# UNDERSTANDING THE SCARRING EFFECT OF RECESSIONS

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Abstract. This paper documents that the earnings cost of job loss is concentrated among workers who find reemployment in lower-skill occupations, and that the cost and incidence of such occupation displacement is higher for workers who lose their job during a recession. I propose a model where hiring is endogenously more selective during recessions, leading some unemployed workers to optimally search for reemployment in lower-skill jobs. The model accounts for existing estimates of the size and cyclicality of the present value cost of job loss, and the cost of entering the labor market during a recession.

Keywords: unemployment, job loss, business cycles, occupation displacement

JEL Codes: E24, E32, J24, J62, J63, J64

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## 1. Introduction

It is well known from the labor literature that the earnings cost of job loss is large, persistent, and countercyclical. In this paper, I establish that the earnings cost of job loss is not dispersed uniformly, but falls primarily upon workers who find reemployment in a lower-paying occupation relative to their prior job. Thus, occupation displacement explains the majority of the cost of job loss. To understand these findings, I propose a model where hiring is endogenously more selective during recessions, leading unemployed workers to optimally search for lower-skill jobs. In explaining the paper's new findings, the model is also able to account for the size and cyclicality of the cost of job loss, quantities which have eluded existing models of cyclical unemployment (Davis and von Wachter, 2011). The model also accounts for the cost of entering the labor market during a recession.

The paper first presents a set of stylized facts from the CPS Displaced Worker Supplement and the PSID to document that the size and cyclicality of the cost of job displacement is almost entirely concentrated among workers who switch occupation subsequent to job loss: The initial earnings losses of workers who lose their job and subsequently switch occupation are more than double those of workers who find reemployment in the same occupation. The cost and incidence of such occupation displacement is higher among workers who lose their job during a recession. While occupation switchers continue to face markedly lower earnings a full decade after job loss, the wage and earnings losses of occupation stayers recover within four years. Together, these facts offer *prime facie* evidence of occupation displacement as the proximate source for the size and cyclicality of the earnings cost of job loss.

To understand these facts, I propose a simple and novel theoretical framework where selective hiring may prevent an unemployed worker from finding reemployment in a job that utilizes previously accumulated specific human capital. To recoup the fixed costs of finding a worker, firms posting vacancies for higher-paying, "skill-sensitive" jobs hire selectively, only directing vacancies towards workers with skill above an endogenously determined threshold. Other workers are left to search for lower-paying "skill-insensitive" jobs that do not utilize skill. A worker who is displaced from a job that uses skill and reemployed in a job that does not suffers larger and more persistent earnings losses. During a recession, the equilibrium skill threshold describing the search behavior of workers in unemployment endogenously tightens, as workers who would otherwise search for skill-sensitive jobs now optimally direct their search for skill-insensitive jobs; and thus, the incidence and earnings loss associated with displacement from skill-sensitive to skill-insensitive jobs increases.

The calibrated model successfully accounts for the size and cyclicality of the cost of job loss.[1] In particular, I show that the non-linear earnings dynamics associated with the equilibrium skill threshold are crucial for generating the cyclical cost of job loss. The model is also able to speak to separate empirical findings that workers who enter the labor market during a recession have persistently lower earnings. The paper is the first to connect the cyclical cost of job loss with the cost of entering the labor market during a recession— two distinct but related dimensions of the scarring effect of recessions. The central economic mechanism of the model – countercyclical hiring standards within skilled occupations – is new to the literature and finds direct support in empirical studies of firm-level vacancy postings, including Hershbein and Kahn (2018) and Modestino, Shoag, and Ballance (2020).

The paper is the first in the literature to account for both the size and cyclicality of the cost of job loss. Davis and von Wachter (2011) estimate large present value costs of job loss in the U.S. that increase by nearly 70% from expansions to recessions, but then document that leading macroeconomic models are unable to speak to either the size or cyclicality of the present value cost of job loss. A subsequent macroeconomic literature has emerged to account for the size of the average cost of job loss but not its cyclicality, e.g. Jarosch (2015), Krolikowski (2017), Jung and Kuhn (2018), and Burdett, Carrillo-Tudela, and Coles (2020). The theory offered here contributes to the existing literature in that it confronts both the size and cyclicality of the cost of job loss in a manner consistent with the stark difference in the cost of job loss across occupation switchers and stayers. Indeed, the new empirical findings from the paper establish a tight link between these two features of costly displacements: the same group of workers who are shown to generate the large cost of job loss during normal times — workers who downgrade to a lower-paying occupation subsequent to job loss — also serve as the margin by which the average cost of job loss across all workers is amplified during recessions.

Although there has been little progress in understanding the cyclical cost of job loss, the subject remains important for research programs within labor economics and macroeconomics. Lucas (2003) concludes that the welfare gains of eliminating business cycles are small, and hence, stabilization policies in the United States are unwarranted as they may serve as an impediment to long-run growth. The subsequent literature has stressed,

[1] A recent paper by Lachowska, Mas, and Woodbury (2020) finds that establishment-level effects have little explanatory power for explaining the earnings losses of displaced workers, similar to findings for Ohio (Moore and Scott-Clayton, 2019) and Portugal (Raposo, Portugal, and Carneiro, 2019). Thus, Lachowska, Mas, and Woodbury (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.

however, that the welfare cost of business cycles increases with the cyclical component of uninsurable idiosyncratic persistent income risk, e.g. Krusell et al. (2009). Along these lines, Krebs (2007) shows that calculations of the welfare cost of business cycles that explicitly account for the dominant role of job loss in explaining earnings losses produce higher estimates of the cost of business cycles, as job loss is experienced by a small subset of the population and welfare costs are increasing in the concentration of income risk. The empirical findings here show that the earnings cost of job loss is not uniformly distributed within the subset of job-losers, and hence may be even more important for welfare than previously thought. In providing a model for understanding these features of the data, the paper contributes to a growing empirical literature on non-linear earnings processes (Arellano, Blundell, and Bonhomme, 2017) and the cyclical distribution of income risk (Guvenen, Ozkan, and Song, 2014).

Both the empirical and theoretical parts of the paper relate the cyclical cost of job loss to the cost of entering the labor market during a recession (Kahn, 2010). Insofar as displaced workers and new labor market entrants are exposed to the same aggregate conditions while searching for a job during a recession, some have speculated on whether their employment outcomes are driven by similar forces, e.g. Rogerson (2011). The empirical literature has found that the cost of entering the labor market during a recession is larger for lower-skill workers (Oreopoulos, von Wachter, and Heisz, 2012), and that much of the cost can be explained by initial employment in a lower paying occupation (Altonji, Kahn, and Speer, 2016). The cost of entering the labor market during a recession computed from the model here is close to that estimated by Schwandt and von Wachter (2019) and von Wachter (2020).

Of the stylized facts documented in the paper, several are novel to the literature, including that (*i*) the earnings losses associated with job displacement are predominantly explained by reemployment in lower-paying occupations, and that (*ii*) such outcomes are more common (and more costly) for workers who lose their job during a recession. These findings are of independent interest and serve as further evidence of vertical sorting across occupations under absolute advantage, as in Groes, Kircher, and Manovskii (2015).

In the following section, I show that the cost of job loss is largely concentrated among workers who switch occupations, and that there is a greater incidence of such occupation displacement during a recession. In section 3, I develop a model that is capable of addressing these empirical findings. Calibration and estimation of the model is discussed in section 4. In section 5, I show that the model is quantitatively consistent with the empirical facts documented by the paper, while also accounting for the cyclical cost of job loss and the cost of entering the labor market during a recession.

## 2. The cost and incidence of occupation displacement: evidence

I use data from the Current Population Study Displaced Worker Supplement and the Panel Study of Income Dynamics to document that the earnings cost of job displacement is most acute for workers who find reemployment in a different occupation to that of their prior job, i.e. workers who suffer *occupation displacement*. I establish the following stylized facts: *1)* Immediate earnings losses of displaced workers who switch occupation upon reemployment are up to three times those of occupation stayers; *2)* Workers displaced during a recession are more likely to switch occupation upon reemployment; *3)* The earnings losses and countercyclical incidence of occupation displacement is almost entirely accounted for by workers who switch to lower-paying occupations; *4)* While workers may find reemployment in a lower-paying occupation as a stop-gap, transitory measure, countercyclical occupation displacement represents a persistent phenomenon; and among those workers for whom occupation displacement is a persistent phenomenon, earnings losses are strongly countercyclical with respect to aggregate conditions at the time of job displacement; and finally, *5)* long-run earnings, hours, and wage recoveries are far slower for workers who switch occupation upon reemployment. Collectively, the empirical findings suggest occupation displacement as a proximate source for the size and cyclicality of the earnings cost of job loss estimated by Davis and von Wachter (2011).[2]

The first four facts are documented using the Displaced Worker Supplement, a supplement to the Current Population survey that has been administered in the January or February of every even year since 1984. The DWS identifies workers who have been separated from their jobs for reasons of slack work, plant closings, and abolished jobs—reasons which have been taken by the literature to capture "exogenous" layoffs.[3] The DWS inherits the large sample size and representative structure of the CPS and records information on earnings and occupation on the displacement and current job. The fifth set of findings concerns longer-term outcomes subsequent to job loss, and hence they are established using data from the Panel Study of Income Dynamics from 1968 to 1997. 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, Smith, and Vidangos (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

[2]The U.S. Social Security earnings records used in Davis and von Wachter (2011) do not include a measure for occupation, and there are no comparable datasets for the United States with both a measure of occupation and the necessary sample size (in both cross-sectional and longitudinal dimensions) to directly adopt the methodology set out by those authors. Hence, I establish the facts separately from multiple public-use datasets.

[3]Some examples include Podgursky and Swaim (1987), Topel (1990), Farber (1997), Schmieder and von Wachter (2010), and Farber (2015).

TABLE 1. Immediate earnings losses are higher for occupation switchers

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) | (0.0063) | (0.0052) | (0.0053) |
| Recession | $-0.055^{***}$ | $-0.055^{***}$ | $-0.055^{***}$ | $-0.058^{***}$ | $-0.058^{***}$ | $-0.058^{***}$ |
| | (0.0115) | (0.0115) | (0.0116) | (0.0099) | (0.0101) | (0.0100) |
| Constant | $-0.056^{***}$ | $-0.036^{***}$ | $-0.040^{***}$ | $-0.063^{***}$ | $-0.042^{***}$ | $-0.047^{***}$ |
| | (0.0073) | (0.0076) | (0.0073) | (0.0110) | (0.0108) | (0.0106) |
| $N$ | 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 | 2.02 | 2.93 | 2.58 | 2.04 | 2.83 | 2.53 |

*** 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.

displacement: see Topel (1990), Ruhm (1991), and Stevens (1997) for similar studies that use the PSID.[4] Additional information on sample construction is presented below and in the appendix.

2.1. **Immediate earnings losses are higher for occupation switchers.** I first show that workers who are involuntarily displaced from a job and reemployed into a different occupation suffer larger immediate earnings losses than other workers.[5,6] I use the

[4]Couch and Placzek (2010) argue that estimates of the cost of job loss from the PSID are similar to those that they obtain from administrative data using a mass-layoff instrument.

[5]Similar findings are established for the United States by Jacobson, LaLonde, and Sullivan (1993), Stevens (1997), Kambourov and Manovskii (2009), Couch and Placzek (2010), and Raposo, Portugal, and Carneiro (2019).

[6]Schmieder, von Wachter, and Heining (2020) find that establishment effects explain the vast majority of the earnings losses of displaced workers in Germany, leaving little explanatory power for occupation-switching. However, the importance of establishment effects seems particular to Germany: Lachowska, Mas, and Woodbury (2020), Moore and Scott-Clayton (2019), and Raposo, Portugal, and Carneiro (2019) find that establishment effects offer little explanatory power for the earnings losses of displaced workers in Washington State, Ohio, and Portugal. Indeed, Raposo, Portugal, and Carneiro (2019) control for establishment effects, but find that changes in "job-title" (related to changes in occupation) explains the majority of the earnings cost of job loss. Hence, it is difficult to conceive that establishment effects —

DWS to construct a sample of workers who were involuntarily displaced from a full-time job within the previous three years and are reemployed in a full-time job at the time of their interview.[7] Other selection criteria are similar to Farber (2015) and are discussed in greater detail in the appendix. I employ three different definitions of occupation to identify occupation switchers: "CPS/Fine", the fully disaggregated three-digit occupation code available from the CPS, with over 300 values, depending on the survey year; "CPS/Broad", the more coarsely aggregated two-digit occupation code provided by the CPS with between eleven and fifteen possible values depending on the year; and "AD", the time-consistent occupation code developed in Autor and Dorn (2013), with 334 possible values.[8] I regress the log differential in weekly earnings in the job at the time of observation and the displacement job on a constant and a dummy variable indicating whether the individual changed occupations across jobs. I include an additional dummy variable indicating whether the individual lost his or her job during a recession.[9] Separate specifications are estimated with and without controls for each definition of occupation switcher, all with robust standard errors clustered by year of job loss. Where additional controls are introduced, the baseline group is composed of white male college graduates displaced during an expansion. Controls for experience and the linear time trend are normalized so that the coefficient on the constant can be directly interpreted as the average earnings loss among workers in the baseline group. Observations are weighted using CPS final weights. Results are given in Table 1.

The results show significantly higher earnings losses for occupation switchers, by factors between 2.02 and 2.93. Across all occupation codings, between 45% and 67% of all workers

which have been found as decidedly unimportant for explaining the earnings losses of displaced workers in the United States — could reverse findings for the U.S. emphasizing the importance of occupation.

[7]I focus workers employed full-time on the previous and current job to isolate the wage channel of earnings losses. The focus on wages follows from findings emphasizing the importance of immediate and persistent wage losses in accounting for the earnings losses of displaced workers; e.g., Lachowska, Mas, and Woodbury (2020, pg. 3233), who find that "wage rates drop suddenly at the time of displacement and recover far more sluggishly [than earnings and hours]." See Section 2.5 for further discussion.

[8]This latter classification has been used by Autor and Dorn (2013) and Jaimovich and Siu (2012) to generate wage and skill-based rankings of occupation, and it will be used similarly later in the paper.

[9]A recession year is defined as a year with more than one quarter in recession according to the NBER classification. Similar results are obtained with a variable measuring the fraction of the year the economy is in recession. See Appendix A.

in the sample are observed to switch occupation.[10,11] The immediate cost of job loss for occupation switchers exceeds the cost for occupation stayers.

2.2. **Occupation switching is countercyclical for displaced workers.** Next, I document a new result to the literature: workers displaced during a recession are more likely to switch occupation upon reemployment. Using the sample of the previous section, I estimate a linear probability model for the event that a displaced worker is observed to be working in a different occupation from their pre-displacement job, with robust standard errors clustered by displacement year. The first regression specification includes only a constant and a dummy variable for recession. The coefficient on the constant represents the average fraction of occupation switchers among workers who are displaced during an expansion, while the coefficient on the recession dummy indicates additional switching among workers who lose their job during a recession. The second regression specification includes additional controls, as in the previous section. Results are given in Table 2. There is statistically significant evidence for countercyclical occupation switching across all specifications.

The findings of countercyclical occupation switching is consistent with vertical sorting across occupations under absolute advantage à la Groes, Kircher, and Manovskii (2015), combined with countercyclical hiring standards. As in Groes, Kircher, and Manovskii (2015), suppose that occupations differ in the rate of return to a general skill that is distributed non-uniformly across the population of workers. If firms require greater skill of an applicant during a recession, a worker that is randomly displaced to unemployment during a recession is more likely to switch to an occupation characterized by a lower return to skill. Such countercyclical "upskilling" within occupations finds direct support from Hershbein and Kahn (2018), who use firm-level vacancy data to show evidence of countercylical hiring standards.[12]

[10] An important paper by Fujita and Moscarini (2017) documents that a substantial portion of separated workers return to their previous employers as "recalls." To my knowledge, this issue has not yet received much attention within the literature on displaced workers, and the data from the CPS leave me poorly equipped to tackle this issue. However, an earlier version of that paper, Fujita and Moscarini (2013), shows that occupation switching is far less prominent among recalls (pg. 1). Hence, the more extensive earnings losses of displaced workers who switch occupation upon reemployment are much less likely to reflect phenomena associated with recall reemployment.

[11] These results are similar to Fujita and Moscarini (2013), who find from the SIPP that over 50% of unemployed workers switch occupation from unemployment.

[12] In particular, Hershbein and Kahn (2018) show that employers in MSA's disproportionately affected by the Great Recession redirect vacancies towards higher skill workers. Additional supporting findings of countercyclical reallocation of workers across occupations come from Jaimovich and Siu (2012), who show that employment of certain routine occupations declines irreversibly during recessions; and Barnichon and Zylberberg (2019), who document that workers are more likely to be hired into jobs for which they are overqualified during a recession. A recent paper by Schmieder, von Wachter, and Heining (2020) offers similar findings for Germany (see pg. 21), although the paper also finds that a smaller fraction of

Table 2. Occupation switching is countercyclical for displaced workers

Dependent variable: indicator for occupation switcher

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Recession | 0.040*** | 0.029*** | 0.030** | 0.030*** | 0.021*** | 0.022*** |
| | (0.0125) | (0.0111) | (0.0120) | (0.0051) | (0.0069) | (0.0062) |
| Constant | 0.461*** | 0.670*** | 0.654*** | 0.333*** | 0.547*** | 0.519*** |
| | (0.0048) | (0.0043) | (0.0044) | (0.0146) | (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.

2.3. **Occupation displacement is vertical.** As argued above, the previous findings of ($i$) greater earnings losses among displaced workers who switch occupation, and ($ii$) countercyclical occupation displacement can be rationalized in terms of a model of vertically ranked occupations. Here I show that such an interpretation is supported by the data: the evidence for countercyclical occupation switching and greater immediate earnings losses for occupation switchers is entirely accounted for by the ranking of occupation by average wage.[13]

To establish these findings, I consider the longitudinally consistent occupation classification of Autor and Dorn (2013) at three different levels of aggregation: I first use the fully disaggregated occupation classification, henceforth referred to as "AD."[14] Then, I consider the broader, six-category occupation classification considered by Autor and Dorn (2013),

workers switch occupation subsequent to job loss in Germany relative to the findings here for the United States.

[13]Both Autor and Dorn (2013) and Altonji, Kahn, and Speer (2016) associate the relative skill content of an occupation with its relative wage.

[14]Accurately ranking occupation by average wage requires a larger sample than provided by 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.

Table 3. The verticality of countercyclical occupation displacement

Dependent variable: indicator for occupation switcher

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Recession | 0.030*** | −0.008 | 0.019*** | 0.009 | 0.015** | −0.001 |
| | (0.0090) | (0.0070) | (0.0054) | (0.0054) | (0.0068) | (0.0064) |
| Constant | 0.270*** | 0.250*** | 0.110*** | 0.081*** | 0.090*** | 0.068*** |
| | (0.0117) | (0.0111) | (0.0070) | (0.0074) | (0.0074) | (0.0073) |
| $N$ | 24,920 | 24,920 | 24,920 | 24,920 | 24,920 | 24,920 |
| 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.

henceforth "AD6." Finally, I consider occupation transitions according the classification used by Jaimovich and Siu (2012), henceforth "JS3."[15]

First, I estimate a linear probability model to establish that the higher incidence of occupation switching among workers who lose their job during a recession is entirely due to downwards switchers. Results are given in Table 3. Columns one and two offer estimates from downwards (AD↓) and upwards (AD↑) switchers using the fully disaggregated AD classification. While workers are observed to make both downward and upward occupation changes, a recessionary increase in occupation switching is only observed for downwards switchers. The results hold for greater levels of aggregation, as shown in columns three and four for the AD6 classification, and in columns five and six for the JS3 classification. In percentage terms, recessionary increases in downward occupation switching are greater for higher levels of aggregation.[16]

[15]Listed in declining order of average wage, JS3 include *1*) non-routine cognitive, *2*) routine, and *3*) non-routine manual, i.e. low-skill service. Similarly listed, AD6 include are *1*) managers, professionals, technicians, finance, and public safety; *2*) production and craft; *3*) transportation, construction, mechanics, mining, and farm; *4*) machine operators and assemblers; *5*) clerical and retail sales; and *6*) service occupations. Note, groups four and five of the six-category classification do not have consistently higher (or lower) wages in the post-1980 period. Thus, I categorize switches between these categories as neither upwards or downwards.

[16]The finding of countercyclical displacement for JS↓ workers is consistent with the Jaimovich and Siu (2012) observation that recessions are accompanied by an acceleration in the trend reallocation of employment towards service occupations. Indeed, the results are robust to a more restrictive definition of JS↓ that only includes transitions to service occupations.

Table 4. Vertical displacement and re-employment earnings losses

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 | −0.056*** | −0.058*** | −0.058*** |
| | (0.0099) | (0.0099) | (0.0098) |
| Constant | −0.049*** | −0.073*** | −0.075*** |
| | (0.0103) | (0.0105) | (0.0107) |
| $N$ | 24,920 | 24,920 | 24,920 |
| Occ. def. | AD | AD6 | JS3 |
| Predicted loss: Switcher/Stayer | 3.84 | 2.63 | 2.79 |

*** 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.

Next, I show that earnings losses are higher for workers making downward shifts in occupation. I estimate a similar specification to that of Table 1, but I allow separate intercepts for downward and upward occupation switchers. Separate regressions are estimated for each of the three different occupation rankings. Results are given in Table 4. The coefficient estimates reveal a striking non-linearity for upward and downward occupation switchers. While reemployment in a lower-paying occupation is associated with substantially larger earnings losses relative to non-switchers, reemployment in a higher-paying occupation is associated with only mildly lower reduction in earnings. The milder earnings reduction for upward-switchers is only statistically significant under the JS3 occupation categorization. The results imply a distinct role for displacement to a lower-paying occupation in understanding the earnings losses of displaced workers

Across Tables 3 and 4, the results indicate that the earnings cost and cyclical incidence of occupation displacement can both be attributed to workers moving to lower-skill occupations. These results are consistent the aforementioned empirical literature emphasizing the importance of the vertical ranking of occupations for explaining occupation flows, e.g.

Groes, Kircher, and Manovskii (2015). But moreover, they bear commonality to findings from the empirical literature on workers who enter the labor market during a recession, e.g. Altonji, Kahn, and Speer (2016), who show that nearly half of the initial relative wage losses of such workers can be attributed to employment in a lower paying occupation.

2.4. **Displacement to a lower-paying occupation is a persistent source of countercyclical earnings losses.** The results of the previous section show that the immediate earnings cost of job loss is concentrated upon workers displaced to a lower-paying occupation upon reemployment; and that the incidence of such displacement is higher for workers who lose their job during a recession. However, such patterns of occupation displacement may be associated with temporary, stop-gap employment that resolves upon successful employment in a stable job of the worker's previous occupation.[17]

Here, I document that occupation displacement represents a large and persistent component to the earnings cost of job loss. The findings show that occupation displacement is only slightly less prevalent among workers surveyed more than two years subsequent to job loss (referred to here as the medium-run) as it is among workers surveyed within zero to two years subsequent to job loss (the short-run); and that the incidence of occupation displacement displays greater counter-cyclicality with respect to the state of the economy at job loss in the medium run. Among workers for whom occupation displacement is a persistent phenomenon, earnings losses display greater cyclicality with respect to the state of the economy at job loss. These estimates for workers who are persistently displaced from their prior occupation imply a near doubling in the cyclicality of the component of the earnings cost of job loss due to occupation-displaced workers.

To document the persistence of occupation displacement, I estimate a variant of the linear probability model of the previous sections, with AD$\downarrow$ as the dependent variable indicating whether a worker has moved to a lower-paying occupation. I consider two separate samples: workers displaced within two years of the survey date (the short-run) and workers more than two years subsequent to the survey date (the medium-run). I estimate separate coefficients for the entirety of both samples, but also for sub-samples of workers that are employed at their first job since job loss.[18] Results are given in Table 5. As can be seen from the coefficient on the constant term, the incidence of occupation displacement is similar for both the short-run and medium-run samples. The magnitude of the recessionary increase in occupation displacement, however, is greater in the medium

[17]See Jarosch (2015) for a model where stability is a fundamental characteristic of a job, and hence workers may optimally accept a lower-paying job as stop-gap employment.

[18]This information is not available for the 1984 sample. Hence, the 1984 sample is dropped for the "first job" subsamples.

