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-paying occupations, and that the 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, forcing some unemployed workers to search for lower-skill jobs. In accounting for the cost and cyclical incidence of occupation displacement, the model accounts for existing estimates of the present value cost of job loss during expansions and recessions, 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

This paper presents new evidence on the importance of occupation switching for explaining the earnings losses of displaced workers. Using data from the CPS Displaced Worker Supplement and PSID, I show that the cost of job loss in the United States is almost entirely concentrated among workers who find reemployment in lower-paying occupations, and that the incidence of such occupation displacement is higher for workers who are displaced during a recession. To understand these findings, I propose a new model where hiring is endogenously more selective during recessions, forcing some workers to search for jobs in a lower skill occupation. The model accounts for over sixty percent of the present value cost of job loss in expansions and recessions, representing an over three-fold improvement in explanatory power over leading models. The framework also explains the cost of entering the labor market during a recession.

The paper first presents a set of stylized facts to document that 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 up to four times larger than of workers who find reemployment in the same occupation. Persistence of initial wage losses are only observed for workers who switch occupation: while occupation stayers make a full earnings recovery within three years of job loss, occupation switchers maintain 10% earnings losses a full decade after job displacement. The incidence of occupation displacement is higher among workers who lose their jobs during recessions, suggesting that the shift in the composition of displaced workers during recessions towards occupation switchers can help account for the cyclical cost of job loss. The changes in occupation relevant for explaining earnings losses are vertical: excess earnings losses are only observed for workers moving to lower-paying occupations, and the increase in occupation switching during recessions is entirely accounted for by displacement to lower-paying occupations. Workers in the U.S. are observed to quickly reestablish stable attachment to employment subsequent to job loss, implying that the persistent wage loss associated with moving to a lower paying occupation is a first-order determinant of earnings losses.

To understand these facts, I propose a novel theoretical framework where endogenously selective hiring may prevent an unemployed worker from finding reemployment in a previously held occupation. Wages move less than one-for-one with aggregate productivity: to recoup the fixed costs of job creation after a negative shock, firms posting vacancies for skill-utilizing jobs hire more selectively, only directing vacancies towards workers with skill above an endogenously higher threshold. Other workers are left to search for lower paying jobs that do not use skill. A worker who is displaced from a skill-utilizing job and reemployed in a job that does not use accumulated skill suffers larger and more persistent earnings losses. Hiring is endogenously more selective during recessions, increasing the incidence of such displacements.

The model successfully accounts for the size and cyclicality of the cost of job loss, primarily through a component of the cost of job loss associated with occupation displacement. But moreover, the model is able to match 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 – finds direct support in empirical studies of firm-level vacancy postings, including Modestino, Shoag, and Ballance (2015a,b) and Hershbein and Kahn (2016). The mechanism is generated through a novel application of segmented and directed search within and across occupations, achieved through a non-trivial extension of block recursivity (Menzio and Shi, 2010, 2011).

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 the present value cost of job loss in the U.S. to be 11.0% and 18.6% during expansions and recessions, but in evaluating the ability of various models to match the data, they find that the best performing model generates present value costs of just 2.4% and 2.7%. A subsequent macroeconomic literature has emerged to account for the size of the average cost of job loss without explaining the cyclical cost of job loss, e.g. Jarosch (2015), Jung and Kuhn (2014), and Krolikowski (2015).[1] The model here accounts for the average present value cost of job in a manner that matches the disparate earnings recoveries for occupation switchers and stayers, and the rapid recovery of hours for displaced workers in the United States.[2] In contrast, Jarosch (2015) documents a slow recovery of hours for displaced workers in Germany and offers a model to account for the cost

[1]Krolikowski (2015) and Jarosch (2015) consider models without aggregate cyclicality and without vacancy posting. Jung and Kuhn (2014) study a model with vacancy posting, but also abstract from aggregate uncertainty.

[2]For evidence of the former, see Jacobson, LaLonde, and Sullivan (1993), Stevens (1997), Kambourov and Manovskii (2009), and Couch and Placzek (2010). For evidence of the latter, see Ruhm (1991), Stevens (1997), and Altonji, Smith, and Vidangos (2013).

of job loss in Germany that operates precisely through this margin. This paper is distinct from Jarosch (2015) in its focus on displaced workers in the United States; and also for addressing the cyclical cost of job loss and the cost of entering the labor market during a recession.

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 from existing studies that the welfare gains of eliminating business cycles are small, and hence, further stabilization policies in the U.S. are unwarranted and would likely impede long-run growth. As stressed by Lucas, however, estimates of the welfare cost of business cycles are sensitive to assumptions regarding the persistence and cyclicality of idiosyncratic shocks to individuals— see, for example, Krusell, Mukoyama, Şahin, and Smith (2009). By this logic, such welfare calculations should explicitly account for the experience of displaced workers. Similarly, economists have offered empirical and theoretical results consistent with a Schumpeterian notion of recessions whereby a temporary slowdown in economic activity frees resources to be redirected to more efficient use, including Davis and Haltiwanger (1992), Mortensen and Pissarides (1994), and Caballero and Hammour (1996). But if the earnings losses of displaced workers stem from a reduction in their productive capacity, the larger and more persistent earnings losses of workers who lose their job during a recession signify persistent output losses for the economy as a whole, possibly offsetting any such "cleansing" effect.

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 Oreopoulos, von Wachter, and Heisz (2012).

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 for workers who lose their job during a recession. These findings are of independent interest, and they are complementary to an existing literature that documents procyclical occupation mobility among the general population of workers, particularly of workers making job-to-job transitions, e.g. Moscarini and Thomsson (2007). While procyclical occupation switching can be rationalized by variants of the Lucas and Prescott (1974) island model with horizontal ranking across sectors, e.g. Jovanovic (1987), such models cannot at the same time generate countercyclical occupation switching among displaced workers. To account for both phenomena, I study a model that appeals to a notion of vertically ranked occupations similar to Groes, Kircher, and Manovskii (2015), where occupations differ in the rate of return to a single skill.[3] The model generates both countercyclical occupation switching among unemployed workers and procyclical occupation switching among employed workers, offering a single mechanism to account for both sets of findings.

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 the following stylized facts: *1)* Immediate earnings losses for displaced workers are up to four times higher for occupation switchers than occupation stayers; *2)* Workers displaced during a recession are more likely to switch occupation; *3)* Both the earnings losses of occupation switchers and the countercyclical increase in occupation displacement are accounted for by the vertical ranking of occupations; *4)* Except for the year of job displacement, earnings losses are almost entirely explained by wage losses; and *5)* Only occupation switchers suffer persistent earnings and wage losses. This paper is the first to document *2*) and *3*).

[3]Groes, Kircher, and Manovskii (2015) also reject implications of the horizontal island search model in favor of vertical sorting of occupations under absolute advantage for explaining worker reallocation.

Collectively, the empirical findings imply occupation displacement as a proximate source for the size and cyclicality of the earnings cost of job loss (Davis and von Wachter, 2011).[4]

The first three facts are documented using the Displaced Worker Supplement, a supplemented 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 instrument for "exogenous" layoffs.[5] The DWS inherits the large sample size and representative structure of the CPS and also records information on earnings and occupation on the displaced and current job. The fourth and fifth facts concern long-term outcomes subsequent to job loss, and hence are established using data from the Panel Study of Income Dynamics from 1968 to 1999. 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 displacement: see Topel (1990), Ruhm (1991), and Stevens (1997) for similar studies that use the PSID.[6] Additional information on sample construction is presented below and in the appendix.

2.1. **Immediate wage losses are higher for occupation switchers.** I first show that workers who are involuntarily displaced from a job and are reemployed into a

[4]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.

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

[6]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. To the extent that the lack of an "exogenous" displacement instrument biases findings towards more severe effects of job loss, my findings that (*i*) displaced workers experience a rapid recovery in hours and employment, and (*ii*) displaced workers who find reemployment in the same occupation experience a rapid recovery in earnings are robust.

TABLE 1. Immediate wage 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	−0.071***	−0.059***	−0.066***	−0.078***	−0.067***	−0.073***
	(0.0062)	(0.0078)	(0.0067)	(0.0059)	(0.0078)	(0.0063)
Recession	−0.050**	−0.050**	−0.050**	−0.049***	−0.049***	−0.049***
	(0.0185)	(0.0183)	(0.0185)	(0.0106)	(0.0104)	(0.0106)
Constant	−0.031***	−0.051***	−0.035***	−0.022**	−0.042***	−0.026**
	(0.0081)	(0.0086)	(0.0077)	(0.0105)	(0.0106)	(0.0101)
N	20957	20957	20957	20957	20957	20957
Occ. def.	CPS/Fine	CPS/Broad	AD	CPS/Fine	CPS/Broad	AD
Controls?	No	No	No	Yes	Yes	Yes
Predicted loss: Switcher/Stayer	3.30	2.16	2.86	4.63	2.60	3.78

Data from CPS DWS, 1984-2012. *** significant at 0.01, ** at 0.05, * at 0.10.

different occupation suffer larger immediate wage losses than workers who are reemployed into the same occupation.[7] I use the 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. 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 between 465 and 526 separate occupations depending on the 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. I regress the log differential in wages across 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 a dummy variable indicating whether the individual lost his or her job during a recession.[8] Separate

[7]Similar findings are established by Jacobson, LaLonde, and Sullivan (1993), Stevens (1997), Kambourov and Manovskii (2009), and Couch and Placzek (2010).

[8]A recession year is defined as a year with at least three months in a recession according to the NBER classification.

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 time 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 2.16 and 4.63. Across all occupation codings, between 45% and 67% of all workers in the sample are observed to switch occupation, indicating that occupation switching is neither an uncommon nor uniform experience among displaced workers, and so is indeed a true source of heterogeneity in post-displacement outcomes.[9] The immediate cost of job loss for occupation switchers greatly exceeds the cost for occupation stayers, suggesting that the present value cost of job loss is largely accounted for by workers who are displaced from their previous occupation.[10]

2.2. **Occupation switching is countercyclical.** 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 his pre-displacement job.[11] Robust standard errors are provided, clustered by year of displacement. 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.

[9]These results are similar to Fujita and Moscarini (2013), who find from the SIPP that over 50% of unemployed workers switch occupation from unemployment.
[10]A separate literature has focused on firm-side characteristics on explaining pay differentials across workers. The focus of this literature and that of this paper are not mutually exclusive: if occupation switchers are more likely to be lower-skill workers within their initial occupation, the presence of positive assortative matching (as estimated by Lise, Meghir, and Robin 2013) will predict that occupation switchers are more likely to match to less productive firms.
[11]Similar results were obtained from a probit model.

Table 2. Post-displacement occupation switching is countercyclical

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)	(4)	(5)	(6)
Recession	0.030**	0.039***	0.030**	0.031***	0.041***	0.033***
	(0.0111)	(0.0123)	(0.0117)	(0.0094)	(0.0070)	(0.0087)
Constant	0.671***	0.465***	0.655***	0.624***	0.458***	0.611***
	(0.0055)	(0.0054)	(0.0054)	(0.0127)	(0.0114)	(0.0125)
N	20957	20957	20957	20957	20957	20957
Occ. def.	CPS/Fine	CPS/Broad	AD	CPS/Fine	CPS/Broad	AD
Controls?	No	No	No	Yes	Yes	Yes

Data from CPS DWS, 1984-2012. *** significant at 0.01, ** at 0.05, * at 0.10.

