firm under a wage offered by a worker, $\tilde{J}_i$ and $\tilde{W}_i$ for $i = L, H$. Also, it will be useful to have expressions for the surplus accruing to the worker for the cases in which the match operates under a wage offered by the firm and worker, S_i and $\tilde{S}_i$ for $i = L, H$. Thus, the following value functions will be useful:

(1) Value of employment, skill-sensitive job, worker offer
$$\tilde{W}_H(h, Z) = \tilde{w}_H(h, Z) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(1-\delta)\tilde{W}_H(h', Z') + \delta U_H(h', Z')\right]$$

(2) Value of employment, skill-insensitive job, worker offer
$$\begin{aligned}\tilde{W}_L(h, Z) = \tilde{w}_L(h, Z) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[&p_{H_+}(h', Z')(1-\delta)W_H(h', Z') \\ &+ \left(1 - p_{H_+}(h', Z')\right)(1-\delta)\tilde{W}_L(h', Z') + \delta U_L(h', Z')\Big]\end{aligned}$$
where $p_{H_+}(h, Z) = \mathbb{I}\left\{W_H(h, Z) > \tilde{W}_L(h, Z)\right\} p_H(h, Z)$

(3) Firm's job value, skill-sensitive job, worker offer
$$\tilde{J}_H(h, Z) = Zh - \tilde{w}_H(h, Z) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\Big[(1-\delta)\tilde{J}_H(h', Z')\Big]$$

(4) Firm's job value, skill-insensitive job, worker offer
$$\tilde{J}_L(h, Z) = Z - \tilde{w}_L(h, Z) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[\left(1 - p_{H_+}(h, Z)\right)(1-\delta)\tilde{J}_L(h', Z')\Big]$$

(5) Worker surplus, skill-insensitive job

[2]The proof assumes the outside option for workers and firms is never binding. Hall and Milgrom (2008) similarly focus on such a case. For the quantitative analysis, wages are computed directly from equations (5), (6), (7), and (8), so the constraint is never artificially imposed.

$$\begin{aligned} S_L(h,Z) &\equiv W_L(h,Z) - U_L(h,Z) \\ &= w_L(h,Z) - u_L^b(h) \\ &+ (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big\{p_{H_+}(h',Z')(1-\delta)S_H(h',Z') \\ &+ \Big(1-p_{H_+}(h',Z')\Big)(1-\delta)S_L(h',Z')\Big\} \\ &+ (1-\nu)\beta\mathbb{E}^L_{h,Z}\left[p_{H_+}(h',Z')(1-\delta)\left(U_H(h',Z')-U_L(h',Z')\right)\right] \\ &+ (1-\nu)\beta\left[\mathbb{E}^L_{h,Z}-\mathbb{E}^U_{h,Z}\right]U_L(h',Z') \\ &- (1-\nu)\beta\mathbb{E}^U_{h,Z}\max\Big\{p_H(h',Z')S_H(h',Z') \\ &+ p_H(h',Z')\left[U_H(h',Z')-U_L(h',Z')\right], p_L(h',Z')S_L(h',Z')\Big\} \end{aligned}$$

(6) Worker surplus, skill-sensitive job

$$\begin{aligned} S_H(h,Z) &\equiv W_H(h,Z) - U_H(h,Z) \\ &= w_H(h,Z) - u_H^b(h) \\ &+ (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(1-\delta)S_H(h',Z')\right] \\ &+ (1-\nu)\left[\mathbb{E}^H_{h,Z}-\mathbb{E}^U_{h,Z}\right]U_H(h',Z') \\ &+ (1-\nu)\beta\mathbb{E}^U_{h,Z}\max\Big\{p_H(h',Z')S_H(h',Z'), \\ &p_L(h',Z')S_L(h',Z') - p_L(h',Z')\left[U_H(h',Z')-U_L(h',Z')\right]\Big\} \end{aligned}$$

B.3. **Proof of Proposition 1.** First, consider the H-type wages, $w_H(h,Z)$ and $\tilde{w}_H(h,Z)$. The wage $w_H(h,Z)$ is set such that

$$W_H(h,Z) = \max\left\{u_H^d(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(1-\varsigma)\tilde{W}_H(h',Z') + \varsigma U_H(h',Z')\right], U_H(h,Z)\right\}.$$

Assume that the participation constraint does not bind, and solve for $w_H(h,Z)$:

$$w_H(h,Z) = u_H^d(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\Big[(1-\delta)\left(\tilde{S}_H(h',Z') - S_H(h',Z')\right) + (\varsigma-\delta)\tilde{S}_H(h',Z')\Big]$$

Use the equations for W_H and $\tilde{W}_H$ to solve for $\tilde{S}_H(h,Z) - S_H(h,Z)$, and substitute in the above equation for w_H:

$$\tilde{S}_H(h,Z) - S_H(h,Z) = \tilde{w}_H(h,Z) - u_H^d(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(\varsigma-\delta)\tilde{S}_H(h',Z')\right]$$

The wage $\tilde{w}_H(h,Z)$ is set such that

$$\tilde{J}_H(h,Z) = \max\Big\{-d_H(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(1-\varsigma)J_H(h',Z')\right], 0\Big\}.$$

Assume the participation constraint does not bind and combine with the equation for $J_H(h,Z)$ to solve for $J_H(h,Z) - \tilde{J}_H(h,Z)$:

$$J_H(h,Z) - \tilde{J}_H(h,Z) = Zh - w_H(h,Z) + d_H(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(\varsigma-\delta)J_H(h',Z')\right]$$

