Job Displacement and Transferability of Human Capital*

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Abstract

This paper proposes and quantifies a search model where human capital is neither fully match specific nor fully transferable. We endogenize the degree of transferability of human capital by explicitly modeling the re-matching problem. Following a job displacement, the extent to which previously accumulated human capital will be available in a new job depends on the quality of the new match, worker's prior experience and the ability to learn. We estimate the model, derive distributions of accepted and rejected matches, show how unemployment spells vary with individual characteristics and decompose value and wage losses. We show that most of the post-displacement losses are due to the imperfect transferability of human capital.

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1 Introduction

General human capital improves productivity across the labor market, while firm-specific human capital contributes to the productivity of workers within a particular firm but not outside of it. Since Becker (1964), the distinction between general and specific human capital has been a central theme in labor economics. Examples of firm-specific human capital include learning skills, techniques, and workplace structures that are unique to a particular firm. Understanding how workers accumulate general and specific human capital, as well as how this capital is transferred across jobs, is crucial for addressing a range of important economic questions.

Following Becker (1964), the traditional analyses of the role of human capital in labor markets have focused on theoretical extremes in which capital is either purely match-specific or perfectly transferable. In these theoretical extremes, once the overall experience is taken into account, the specific experience in the previous job has no effect on job search or wages upon re-employment of a displaced worker. However, an extensive empirical literature suggests that specific experience does play an important role, indicating that an intermediate approach is more consistent with the data.[1]

We concentrate on the transferability of human capital, moving away from the extremes of purely general or purely specific capital. Our model centers on the optimal reallocation of semi-specific capital following job displacement. We develop and quantify a framework that addresses the problem of human capital reallocation and generalizes the concept of specific human capital. In our model, the quality of a match between a firm and a worker determines the transferability of previously acquired capital.

The proposed model is motivated by a number of observations reported in the related literature. First, human capital accumulation leads to increasing wages with tenure, (see Topel, 1991; Altonji and Williams, 2005; Dustmann and Meghir, 2005; Buchinsky et al., 2010, for example). Second, displaced workers incur substantial wage losses upon re-employment, (Jacobson et al., 1993;

[1] See for example, Neal (1995), Parent (2000), Lazear (2009), Sullivan (2010), Gathmann and Schönberg (2010), Gibbons and Waldman (2004), Kambourov and Manovskii (2009), and Pavan (2011).

Podgursky and Swaim, 1987; Ruhm, 1987; Topel, 1990; Seitchik and Zornitsky, 1989; Kambourov and Manovskii, 2009; Couch and Placzek, 2010; Carrington and Fallick, 2014). This observation suggests that the accumulated job skills are not perfectly transferable. Third, the unemployment spell following a displacement, as well as the wage loss after reemployment, increase with tenure and with the wage in the previous job (see Podgursky and Swaim, 1987; Seitchik and Zornitsky, 1989; Carrington, 1993; Addison and Portugal, 1987). Wage loss is proportional to the pre-displacement wage, as seen in Podgursky and Swaim (1987). Tenure in the previous job has a much stronger impact on the relative wage loss at reemployment than overall experience (Topel, 1990; Ruhm, 1987; Burdett and Coles, 2003).

Our framework provides a simple way to examine the costs of displacement by generalizing the concept of human capital accumulation. In our model, heterogeneous workers accumulate human capital at different rates while employed. Jobs disappear at an exogenous rate and workers are displaced when jobs disappear. Displaced workers search to be matched with a new job. A worker who accepts an offer loses a part of his capital. Match quality defines the fraction of human capital transferable to the next job, the worker decides whether or not to accept the job and therefore how much human capital to transfer. The decision rule that solves this problem determines the wages of displaced workers upon reemployment, together with the arrival rate of new offers, it also determines the duration of unemployment. The level of human capital determines wages at re-employment and the duration of unemployment. The history of prior employment spells, displacements, the quality of the reemployment match, and individual accumulation rate determine the level of human capital.

The theory delivers several implications. The match quality on the new job, the worker's prior experience, and their ability to learn determine how much of the previously accumulated human capital is transferred to the new job, the wage at re-employment, and the duration of unemployment. Match quality is endogenous and results from the re-matching problem. Consequently, the transferability of human capital and the degree to which human capital is specific are a function of the parameters of the search problem. We show that workers with higher learning abilities are

more likely to accept matches of lower quality and forfeit a larger fraction of their previously accumulated human capital.

These theoretical implications find support in the data. First, the predictions of the model align with observations on the costs of job displacement documented in the existing literature. Second, utilizing data from the 1979 National Longitudinal Survey of Youth (NLSY79), we show empirically that pre-displacement levels of human capital, measured by pre-displacement job tenure and wages, are positively correlated with unemployment spells and the magnitude of wage loss upon re-employment. Furthermore, individuals who accumulate human capital at higher rates, as identified by faster wage growth on the job, are more likely to experience shorter unemployment spells and encounter larger wage losses upon re-employment.

We estimate the average wage loss associated with displacement to be around 8.7% and the average unemployment duration around 19.5 weeks. We estimate the parameters of the model to match these and other key moments in the data. The model predicts larger wage losses for displaced workers with higher human capital and for those with higher learning abilities. The duration of unemployment increases with tenure in the previous job and declines with learning ability. The average offer acceptance rate is 62.2%, with higher rates observed for individuals with greater learning ability and those with lower tenure. The average match quality, denoting the fraction of accumulated human capital transferred to the new job, is estimated at 45.8%, with a lower value for workers with higher learning ability. The imperfect transferability of human capital implies that displaced workers do not fully recover compared to continuously employed individuals. On average, it would take around 48 weeks for a worker to regain the wage loss and return to the pre-displacement wage rate. Approximately 92% of the wage loss upon re-employment is attributed to the imperfect match at the new job, while human capital depreciation during unemployment explains only a small fraction of the loss.

We characterize the dynamics of the model through both analytical and numerical approaches. Model parameters are adjusted to illustrate shifts in policy and technology, highlighting the impact of such changes on key model outcomes. Additionally, we examine how these changes affect

various types of workers, heterogeneous in their levels of human capital and ability to acquire human capital. Numerical simulations show that a substantial increase in unemployment benefits is required to yield a material effect on match quality of accepted offers, duration of unemployment, and wage losses. A 10% increase in the replacement rate results in an average unemployment spell increase of four days, corresponding to a 2.9% increase in unemployment duration.This increase in the replacement rate also reduces the average wage loss by 0.6%, attributed to the acceptance of better matches. A decrease in the job arrival rate, consistent with changes in post-displacement dynamics in a recession, leads to a higher unemployment duration, an increase in the fraction of accepted matches, and a lower match quality. Improved transferability of human capital reduces the duration of unemployment and the magnitude of wage losses. These simulations demonstrate how changes in labor market conditions and public policies can impact the reemployment process for displaced workers.

The paper is organized as follows. Section 2 develops the model. Section 3 provides a description of the data and the empirical analysis. The calibration and simulation of the theoretical model is developed in Section 4. We conclude in Section 6.

2 The Model

A worker is endowed with a stock of general human capital $k_0 \geq 0$ that remains invariant over time and is perfectly transferable across jobs and a specific component of human capital k_s that is imperfectly transferable. While employed, the worker receives a flow wage $f(k)$ where $k = k_0 + k_s$. Human capital of the worker grows at rate $\dot{k} = \delta k$.[2] Jobs disappear at an exogenous rate given by a Poisson process with parameter ρ. That is, the probability that a job is still in existence after a time interval of length τ is equal to $e^{-\rho\tau}$.

Once a job disappears, the worker becomes unemployed and must search. While unemployed, workers receive a flow utility $L(k)$, that can be interpreted as the value of leisure, unemployment

[2]The latter can be interpreted as a particular case of a human capital accumulation function $\dot{k} = h(k_0, k_s)$ where $h(k_0, k_s) = k_0 + k_s$.

benefit, or the output produced at an alternative job outside the industry or at home. The specific human capital of unemployed workers depreciates at a rate $\lambda \geq 0$.

Unemployed workers search for new jobs. The search problem is modelled along the lines of Mortensen (1988) (see also Mortensen and Neumann, 1988). Job offers arrive according to a Poisson process with parameter α. Associated with each offer is a match-specific random variable denoted by $s \in [0, 1]$ with distribution function $G(s)$. If the worker chooses to accept the offer, his specific capital stock in the new position is given by sk_s and the new total human capital $k' = k_0 + sk_s$. The variable s captures the quality of the match between the worker's prior experience and this job, as measured by the degree of transferability of the specific capital. What we have in mind is that industry specific capital is composed of an array of skills. Different jobs require different levels of specialization in the array of skills. We have chosen to capture this array by a single-dimensional variable called the worker's specific capital stock k_s. Note that due to our assumption or invariance of the general component k_0 we can conveniently write $k' = k_0 + s(k - k_0) = (1 - s)k_0 + sk$.

The match specific random variable then captures how valuable this capital is to the new job. Note that our model captures cases in which all acquired capital is job-specific ($s = 0$ for all matches) and that in which all capital is transferable ($s = 1$ for all matches). Our specification implicitly assumes that once a new job is accepted the worker loses a part of his acquired capital for all subsequent matches. This assumption of convenience allows us to summarize a worker's history by a single index, $k = k_0 + k_s$.