This paper is the first to document the countercyclical occupation switching of displaced workers. The existing empirical literature on worker mobility typically focuses on workers making job-to-job transitions, documenting procyclical mobility of workers over occupations, industries, and types of firms during expansions.[12] Examples include McLaughlin and Bils (2001), who document procyclical inter-industry mobility; Moscarini and Thomsson (2007), who document procyclical occupation switching among employed workers; and Haltiwanger, Hyatt, and McEntarfer (2015), who find evidence for procyclical movements of workers from low to high-paying firms. The typical finding of this literature is not only that the reallocation of employed workers is procyclical (compared to countercyclical mobility for displaced workers), but also, the reallocation of workers is associated with increases in earnings, as opposed to the observed earnings decreases among displaced workers who switch occupation.

The apparently conflicting findings on reallocation of displaced versus employed workers can be reconciled with a model of vertically ranked occupations with countercyclical hiring standards. Suppose, as in Groes, Kircher, and Manovskii (2015),

[12]Carrillo-Tudela and Visschers (2014) offer point estimates suggestive of procyclical occupation switching, but do not consider issues of statistical inference. There are two major methodological differences between their paper and mine: First, Carrillo-Tudela and Visschers consider workers in unemployment for any reason, including voluntary separation, whereas my paper only looks at workers in unemployment due to involuntary displacement. Second, Carrillo-Tudela and Visschers define the aggregate state associated with an occupation transition to be that when the worker finds a new job, not the date at which a worker enters unemployment. For the purposes of this study, the latter measure is the relevant one; and given the short duration of recessions and the lower job-finding rates during recessions relative to expansions, workers separated to unemployment during a recession are more likely to find a job during an expansion than a worker separated from a job during an expansion is to find a job during a recession.

Table 3. The verticality of cyclical displacement

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)	(4)	(5)	(6)
Recession	0.030**	0.035***	−0.005	0.033***	0.037***	−0.005
	(0.0117)	(0.0090)	(0.0094)	(0.0087)	(0.0078)	(0.0092)
Constant	0.655***	0.350***	0.305***	0.611***	0.344***	0.266***
	(0.0054)	(0.0049)	(0.0063)	(0.0125)	(0.0164)	(0.0144)
N	20957	20957	20957	20957	20957	20957
Occ. def.	AD	AD↓	AD↑	AD	AD↓	AD↑
Controls?	No	No	No	Yes	Yes	Yes

Data from CPS DWS, 1984-2012. *** significant at 0.01, ** at 0.05, * at 0.10.

that occupations differ in the rate of return to a general skill, and that workers differ in their endowment of that skill. If firms require more skill of an applicant when hiring for a skilled occupation 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. But workers searching on-the-job are more likely to switch to a more skilled occupation during an expansion, their mobility facilitated in part by more relaxed hiring standards. Such countercyclical "upskilling" within occupations finds direct support from Modestino, Shoag, and Ballance (2015a,b), who use firm-level vacancy data to show that hiring is more selective within occupations when the labor markets are slack. My model generates countercyclical selective hiring, countercylical occupation displacement, and procyclical mobility among employed workers as endogenous outcomes.

2.3. **Occupation displacement is vertical.** As argued earlier, the previous findings of (i) greater earnings losses among displaced workers who switch occupation, and (ii) countercyclical occupation displacement can be interpreted in terms of vertically ranked occupations. I now 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] These findings are novel to the literature.

I estimate a linear probability model to estimate the association of occupation switching and the state of the economy at job loss. As in sections 2.1 and 2.2,

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

Table 4. Reemployment wage losses and vertical displacement

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

	(1)	(2)	(3)
Switcher	-0.073^{***} (0.0063)	—	0.007 (0.0067)
Switcher & ↓	—	-0.144^{***} (0.0085)	-0.148^{***} (0.0097)
Recession	-0.049^{***} (0.0106)	-0.046^{***} (0.0104)	-0.046^{***} (0.0104)
Constant	-0.026^{**} (0.0101)	-0.028^{**} (0.0106)	-0.031^{***} (0.0100)
N	20957	20957	20957
Predicted loss: Switcher/Stayer	3.78	6.11	—

Data from CPS DWS, 1984-2012.
*** significant at 0.01, ** at 0.05, * at 0.10.

I estimate the specification with and without controls. I use the Autor and Dorn (2013) coding (AD) to identify occupation switchers, and also separately condition on whether the occupation change was downward (AD↓) or upward (AD↑).[14] Estimates are given in Table 3. The results show that the countercyclical increase in occupation switching is entirely accounted for by downward shifts in occupation. This fact is particularly clear in the first three columns of Table 3, where the lack of controls imply that the coefficient estimates of the first column equal the sum of the coefficient estimates of the second and third column. While there is 3.5 percentage point increase in downward occupation switches during recessions, there is a 0.5 percentage point decline in upward shifts in occupation, generating a 3.0 percentage point net increase in occupation switches for workers displaced during recessions. Across all of the specifications, however, only the regression coefficients for total and downward occupation switches are statistically significant.

[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.

Next, I show that wage losses are concentrated among workers making downward shifts in occupation. Using the "AD" occupation coding, I consider the regression of earnings losses on observables across three specifications, including (*i*) a dummy variable for switcher, with controls; (*ii*) an indicator for downward switcher, with controls; and (*iii*) indicators for switcher and downward switcher, and controls.

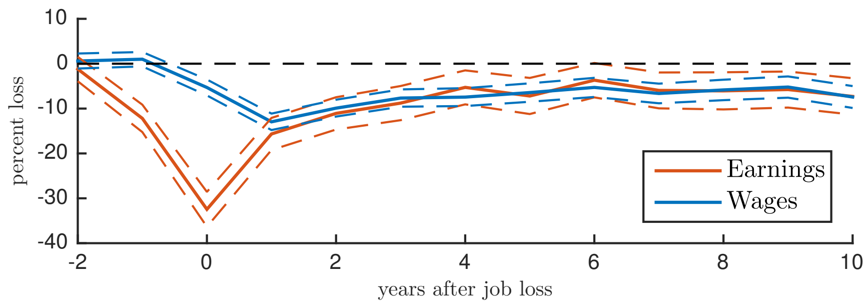
Results are given in Table 4. The first column shares the same specification as that of column six of Table 1 and shows that occupation switching is countercyclical according to the "AD" measure. The second column only includes as switchers those who make downward shifts in occupation— recall from Table 3, this is the exact subset of occupation switches that increases during recessions. The immediate earnings loss associated with finding reemployment in a lower skill occupation exceeds that associated with remaining in the same occupation (or moving to a higher skill occupation) by a factor of over six. The third column provides coefficient estimates from a regression with both unconditional switchers and downward switchers. Given that switchers either make downward or upward moves, the coefficient on switchers in this regression corresponds to the earnings loss associated with making an upward shift in occupation. The estimated coefficient is not statistically different from zero.

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 with existing empirical findings of 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. **Rapid recovery of hours.** Here, I show that there is a rapid recovery of hours among displaced workers, suggesting that the earnings cost of job loss is not due to unstable job attachment. This finding is characteristic of the existing literature on job loss and earnings dynamics in the United States, e.g. Ruhm (1991), Stevens (1997), and Altonji, Smith, and Vidangos (2013).[15]

[15] For example, Altonji, Smith, and Vidangos (2013) estimate hours losses of less than 5% the year after job loss, and a complete recovery thereafter (see Figure 4, pg. 1438)

FIGURE 1. Convergence of earnings and wage losses (PSID)



I use data from the Panel Study of Income Dynamics from 1968 to 1997.[16] Details of the sample construction are given in Appendix A. The general regression specification that I adopt is common to the literature, e.g. Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997). The first regression equation is

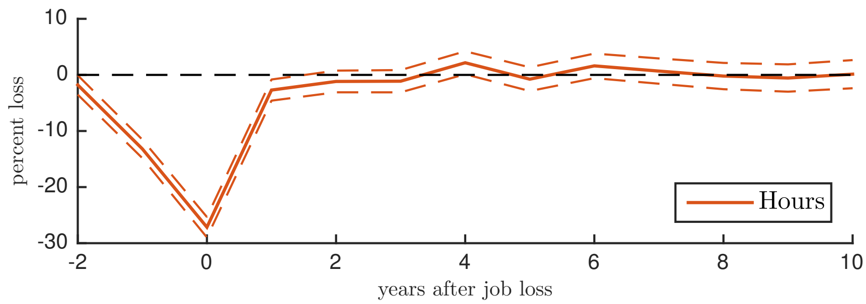
$$y_{it} = x_{it}'\beta + \sum_{k\geq -2}^{10} \delta_k D_{it}^k + \varphi F_{it} + \alpha_i + \gamma_t + \varepsilon_{it}. \tag{1}$$

The outcome variables include log annual earnings, log hourly wage, and log annual hours. The variable x_{it} is a vector of time-varying individual characteristics, including experience and schooling; α_i is a time invariant unobserved error component associated with person i; and γ_t is an error component common to all individuals in the sample at year t.[17] The indicator variables D_{it}^k are used to identify displaced workers in the k^{th} year after job displacement. Following Stevens, I estimate the relative earnings losses for workers in the two years preceding job loss ($k = -2, -1$), the year of job loss ($k = 0$), and the ten years subsequent to job loss ($k = 1, 2, \ldots 10$). As in Jacobson, LaLonde, and Sullivan (1993), the indicator variable F_{it} identifies workers in years 0 through 10 following job displacement. Accordingly, the sum $\delta_k + \varphi$ reflects the effect of job displacement for workers who were displaced k years prior relative to workers who have not been displaced within the past ten years. The regressions are estimated with fixed effects and robust standard errors clustered by individual.

Figure 1 gives the estimated recovery of earnings and wages relative to workers who have not been displaced in the prior ten years. The recovered estimates are broadly

[16]After 1997, the survey began interviewing respondents at a biennial rather than annual frequency, complicating the subsequent analysis of post-displacement occupation changes.
[17]Time-invariant characteristics are subsumed by the fixed effect.

Figure 2. Rapid recovery of hours (PSID)



consistent with the existing literature on job displacement.[18] Displaced workers experience a 32.5% reduction in relative earnings in the displacement year. The relative earnings loss drops by half the next year, but the subsequent earnings recovery is slow. Earnings losses remain around 5% in post-displacement years five through ten. A similar pattern is observed for hourly wages.[19]

While the initial drop in earnings is larger than that for wages, relative losses in earnings and wages lay within about a percentage point of the other starting in the second year after displacement. This suggests that earnings losses past the year of displacement are due to a sustained fall in wages and not in hours worked. These findings are consistent with Stevens (1997), whose estimates reveal a similar convergence of wage and earnings losses.[20] Data on annual hours worked can be similarly used to study the hours recovery from displacement, as in Ruhm (1991). Figure 2 plots the estimated recovery of annual hours. There is a 27% drop in hours in the year of job displacement, a 3% drop in the following year, but thereafter, the drop in hours is not statistically significant.