Table 5. Vertical occupation displacement in the short- and medium-run

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 | 0.022** | 0.020* | 0.044*** | 0.049*** |
| | (0.0101) | (0.0112) | (0.0156) | (0.0160) |
| Constant | 0.286*** | 0.279*** | 0.305*** | 0.285*** |
| | (0.0095) | (0.0106) | (0.0138) | (0.0118) |
| $N$ | 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.

run.[19] These results reveal reemployment to a lower-paying occupation is not merely a stop-gap phenomenon, but a persistent one.

Next, I show that in the medium-run, the earnings losses of occupation-displaced workers are more persistent and more cyclical than those of workers that are not occupation-displaced. To do so, I introduce an interaction term for AD↓ and the variable identifying displacements occurring during a recession year. Columns one and two give results from the full and "first jobs" short-run sample. The results appear similar to those from column one of Table 4: the earnings losses of the occupation-displaced are considerably higher than those of other workers. Notably, the interaction term is small in magnitude and positive, but not statistically significant.

The medium-run sample shows findings of even more severe earnings losses for workers displaced from their previous occupation. The constant term, representing the average reduction in earnings conditional on no occupation-displacement, is smaller in magnitude and not significantly different from zero, indicating a recovery of previous earnings for

[19]Note that Table 10 does not offer the requisite information for a complete decomposition of the dynamic behavior of occupation displacement across multiple jobs, given that sample selection criterion excludes the non-employed and workers in part-time jobs. That said, among respondents meeting the selection criterion, more workers are observed at their first position since job loss (≈ 65%) in the short-run sample than in the medium-run sample (≈ 55%).

Table 6. Short- and medium-run earnings losses of vertical occupation displacement

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) |
| Switch↓ | $-0.151^{***}$ | $-0.139^{***}$ | $-0.127^{***}$ | $-0.119^{***}$ |
| | (0.0080) | (0.0077) | (0.0142) | (0.0184) |
| Switch↓ × Recession | $0.037^{*}$ | 0.007 | $-0.071^{***}$ | $-0.076^{***}$ |
| | (0.0197) | (0.0286) | (0.0226) | (0.0209) |
| Recession | $-0.059^{***}$ | $-0.043^{***}$ | $-0.045^{***}$ | $-0.067^{***}$ |
| | (0.0082) | (0.0099) | (0.0150) | (0.0144) |
| Constant | $-0.050^{***}$ | $-0.029^{**}$ | $-0.028$ | 0.009 |
| | (0.0182) | (0.0131) | (0.0170) | (0.0178) |
| $N$ | 17,101 | 11,052 | 7,819 | 4,273 |
| $R^2$ | 0.048 | 0.048 | 0.066 | 0.077 |
| First jobs only? | No | Yes | No | Yes |
| Recessionary increase in predicted earnings losses, occ. switchers component | -18.5% | 2.1% | 78.4% | 92.1% |

*** 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.

non-occupation-displaced workers who lose their job during an expansion. However, the estimates reveal highly cyclical and persistent earnings losses among workers switching to a lower-paying occupation.[20] Indeed, there is a near doubling in the component of the recessionary increase in the earnings cost that is specific to occupation displacement.[21]

[20]There are several explanations for the deeper recessionary wage losses that emerge for workers two years from displacement. In particular, to the extent that workers who switch to lower-paying occupations as a stop-gap measure realize characteristically different wage reductions than workers whose reemployment in lower-paying occupations is a persistent outcome, the estimates from medium-term sample offer a better measure of the wage outcome from occupation displacement

[21]In Appendix A.3, I define the earnings cost of job loss (in terms of pre-displacement earnings) using the estimated parameters from Tables 5 and 6. The cost of job loss can then be expressed as a convex combination of a common component and a component that is specific to workers who switch occupation upon reemployment.

Hence, the cost of job loss of workers displaced from their most recent occupation is large, persistent, and highly cyclical.

2.5. **Long-run costs of job loss in earnings, wages, and hours are higher and more persistent for occupation switchers.** The findings of the previous section reveal that the size and cyclicality in the cost of job loss can be attributed to workers displaced to a lower-paying occupation. However, these results are established using a dataset that follows workers over a relatively short time frame, and hence do not rule out the possibility that the earnings recoveries of occupation stayers and switchers appear more similar in the long term. In this section, I use the Panel Study of Income Dynamics from 1968 to 1997 to show that the long-term cost of job loss in earnings, wages, and hours is higher for occupation switchers.[22] Meanwhile, occupation stayers display relatively quick recoveries in earnings, wages, and hours subsequent to job loss.

To assess the cost of job loss of occupation switchers and stayers, I compare their outcomes to those of workers who have not been dismissed from their job within the past ten years.[23] I employ a regression similar to that of the existing literature, e.g. Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997). The regression equation is

$$y_{it} = x_{it}'\beta + \sum_{k\geq -2}^{10} \delta_{ns}^{k} D_{it}^{ns,k} + \varphi_{ns} F_{it}^{ns} + \sum_{k\geq -2}^{10} \delta_{s}^{k} D_{it}^{s,k} + \varphi_{s} F_{it}^{s} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

The outcome variables including log annual earnings, log hourly wages, and log annual hours. The variable $x_{it}$ is a vector of time-varying individual characteristics, including experience and schooling; $\alpha_i$ is a time invariant unobserved error component associated with person $i$; and $\gamma_t$ is an error component common to all individuals in the sample at year $t$.[24] The indicator variables $D_{it}^{j,k}$ are used to identify displaced workers in the $k^{\text{th}}$ year after job displacement, where $j = ns$ indicates that the worker does not switch occupation upon reemployment, and $j = sw$ indicates that the worker does switch occupation upon reemployment.[25] As in Stevens (1997), I focus on the first displacement recorded for each

[22]After 1997, the survey began interviewing respondents at a biennial rather than annual frequency, complicating the subsequent analysis of post-displacement occupation changes. Details of the sample construction are given in Appendix A.1.

[23] The definition of the control sample is motivated by data limitations: in the 1968 survey, PSID respondents are asked whether or not they have been dismissed from a job within the past ten years. To generate ($i$) a longitudinally consistent control sample, and ($ii$) maximize the number of observations, I drop workers who report displacement in the past ten years at the 1968 survey, similar to Stevens (1997). I then define the control sample as workers who have been displaced within the past ten years. Stevens takes a slightly different approach: while Stevens drops the 1968 previously-displaced workers as I do, she includes a worker in the control sample if they are ever observed to be displaced. This is a more restrictive control sample, but is not longitudinally consistent. The results, however, are largely similar.

[24]Results are robust to interacting the coefficients $\beta$ and $\gamma$ with job-loss status.

[25]I use the PSID three-digit occupation coding to identify switchers and stayers.

individual in the sample.[26] To control for possible impacts of subsequent displacements, the indicator variable $F_{it}^{j}$ is equal to one for zero to ten years following the most recent job loss. Accordingly, $\delta_j^k + \varphi_j$ represents the effect of job displacement for post-displacement occupation stayers and switchers in years $k \in [0, 10]$ after job loss, relative to workers who have not been dismissed from their job in the previous ten years. The regressions are estimated with fixed effects and robust standard errors clustered by individual.

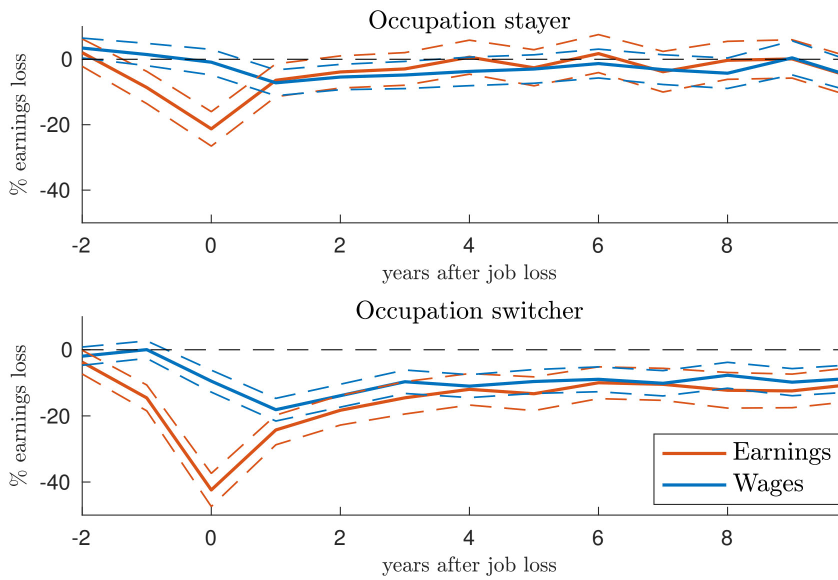
Figure 1 shows the earnings and wage losses for occupation switchers and stayers relative to counterfactual outcomes under no displacement, with dashed lines indicating 95% confidence intervals around the estimates. Workers who switch occupations subsequent to job displacement experience a 42% percent drop in earnings, twice as large as the 21% drop in earnings for workers who remain in the same occupation. The subsequent earnings recovery of occupation stayers is estimated to be complete within several years: relative earnings losses recover to 6.4% one year after displacement, and thereafter are not significantly different from zero. Meanwhile, for occupation switchers, there is a slow and incomplete recovery in annual earnings, with relative losses remaining around 10% ten years after job displacement. A similar pattern is observed for the recovery of hourly wages. Workers who remain in the same occupation experience relative wage losses of around 7% in their first year after job loss, with subsequent relative wage losses that rapidly approach zero. In contrast, occupation switchers experience relative wage losses of 18.1% in the year after displacement, with an incomplete recovery that leaves wages around 10% below those of comparable workers who did not lose their job. Figure 2 shows the recovery in hours worked per year. Occupation stayers experience a 20% reduction in hours the year of displacement, and a full recovery thereafter. In contrast, occupation switchers experience a 33% reduction in hours the year of displacement, with losses that persist more than three years subsequent to displacement.[27]

The empirical findings highlight two important features of the earnings cost of job loss: First, there is significant ex-post heterogeneity in earnings outcomes among workers who

[26]Note, to the extent that the individual suffers subsequent displacements, the effects will be recovered by the coefficients $\varphi_j$ and $\delta_j^k$. Stevens (1997) estimates a separate equation to isolate the effect of subsequent replacements. The effects are smaller.

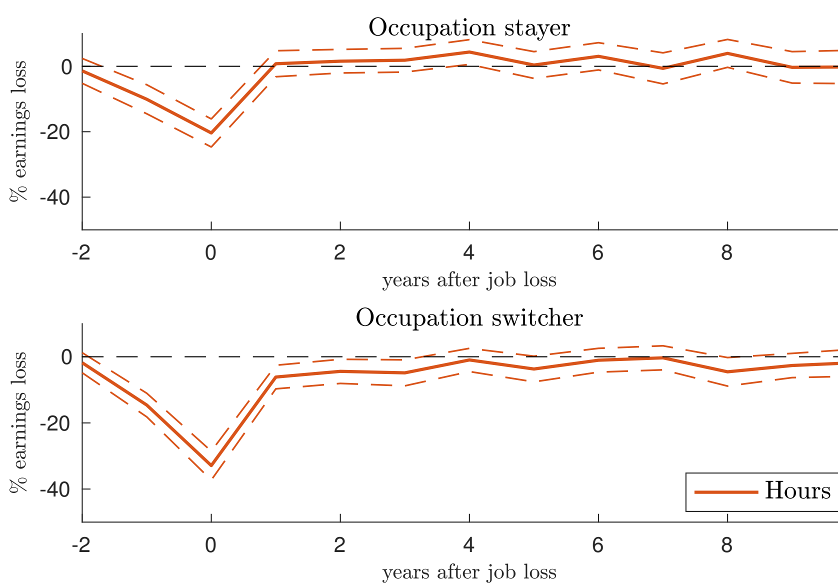
[27]The fairly quick convergence of earnings and wage losses (and the fairly quick hours recovery) is consistent with findings from the existing literature using the PSID to study the decomposition of earnings losses of displaced workers into wages and hours, e.g. Stevens (1997) and Altonji, Smith, and Vidangos (2013). A more recent literature using administrative data establishes similar outcomes as those from the prior literature using the PSID. For example, Lachowska, Mas, and Woodbury (2020) study workers displaced during the Great Recession and describe their findings as "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" (pg. 3248). See also Schmieder, von Wachter, and Heining (2019) and Burdett, Carrillo-Tudela, and Coles (2020).

FIGURE 1. Earnings and wage losses are more persistent for occupation switchers




Source: PSID. Dashed lines represent 95% confidence intervals around estimates.

FIGURE 2. Longer hours recoveries for occupation switchers




Source: PSID. Dashed lines represent 95% confidence intervals around estimates.

lose their job. In particular, the cost of job loss does not appear particularly severe for workers who find reemployment in their pre-displacement occupation. More severe earnings losses only appear to manifest when a worker is unable to obtain reemployment in a job that uses previously acquired skill. Second, aggregate conditions have an important influence on the types of employment opportunities available to a worker in unemployment. Workers displaced during a recession are less likely to find reemployment in a job similar to that which they held pre-displacement; and the earnings losses associated with such an employment outcome are greater.

In what follows, I propose a new model that generates the type of nonlinear earnings dynamics discussed above. A small loss in human capital can generate either small or large earnings losses, depending on whether the human capital loss prevents a worker from finding a job that utilizes the previously acquired human capital. The likelihood that a worker is unable to find reemployment in a job utilizing previously acquired skill increases during a recession, as do the associated loss in earnings.

## 3. A model of unemployment, skill, and selective hiring

To understand the facts documented in the previous section, I develop a new model of unemployment, skill, and selective hiring. The model combines elements of a Diamond-Mortensen-Pissarides search and matching model with the Ljungqvist and Sargent (1998) model of human capital accumulation and depreciation. The framework also borrows insights from Acemoglu (1999), as the qualitative composition of jobs changes endogenously with the skill-composition of the labor force. The notion of occupation in the model is adopted from the "task-based" framework of Acemoglu and Autor (2011), where the skill content of a job is defined by its production technology.

There are two types of jobs in the model, each associated with a large measure of occupations: "skill-sensitive" and "skill-insensitive".[28] Jobs in skill-sensitive occupations are characterized by a production technology that requires a human capital input. Jobs in skill-insensitive occupations are characterized by a production technology that does not require a human capital input.[29] This novel feature of the model allows it to match the heterogeneity and cyclicality in the cost of job loss documented in the previous section of the paper: Displaced workers from skill-sensitive jobs who find reemployment in lower-paying skill-insensitive jobs suffer larger and more persistent earnings losses. The greater

[28]In a previously circulating version of the paper, the job-types were referred to as "skill-intensive" and "skill-neutral". I thank a referee for recommending the terminology adopted here.

[29]See Moscarini (2001) for a model of sorting across occupations by comparative advantage, also featuring two production functions.

occurrence (and earnings losses) of such displacement during recessions lends cyclicality to the cost of job loss.

The stochastic process for human capital accumulation is standard to the literature, e.g. Ljungqvist and Sargent (1998), except that workers in unemployment are subject to the risk that their skills become obsolete, wherein they draw a new value of human capital from the initial distribution. This feature of the model captures the increasing income disaster risk over the lifecycle documented by Guvenen, Karahan, Ozkan, and Song (2015), but also lends a broader interpretation of the mapping of occupation in the model to occupation in the data.[30] A worker may be displaced from a job as a machinist (skill-sensitive employment); discover during his time in unemployment that his skills are no longer relevant to new vintages of technology (obsolescence shock); subsequently find employment as a salesperson (skill-insensitive employment); and then work his way up to a job as a manager (skill-sensitive employment).

A full description of the environment is given in Sections 3.1 through 3.6. The problems of workers and firms are given in Sections 3.7 and 3.8. Formal results describing how the model generates a non-uniform and countercyclical cost of job loss are offered in Sections 3.9. Finally, the wage bargaining protocol is described in Section 3.10, and the equilibrium is defined in Section 3.11.

3.1. **Setting.** The model is set in discrete time with an infinite horizon. There is a unit measure of workers and a large measure of firms. Workers have linear preferences over the consumption good, suffer no disutility of labor, and discount the future by a factor $\beta < 1$. Workers are either unemployed, employed in a skill-insensitive job, or employed in a skill-sensitive job. Jobs are subject to an exogenous destruction probability $\delta$. Workers are endowed with $h$ units of human capital (skill). A cumulative distribution function $\lambda$ gives the measure of workers over human capital and employment. Workers have geometric lifespans: each period a measure $\nu$ of workers die and a measure $\nu$ are born into unemployment. There are two aggregate state variables: productivity $Z$ and the distribution of workers across human capital and employment states, $\lambda$. $Z$ takes on finite values and evolves according to a first-order Markov chain.

3.2. **Production.** Production occurs within single worker firms. In firms operating the skill-neutral technology, output $y_L$ varies with aggregate productivity $Z$ but not the worker's skill $h$. Skill-intensive firms operate a production technology that is linear in

[30]See also Braxton and Taska (2020), who use detailed vacancy posting data from Burning Glass and estimate that over half of the earnings cost of job loss can be attributed to workers who lack the requisite new skills required to find reemployment in their pre-displacement occupation. The obsolescence shock here can be interpreted as a reduced form for such phenomena.

the worker's human capital input $h$ and aggregate productivity $Z$ to produce $y_H$:

$$y_L(h, Z) = Z, \quad y_H(h, Z) = Zh. \tag{2}$$

Once a firm and worker are matched, the job type is fixed: a skill-insensitive job cannot be converted into a skill-sensitive job, and vice versa.

3.3. **Human capital dynamics.** Human capital lies in an equispaced grid $\mathcal{H}$ with lower bound $h_{lb}$ and upper bound $h_{ub}$. New entrants draw an initial value of human capital from a distribution function $F$ with support over the entire grid $\mathcal{H}$.

Workers in skill-sensitive and skill-insensitive jobs stochastically accumulate human capital. Each period, the human capital endowment of a worker in a skill-sensitive (skill-insensitive) job increases by amount $\Delta_{\mathcal{H}}$ with probability $\pi_H$ ($\pi_L$).[31,32] Hence, for a worker with human capital $h$ employed in a job of type $i$, human capital evolves as follows:

$$h' = \begin{cases} h + \Delta_{\mathcal{H}} & \text{with probability } \pi_i \\ h & \text{with probability } 1 - \pi_i \end{cases} \qquad i = L,\ H. \tag{3}$$

Workers in unemployment face two sources of human capital risk: obsolescence and gradual depreciation. With probability $\xi$, a worker who enters the period with human capital $h$ finds his skills rendered obsolete and must draw a new value of human capital $h_{obs}$ from a distribution $F_{obs}(\cdot; h)$ constructed from the initial distribution $F$, defined as

$$F_{obs}(h_{obs}; h) = \frac{1}{F(h)} \int_{h_{lb}}^{h_{obs}} dF(h')dh'. \tag{4}$$

The upper bound for the support of the distribution is the beginning-of-period level of human capital, and the lower bound is $h_{lb}$.[33] Immediately after the realization of the obsolescence shock (and within the same period), the worker faces a probability $\pi_U$ of losing a quantity $\Delta_{\mathcal{H}}$ of human capital. Hence, the human capital of a workers in unemployment who enters the period with human capital $h$ evolves according to the following:

$$h' = \begin{cases} h_{obs} & \text{with probability } \xi(1 - \pi_U) \\ h_{obs} - \Delta_{\mathcal{H}} & \text{with probability } \xi\pi_U \\ h & \text{with probability } (1 - \xi)(1 - \pi_U) \\ h - \Delta_{\mathcal{H}} & \text{with probability } (1 - \xi)\pi_U \end{cases}. \tag{5}$$

[31]Consider skill accumulation in skill-insensitive jobs as a form of workplace learning, e.g. learning from observing the activities of workers in skill-sensitive jobs.
[32]In the calibrated model, the estimated value of $\pi_H$ is higher than $\pi_L$.
[33]The construction of the distribution ensures that workers do not gain skill from an obsolescence shock.

3.4. **Search and matching.** Workers must be matched with firms in order to produce. Firms post vacancies at submarkets specific to a single level of human capital, i.e. search is segmented in $h$.[34] Given the vacancy posting decision of firms, workers of a particular $h$ choose whether to search for either skill-insensitive or skill-sensitive employment. The worker-specific state variables are given by $\psi = \{h, j\}$, where $h$ is human capital, and $j$ represents the type of job with which a worker has most recently matched.[35]

Given aggregate productivity $Z$ and the worker distribution $\lambda$, the number of vacancies for a worker of skill $h$ in the skill-insensitive and skill-sensitive submarkets are $\upsilon_L(\psi, Z)$ and $\upsilon_H(\psi, Z)$.[36] Searchers $s_L(\psi, Z)$ for skill-insensitive jobs consist only of workers searching from unemployment, whereas searchers $s_H(\psi, Z)$ for skill-sensitive vacancies comprise both unemployed workers and workers in skill-insensitive jobs. Workers in skill-insensitive jobs search with the same efficiency as unemployed workers and hence never quit to unemployment to improve search outcomes.[37]

The total number of matches generated within a particular submarket $m_i(\psi, Z)$, $i = L, H$, is determined by a constant returns to scale matching function:

$$m_i(\psi, Z) = \phi_i s_i(\psi, Z)^{\sigma} \upsilon_i(\psi, Z)^{1-\sigma}, \ i = L, H. \tag{6}$$

The job-finding probability $p_i(\psi, Z)$ for a worker with human capital $h$ searching for a job of type $i$ when aggregate productivity is $Z$ (and the corresponding vacancy filling probability $q_i(\psi, Z)$) are given as follows:

$$p_i(\psi, Z) = \frac{m_i(\psi, Z)}{s_i(\psi, Z)}, \quad q_i(\psi, Z) = \frac{m_i(\psi, Z)}{\upsilon_i(\psi, Z)}, \quad i = L, H. \tag{7}$$

Job-finding and vacancy-filling probabilities can be expressed as functions of the ratio of vacancies to unemployment within each submarket, i.e. the market tightness ratios $\theta_i(\psi, Z)$, $i = L, H$.

3.5. **Occupation switching.** For each type of job, there is a continuum of occupations. If a worker from unemployment finds a job using the production function of their previous job, the worker's occupation changes with probability $\chi$ upon reemployment to their new job. If the worker finds a job using a different type of production technology, the worker's

[34]Such segmented search à la Mortensen and Pissarides (1999) is distinct from directed search à la Moen (1997), as the segmentation of matching markets is taken as a constraint.

[35]This implies that $j \in \psi$ updates immediately upon a worker and firm meeting, e.g. the $j \in \psi$ of a worker who was previously matched with an skill-insensitive job changes from $L$ to $H$ upon matching with a skill-sensitive job, so the worker bargains with $j = H$. I assume $j = L$ for newly born workers.

[36]The assumption of segmented search eliminates $\lambda$ as a state variable, and hence I suppress $\lambda$ as an argument to the equilibrium labor market quantities and value functions.

[37]For simplicity, workers in skill-insensitive jobs search with the same efficiency as unemployed workers, and workers in skill-sensitive jobs do not search at all. These features can be introduced into the environment with little bearing for the quantitative results.

occupation changes with probability one. Hence, the only type of occupation change that is relevant for computing future values are occupation switches across types of jobs, skill-sensitive to skill-insensitive or vice versa.[38] As will be shown, this feature of the model allows for acyclical, non-costly occupation switches to coexist alongside countercyclical occupation displacement, as documented in Section 2.3.

3.6. **Timing.** A single period is divided into three sub-periods. In the first sub-period, a measure $\nu$ of workers die and are replaced by new entrants, and new values of productivity $Z$ and human capital of $h$ are realized. Search and matching occurs in the second sub-period. In the third and final sub-period, matches produce and wages are paid to workers.

3.7. **Worker and firm value functions.** The value functions of workers and firms are written in terms of the value in the third sub-period, after search and matching has taken place.