Workers are risk-neutral and maximize expected discounted consumption. The interest rate is denoted by r. We analyze now the decision problem of the workers. Let $V(k)$ denote the value function or the expected discounted utility of a currently employed worker and $W(k)$ the value function or the expected discounted utility of a currently unemployed worker. For a small time interval h, the value function of an employed worker is approximately

$$V(k) \doteq f(k)h + e^{-rh}\left[e^{-\rho h}V(ke^{\delta h}) + (1 - e^{-\rho h})W(ke^{\delta h})\right] \tag{1}$$

where h is small enough that we may ignore higher order terms. The first term in (1) is the flow of output produced by the worker. The first term in the brackets is the product of the probability that the current job is not destroyed and the value conditional on its continuation. The second term is the product of the probability of job destruction and the value of an unemployed worker. Rearranging terms, dividing by h and taking limits we get

$$rV(k) = f(k) + \rho\left[W(k) - V(k)\right] + V'(k)\delta k \tag{2}$$

This equation gives the flow equivalent of $V(k)$ which consists of $f(k)$, the flow of output, the term in brackets which gives the capital loss due to job termination and $V'(k)\delta k$, the value of the appreciation of human capital. Solving for $V(k)$ we obtain a more convenient expression

$$(r+\rho)V(k) = f(k) + \rho W(k) + V'(k)\delta k \tag{3}$$

The differential equation that corresponds to $W(k)$ is similarly derived and given by

$$rW(k) = L(k) + \alpha \int \max\{V(k_0 + s(k-k_0)) - W(k), 0\}G(ds) - W'(k)\lambda(k-k_0) \tag{4}$$

where the first term is the flow of output (or leisure) while unemployed, the second term represents the value of the option of becoming reemployed and the third term the loss of value due to depreciation. As usual, a worker will accept a job only if its value exceeds the value of remaining unemployed. For each level of k, the acceptance rule is given by a reservation value $z(k)$ which solves

$$V(k_0 + z(k)(k-k_0)) = W(k) \tag{5}$$

unless $V(k_0) > W(k)$, in which case the worker accepts the first job offered, i.e. $z(k) = 0$. This happens when the specific capital $k - k_0$ is small relative to the general component k_0. All jobs with $s \geq z(k)$ are accepted and all other jobs are rejected. Equations (3), (4) and (5) fully describe

the problem faced by a worker.

The model has implications for the duration of unemployment, the wage loss, and the value loss for workers as a function of their capital k, which we now analyze. Workers with higher k benefit relatively more from a favorable match. But the opportunity cost of rejecting an offer is also likely to be higher. At one extreme, where $k = k_0$, the first effect dominates and the worker accepts any offer, so $z(k) = 0$. As k grows very large, the impact of the general capital k_0 becomes negligible, so it follows that $z(k)$, must be increasing in some range as far as $k_0 > 0$.

More generally, the behavior of $z(k)$ depends in a complicated way on properties of f and L, the values of the parameters in the model and the size of k_0. In general there is no explicit solution for the integral- differential system given by equations (3), (4) and (5) . But for a special case, which we now analyze, there is a simple solution.

Homogeneous case. $k_0 = 0, f(k) = ak^\theta$ and $L(k) = bk^\theta$, $\theta \in (0, 1]$.[3] Conjecture that the solution is of the form $V(k) = vk^\theta$, and $W(k) = wk^\theta$. Equation (3) is now given by $(r + \rho)vk^\theta = ak^\theta + \rho wk^\theta + \delta\theta vk^\theta$ which implies

$$v = \frac{a + \rho w}{r + \rho - \delta\theta} \tag{6}$$

Equation (5) is now given by $vz(k)^\theta k^\theta = wk^\theta$ so $z(k)$ is independent of k and satisfies $z(k) = z = \left(\frac{w}{v}\right)^{\frac{1}{\theta}}$. Using this equation (4) can be written as

$$(r + \lambda\theta)w = b + \alpha \int_{(\frac{w}{v})^{\frac{1}{\theta}}} (vs^\theta - w)G(ds) \tag{7}$$

To analyze the equilibrium it is convenient to divide both sides of the equations by w and use $z = \left(\frac{w}{v}\right)^{\frac{1}{\theta}}$, obtaining

$$z^{-\theta} = \frac{\frac{a}{w} + \rho}{r + \rho - \delta\theta} \tag{8}$$

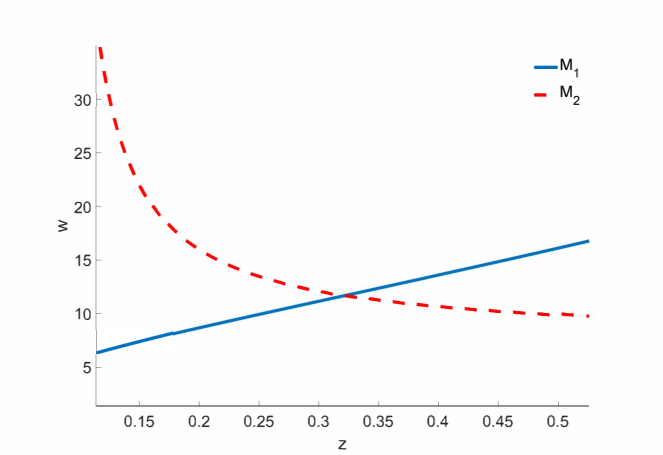
[3] k_0 in this example represents the general human capital, not subject to loosing upon reemployment. To sustain positive $k > 0$, we must assume some initial $k_s > 0$ when the agent joins the first job.

and

$$r + \lambda\theta - \frac{b}{w} = \alpha \int_z \left(z^{-\theta} s^{\theta} - 1\right) G(ds) \tag{9}$$

These two equations are depicted in Figure (1).[4] Curve M_1 corresponds to equation (8) and curve M_2 to equation (9). The signs of the slopes as well as the intercepts can be easily derived from these equations. There is a unique solution to the agent's problem. Using Figure (1), some comparative static results can be easily derived.

Figure 1: Model equilibrium



Note: Curves M_1 and M_2 correspond to equations (8) and (9), respectively.

An increase in a shifts the M_1 curve upwards, resulting in a decrease in z and an increase in w. Similar results are obtained from an increase in δ. This result implies that those that face better opportunities in the market or learn the specific skills faster will have lower reservation values, therefore having shorter unemployment spells. Furthermore, those agents with higher growth rates of capital δ will, on average, have higher wages at the time of displacement and because of the lower reservation value will exhibit larger percentage wage losses but faster wage growth after reemployment. This is consistent with the findings obtained from the Displaced Workers survey reported in Horvath (1987).

[4] See Table 3 for parameter values.

It is easy to show that an increase in ρ moves the M_1 curve downwards, leading to a higher reservation value but lower w. An increase in r shifts both curves downwards, with an ambiguous effect on z. An increase in b has the opposite effect of an increase in a, leading to a higher reservation value. This effect is similar to an increase in unemployment benefits. An increase in λ shifts the M_2 curve downwards, resulting in lower z. An increase in the arrival rate α shifts the M_2 curve upwards, leading also to higher z. Proposition 1 summarizes these results.

An increase in θ shifts the M_1 curve upwards. This results from the increase in wage growth while employed $\delta\theta$. The effect on M_2 is ambiguous as both, left and right hand side of equation (9) increase. On the one hand, a higher θ implies that the utility from unemployment falls faster with human capital depreciation, reducing the value of remaining unemployed. On the other hand, as θ increases, the wage at reemployment $as^\theta k^\theta$ becomes more sensitive to match quality s, which makes the unemployed worker more picky. Depending on which of the two effects dominates, the net impact of increasing θ will either lead to lower or higher unemployment duration while it is likely to increase the average wage loss at reemployment.

Proposition 1. *Consider the homogeneous case, where $k_0 = 0, f(k) = ak^\theta$ and $L(k) = bk^\theta$, $\theta \in (0, 1]$. The optimal threshold $z(k) = z^*$ is independent of k and has the following properties:*

1. *An increase in δ lowers the threshold z^*, decreasing the length of the unemployment spell and increasing the average wage loss at reemployment. Similar results are obtained for an increase in the ratio a/b*

2. *An increase in the arrival rate α results in a higher threshold, higher unemployment duration, and higher wage loss. The opposite effect results from an increase in human capital depreciation rate λ.*

The homogeneous case is useful as a benchmark and to highlight the comparative statics of the search model. But, since reservation values are independent of k, specific experience *per se* has no effect on reemployment behavior. But this conclusion relies on the assumption that $k_0 = 0$. When $k_0 > 0$, there must be a range where $z(k)$ increases, and in this range workers

with higher seniority will exhibit higher unemployment duration. In our quantitative results, with a homogeneous wage function and $k_0 > 0$, we find that following an interval close to k_0 where workers accept all offers, the reservation threshold is always increasing.[5] This result is consistent with a range of empirical studies which show that seniority in the previous job has a positive effect on unemployment duration after displacement.

3 Empirical analysis

In the model, workers accumulate human capital while employed, jobs disappear at an exogenous rate, and workers are displaced when jobs disappear. Displaced workers search to be matched with a new job. A worker who accepts an offer may lose a fraction of his/her capital, this fraction is determined by match quality.

The model yields several implications. (1) Due to the imperfect match at reemployment, displaced workers will experience a wage loss. (2) Wage losses are more pronounced, and unemployment spells are longer for displaced workers with higher specific human capital. (3) The accepted match quality of the displaced worker increases with human capital. (4) Workers with higher learning ability earn higher wages before the displacement, have lower reservation values, experience shorter unemployment spells, and encounter larger wage losses. Empirical findings from a range of studies are consistent with implications (1) and (2). We test whether the remaining implications find support in the data.