Use the equation for $\tilde{J}_H(h,Z)$ with the indifference equation for $\tilde{w}_H$ to solve for $\tilde{w}_H$, assuming that the participation constraint does not bind:

$$\tilde{w}_H(h,Z) = Zh + d_H(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(1-\delta)\left(\tilde{J}_H(h',Z') - J_H(h,Z)\right) + (\varsigma-\delta)\,J_H(h',Z')\right]$$

Invoking $\tilde{S}_H(h,Z) - S_H(h,Z) = J_H(h,Z) - \tilde{J}_H(h,Z)$, substitute the expression for $\tilde{S}_H - S_H$ into the equation for $\tilde{w}_H$, and substitute the expression for $J_H - \tilde{J}_H$ into the equation for w_H:

$$\begin{aligned} w_H(h,Z) &= u^d_H(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\Big[(1-\delta)\left(Z'h' + d_H(h',Z') - w_H(h',Z')\right) \\ &\quad - (\varsigma-\delta)\tilde{S}_H(h',Z') + (1-\delta)(1-\nu)\beta\mathbb{E}^H_{h',Z'}\left[(\varsigma-\delta)J_H(h'',Z'')\right]\Big] \\ \tilde{w}_H(h,Z) &= Zh + d_H(h) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\Big[(1-\delta)\left(u^d_H(h') - \tilde{w}_H(h',Z')\right) \\ &\quad + (\varsigma-\delta)J_H(h',Z') - (1-\delta)(1-\nu)\beta\mathbb{E}^H_{h',Z'}\left[(\varsigma-\delta)\,S_H(h'',Z'')\right]\Big]. \end{aligned}$$

Set $\varsigma = \delta$ to obtain the wage equation of Proposition 1 for matches operating the skill-sensitive production function.

Next, consider the L-type wages, $w_L(h,Z)$ and $\tilde{w}_L(h,Z)$. The wage $w_L(h,Z)$ is set such that

$$\begin{aligned} W_L(h,Z) = \max\Big\{&u^d_L(h) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[p_{H_+}(h',Z')(1-\varsigma)W_H(h',Z') \\ &+ (1-\varsigma)\left(1-p_{H_+}(h',Z')\right)\tilde{W}_L(h,Z) + \varsigma U_L(h',Z')\Big], U_L(h,Z)\Big\}. \end{aligned}$$

Assume the participation constraint does not bind. Substitute in the equation for $W_L(h,Z)$ and solve for $w_L(h,Z)$:

$$\begin{aligned} w_L(h,Z) = u^d_L(h) &+ (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[(1-\delta)\left(1-p_{H_+}(h',Z')\right)\left(\tilde{S}_L(h',Z') - S_L(h',Z')\right) \\ &- (\varsigma-\delta)\left(\left(1-p_{H_+}(h',Z')\right)\tilde{S}_L(h',Z') + p_{H_+}(h',Z')S_H(h',Z')\right) \\ &- (\varsigma-\delta)\,p_{H_+}(h',Z')\left(U_H(h',Z') - U_L(h',Z')\right)\Big] \end{aligned}$$

Solve for $\tilde{S}_L(h,Z) - S_L(h,Z)$, and substitute in the above equation for w_L:

$$\begin{aligned} \tilde{S}_L(h,Z) - S_L(h,Z) = \tilde{w}_L(h,Z) - u^d_L(h) &+ (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[(\varsigma-\delta)\,p_{H_+}(h,Z)S_H(h',Z') \\ &+ (\varsigma-\delta)\left(1-p_{H_+}(h',Z')\right)\tilde{S}_L(h',Z') \\ &+ (\varsigma-\delta)p_{H_+}(h',Z')\left(U_H(h',Z') - U_L(h',Z')\right)\Big] \end{aligned}$$

The wage $\tilde{w}_L(h,Z)$ is set such that

$$\tilde{J}_L(h,Z) = \max\left\{-d_L(h) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\left[\left(1-p_{H_+}(h',Z')\right)(1-\varsigma)J_L(h',Z')\right], 0\right\}.$$

Combine with the equation for $J_L(h,Z)$ and solve for $\left(J_L(h,Z)-\tilde{J}_L(h,Z)\right)$, assuming the participation constraint does not bind:

$$J_L(h,Z)-\tilde{J}_L(h,Z)=Z-w_L(h,Z)+d_L(h)+(1-\nu)\beta\mathbb{E}^L_{h,Z}\left\{(\varsigma-\delta)\left(1-p_{H_+}(h',Z')\right)J_L(h',Z')\right\}$$

Use the equation for $\tilde{J}_L(h,Z)$ with the indifference equation for $\tilde{w}_L$ to solve for $\tilde{w}_L$, assuming the participation constraint does not bind:

$$\begin{aligned}\tilde{w}_L(h,Z)=Z+d_L(h)+(1-\nu)\beta\mathbb{E}^L_{h,Z}\Bigg[&\left(1-p_{H_+}(h',Z')\right)\Big((1-\delta)\left(\tilde{J}_L(h',Z')-J_L(h',Z')\right)\\&+(\varsigma-\delta)\,J_L(h',Z')\Big)\Bigg]\end{aligned}$$