The decision of workers in unemployment is whether to search for a skilled or unskilled job.[39] Let $U(\psi, Z)$, $W_H(\psi, Z)$, and $W_L(\psi, Z)$ be the value of a worker of type $\psi$ in unemployment, a skill-sensitive job, and a skill-insensitive job when aggregate productivity is $Z$. The value of a worker in unemployment satisfies

$$\begin{aligned} U(\psi, Z) = u^b(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z} \max\Big\{ & p_H(\psi', Z')W_H(\psi', Z') \\ & + (1 - p_H(\psi', Z'))\, U(\psi', Z'),\ p_L(\psi', Z')W_L(\psi', Z') \\ & + (1 - p_L(\psi', Z'))\, U(\psi', Z')\Big\} \end{aligned} \tag{8}$$

subject to the laws of motion for $\psi$ and $Z$, where $u^b(\psi)$ represents the period value of leisure for an unemployed worker of type $\psi$.[40] Note that the continuation value of a worker reflects the optimal search decision in the subsequent period: a worker searches for a skill-sensitive job from unemployment if and only if $p_H\,(W_H - U) \geq p_L\,(W_L - U)$, and the worker searches for a skill-insensitive job from unemployment otherwise.[41]

The value of a worker employed in a skill-sensitive job, $W_H(\psi, Z)$, satisfies

$$W_H(\psi, Z) = w_H(\psi, Z) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\left[(1-\delta)W_H(\psi', Z') + \delta U(\psi', Z')\right] \tag{9}$$

[38]As in Acemoglu and Autor (2011), a single factor-augmenting technology is used across multiple occupations. But whereas workers are exogenously assigned to a "skill group" characterized by a group of occupations and a single factor-augmenting technology in Acemoglu and Autor (2011), workers here potentially move across different production technologies as they change jobs.

[39]This may be a trivial decision, as only one type of vacancy may be posted for certain values of human capital $h$.

[40]For economy of notation, the arguments to the Bellman equations include $Z$ as the only aggregate state variable, as the equilibrium is block recursive.

[41]The same tie-breaking assumption, that a worker searches for a skill-sensitive job when $p_H\,(W_H - U) = p_L\,(W_L - U)$, is used consistently throughout the paper.

subject to the laws of motion for $\psi$ and $Z$, where $w_H(\psi, Z)$ is the period wage. Note, the continuation value of a worker in a skill-sensitive job reflects the possibility of possible unemployment, occurring with probability $\delta$.

The value of a worker employed in a skill-insensitive job, $W_L(\psi, Z)$, satisfies

$$\begin{aligned} W_L(\psi, Z) = w_L(\psi, Z) + (1-\nu)\beta \mathbb{E}_{\psi,Z}\Big[& p_{H_+}(\psi', Z')(1-\delta) W_H(\psi', Z') \\ &+ \Big(1 - p_{H_+}(\psi', Z')\Big)(1-\delta) W_L(\psi', Z') + \delta U(\psi', Z')\Big] \end{aligned} \tag{10}$$

subject to the laws of motion for $\psi$ and $Z$, where $w_L(\psi, Z)$ is the period wage. Here, the continuation value reflects not only the possibility of future unemployment, but also the optimal decision of a worker in a skill-insensitive job to search on-the-job for a skill-sensitive job and the probability that the worker's search (if taken) is successful:

$$p_{H_+}(\psi, Z) = \mathbb{I}\left\{W_H(\psi, Z) > W_L(\psi, Z)\right\} \cdot p_H(\psi, Z).$$

As we shall see, the value of a worker in a skill-insensitive job increases with probability of successful on-the-job search for a skill-sensitive job.

Let $J_H(\psi, Z)$ denote the value of a skill-sensitive firm employing a worker of type $\psi$ when aggregate productivity is $Z$,

$$J_H(\psi, Z) = Zh - w_H(\psi, Z) + (1-\nu)\beta \mathbb{E}_{\psi,Z}\Big[(1-\delta) J_H(\psi', Z')\Big] \tag{11}$$

subject to the laws of motion for $\psi$ and $Z$. As will be seen, the value of a skill-sensitive job to a firm is increasing in human capital $h \in \psi$, implying correspondingly increasing job-finding probabilities.

The value $J_L(\psi, Z)$ of a skill-sensitive firm employing a worker of type $\psi$ when aggregate productivity is $Z$ satisfies

$$J_L(\psi, Z) = Z - w_L(\psi, Z) + (1-\nu)\beta \mathbb{E}_{\psi,Z}\Big[\Big(1 - p_{H_+}(\psi', Z')\Big)(1-\delta) J_L(\psi', Z')\Big] \tag{12}$$

subject to the laws of motion for $\psi$ and $Z$. Note, the continuation values of both the worker and a firm in a skill-insensitive match depend on the probability of successful on-the-job search, $p_{H_+}$. But unlike for the worker, a higher probability of successful on-the-job search $p_{H_+}$ yields lower expected payoffs to the firm. Hence, while output in such a match does not depend on the worker's endowment of human capital $h \in \psi$, firms discount skill-insensitive matches more as $h$ due to retention concerns: as $h$ increases, so too does $p_{H_+}$.[42] As we will be seen, this generates a channel whereby higher $h$ and (thus higher

[42]We will consider a bargaining protocol where the equilibrium wage in a skill-insensitive job is decreasing in the probability of successful on-the-job search. Quantitatively, however, the declining wage is not enough to offset the retention effect described above.

job-finding probabilities for skill-sensitive jobs) deter vacancy posting for skill-insensitive jobs, reducing job-finding probabilities for skill-insensitive jobs $p_L(\psi, Z)$ accordingly.

3.8. **Vacancy posting and free entry.** Firms pay a period cost $\kappa_H$ ($\kappa_L$) to post a vacancy in a skill-sensitive (skill-insensitive) submarket. In equilibrium, free entry drives the value of posting a vacancy in any market to zero, reflected in a complementary slackness condition:

$$J_i(\psi, Z) \leq \frac{\kappa_i}{q_i(\psi, Z)},\ \theta_i(\psi, Z) \geq 0,\ i = L, H. \tag{13}$$

In equilibrium, the expected value associated with posting a vacancy for a job of type $i$, $q_i(\psi, Z)J_i(h, Z)$, is equal to the vacancy posting cost $\kappa_i$ across active submarkets. In inactive submarkets, I assume $\theta_i(\psi, Z) = 0$, following Menzio and Shi (2010).

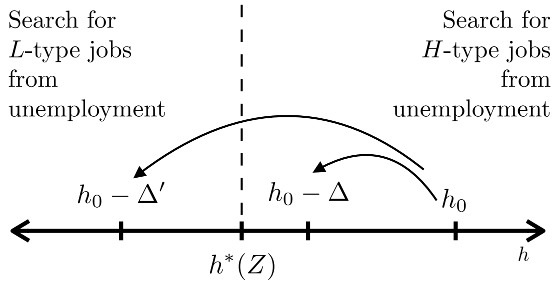
Note that search is fully segmented, and the value associated with filling a vacancy is independent of the distribution of workers across unemployment and jobs. Hence, market tightness $\theta_i(\psi, Z)$ and implied job-finding probabilities do not depend on the distribution of workers, and thus the distribution $\lambda$ does not enter the value functions of workers or firms. In this sense, the equilibrium of the model inherits a "block recursive structure," as defined in Menzio and Shi (2010, 2011).

3.9. **Countercyclical selective hiring and the equilibrium skill threshold.** Before establishing the dynamic bargaining protocol employed under the fully calibrated model, it is useful to describe how the optimal search decision of a worker in unemployment varies with $h$ and $Z$ under a simple wage rule. In the fully calibrated model, the search behavior from unemployment for a worker of type $\psi$ when aggregate productivity is $Z$ can be summarized by the position of $h$ relative to some threshold value. This is formalized below as the *equilibrium skill-threshold*; and as will be established, this object is useful for describing the extent of earnings losses associated with job loss.

**Definition 1** (Equilibrium skill-threshold)**.** *An equilibrium admits an equilibrium skill-threshold when aggregate productivity is $Z$ if there exists a value $h^*(Z)$ such that a worker searches for a skill-sensitive job if and only if $h \geq h^*(Z)$; otherwise, the worker searches for a skill-insensitive job.*

Note, the search behavior of workers in the fully calibrated model is consistent with an equilibrium skill threshold that decreases with aggregate productivity. However, it is convenient to develop formal results regarding the properties the countercyclical equilibrium skill threshold under a limiting case of the model where wages are determined by generalized Nash bargaining over flow payoffs; and where $\xi$, $\sigma_z$, and $\pi_i$, go to zero for $i = U, L, H$. In doing so, I adopt a set of regularity assumptions describing a minimal

FIGURE 3. Search behavior is described by an equilibrium skill threshold $h^*$




Proposition 1 establishes the existence of an *equilibrium skill threshold*, $h^*$. Workers with $h \geq h^*(Z)$ search for $H$-type jobs, whereas workers with $h < h^*(Z)$ search for $L$-type jobs. A worker who enters unemployment from an $H$-type job with skill $h_0$ searches for $H$-type jobs if shocks to skill are sufficiently small, e.g. of size $\Delta$. For sufficiently larger shocks, e.g. of size $\Delta'$, the worker switches their search to $L$-type jobs.

set of conditions under which workers face a trade-off between pursuing the higher value associated with a skill-sensitive job, on the one hand; and the higher probability of exiting unemployment through search for a skill-insensitive job, on the other. The full set of conditions are given under Assumption 1 in Appendix B.2.[43]

**Proposition 1** (Existence and uniqueness of equilibrium skill threshold)**.** *The equilibrium skill threshold $h^*(Z)$ exists and is unique for a given $Z$.*

*Proof.* See Appendix, section B.2.2. □

Proposition 1 establishes that the search behavior of workers from unemployment in the auxiliary model is determined by the position of their skill-endowment relative to the equilibrium skill threshold. Recall, an unemployed worker searches for a skill-sensitive job if and only if $p_H\left(W_H - U\right) \geq p_L\left(W_L - U\right)$. The proposition is established by showing that $p_H\left(W_H - U\right) - p_L\left(W_L - U\right)$ is continuous and strictly increasing in $h$. Intuitively, $p_H$ is increasing in $h$ because the firm value from a skill-sensitive job $J_H$ increases in $h$ through firm profits; whereas $J_L$ and $p_L$ are decreasing in $h$, as workers with higher human capital are retained with lower probability due to on-the-job search for skill-sensitive jobs. Then, the composite term $p_H\left(W_H - U\right)$ is increasing in $h$ through increasing wages in skill-sensitive jobs and $p_H$, and the composite term $p_L\left(W_L - U\right)$ is decreasing in $h$ through $p_L$. We can then establish that, for a given $Z$, $p_H\left(W_H - U\right) = p_L\left(W_L - U\right)$ at a unique point $h^*(Z)$.

[43]Note, Menzio and Shi (2010, 2011) establish similar results under an environment where worker and firm value functions are strictly increasing in match-specific state variables that enter as arguments to both value functions. The machinery developed by Menzio and Shi does not apply here, however, as value of a worker employed in a skill-insensitive job may be increasing in $h$ while the value of the firm is decreasing in $h$.

Two corollaries to Proposition 1 immediately follow:

**Corollary 1.1** (The $\epsilon$-maximal cost of job loss is realized at $h^*$)**.** *Define the $\epsilon$-maximal cost of job loss as the maximum percent change of prior and reemployment wages for a worker who loses their job and subsequently loses an arbitrarily small but positive quantity of human capital $\epsilon > 0$. The $\epsilon$-maximal cost of job loss when aggregate productivity is $Z$ is realized for a worker of human capital $h = h^*(Z)$ employed at a skill-sensitive job. Such a worker is forced to search for a skill-insensitive job upon employment, and hence undergoes costly occupation displacement.*

*Proof.* See appendix, section B.2.2. □

**Corollary 1.2** (Expected duration of unemployment is highest around $h^*$)**.** *Suppose aggregate productivity is $Z$. Expected duration of unemployment increases in $h$ for $h < h^*(Z)$ and decreases in $h$ for $h \geq h^*(Z)$. In particular, the longest expected duration of unemployment of a worker searching for a skill-sensitive job is realized at $h = h^*(Z)$; while the longest expected duration of unemployment of a worker searching for a skill-insensitive job is realized at $h = h^*(Z) - \epsilon$ for an arbitrarily small $\epsilon > 0$.*

*Proof.* See appendix, section B.2.2. □

Corollary 1.1 establishes that the earnings cost of job loss is a discontinuous function of skill for workers previously employed in a skill-sensitive job whose human capital places them exactly at the equilibrium skill threshold. Upon job loss and the loss of an infinitesimal quantity of skill, such workers will optimally redirect their search towards the less remunerative job of a skill-insensitive occupation. These workers achieve the highest earnings loss associated with an infinitesimal loss of skill that drives the workers towards "occupation displacement." The corollary emphasizes a unique property of the model: the earnings losses from occupation displacement are nonlinear in human capital, so large earnings losses need not be accompanied by large reductions in human capital.

Then, Corollary 1.2 establishes that the highest expected duration of unemployment is realized for a worker with skill $h$ arbitrarily close to $h^*(Z)$. This property of the auxiliary model is important for understanding the full model's ability to generate a persistent cost of job loss. In the full model, expected skill depreciation is increasing in realized unemployment duration. This magnifies the effect described in Corollary 1.2. If a worker of skill $h > h^*(Z)$ is displaced from a skill-sensitive job, not only does expected skill depreciation increase with realized unemployment duration, but expected unemployment duration also increases with realized skill depreciation. Only after the worker's human capital $h$ falls below $h^*(Z)$ and the worker switches their search from skill-sensitive to skill-insensitive employment does the worker's expected duration of unemployment begin to decline with further skill loss.[44]

Corollary 1.2 thus explains how the full model can generate persistence in earnings losses from occupation displacement: workers whose human capital places them in the neighborhood of $h^*$ not only experience the greatest reemployment wage losses (from switching to the job of a less remunerative occupation), but also have among the highest expected unemployment durations and highest expected quantity skill loss. The earnings recovery of such workers thus proceeds slower, as they must recover a greater amount of skill, and at the slower rate of human capital accumulation in skill-insensitive jobs $\pi_L$. The full effect is naturally magnified during recessions, when aggregate productivity $Z$ is lower and thus expected durations of unemployment are higher.

The empirical section of the paper establishes that immediate earnings losses are higher for workers who find reemployment in a job of a lower-skill occupation, and persistent earnings losses are only observed for workers who switch occupation upon reemployment. The discussion above of Corollaries 1.1 and 1.2 establishes the existence of similar phenomenon in the model, whereby workers who lose a job in a skill-sensitive occupation and find reemployment in the job of a skill-insensitive occupation experience larger and more persistent earnings losses. The next proposition is used to show that the model generates a higher incidence of such displacement when there is an unanticipated decrease in $Z$.[45]

**Proposition 2** (Equilibrium skill threshold decreases with productivity)**.** *The equilibrium skill threshold $h^*(Z)$ is strictly decreasing in $Z$.*

*Proof.* See Appendix, section B.2.2. □

To understand the logic behind the proof, consider an $h$ where a worker searches for a skill-insensitive job from unemployment and searches for a skill-sensitive job once employed. An increase in $Z$ will increase job-finding probabilities for skill-sensitive jobs, which lowers firms' job values and thus also job-finding probabilities for skill-insensitive jobs. Hence, for such an $h$, the value of searching for a skill-insensitive job from unemployment relative to a skill-sensitive job is diminished. Therefore, $h^*$ must decrease.

Two corollaries to Proposition 2 immediately follow:

**Corollary 2.1** (The $\epsilon$-maximal cost of job loss decreases in $Z$)**.** *The $\epsilon$-maximal cost of job loss — i.e., the maximum percent change between prior and reemployment wages for a*

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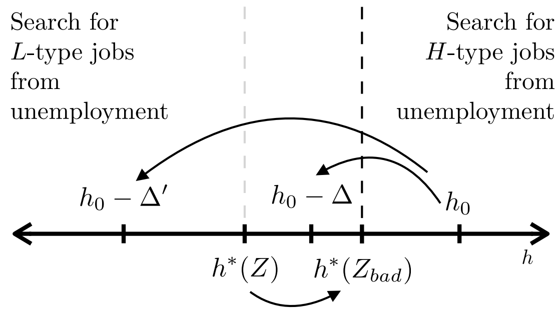
[44]However, note that if $p_L\left(h^*(Z)-\epsilon, Z\right) < p_H\left(h^*(Z), Z\right)$, the worker realizes a discontinuous increase in the expected duration of unemployment the instant they optimally switch their search from skill-intensive to skill-neutral employment.

[45]Of course, workers fully anticipate changes to skill and aggregate productivity under the full model.

Figure 4. The equilibrium skill threshold $h^*$ increases during recessions




Proposition 2 establishes that the equilibrium skill threshold is decreasing in aggregate productivity. In the figure above, productivity falls from $Z$ to $Z_{bad}$ and the equilibrium skill threshold increases from $h^*(Z)$ to $h^*(Z_{bad})$. As in the previous figure, a worker who enters unemployment from an $H$-type job with skill $h_0$ searches for $H$-type jobs in the absence of skill depreciation. However, small shocks that would have previously left the worker's search behavior unaltered — such as a reduction in skill from $h_0$ to $(h_0 - \Delta)$ — now induce the worker to search for an $L$-type job.

*worker who loses their job and subsequently loses an arbitrarily small but positive quantity of human capital $\epsilon > 0$ — is decreasing in $Z$.*

*Proof.* See Appendix, section B.2.2. □

**Corollary 2.2** (Costly occupation displacement is countercyclical)**.** *Suppose there is a one-time, unanticipated decrease in aggregate productivity $Z$. Then a greater fraction of workers in unemployment who were previously employed in the job of a skill-sensitive occupation will now search for employment in a skill-insensitive job.*

*Proof.* See Appendix, section B.2.2. □

Corollary 2.1 establishes that the maximal wage reduction associated with job loss and an infinitesimal reduction in skill is decreasing in aggregate productivity $Z$. This establishes another property of the model: earnings losses from occupation displacement generate earnings dynamics that are not only non-linear in skill $h$, but also in aggregate productivity $Z$. Hence, a small change in aggregate productivity can generate large potential earnings losses, providing scope for the model to account for the cyclical cost of job loss. Then, Corollary 2.2 establishes that a worker who loses their job in the aftermath of an unanticipated drop in aggregate productivity $Z$ is more likely to switch from a skill-sensitive to a skill-insensitive job upon reemployment. Under the calibration of the full stochastic model, these forces generate a countercyclical incidence and higher cost of occupation displacement similar to that in the data.

The previous discussion has emphasized the qualitative forces by which the full quantitative may generate a large and cyclical cost of job loss. These same forces may influence the wage negotiated between a worker and a firm in a non-trivial manner. For example, the proximity of a worker to the optimal skill threshold may influence the bargaining position of the worker. These issues are explored in the next section, where I propose a bargaining protocol à la Binmore, Rubinstein, and Wolinsky (1986) and Hall and Milgrom (2008), but where the exposure of resulting wages to the outside values of the firm and worker can be exactly characterized.

3.10. **Wage bargaining.** The earnings cost of job loss depends on wages. But to the extent that wages are the outcome of a bargaining protocol that is responsive to the outside values of negotiating parties, the dependence goes both ways: wages depend on the earnings cost of job loss. If the bargaining protocol is too sensitive to outside values, a worker may be able to transfer enough of their surplus to the firm to avoid prolonged exposure to unemployment and further skill loss. To the extent that the worker is successful in doing so, they may not incur a quantitatively meaningful cost of job loss.[46] To carefully analyze this issue, I develop a bargaining protocol à la Binmore, Rubinstein, and Wolinsky (1986) and Hall and Milgrom (2008), but with the unique feature that the dependence of wages on outside values can be exactly characterized.

The concern regarding the sensitivity of wages to outside values is not unique to this paper. The literature following Shimer (2005) and Hall (2005) shows that a DMP model can generate unemployment volatility if firm and worker surpluses are sufficiently cyclical. For such cyclicality in surpluses to obtain, however, wages must have limited exposure to market tightness, surpluses, and any other forward-looking variables, e.g. Hagedorn and Manovskii (2008), Hall and Milgrom (2008), and Gertler and Trigari (2009). The issue takes on added importance if a model is intended to incorporate both realistic volatility in unemployment and a realistic cyclical cost of job loss. Intuitively, a cyclical cost of job loss requires greater cyclicality in the present value of wages for workers who suffer

[46]Jarosch (2015) identifies a related issue in studying a model where workers accumulate human capital while employed, lose human capital while unemployed, and bargain wages à la Cahuc, Postel-Vinay, and Robin (2006). Under this setting, wages for workers from unemployment are determined according to Nash bargaining, where the outside value of the worker is unemployment. Jarosch points out that the bargaining power of workers must be sufficiently high for workers to receive a non-negative wage from unemployment. While Jarosch (2015) considers a partial equilibrium model and thus abstracts from aggregate shocks, the observation relates to a separate quantitative issue regarding business cycle dynamics. As established by Hagedorn and Manovskii (2008), DMP models with Nash bargaining typically require worker bargaining power to be close to zero to achieve realistic unemployment volatility. Therefore, achieving both a realistic cost of job loss and unemployment volatility may be difficult under Nash bargaining where the threat point is determined by the value of unemployment— hence the focus here on a bargaining protocol where the threat point is determined by the value of delay.

occupation displacement. This increases the cyclicality of outside values for workers and firms.[47] The exact characterization of the exposure of wages to outside values permitted under the bargaining protocol here is useful for isolating the maximal such exposure under which the model can obtain unemployment volatility similar to that in the data.[48]

Bargaining is as follows: Workers and firms in a match of type-$i$ bargain period-by-period over wages in a series of alternating offers.[49] 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 $u^d(\psi)$, and firms incur delay cost $d(\psi)$.[50] The matched pair are subject to a possibly higher exogenous separation probability $\varsigma$ 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.[51] 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.

[47]Indeed, Davis and von Wachter (2011) calculate the cyclical cost of job loss implied under a range DMP models directly from the worker surplus, which itself is a function of the present value of wages.

[48] One of the most important features of the bargaining mechanism is that it makes computation practical. Note that the term $\max\{p_H(W_H - U), p_L(W_L - U)\}$ from equation (8) is non-convex in the neighborhood of $h^*(Z)$. Generically, such non-convexities create computational difficulties when solving for functional equations. Under the parameterization of the wage to outside values developed below, value functions and wages can be solved for iteratively, with increasing levels of exposure of the wage to outside values. This is not possible under the protocol of Hall and Milgrom (2008).

[49]See Gottfries (2021) to see that such a bargaining protocol with a non-zero probability of renegotiation breaks the Shimer (2006) critique of wage bargaining with on-the-job search.

[50]Both the worker's flow value of leisure under delay and the firm's delay cost depend on $j \in \psi$, the type of job with which the worker has most recently matched; but given that the most recent match of the worker is that with the firm with whom they are currently bargaining, both the flow value of delay to the worker and the delay cost to the firm are effectively indexed by the job-type of the match.

[51]Note, the bargaining protocol allows no additional flexibility to the wage of newly hired workers versus existing workers. Some have questioned the validity of such an implication, most notably Pissarides (2009). See Gertler, Huckfeldt, and Trigari (2020) and Grigsby, Hurst, and Yildirmaz (2021) for evidence that the wages of new hires are no more flexible than of existing workers.

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

$$\begin{aligned} W_L(\psi, Z) = \max\Big\{ & u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\Big[p_{H_+}(\psi', Z')(1-\varsigma)W_H(\psi', Z') \\ & + \Big(1 - p_{H_+}(\psi', Z')\Big)(1-\varsigma)\tilde{W}_L(\psi', Z') + \varsigma U(\psi', Z')\Big], U(\psi, Z)\Big\} \end{aligned} \tag{14}$$

and

$$\tilde{J}_L(\psi, Z) = \max\Big\{-d(\psi, Z) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\left[\Big(1 - p_{H_+}(\psi, Z')\Big)(1-\varsigma)J_L(\psi, Z')\right], 0\Big\} \tag{15}$$

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. Then, the wage pair $\{w_H(\psi, Z), \tilde{w}_H(\psi, Z)\}$ satisfy

$$W_H(\psi, Z) = \max\left\{u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\left[(1-\varsigma)\tilde{W}_H(\psi', Z') + \varsigma U(\psi', Z')\right], U(\psi, Z)\right\} \tag{16}$$

and

$$\tilde{J}_H(\psi, Z) = \max\Big\{-d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\left[(1-\varsigma)J_H(\psi', Z')\right], 0\Big\}. \tag{17}$$

The next proposition establishes that the wage pair $\{w_L(\psi, Z), w_H(\psi, Z)\}$ can be expressed recursively, and that wages are a linear function of outside values.[52]

**Proposition 3** (Wage equations)**.** *Assume that the outside option for workers or firms never binds during bargaining. Then, the wages $w_H(\psi, Z)$ and $w_L(\psi, Z)$ can be expressed as*

$$\begin{aligned} w_H(\psi, Z) = u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\Big[ & (1-\delta)\left(Z'h' + d(\psi') - w_H(\psi', Z')\right) \\ & - (\varsigma - \delta)\tilde{S}_H(\psi', Z') + (1-\delta)(1-\nu)\beta\mathbb{E}_{\psi',Z'}(\varsigma - \delta)J_H(\psi'', Z'')\Big] \end{aligned} \tag{18}$$

[52]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 (14), (15), (16), and (17), so the constraint is never artificially imposed.