3.1 Data and summary statistics

The data are from the 1979 National Longitudinal Survey of Youth (NLSY79). We employ both cross-sectional and supplemental samples (excluding the military supplement) and use the base year weights to achieve representativeness of the population. The survey contains a rich set of individual characteristics, including employment, education, training, family background, and mea-

[5] While we don't have a proof, we conjecture that this result is generally true for this specification.

sures of achievement and cognitive ability.[6] The NLSY79 Work History Files provide detailed information on job transitions, periods of unemployment, and job characteristics.

We restrict the sample to observations after individuals made their transition to the labor market. The first, long-term job is defined as the initial employment for an individual who is not enrolled in school, has completed their highest education degree, and is working 10 or more hours per week. We focus on men aged 18 to 55 years old, who have a minimum of 6 years of schooling, not in military service, and earning an hourly wage between 1 to 300 dollars (adjusted using the 2000 Consumer Price Index). Individuals with missing information on key variables are excluded from the analysis.

We collect detailed information on job transitions and other work-related variables from the NLSY79 work-history files. When respondents report that they have left a job, they are asked to provide the reason for leaving. We focus on workers who were displaced due to employment cutbacks (layoffs) and plant closures.

Unemployment spells, tenure variables and work experience are constructed using the work history files and are measured in weeks. We further restrict the sample to those who have one job, have held their pre-displacement job for at least half a year and those who spent at least one week and less than three years being unemployed following the displacement.

3.1.1 Human capital accumulation rate

We estimate wage growth for each individual using within job wage observations. For each job held for at least one year, we calculate the annual wage growth rate using the first and last real hourly wages observed for the job. If a job was held longer than 4 years, we do not consider the first and last wage but use the second and penultimate wages, unless values are missing or invalid. For each individual, we obtain one or more estimates of wage growth, depending on the number of jobs held over all the waves of NLSY79. We average these values using relevant job tenures as

[6]Cognitive ability is measured as follows. Using outcomes from Arithmetic Reasoning, Numerical Operations, Word Knowledge and Paragraph Comprehension tests in the Armed Services Vocational Aptitude Battery (ASVAB), we construct the age adjusted normalized Armed Forces Qualifications Test (AFQT) scores. The AFQT score is widely used as a measure of cognitive ability and achievement.

weights. The average annual within job wage growth is 4.3% (1.6% and 5.9% for the lowest and highest quartiles, respectively). For about 5% of respondents we obtain negative values, we drop these individuals from the sample.

3.2 Estimation

We empirically examine the duration of unemployment and wage losses following job displacement. Our focus is on displacements caused by layoffs and plant closures, excluding separations due to voluntary quits, job-to-job transitions, or poor performance. Other categories, such as family reasons, migration, retirement, and personal reasons, are also excluded to limit the influence of other factors on unemployment duration and wage losses.

We examine how the duration of unemployment following a displacement and wage losses upon reemployment vary with variables of interest using the following specification,

$$Y_{ij} = \beta_0 + X_{ij}\beta_1 + \beta_2\tilde{\delta}_i + \beta_3 Tenure_{i,j-1} + \beta_4 Tenure^2_{i,j-1} + \beta_5 Exp_i + \beta_6 Exp_i^2 + \xi^U_{j-1,i}, \quad (10)$$

where $Y_{j,i}$ is the unemployment spell following a displacement or the wage loss upon reemployment; i indicates individual and $j-1$ and j refer to job held at the time of displacement or currently, respectively. Wage loss is measured as the difference between $\log$ of wage before and after the displacement, such that $wage\ \ loss$=$\log W_{i,j-1} - \log W_{i,j}$. The variable $\tilde{\delta}_i$ is the individual wage growth variable is constructed using the procedure outlined in Section 3.1.1, and it is a proxy for the human capital accumulation rate (*i.e.*, the learning ability). Tenure and experience variables, $Tenure$ and Exp, represent the years spent on the job and in the labor market (actual experience). Tenure variables are included as proxies to control for the accumulated human capital prior to the job displacement. The vector X_{ij} includes individual and geographic characteristics: cognitive skills, education, race, ethnicity, and region and year fixed effects.

We estimate equation 10 using a subsample of workers who were displaced due to a layoff.

The sample is limited to male workers with prior tenure of 26 weeks or above, who spent less than three years being unemployed following the layoff, and currently working between 25 to 80 hours per week.

Table 1: Unemployment duration and log wage loss

	Unemployment duration		Log wage loss	
Wage growth ($\tilde{\delta}_i$)	-0.701**	-0.673**	0.014**	0.014**
	(0.335)	(0.333)	(0.006)	(0.006)
Tenure$_{j-1}$	0.787*	0.752*	0.029***	0.029***
	(0.417)	(0.418)	(0.006)	(0.006)
Tenure$^2_{j-1}$	-0.034	-0.032	-0.001***	-0.001***
	(0.022)	(0.022)	(0.000)	(0.000)
Experience	-3.421***	-3.370***	0.005	0.005
	(0.684)	(0.679)	(0.009)	(0.009)
Experience^2	0.052**	0.052***	-0.000	-0.000
	(0.020)	(0.020)	(0.000)	(0.000)
AFQT		-1.427*		0.009
		(0.840)		(0.014)
Education		0.001		-0.011**
		(0.377)		(0.005)
Region FE, year FE, Region FE x year FE	yes	yes	yes	yes
R^2	0.090	0.092	0.140	0.142

Note: N=1839. All statistics are weighted using the cross-sectional weights. All estimations include controls for race, ethnicity and constant. Wage growth refers to the mean individual wage growth, $\tilde{\delta}$, and it is normalized to have mean 0 and standard deviation 1. Coefficients presented, clustered at individual level standard errors in parentheses. Significance levels are indicated as follows: * 10%; ** 5%; *** 1%.

Table 1 presents the estimation results. Columns (1)-(2) show results for unemployment duration; columns (3)-(4) report results for wage losses. Unemployment duration is negatively correlated with wage growth ($\tilde{\delta}_i$) and positively with tenure. A one standard deviation increase in individual wage growth is associated with a 0.7 weeks shorter unemployment spell following displacement. Wage loss upon reemployment is larger for workers with higher wage growth ($\tilde{\delta}_i$) and longer pre-displacement tenure. A one standard deviation increase in wage growth is linked to a 1.4% larger wage loss upon reemployment. In Section 2 we developed a model where wage growth is given by $\theta \ln(1+\delta)$. Therefore, we interpret the correlations between unemployment duration, wage loss and wage growth, ($\tilde{\delta}_i$), as correlations with the learning ability, δ. In columns (2) and (4),

we also include the AFQT score as an alternative or complementary measure of learning ability and find that it is negatively correlated with unemployment duration.

Existing literature extensively documents that longer previous job tenure is associated with longer unemployment duration and larger wage losses. We extend the commonly used specification by incorporating individual learning skills, proxied by wage growth. The resulting estimates align with the theoretical implications derived in Section 2.

4 Model estimation and simulation

We estimate the parameters of the model targeting a set of key moments in the data. Through this numerical analysis, we derive a measure of the value loss experienced by workers at various experience levels following a displacement. This exercise enables us to decompose the sources of these losses and facilitates quantitative comparative statics, providing a better understanding of workers' dynamics and employment decisions. For this estimation, we solve the model in discrete time, implementing the homogeneous case setup as described in Proposition 1, setting $k_0 > 0$. We set the model frequency to weekly and calibrate it to the 1979-2016 period.

4.1 Parameters and estimation

The model has the following set of parameters:

$$\Omega = \{\beta, k_0, a, b, \delta, \rho, \lambda, \alpha, \theta, \alpha^{beta}, \beta^{beta}\},$$

where α^{beta} and β^{beta} are the parameters of the match quality distribution function, $G(s)$.

We assume that all parameters, with the exception of δ and k_0 are common to all agents. In the discrete time model, wage growth of agent i is given by $\theta \ln(1 + \delta_i)$, so given an estimate of θ, we back-out the distribution of $\delta_i' s$ from the distribution of wage growth in the data. Proposition 2 (in the Appendix) shows that the parameter k_0 has the effect of scaling proportionately $k(t)$ after

any history, without changing the acceptance thresholds $z(k/k_0)$. Variations in k_0 can account for individual fixed effects on the level of wages, but are neutral with respect to the moments used in the estimation (wage growth, unemployment duration and the distribution of wage losses upon reemployment). We conveniently choose to set $k_0 = 1$.

Likewise, all decision rules and the corresponding moments considered in the paper are neutral to proportional changes in the technology and replacement parameters, a and b, as shown in Proposition 3 (in the Appendix). Loosely speaking, these correspond to units of measurement of wages and the utility of leisure. In particular, when the utility of leisure is limited to unemployment insurance payments, the ratio b/a can be interpreted as the replacement ratio. We normalize the parameter $a = 1$.

We split the parameter space (Ω) in two, parameters set externally from the NLSY79 data or reported in the existing literature, (Ω_d), and internally set parameters, (Ω_e), which we estimate by minimizing the distance between data and model generated moments.