Invoking $\tilde{S}_L(h,Z)-S_L(h,Z)=J_L(h,Z)-\tilde{J}_L(h,Z)$, substitute the expression for $\tilde{S}_L-S_L$ into the equation for $\tilde{w}_L$, and substitute the expression for $J_L-\tilde{J}_L$ into the equation for w_L:

$$\begin{aligned}w_L(h,Z)=\,&u^d_L(h)+(1-\nu)\beta\mathbb{E}^L_{h,Z}\left[(1-\delta)\left(1-p_{H_+}(h',Z')\right)(Z'-w_L(h',Z')+d_H(h'))\right]\\&+(1-\nu)\beta\mathbb{E}^L_{h,Z}(1-\delta)\left(1-p_{H_+}(h',Z')\right)(1-\nu)\beta\mathbb{E}^L_{h',Z'}(\varsigma-\delta)\left(1-p_{H_+}(h'',Z'')\right)J_L(h'',Z'')\\&-(1-\nu)\beta\mathbb{E}^L_{h,Z}(\varsigma-\delta)\left(\left(1-p_{H_+}(h',Z')\right)S_L(h',Z')+p_{H_+}(h',Z')S_H(h',Z')\right)\\&-(1-\nu)\beta\mathbb{E}^L_{h,Z}(\varsigma-\delta)p_{H_+}(h',Z')\left(U_H(h',Z')-U_L(h',Z')\right)\end{aligned}$$

and

$$\begin{aligned}\tilde{w}_L(h,Z)=Z+d_L(h)+(1-\nu)\beta\mathbb{E}_L\Bigg[&(1-\delta)\left(1-p_{H_+}(h',Z')\right)\Big[\left(u^d_L(h')-\tilde{w}_L(h',Z')\right)\\&-(1-\nu)\beta\mathbb{E}^L_{h',Z'}(\varsigma-\delta)\Big[\Big(p_{H_+}(h'',Z'')S_H(h'',Z'')+\left(1-p_{H_+}(h'',Z'')\right)\tilde{S}_L(h'',Z'')\Big)\\&+p_{H_+}(h'',Z'')\left(U_H(h'',Z'')-U_L(h'',Z'')\right)\Big]\Big]+(\varsigma-\delta)J_L(h',Z')\Bigg]\end{aligned}$$

Set $\varsigma=\delta$ to obtain the wage equation of Proposition 1 for matches operating the skill-insensitive production function.

Table C.1. Distribution of aggregate productivity during recessions and expansions (simulated data)

	Z_L	Z_M	Z_H
Expansion	0.156	0.500	0.344
Recession	0.950	0.047	0.003

Appendix C. Quantitative appendix

C.1. **Construction of targets from IPUMS 2000 Census.** In constructing moments from the IPUMS 2000 Census, I adopt sample restrictions adopted from Hornstein et al. (2007). In particular, I consider only individuals age 20 to 60 who are not in school, not self-employed, and not disabled. Moreover, I exclude workers with zero wage income and zero weeks worked per year. I exclude workers whose earnings are top-coded, and I exclude earnings of workers making less than the minimum wage in 2000.

Wage residuals are calculated from a Mincer wage regression of log wages on a cubic in potential experience, four education dummies, and dummies for white, Black, male, and never married. The analysis is at the individual level, and hence person weights are used. The regression is estimated from the full sample, and the average wage residuals are constructed from the sub-sample of individuals with less than five years of experience. Average wage growth is calculated from the average implied wage growth from the cubic polynomial in potential experience over a 40 year career. The experience premium and statistics describing the wage distribution are calculated directly from wages.

C.2. **Identifying recessions in model-simulated data.** Davis and von Wachter calculate the cost of job loss during a recession by averaging across NBER recession years, accounting for 12% of the years in their sample; the remaining 88% are classified as expansions. To facilitate comparison between estimates from the model and the data, I develop a criteria through which to label episodes from model simulated data as expansions or recessions. I apply an HP filter to a series for annual unemployment simulated from 40,000 workers over a 500 year period, from which a quarter is classified as a recession if the detrended realization of log output is in the bottom 12% of the sample. I record the distribution of the realization of aggregate productivity over recessions and expansions, given in Table C.1. I recover the distribution of workers over employment states and human capital conditional on the state of the economy (recession or expansion) and the value of aggregate productivity.

The distributions of workers over human capital and job types are used to simulate the twenty-year panel of earnings realizations for separate samples of job losers and job stayers, keeping the sequences of shocks the same across both samples. From this, I compute the average earnings path for displaced workers and the counterfactual path associated with continued employment.

C.3. **Solution and simulation details.**

C.3.1. *Calibration.* For each parameter draw in the estimation procedure, the model is simulated with 35,000 workers over 400 years, with a 10,000 week burn-in. All targets are taken from the CPS displaced worker supplement using the harmonized "AD" occupation definition. To calculate the corresponding moments from the model, I administer a synthetic displaced worker supplement within the simulation, gathering information about the most recent job displacement for workers within the previous two years of the simulation. Then, I match the model simulated data to moments from a sub-sample of reemployed workers in the DWS who are similarly displaced no more than two years prior to their interview. Finally, I restrict attention in the DWS sample and in the simulated data to workers who are observed at their first job since displacement.

C.3.2. *Construction of Figure 5.* The cost of job loss is calculated relative to the counterfactual earnings path associated with no job displacement. To do so, I simulate a panel of 10,000 individuals over 1000 realizations of aggregate productivity, two different times: one for job loss, another for no job loss. The values of aggregate productivity used to initiate the simulated path of aggregate productivity are drawn from the invariant distribution of aggregate productivity. The panel is constructed so that it is representative of the invariant distribution of workers across jobs and human capital, conditional on the initializing value of aggregate productivity.

C.3.3. *Comparison of model and empirical earnings loss profiles, Figure 6 and Table 10.* The sample used in the model analysis is drawn from a simulated panel of 9,500,000 individuals observed over a span of 200 years.