*and*

$$\begin{aligned}
w_L(\psi) = u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\Big[&\Big(1 - p_{H_+}(\psi', Z')\Big)\Big((1-\delta)\left(Z' + d(\psi') - w_L(\psi', Z')\right)\\
&+ (1-\delta)(1-\nu)\beta\mathbb{E}_{\psi',Z'}\left(\varsigma - \delta\right)\Big(1 - p_{H_+}(\psi'', Z'')\Big) J_L(\psi'', Z'')\Big)\\
&- (\varsigma - \delta)\Big(p_{H_+}(\psi', Z')S_H(\psi', Z') + \Big(1 - p_{H_+}(\psi', Z')\Big) S_L(\psi', Z')\Big)\\
&- (\varsigma - \delta)p_{H_+}(\psi', Z')\left(U_H(\psi', Z') - U_L(\psi', Z')\right)\Big]
\end{aligned} \tag{19}$$

*Hence, the exposure of wages to outside values is linear in the difference of the separation rates under disagreement and agreement, $\varsigma - \delta$.*[53] *Indeed, when $\varsigma = \delta$, the outcome of bargaining is independent of outside values, and the wage equations simplify further:*

$$w_H(\psi, Z) = u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\Big[(1-\delta)\left(Z'h' + d(\psi') - w_H(\psi', Z')\right)\Big]$$

$$w_L(\psi, Z) = u^d(\psi) + (1-\nu)\beta\mathbb{E}_{\psi,Z}\Big[\Big(1 - p_{H_+}(\psi', Z')\Big)(1-\delta)\left(Z' + d(\psi') - w_L(\psi', Z')\right)\Big]$$

*Proof.* See appendix, section B.1.2. □

The proposition offers a sharp characterization of the sensitivity of wages to outside values. Note, even under parameterizations where wages are completely independent of outside values, wages still reflect forward-looking properties associated within a given match: for example, the wage of a worker employed in a skill-insensitive job is declining in the probability of successful on-the-job search.

3.11. **Equilibrium.** An equilibrium is a schedule of market tightness for the skill-sensitive market, a schedule of market tightness for the skill-insensitive market, and an optimal search policy of workers such that (*i*) vacancy posting in skill-sensitive labor markets is consistent with the schedules for market-tightness in the skill-sensitive and skill-insensitive labor markets and the optimal search policy of workers; (*ii*) vacancy posting in the skill-insensitive labor market is consistent with schedules for market-tightness in the skill-sensitive and skill-insensitive labor markets and the optimal search policy of workers; and (*iii*) the optimal search policy of workers is consistent with market tightness in the skill-sensitive and skill-insensitive labor markets.

## 4. Calibrating the model

I calibrate the model to assess its ability to match the size and cyclicality of the present value earnings cost of job loss. The model is fitted to match a combination of aggregate and micro moments, many of which depend on the endogenous distribution of workers

[53]Note, when this restriction is applied under bargaining à la Hall and Milgrom, the resulting wage still depends on worker outside values. See Boitier and Lepetit (2018), equation 10.

across human capital and employment states. As such, only a subset of the model parameters are directly assigned and the rest are estimated by simulated method of moments. The model is calibrated in part to match moments related to average unemployment duration and cross-sectional variation in the immediate earnings cost of job loss. I leave moments describing the cyclicality and persistence of the earnings losses of displaced workers untargeted, preserving these as outcomes by which the model can be evaluated.

I consider three parameterizations of the model. The first two parameterizations are used to assess the robustness of the model to alternative assumptions about the influence of outside values on the wage. The third parameterization is used to assess the quantitative importance of countercyclical hiring standards and human capital that is non-transferable across tasks in generating a large and cyclical cost of job loss. Under the baseline parameterization, the separation probability is the same whether or not bargaining fails, i.e. $\varsigma = \delta$. Hence, while wages contain forward-looking terms, they do not depend on outside values. For the second parameterization, the probability that negotiations end exogenously when bargaining fails $\varsigma$ exceeds the separation probability under successful bargaining $\delta$ by a factor of 1.025.[54] For this "outside option" parameterization, outside values matter for wages, as discussed in Section 3.10. In the third "single factor" parameterization, the separation probability does not vary by whether or not bargaining fails, but all jobs in the model use the skill-sensitive task.

The model is calibrated to a weekly frequency. The assigned parameters are common across the three parameterizations of the model, and are given in Table 7. Most assigned values are standard to the literature. Following Ljungqvist and Sargent (1998), workers have an expected 40-year working career, implying $\nu = 4.8 \times 10^{-4}$. The maximum and minimum values of human capital $h_{ub}$ and $h_{lb}$ are set so that significant masses in the ergodic distribution do not accumulate at the endpoints of the human capital distribution. I use a grid with 150 equispaced points, implying $\Delta_{\mathcal{H}} = 0.0638$.[55]

[54] This factor is at the upper-bound for which the estimation procedure converges with an empirically reasonable unemployment volatility. As described in Section 3.10, 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, $\kappa_H$. 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.

[55] Increasing the number of grid points and expanding the bounds of the grid had no appreciable impact on results.

Table 7. Assigned parameters

| Parameter | Description | Value/Source |
|---|---|---|
| $\beta$ | discount factor | 0.9992 |
| $b$ | value of leisure | 0.71 (Hall and Milgrom, 2008) |
| $\delta$ | match survival prob. | 0.0060 (Menzio and Shi, 2010) |
| $\sigma$ | matching function elasticity | 0.5 (Pissarides and Petrongolo, 2001) |
| $\nu$ | death probability | $4.8 \times 10^{-4}$, 40 year expected career duration |
| $h_{ub}$ | human capital upper bound | 10.0, see text |
| $h_{lb}$ | human capital lower bound | 0.5, see text |
| $\Delta_{\mathcal{H}}$ | human capital increment | 0.0638 |

The flow values of unemployment are set such that higher skill workers coming from skill-sensitive jobs enjoy a greater value of leisure.[56] Workers who last matched with a firm posting a vacancy for a skill-sensitive job (i.e., $j = H$) receive flow utility $u^b h$; whereas workers who last matched with a firm posting a vacancy for a skill-insensitive job (i.e., $j = L$) receive a flow utility $u^b$.[57] Hence, the ratio of the flow value of unemployment to output for $Z = 1$ is equal to $u^b$ for all workers, regardless of production technology or human capital. I set $u^b$ equal to the estimate of this ratio from Hall and Milgrom (2008), 0.71. Following Hall and Milgrom (2008) and Christiano, Eichenbaum, and Trabandt (2016), I assume that a worker's flow value of delay is equal to their flow value of leisure.

The remaining thirteen parameters are estimated by simulated method of moments, with targeted moments that describe labor productivity, employment flows, individual-level wage growth, and the wage distribution.[58] There are as many parameters as there are targeted moments. The list of targeted moments and model generated counterparts are given in Table 8. The associated parameter values are given in Table 9. While the model parameters are jointly estimated, certain moments are more informative about some parameters than others. I discuss identification of model parameters using this correspondence below. Additional descriptive moments to be discussed in the text are given in Table 10. Unless otherwise stated, the discussion below focuses on moments and parameter estimates from the baseline model.

[56]Similar assumptions are made in Postel-Vinay and Robin (2002) and Bagger, Fontaine, Postel-Vinay, and Robin (2014). This assumption can be interpreted as a reduced form for complementarity of utility in consumption and leisure, or higher replacement UI income for workers from higher-paying jobs.

[57]Note, from the definition of $j \in \psi$, this implies that a worker previously employed in a skill-neutral job bargains from the flow value of unemployment $u^b h$ immediately upon matching with a skill-sensitive job. Thus, given that the first wage offer is accepted in equilibrium, the flow value of unemployment of unemployed workers is solely determined by the last job at which they worked.

[58]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.

Table 8. Targeted moments

| Moment | Target | Simulated moments: Baseline model | Outside value | Single factor |
|---|---|---|---|---|
| Mean wage change following displacement | 0.070 | 0.069 | 0.070 | 0.0805 |
| 10th percentile wage loss following displacement | 0.034 | 0.015 | 0.014 | 0.0108 |
| Average wage loss occupation switchers/stayers | 1.300 | 1.306 | 1.300 | 1.0000 |
| Fraction of occupation switchers | 0.660 | 0.667 | 0.657 | 0.6342 |
| Persistence of measured labor productivity (quarterly) | 0.765 | 0.747 | 0.720 | 0.7299 |
| Standard dev. of measured labor productivity | 0.013 | 0.014 | 0.015 | 0.0145 |
| Relative volatility of unemployment | 11.150 | 11.083 | 11.276 | 11.0205 |
| Weekly UE rate | 0.096 | 0.096 | 0.096 | 0.1031 |
| Average wage growth | 0.013 | 0.009 | 0.009 | 0.0104 |
| Experience premium, $\geq 5$ years experience | 1.350 | 1.471 | 1.446 | 1.5341 |
| P90/P10 log wage residuals, $< 5$ years experience | 0.963 | 0.819 | 0.789 | 0.7049 |
| Wage distribution, P90/P50 | 2.122 | 2.035 | 1.859 | 1.9667 |
| Wage distribution, P50/P25 | 1.452 | 1.535 | 1.408 | 1.2690 |

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.

To facilitate comparison to Davis and von Wachter (2011) and the literature following Shimer (2005), labor productivity is taken to be the driving force for business cycles. The dynamics of measured labor productivity here depend on the dynamics of the distribution of workers. Estimates of the persistence and standard deviation of measured labor productivity from Hagedorn and Manovskii (2008) are included as targeted moments, where the process for labor productivity is discretized as a three-state Markov chain using the Rouwenhorst method (Kopecky and Suen, 2010).[59] Following Hall and Milgrom (2008), the volatility of unemployment is included as a targeted moment. Similar to the functional form of the worker's flow value of delay, the delay cost for a firm employing a worker of human capital $h$ in a skill-sensitive match is $\gamma h$, whereas the delay cost associated with a skill-insensitive match is $\gamma$ no matter the worker's human capital. Hence, the ratio of the cost of delay to output when $Z = 1$ is $\gamma$ for all jobs, regardless of production technology or worker human capital. The estimated value for $\gamma$ under the baseline calibration is 0.2592.

Three parameters are particularly important for determining human capital loss and reallocation across job types: the probability of gradual skill loss $\pi_U$, the obsolescence

[59] As discussed in Kopecky and Suen (2010), the Rouwenhorst method generates the unique transition matrix and set of equispaced grid points that exactly match the conditional and unconditional mean, the conditional and unconditional variance, and the first-order autocorrelation of a stochastic process. The values of productivity are referred to as $Z_L$, $Z_M$, and $Z_H$ (in ascending order).

Table 9. Estimated parameters

| | | Model parameterization | | |
|---|---|---|---|---|
| Parameter | Description | Baseline model | Outside value | Single factor |
| Labor productivity: | | | | |
| $\rho_Z$ | Persistence of labor productivity | 0.9819 | 0.9795 | 0.9727 |
| $\sigma_Z$ | Standard dev. of labor productivity | 0.0041 | 0.0050 | 0.0035 |
| Labor market: | | | | |
| $\gamma$ | Firm cost of delay | 0.2592 | 0.2619 | 0.2682 |
| $\kappa_H$ | Vacancy posting cost (skill-sensitive) | 3.9238 | 2.1620 | 0.9238 |
| $\phi_H$ | Matching efficiency (skill-sensitive) | 0.2548 | 0.2272 | 0.2483 |
| $\phi_L$ | Matching efficiency (skill-insensitive) | 0.0720 | 0.0990 | — |
| $\chi$ | Task-common occupation switching | 0.6342 | 0.6220 | — |
| Human capital: | | | | |
| $\mu_{nb}$ | Human capital initial distribution mean | 0.2557 | 0.2310 | $-1.0183$ |
| $\sigma_{nb}$ | Human capital initial distribution, standard deviation | 0.0908 | 0.1318 | 0.0440 |
| $\pi_H$ | Probability of human capital increase (skill-sensitive) | 0.0317 | 0.0273 | 0.0220 |
| $\pi_L$ | Probability of human capital increase (skill-insensitive) | 0.0012 | 0.0025 | — |
| $\pi_U$ | Probability of human capital decrease (unemployment) | 0.1051 | 0.1023 | 0.1293 |
| $\xi$ | Obsolescence probability | 0.0344 | 0.0307 | 0.0705 |

probability $\xi$, and the vacancy posting cost in the skill-sensitive market $\kappa_H$. While the role of $\pi_U$ and $\xi$ in determining human capital dynamics is clear, the role of $\kappa_H$ may be less so. A higher value of $\kappa_H$ represents a direct increase in the fixed cost of job creation for skill-sensitive jobs and will thus increase the equilibrium skill threshold, directing more job creation towards skill-insensitive jobs. Hence, a higher $\kappa_H$ will increase the probability that a worker is reallocated from the skill-sensitive to skill-insensitive sector upon separation. Three moments are important for determining these parameters: the average wage loss of displaced workers, the 10th percentile wage change of displaced workers, and the average wage loss of displaced workers who switch occupations.[60] The estimated weekly probability of gradual skill loss in unemployment is 0.1051, corresponding to an

[60] 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.

TABLE 10. Descriptive statistics, model

| Moment | Simulated moments | | |
|---|---|---|---|
| | Baseline model | Outside value | Single factor |
| *1)* Unemployment rate | 0.0664 | 0.0640 | 0.0674 |
| *2)* Average profit share | 0.0171 | 0.0119 | 0.0120 |
| *3)* Skill-sensitive recruitment costs as a fraction of wage bill | 0.1973 | 0.1355 | 0.1378 |
| *4)* Earnings loss, type-distinct occupation switches | 0.4976 | 0.4612 | — |
| *5)* Fraction of workers in skill-sensitive jobs | 0.7711 | 0.8370 | 1.0000 |
| *6)* Occupation switching, expansion | 0.6634 | 0.6525 | — |
| *7)* Occupation switching, recession | 0.7028 | 0.6998 | — |
| *8)* Avg. value of human capital | 2.2991 | 2.2723 | 1.2490 |
| *9)* Avg. value of human capital, new-born | 1.2967 | 1.2708 | 0.5000 |
| *10)* Avg. value of human capital, skill-sensitive | 2.6765 | 2.5077 | 1.2761 |
| *11)* Avg. value of human capital, skill-insensitive | 1.1268 | 1.1906 | — |
| *12)* Avg. value of human capital, unemployed | 1.9553 | 1.9489 | 0.8739 |
| *13)* Avg. % h.c. accumulation in skill-sensitive job, one quarter | 0.9808 | 0.9029 | 1.4272 |
| *14)* Avg. % h.c. accumulation in skill-insensitive job, one quarter | 0.0881 | 0.1737 | — |
| *15)* Avg. % h.c. deaccumulation in unemployment, one quarter | 3.7896 | 3.7303 | 8.5805 |

See text for further description of moments.

average 3.79% loss in human capital over a full quarter of unemployment. The estimated obsolescence probability $\xi$ is 0.0344, and the estimated vacancy posting cost $\kappa_H$ is 3.92.[61]

The calibration of the model accounts for the finding in Section 2 that only a subset of displaced workers in the data who switch occupation upon reemployment incur higher earnings losses relative to workers who find reemployment in the same occupation. As discussed in section 3.5, such non-costly occupation switches can be rationalized under the model as occupation changes within a class of occupations using the same of factor-augmenting technology, where a fraction $\chi$ of workers from unemployment who find reemployment in job of the same task are recorded as occupation switchers. Hence, if a fraction $x$ of displaced workers switch across skill-sensitive and skill-insensitive jobs subsequent to displacement, measured occupation switching is $x + (1-x)\chi$.[62]

[61]The estimated values for $\kappa_H$ can be used to calculate recruiting costs for a job as a fraction of the quarterly wage bill, reported in Table 10. The associated moments are close to the figure of 0.14 reported in Hall and Milgrom (2008). Intuitively, jobs posted for workers with low human capital have a lower wage bill, but the vacancy filling probability is high. Conversely, jobs posted for workers with high human capital have a high wage bill but the vacancy filling probability is low.

[62]Likewise, if the average wage loss for displaced workers reemployed within a job of the previous factor-augmenting technology is $\Delta w^s$ and the average wage loss for displaced workers reemployed within a job of a different technology is $\Delta w^{ns}$, the measured average wage loss of occupation switchers is $\big(x\Delta w^s + (1-x)\chi\Delta w^{ns}\big)/\big(x+(1-x)\chi\big)$.

Note, the correspondence of production technologies to occupations in the data could be fixed, change over the business cycle, or shift over lower frequencies; the calibration procedure offers a deliberately agnostic stance on this issue. However, the calibrated model offers empirical implications for the wage loss associated with costly occupation changes. The average short-run earnings reduction for workers who complete such an occupation change upon reemployment is 49.76% in the baseline parameterization and 46.12% in the "outside value" parameterization. Both figures fall into a 95% confidence interval for the average short-run earnings reduction for workers who switch into the low-skill service sector, 41.2%.[63] The fraction of workers in skill-sensitive jobs ranges from 16.3% (for the outside value parameterization) and 22.9% (for the baseline parameterization), consistent with the share of workers in the low-skill service sector from 1980 onwards reported in Autor and Dorn (2013). Hence, the quantitative results echo the empirical findings discussed in Section 2.3, as both hint at the importance of worker reallocation to low-skill service jobs in accounting for the earnings cost of job loss.

The monthly transition rate from unemployment to employment (from Menzio and Shi 2011) and the p90/p50 wage ratio calculated from the 2000 U.S. Census help identify the matching efficiency parameters for the skill-insensitive and skill-sensitive labor markets, $\phi_L$ and $\phi_H$.[64] Wage dispersion in the upper ends of the wage distribution is generated through continuous human capital accumulation of workers within skill-sensitive jobs. Intuitively, if the model matches the average job-finding probability but job-finding rates for skill-sensitive jobs are too low, longer spells of unemployment for workers separated from skill-sensitive jobs will dampen the rate at which such workers find new jobs and resume skill accumulation, decreasing the p90/p50 wage ratio.

While the model is forced to match moments describing the range of negative outcomes associated with job displacement, the calibration strategy still preserves a role for human capital in translating accumulated labor market experiences into higher wages, as shown in Table 8. The parameter estimates for $\pi_H$ and $\pi_L$ suggest that skill accumulation is much slower in skill-insensitive employments: the average worker in a skill-sensitive job

[63] In comparison, average earnings losses, 50th percentile earnings losses, and 75th percentile earnings loss among all downward occupation switchers are 38.6%, 29.6%, and 56.8%. These figures are calculated from a sample of displaced workers from the CPS DWS with lower earnings upon reemployment. For comparability to the model simulated moments, the sample is further restricted to workers whose initial displacement occurred within two years of their interview, and whose current job is their first post-displacement job.

[64] I set $\kappa_L = 0.05$ and estimate $\phi_L$, as these parameters only determine quantities through the ratio $\kappa_L/\phi_L$. This identification strategy fails if $\kappa_L$ is sufficiently high that there is a range of human capital — just below the minimum $h$ such that $p_H(h, Z) > 0$ — where it is unprofitable for firms to post $H$- or $L$-type jobs. In practice, such an outcome requires an implausibly high value of $\kappa_L$, and hence is not of particular interest.

expects a 0.98% increase in human capital over a quarter of continuous employment, versus a 0.09% increase for the average worker in a skill-insensitive jobs (as reported in Table 10).

Workers have a stochastic lifecycle, and the distribution of the initial skill draw for new entrants is parameterized as discretized log-normal.[65] Entrants enter the economy in unemployment, where their skill is subject to depreciation until they find a job: the average human capital of a newly employed entrant is 1.30, compared to 2.68 for all employed workers under the baseline parameterization. As should be expected, workers in skill-sensitive jobs have on average higher human capital than workers in skill-insensitive jobs: 2.68 versus 1.13 under the baseline.

Note, while all three parameterizations of the model do well at matching the targeted moments (see Table 8), estimated parameters naturally differ across the various parameterizations, and so the models offer different implications for the non-targeted descriptive moments listed in Table 10. Comparing parameter estimates and untargeted moments across parametrizations, the baseline and "outside value" parameterizations appear similar. The most notable difference between these two parameterizations appears from the estimate of the vacancy posting cost, $\kappa_H$, which is substantially lower under the outside value parameterization. However, the average profit share is quite similar.

The most striking difference across parameterizations comes from the comparison of the "single factor" parameterization to the baseline and "outside value" parameterizations. A given earnings loss in the single factor parameterization requires a proportionate reduction in human capital; whereas earnings losses in the baseline and outside value parameterization can occur through reallocation across jobs of different production technologies, obviating the need for such large human capital losses to match the data. Hence, the parameters dictating the rate of human capital depreciation $\pi_u$ and $\xi$ are larger for the single factor parameterization, implying less durability of accumulated skill.

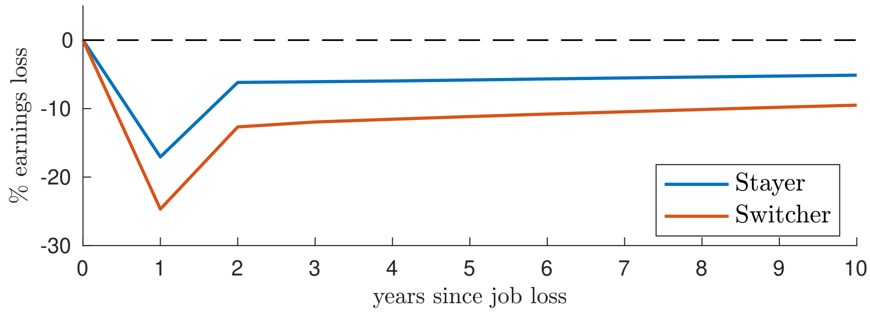
## 5. The scarring effect of recessions: model implications

I evaluate the quantitative implications of the model on the cost and incidence of occupation displacement. In doing so, I show that the large earnings losses and countercyclical incidence of occupation displacement can explain the cost of job loss during expansions and recessions. The model also generates a persistent earnings loss for workers who enter the labor market during a recession.[66]

[65] Note, the parameters defining the entrant distribution under the "single factor" parameterization includes points below the minimum value of human capital, $h_{lb}$. When a newborn draws such a value of human capital, it is replaced with $h_{lb}$.

[66] Going forward, we require a measure of recessions in the model that is similar to that in the data. I generate a mapping of aggregate productivity and the distribution of workers across human capital and

FIGURE 5. Earnings losses, stayers and switchers: model




Earnings losses relative to counterfactual for occupation stayers and switchers under benchmark parameterization. See text for details.

Figure 5 shows the simulated time series of relative earnings losses for occupation stayers and switchers in the model.[67] As in the data, occupation switchers in the model suffer higher and more persistent earnings losses than occupation stayers. Although the immediate drop in earnings for displaced workers and the relative immediate earnings drop of occupation switchers are included as a calibration targets, no moments related to the persistence of earnings losses or the divergent earnings recovery from job displacement for occupation switchers and stayers are targeted. Hence, the persistence of earnings losses for displaced workers who switch occupation upon reemployment speaks to the quantitative success of the model. The model is also successful in matching the higher incidence of occupation displacement among workers who lose their job during a recession relative to an expansion: there is a 3.9 percentage point increase in the model (see Table 10), close to the estimated 2.9 percentage point increase recorded in the data. So while the estimation only includes average measured occupation switching as a targeted moment, the model well accounts for the cyclicality of occupation displacement.

The estimated model matches the essential features of occupation displacement discussed in empirical section, including moments that are not targeted in the estimation. I now use the model to consider two separate but related aspects of the scarring effect of recessions: the cyclical cost of job loss (Davis and von Wachter, 2011), and the cost of

employment into a binary expansion/recession state variable. Details of the mapping and simulation procedures are given in Appendix C.2.

[67]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.

entering the labor market during a recession (Kahn, 2010; Oreopoulos, von Wachter, and Heisz, 2012; Altonji, Kahn, and Speer, 2016; von Wachter, 2020).

