Wage Scars from Job Loss

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Abstract

Using a panel survey of workers from the PSID, we estimate the decrease in wages due to involuntary job loss. We find that this decrease leaves a lasting scar of over 20 years, costing average displaced workers 11.6% of their predicted hourly wages every year after reemployment. These losses vary: laid off workers lose 14.4% and workers displaced from company closings lose 5.7%. We use these facts to motivate a theory of permanent wage loss where the endogenously created worker scars vary based on the reason for displacement. The theory is useful in understanding the cause for these scars and it is also useful for understanding the lasting effects of the latest US recession.

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1 Introduction

The official unemployment rate is at nearly its highest level since record keeping began. In 2008 and 2009, the United States suffered the largest drops in total nonfarm payroll employment since the Great Depression. This decade has been a difficult decade for workers; however, the effects of job loss are not well understood. What happens to wages after job loss? Understanding the answer to this question is obviously important for understanding the plight of those unemployed but it is also provides critical insight into the nature of wage determination and labor income risk. The evolution of wages after job loss is also important for understanding the underpinnings of the US macroeconomy. For example, how do recessions affect income inequality?

We estimate the loss in predicted hourly wages for workers displaced from their job due to lay off or company closing. This decrease in wages lasts 20 years causing a scar indeed. Workers laid off lose 12.8% of their predicted hourly wage upon reemployment and this loss is still 11.3% 20 years after displacement. Workers displaced from a company closing also experience a scar to wages. We find that these workers lose approximately 5.7% of their predicted hourly wage and that this loss disappears for the most part after eight years.

A standard labor economics textbook may claim this loss in wages is due to lost human capital but this cannot explain why a job loss from being fired is so much more costly than a job loss from company closing. The scar from lost human capital would recover over time with a concave human capital accumulation function. This is essentially what we see for workers displaced due to a company closing.

Understanding how these scars are created is important as they lead to drastically different policy implications. If this scar is due to human capital loss, the policy prescription would require an effort to retrain. If this scar is due to information being
revealed about the quality of worker, there would be no policy prescription. Therefore it is important to decipher the cause of the scar.

Gibbons and Katz 1991 find that the immediate loss in wages from losing a job due to lay off is in fact larger than the loss in wages due to a company closing. These results have been questioned in the literature due to their use of the Displaced Worker Survey (DWS). Stevens 1997 uses an advantage in the Panel Study of Income Dynamics (PSID) over the DWS to control for wages prior to separation as well as individual fixed effects. She estimates that the predisplacement wage experience is worse for those displaced through company closings. This along with the estimation method documented in Jacobson, Lalonde and Sullivan 1993, results in no difference in losses for the two groups after displacement.

Our paper follows Stevens 1997 by using the PSID and the same method for estimating scars in the data. While Stevens finds that there is no difference between the two groups throughout the first six years of post job displacement, the difference in our estimates shows up immediately with the difference becoming much more drastic after the ninth year of postdisplacement. These long scars are essential to understanding the cause of wage scars from job loss.\(^1\)

We propose a theory of imperfect and asymmetric information that is consistent with the long scars we estimate. We build a dynamic general equilibrium model with learning on ability types along with different rates of human capital accumulation. There is imperfect information on the worker’s productivity and firms gradually learn the productivity of their workers. Firms then choose whether to keep incumbent workers or search for new workers. Outside firms observe a worker’s reason for unemployment. When a worker is fired, outside firms assume the productivity for the worker was low. For this reason, these workers will have deep scars on average. If a

\(^1\)Till Marco von Wachter mentions a finding similar to our long lasting scars in several popular media outlets using Social Security Administrative records. We will comment on how his approach differs from our approach once permission is granted to cite his working paper.
A worker loses a job due to a company closing, no additional information is revealed; the scar is not as deep.

The fact that the scars last for such a long period using a fixed effects estimator is puzzling. If the rate of human capital accumulation is the same for laid off workers and workers displaced due to company closings, scars for laid off workers will not stay deep like we see in the data. Therefore, a dynamic model allows us to quantify the rate at which human capital accumulation drops.

A dynamic general equilibrium model is also important for understanding the effect that this recession will have on wages and income inequality. If a recession is a time when more companies close, average scars should be smaller. This simple composition effect may fall apart in a general equilibrium setting because firms may choose to fire more workers due to the availability of more workers. Therefore, our framework allows us to explore these effects by changing a single exogenous parameter: probability of firm closure. Our findings shed light on whether imperfect information can account for changes in the effects of unemployment over the business cycle and provide insight on how cyclical unemployment should be understood.

2 Econometric Approach

2.1 The Panel Study of Income Dynamics (PSID)

The Panel Study of Income Dynamics (PSID) is a longitudinal study of US individuals and their family units conducted by the Survey Research Center, the Institute of Social Research and the University of Michigan. The study originally consisted of approximately 4,800 families with heads under the age of 60 years old. The Survey Research Center put together roughly 3,000 families from an equal probability sample for the 48 contiguous states of the United States. The rest of the original families
come from low income families from the Survey of Economic Opportunities conducted by the Bureau of the Census for the Office of Economic Opportunity. Through 1996, the PSID follows this group and its children regardless of residence.