C.3.4. *Computing the cost of entering the labor market during a recession.* I simulate labor market outcomes for a panel of 10,000 agents whose human capital is drawn from the initial distribution for entrants. The initial aggregate productivity draw is drawn from the distribution of aggregate productivity conditional on the year falling into an expansion or a recession. For each initial productivity draw, I track the workers for ten years. The paths of the 10,000 agents are averaged across 1000 productivity draws during expansions and 1000 productivity draws during recessions.

C.4. **Further comparison of model to data.** The empirical section of the paper shows the central role of occupation in generating the size and cyclicality of the cost of job loss. These findings are then used to motivate a simple model with a role for occupation displacement. The model naturally does not contain all of the features of the underlying data used to produce the findings used as motivatation; and thus some consideration must be taken when bringing the model to the data. Such considerations are discussed in the main text of the paper: for example, Section 2.5 discusses how the model generates occupation switching from switches across jobs of the same and different production functions. Then, as discussed in Section 3 of the main text, the model is calibrated to match the average wage loss from occupation displacement and the frequency of occupation displacement. In reviewing the non-targeted findings of the paper, I show that the model does well at matching the cyclicality of occupation switching and the cyclicality of the cost of job loss.

Nonetheless, some of the assumptions made in the mapping of occupation in the data to occupation in the model may be seen as strong; and the mapping does not allow the model to capture some aspects of the data. In particular, occupation switching in the model is measured by assuming that all switches across job-types count as occupation switches, and that a fixed fraction of switches within job-types count as occupation switches. While simple and useful, the approach could be subject to two criticisms: the former assumption is too strong, as some occupations might include jobs that utilize more than one production technology; and the latter assumption precludes one from inferring upward and downward switches in the model. The latter assumption is most worrying if one wanted to simulate data from the model to exactly match, for example, the countercyclicality of downward occupation switching versus the relative acyclicality of upward occupation switching.

To engage this concern, I simulate data from the baseline calibration of the model. Then, I label all switches from the skill-insensitive to the skill-sensitive production function as "upward switches"; and vice versa for switches from the skill-sensitive to the skill-insensitive production functions.[3] However, rather than assuming a single probability of switching occupation within the same production functions, I estimate two separate switching probabilities $\chi_{\uparrow} = 0.24$ and $\chi_{\downarrow} = 0.23$, which are calibrated to match the fraction of upward and downward occupation switches during an expansion.[4] Then, I use these

[3]Thus, the calibration is still subject to the first criticism.

[4]As discussed in Section 2.5, the parameter χ does not matter for allocations, and thus, the approach here is valid. Moreover, this calibration strategy implies that average occupation switching (unconditional of direction) matches the data, similar to that taken in the main text of the paper.

TABLE C.2. Comparison of data and model for all regressions

Table 1: $\Delta \log w$

	Switcher	Recession	Constant
Data	−0.069	−0.055	−0.036
Model	−0.114	−0.083	−0.026

Table 2: Switching indicator

	Recession	Constant
Data	0.022	0.519
Model	0.105	0.459

Table 3a: Switch $\downarrow$

	Recession	Constant
Data	0.030	0.270
Model	0.143	0.274

Table 3b: Switch $\uparrow$

	Recession	Constant
Data	−0.008	0.250
Model	−0.005	0.253

Table 4: $\Delta \log w$

	Switch $\uparrow$	Switch $\downarrow$	Recession	Constant
Data	0.010	−0.140	−0.056	−0.049
Model	0.024	−0.158	−0.100	−0.028

Table 5: Switch $\downarrow$, ≤ 2 yrs

	Recession	Constant
Data	0.020	0.279
Model	0.134	0.275

Table 5: Switch $\downarrow$, > 2 yrs

	Recession	Constant
Data	0.020	0.279
Model	0.194	0.268

Table 6: $\Delta \log w$, ≤ 2 yrs

	Sw. $\downarrow$	Sw. $\downarrow$ $\times$ Rec.	Rec.	Constant
Data	−0.139	0.007	−0.043	−0.029
Model	−0.113	−0.324	0.037	−0.037

Table 6: $\Delta \log w$, > 2 yrs

	Sw. $\downarrow$	Sw. $\downarrow$ $\times$ Rec.	Rec.	Constant
Data	−0.119	−0.076	−0.067	0.009
Model	−0.106	−0.393	0.017	−0.016

Note: To compare upward and downward occupation switchers for workers making transitions across occupations using the same production technology, the table introduces a different notion of occupation switcher than what is used to calibrate the model. This different definition of switcher is not fully calibrated to match the data; hence, although the qualitative patterns in the model and data are consistent, there are some quantitative differences.

data with measures of upward and downward switching to estimate all of the regressions from Section 1 of the paper.

The purpose of these regressions are two-fold: First, they allow one to evaluate whether the model captures all of the qualitative patterns of occupation displacement from all of the regression equations in the paper. Second, to the extent that estimates from the model-simulated regressions are differ quantitatively from the empirical estimates, one can assess whether it is too strong of an assumption to classify all switches across a job-type as an occupation switch.

Table C.2 shows the model estimates against the empirical estimates. In general, the fit is surprisingly good, especially given that the mapping of occupation necessary for producing the tables is not the same as is used to calibrate the model. Qualitatively, the model explains the strong countercyclical downward switching in occupation relative to the weak procyclical upward switching in occupation. The model also generates the correct response of wages to occupation displacement, and occupation displacement during a recession. However, downward occupation switching appears to be too countercyclical; and the effect of downward occupation switching during a recession is too strong.