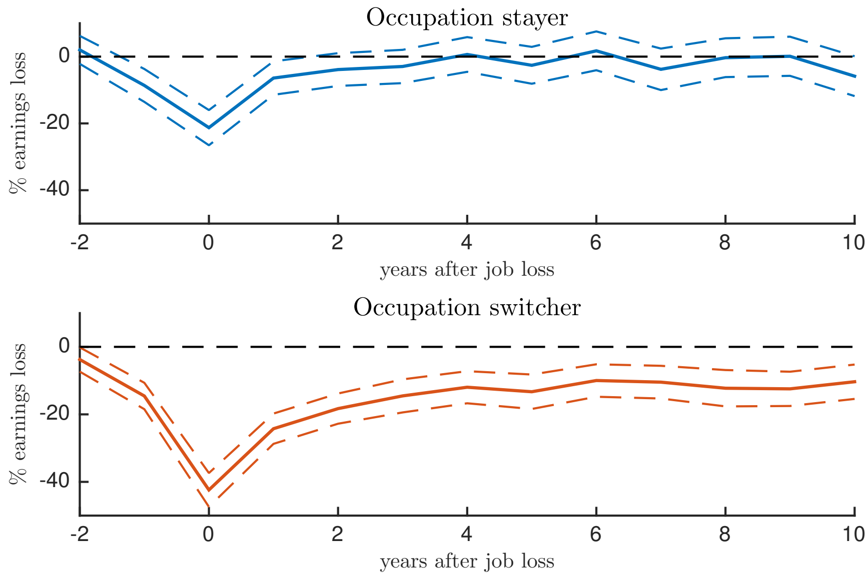
The quick convergence of relative earnings and wage losses and the rapid recovery of hours imply that long-run earnings losses of displaced workers in the United States are not propagated through unstable attachment to employment, but rather through stable attachment to lower paying jobs. Although this is a typical result for the U.S., it contrasts with recent findings of Jarosch (2015), who documents a very slow

[18] The drop in earnings preceding job loss has been found elsewhere in the literature, including Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997). Stevens's results are also suggestive that the earnings reduction preceding job loss is driven by hours.

[19] There is a smaller drop in hourly wages in the year of displacement – note that hourly wages in this year are an average of wages earned at the displacement job and at any subsequent job – but there is a large and persistent drop thereafter.

[20] See Altonji, Smith, and Vidangos (2013, p. 1437) and Altonji, Kahn, and Speer (2016, p. S379) for similar interpretations of Stevens (1997).

FIGURE 3. Earnings losses are more persistent for occupation switchers



convergence of earnings and wage recoveries from German data.[21] Jarosch uses these findings to motivate a quantitative model where serially correlated separation risk generates a high present value cost of job loss. While the model of this paper can be accommodated to allow for risk of repeated job loss, the findings for the U.S. suggest that repeated displacement does little to slow the hours recovery of displaced workers— a necessary outcome for repeated displacement to generate a high cost of job loss.[22] The quick recovery of hours implies that repeated job loss is not the primary mechanism for explaining the present value cost of job loss in the United States.

2.5. **Earnings losses are persistent for occupation switchers, but not for stayers.** Having established that immediate earnings losses are larger for occupation switchers, I now show that earnings losses for such workers are also more persistent.

[21]To see the difference, compare Jarosch's Figure 4 to this paper's Figure 1. Jarosch's findings on job loss in Germany differ from those on the U.S. along other dimensions. For example, he computes a present value cost of job loss almost double that estimated by Davis and von Wachter (2011) for the United States, and he finds that the earnings recoveries of industry/occupation stayers are roughly the same as for changers. These differences suggest the relevance of separate mechanisms across the two labor markets.

[22]Indeed, Krolikowski (2015) considers a model of repeated job loss that is calibrated to match certain features of U.S. data. In order to generate a large average present value cost of job loss, the model also generates a counterfactually large and persistent gap between relative earnings and relative wage losses.

The regression equation is

$$y_{it} = x'_{it}\beta + \sum_{k\geq -2}^{10} \delta_{ns}^{k} D_{it}^{ns,k} + \varphi_{ns} F_{it}^{ns} + \sum_{k\geq -2}^{10} \delta_{s}^{k} D_{it}^{s,k} + \varphi_{s} F_{it}^{s} + \alpha_i + \gamma_t + \varepsilon_{it}, \qquad (2)$$

where the index ns represents non-switchers and s represents switchers, defined by the occupation of the first primary job held subsequent to displacement. Accordingly, $\delta_i^k + \varphi_i$ represents the effect of job displacement for post-displacement occupation stayers ($i = ns$) and switchers ($i = s$) in years $k \in [0, 10]$ after displacement. I use the PSID three-digit occupation coding to identify switchers and stayers.[23]

Figure 3 shows the relative earnings losses for both switchers and stayers, with dashed lines indicating 95% confidence intervals around the estimates. The full results are given in Table A.2. 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 rapid. 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.

In Figure 3, occupation switchers appear to have lower earnings than non-displaced workers in the years prior to displacement. In particular, two years prior to displacement, the earnings of occupation switchers are significantly lower than non-displaced workers, compared to the statistically indistinguishable earnings of occupation stayers and non-displaced workers. Hence, workers who switch occupation subsequent to displacement tend to be of below-average earnings.[24] But moreover, some process of dynamic selection is also active in determining whether a displaced worker becomes an occupation switcher or a stayer.

[23]In Appendix A, I show that occupation switching is also countercyclical in the PSID.

[24]This characteristic of selection into occupation displacement is matched by the quantitative model.

3. A model of unemployment, occupation, and selective hiring

To understand the facts documented in the previous section, I develop a model of unemployment, occupation, 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 new feature of my model is that firms posting vacancies for skill-utilizing jobs hire selectively on the basis of skill, unwilling to hire workers with skill below some endogenous threshold. Wages move less than one-for-one with productivity, and hence, firms filling vacancies for skilled jobs are more selective during recessions: given a fall in aggregate productivity, the firm must hire a more skilled worker to earn a non-negative return from maintaining a vacancy.[25] Displaced workers who find reemployment in lower-skill jobs suffer large and persistent earnings losses. The greater occurrence of such displacements during recessions lends cyclicality to the cost of job loss.

In the model, an occupation is a type of job. I consider two types of jobs: skill-intensive and skill-neutral. If a worker is employed in a skill-intensive job, output is increasing in the worker's endowment of skill. If a worker is employed in a skill-neutral job, the worker's quantity of skill is irrelevant to production.[26] The quantity of human capital (skill) held by an individual determines whether he is able to search for one or both of the jobs. The worker accumulates skill stochastically, but at different rates in either type of job.[27] While skill is not used for production in the skill-neutral job, it is nonetheless relevant to the worker's expected tenure at the job, as the worker will accumulate skill while employed and eventually search (in expectation) for a skill-utilizing job.

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

[25]See Gertler, Huckfeldt, and Trigari (2015) for a discussion of new and existing evidence that new hire wages move less than one-for-one with aggregate productivity.

[26]The model can be generalized to introduce additional occupations characterized by different returns to skill. In practice, this complicates the computation of the model, as it introduces additional complementary slackness conditions that need to be computed for the numerical solution and simulation.

[27]Consider skill accumulation in skill-neutral jobs as a form of workplace learning, e.g. learning from observing the activities of workers in skill-intensive jobs.

in the model to occupation in the data. A worker may be displaced from a job as a machinist (skill-intensive 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-neutral employment); and then work his way up to a job as a manager (skill-intensive employment). While the notion of occupation in the model is too stylized to directly map to particular occupations in the data, it is general enough to capture such patterns of mobility within and across occupation hierarchies.

The model generates an endogenous distribution of workers over skill and the different employment states. But the model remains tractable, in part because firms are restricted to direct any particular vacancy towards a single level of skill.[28] This ensures that the solution of the model is independent of the distribution of workers, i.e. the model is block recursive (Menzio and Shi, 2010, 2011). Relative to a typical block recursive model in which the equilibrium schedule of job-finding rates is determined by a complementary slackness condition along a single dimension of worker or match heterogeneity, the equilibrium here is characterized by two such conditions, one each for skill-intensive and skill-neutral jobs. The two complementary slackness conditions are related in a non-trivial manner: firms find it less profitable to direct skill-neutral vacancies towards workers attractive to firms filling skill-intensive vacancies.

A full description of the environment is given in Sections 3.1 through 3.5. The optimization problems of workers and firms are given in Section 3.6. Finally, the key mechanism of the model – countercyclical selective hiring within skilled occupations – is described in Section 3.7.

3.1. **Setting.** The model is set in discrete time with an infinite horizon. There is a unit measure of agents (workers). 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-neutral job, or employed in a skill-intensive job. Jobs are subject to an exogenous destruction probability δ. Workers are endowed with h units of human capital (skill). A cumulative distribution function λ gives the measure of workers over human capital and employment. Workers have geometric lifespans: each period a measure ν of workers die and a measure ν are born into unemployment. There are two aggregate state variables: productivity Z and the

[28]Vacancies are typically listed with an occupation and often minimum education or experience requirements, supporting the assumption of segmented labor markets. See Şahin et al. (2014), Modestino, Shoag, and Ballance (2015a,b) and Hershbein and Kahn (2016).

distribution of workers across human capital and employment states, λ. Z takes on finite values and evolves according to a first-order Markov chain.

3.2. **Production and wages.** Production occurs within single worker firms. Skill-neutral firms operate a technology where output y_L varies with aggregate productivity Z but not the worker's skill h.[29] Skill-intensive firms operate a production technology that is linear in the worker's human capital input h and aggregate productivity Z to produce y_H:

$$y_L(h, Z) = Z, \quad y_H(h, Z) = Zh. \tag{3}$$

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

Wages are bargained to divide the additional income that can be generated by the worker and the firm within the period. Workers have a fixed bargaining power, $\eta \in (0, 1)$, and firms face a cost of delay γ should the worker and firm not come to agreement, as in Hall and Milgrom (2008). Wages are given by the following:

$$w_L(h, Z) = (1 - \eta)b + \eta(Z + \gamma), \quad w_H(h, Z) = \Big[(1 - \eta)b + \eta(Z + \gamma)\Big]h. \tag{4}$$

The wages correspond to the Generalized Nash Bargaining solution with the following outside options: For a worker employed in a skill-neutral firm, the outside option if negotiations break down is to enjoy home production b and enter the next period still matched to firm.[30] The outside option of the skill-neutral firm is to produce no output that period, incur a fixed cost of delay γ, and enter the next period attached to the worker. The outside options of workers and firms in skill-intensive matches are the same, but scaled by the human capital input of the worker.[31]

[29]As higher skill workers will tend to be employed in skill-intensive jobs and lower skill workers will tend to be employed in skill-neutral jobs, I occasionally refer to skill-intensive jobs as "high skill" or "skilled"; and skill-neutral jobs as "low skill" or "unskilled". As such, "L" stands for low skill (skill-neutral), "H" for high skill (skill-intensive).

[30]I follow Kaplan and Menzio (forthcoming) in assuming that failure to come to agreement does not separate the firm and the worker. The assumption simplifies the quantitative analysis by making the wage only a function of period variables. This eliminates the need to integrate forward-looking variables over regions of the state-space where the optimal search decision of the worker changes from low- to high-skill, and where it is difficult to achieve numerical accuracy. In the quantitative analysis, I verify that the outside options are never binding. Other papers with search that consider wages as the outcome of a static bargaining problem include Acemoglu (1996), Violante (2002), and Şahin, Song, Topa, and Violante (2014).

[31]I follow Postel-Vinay and Robin (2002) and Bagger, Fontaine, Postel-Vinay, and Robin (2014) in assuming that the worker's value of leisure is linear in the productive input he brings to the firm. The proportionality of the firm cost of delay to the human capital input of the worker can be interpreted as due to complementarity of worker skill with non-modeled factors of production. These assumptions imply a constant profit share across both types of jobs for all levels of human capital.