The set of externally assigned parameters is given by $\Omega_d = \{\beta, a, b, \rho, \lambda\}$ and includes the discount factor, β, the replacement rate, b, separation rate, ρ, human capital depreciation rate, λ; as mentioned above, we normalize $a = 1$. The discount factor is set to 0.96 in annual terms. Unemployment benefit, b, is set to 0.57 as to match the net replacement rate for unemployment insurance documented for the US.[7] The value of leisure is set to zero for all k, implying that the cost of job loss is an upper bound. The job loss rate, ρ, is estimated at 8.1% per year using the layoffs data in the NLSY79.[8] The human capital depreciation rate, λ, is set to 6.3% per year, which is consistent with estimates reported in the literature, see for example Heckman (1976). Wage growth in the model is specified as $\theta \ln(1 + \delta)$. Given the value for θ, we obtain the distribution of $F(\delta)$ using the average within-job wage growth distribution estimated from the NLSY79 data. The productivity parameter θ is estimated concurrently with other parameters in Ω_e.

We jointly estimate the remaining four parameters in $\Omega_e = \{\alpha, \theta, \alpha^{beta}, \beta^{beta}\}$. The set of in-

[7] OECD, General policies to improve employment opportunities for all, 2004.

[8] The layoff rate is consistent with estimates in other studies. For example, Topel (1990) finds the separation rate to range from 2% in 1968 to 11% in 1982-83. Akerlof and Main (1980) finds that at any given point in time, the typical worker has held a job for 9 years.

ternally estimated parameters, Ω_e, includes the arrival rate of job offers, α, the production function parameter, θ, and the parameters of the match quality distribution function, $G(s)$. We assume that $G(s)$ follows the $Beta$ distribution with parameters α^{beta} and β^{beta}.[9] We estimate the four parameters by minimizing the equally weighted sum of squared percentage deviations between seven moments in the model and the data.

We consider the following moments: average unemployment duration, average wage loss upon reemployment and the corresponding wage losses for each quartile of the learning ability distribution, and the partial correlation between unemployment duration and wage growth. In the model, the arrival rate of offers above the threshold is given by $\alpha(1 - G(z))$, where the parameter α is the offer arrival rate and z is the lowest accepted match quality. The threshold z varies with the level of capital k and learning ability, δ. The arrival rate of offers above z is tightly connected to the duration of unemployment.

Higher δ leads to a lower $z(\delta)$, which in turn affects the unemployment duration, which depends on the variation of z with respect to δ and on the area under the distribution $G(s)$ for a given z. Wage losses for each quartile of δ inform how z varies with δ; partial correlation between unemployment duration and δ informs about the shape of $G(s)$.[10]

More precisely, in the model, wage loss is given by $1 - \left(\frac{s(k-k_0)+k_0}{k}\right)^{\theta}$, which is increasing with θ and decreasing with s.[11] As a result, the wage loss moments and the correlation between unemployment duration and δ, inform about the shape of the distribution of match qualities and the productivity parameter θ.

We calibrate the model to NLSY79 data and evaluate the initial 15 years in weekly intervals, simulating a population of $n = 10,000$ agents, characterized by heterogeneity in learning ability (δ), with an initial human capital level of $k_0 = 1$. In $t = 0$, agents are randomly assigned an

[9] The $Beta$ distribution is defined on the interval [0, 1], which, in the context of the model, allows workers to accept jobs where they transfer no accumulated human capital ($\underline{s} = 0$), and jobs where they transfer all current human capital ($\bar{s} = 1$).

[10] We employ the partial correlation between unemployment duration and wage growth to account for the positive correlation between k and unemployment. Learning ability, δ, and consequently, wage growth, are positively correlated with human capital, k. We use wage in the previous job as a proxy for k. By controlling for k, we specifically examine the negative relationship between unemployment duration and δ.

[11] By simplifying and assuming $k_0 = 0$ or $k \to \infty$, it is easy to show that wage loss is determined by s^{θ}.

initial employment status $\{e, u\}$. Equations (3), (4) and (5) define a system of equations that fully characterizes the dynamics of the model.

4.2 Results

Table 2 reports the estimated parameters, panel A in Table 3 displays the targeted moments, and Figure 2 reports the learning ability distribution. We estimate the weekly job arrival rate to be 8.0%; the productivity parameter θ is 0.35; and match quality distribution parameters are $\alpha^{beta} = 7.3$ and $\beta^{beta} = 10.7$, the top panel of Figure 4 displays the distribution of match quality.

Table 2: Model parameters

Parameter		value	
β	discount factor	0.96 pa	Literature
a	wage function	1	Normalization
b	leisure function	0.57	Source: OECD (2004)
ρ	separation rate	8.1% pa	Estimated: NLSY79
λ	depreciation rate	6.3% pa	Heckman (1976)
$G(\delta)$	learning distribution		Estimated: NLSY79
α	arrival rate	8.0%	Estimated
θ	wage function	0.345	Estimated
$F_{beta}(s) : \alpha^{beta}, \beta^{beta}$	match quality dist.	(7.26,10.66)	Estimated

Panel A in Table 3 shows that the model performs well in matching the data moments. The estimated job arrival rate, α, is 8.0% per week, implying that if any offer were to be accepted, the mean unemployment duration would have been 12.5 weeks. In Panel A of Table 3, the mean unemployment duration is estimated to be 19.5 weeks, emphasizing the importance of the match quality component.

The model successfully matches the set targets, and it generates related outcomes that broadly align with the data. These outcomes are detailed in Panel B of Table 3, Figure 3, and Table 4.

As shown in Panel B of Table 3, wage losses are larger for individuals with higher learning ability, longer previous job tenure, and longer unemployment spells. Unemployment duration

Figure 2: Learning ability distribution

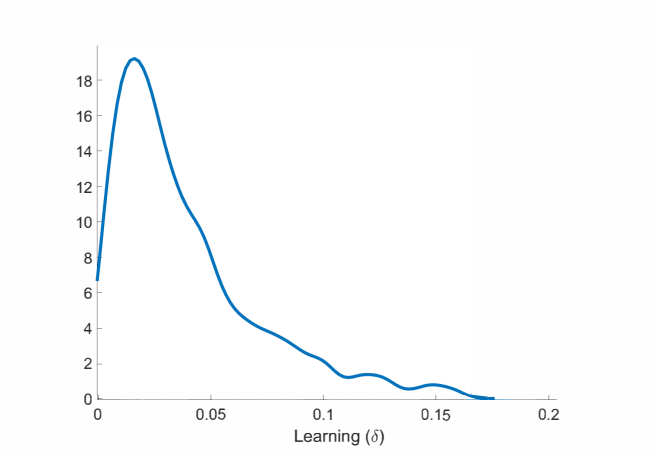


Table 3: Target moments

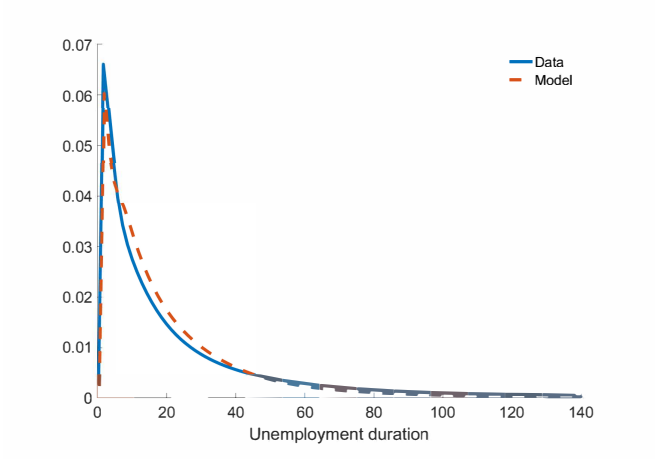
Model Outcomes	Data	Model
A. Targeted moments		
mean unemployment duration	19.45	19.54
% mean wage loss (W_{loss})	8.70%	8.46%
corr (une dur, $\tilde{\delta} \mid \text{wage}_{j-1}$)	-0.065	-0.065
% wage loss Q1($\tilde{\delta}$)	6.2%	2.7%
% wage loss Q2($\tilde{\delta}$)	6.9%	6.2%
% wage loss Q3($\tilde{\delta}$)	9.4%	9.5%
% wage loss Q4($\tilde{\delta}$)	11.7%	15.3%
B. Non-targeted moments		
corr(W_{loss},$\tilde{\delta}$)	0.07	0.70
corr(W_{loss}, une dur)	0.07	0.30
corr(W_{loss}, tenure$_{j-1}$)	0.17	0.47
corr(une dur, tenure$_{j-1}$)	0.13	0.20

increases with previous job tenure. The correlations produced by the model align with all non-targeted moments, however, when using the model generated data we obtain higher magnitudes.

Figure 3 compares the distributions of unemployment spells in the model and the data. The model closely matches the data, even without specifically targeting the unemployment spell distribution. The model shows that 5.6% of displaced workers spend one week unemployed, 20.5% find a job within four weeks, and the median unemployment duration is 13 weeks. Around 20% of

unemployed workers take over 31 weeks to find a job, while the top 10% remain unemployed for more than 45 weeks.

Figure 3: Distribution of unemployment spells, model vs data



Note: Kernel density estimation.

The model predicts that with an increasing number of previous displacements, specific human capital plays a larger role in determining wages, while overall labor market experience becomes less important. We estimate a wage equation controlling for tenure, experience, and their interactions with the number of past displacements. In the NLSY79, wage observations are available annually or when respondents change jobs. For consistency, we select a similar sample in the model-generated data. Table 4 presents the results. The first column shows estimates for the NLSY79 data, and the second column reports results from the model-generated data. Both data sources yield comparable findings: the role of tenure increases with the number of previous displacements, while the importance of overall experience declines.