Both of these responses would be muted if not all workers switching production technologies were deemed occupation switchers. Intuitively, if some workers switching from skill-sensitive to skill-insensitive jobs remained in the same occupation, the wage losses of downward occupation switchers would not appear so cyclical relative to the wage losses of non-switchers. Such a classification would also help account for the suprisingly high degree of wage dispersion observed within even low-skill occupations (Hornstein et al., 2007). I leave this extension to further research.

C.5. **A role for outside options, and additional moments.** In this section I offer additional results where the probability of separation following a delay in bargaining is greater than the probability of separation following no delay in bargaining, i.e. $\varsigma > \delta$. As shown in the Proof of Proposition 1 in Section B.3 of the Online Appendix, the influence of outside values of bargaining powers on the wage is linear in $(\varsigma - \delta)$. Thus, I consider a third "outside option" parameterization where $\varsigma = 1.025 \cdot \delta$. This factor is at the upper bound for which the estimation procedure converges with an empirically plausible level of unemployment volatility. As alluded to in Section 2.9 and discussed at greater lengths in earlier versions of the paper, a small increase in exposure of wages to outside values has a large impact on outcomes. This can be most readily seen by variation in the best-fitting value for vacancy posting cost for skill-sensitive jobs, κ_H. The value is roughly half the size for the "outside value" parameterization as it is for the baseline. Indeed, the outside value parameterization implies far fewer skill-sensitive jobs when evaluated at the best-fit parameters from the benchmark parameterization; e.g., no skill-sensitive vacancies are posted when aggregate productivity is at its lowest value.

Here, I offer tables with parameter estimates, targeted moments, and non-targeted moments from all three parameterizations of the full model.

- Table C.3 corresponds to Table 8 of the main paper, but for all three parameterizations of the model.
- Table C.4 corresponds to Table 9 of the main paper, but for all three parameterizations of the model.
- Table C.5 offers a set of descriptive moments from all three calibrations, including moments that are discussed in the main body of the paper.
- Table C.6 corresponds to Table 10 of the main paper, but for all three parameterizations of the model.

Here, I offer additional figures from all three parameterizations of the model.

- Figure C.1 plots the initial distribution for the benchmark parameterization of the model.
- Figure C.2 plots the initial distribution for the "outside value" parameterization of the model.
- Figure C.3 plots the earnings losses of switches and stayers under the "outside value" parameterization of the model.
- Figure C.4 offers a comparison of model and earnings losses, but for all three parameterizations of the model.
- Figure C.5 plots job-finding probabilities for the "outside value" parameterization of the model.
- Figure C.6 plots wages for the "outside value" parameterization of the model.
- Figure C.7 plots the total present value cost of job loss under the "outside value" parameterization of the model.

Note, the role of the equilibrium skill threshold in describing maximal earnings losses from job loss is altered somewhat under the "outside value" parameterization of the model. See in Figure C.7 that the maximal cost of job loss is realized to the left of the equilibrium skill threshold. Then see Figure C.5, which shows that the spikes in the total cost of job loss occurs where either on-the-job search for a skill-sensitive job from a skill-insensitive job is no longer possible; or at values of h where dramatic decreases in job-finding probabilities for skill-insensitive jobs are realized. The declines in job-finding probabilities for skill-insensitive jobs in particular are due to anticipated increases in job-finding probabilities for skill-sensitive jobs, should aggregate productivity suddenly improve.

Table C.3. Targeted moments

Moment	Target	Simulated moments: Baseline model	Outside value	Single technology
Mean wage change following displacement	0.0700	0.0696	0.0704	0.0793
10th percentile wage loss following displacement	0.0345	0.0122	0.0140	0.0108
Average wage loss occupation switchers/stayers	1.3000	1.2955	1.3007	—
Fraction of occupation switchers	0.6580	0.6666	0.6573	—
Persistence of measured labor productivity	0.7654	0.7609	0.7231	0.7268
Standard dev. of measured labor productivity	0.0132	0.0143	0.0150	0.0141
Relative volatility of unemployment	11.1500	11.2422	11.2365	10.9809
Weekly UE rate	0.0966	0.0966	0.0958	0.1000
Average wage growth	0.0117	0.0090	0.0087	0.0106
Experience premium, $\geq$ 5 years experience	1.3501	1.4600	1.4395	1.5423
P90/P10 log wage residuals, $<$ 5 years experience	0.9628	0.7720	0.7947	0.7078
Wage distribution, p90/p50	2.1333	1.9619	1.8564	1.9754
Wage distribution, p50/p25	1.4563	1.4851	1.4123	1.2783

Moments describing "Mean wage change following displacement" up through "Fraction of occupation switchers" are taken from the CPS DWS, 1984-2018. "Persistence . . . ," "Standard dev. of measured labor productivity," and "Relative volatility of unemployment" is taken from Hagedorn and Manovskii (2008). "Weekly UE rate" is taken from Menzio and Shi (2010). All other moments are calculated from the 2000 Census.

It should not be surprising that job-finding probabilities would display a more complex dependence on the outside values of workers, given the nature of the parameterization. Moreover, the results further instill that a small increase in separation probability under non-agreement (0.025 $\times$ the separation rate under agreement) has a non-negligible impact on outcomes.