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-intensive and skill-neutral jobs stochastically accumulate human capital. Each period, the human capital endowment of a worker in a skill-intensive (skill-neutral) job increases by amount $\Delta_{\mathcal{H}}$ with probability π_H (π_L).[32] Hence, for a worker with human capital h employed in a job of type i, human capital evolves as the following:

$$h' = \begin{cases} h + \Delta_{\mathcal{H}} & \text{with probability } \pi_i \\ h & \text{with probability } 1 - \pi_i \end{cases} \qquad i = L,\ H. \tag{5}$$

Workers in unemployment face two sources of human capital risk: obsolescence and gradual depreciation. With probability ξ, 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_0 from a distribution $F^o(\cdot; h)$ constructed from the initial distribution F, defined as

$$F^o(h_0; h) = \frac{1}{F(h)} \int_{h^{lb}}^{h_0} dF(h')dh'. \tag{6}$$

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}. The construction of the distribution ensures that workers do not gain skill from an obsolescence shock. Immediately after the realization of the obsolescence shock (and within the same period), the worker faces a probability π_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:

$$h' = \begin{cases} h_0 & \text{with probability } \xi(1-\pi_U) \\ h_0 - \Delta_{\mathcal{H}} & \text{with probability } \xi\pi_U \\ h & \text{with probability } (1-\xi)(1-\pi_U) \\ h - \Delta_{\mathcal{H}} & \text{with probability } (1-\xi)\pi_U \end{cases}. \tag{7}$$

3.4. **Search and matching.** Workers must be matched with firms in order to produce. Firms direct vacancies towards submarkets specific to a single level of human

This is crucial for generating an empirically realistic aggregate profit share— close to zero. See Hornstein, Krusell, and Violante (2005) for a discussion of the role of the profit share in generating unemployment volatility in a DMP framework, as well as for comparisons of implied profit shares across various calibrations of the DMP model.

[32]The estimated value of π_H is higher than π_L.

capital, i.e. search is segmented in h. For a given level of human capital, search is directed: workers choose whether to search for either skill-neutral or skill-intensive employment.

Given aggregate productivity Z and the worker distribution λ, the number of vacancies for a worker of skill h in the skill-neutral and skill-intensive submarkets are $\upsilon_L(h, Z, \lambda)$ and $\upsilon_H(h, Z, \lambda)$. Searchers $s_L(h, Z, \lambda)$ for skill-neutral jobs consist only of workers searching from unemployment, whereas searchers $s_H(h, Z, \lambda)$ for skill-intensive vacancies comprise both unemployed workers and workers in skill-neutral jobs. Workers in skill-neutral jobs search with the same efficiency as unemployed workers and hence never quit to unemployment to improve search outcomes.[33]

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

$$m_i(h, Z, \lambda) = \phi_i s_i(h, Z, \lambda)^{\sigma} \upsilon_i(h, Z, \lambda)^{1-\sigma}, \; i = L, H. \tag{8}$$

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

$$p_i(h, Z) = \frac{m_i(h, Z, \lambda)}{s_i(h, Z, \lambda)}, \quad q_i(h, Z) = \frac{m_i(h, Z, \lambda)}{\upsilon_i(h, Z, \lambda)}, \quad i = L, H. \tag{9}$$

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 $\theta_i(h, Z)$, $i = L, H$. Given the block recursive structure of the model, market tightness ratios – and hence job-finding and vacancy-filling probabilities – are independent of the worker distribution λ.

3.5. **Timing.** A single period is divided into three sub-periods. In the first sub-period, a measure ν 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.

3.6. **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 occurred.

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

The decision of workers is whether to search for a skilled or unskilled job from unemployment.[34] Let $U(h, Z)$ be the value of a worker of skill h in unemployment when aggregate productivity is Z.[35] Let $U_H(h, Z)$ be the value to a worker with skill h of searching in the skill-intensive market when aggregate productivity is Z; and let $U_L(h, Z)$ be the corresponding value of searching in the skill-neutral market. Then,

$$U_i(h, Z) = p_i(h, Z)W_i(h, Z) + \Big(1 - p_i(h, Z)\Big)U(h, Z),\ \ i = L, H \tag{10}$$

and

$$U(h, Z) = b + (1 - \nu)\beta\mathbb{E}\max\Big\{U_L(h', Z'), U_H(h', Z')\Big\}, \tag{11}$$

subject to the law of motion for h and Z. The period utility of not working is given by b.

For levels of human capital above a given cutoff $h^*(Z)$, the value associated with a skill-intensive job compensates for the lower job-finding probability, and the worker only searches for skill-intensive jobs:

$$h^*(Z) = \min\{h \mid U_H(h, Z) \geq U_L(h, Z)\}. \tag{12}$$

An unemployed worker previously employed in a skill-intensive job might optimally search for a skill-neutral job if he faces a low (or zero) probability of finding a skill-intensive job, due to increased selectivity by firms caused by either a drop in productivity Z or skill depreciation. Such an event corresponds to displacement to a lower paying occupation in the data.

Let $W_H(h, Z)$ denote the value of employment in a skill-intensive job. Then,

$$W_H(h, Z) = w_H(h, Z) + (1 - \nu)\beta\mathbb{E}\Big\{\delta U(h', Z') + (1 - \delta)W_H(h', Z')\Big\} \tag{13}$$

subject to the law of motion for h and Z. Let $W_L(h, Z)$ be the value of employment in a skill-neutral job for a worker with human capital h when aggregate productivity is Z. Then,

$$\begin{aligned} W_L(h, Z) = w_L(Z) + (1 - \nu)\beta\mathbb{E}\Big\{&\delta U(h', Z') + \Big(1 - p_H(h', Z')\Big)(1 - \delta)W_L(h', Z') \\ &+ p_H(h', Z')(1 - \delta)\max\Big\{W_H(h', Z'), W_L(h', Z')\Big\}\Big\}, \end{aligned} \tag{14}$$

subject to the law of motion for h and Z.

[34]As has be discussed, this may be a trivial decision, as only one type of vacancy may be posted for certain values of human capital h.

[35]The assumption of joint segmented/directed search eliminates λ as a state variable in decisions of workers and firms, and hence I suppress λ as an argument to the value functions.

The value of a skill-intensive firm employing a worker of skill h when aggregate productivity is Z is given by $J_H(h, Z)$, where

$$J_H(h, Z) = Zh - w_H(h, Z) + (1 - \nu)\beta\mathbb{E}\Big\{(1 - \delta)J_H(h', Z')\Big\}, \tag{15}$$

subject to the law of motion for h and Z. As period profits $Zh - w_H(h, Z)$ are increasing in h, it is straightforward to see that the value of a skill-intensive firm is increasing in h, implying increasing job-finding probabilities in h.

Let $J_L(h, Z)$ be the value of a skill-intensive firm employing a worker of skill h when aggregate productivity is Z, where

$$J_L(h, Z) = Z - w_L(Z) + (1 - \nu)\beta\mathbb{E}\Big\{(1 - \delta)(1 - p_H(h', Z'))J_L(h', Z')\Big\}, \tag{16}$$

subject to the law of motion for h and Z. Although output y_L does not depend on the worker's endowment of human capital, the probability of match separation does, as the job-finding probability for workers searching for high-skill jobs will be increasing in h. Hence, the value of a skill-neutral job to the firm is *decreasing* in the skill endowment of the worker, implying decreasing job-finding rates in human capital for skill-neutral jobs.

3.7. **Countercyclical selective hiring and free entry.** Firms pay a period cost κ_L (κ_H) to post a vacancy in a skill-neutral (skill-intensive) submarket. Free entry drives the value of posting a vacancy in any market to zero, reflected in a complementary slackness condition:

$$J_i(h, Z) \leq \frac{\kappa_i}{q_i(h, Z)}, \ \theta_i(h, Z) \geq 0, \ i = L, H. \tag{17}$$

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

The core economic mechanism of the model – countercyclical selective hiring within skilled occupations – is summarized by the two complementary slackness conditions described by equation (17). Firms filling a vacancy for a skill-intensive job must receive a value $J_H(h, Z)$ that satisfies free entry. In particular, the present value of the job to the firm must at least recoup the period fixed cost of posting a vacancy, κ_H. But given that $J_H(h, Z)$ is increasing in h, there exists a value $\underline{h}(Z)$ such that the value of posting a vacancy is always negative, and thus skill-intensive vacancies are not posted for $h < \underline{h}(Z)$:

$$J_H(h, Z) < \kappa_H,\ \theta_H(h, Z) = 0 \text{ for all } h < \underline{h}(Z).$$

A similar condition holds for skill-neutral jobs. Given that $J_L(h, Z)$ is decreasing in h due to the search activity of workers, there exists some $\overline{h}(Z)$ such that firms do not post skill-neutral vacancies for h above $\overline{h}(Z)$:

$$J_L(h, Z) < \kappa_L,\ \theta_L(h, Z) = 0 \text{ for all } h > \overline{h}(Z).$$

Hence, only unemployed workers with human capital h in the interval $[\underline{h}(Z), \overline{h}(Z)]$ have a non-degenerate search decision. Therefore, $\underline{h}(Z) \leq h^*(Z) \leq \overline{h}(Z)$.[36]

The optimal skill cutoff $h^*(Z)$ varies with aggregate conditions. Should productivity Z fall, the firm's value of a high skill match $J_H(h, Z)$ falls for all h. As is typical in a DMP model, firms respond by reducing vacancy postings, and hence, vacancy-filling probabilities rise and job-finding probabilities fall. Beyond posting fewer vacancies, firms also adjust along an extensive margin, terminating vacancy creation for a group of workers for whom the job value $J_H(h, Z)$ no longer recoups the expected present value cost of posting a vacancy. This implies an increase in the minimum skill threshold $\underline{h}(Z)$ necessary for maintaining a skill-intensive vacancy, excluding a wider population of workers from searching for skilled jobs— and thus making it more probable that a worker who is separated from a skilled job to unemployment will be forced to search for an unskilled job. These outcomes – the fall in job-finding probabilities $p_H(h, Z)$ and rise in the minimum skill threshold $\underline{h}(Z)$ – increase expected worker retention at skill-neutral jobs, allowing for an increase in the maximum threshold for unskilled jobs $\overline{h}(Z)$. Hence, the optimal skill cutoff $h^*(Z)$ for workers searching from unemployment also increases. The responsiveness of $h^*(Z)$ to changes in productivity Z dictates the cyclicality of selective hiring, and thus in part determines the cyclicality of occupation displacement that can be generated by the model.

3.8. **Equilibrium.** An equilibrium is a schedule of market tightness for the skill-neutral market, a schedule of market tightness for the skill-intensive market, and an optimal skill cutoff such that the free entry conditions are satisfied and the optimal skill cutoff solves the problem of the unemployed worker, taking market tightness as given.

[36]An example of an equilibrium schedule of job-finding probabilities for a single Z is given in Appendix B.