We derive distributions of match quality for accepted and rejected offers. The top panel in Figure 4 reports the distribution of match quality, with the average match quality of 40.5%. The bottom panel in Figure 4 depicts the distributions of accepted and rejected matches. The average match quality of an accepted and rejected job offer is 45.8% and 31.1%, respectively; 62% of job offers are accepted.

Table 4: Past displacements, experience, tenure and wages

	NLSY79, N=39,435	Model generated data
Experience	0.0076***	0.0457***
	(0.0000)	(0.0010)
Tenure	0.0184***	0.0198***
	(0.0000)	(0.0011)
# Layoffs	-0.0162**	-0.0471***
	(0.0290)	(0.0061)
# Layoffs x Tenure	0.0027***	0.0013*
	(0.0020)	(0.0007)
# Layoffs x Experience	-0.0009**	-0.002***
	(0.0170)	(0.0006)
Constant	6.6767***	0.9676***
	(0.0000)	(0.0073)

Note: NLSY79 statistics are weighted by the cross-sectional weights. Dependent variables are data and model-generated $\log$ wage rates. $\#Layoffs$ counts the number of previous layoffs. Experience and tenure are in years. Significance levels are indicated by *: $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

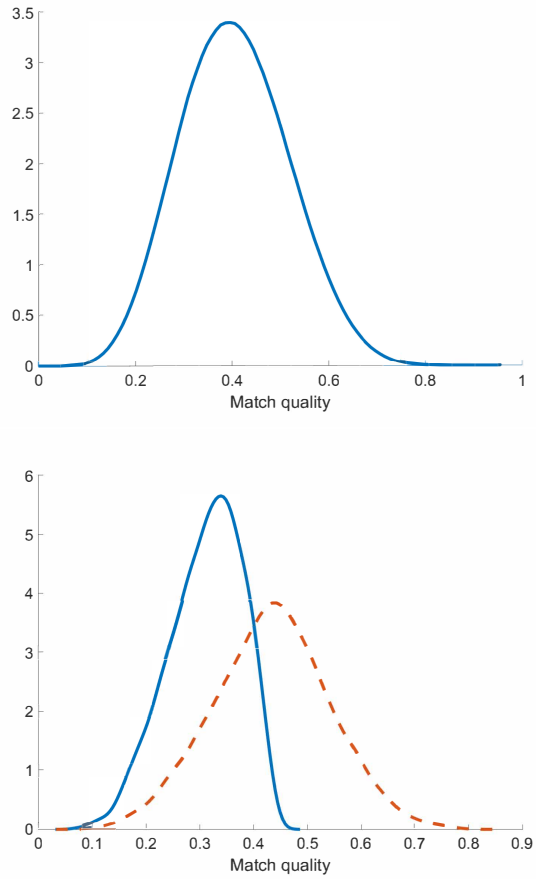
We examine how unemployment duration varies with human capital. Figure 5 shows that workers with k close to k_0 accept any job offer, resulting in a 12-13 weeks period of unemployment. Workers with higher values of k tend to be more selective, leading to longer unemployment spells and higher match quality thresholds.

Figures 5 and 6 show how model-generated unemployment spells and implied unemployment duration vary with human capital, k.[12] Figure 7 shows how acceptance rates vary with human capital, k. Higher levels of k imply larger wage losses following a displacement. Workers with higher pre-displacement human capital tend to wait longer for a better match quality, which implies longer unemployment spells and a lower probability of accepting a job offer.

Workers with low human capital, or those with human capital closer to the k_0 level, are willing to accept any job offer, implying that $z(k)$ is zero. Figures and 6 and 7 also show the differences in unemployment durations and acceptance rates for workers in the first and third quartiles of the learning ability distribution. For any level of k, a higher human capital accumulation rate, δ,

[12]Implied unemployment duration is calculated as $1/\alpha(1 - F(z))$.

Figure 4: Distribution of match quality



Note: Top panel: all job offers. Bottom panel: distributions of accepted (dotted line) and rejected (solid line) matches.

implies higher acceptance probabilities and shorter unemployment spells. This result is consistent with the estimated relationship between wage loss and learning ability. Table 3 shows that wage losses increase with learning ability and human capital (measured by previous tenure). Figure 8 uses model-generated data and shows the positive relationship between the size of wage loss and the level of human capital, k.

Figure 5: Human capital and unemployment duration

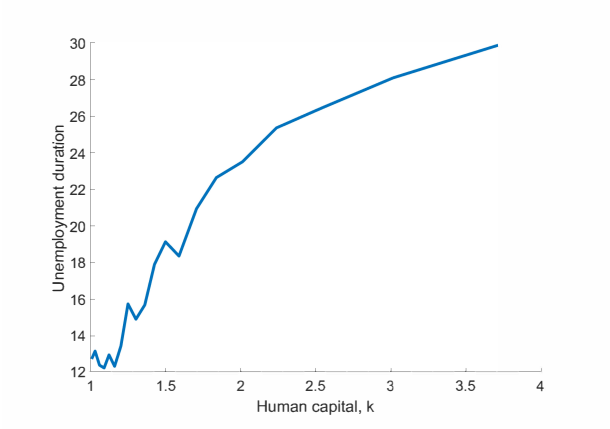
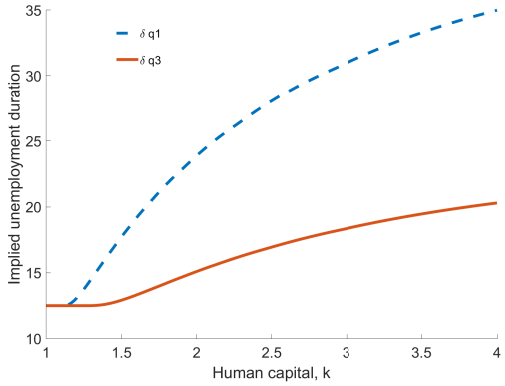


Figure 6: Human capital and implied unemployment duration



4.3 Wage and value losses

We decompose the wage loss and value loss into match quality and human capital depreciation components. We isolate each component by simulating the model with no human capital depreciation and accounting for the losses generated by imperfect match quality, abstracting from interactions between human capital depreciation and match quality. We perform this analysis for

Figure 7: Human capital and acceptance rate

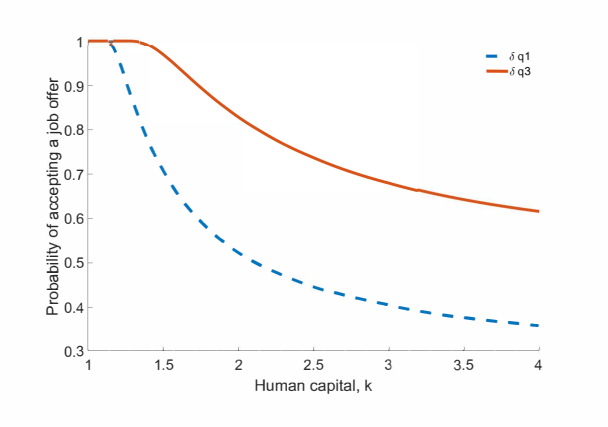
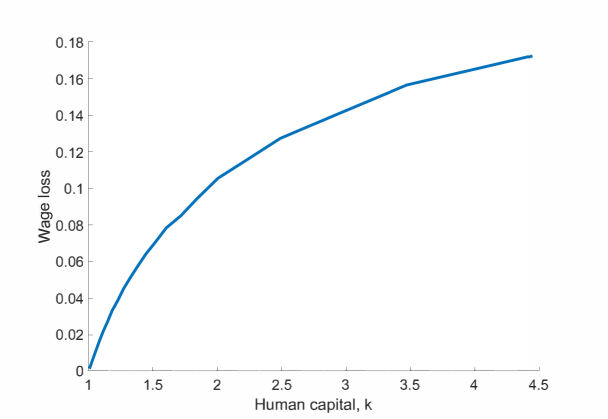


Figure 8: Human capital and wage loss

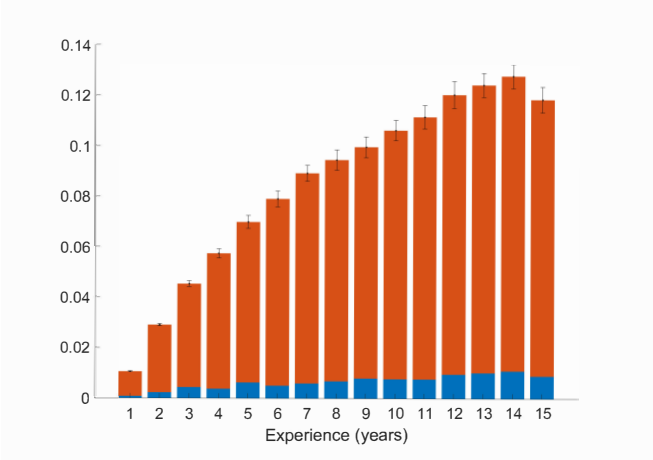


each level of pre-displacement work experience.