Table C.4. Estimated parameters

		Model parameterization		
Parameter	Description	Baseline model	Outside value	Single task
Labor productivity:				
ρ_Z	Persistence of labor productivity	0.9821	0.9796	0.9728
σ_Z	Standard dev. of labor productivity	0.0040	0.0050	0.0035
Labor market:				
γ	Firm cost of delay	0.2592	0.2619	0.2680
κ_H	Vacancy posting cost (skill-sensitive)	3.9382	2.1636	0.9238
ϕ_H	Matching efficiency (skill-sensitive)	0.2581	0.2270	0.2410
ϕ_L	Matching efficiency (skill-insensitive)	0.0743	0.0989	—
χ	Task-common occupation switching	0.6343	0.6218	—
Human capital:				
μ_{nb}	Human capital initial distribution mean	0.2495	0.2327	−1.0434
σ_{nb}	Human capital initial distribution, standard deviation	0.0001	0.1360	0.0001
π_H	Probability of human capital increase (skill-sensitive)	0.0315	0.0274	0.0220
π_L	Probability of human capital increase (skill-insensitive)	0.0011	0.0026	—
π_U	Probability of human capital decrease (unemployment)	0.1121	0.1022	0.1296
ξ	Obsolescence probability	0.0364	0.0311	0.0645

Table C.5. Descriptive statistics, model

Moment	Simulated moments		
	Baseline model	Outside value	Single task
1) Unemployment rate	0.0667	0.0643	0.0690
2) Average profit share	0.0170	0.0119	0.0121
3) Skill-sensitive recruitment costs as a fraction of wage bill	0.1968	0.1352	0.1389
4) Earnings loss, task-distinct occupation switches	0.4945	0.4625	—
5) Fraction of workers in skill-sensitive jobs	0.7863	0.8357	1.0000
6) Occupation switching, expansion	0.6625	0.6529	—
7) Occupation switching, recession	0.7069	0.6999	—
8) Avg. value of human capital	2.2953	2.2642	1.2770
9) Avg. value of human capital, new-born	1.2833	1.2737	0.5000
10) Avg. value of human capital, skill-sensitive	2.6398	2.4994	1.3055
11) Avg. value of human capital, skill-insensitive	1.1326	1.1930	—
12) Avg. value of human capital, unemployed	1.9538	1.9444	0.8914
13) Avg. % h.c. accumulation in skill-sensitive job, one quarter	0.9892	0.9097	1.3945
14) Avg. % h.c. accumulation in skill-insensitive job, one quarter	0.0772	0.1835	—
15) Avg. % h.c. deaccumulation in unemployment, one quarter	4.0468	3.7419	8.4118

Although most of the moments do not have directly observable counterparts in the data, several do, as follows: *1*) Unemployment rate: 0.055 (Hall and Milgrom, 2008); *2*) Average profit share: 0.03 (Hornstein et al., 2005); *3*) Recruitment costs (pooled): 0.14 (Hall and Milgrom, 2008); *6*) Occupation switching, expansions: 0.654, Column 3 of Table 2 in the main text; *7*) Occupation switching, recessions: 0.684, Column 3 of Table 2 in the main text.

TABLE C.6. Present value cost of job loss, data and model

		by NBER recession			by unemployment rate		
	All	Exp.	Rec.	Δ/Avg.	u_{low}	u_{high}	Δ/Avg.
1) Data	11.9	11.0	18.6	63.9	9.9	15.9	50.4
2) Baseline	13.8	13.7	17.1	24.0	11.8	16.8	36.0
3) Outside value	13.4	13.2	17.8	33.9	10.9	16.6	42.4
4) Single task	16.0	16.0	17.7	11.0	14.9	16.9	12.8
% of sample	100	88	12	—	23	29	—

Data from Davis and von Wachter (2011). Davis and von Wachter report the average cost of job loss across years in the lower 23rd and upper 29th percentiles of annual unemployment rates, denoted above as u_{low} and u_{high}. Moments from the model are calculated similarly. Construction of "recessions" and "expansions" in the model-simulated data is described in the text. "Baseline" parameterization allows no influence for outside values on wages, whereas the "outside value" parameterization does. The "single task" parameterization assumes an economy where all jobs utilize perfectly transferable human capital, effectively shutting down the primary mechanism of the model.

FIGURE C.1. Distribution of workers over human capital, benchmark calibration

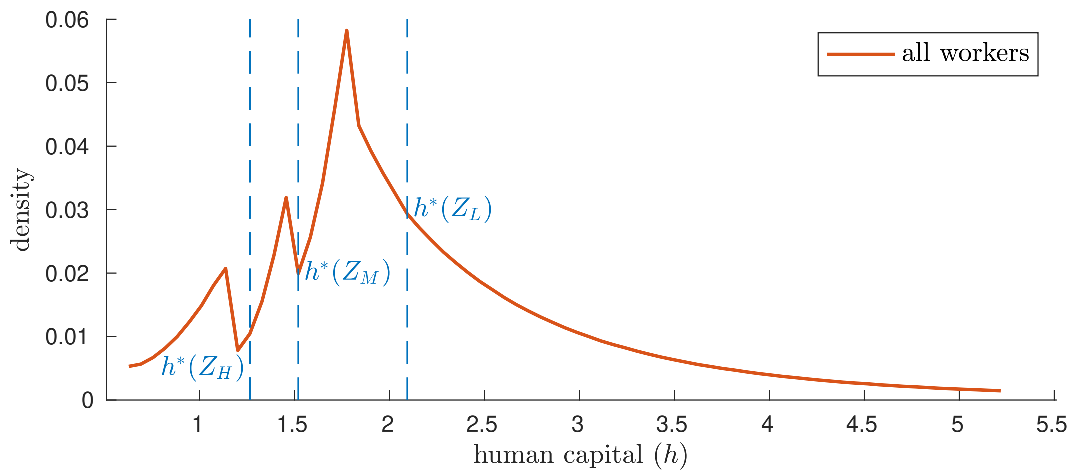


FIGURE C.2. Distribution of workers over human capital, "outside value" calibration