5.1. **The cyclical cost of job loss.** I now consider the model implications for the size and cyclicality of the present value cost of job loss for each of the three model parameterizations. In doing so, I establish the importance of the non-linear earnings dynamics associated with the equilibrium skill threshold for generating a cyclical cost of job loss.

I compute the cost of job loss using simulated data from the model using the regression equation and sample restrictions as in Davis and von Wachter (2011). The simulated data are organized by displacement year, $y$. For each displacement year $y$, I construct a sample of workers who have been continuously employed at the same job for six years as of $y$. Workers who separate from their job to unemployment at either year $y$, $y+1$, or $y+2$ constitute the subsample of displaced workers for displacement year $y$. Workers who do not separate from their job at years $y$, $y+1$, or $y+2$ constitute the subsample of displaced workers for sample $y$. From this data, I estimate the regression equation

$$e_{it}^y = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + \beta_t^y + \beta^y X_{it} + \sum_{k=-6}^{20} \delta_k^y D_{it}^k + u_{it}^y \tag{20}$$

where $e_{it}^y$ represents real annual earnings of an individual $i$ at time $t$ for displacement year sample $y$, $\alpha_i^y$ is an individual fixed effect, $\gamma_t^y$ is a year fixed effect, $\bar{e}_i^y$ represents average earnings from years $y-5$ to $y-1$, $X_{it}$ is a quartic polynomial in age, and $D_{it}^k$ equals one at year $k$ subsequent to displacement and zero otherwise, where $k=0$ represents a displaced worker's final year in the displacement job.[68] The coefficients $\delta_k^y$ are identified from earnings differentials between displaced and non-displaced workers and represent the reduction in earnings due to displacement $k$ years prior. The earnings cost of job loss for displacement year $y$ is computed using these and the other coefficient estimates from equation (20).[69]

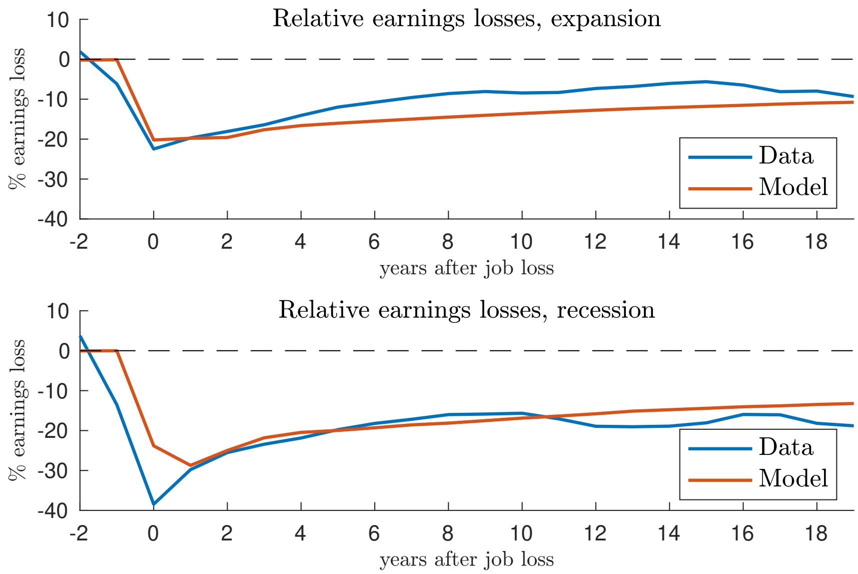
Figure 7 shows the earnings losses of displaced workers relative to non-displaced workers at various horizons from the baseline model, with separate plots for workers displaced during for recessions and expansions.[70] The empirical measures of expansion and recession come from the NBER Business Cycle Dating Committee, with roughly 12% of the years in the data falling during recessions. For comparability, I adopt an ad hoc rule for model-simulated data where a year is identified to fall in a recession if the annual unemployment rate is in the upper 12% of the annual unemployment rate distribution. While there

[68]Note, the dating convention is shifted in Figure 7, where "year zero" is the displacement year.

[69]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.

[70]Note that Figure 5 reveals milder earnings losses than Figure 7. This is because the latter figure conditions on a sample of high-tenure workers, as in Davis and von Wachter (2011).

FIGURE 7. Comparison of model and empirical earnings loss profiles




Earnings losses relative to counterfactual under the benchmark parameterization, as computed according to equation (20). Data from Davis and von Wachter (2011)

are some discrepancies between the empirical estimates and the simulated data from the model — for example, earnings recover quicker during expansions in the data than in the model — the overall fit of the model to the data is good.[71]

The regression estimates from equation (20) can be used to construct an estimate of the present value of annual earnings losses from job displacement as a fraction of the present value of the earnings the worker would have received absent displacement. As in Davis and von Wachter (2011), I compute the present value losses over a twenty year horizon with a discount rate of 5%. I assess the ability of the model to generate a cyclical cost of job loss using two measures provided in Davis and von Wachter (2011): *1)* the present value cost of job loss according to whether a job is lost during a recession year or expansion year and *2)* the average present value cost of job loss across years in the lower 23$^{\text{rd}}$ and upper 29$^{\text{th}}$ percentiles of the annual unemployment rate distribution.

The first column of Table 11 reports the average cost of job loss in the data and across the three parameterizations of the model. The second and third columns of Table 11 report the cost of job loss during expansions and recessions. All three parameterizations of the

[71]Likely, the inclusion of several features missing from the model that have been identified as important elsewhere in the literature would help improve the model fit: for example, exogenous job insecurity à la Jarosch (2015) or endogenous job insecurity à la Krolikowski (2017).

Table 11. Present value cost of job loss, data and model

| | | by NBER recession | | | by unemployment rate | | |
|---|---|---|---|---|---|---|---|
| | All | Exp. | Rec. | $\Delta$/Avg. | $u_{\text{low}}$ | $u_{\text{high}}$ | $\Delta$/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 | — |

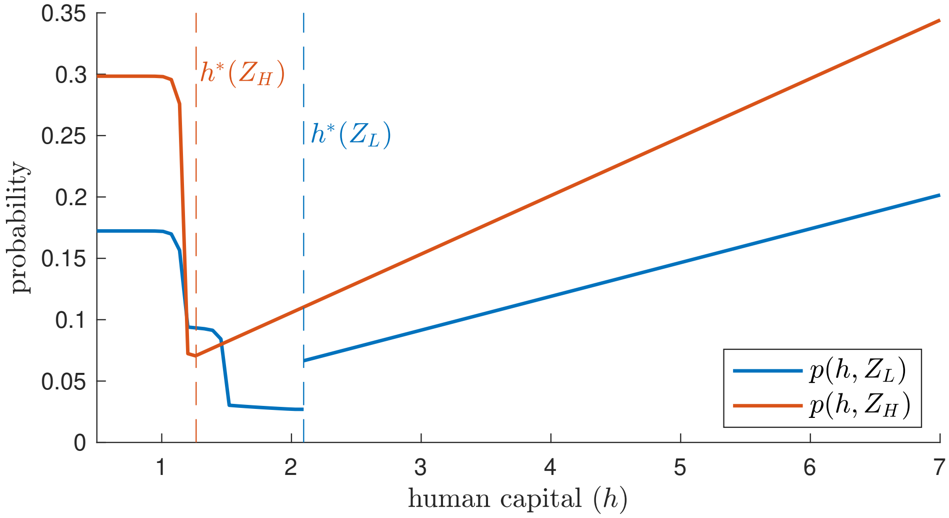
Data from Davis and von Wachter (2011). Davis and von Wachter report the average cost of job loss across years in the lower 23rd and upper 29th percentiles of annual unemployment rates, denoted above as $u_{\text{low}}$ and $u_{\text{high}}$. Moments from the model are calculated similarly. Construction 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.

model are successful in generating a large and cyclical cost of job loss.[72] A closer look, however, reveals that the two parameterizations that incorporate the nonlinear earnings dynamics associated with the countercyclical equilibrium skill threshold do far better than the "single factor" parameterization. The single factor model generates too large of an average present value cost of job loss compared to the data and those generated from the baseline and "outside value" parameterizations. The single factor model also generates a small percentage increase in the cost of job loss from expansions to recessions of 11.0%, representing roughly one-sixth of the 63.9% increase recorded in the data. In comparison, the baseline and outside value parameterizations capture 38% and 53% of the increase in the cost of job loss from expansions to recessions.

Although the models incorporating the equilibrium skill threshold are more quantitatively successful than the "single factor" model, one might be worried that this is due to the somewhat arbitrary distinction of expansions and recessions in the model. To address this concern, I compute the average present value cost of job loss for workers who lose their job in a year when the average unemployment rate is high, falling in the upper $29^{\text{th}}$ percentile of the annual unemployment rate distribution; and for workers who lose their job in a year when the average unemployment rate is low, falling in the lower $23^{\text{th}}$

[72]By way of comparison, the best-performing models considered by Davis and von Wachter (2011) generate a present value cost of job loss of 2.44% when the aggregate state is "good" and 2.71% when the aggregate state is "bad."

FIGURE 9. Job-finding probabilities from unemployment, benchmark parameterization: high and low productivity




The equilibrium skill thresholds are given by $h^*(Z_H)$ and $h^*(Z_L)$ for high and low productivity. Job-finding probabilities from unemployment for skill-insensitive jobs associated with a certain $Z$ are plotted to the left the of the relevant equilibrium skill threshold $h^*(Z)$; job-finding probabilities from unemployment for skill-sensitive jobs are to the right.

percentile of the distribution of annual unemployment rates.[73] Results are given in the fifth through seventh columns of Table 11. Here, the relative quantitative success of the model parameterizations incorporating an equilibrium skill threshold becomes even more apparent: the baseline and "outside value" parameterizations generate 71.4% and 84.1% of the percentage increase in the cost of job loss. This compares to about one-fourth for the "single factor" parameterization.

To understand the quantitative performance of the model parameterizations that incorporate the non-linear earnings dynamics associated with the equilibrium skill threshold, it is helpful to study the schedule of job-finding probabilities for workers from unemployment. Figure 9 shows job-finding probabilities as a function of human capital along with the equilibrium skill thresholds, for high and low aggregate productivity. For a given level of aggregate productivity, the equilibrium skill threshold indicate job-finding probabilities corresponding to skill-insensitive jobs (to the left) and skill-sensitive jobs (to the right).

As is typical for a DMP model, a drop in aggregate productivity leads to an overall drop in job-finding probabilities. But here, a fall in aggregate productivity also shifts mass

[73]The choice of percentiles is due to what is reported by Davis and von Wachter (2011). See their Table 1.

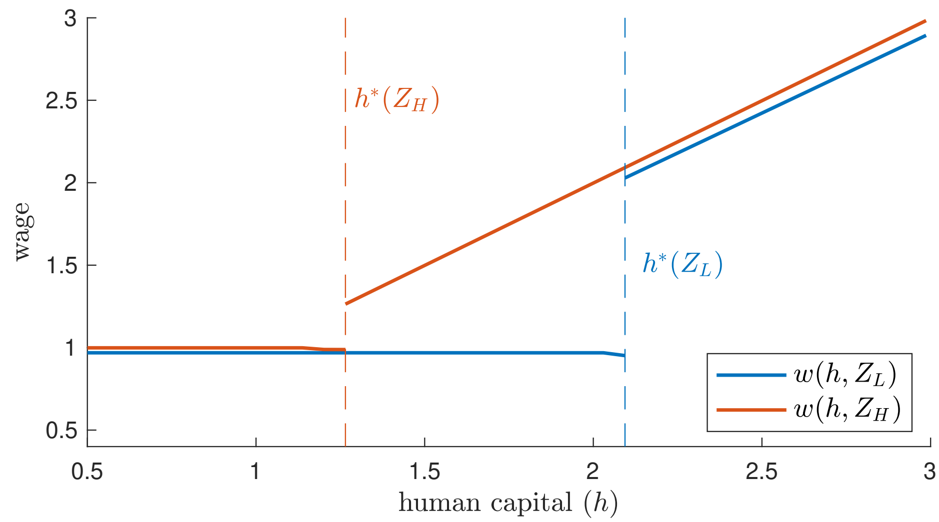
in the distribution of vacancy postings from skill-sensitive vacancies to skill-insensitive vacancies: the vertical line indicating the skill threshold for low productivity $h^*(Z_L)$ lies to the right of the skill threshold for high productivity $h^*(Z_H)$, indicating that a greater proportion of workers across the human capital distribution is restricted to search for low-skill jobs when productivity $Z$ is low. The shift in the equilibrium skill-threshold is a function of the optimal vacancy posting decision of firms hiring workers for skill-sensitive jobs, firms hiring workers for skill-insensitive jobs, and the optimal search decision of unemployed workers. Firms posting vacancies for skill-sensitive jobs respond to a drop in productivity by posting fewer vacancies and directing vacancies towards workers of greater human capital. Firms posting vacancies for skill-insensitive jobs take over the bottom end of the market, as the reduction in job-finding probabilities for skilled-sensitive jobs increases the expected tenure for new hires in skill-insensitive jobs over all values of $h$. Given the vacancy-posting decisions of firms, the equilibrium skill-threshold $h^*$ describes the lowest level of human capital at which unemployed workers search for skill-sensitive jobs.

When productivity is $Z_L$, the job-finding probabilities for the skill-insensitive job are particularly low for workers with $h$ in the region between $h^*(Z_H)$ and $h^*(Z_L)$. Should a firm posting a skill-insensitive vacancy hire such a worker and aggregate productivity increase to $Z_M$ or $Z_H$ in the next period, the expected tenure of that worker would be instantly reduced by a discrete quantity. Hence, workers in this region are less attractive as potential job candidates and face lower job-finding probabilities.[74] The wage bargaining protocol used in the model generates this retention effect in hiring as an endogenous outcome: although wages of workers in skill-insensitive jobs decrease with the probability of successful on-the-job search, they do not decrease enough to fully offset the loss in value due to lower retention, and so fewer skill-insensitive vacancies are posted for high-$h$ workers.

The countercyclical equilibrium skill threshold finds support from a recent literature documenting countercyclical "upskilling" from vacancy postings. Hershbein and Kahn (2018) use a nationally representative dataset of firm-level vacancy postings from Burning Glass Technologies from 2007 and 2010-2015 with information on occupation, required experience, and required education. They find that employers in MSA's disproportionately affected by the Great Recession redirect vacancies for medium-skill jobs towards workers of higher skill. Similar evidence of countercyclical upskilling is presented in Modestino, Shoag, and Ballance (2020).

[74]Survey research and anecdotal evidence confirms that firms avoid hiring over-qualified workers. See Erdogan et al. (2011) for a survey.

FIGURE 10. Wage profiles from unemployment, benchmark parameterization: high and low productivity




The equilibrium skill thresholds are given by $h^*(Z_H)$ and $h^*(Z_L)$ for high and low productivity. Wages for skill-insensitive jobs associated with a certain $Z$ are plotted to the left the of the relevant equilibrium skill threshold $h^*(Z)$; wages for skill-sensitive jobs are to the right.

In the model, job-finding probabilities from unemployment are a V-shaped function of skill. Firms post vacancies for skill-insensitive jobs up to the equilibrium skill threshold $h^*$; but given that the expected retention of a worker is decreasing in $h$, the firm value and hence market tightness and job-finding probabilities are decreasing in $h$, too. For $h \geq h^*$, however, firm values are increasing in $h$ from higher profits, so market tightness and job-finding probabilities are also increasing in $h$. This feature of the model rationalizes empirical findings from Mueller et al. (2020), who analyze vacancy data from the Austrian public labor market administration. The vacancy data, which accounts for the majority of vacancies posted by establishments in Austria, is linked to establishment- and worker-level data from the Austrian Social Security Database, allowing the authors study the relation of vacancy duration to worker, job, and employer characteristics.[75] Log vacancy duration — which is an increasing function of the job-finding probability under a constant returns to scale matching function — is found to be a V-shaped function of both a worker effect à la Abowd, Kramarz, and Margolis (1999) and log starting wages.

[75]Pries and Rogerson (2005) argue that different labor market institutions in Western Europe generate substantially different labor market dynamics from the United States, as measured by the magnitude of worker turnover. However, Borovičkovà (2016) documents that worker turnover in Austria is roughly of the same magnitude as in the U.S.

Just as the equilibrium skill thresholds describe important implications for job-finding probabilities and search behavior, they also describe important implications for reemployment wages. Figure 10 plots reemployment wages as a function of human capital, for high and low aggregate productivity. Once again, the equilibrium skill threshold for low productivity $h^*(Z_L)$ lies to the right of the skill threshold for high productivity $h^*(Z_H)$. Conditional on $h \notin (h^*(Z_H), h^*(Z_L))$, wages vary only mildly with the aggregate state. But consider a worker with human capital $h_0 \in (h^*(Z_H), h^*(Z_L))$ employed at a skill-sensitive job when $Z = Z_H$. Should the worker lose their job and productivity remain high at $Z_H$, the worker will search for a job the pays the same wage as they earned previously. If, however, the aggregate productivity should decrease to $Z_L$, the worker will now optimally search for a skill-insensitive job with a much lower wage. Hence, earnings losses are a non-linear function of changes in aggregate productivity.[76]

Figure 10 establishes that immediate earnings losses from job loss are higher for skill-sensitive workers in the neighborhood of the equilibrium skill-threshold who must search for skill-insensitive employment if they lose their job. Next, I show that such earnings losses are persistent. To do so, I calculate the values of employment and unemployment absent the flow utility of non-employment via value function iteration. I use these quantity to calculate the lifetime present value cost of job loss for workers in skill-sensitive and skill-insensitive jobs. Then, I calculate the total cost of job loss for a given $h$ and $Z$ using the simulated distribution of workers across skill-sensitive and skill-sensitive jobs for a given $(h, Z)$ pair.

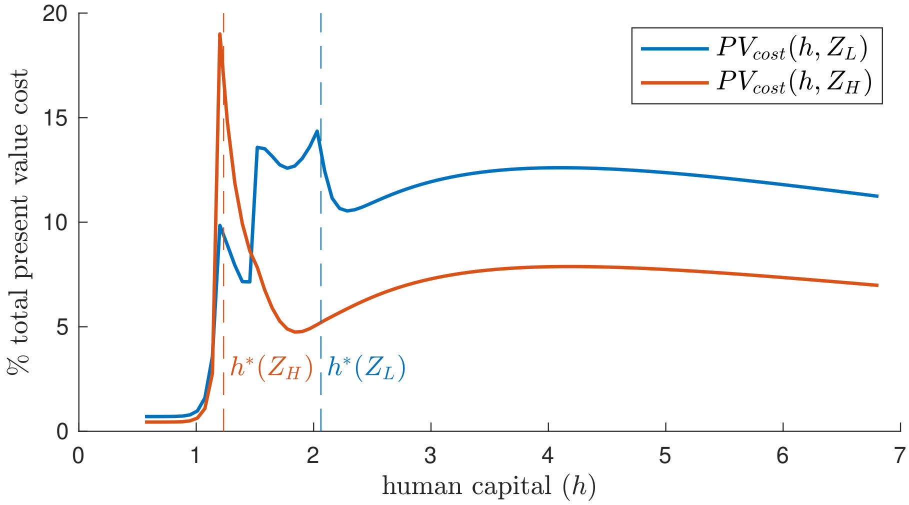
The schedule of the total cost of job loss is given in Figure 11. Notably, for a given $Z$, the total cost of job loss achieves a maximum in the neighborhood of the equilibrium skill threshold. Moreover, the cost of job loss when $Z = Z_L$ shows local maximum around the equilibrium skill thresholds for $Z_M$ and $Z_H$; should the aggregate state change to one of these values, such workers will be more exposed to the risk of occupation displacement.[77] Figure 11 reveals that total present value cost of job loss is highest not for workers with the most human capital to lose, but rather for workers whose continued employment in skill-sensitive jobs is most tenuous.

Having established how the non-linear earnings dynamics associated with the equilibrium skill threshold and occupation displacement generate a large and cyclical cost of job loss, I explore the implications of the model for the cost of entering the labor market during a recession.

[76]Similar patterns were shown in the empirics of Section 2.4, and then formally established as implications of the limiting model in Section 3.9.

[77]Note, the total present value cost of job loss integrated over the worker distribution is lower than the present value cost of job loss calculated by Davis and von Wachter (2011). This is due in part because of the longer horizon and the lack of a minimum tenure restriction.

FIGURE 11. Total present value cost of job loss, benchmark parameterization

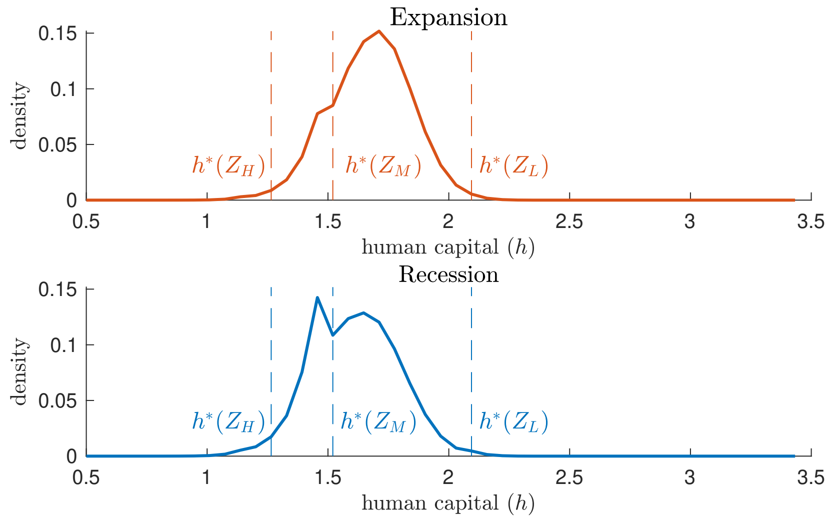



The total present value cost of job loss is calculated from the lifetime earnings loss associated with job displacement relative to the counterfactual path of earnings absent job displacement. Note, the total cost for a given $Z$ achieves global maxima at the equilibrium skill-threshold, indicating the importance of occupation-displacement in generating a persistent cost of job loss, as well establishing the link between future earnings losses and the aggregate state at the time of job-displacement.

5.2. **The cost of entering the labor market during a recession.** Starting with Kahn (2010), an empirical literature has established that labor market entrants fare worse during recessions. Oreopoulos, von Wachter, and Heisz (2012) study Canadian administrative data and find that the median college graduate entering the labor market during a recession year receives an earnings stream with a 10-year present discounted value that is 6% lower than that associated with entry during an average year. Lower-skill workers are predicted to experience larger present value earnings losses. Recovery of earnings after entry is facilitated in part by mobility from the job and industry of initial employment. Altonji, Kahn, and Speer (2016) find that nearly half of the initial wage losses associated with entering the labor market during a recession can be explained by employment in lower-paying occupations. They find that high-skill workers fare better in part because they are more likely to find employment in an occupation typical to their field of study during a recession. For a broader sample of young workers, Schwandt and von Wachter (2019) and von Wachter (2020) estimate the 10-year present value cost of entering the labor market during a recession to be 9% of the present value earnings the entrant would have received otherwise.

As labor market entrants and displaced workers must search for employment in the same aggregate environment, one might suspect that their subsequent earnings profiles are shaped by related forces. Outcomes of the model closely correspond to the empirical

FIGURE 13. Human capital distribution of new entrants at initial employment




The figure shows the distribution of human capital upon initial employment for workers entering the labor market during a recession and an expansion. The distribution of human capital during a recession is worse due lower job-finding probabilities, but also the higher equilibrium skill threshold associated with lower values of aggregate productivity.

findings discussed above. As in Oreopoulos, von Wachter, and Heisz (2012) and Altonji, Kahn, and Speer (2016), workers of lower skill in the model fare worse both in the short and long-term. In the model, workers who enter the labor market during a recession face longer initial unemployment durations and more stringent hiring standards, and hence are more likely to find initial employment in a skill-insensitive job, similar to the findings of Altonji, Kahn, and Speer (2016). Among entrants who find skill-sensitive employment during an expansion, the probability that a given worker also finds a skill-sensitive job during a recession is increasing in skill $h$. Hence, entrants at the top of the skill distribution are less likely to be forced to search for employment in a skill-insensitive job during a recession. This is consistent with Altonji, Kahn, and Speer's finding that high-skill workers are largely insulated from the cost of entering the labor market during a recession by the fact that they are more likely to find employment in a typical occupation.