Figure 9 displays the results. Most of the wage loss is explained by the match quality channel. On average, match quality explains 92% of the total wage loss, which is relatively uniform across workers experience levels. A displaced worker with one year of experience faces a 1% wage loss, most of which is attributed to match quality. At 5 years of experience, the wage loss increases to 7%, with 6.4% attributed to the match quality component. At 15 years of experience, the loss is 11.9%, with 10.9% due to match quality.

Following a displacement, the average time to recover the wage loss and reach the pre-displacement wage rate is 48 weeks. For workers in the lowest quartile of learning ability, the time to recover is 60 weeks, while for those in the highest quartile it takes 35 weeks. Although the wage growth for the latter group is significantly higher, the wage loss they experience after displacement is also greater.

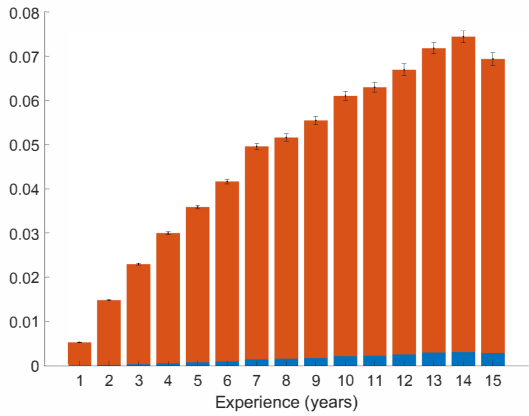
Figure 9: Wage loss decomposition



Note: Wage loss decomposition by years of experience. Blue bars: human capital depreciation component; red bars: match quality component.

Equation (3) specifies the value of being employed as a function of current earnings and continuation values, where the stock of human capital plays an important role. Displacement affects the stock of human capital and, therefore, the value of being employed. Value loss is larger for workers with higher levels of human capital. We decompose the value loss comes into two components, the depreciation of human capital when unemployed and the loss of the specific human capital at re-employment due to the imperfect match quality. We calculate the average displacement value loss to be 5%. Figure 10 shows an increasing value loss with experience. At three years of experience, the value loss is 2.3%, of which 98% is explained by imperfect match; at eight years of experience, the value loss is 5.2%, with 5% due to match quality; at 15 years of experience, the value loss is 6.9%, with 6.7% due to the match quality component.

Figure 10: Value loss decomposition



Note: Value loss by years of experience. Blue bars: losses due to the human capital depreciation; red bars: losses due to the match quality.

The value losses also vary with learning ability, for all levels of work experience. The average loss for a worker in the lowest quartile of learning ability is 1.6%, increasing at a relatively constant rate from 0.1% for workers with one year of experience, to 1.5% for workers with 15 years of experience. The average loss for a worker from the highest ability quartile is 6.7%, constantly increasing from 1% to 9% for workers with one to 15 years of experience.

5 Discussion

Section 2 analytically characterizes the model's dynamics, demonstrating how parameter changes affect key outcomes. In this section, we numerically analyze how policy and technology shifts impact individual allocations. We also explore the model's dynamics through a series of examples.

5.1 Unemployment benefit, b

The positive effect of unemployment insurance (UI) on unemployment duration is a well-documented empirical finding. For example, Moffitt and Nicholson (1982) show that a 10% increase in the re-

placement rate is associated with an increase in unemployment duration of about 0.9 weeks. Meyer (1990) estimates this effect at 1.0–1.5 weeks, while Moffitt (1985) estimates it at 0.5 weeks.

However, the literature on the relationship between unemployment benefits and post-unemployment job quality is less conclusive. For instance, Van Ours and Vodopivec (2006) and Card et al. (2007) find no effect of benefit duration on post-unemployment job quality, whereas Nekoei and Weber (2017) find that extending unemployment benefits by nine weeks increases wages by 0.5%, on average.

We examine how changes in the replacement ratio, b, affect unemployment duration, wage loss, average accepted match quality, and the fraction of accepted matches. Figure 11 presents results for workers with varying levels of learning ability (where q1 is the lowest learning ability quartile).

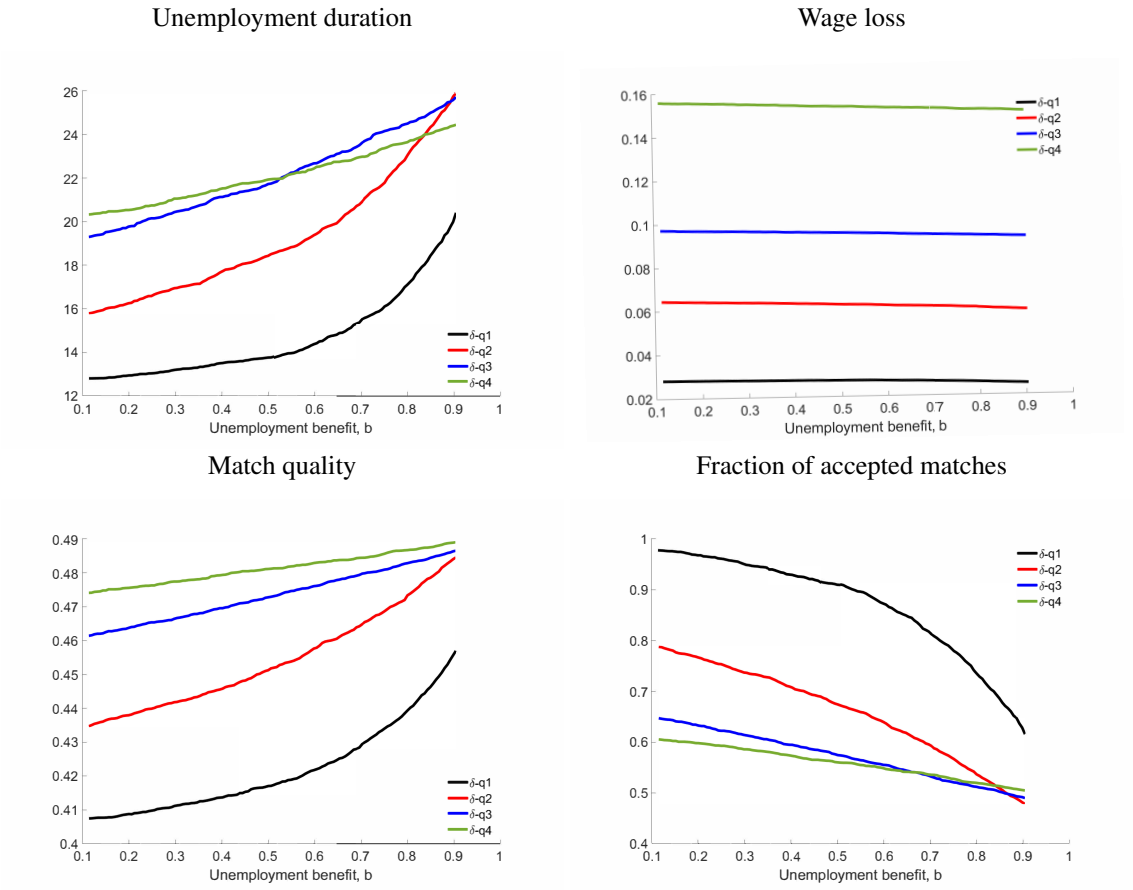
An increase in the value of being unemployed leads to a decrease in the fraction of accepted matches and a longer unemployment duration. There are small improvements in match quality and slight reductions in wage losses upon reemployment. The modest increase in match quality is offset by the greater depreciation of human capital during unemployment. These findings align with previous literature on unemployment duration and job quality.

5.2 Job offer arrival rate, α

It is well documented that the job finding rate plays a key role in explaining unemployment dynamics during economic cycles. Economic downturns are marked by rising job separation rates and falling job finding rates. For example, Shimer (2012) finds that the job finding rate accounts for three-quarters of the fluctuations in the unemployment rate.

We examine how changes in the job offer arrival rate, α, affect unemployment duration, wage loss, average accepted match quality, and the fraction of accepted matches. Analyzing displacement dynamics related to changes in the job offer arrival rate helps to understand the sources of cyclical costs of job losses. Figure 12 presents results for workers with different levels of learning ability. A decrease in the job offer arrival rate leads to longer unemployment durations and a higher fraction of accepted matches, which lowers average match quality. The combination of