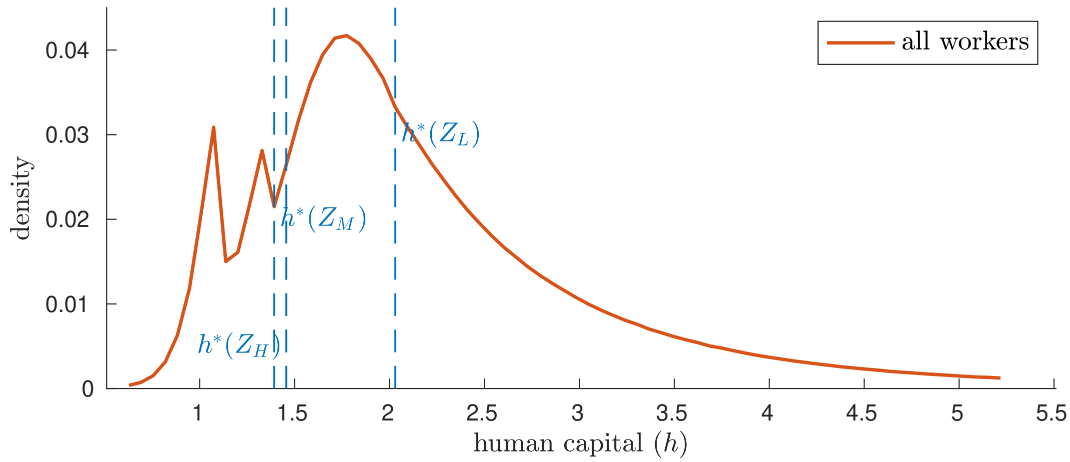


FIGURE C.3. Earnings losses, stayers and switchers: model

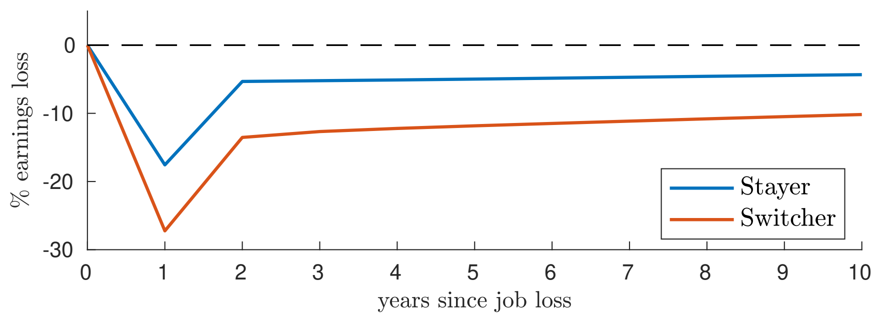


Figure C.4. Comparison of model and empirical earnings loss profiles, all parameterizations

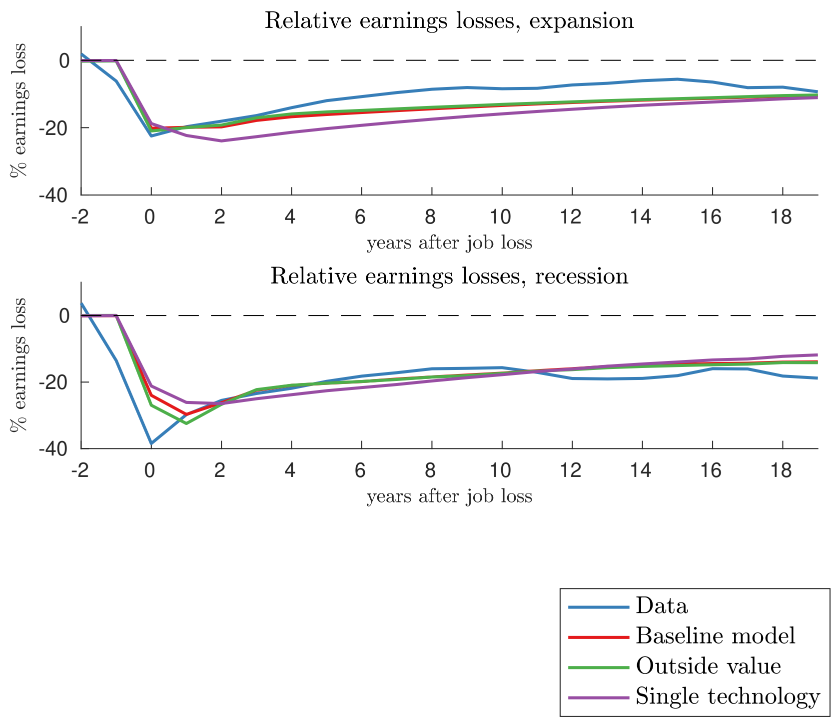
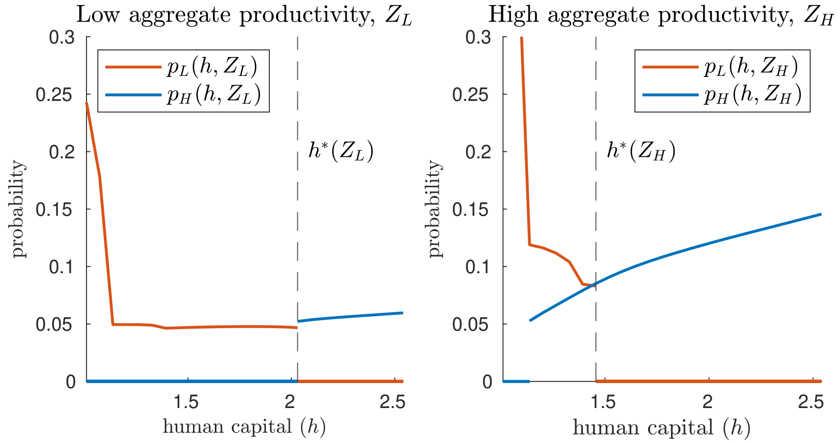
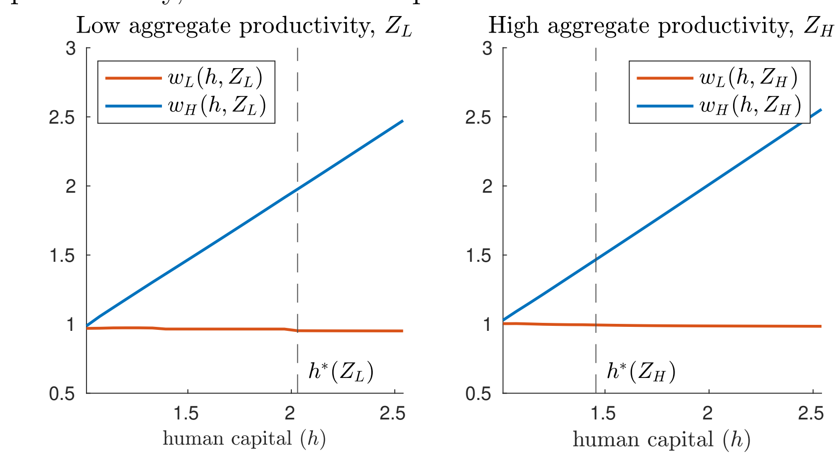