To evaluate the cost of entering the labor market during a recession, I simulate outcomes for two cohorts of new entrants: the first cohort enters the labor market (through unemployment) during an expansion, the second 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.

Figure 13 plots the distribution of human capital of new entrants at the time of their first job, illustrating the impact of aggregate conditions on the labor market experiences of new entrants. As the initial distribution of human capital for labor market entrants is invariant to the aggregate state, the differences in the two distributions entirely reflect variation in job-finding probabilities and the equilibrium skill thresholds across recessions and expansions. For both expansions and recessions, there are irregularities in the distribution corresponding to workers who are hired exactly at the equilibrium skill threshold. During recessions, a significant mass of the distribution lies to the left of the hiring standard. This is due to the depressed job-finding probabilities during recessions for workers with human capital just below the equilibrium skill threshold, as illustrated in Figure 9. During expansions, only 23.6% and 23.2% of workers start in skill-insensitive jobs in the baseline and outside value parameterizations. This increases to 75.2% and 74.1% during recessions.

The present value cost of entering the labor market in the baseline and outside value parameterization of the model are 10.9% and 7.7%, falling close to the estimate of 9% of Schwandt and von Wachter (2019) and von Wachter (2020).[78] Meanwhile, the single factor parameterization of the model predicts a ten-year present value cost of only 1.23%.

## 6. Conclusion

This paper has documented that the large and persistent earnings losses of involuntary job displacement are concentrated among workers who switch occupation after job displacement. The incidence and earnings cost of such occupation displacement increases during recessions. I propose a model of unemployment where hiring is endogenously more selective during recessions, and thus a greater fraction of unemployed workers – both displaced workers and labor market entrants – are left to search for employment in worse jobs. In accounting for the new empirical findings of the paper, the calibrated model accounts for the size and cyclicality of the earnings cost of job loss, and the earnings cost of entering the labor market during a recession.

[78] As discussed by von Wachter (2020), the literature has adopted a variety of methodologies for computing the cost of entering the labor market during a recession, but findings are generally consistent across particular approaches. This serves as some indication that the variety of regression frameworks in the literature are successful at computing the "true" cost of entering the labor market during a recession. As such, I compute the cost of entering the labor market during a recession using simulated counterfactuals, which can be interpreted more transparently and offer more generality than that estimated from any particular empirical approach.

The paper leaves open many interesting avenues for research. As discussed earlier, several of the empirical findings and the implications of the calibrated model suggest a non-negligible role for transitions to the low-skill service sector in the explaining earnings cost of job loss. The model could be further expanded to allow for additional type of jobs and skills to account for the transition of workers across a broader array of occupation groups.

The paper also has implications for computing the welfare cost of business cycles à la Lucas (2003). Lacking an appropriate framework, the welfare cost of business cycles is computed from models that do not sufficiently account for the large and cyclical cost of job loss. This paper offers an appropriate framework. In identifying displacement to lower-skill jobs as a primary factor in accounting for the size and cyclicality of the earnings losses from job displacement, the paper indicates a starting point for the formulation of optimal policy to reduce the cost of job loss.

As I complete this manuscript, the United States enters the second year of the COVID-19 recession. Since the onset of the recession, the U.S. economy has sustained record levels of job loss, and the ensuing unemployment has been highly concentrated among workers in "contact" occupations and sectors where remote work is less feasible. The findings of this paper suggest that many such unemployed workers will have difficulty finding reemployment in jobs similar to that which they held before the onset of the recession, thus potentially incurring large associated welfare losses. Policy, as always, faces a delicate balancing act: one of sustaining employment in sectors facing temporary shocks through programs such as PPP, thus shielding workers from the long-run effects of occupation displacement; while simultaneously avoiding undue efficiency costs incurred through impeding the reallocation of workers out of sectors facing lower labor demand. This paper offers evidence that the former costs associated with occupation displacement are more severe than has been previously recognized.

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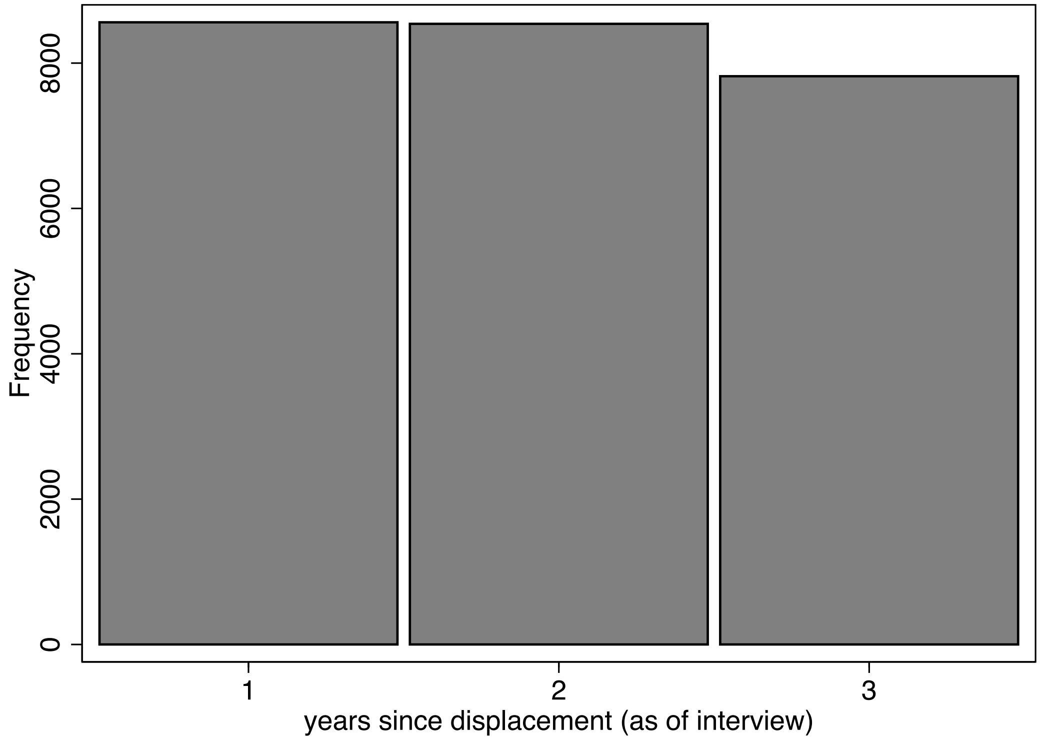
## Appendix A. Empirical appendix

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.

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.

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




A.2. **Histograms of DWS samples.**

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

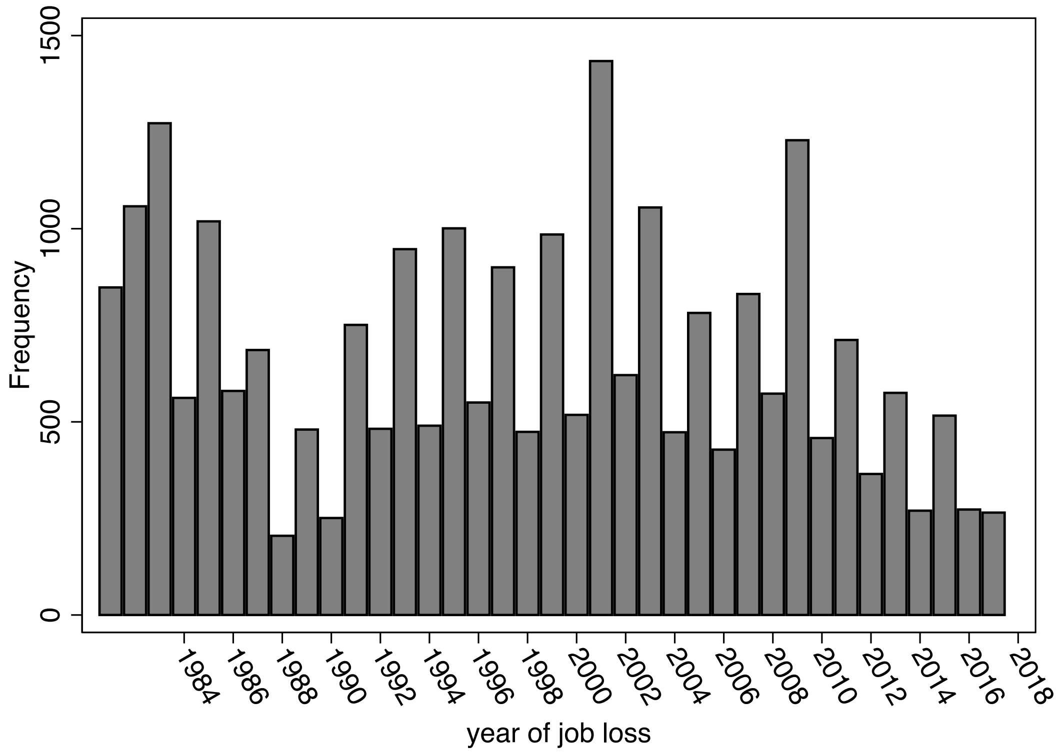


Figure A.3. CPS DWS: Histogram of displacement year, estimation sample, interviewed within two years of displacement

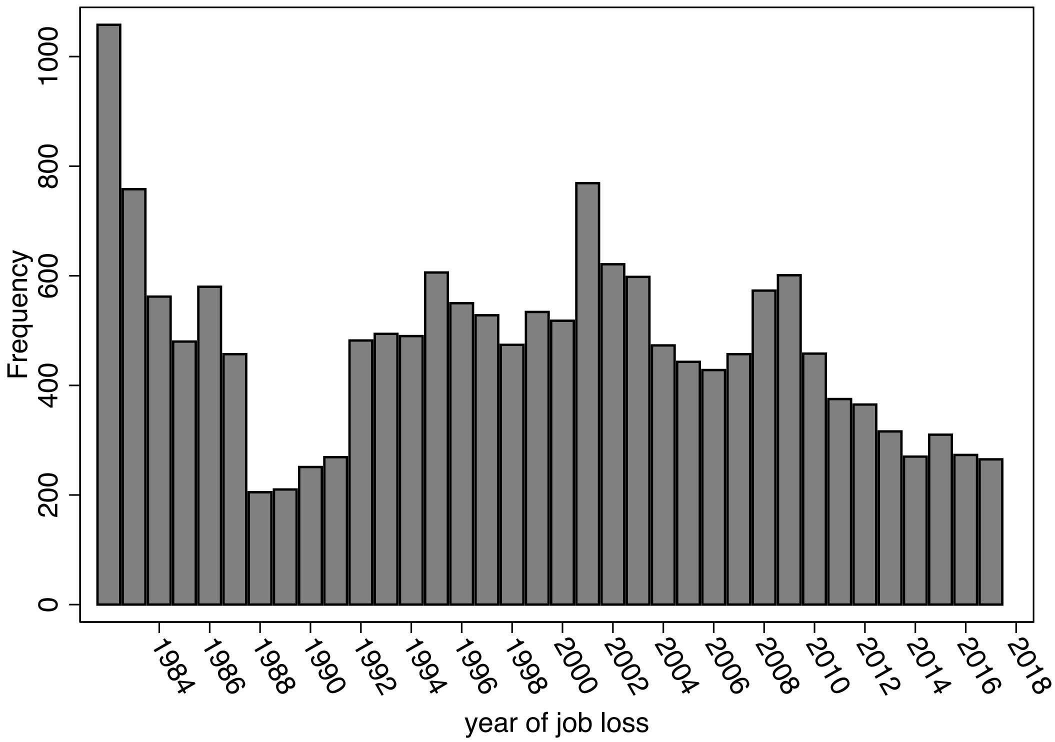
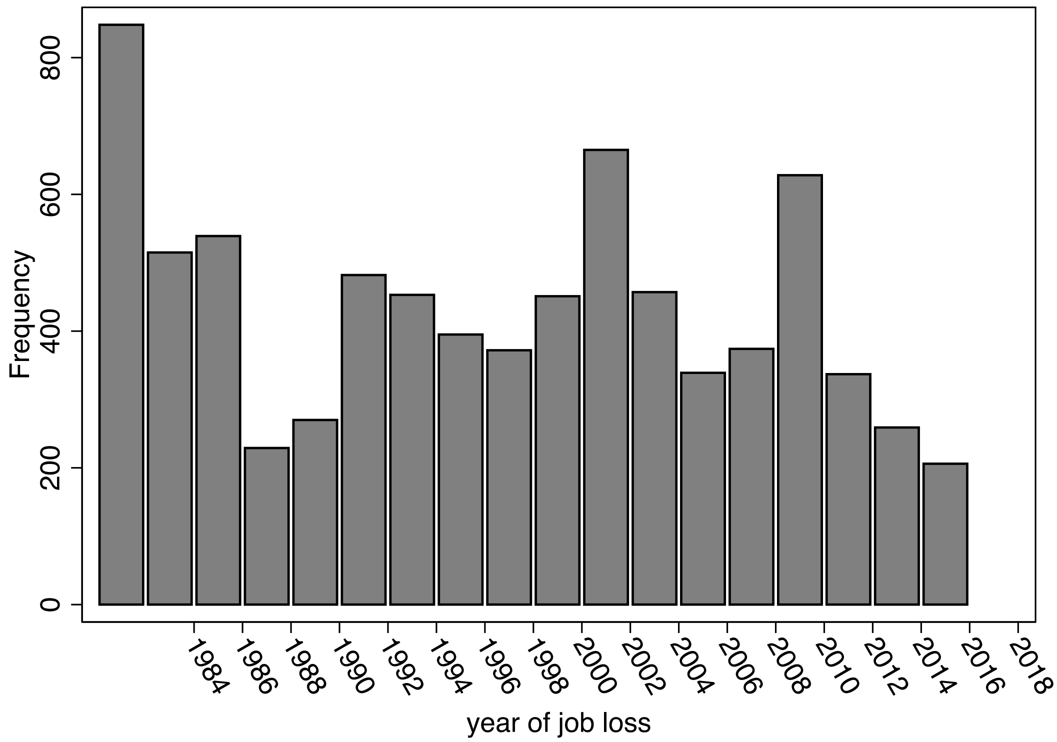


Figure A.4. CPS DWS: Histogram of displacement year, estimation sample, interviewed more than two years past displacement



A.3. **Cost of job loss from CPS DWS.** Write the regression equations for Tables 5 and 6 as

$$\mathbb{I}\left\{\mathrm{AD}\downarrow_{it}\right\} = \alpha_0 + x_{it}'\alpha_x + \alpha_{rec} \cdot \mathbb{I}\left\{\mathrm{Rec}_{it}\right\} + \varepsilon_{it} \tag{21}$$

$$\begin{aligned} \Delta \log w_{it} = \beta_0 + x_{it}'\beta_x + \beta_{rec} \cdot \mathbb{I}\left\{\mathrm{Rec}_{it}\right\} + \beta_{sw} \cdot \mathbb{I}\left\{\mathrm{AD}\downarrow_{it}\right\} \\ + \beta_{sw,rec} \cdot \mathbb{I}\left\{\mathrm{AD}\downarrow_{it}\right\} \cdot \mathbb{I}\left\{\mathrm{Rec}_{it}\right\} + \epsilon_{it} \end{aligned} \tag{22}$$

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

$$c_{exp} = \beta_0 + \alpha_0 \cdot \beta_{sw}, \tag{23}$$

where $\beta_0$ is the average earnings losses of non-switchers, $\beta_{sw}$ is the average earnings losses of switchers, and $\alpha_0$ is the fraction of switchers. Similarly, the average cost of job loss during recessions can be expressed as

$$c_{rec} = \beta_0 + \beta_{rec} + \left(\alpha_0 + \alpha_{rec}\right)\left(\beta_{sw} + \beta_{sw,rec}\right), \tag{24}$$

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.4. **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.[79]

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.

[79]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 $\downarrow$ | — | −0.063*** | — | −0.062*** | — | −0.026 | — | −0.037* |
| | | (0.0115) | | (0.0078) | | (0.0236) | | (0.0190) |
| Switch $\downarrow \times$ 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

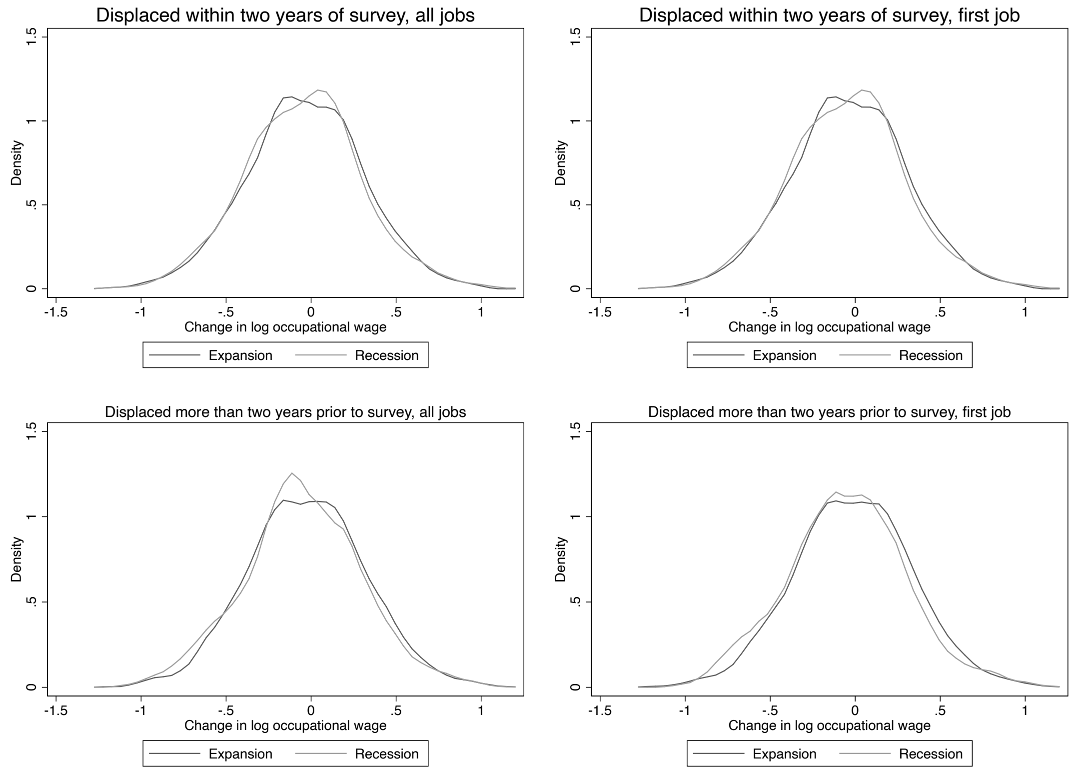


TABLE A.3. Immediate earnings losses are higher for occupation switchers: with occupation/industry/year fixed-effects for displacement job

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.5. **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. Theory appendix

B.1. **Derivation of wage equations.** Recall that the individual's state vector is $\psi = \{h, j\}$, where $h$ is human capital, and $j$ represents the type of job with which a worker has most recently matched. The previous type of job $j$ only necessary for determining the value of leisure and delay; hence, $j \in \psi$ can be eliminated as a state value by indexing the value of unemployment by previous type of employment; and indexing the expectations operator by the worker's current employment state ($H$, $L$, or $U$). With these substitutions, the value functions can be expressed as a function of just $h$ and $Z$, as follows.

B.1.1. *Value functions.*

(1) Value of unemployment, last matched with skill-sensitive job
$$U_H(h,Z) = u_H^b(h) + (1-\nu)\beta\mathbb{E}^U_{h,Z}\Big[\max\Big\{p_H(h',Z')W_H(h',Z') + (1-p_H(h',Z'))\,U_H(h',Z'), p_L(h',Z')W_L(h',Z') + (1-p_L(h',Z'))\,U_H(h',Z')\Big\}\Big]$$

(2) Value of unemployment, last matched with skill-insensitive job
$$U_L(h,Z) = u_L^b(h) + (1-\nu)\beta\mathbb{E}^U_{h,Z}\Big[\max\Big\{p_H(h',Z')W_H(h',Z') + (1-p_H(h',Z'))\,U_L(h',Z'), p_L(h',Z')W_L(h',Z') + (1-p_L(h',Z'))\,U_L(h',Z')\Big\}\Big]$$

(3) Value of employment, skill-sensitive job
$$W_H(h,Z) = w_H(h,Z) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\left[(1-\delta)W_H(h',Z') + \delta U_H(h',Z')\right]$$

(4) Value of employment, skill-insensitive job
$$W_L(h,Z) = w_L(h,Z) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[p_{H_+}(h',Z')(1-\delta)W_H(h',Z') + \Big(1-p_{H_+}(h',Z')\Big)(1-\delta)W_L(h',Z') + \delta U_L(h',Z')\Big]$$
where $p_{H_+}(h,Z) = \mathbb{I}\left\{W_H(h,Z) > W_L(h,Z)\right\}p_H(h,Z)$

(5) Firm's job value, skill-sensitive job
$$J_H(h,Z) = Zh - w_H(h,Z) + (1-\nu)\beta\mathbb{E}^H_{h,Z}\Big[(1-\delta)J_H(h',Z')\Big]$$

(6) Firm's job value, skill-insensitive job
$$J_L(h,Z) = Z - w_L(h,Z) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[\Big(1-p_{H_+}(h,Z)\Big)(1-\delta)J_L(h',Z')\Big]$$

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

(8) Value of employment, skill-insensitive job, worker offer

$$\tilde{W}_L(h,Z) = \tilde{w}_L(h,Z) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[p_{H_+}(h',Z')(1-\delta)W_H(h',Z') + \Big(1-p_{H_+}(h',Z')\Big)(1-\delta)\tilde{W}_L(h',Z') + \delta U_L(h',Z')\Big]$$

where $p_{H_+}(h,Z) = \mathbb{I}\left\{W_H(h,Z) > \tilde{W}_L(h,Z)\right\} p_H(h,Z)$

(9) Firm's job value, skill-sensitive job, worker offer

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

(10) Firm's job value, skill-insensitive job, worker offer

$$\tilde{J}_L(h,Z) = Z - \tilde{w}_L(h,Z) + (1-\nu)\beta\mathbb{E}^L_{h,Z}\Big[\Big(1-p_{H_+}(h,Z)\Big)(1-\delta)\tilde{J}_L(h',Z')\Big]$$

(11) Worker surplus, skill-insensitive job

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

(12) Worker surplus, skill-sensitive job

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

(13) Indifference equation for wage $w_L$

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

(14) Indifference equation for wage $\tilde{w}_L$

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

(15) Indifference equation for wage $w_H$

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

(16) Indifference equation for wage $\tilde{w}_H$

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

B.1.2. *Proof of Proposition 3.* 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

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

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

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

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 $w_H$:

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

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 $w_H$:

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

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

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

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

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

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

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

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

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

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:

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

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:

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

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

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

B.2. **Formal results from the auxiliary model.**

B.2.1. *Setting.* The auxiliary model is similar to the full model, except we abstract from dynamics for human capital and aggregate productivity. Assume $u_b(\psi) = u_d(\psi) = u^b$ for all $\psi$. Then, the only relevant state for value functions is the human capital of the worker, $h$. Let $d(\psi) = h\gamma$ for $j = H$ and $d_L(\psi) = \gamma$ for $j = L$. Wages are set via generalized Nash bargaining over flow payoffs, so

$$w_L = (1-\chi)u^b + \chi(Z+\gamma)$$

and

$$w_H = (1-\chi)u^b + \chi(Z+\gamma)h.$$[80]

For reasons of notational convenience, assume $\nu = 0$.

The value functions can thus be written as follows:

[80] Such a wage rule can be motivated by the wage from the full model without dynamics for human capital or aggregate productivity, as in section B.1.2. Here, however, we abstract from any dependence of the bargaining weights on the human capital input of the worker.