Figure 11: Changes in unemployment benefit



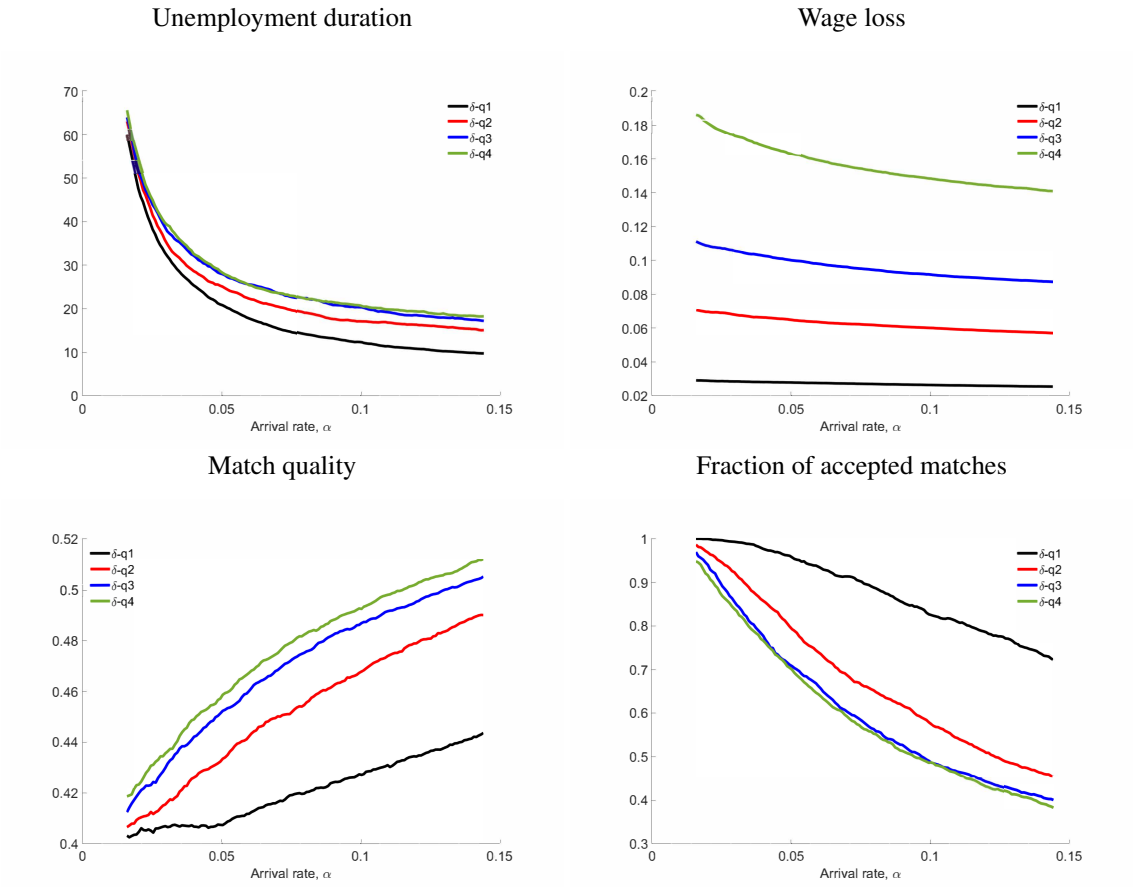
lower match quality and extended unemployment contributes to increased wage loss upon reemployment.

We examine how changes in the arrival rate affect unemployment duration for workers with different levels of work experience. We use the monthly Current Population Survey (CPS) to calculate unemployment duration before and during the GFC.[13] In 2003-2005 the mean unemployment duration for workers with 1-15 years of experiences was 19 weeks and in 2010-2013 it was 32.9 weeks. Figure 12 shows that to generate unemployment duration of 32.9 weeks, the job arrival rate, α, needs to decline from 8% to 3.6% per week.

We set α to 8% and 3.6% to simulate job search conditions in 2003-2005 and 2010-2013. Us-

[13]The sample is restricted to unemployed men between 18-50 years old who are not enrolled in school. Mean unemployment duration for each level of experience is calculated using the CPS weights. We use 2003-2005 and 2010-2013 samples to construct measures of unemployment before and during the GFC.

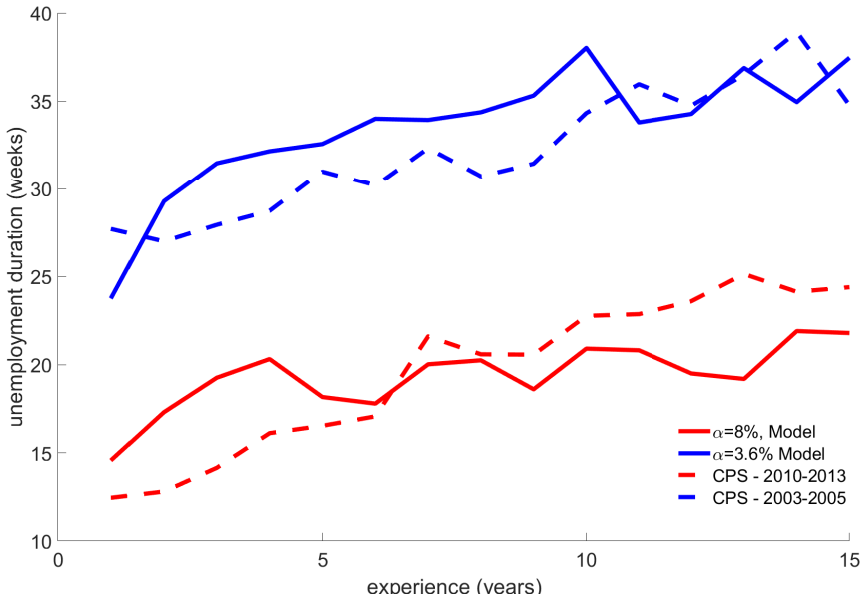
Figure 12: Changes in arrival rate



ing the model and CPS data, we calculate the mean unemployment spells by experience in these two environments. Figure 13 reports the results. Unemployment duration tends to rise with experience. In both data and model, a lower job arrival rate is associated with a longer unemployment duration for all workers. In the model, the effect of a lower arrival rate is more pronounced for those with lower experience; the data shows a similar pattern for workers with more than 5 years of experience.[14] In the model, the direct effect of a decline in the arrival frequency is a longer unemployment. However, it also reduces the reservation value of match quality which mitigates the impact on unemployment duration. Reservation value increases with human capital, while a decline in the arrival rate has the opposite effect, which implies that workers with a higher stock of human capital are less selective when the arrival rate is low.

[14]For example, using the CPS, we calculate that during the GFC, the average unemployment spell increased by 81% for workers with 6-10 years of experience and by 73% for those with 10-15 years of experience.

Figure 13: Unemployment duration by experience



5.3 Match quality distribution

We estimate the parameters of the match quality distribution and find that the average match quality is 40.5%, while the average match quality of an accepted offer is 45.8%. The match quality distribution can shift due to changes in the distribution of occupations and skill requirements. These shifts in labor market structure may be driven by factors such as technological advancements, offshoring, or a decline in demand for certain skills alongside rising demand for others. Another example is the expansion of remote work, which exposes workers to a broader range of job opportunities. We analyze how such shifts influence unemployment dynamics for displaced workers.

We conduct two exercises. First, we assess how changes in average match quality affect key post-displacement outcomes. Second, we evaluate the effects of changes in the variance of the match quality distribution on these outcomes.

Figure 14 shows that an increase in average match quality leads to a higher rate of accepted job

offers, resulting in shorter unemployment durations and reduced wage loss.