Table 5. Assigned parameters

Parameter	Description	Value/Source
β	discount factor (quarterly)	0.95
b	value of leisure	0.4 (Shimer, 2005)
δ	match survival prob.	0.0053, weekly EU rate
η	worker bargaining power	0.5, see text
σ	matching function elasticity	0.5 (Pissarides and Petrongolo, 2001)
ν	death probability	4.8×10^{-4}, 40 year career
h^{ub}	human capital upper bound	6.1, see text
h^{lb}	human capital lower bound	0.4, see text
$\Delta_{\mathcal{H}}$	human capital increment	0.0584

4. Calibrating the model

I calibrate the model to assess its ability to match the size and cyclicality of the discounted 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 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.[37] 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 do not target moments describing the cyclicality and persistence of the earnings losses of displaced workers, preserving these as outcomes by which the model can be evaluated.

The calibration is weekly. The list of assigned parameters are given in Table 5. Most assigned values are standard to the literature. Specific to this paper, workers have a 40-year working career, implying $\nu = 4.8 \times 10^{-4}$. Worker's bargaining power η is set to 0.5, and the cost of delay to the firm γ is estimated. 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 $\Delta_{\mathcal{H}} = 0.0584$.[38] The full list of assigned parameters and associated targets is given in Table 5.

[37]As is typically the case for nonlinear business cycles models with non-trivial heterogeneity across agents, it is infeasible to estimate standard errors. I follow Lise and Robin (2014) in referring to the procedure as estimation, although it has also been described as "internal calibration".

[38]Increasing the number of grid points had no appreciable impact on results.

Table 6. Targeted moments

Moment	Target	Model output
Mean wage change following displacement	−0.085	−0.084
10th percentile wage loss following displacement	−0.604	−0.455
Average wage loss occupation switchers/stayers	1.471	1.538
Fraction of occupation switchers	0.468	0.470
Persistence of measured labor productivity	0.765	0.763
Standard dev. of measured labor productivity	0.013	0.013
Relative volatility of unemployment	11.15	11.17
Weekly UE rate	0.097	0.096
Average wage growth	0.013	0.009
Experience premium, ≥ 5 years experience	1.350	1.415
P90/P10 log wage residuals, < 5 years experience	0.963	0.951
Wage distribution, p90/p50	2.122	1.913
Wage distribution, p50/p25	1.452	1.433

The remaining thirteen parameters are estimated by simulated method of moments, with targeted moments that include labor productivity, employment flows, individual-level wage growth, and the wage distribution.[39] There are as many parameters as there are targeted moments. The list of targeted moments and model generated counterparts are given in Table 6. The associated parameter values are given in Table 7. 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 and continued in Appendix C.

As in Davis and von Wachter (2011), 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).[40]

Following Hall and Milgrom (2008) and Lise and Robin (2014), the volatility of unemployment is included as a targeted moment. Given the assigned parameter for the worker's bargaining power, the delay cost γ to the firm determines the profit share of firms and the size of the effective bargaining surplus. The estimated value for γ

[39]For each parameter draw in the estimation procedure, the model is simulated with 40,000 workers over 400 years, with a 200 year burn-in.

[40]The values of productivity are referred to as Z_L, Z_M, and Z_H (in ascending order).

TABLE 7. Estimated parameters

Parameter	Description	Value
Labor productivity:		
ρ_Z	Persistence of labor productivity	0.9894
σ_Z	Standard dev. of labor productivity	0.0042
Labor market:		
γ	Firm cost of delay	0.5681
κ_H	Vacancy posting cost (skill-intensive)	3.5151
ϕ_H	Matching efficiency (skill-intensive)	0.2562
ϕ_L	Matching efficiency (skill-neutral)	0.0902
χ	Task-common occupation switching	0.3989
Human capital:		
μ_{nb}	Human capital initial distribution, mean	0.3710
σ_{nb}	Human capital initial distribution, standard deviation	0.2254
π_H	Weekly probability of human capital increase (skill-intensive)	0.0333
π_L	Weekly probability of human capital increase (skill-neutral)	0.0108
π_U	Weekly probability of human capital decrease (unemployment)	0.0941
ξ	Obsolescence probability	0.0422

is 0.568, implying a steady state profit share of 0.98, well within the range of typical values cited by Hornstein, Krusell, and Violante (2005).[41]

The model generates cyclicality in the present value cost of job loss through countercyclical occupation displacement. To evaluate this channel of the model, I target post-displacement occupation switching in the estimation and leave the cyclicality of occupation switching as non-targeted moment. As the focus of the paper is to isolate the role of cyclical variation in selective hiring, the model offers a necessarily stylized notion of occupation. But to successfully match the average incidence and earnings cost of occupation switching, the calibration must take into account that, while occupation is a perfect measure of the productive task of a job in the model, it is a far less perfect measure in the data.

[41]As argued by Ljungqvist and Sargent (2015), a delay cost in bargaining à la Hall and Milgrom (2008) can be reinterpreted in terms of the Hagedorn and Manovskii (2008) calibration. If we set the delay cost γ to zero and set the worker's bargaining power η to the value of 0.052 from Hagedorn and Manovskii (2008), the implied value of leisure b that maintains the same profit share is $b = 0.9832$, close to the value of 0.955 estimated by Hagedorn and Manovskii. Hence, the mechanism by which the model achieves cyclicality of unemployment is well understood within the literature.

To bring the calibrated model closer to the data, occupation is measured within the simulation such that workers can perform the same task across multiple occupations. Specifically, a fixed fraction χ of workers reemployed within their previous job type are recorded as occupation switchers. Hence, if a fraction x of displaced workers switch across skill-intensive and skill-neutral jobs subsequent to displacement, measured occupation switching is $x + (1-x)\chi$. Likewise, if the average wage loss for displaced workers reemployed within a job of the previous task is Δw^s and the average wage loss for displaced workers reemployed within a job of a different task is Δw^{ns}, the measured average wage loss of occupation switchers is $\left(x\Delta w^s + (1-x)\chi\Delta w^{ns}\right)/\left(x + (1-x)\chi\right)$.[42] The estimated value of χ is 0.40, implying that about one quarter of measured occupation switching in the model occurs across jobs of separate tasks.[43]

Three parameters are particularly important for determining human capital loss and reallocation across job types: the probability of gradual skill loss π_U, the obsolescence probability ξ, and the vacancy posting cost in the skill-intensive market κ_H. While the role of π_U and ξ in determining human capital dynamics is clear, the role of κ_H may be less so. A higher value of κ_H represents a direct increase in the fixed cost of job creation for skill-intensive jobs and will thus increase the average optimal skill cutoff, directing more job creation towards skill-neutral jobs. Hence, a higher κ_H will increase the probability that a worker is reallocated from the skill-intensive to skill-neutral 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. All targets are taken from the CPS displaced worker supplement using the "broad" CPS occupation definition.[44] The estimated probability of skill loss in unemployment is 0.0941, corresponding to an average 1.13% loss in human capital

[42]If such measurement issues are ignored, the model cannot simultaneously account for the wage cost and frequency of occupation switching. If the model matches the excess wage loss of occupation switchers, occupation switching occurs too infrequently. Similarly, if the model matches the frequency of occupation switching, the relative wage loss associated with occupation switching is too small.

[43]Workers who switch occupations across jobs of the same task are predicted to have the same earnings loss of workers who find new jobs within the same occupation. This is similar to the findings from Table 4, where only a subset of occupation switchers are found to experience significantly larger earnings losses relative to occupation stayers.

[44]To calculate these moments from the model, I administer a synthetic displaced worker supplement within the simulation for every two years of the simulated data, exactly following the structure of the DWS. In order that a single displacement event informs only a single synthetic questionnaire, I match the model simulated data to moments from a subsample of reemployed workers in the DWS who were displaced no more than two years prior to their interview.

over a four week period unemployment. The estimated obsolescence probability ξ is 0.0422, and the estimated vacancy posting cost κ_H is 3.51.

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 6. The parameter estimates for π_H and π_L suggest that skill accumulation is much slower in skill-neutral employments: a worker in a skill-intensive job expects a 0.983% increase in human capital over a quarter of continuous employment, versus 0.651% increase for workers in skill-neutral jobs.

Workers have a stochastic lifecycle, and the distribution of the initial skill draw for new entrants is parameterized as discretized log-normal. 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 1.71, compared to 2.43 for all employed workers.

Finally, the model generates a small fraction of workers in skill-neutral jobs. In the ergodic distribution, roughly 6.49% of workers are unemployed, 10.4% of workers are employed in skill-neutral jobs, and 83.0% of workers are employed in skill-intensive jobs. Skill-intensive workers thus account for 88.9% of the employed population.

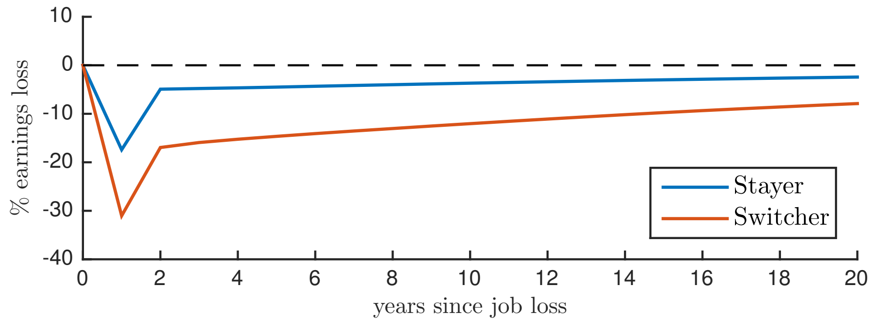
5. The scarring effect of recessions: model implications

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.[45]

Figure 4 shows the simulated time series of relative earnings losses for occupation stayers and switchers in the model. 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.

[45]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 employment into a binary expansion/recession state variable. Details of the mapping and simulation procedures are given in Appendix D.

Figure 4. Earnings losses, stayers and switchers: model



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 are lose their job during a recession relative to an expansion: there is a 4.2 percentage point increase in the model, close to the estimated 3.9 percentage point increase recorded in the second column of Table 2. So while the estimation only includes average measured occupation switching as a targeted moment, the model well accounts for the cyclicality of occupation displacement.[46]

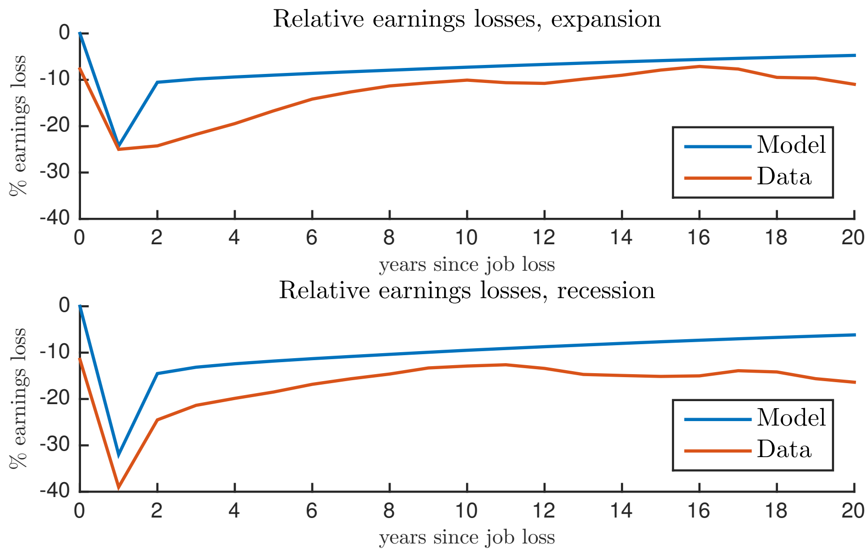
The estimated model matches the essential features of occupation displacement discussed in empirical section, including moments that are not targeted in the estimation. I now use the model to consider two separate but related aspects of the scarring effect of recessions: the cyclical cost of job loss (Davis and von Wachter, 2011), and the cost of entering the labor market during a recession (Kahn, 2010; Oreopoulos, von Wachter, and Heisz, 2012; Altonji, Kahn, and Speer, 2016).