(1) Value of unemployment
$$U(h,Z) = u^b + \beta\left[U(h,Z) + \max\left\{p_H(h,Z)S_H(h,Z), p_L(h,Z)S_L(h,Z)\right\}\right]$$

(2) Value of unemployment, $H$-type
$$W_H(h,Z) = w_H(h,Z) + \beta\left[(1-\delta)S_H + U\right]$$

(3) Value of employment, $L$-type
$$\begin{aligned} W_L(h,Z) = w_L(h,Z) + \beta[&p_{H_+}(h,Z)(1-\delta)S_H(h,Z) \\ &+ \left(1 - p_{H_+}(h,Z)\right)S_L(h,Z) + U(h,Z)] \end{aligned}$$

where $p_{H_+}(h,Z) = p_H(h,Z)\cdot\mathbb{I}\left\{W_H(h,Z) > W_L(h,Z)\right\}$

(4) Worker surplus, $H$-type
$$S_H(h,Z) = W_H(h,Z) - U(h,Z)$$

(5) Worker surplus, $L$-type
$$S_L(h,Z) = W_L(h,Z) - U(h,Z)$$

(6) Job value, $H$-type
$$J_H(h,Z) = Zh - w_H(h,Z) + \beta\left[(1-\delta)J_H(h,Z)\right]$$

(7) Job value, $L$-type
$$J_L(h,Z) = Z - w_L(h,Z) + \beta\left[(1-\delta)(1-p_{H_+}(h,Z)J_L(h,Z)\right]$$

(8) Free entry:
$$c_i \geq q_i(h,Z)J_i(h,Z),\;\; \theta_i(h,Z) \geq 0$$

B.2.2. *Proofs of propositions 1 and 2 (and corollaries) from section 3.9.*

**Lemma 1** (Properties of $p_H$ and $p_L$)**.** *In the non-stochastic equilibrium, $p_H$ is strictly increasing in $h$ wherever $p_H > 0$, and $p_L$ is strictly decreasing in $h$ wherever $W_H > W_L$, $p_H > 0$, and $p_L > 0$.*

*Proof.* Under free entry, $p_H$ and $p_L$ are determined as follows:

$$p_L(h) = \varphi_L^{\frac{1}{\alpha}}\left(\frac{1}{c_L}\left(\frac{\pi_L^f}{1-\beta(1-\delta)\left(1-p_{H_+}\right)}\right)\right)^{\frac{1}{\alpha}-1} \tag{25}$$

$$p_H(h) = \varphi_H^{\frac{1}{\alpha}}\left(\frac{1}{c_H}\left(\frac{\pi_H^f}{1-\beta\left(1-\delta\right)}\right)\right)^{\frac{1}{\alpha}-1} \tag{26}$$

As $W_H > W_L$, $p_{H_+} = p_H$. Take derivatives with respect to $h$:

$$\frac{\partial p_H}{\partial h} = p_H \left(\frac{1}{\alpha} - 1\right)\left(\frac{1}{h}\right) \tag{27}$$

$$\frac{\partial p_L}{\partial h} = -p_H p_L \left(\frac{1}{\alpha} - 1\right)^2 \left(\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-p_H)}\right)\left(\frac{1}{h}\right) \tag{28}$$

□

**Lemma 2** ($S_L$ relative to $S_H$)**.** *$S_L < S_H$ only if $\pi_L^w < \pi_H^w$. Moreover, $S_L = S_H$ only at $h = 1$*

*Proof.* In the non-stochastic equilibrium, $S_L$ and $S_H$ are determined as follows:

$$S_L = \pi_L^w + \beta\Big[p_{H_+}(1-\delta)S_H + \Big(1 - p_{H_+}\Big)(1-\delta)S_L - \max\{p_H S_H, p_L S_L\}\Big] \tag{29}$$

$$S_H = \pi_H^w + \beta\left((1-\delta)S_H - \max\{p_H S_H, p_L S_L\}\right) \tag{30}$$

where $p_{H_+} \equiv p_H \cdot \mathbb{I}\{S_H > S_L\}$. Evaluate $S_H - S_L$ using (29) and (30) for (*i*) $S_H < S_L$ and $p_H S_H < p_L S_L$ and (*ii*) $S_H < S_L$ and $p_H S_H > p_L S_L$. In both cases,

$$S_L - S_H = \frac{\pi_L^w - \pi_H^w}{1-\beta(1-\delta)}$$

Then note that $\pi_H^w = \pi_L^w$ only at $h = 1$. □

**Lemma 3** (Existence of OTJ-search for $H$-type jobs. . . )**.** *For $h > 1$, $S_H > S_L$, so it will always be optimal for workers in $L$-type jobs to search on-the-job for $H$-type jobs.*

*Proof.* Suppose that $S_H < S_L$ for $h > 1$. Then from Lemma 2, it must be that $\pi_H^w < \pi_H^w$, a contradiction. □

**Lemma 4** (. . . and no OTJ-search for $L$-type jobs)**.** *Suppose $p_L > p_H$ at $h = 1$, so that workers with $h = 1$ find it optimal to search for $L$-type jobs from unemployment and $H$-type jobs from employment. Then, there does not exist an $h$ such that on-the-job search from $H$-type jobs for $L$-type jobs is optimal.*

*Proof.* If $p_L > p_H$ at $h = 1$, then also $p_L S_L > p_H S_H$. For workers to find it optimal at some $h$ to search on-the-job for $L$-type jobs from $H$-type jobs, it must be that $S_L > S_H$ but $p_H S_H > p_L S_L$. But $S_L > S_H$ only for $h < 1$, and by Lemma 1, $p_L > p_H$ for all $h < 1$, so $p_L S_L > p_H S_H$ for all $h < 1$. Hence, it is never optimal for workers in $H$-type jobs to search on-the-job for $L$-type positions. □

**Lemma 5** (Elasticity of firm flow surpluses)**.** *The elasticity of the flow surplus of a firm operating an $H$-type job is equal to (greater than) the elasticity of the flow surplus of a worker in an $L$-type job with respect to $Z$ $(h)$.*

*Proof.* $\eta_{\pi^f_L,h} = 0$, and $\eta_{\pi^f_H,h} = \frac{1}{h}$. That $\eta_{\pi^f_L,Z} = \eta_{\pi^f_H,Z}$ follows from inspection. □

**Lemma 6** (Elasticity of worker flow surpluses). *Consider the case where workers in $L$-type jobs search on-the-job for $H$-type jobs. Then the elasticity of the flow surplus of a worker in an $H$-type job is higher than the elasticity of the flow surplus of a worker in an $L$-type job with respect to both $Z$ and $h$.*

*Proof.* Denote the elasticity of $y$ to $x$ as $\eta_{y,x}$. Then,

$$\begin{aligned}\eta_{\pi^w_H,x} - \eta_{\pi^w_L,x} &= \frac{\partial \pi^w_H/\partial x}{\pi^w_H} - \frac{\partial \pi^w_L/\partial x}{\pi^w_L} \\ &> \frac{\partial \pi^w_H/\partial x - \partial \pi^w_L/\partial x}{\pi^w_L}\end{aligned}$$

for $x = Z$ and $h$, as we know that workers in $L$-type jobs only search on-the-job for $H$-type jobs when $h > 1$ and $\pi^w_H > \pi^w_L$. Then,

$$\eta_{\pi^w_H,Z} - \eta_{\pi^w_L,Z} > \frac{\chi - \chi}{\pi^w_L} = 0$$

and

$$\eta_{\pi^w_H,Z} - \eta_{\pi^w_L,Z} > \frac{\chi(Z+\gamma)}{\pi^w_L} > 0$$

□

The following assumption allows us to prove the existence of a unique $h^*$ where $p_H S_H < p_L S_L$.

**Assumption 1** (Regularity conditions). *Assume the following:*

*(i)* $\varphi_L = \varphi_H = \varphi = 1$
*(ii)* $Z + \gamma - u^b > 0$
*(iii)* $1/2 < (1-\delta)\beta < 1$
*(iv)* $0 < \frac{(1-\chi)\left(Z-u^b\right)-\chi\gamma}{1-\beta(1-\delta)}(1+\Delta)^{\frac{\alpha}{1-\alpha}} < c_L < c_H$ *for some arbitrary* $\Delta \in (0,\infty)$

**Lemma 7** (Left boundary). *Assume that the regularity conditions of Assumption 1 hold. At $h = 1$, $p_L S_L > p_H S_H$. Furthermore, $0 < p_H < p_L < 1$, and $0 < S_L = S_H < \infty$.*

*Proof.* Examine (29) and (30) to verify

$$S_L = S_H = \frac{\chi(Z+\gamma-u^b)}{1-\beta(1-\delta)} > 0,$$

at $h = 1$, where the inequality follows from Assumption 1. That $0 < p_H < p_L < 1$ follows directly from (25), (26), and Assumption 1. □

**Lemma 8** (Right boundary)**.** *Assume that the regularity conditions of Assumption 1 hold. There exists $h > 1$ such that $p_H S_H > p_L S_L$, $S_L < S_H < \infty$, and $0 < p_L < p_H < 1$.*

*Proof.* Consider

$$\bar{h} = c_H \frac{1-\beta(1-\delta)}{(1-\chi)\left(Z-u^b\right)-\chi\gamma}\left(1-\epsilon\right)^{\frac{\alpha}{1-\alpha}}$$

for an arbitrarily small $\epsilon \in (0,1)$. By Assumption 1, $\bar{h} > 1$. Then, by Lemma 3, $S_H > S_L$. Hence, we need only show that $p_H > p_L$ at $\bar{h}$. Compute $p_H$ at $\bar{h}$:

$$\begin{aligned}
p_H(\bar{h}) &= \left(\frac{1}{c_H}\frac{\pi_H^f(\bar{h},Z)}{1-\beta(1-\delta)}\right)^{\frac{1}{\alpha}-1} \\
&= \left(\frac{1}{c_H}\frac{\left((1-\chi)\left(Z-u^b\right)-\chi\gamma\right)\bar{h}}{1-\beta(1-\delta)}\right)^{\frac{1}{\alpha}-1} \\
&= (1-\epsilon)
\end{aligned}$$

Use the expression above to compute $p_L$ at $\bar{h}$:

$$p_L(\bar{h}) = \left(\frac{1}{c_L}\frac{(1-\chi)\left(Z-u^b\right)-\chi\gamma}{1-\beta\left(1-\delta\right)\epsilon}\right)^{\frac{1}{\alpha}-1} < \left(\frac{1}{c_L}\frac{(1-\chi)\left(Z-u^b\right)-\chi\gamma}{1-\beta\left(1-\delta\right)}\right)^{\frac{1}{\alpha}-1} < \frac{1}{1+\Delta},$$

by Assumption 1. Since $\Delta$ and $\epsilon$ are arbitrary, pick $\Delta$ and $\epsilon$ such that $p_L(\bar{h}) < p_H(\bar{h}) < 1$. $\square$

**Lemma 9** (Elasticity of $p_L$ in terms of $p_H$)**.** *Assume that the regularity conditions of Assumption 1 hold, and consider values for $h$ and $Z$ such that workers search for $L$-type jobs from unemployment and search on-the-job for $H$-type jobs. Then,*

$$\begin{aligned}
\eta_{p_L,Z} &= \left(1-\left(\frac{1}{\alpha}-1\right)\left(\frac{\beta(1-\delta)p_H}{1-\beta(1-\delta)(1-p_H)}\right)\right)\eta_{p_H,Z} \\
\eta_{p_L,h} &= -\left(\frac{1}{\alpha}-1\right)\left(\frac{\beta(1-\delta)p_H}{1-\beta(1-\delta)(1-p_H)}\right)\eta_{p_H,h}
\end{aligned}$$

*with*

$$\frac{\beta(1-\delta)p_H}{1-\beta(1-\delta)(1-p_H)} > 1$$

*Proof.* Denote the log derivative of a variable $x$ as $\widehat{x}$:

$$\begin{aligned}
\widehat{p}_H &= \left(\frac{1}{\alpha}-1\right)\widehat{\pi}_H^f \\
\widehat{p}_L &= \widehat{p}_H - \left(\frac{1}{\alpha}-1\right)^2\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-p_H)}\widehat{\pi}_L^f
\end{aligned}$$

Recall that $\eta_{\pi_H^f,Z} = \eta_{\pi_L^f,Z}$, $\eta_{\pi_H^f,Z} = \frac{1}{h}$, and $\eta_{\pi_L^f,h} = 0$. The rest follows from inspection. $\square$

**Lemma 10** (Properties of eq'n for $h^*$ from below)**.** *Denote $S_H^b$ and $S_L^b$ to be the surplus sub-functions where $S_L < S_H$ and $p_L S_L > p_H S_H$. Assume that the regularity conditions of Assumption 1 hold. Then*

$$g_b = \left(\log S_H^b - \log S_L^b\right) + (\log p_H - \log p_L)$$

*is strictly increasing in $x = h, Z$.*

*Proof.* Let $\eta_{y,z}$ denote the elasticity of $y$ to $z$, i.e. $\eta_{y,x} = \frac{dy/dz}{y/z}$. Then it is enough to show that the derivative of $g_a$ with respect to $x$

$$g_{b,x} = \left(\eta_{S_H^b,x} - \eta_{S_L^b,x}\right) + (\eta_{p_H,x} - \eta_{p_L,x})$$

is strictly positive for $x = h$, $Z$.

$S_L^b$ and $S_H^b$ satisfy

$$S_L^b = \frac{1}{(1 - \beta\left[(1 - \delta - p_L) - p_H (1 - \delta)\right])} \left(\pi_L^w + \beta(1-\delta)p_H S_H^b\right) \tag{31}$$

$$S_H^b = \frac{\pi_H^w}{1 - \beta(1-\delta)} - \frac{\beta p_L}{1 - \beta(1-\delta)} S_L^b \tag{32}$$

or equivalently,

$$S_L^b = \frac{(1 - \beta(1-\delta))\,\pi_L^w + \beta(1-\delta)p_H \pi_H^w}{\beta^2(1-\delta)p_H p_L + (1 - \beta(1-\delta))\,(1 - \beta\left[(1-\delta-p_L) - p_H(1-\delta)\right])}$$

$$S_H^b = \frac{\pi_H^w}{1 - \beta\,(1-\delta)} - \left(\frac{\beta p_L}{1 - \beta(1-\delta)}\right) \frac{(1 - \beta(1-\delta))\,\pi_L^w + \beta(1-\delta)p_H \pi_H^w}{\beta^2(1-\delta)p_H p_L + (1 - \beta(1-\delta))\,(1 - \beta\left[(1-\delta-p_L) - p_H(1-\delta)\right])}$$

Then,

$$\eta_{S_L^b,x} = \omega_{S_L^b,\pi_L^w} \cdot \eta_{\pi_L^w,x} + \omega_{S_L^b,\pi_H^w} \cdot \eta_{\pi_H^w,x} + \left(\omega^\alpha_{S_L^b,p_H} - \omega^\beta_{S_L^b,p_H}\right) \cdot \eta_{S_L^b,p_H} - \omega_{S_L^b,p_L} \cdot \eta_{p_L,x}$$

with

$$\begin{aligned}
\omega_{S_L^b,\pi_L^w} &= \frac{(1-\beta(1-\delta))\,\pi_L^w}{(1-\beta(1-\delta))\,\pi_L^w+\beta(1-\delta)p_H\pi_H^w} < 1\\
\omega_{S_L^b,\pi_H^w} &= \frac{\beta(1-\delta)p_H\pi_H^w}{(1-\beta(1-\delta))\,\pi_L^w+\beta(1-\delta)p_H\pi_H^w} = 1-\omega_{S_L^b,\pi_L^w}\\
\omega^{\alpha}_{S_L^b,p_H} &= \frac{\beta(1-\delta)p_H\pi_H^w}{(1-\beta(1-\delta))\,\pi_L^w+\beta(1-\delta)p_H\pi_H^w} < 1\\
\omega^{\beta}_{S_L^b,p_H} &= \frac{\beta p_L\left(1-(1-\delta)\beta(1-p_H)\right)}{\beta^2(1-\delta)p_Hp_L+(1-\beta(1-\delta))\left(1-\beta\left((1-\delta-p_L)-p_H(1-\delta)\right)\right)}\\
\omega_{S_L^b,p_L} &= \frac{\beta(1-\delta)p_H\left(1-\beta(1-\delta-p_L)\right)}{\beta^2(1-\delta)p_Hp_L+(1-\beta(1-\delta))\left(1-\beta\left((1-\delta-p_L)-p_H(1-\delta)\right)\right)}
\end{aligned}$$

and

$$\eta_{S_H^b,x} = \omega_{S_H^b,\pi_H^w}\cdot\eta_{\pi_H^w,x} - \omega_{S_H^b,p_L}\cdot\eta_{p_L,x} - \omega_{S_H^b,S_L^b}\cdot\eta_{S_L^b,x}$$

with

$$\begin{aligned}
\omega_{S_H^b,\pi_H^w} &= \frac{\pi_H^w}{\pi_H^w-\beta p_L S_L^b} = \frac{\pi_H^w}{(1-\beta(1-\delta))\,S_H^b} > 1\\
\omega_{S_H^b,p_L} &= \frac{\beta p_L S_L^b}{\pi_H^w-\beta p_L S_L^b} = \frac{\pi_H^w-(1-\beta(1-\delta))\,S_H^b}{(1-\beta(1-\delta))\,S_H^b} = \omega_{S_H^b,\pi_H^w}-1\\
\omega_{S_H^b,S_L^b} &= \omega_{S_H^b,p_L}
\end{aligned}$$

Then,

$$\begin{aligned}
g_{b,x} &= \omega_{S_H^b,\pi_H^w}\cdot\eta_{\pi_H^w,x} - (1+\omega_{S_H^b,S_L^b})\cdot\eta_{S_L^b,x} + \eta_{p_H,x} - (1+\omega_{S_H^b,S_L^b})\cdot\eta_{p_L,x}\\
&= \omega_{S_H^b,\pi_H^w}\cdot\eta_{\pi_H^w,x} - \omega_{S_H^b,\pi_H^w}\cdot\eta_{S_L^b,x} + \eta_{p_H,x} - \omega_{S_H^b,\pi_H^w}\cdot\eta_{p_L,x}\\
&> \omega_{S_H^b,\pi_H^w}\cdot\eta_{\pi_H^w,x} - \eta_{S_L^b,x} + \eta_{p_H,x} - \eta_{p_L,x}
\end{aligned}$$

where in the second equality we invoke $\omega_{S_H^b,\pi_H^w} = 1+\omega_{S_H^b,S_L^b}$ and in the last inequality we invoke $\omega_{S^b,\pi_H^w} > 1$. Then, substitute in the equation for $\eta_{S_L^b,x}$:

$$\begin{aligned}
g_{b,x} > {}& \omega_{S_H^b,\pi_H^w}\cdot\eta_{\pi_H^w,x} - \left(\omega_{S_L^b,\pi_L^w}\cdot\eta_{\pi_L^w,x} + \omega_{S_L^b,\pi_H^w}\cdot\eta_{\pi_H^w,x}\right)\\
&- (1-\omega_{S_L^b,p_L})\eta_{p_L,x} + \left(1+\omega^{\beta}_{S_L^b,p_H} - \omega^{\alpha}_{S_L^b,p_H}\right)\cdot\eta_{p_H,x}
\end{aligned}$$

Note, from $\omega_{S_H^b,\pi_H^w} > 1$ and $\omega_{S_L^b,\pi_H^w} + \omega_{S_L^b,\pi_L^w} = 1$,

$$\omega_{S_H^b,\pi_H^w}\cdot\eta_{\pi_H^w,x} > \eta_{\pi^w_{H,x}} \geq \omega_{S_L^b,\pi_L^w}\cdot\eta_{\pi_L^w,x} + \omega_{S_L^b,\pi_H^w}\cdot\eta_{\pi_H^w,x}$$

as $\eta_{\pi^w_H,x} > \eta_{\pi^w_L,x}$ for $x = h, Z$ from Lemma 6. Hence,

$$g_{b,x} > -(1-\omega_{S^b_L,p_L})\eta_{p_L,x} + \left(1 + \omega^{\beta}_{S^b_L,p_H} - \omega^{\alpha}_{S^b_L,p_H}\right) \cdot \eta_{p_H,x}$$

Then note that $\omega^{\alpha}_{S^b_L,p_H} < 1$, so

$$g_{b,x} > -(1-\omega_{S^b_L,p_L}) \cdot \eta_{p_L,x} + \omega^{\beta}_{S^b_L,p_H} \cdot \eta_{p_H,x} \tag{33}$$

Finally, we show $\omega_{S^b_L,p_L} < 1$. Suppose otherwise. Then,

$$\beta(1-\delta)p_H\left(1-\beta(1-\delta-p_L)\right) > \beta^2(1-\delta)p_Hp_L + \left(1-\beta(1-\delta)\right)\left(1-\beta((1-\delta-p_L)-p_H(1-\delta))\right)$$

Subtract $\beta^2(1-\delta)p_Hp_L$ from both sides and then divide by $1-\beta(1-\delta)$:

$$\beta(1-\delta)p_H > (1-\beta((1-\delta-p_L)-p_H(1-\delta)))$$

which implies

$$\beta(1-\delta-p_L) > 1$$

a contradiction by Assumption 1. Hence, $1-\omega_{S^b_L,p_L} > 0$.

Evaluate (33) at $x = Z$, and invoke Lemma 9:

$$\begin{aligned} g_{b,Z} &> (1-\omega_{S^b_L,p_L})\left(\left(\frac{1}{\alpha}-1\right)\left(\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-p_H)}\right)-1\right) \cdot \eta_{p_H,Z} + \omega^{\beta}_{S^b_L,p_H} \cdot \eta_{p_H,Z} \\ &> 0 \end{aligned}$$

Evaluate (33) at $x = h$, and invoke Lemma 9:

$$\begin{aligned} g_{b,h} &> (1-\omega_{S^b_L,p_L})\left(\left(\frac{1}{\alpha}-1\right)\left(\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-p_H)}\right)\right) \cdot \eta_{p_H,h} + \omega^{\beta}_{S^b_L,p_H} \cdot \eta_{p_H,h} \\ &> 0 \end{aligned}$$

□

**Lemma 11** (Properties of eq'n for $h^*$ from above)**.** *Denote $S^a_H$ and $S^a_L$ to be the surplus sub-functions where $S_L < S_H$ and $p_LS_L < p_HS_H$. Assume that the regularity conditions of Assumption 1 hold. Then*

$$g_a = (\log S^a_H - \log S^a_L) + (\log p_H - \log p_L)$$

*is strictly increasing in $x = h, Z$.*

*Proof.* Let $\eta_{y,z}$ denote the elasticity of $y$ to $z$, i.e. $\eta_{y,x} = \frac{dy/dz}{y/z}$. Then it is enough to show that the derivative of $g_a$ with respect to $x$

$$g_{a,x} = \left(\eta_{S^a_H,x} - \eta_{S^a_L,x}\right) + \left(\eta_{p_H,x} - \eta_{p_L,x}\right)$$

is strictly positive for $x = h$, $Z$.