Figure 14: Changes in average match quality

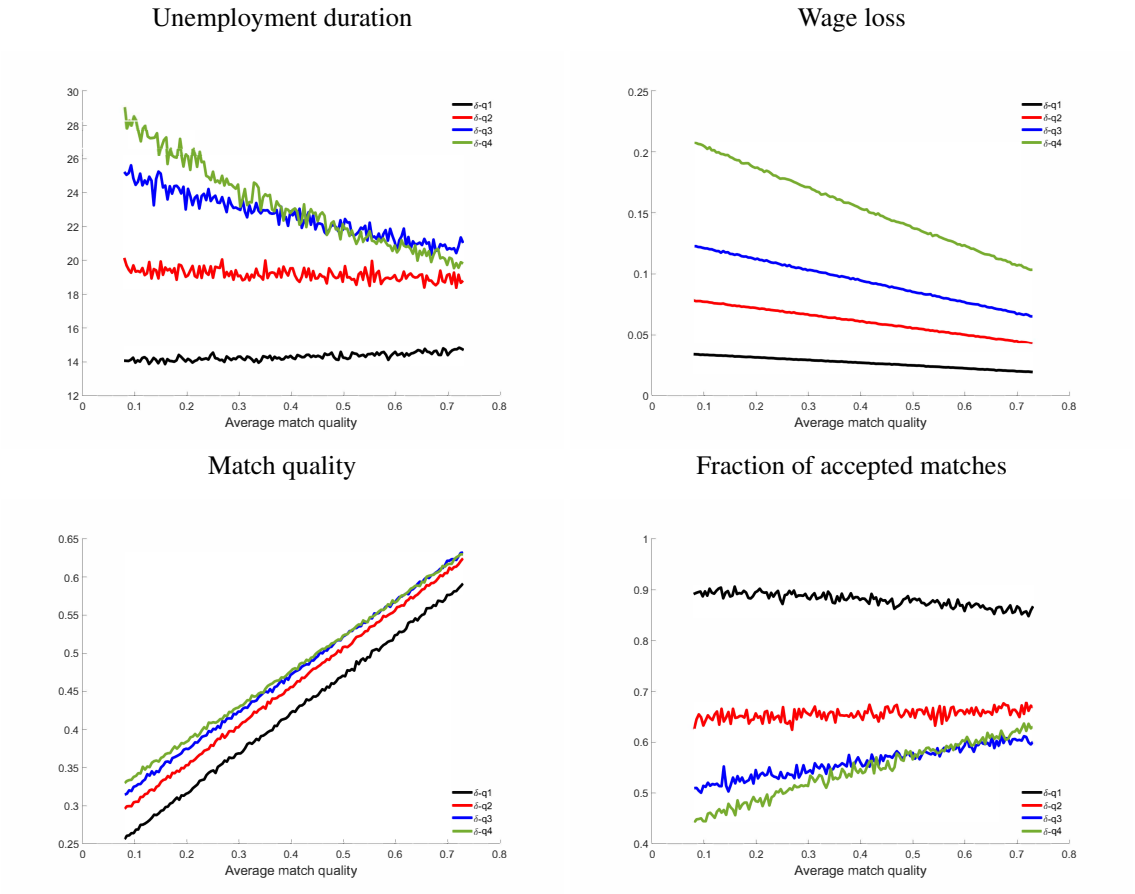
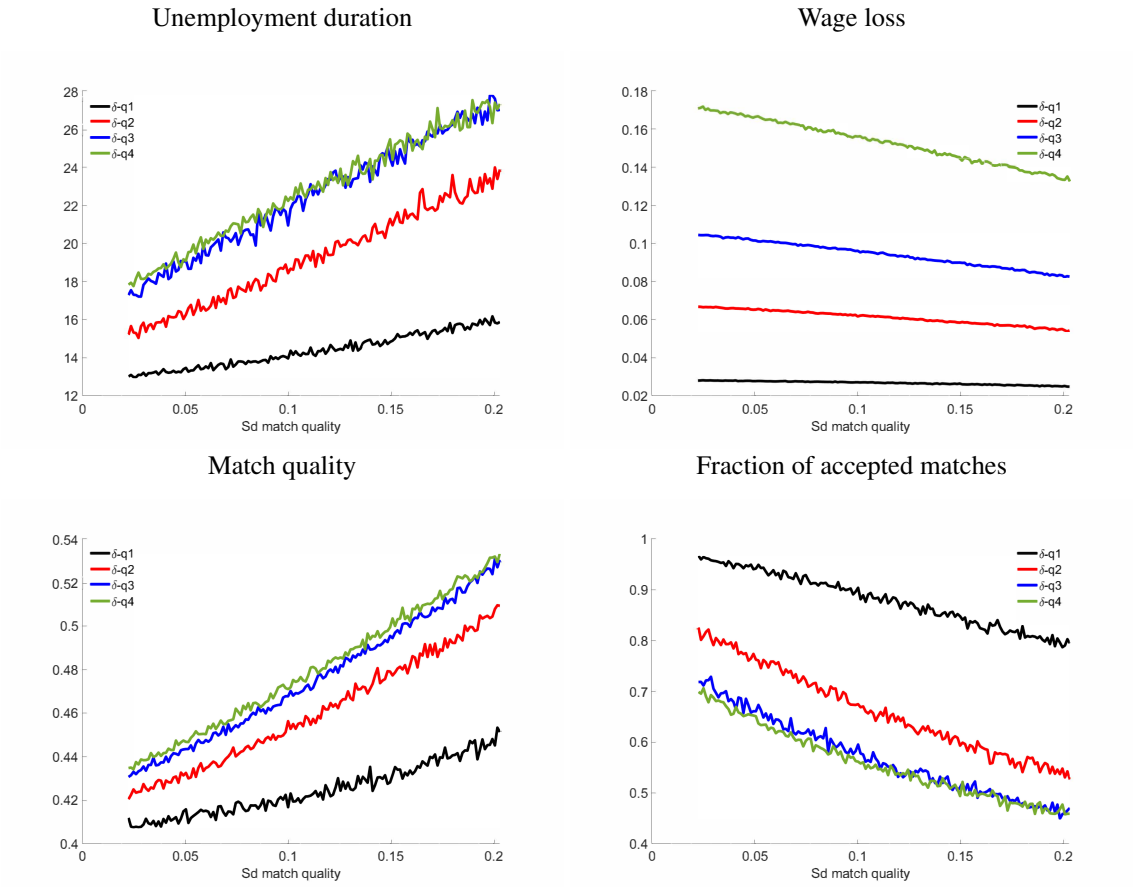


Figure 15 shows how changes in the variance of the match quality distribution on post-displacement dynamics. An increase in the variance of the match quality distribution raises the likelihood of securing a better match. This reduces the rate of accepted offers and raises the threshold for acceptable matches, leading to longer unemployment durations and smaller wage losses.

Figure 15: Changes in the variance of match quality



6 Conclusion

It is well documented that displaced workers experience large wage losses. We study the sources of these losses by generalizing the concept of human capital accumulation in a search model where human capital is neither purely match-specific nor purely transferable. The degree of human capital transferability is endogenous, with job match quality determining how much previously acquired capital a worker can transfer into a new job. The rematching process is a function of worker's prior experience and the ability to learn. Efficient reallocation of semi-specific human capital is central in the reemployment process and determines unemployment duration and post-displacement earnings. Using this framework we quantify the costs of displacement and assess how individual characteristics affect post-displacement outcomes.

We use the model to show that match quality on the new job, worker's prior experience and

ability to learn determine how much of the previously accumulated human capital is transferred to the new job, the wage at reemployment, and unemployment duration. Out of the 8.5% mean wage loss, 92% are attributed to the imperfect transferability of human capital. Workers accept 62% of offers and mean match quality is 45.8%. Wage losses are higher and unemployment is shorter for displaced workers with higher human capital and for those with higher learning abilities. Workers with higher pre-displacement human capital search longer for new jobs and accept higher match quality offers. The average recovery time is 48 weeks; however, and consistently with other studies, displaced workers do not catch up with those who were continuously employed. Many studies document positive relationships between the unemployment duration, size of post-displacement wage loss and work experience. Our framework generates a similar results and attributes it to the accumulated human capital.

In a range of theoretical and empirical exercises we show how the main outcomes of displaced workers respond to changes in model parameters. Our results are consistent with a range of empirical findings which relate the post-displacement dynamics to job finding rates, job market structure and unemployment benefits schemes. Labor market structure and policies affect the rematching problem of displaced workers and their losses. For example, the cyclicality in labor demand or spacial distributions of vacancies affects worker outcomes.

Our human capital transferability framework is a starting point to analyze the determinants of displacement losses caused by external shocks. Our framework can be particularly relevant to analyze shocks that have heterogeneous effects on workers, such as the China shock or technological change. Such shocks lead to an increase in demand for some skills while the demand for other skills declines. In such environment, workers in different occupations and sectors face adjustments to the match quality distribution, job arrival rates, and technology. Analyzing interactions between the different segments of the market is feasible by examining our framework in a general equilibrium setup.

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A Appendix

The following proposition relates to scaling all capital. We denote $V(.;\gamma k_0)$ and $W(.;\gamma k_0)$ the value functions for general HK value γk_0 and omit the second argument in the baseline when $\gamma = 1$.

Proposition 2. *(i)* $V(\gamma k;\gamma k_0) = \gamma^\theta V(k)$ *and* $W(\gamma k;\gamma k_0) = \gamma^\theta W(k)$. *(ii) The optimal thresholds are homogeneous of degree zero in* k *and* k_0. *(iii) After any history, the human capital* $k(t)$ *is homogeneous of degree one in* k_0 *and the starting capital* $k(0)$.

Proof. Suppose this holds on the right hand side value functions. Then:

$$\begin{aligned} rV(\gamma k;\gamma k_0) &= \gamma^\theta a k^\theta + \rho\left(W(\gamma k;\gamma k_0) - V(\gamma k,\gamma k_0)\right) + V'(\gamma k,\gamma k_0)\,\delta\gamma k_0 \\ &= \gamma^\theta a k^\theta + \rho\left(\gamma^\theta W(k) - \gamma^\theta V(k)\right) + \left[\frac{1}{\gamma}\gamma^\theta V'(k)\right]\delta\gamma k \\ &= \gamma^\theta V(k) \end{aligned}$$

where we are using:

$$V'(\gamma k;\gamma k_0) = \frac{1}{\gamma}\frac{\partial V(\gamma k;\gamma k_0)}{\partial k} = \frac{1}{\gamma}\gamma^\theta\frac{\partial V(k)}{\partial k}$$

and similarly,

$$\begin{aligned} rW(\gamma k;\gamma k_0) &= \gamma^\theta b k^\theta + \int_{z(k)}\left(V\left(s(\gamma k-\gamma k_0)+\gamma k_0;\gamma k_0\right) - W(\gamma k;\gamma k_0)\right)dF(s) \\ &\quad -V'(k;\gamma k_0)\,\lambda\gamma k \\ &= \gamma^\theta b k^\theta + \int_{z(k)}\gamma^\theta\left(V\left(s(k-k_0)+k_0\right) - \gamma^\theta W(k;\gamma k)\right)dF(s) \\ &\quad -\left[\frac{1}{\gamma}\gamma^\theta W'(k)\right]\lambda\gamma k \\ &= \gamma^\theta r W(k) \end{aligned}$$

Consider now an environment where the initial k_0 is augmented to γk_0 and where the agent starts at that initial capital (or the initial capital from where the agent starts is also scaled up by the

same factor). It follows quite immediately that after any history, the capital stock of the worker will be also scaled by the factor γ. So wage growth, unemployment duration and the percentage wage loss upon reemployment, after any history, will remain the same. □

Proposition 3. *The value functions are homogeneous of degree one in* a, b *and the thresholds invariant.*

Proof. $rV(k;\gamma) = \gamma a k^{\theta} + \gamma\rho(W(k) - V(k)) + \gamma V'(k)\delta k$ then $(Vk;\gamma) = \gamma V(k)$. Similarly for $W(k;\gamma)$. Finally from the third equation it follows immediately that scaling both sides doesn't change $z(k)$ so that:

$$W(k;\gamma) = V(z(k)(k - k_0) + k_0;\gamma)$$

□

ays increase in the average unemployment spell following a displacement. The higher return to human capital also implies an increase in the average wage loss, from 7.7% to 7.8%. The relative increase in the wage loss is similar across learning ability groups.