5.1. **The cyclical cost of job loss.** I now consider the model implications for the present value cost of job loss during expansions and recessions. In doing so, I decompose the total cost of job loss into two components: one that reflects the cost of occupation displacement and another that reflects the depreciation of human capital. The component due to occupation displacement accounts for the majority of the cost of job loss. The model produces a greater cost of job loss during recessions in part through the higher incidence of occupation displacement.

Figure 5 gives the empirical and simulated time series of relative earnings losses of displaced workers during recessions and expansions. The empirical series is taken

[46]While the model generates countercyclical occupation displacement, the weekly probability that a worker in a skill-neutral job moves to a skill-intensive job is strongly procyclical, increasing from .27 percentage points during a recession to 1.03 percentage points during an expansion.

FIGURE 5. Comparison of model and empirical earnings loss profiles



from Davis and von Wachter (2011).[47] Earnings losses the year of displacement fit the data almost perfectly for both expansions and recessions. The model is also able to generate the observed long-run persistence in earnings losses. The first and third rows of Table 8 compare estimates of the present value cost of job loss from Davis and von Wachter (2011) with counterparts computed from model-simulated data.[48] Displaced workers in the model are predicted to suffer a 8.81% present value loss during expansions compared to 11.0% in the data.[49] During recessions, the model predicts displaced workers to suffer a 11.6% present value earnings loss, compared to 18.6% estimated from the data. Hence, the model accounts for 81% of the cost of job loss during expansions and 62% of the cost of job loss during recessions. In contrast, the best-fit model considered by Davis and von Wachter (2011) generates present value costs of only 2.4% during expansions and 2.7% during recessions, accounting for only 21.2% and 14.5% of the estimates from the data.

In Figure 6, I decompose the separate contributions of skill loss and occupation displacement to the average cost of job loss. The contribution of skill loss is calculated as the average earnings losses of workers who lose their job but do not switch occupation.

[47]The earnings losses from the data are computed using the data from Figure 4 of Davis and von Wachter (2011). These data are not available in the online appendix, so I used the software program GraphClick to recover them.
[48]For reference, results from the best-fit model considered by Davis and von Wachter (2011) appear in the second row.
[49]Present values for both model and data are calculated with a 5% discount rate.

TABLE 8. Present value cost of job loss, data and model

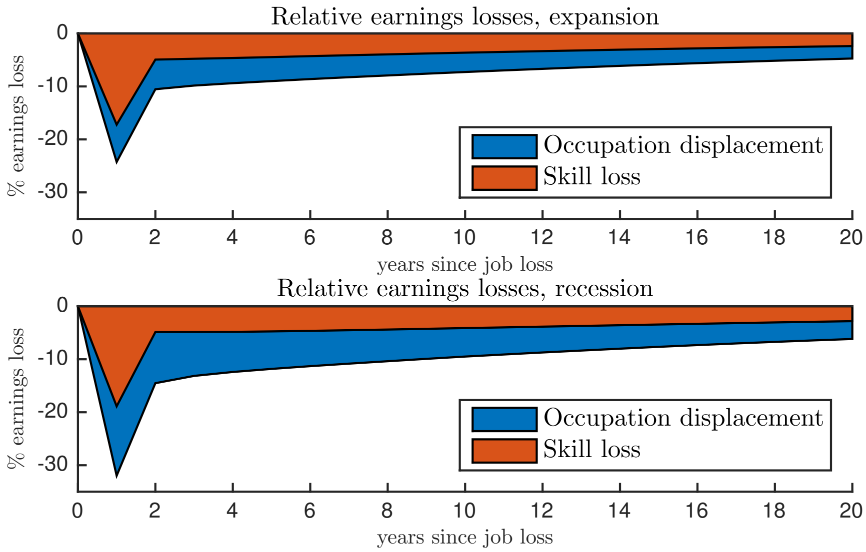
	Expansions		Recessions	
Data†	11.0%		18.6%	
DvW, best-fit model†	2.4%	[0.21]	2.7%	[0.15]
Model	8.81%	[0.81]	11.55%	[0.62]
Model, only skill loss	4.74%	[0.43]	5.42%	[0.28]

Fraction of data explained indicated in brackets
† Source: Davis and von Wachter, 2011

The contribution of occupation displacement is calculated as the residual difference between average earnings losses among all displaced workers and average earnings losses among occupation stayers. As can be seen from the figure, the cost of skill loss hardly increases during recessions, but the contribution of occupation displacement to the cost of job loss increases in both absolute and relative terms, accounting for both the larger initial earnings loss and the slower pace of the subsequent earnings recovery.

The relative contribution of skill loss and occupation displacement to the present value cost of job loss can be determined from the fourth row of Table 8, which gives the present discounted value cost of job loss associated with skill depreciation alone. These present value earnings losses are smaller and notably less cyclical than those of the full sample, increasing from 4.74% during expansions to only 5.42% during recessions— a 14% change. In contrast, the increase in the component of the cost of job loss accounted for by occupation displacement during recessions is 50.6%. For workers who do not switch occupation, earnings losses from job displacement during a recession are only larger because workers lose more skill over longer unemployment durations. But given the estimated parameters, these losses are small; and once these workers find reemployment, their subsequent recovery of lost human capital proceeds at the same rate as that of an identical worker who never lost his job. Hence, just as Davis and von Wachter (2011) find that a search model with a "wage ladder" is unable to generate a cyclical cost of job loss, neither can the "skill ladder" of my model without occupation displacement.

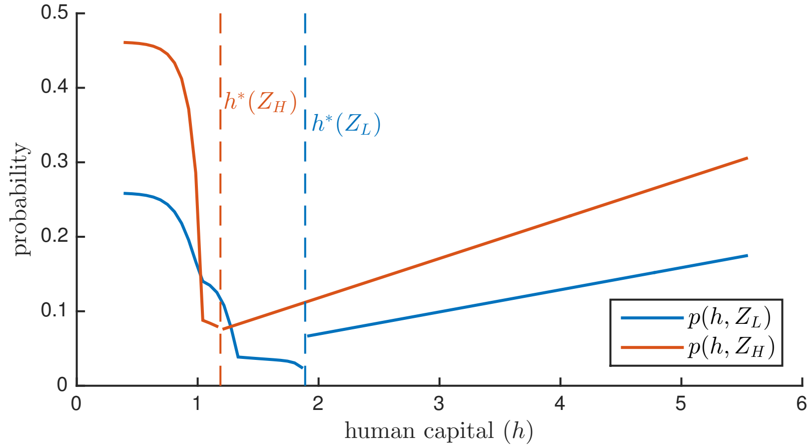
FIGURE 6. Decomposition of earnings losses



The key economic mechanism for generating countercyclical occupation displacement – and therefore the cyclical cost of job loss – is countercyclical selective hiring. The most clear way to understand this mechanism is through Figure 7, which gives the schedule of job-finding probabilities and optimal skill cutoffs for high and low aggregate productivity. For a given level of aggregate productivity, the optimal skill cutoffs indicate job-finding probabilities corresponding to skill-neutral jobs (to the left) and skill-intensive jobs (to the right). As in a typical search 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 in the distribution of vacancy postings from skill-intensive vacancies to skill-neutral vacancies. In Figure 7, the vertical line associated with 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. Firms hiring workers for skill-intensive jobs respond to a drop in productivity by posting fewer vacancies and directing vacancies towards workers of greater human capital. Firms filling skill-neutral vacancies take over the bottom end of the market, as the reduction in job-finding probabilities for skilled-jobs increases the expected tenure for new hires in skill-neutral jobs over all values of h.

This central mechanism of the model finds support from a recent literature documenting countercyclical "upskilling" from vacancy postings. Modestino, Shoag, and

FIGURE 7. Job-finding probabilities: high and low productivity



Ballance (2015a,b) use a national dataset of firm-level vacancy postings from 2007 to 2014 with information on occupation, required experience, and required education. They find that firms require greater experience and education across a range of medium-skill occupations when labor markets are more slack– hence the term "upskilling". Similar evidence of countercyclical upskilling is presented in Hershbein and Kahn (2016).

A related mechanism important for generating a large present value cost of job loss is an endogenous overqualification penalty faced by workers who are only precluded from searching for skilled jobs when aggregate productivity is low. From Figure 7, when productivity is Z_L, the job-finding probabilities for the skill-neutral job are particularly low for workers with h in the region between $h^*(Z_H)$ and $h^*(Z_L)$. Should a firm filling a skill-neutral 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. Given the structure of wages, the reduction in the expected tenure of the worker is entirely borne by the firm; hence, workers in this region are less attractive as potential job candidates and face lower job-finding probabilities. Therefore, unemployed workers whose human capital places them in this region face longer expected unemployment durations and thus stand to lose more human capital from an unemployment spell.

Survey research and anecdotal evidence confirms that firms avoid hiring overqualified workers.[50] Indeed, there is a market for consulting agencies to advise firms

[50]See Erdogan et al. (2011) for a survey.

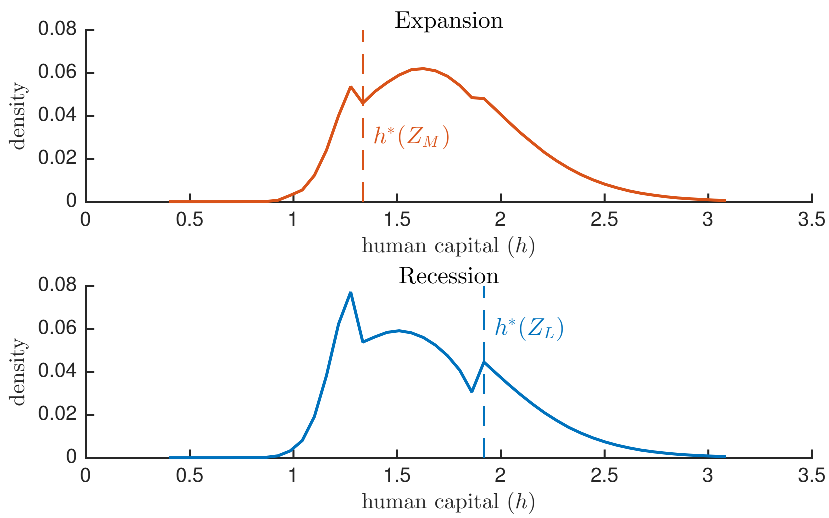
on how to cull overqualified workers from an application pool without violating anti-discrimination laws (see Kuthy and Patchell 2014). The most systematic firm-level study of overqualification and hiring practices comes from interviews of hiring managers conducted by Bewley (1999), who finds that firms avoid hiring overqualified workers for reasons of retention.[51] The pervasive finding that firms avoid hiring overqualified workers suggests that firms are unable to sufficiently adjust wages to redistribute the loss of job value associated with lower retention rates.