FIGURE C.5. Job-finding probabilities from unemployment: high and low productivity, "outside value" parameterization



The equilibrium skill thresholds are given by $h^*(Z_H)$ and $h^*(Z_L)$ for high and low productivity.

FIGURE C.6. Wage profiles from unemployment: high and low productivity, "outside value" parameterization



The equilibrium skill thresholds are given by $h^*(Z_H)$ and $h^*(Z_L)$ for high and low productivity.

FIGURE C.7. Total present value cost of job loss, "outside value" parameterization

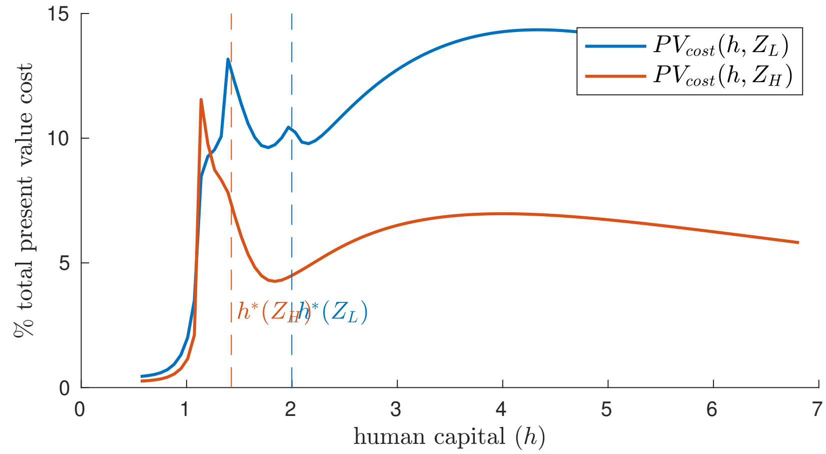
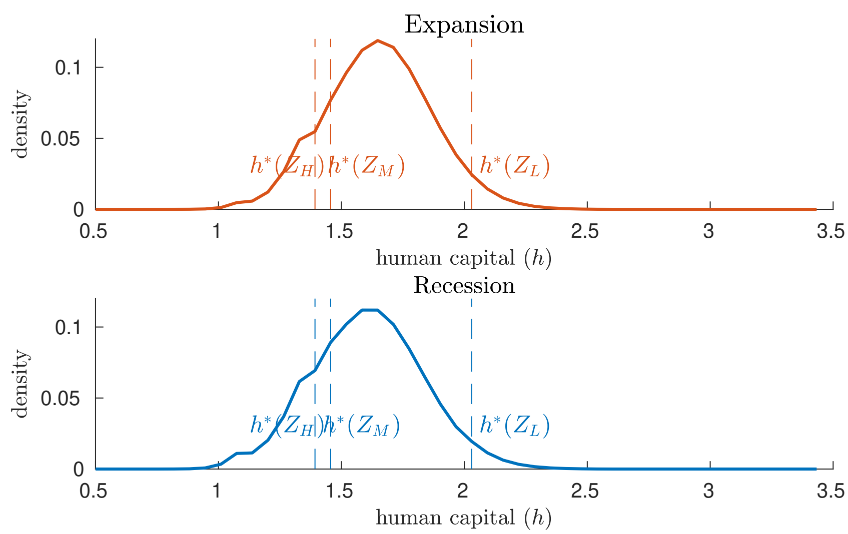


FIGURE C.8. Human capital distribution of new entrants at initial employment, "outside value parameterization"



Note: Under the outside value calibration, 22.5% of entrants begin working in a skill-insensitive job during an expansion, compared to 73.6% during a recession. The cost of entering the labor market during a recession is 7.96% of the ten-year present value of earnings from entering the labor market during an expansion. This is close to the estimate of 9% from Schwandt and von Wachter (2019) and von Wachter (2020).

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