$S_L^a$ and $S_H^a$ satisfy

$$S_L^a = \frac{1}{(1-\beta(1-\delta)(1-p_H))}\left(\pi_L^w - \frac{\beta\delta p_H}{(1-\beta(1-\delta-p_H))}\pi_H^w\right) \tag{34}$$

$$S_H^a = \frac{\pi_H^w}{(1-\beta(1-\delta-p_H))} \tag{35}$$

so

$$\eta_{S_H^a,x} = \eta_{\pi_H^w,x} - \omega_{S_H^a,p_H}\cdot\eta_{p_H,x} \tag{36}$$

with

$$\omega_{S_H^a,p_H} = \frac{\beta p_H}{(1-\beta(1-\delta-p_H))} < 1$$

and

$$\eta_{S_L^a,x} = \omega_{S_L^a,\pi_L^w}\cdot\eta_{\pi_L^w,x} - \omega_{S_L^a,\pi_H^w}\cdot\eta_{\pi_H^w,x} - \left(\omega^\alpha_{S_L^a,p_H}\omega_{S_L^a,\pi_H^w} + \omega^\beta_{S_L^a,p_H}\right)\cdot\eta_{p_H,x} \tag{37}$$

with

$$\begin{aligned}
\omega_{S_L^a,\pi_L^w} &= \frac{(1-\beta(1-\delta-p_H))\,\pi_L^w}{(1-\beta(1-\delta-p_H))\,\pi_L^w - \beta\delta p_H\pi_H^w}\\
\omega_{S_L^a,\pi_H^w} &= \frac{\beta\delta p_H\pi_H^w}{(1-\beta(1-\delta-p_H))\,\pi_L^w - \beta\delta p_H\pi_H^w} = \omega_{S_L^a,\pi_L^w} - 1\\
\omega^\alpha_{S_L^a,p_H} &= \frac{1-\beta(1-\delta)}{1-\beta(1-\delta-p_H)} < 1\\
\omega^\beta_{S_L^a,p_H} &= \frac{\beta(1-p_H)}{1-\beta(1-\delta)(1-p_H)}
\end{aligned}$$

Hence,

$$g_{a,x} = \left(1-\omega_{S_L^a,\pi_H^w}\right)\cdot\eta_{\pi_H^w,x} - \omega_{S_L^a,\pi_L^w}\cdot\eta_{\pi_L^w} + \left(1+\omega^\alpha_{S_L^a,p_H}\omega_{S_L^a,\pi_H^w} + \omega^\beta_{S_L^a,p_H}\right)\cdot\eta_{p_H,x} - \eta_{p_L,x}$$

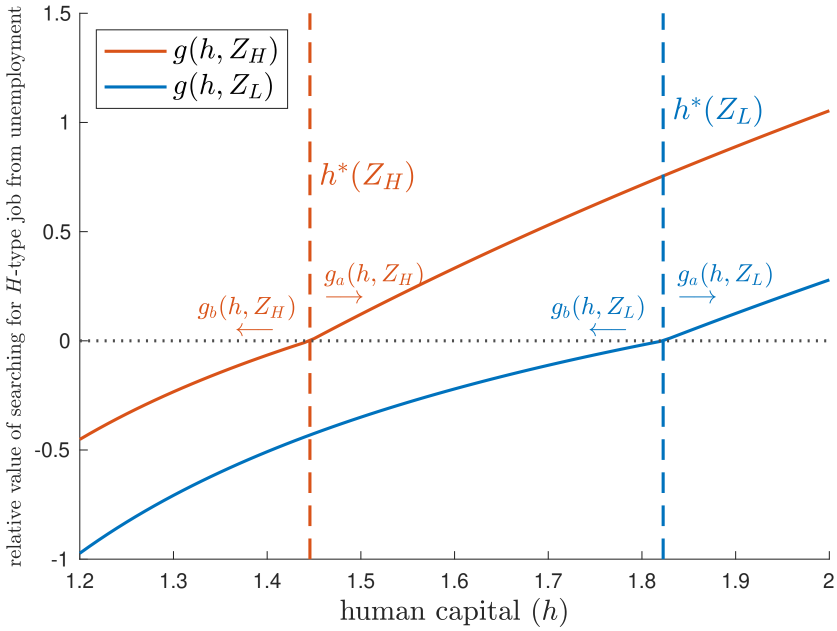
Note that $1-\omega_{S_L^a,\pi_H^w} = \omega_{S_L^a,\pi_L^w}$ and recall $\eta_{\pi_H^w,x} - \eta_{\pi_L^w,x} > 0$ for $x = Z$ and $h$ by Lemma 6, so

$$\begin{aligned}
g_{a,x} &= \omega_{S_L^a,\pi_L^w}\cdot\left(\eta_{\pi_H^w,x} - \eta_{\pi_L^w,x}\right) + \left(1+\omega^\alpha_{S_L^a,p_H}\omega_{S_L^a,\pi_H^w} + \omega^\beta_{S_L^a,p_H}\right)\cdot\eta_{p_H,x} - \eta_{p_L,x}\\
&> \left(1+\omega^\alpha_{S_L^a,p_H}\omega_{S_L^a,\pi_H^w} + \omega^\beta_{S_L^a,p_H}\right)\cdot\eta_{p_H,x} - \eta_{p_L,x}
\end{aligned}$$

First consider $x = Z$. Invoke Lemma 9, and note that $\eta_{\pi_H^w,Z} > \eta_{\pi_L^w,Z}$. Then,

$$g_{a,Z} > \left(\omega^\alpha_{S_L^a,p_H}\omega_{S_L^a,\pi_H^w} + \omega^\beta_{S_L^a,p_H} + \left(\frac{1}{\alpha}-1\right)\left(\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-p_H)}\right)\right)\cdot\eta_{p_H,Z}$$

FIGURE B.1. The equilibrium skill threshold $h^*(Z)$ is unique and decreases with $Z$.




The equilibrium skill threshold $h^*(Z)$ of the auxiliary model is the unique value of $h$ such that $g_b(h, Z) = g_a(h, Z) = 0$, as established in Proposition 1. This value of $h$ decreases with $Z$, as established in Proposition 2.

so $g_{a,Z} > 0$. Then consider $z = h$. Invoke Lemma 9, and note that $\eta_{\pi^w_H,h} = \eta_{\pi^w_L,h}$. Then,

$$g_{a,h} > \left(1 + \omega^{\alpha}_{S^a_L,p_H}\omega_{S^a_L,\pi^w_H} + \omega^{\beta}_{S^a_L,p_H} + \left(\frac{1}{\alpha} - 1\right)\left(\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-p_H)}\right)\right) \cdot \eta_{p_H,h}$$

so $g_{a,Z} > 0$. □

**Proof of Proposition 1.** *The proposition states that the equilibrium skill threshold $h^*$ exists and is unique for a given $Z$.*

*Proof.* By Assumption 1 and Lemmas 3, 4, 7, and 8, we know that workers will search for $L$-type jobs from unemployment and then search on-the-job for $H$-type jobs at $h = 1$, as $p_L S_L > p_H S_H$ and $S_H > S_L$; and moreover, workers will search for $H$-type jobs from unemployment at some $\bar{h} > 1$ where $p_H S_H > p_L S_L$ and $S_H > S_L$. We need only establish that there is a unique point $h^* \in (1, \bar{h})$ such that $p_H S_H = p_L S_L$ at $h^*$. Given that we have established endpoints such that $p_H$, $p_L$, $S_H$, and $S_L$ are strictly positive, it is equivalent to show that $g_b = \log p_H + \log S^b_H - \log p_L - \log S^b_L$ and $g_a = \log p_H + \log S^a_H - \log p_L - \log S^a_L$ are strictly increasing, as is done in Lemmas 10 and 11. Finally, note that our choice of endpoints implies $g_b < 0$ at the left and $g_a > 0$ at the right, and recall that $g_a = g_b = 0$ only at $h^*$ by definition. □

**Proof of Corollary 1.1.** *The corollary begins by defining the $\epsilon$-maximal cost of job loss as the maximum percent difference of prior and reemployment wages for a worker who loses their job and subsequently loses an arbitrarily small but positive quantity of human capital $\epsilon > 0$. The corollary then states that the $\epsilon$-maximal cost of job loss for aggregate productivity $Z$ is realized for a worker of human capital $h = h^*(Z)$ who is employed at a skill-sensitive job. Such a worker is forced to search for a skill-insensitive job upon employment, and hence undergoes costly occupation displacement.*

*Proof.* First, note that the $\epsilon$-maximal cost of job loss goes to zero for a worker who loses a skill-sensitive job and is re-employed in a skill-sensitive job; and likewise for a worker who loses a skill-insensitive job and is re-employed in a skill-insensitive job. By Lemma 4, no worker will lose a skill-insensitive job and search directly for a skill-sensitive job. Hence, it is sufficient to consider the reemployment wage losses of workers who lose a skill-sensitive job and search for reemployment in a skill-insensitive job. By Proposition 1, the maximum human capital for which a worker might lose a skill-sensitive job and search for re-employment in a skill-insensitive job after an arbitrarily small but positive reduction in human capital is $h = h^*(Z)$. Then note that wages for skill-sensitive jobs are increasing in $h$, whereas wages for skill-insensitive jobs are constant. □

**Proof of Corollary 1.2.** *The corollary states that, for a fixed $Z$, the expected duration of unemployment increases in $h$ for $h < h^*(Z)$ and decreases in $h$ for $h \geq h^*(Z)$; and that the longest expected duration of unemployment of a worker searching for a skill-sensitive job is realized at $h = h^*(Z)$, whereas longest expected duration of unemployment of a worker searching for a skill-insensitive job is realized at $h = h^*(Z) - \epsilon$ for an arbitrarily small $\epsilon > 0$.*

*Proof.* By Proposition 1, workers with $h \geq h^*(Z)$ search for skill-sensitive jobs from unemployment, whereas workers with $h < h^*(Z)$ search for skill-insensitive jobs from unemployment. Then, note that $p_H$ is strictly increasing in $h$ for $h \geq h^*$ and strictly decreasing in $h$ for $h < h^*$ by Lemmas 1, 7, and 8. Hence, the lowest job-finding rate for skill-sensitive jobs from unemployment is achieved at $h = h^*(Z)$, and the lowest job-finding rate for skill-insensitive jobs from unemployment is achieved at $h = h^*(Z) - \epsilon$ for an arbitrarily small but positive $\epsilon$. □

**Proof of Proposition 2.** *The proposition states that the equilibrium skill threshold $h^*$ is strictly decreasing in $Z$.*

*Proof.* Define $g$ as in the proof of Proposition 1. Then it is clear that $g$ is strictly increasing in $Z$, by Lemmas 10 and 11. The rest follows from proof by contradiction: suppose that $h^*(Z') \geq h^*(Z)$ for some $Z' > Z$. Then $g(h^*(Z'), Z') = 0$, by definition of $h^*$ and $g$. But $g$ is strictly increasing in $Z$, so $g(h, Z') > g(h, Z)$ for all $h$. But then,

$$g\left(h^*(Z'), Z'\right) \geq g\left(h^*(Z), Z'\right) > g\left(h^*(Z), Z\right) = 0,$$

a contradiction. □

**Proof of Corollary 2.1.** *The corollary states that the $\epsilon$-maximal cost of job loss is decreasing in $Z$.*

*Proof.* Assume the opposite, and let $Z' > Z$. Note that $w_H(h, Z) = w_L(h, Z) \cdot h$. Then,

$$\frac{w_L\left(h^*(Z'), Z'\right)\left(h^*(Z') - (1+\epsilon)\right)}{w_L(h^*(Z'), Z')} \geq \frac{w_L(h^*(Z), Z)\left(h^*(Z) - (1+\epsilon)\right)}{w_L(h^*(Z), Z)}.$$

But this implies $h^*(Z') \geq h^*(Z)$ when $Z' > Z$, a contradiction of Proposition 2. □

**Proof of Corollary 2.2.** *The proof states that, given a one-time, unanticipated decrease in aggregate productivity $Z$, a greater fraction of workers in unemployment who were previously employed in the job of a skill-sensitive occupation will now search for employment in a skill-insensitive job.*

*Proof.* The fraction of workers searching for a skill-insensitive job when aggregate productivity is $Z$ is given by

$$\mathcal{L}(Z) = \int^{h^*(Z)} d\lambda^u(h; Z)dh,$$

where $\lambda^u(h; z)$ gives the stationary distribution of workers searching for skill-insensitive jobs from unemployment when aggregate productivity is $Z$, where we assume $d\lambda^u(h; Z) > 0 \ \forall h$. An unanticipated decrease from $Z$ to some $Z'$ means that an additional quantity

$$\int_{h^*(Z)}^{h^*(Z')} d\lambda^u(h; Z)dh$$

of workers will immediately begin searching for skill-insensitive jobs from unemployment. We know that the quantity is strictly positive because $h^*(Z') > h^*(Z)$, by Proposition 2. And we know that workers with $h \in [h^*(Z), h^*(Z')]$ were previously employed in a skill-intensive job by Proposition 1 and Lemma 4. $\square$

## 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, Krusell, and Violante (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,

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 |

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. **Additional figures.** 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 offers a comparison of model and earnings losses, but for all three parameterizations of the model.
- Figure C.4 plots the job-finding probabilities from the "outside value" parameterization of the model.
- Figure C.5 plots reemployment wages from the "outside value" parameterization of the model.
- Figure C.6 plots the total present value cost of job loss from the "outside value" parameterization of the model.
- Figure C.8 plots all job-finding rates for $Z_H$ and $Z_L$.

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.6 that the maximal cost of job loss is realized to the left of the equilibrium skill threshold. Then see Figure C.8, 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.

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.

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

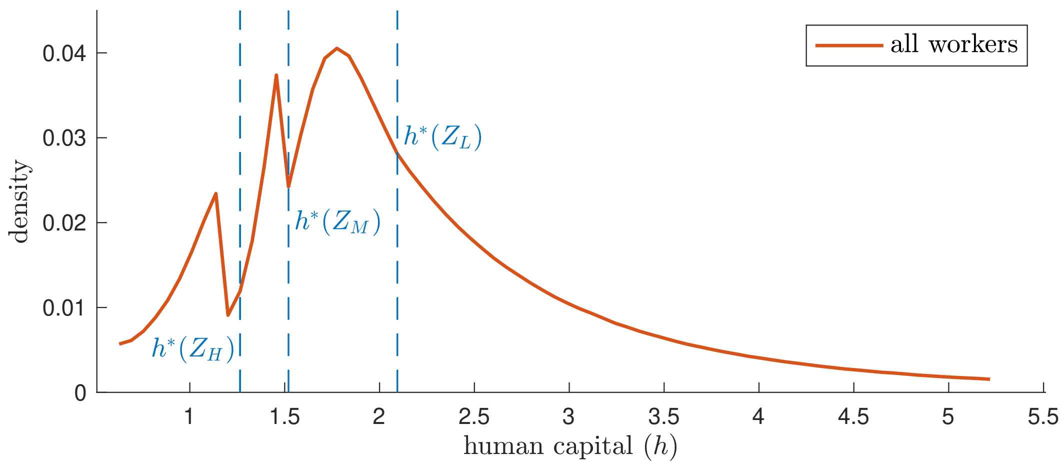



FIGURE C.2. Distribution of workers over human capital, "outside value" calibration

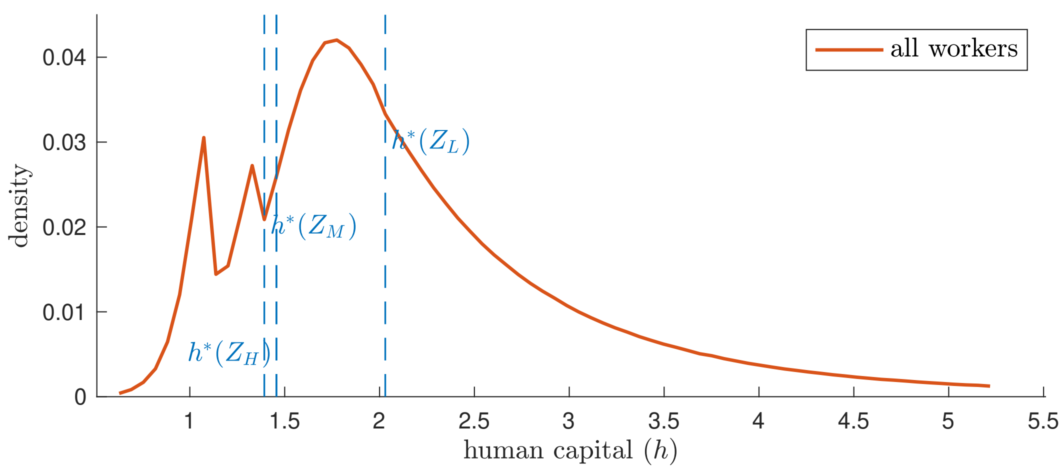


FIGURE C.3. Comparison of model and empirical earnings loss profiles, all parameterizations

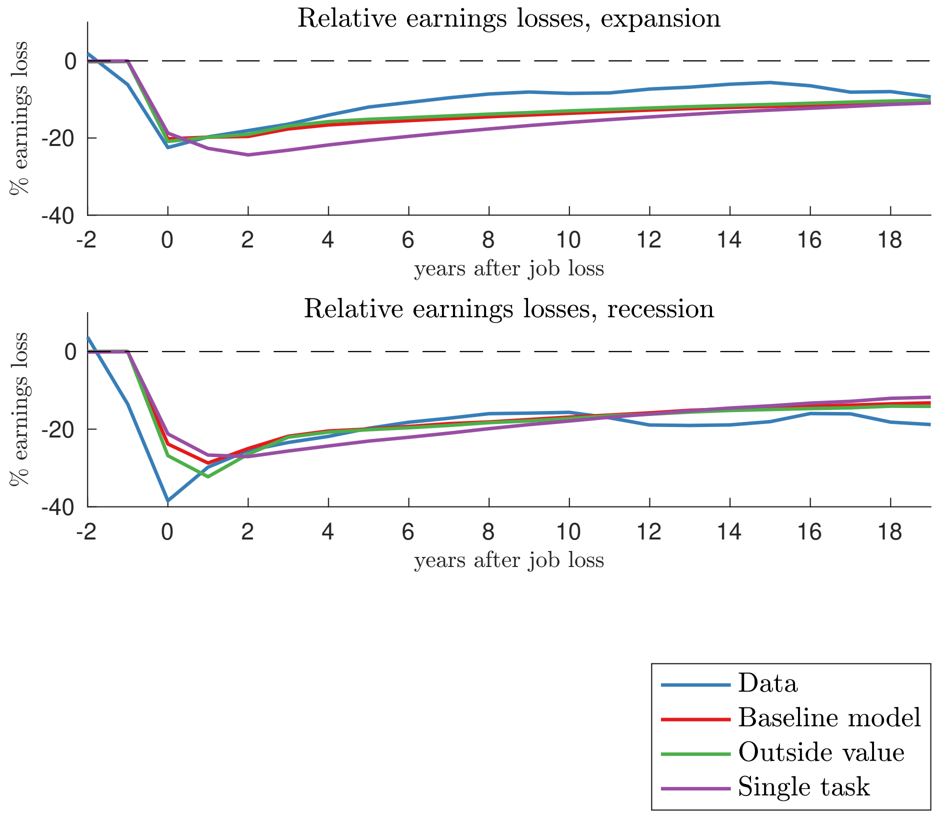
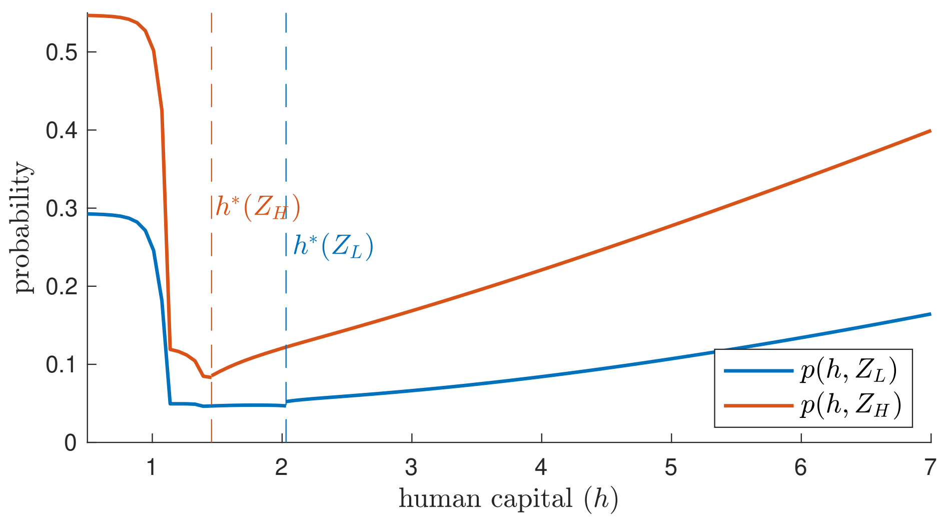
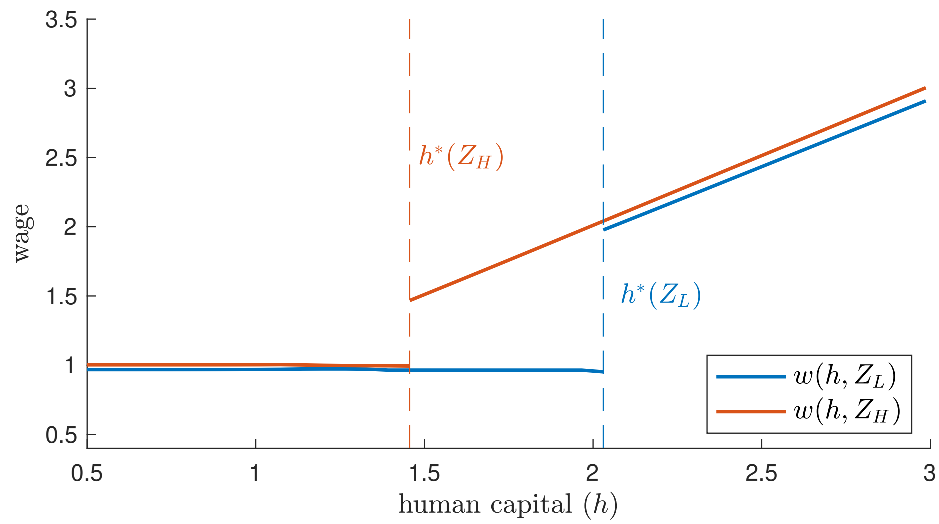


FIGURE C.4. Job-finding probabilities from unemployment: high and low productivity, "outside value" parameterization




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

FIGURE C.5. 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.6. Total present value cost of job loss, "outside value" parameterization

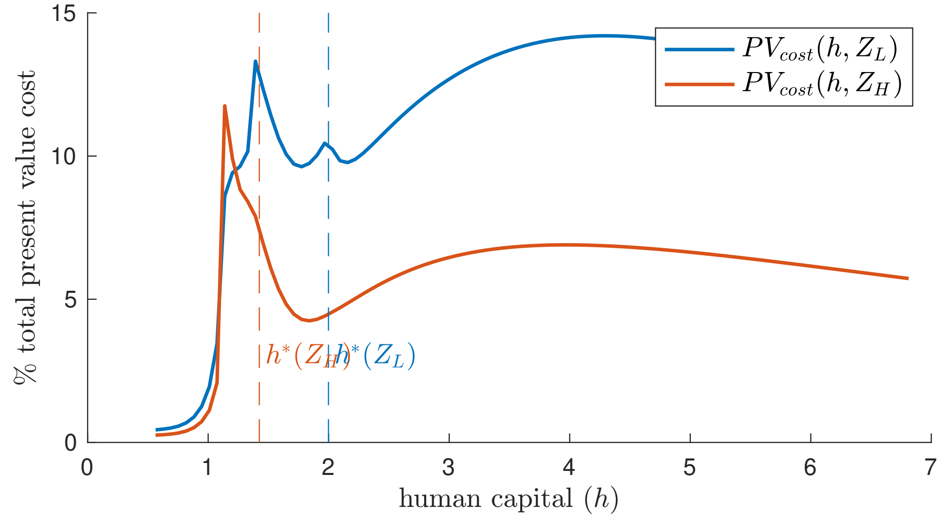



Figure C.7. Human capital distribution of new entrants at initial employment, "outside value parameterization"

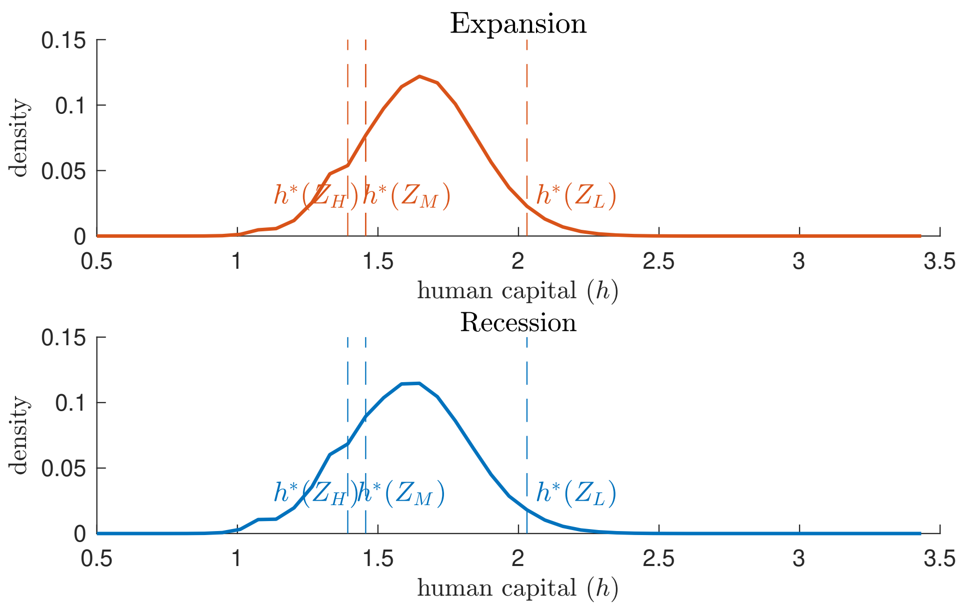


FIGURE C.8. Job-finding rates under "outside value" parameterization, $Z_H$ and $Z_L$