Countercyclical selective hiring implies not only that occupation displacement is countercyclical, but also that the marginal worker displaced to a lower skill occupation during a recession (but not an expansion) suffers larger long-term earnings losses. Figure 7 shows that the marginal worker during a recession (denoted by the right-most vertical dashed line) starts with higher human capital than his counterpart during an expansion (denoted by the left-most vertical dashed line); but due to the overqualification penalty, expects a longer unemployment spell and greater overall human capital depreciation, and hence, a larger present value cost of job loss. The present value cost of job loss among workers who switch occupations implied by the model increases by over 50% from expansions to recessions, from 10.11% to 15.77%. Hence, the cyclical increase in the present value cost of job loss is not only due to a greater proportion of occupation switchers among workers who lose their job during a recession, but also a higher cost of job loss among workers who switch occupation.

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 worker 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

[51]To my knowledge, all empirical studies of the role overqualification on hiring outcomes rely on some form of narrative evidence (i.e., interviewing hiring managers). The reason seems to be related to feasibility: to do otherwise would require observing the entire set of applications for a single job with detailed measurements of applicant characteristics. This data would need to be collected for multiple vacancies across many firms.

FIGURE 8. Human capital distribution of new entrants at initial employment



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.

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 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-neutral job, similar to the findings of Altonji, Kahn, and Speer (2016). Among entrants who find skill-intensive employment during an expansion, the probability that a given worker also finds a skill-intensive 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-neutral 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 find employment in a typical occupation.

Figure 8 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 optimal skill cutoffs across recessions and expansions. The optimal skill cutoffs associated with the modal value of productivity during recessions (Z_L) and expansions (Z_M) are indicated by vertical dashed lines. For both expansions and recessions, there are irregularities in the distribution corresponding to workers who are hired exactly at an optimal skill cutoff. 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 optimal skill cutoff, as illustrated in Figure 7. During expansions, only 35.9% of workers start in skill-neutral jobs. This increases to 67.7% during recessions.

To compare relative earnings losses of workers who enter the labor force during a recession in the model with empirical estimates, I simulate earnings for a large panel of new entrants over a ten year horizon for recessions and expansions and compute present discounted values.[52] The average and median present discounted value costs are 5.80% and 6.30%. By comparison, Oreopoulos, von Wachter, and Heisz (2012) estimate a 6% median present value earnings loss for workers who enter the labor market during a recession.

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 of such occupation displacement increases during recessions. I propose a model of unemployment where, because wages move less than one-for-one with productivity, hiring is endogenously more selective during recessions, and thus a greater fraction of unemployed workers – including displaced workers and labor market entrants – are forced to search for employment in worse jobs, where they subsequently accumulate additional human capital at a lower rate.

In addressing the cost and cyclical incidence of occupation displacement within a macroeconomic model, the paper offers a resolution to Davis and von Wachter's critique that search models are unable to explain the size and cyclicality of the present

[52]Present values in the model and data are again calculated with a 5% discount rate.

value cost of job displacement. The empirical analysis here implies that estimates of the large and persistent earnings losses of displaced workers reflect the experience of a subset of workers who are unable to find reemployment in jobs that fully utilize previously accumulated skills. This subset grows larger during recessions. In explicitly modeling the cyclical heterogeneity in employment outcomes among workers who lose their job, the proposed framework offers an over three-fold improvement over existing models in accounting for the present value cost of job loss during expansions and recessions.

The paper offers an additional contribution in identifying a link between the cost of entering the labor market during a recession and the cyclical cost of job loss. The empirical literature has found that the cost of entering the labor market during a recession is explained in part by placement in lower skill occupations. This paper uncovers a similar pattern for workers who lose their job. The model is able to explain the cost of entering the labor market during a recession, suggesting the importance of this empirical link.

The paper leaves many avenues open for future research. 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. The model also generates predictions for the recovery of aggregate output following recessions: a longer recession allows for greater overall occupation displacement, resulting in a slower recovery. The extent to which greater occupation and job displacement maps into slower recoveries, however, is yet to be explored. In identifying occupation displacement 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.

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Appendix A. for online publication: sample construction and additional empirical results

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 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 losing, 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. Table A.1 corresponds to Figures 1 and 2.

The PSID has separate survey instruments to identify displaced workers from the universe of workers who are report a change in their primary job from the previous year and from the universe of workers who are unemployed at the time of the interview but held a primary job in the previous year. The DWS is less flexible along this dimension, as we can only determine whether an individual is an occupation switcher if they are employed during the time of the survey. The first column of Table A.3 shows that

TABLE A.1. Earnings recovery from job displacement (PSID)

Reported coefficients: $\delta_k + \varphi \times \mathbb{I}(k \geq 0)$

Year relative to displacement (k)	(1) Log annual earnings	(2) Log hourly wage	(3) Log annual hours
-2	-0.012	0.006	-0.018^{**}
	(-0.864)	(0.697)	(-2.041)
-1	-0.122^{***}	0.010	-0.132^{***}
	(-7.827)	(1.219)	(-15.656)
0	-0.325^{***}	-0.053^{***}	-0.272^{***}
	(-16.359)	(-5.863)	(-29.200)
1	-0.157^{***}	-0.130^{***}	-0.027^{***}
	(-8.588)	(-13.862)	(-2.811)
2	-0.111^{***}	-0.099^{***}	-0.012
	(-6.033)	(-10.335)	(-1.184)
3	-0.088^{***}	-0.077^{***}	-0.011
	(-4.522)	(-7.785)	(-1.108)
4	-0.053^{***}	-0.074^{***}	0.022^{**}
	(-2.732)	(-7.333)	(2.076)
5	-0.072^{***}	-0.064^{***}	-0.008
	(-3.507)	(-6.135)	(-0.707)
6	-0.037^{*}	-0.053^{***}	0.016
	(-1.880)	(-4.863)	(1.441)
7	-0.060^{***}	-0.066^{***}	0.007
	(-2.920)	(-5.939)	(0.593)
8	-0.061^{***}	-0.058^{***}	-0.002
	(-2.866)	(-5.029)	(-0.171)
9	-0.058^{***}	-0.052^{***}	-0.006
	(-2.811)	(-4.312)	(-0.447)
10	-0.073^{***}	-0.074^{***}	0.001
	(-3.524)	(-5.968)	(0.104)

$N = 61087$ observations, $n = 5574$ individuals
*** significant at 0.01, ** at 0.05, ** at 0.10
t-statistics in parentheses

occupation switching is countercyclical, just as is shown for the DWS in Table 2; but the table also shows that post-displacement occupation switching is both more common and more cyclical for workers who are interviewed from unemployment.[53]

[53]Where workers have multiple displacements (and therefore could potentially contribute multiple observations to the regression), I only use the first displacement.

Table A.2. Earnings recovery from job displacement by post-displacement occupation mobility (PSID)

Reported coefficients: $\delta_k^i + \varphi_i \times \mathbb{I}(k \geq 0)$, $i = s, ns$

	(1) Log annual earnings			(2) Log hourly wage		
Year relative to displacement (k)	Stayer	Switcher	p-value	Stayer	Switcher	p-value
-2	0.020	-0.037^{**}	0.002	0.034^{**}	-0.019	0.006
	(0.947)	(-2.044)		(2.213)	(-1.373)	
-1	-0.086^{***}	-0.146^{***}	0.002	0.015	0.000	0.087
	(-3.435)	(-7.298)		(0.835)	(0.030)	
0	-0.213^{***}	-0.424^{***}	0.000	-0.009	-0.095^{***}	0.001
	(-7.917)	(-16.596)		(-0.446)	(-5.605)	
1	-0.064^{**}	-0.243^{***}	0.000	-0.072^{***}	-0.181^{***}	0.000
	(-2.510)	(-10.594)		(-3.582)	(-10.361)	
2	-0.039	-0.183^{***}	0.000	-0.054^{***}	-0.139^{***}	0.002
	(-1.548)	(-8.013)		(-2.751)	(-7.851)	
3	-0.030	-0.145^{***}	0.001	-0.048^{**}	-0.097^{***}	0.082
	(-1.160)	(-5.815)		(-2.268)	(-5.346)	
4	0.006	-0.120^{***}	0.001	-0.037^{*}	-0.110^{***}	0.013
	(0.244)	(-4.929)		(-1.664)	(-6.220)	
5	-0.026	-0.133^{***}	0.006	-0.030	-0.096^{***}	0.024
	(-0.922)	(-5.107)		(-1.345)	(-5.210)	
6	0.017	-0.100^{***}	0.002	-0.013	-0.089^{***}	0.011
	(0.586)	(-4.065)		(-0.582)	(-4.662)	
7	-0.038	-0.105^{***}	0.105	-0.032	-0.101^{***}	0.023
	(-1.200)	(-4.230)		(-1.364)	(-5.190)	
8	-0.003	-0.123^{***}	0.003	-0.043^{*}	-0.077^{***}	0.269
	(-0.108)	(-4.460)		(-1.796)	(-3.858)	
9	0.001	-0.124^{***}	0.002	0.004	-0.098^{***}	0.003
	(0.036)	(-4.801)		(0.163)	(-4.683)	
10	-0.059^{*}	-0.103^{***}	0.260	-0.057^{**}	-0.086^{***}	0.351
	(-1.926)	(-3.978)		(-2.421)	(-4.085)	

$N = 56937$ observations, $n = 5358$ individuals
*** significant at 0.01, ** at 0.05, ** at 0.10
t-statistics in parentheses
"p-value" is for F-test that loss is the same for occupation stayers and switchers.

Displaced workers interviewed from unemployment may also be workers who face

TABLE A.3. Post-displacement occupation switching is countercyclical (PSID)

Dependent variable: indicator for occupation switcher

	(1)	(2)	(3)
Recession	0.067**	0.106***	0.065**
	(0.0324)	(0.0368)	(0.0314)
Constant	0.445***	0.525***	0.426***
	(0.0260)	(0.0551)	(0.0280)
Worker type	All	Unemployed	Employed
N	1674	684	1399

*** 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. Robust standard errors clustered by displacement year in parentheses. Data from PSID, 1968-1997.

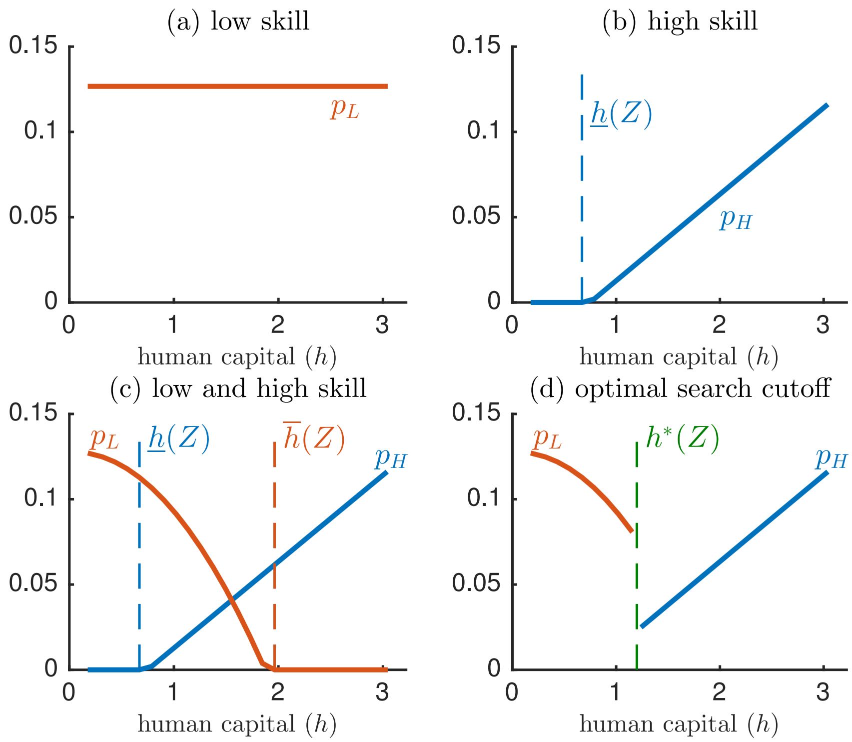
longer unemployment durations after displacement, or relatedly, workers for whom displacement was less anticipated.

APPENDIX B. FOR ONLINE PUBLICATION: A CONSTRUCTIVE EXAMPLE OF EQUILIBRIUM SCHEDULE OF JOB-FINDING RATES AND THE OPTIMAL SKILL CUTOFF

The locations of the optimal skill cutoffs and the values of labor market tightness across human capital submarkets for each Z are jointly determined by equations (12) and (17). Although the division of the human capital grid into optimal search decisions of the worker is described by a set of equations without a closed form, the resulting equilibrium can be understood through a series of examples: (a) the schedule of job-finding rates in an environment of only skill-neutral jobs; (b) the schedule of job-finding rates in an environment of only skill-intensive jobs; (c) the schedule of equilibrium job-finding probabilities in a search environment with both skill-neutral and skill-intensive jobs; and (d) the optimal search decision $h^*(Z)$ given the job-finding probabilities from (c). The sequence of examples is given in Figure B.1.

Figure B.1(a) gives an equilibrium schedule of job-finding probabilities in an environment with only skill-neutral jobs. The job-finding schedule $p_L(h, Z)$ is constant in h as human capital does not contribute to revenue, and there are no skill intensive

FIGURE B.1. Constructive example of equilibrium job-finding probabilities



The schedule p_L denotes the job-finding probabilities over human capital (or skill) in a low skill job, where $\overline{h}(Z)$ denotes the maximum level of skill for which a low skill job can be created with non-negative profits for the firm. The schedule p_H denotes the job-finding probabilities over human capital in a high skill job, where $\underline{h}(Z)$ denotes the minimum level of skill for which a high skill job can be created with non-negative profits for the firm. The optimal skill cutoff is given by $h^*(Z)$.

firms to poach workers of higher h. Should there be a fall in aggregate productivity, firms post fewer vacancies to compensate for the drop in the value of a new job relative to the fixed costs of posting a vacancy. Hence, a fall in aggregate productivity corresponds to a vertical drop in the schedule for $p_L(h, Z)$.

Figure B.1(b) gives an equilibrium schedule of job-finding probabilities in an environment with only skill-intensive jobs. As the value of the skill-intensive job to the firm is increasing in h, firms post more vacancies for higher levels of h and job-finding probabilities $p_H(h, Z)$ increase in h. Below $\underline{h}(Z)$, however, the amount of skill offered by a worker is not enough to recoup the fixed costs of job creation, and hence, no jobs are posted and job-finding probabilities are zero. As in B.1(a), a drop in aggregate productivity pushes the schedule of job-finding probabilities down, but also directs

$\underline{h}(Z)$ to the right (away from zero), further restricting the range of workers able to find a skill intensive job. The intuition is as before: to maintain non-negative profits with the drop in aggregate productivity, the firm reduces the number of vacancies posted, increasing the probability that any given vacancy is filled. For low enough h, however, even a vacancy-filling probability equal to one is not enough to compensate for the fixed costs of job creation, forcing $\underline{h}(Z)$ higher and further away from zero.

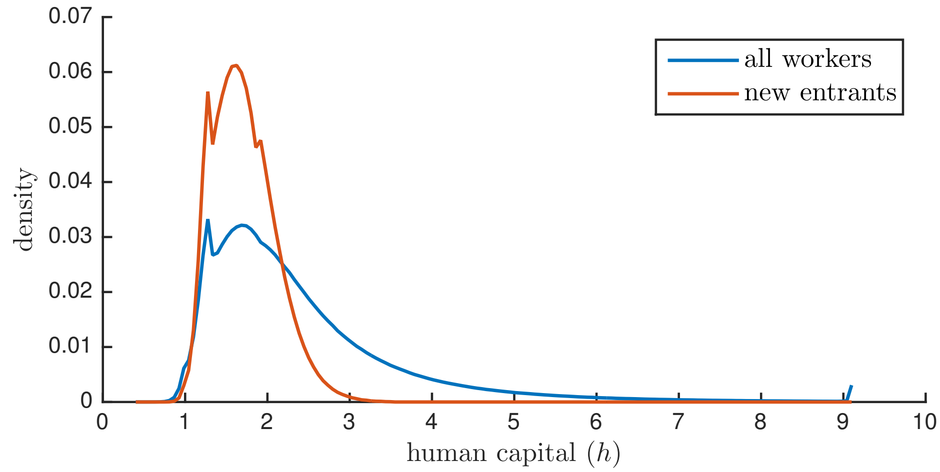
Figure B.1(c) depicts an equilibrium schedule of job-finding rates for a market in which both skill-intensive and skill-neutral jobs coexist. We see that $p_L(h, Z)$ is now declining in h and is equal to zero for all $h > \overline{h}(Z)$; as h increases, firms opening low-skill vacancies anticipate lower expected tenure for new hires, and hence post fewer vacancies for higher h, generating a fall in the job-finding probability in h that eventually reaches zero. In the equilibrium depicted, there is a non-degenerate interval between $\underline{h}(Z)$ and $\overline{h}(Z)$ where workers can choose to search for either skill-neutral or skill-intensive jobs. Skill intensive jobs generally offer a higher wage, but for lower h, unemployed workers face a trade-off between the higher value of a high skill job with the higher probability of finding a low skill job. As before, a decrease in aggregate productivity pushes both job-finding probability schedules down, also pushing $\underline{h}(Z)$ to the right, away from zero. For a given h, the drop in Z reduces the probability that a worker will be poached by a firm offering a high skill vacancy; hence, the drop in Z moves $\overline{h}(Z)$ further to the right. Relative to Menzio and Shi (2010), there are two complementary slackness conditions to be solved: one for the low skill job, another for the high skill job. Given the assumption of segmented/directed search, however, the model can be solved without reference to the distribution of workers as a state variable.

Figure B.1(d) depicts the final equilibrium schedule of job-finding rates implied by the model for a given Z. The vertical green line labeled as $h^*(Z)$ depicts the skill cutoff that corresponds to the optimal search decision of the worker. The ability of the model to generate reallocations of workers from high to low-skill jobs during recessions depends in part on how sensitive the optimal cutoff $h^*(Z)$ is to movements in productivity.

Appendix C. for online publication: further discussion of calibration

Here, I continue to discuss identification and estimation of model parameters. The monthly transition rate from unemployment to employment (from Menzio and Shi

Figure C.1. Distribution of workers over human capital



2011) and the p90/p50 wage ratio calculated from the 2000 U.S. Census help identify the matching efficiency parameters for the skill-neutral and skill-intensive labor markets, ϕ_L and ϕ_H.[54] Wage dispersion in the upper ends of the wage distribution is generated through continuous human capital accumulation of workers within skill-intensive jobs. Intuitively, if the model matches the average job-finding probability but job-finding rates for skill-intensive jobs are too low, longer spells of unemployment for workers separated from skill-intensive jobs will dampen the rate at which such workers find new jobs and resume skill accumulation, decreasing the p90/p50 wage ratio. The estimated values for ϕ_L and ϕ_H are 0.0902 and 0.2562.

The selected moments force the model to account for both the wage losses of displaced workers and the accumulation of higher wages with greater labor market experience. I target average annual wage growth estimated from a Mincer wage regression with a quartic in experience from the 2000 U.S. Census. This moment is helpful for identifying the rate of human capital accumulation in skill-intensive jobs, π_H. But the accumulation of human capital is also described by the rate at which workers accumulate human capital at skill-neutral jobs, π_L. This parameter is well informed by the p50/p25 wage ratio in the model, estimated from the 2000 U.S. Census. If π_L is too low, it takes too long for workers in skill-neutral jobs to obtain the necessary human capital to progress into skill-intensive employment, increasing the proportion of the workforce in skill-neutral jobs and decreasing the p50/p25 wage ratio. The estimated values of π_H and π_L are 0.033 and 0.011, implying that that the average worker in a

[54] κ_L and ϕ_L only matter through the ratio κ_L/ϕ_L. I set $\kappa_L = 0.05$ and estimate ϕ_L.

skill-intensive and skill-neutral job experience 0.983% and 0.651% increases in their human capital endowment over a three month period of continuous employment. The slow accumulation of human capital for workers in low-skill jobs prolongs the time that workers displaced from skill-intensive to skill-neutral jobs spend in a skill-neutral jobs, adding persistence to the cost of job loss for such workers.

Workers in the model have a stochastic lifecycle. New entrants draw an initial value of human capital, thereafter accumulating additional human capital through labor market experience. I parameterize the initial distribution of human capital as a discretized log-normal distribution. To identify the mean, I match the ratio of the average wage of workers with five or more years of labor market experience to the average wage of workers with less than five years of experience. To identify the standard deviation, I match the difference in the 90th and 10th percentile log wage residuals among workers with less than 5 years of labor market experience from a Mincer wage regression. Both of these moments are calculated using data from the 2000 U.S. Census. The estimated values of μ_{nb} and σ_{nb} are 0.371 and 0.225.

Note that newly-born agents enter the labor market unemployed and thereafter are subject to shocks that erode their initial endowment of human capital until they find a job. Figure C.1 compares the ergodic distribution of human capital across all workers and across new entrants upon first employment. The skill density of new entrants has greater mass towards the bottom of the human capital distribution: the average value of human capital of newly employed entrants is 1.71, compared to 2.43 across all employed workers. There are two peaks at the middle of the new entrant distribution and slight bump just above $h = 2$. Similar features are observed for the distribution of human capital across all workers. These irregularities are due to discontinuities in the schedules of job-finding probabilities at the optimal skill cutoffs, as discussed in Section 5.

The relation of the two distributions is important for understanding the role of obsolescence shocks in determining human capital dynamics. Recall that a worker with human capital h hit by an obsolescence shock draws a new value of human capital from a distribution constructed from the initial distribution with support bounded above by h and normalized to integrate to one. Only workers with substantially higher human capital expect to lose more human capital when they experience an obsolescence shock. But as is shown in Section 5, these workers are predicted to have higher job-finding probabilities and lower expected durations of unemployment,

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

	Z_L	Z_M	Z_H
Expansion	0.175	0.493	0.331
Recession	0.859	0.139	0.002

Note: due to rounding, rows do not necessarily add to one.

dampening the overall effect of the obsolescence shock in determining wage growth among high-income workers.

Appendix D. for online publication: identifying recessions in model-simulated data

Davis and von Wachter calculate the cost of job loss during a recession by averaging across NBER recession years, accounting for 12% of the years in their sample; the remaining 88% are classified as expansions. To facilitate comparison between estimates from the model and the data, I develop a criteria through which to label episodes from model simulated data as expansions or recessions. I apply an HP filter to a series for quarterly output 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 D.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. A simple alternative to this this procedure would be to track the earnings of job losers from the initial simulation. But given that job displacement is a low probability event, such a series would be subject to significant sampling error.