We restrict our sample to male heads of households from the nationally-representative sample designed by the Survey Research Center. We want to avoid issues of young workers exiting the workforce for more education and we similarly want to avoid issues of older workers exiting the workforce to retire; therefore, we restrict our sample to 25 through 60 year old workers. We only consider hourly earnings above $1.00 in 1982-4 dollars and we ignore any worker that has ever been topcoded. Finally, we avoid issues that arise with using the PSID after the switch to biennial data collection in 1997 and only consider data through 1997. Throughout the coming analysis we have 4,069 individuals for approximately eight years on average resulting in 33,709 observations.

2.2 Estimation

We are interested in the effect of involuntary job loss at time $t - n$ on current wages $w_t$. Following Stevens 1997, this can be estimated by regressions of the following equation for individuals indexed by $i$:

$$\ln(W_{i,t}) = \alpha X_{i,t} + \beta D_{i,t-n} + \gamma y_t + \delta I + \epsilon_{i,t}$$

The dependent variable is the natural log of real hourly earnings in 1982-4 dollars. The independent variables include a vector of non-time stationary observable characteristics($X$), a dummy variable that captures involuntarily displacement ($D_{i,n}$) in year $t - n$, a year dummy ($y_t$) and an individual fixed effects dummy ($I$). Note that the displacement variable $D_{i,n}$ includes separate dummies for each year prior to displacement, the year of each displacement, and each of the first through 20th years.
following each displacement (ie: \( n \in \{-3, -2, -1, 0, 1, \ldots, 20\} \)).

We chose the individual fixed effects specification because of the presence of unobserved heterogeneity that is likely to be correlated in a systematic manner with both wages and probability of displacement. If these fixed effects are omitted and individuals differ in some respect, say ability, that causes workers with lower wages to be more likely to get displaced. The effect of displacement \( \beta \), would be overstated. In general, the individual component of the error term will not be orthogonal to the explanatory variables and a random effects or pooled OLS estimate will be inconsistent.

There are two main drawbacks to the use of a fixed effects specification. We cannot control for non-time varying observed characteristics. However, it is unclear that these characteristics would bias our estimates in any systematic way. Second, we are likely to underestimate the effect of displacement on younger workers. If displacement essentially shifts the age-earnings profile downwards, it will lower lifetime mean earnings. This is an effect that will be captured by the individual fixed effect and not the displacement dummy. A possible alternative strategy would be to control for individual heterogeneity by including wages prior to displacement as an independent variable. This specification is not without fault because wages often stagnate or fall prior to displacement and prior wages are likely to be absent or uninformative for younger workers.

Year fixed effects are included to control for macroeconomic conditions. This is necessary because probability of displacement is correlated with aggregate wage growth stagnation. Not including year fixed effects would likely overstate the effect of displacement. The vector of non-time stationary observable characteristics \( \mathbf{X} \) includes the individual’s age and age-squared. This will control for the typical age-earnings profile.

We chose real hourly wages as the dependent variable for several reasons. First, we
are interested in permanent scars of unemployment and not the transitory effects. For this reason we do not include total earnings because they would take into account losses during the period an individual is unemployed; these are temporary losses. Additionally, total earnings may be less following a job loss because an individual may choose to work reduced hours for a variety of reasons. Again, this is a temporary effect. We claim hourly wages are more likely to capture things like match-quality and match or sector specific human capital which may be lost permanently upon displacement. In a similar vein, hourly wages may be more likely to capture depreciation in general human capital or stigma effects which may have varying levels of persistence. Second, wages are better for capturing welfare effects of job loss. Total earnings can be large or small depending on income and substitution effects with leisure and may not reflect changes in welfare.

In our analysis we assume classical measurement error in the dependent variable, hourly earnings. We do not know of any evidence of measurement error otherwise for hourly earnings measures in the PSID. Additionally, the PSID has the advantage that the hourly earnings variables were hand-coded and checked for errors both electronically and by hand for the majority of our sample.

### 3 Econometric Results

The lasting scar from job loss is quite clear in Figure 1. This figure depicts the scar to all displaced workers whether the job loss is due to the company closing or whether the job loss is due to being laid off. The x-axis accounts for the years since displacement and the y-axis depicts the percentage loss in real hourly earnings.

These losses are computed as $e^{z} - 1$.
The loss to wages is substantial after the first year when workers lose 12.8% of their hourly wage. There is some recovery culminating six years after job loss when displaced workers have wages that are 9.5% lower than would be expected. After this, the loss to wages gets worse. To understand this, we differentiate between the experiences of the two types of displaced workers.

The experience of displacement is quite different. Figure 2 depicts the experience for workers displaced due to lay off that have never experienced job loss due to a company closing. We see that they experience a sharper drop losing 16.2% of their expected wages a year after displacement. These losses follow a pattern similar to the one described above where losses on average are at their lowest six years after displacement. However, the drop after year six is much deeper. Wages are 19.8% lower 17 years after job loss for workers that lose their jobs due to a layoff; this loss is still at 13.3% after 20 years.

Figure 3 demonstrates the experience of workers that lose their job due to a
Figure 2:

[Graph showing the estimated change in wages for laid off workers over time from a company closing. The x-axis represents years since displacement, ranging from 0 to 20, and the y-axis represents the estimated change in expected wages, ranging from -0.25 to 0.25. The graph indicates a significant drop in wages within the first few years, followed by a gradual recovery over time.]
company closure. These displaced workers also suffer losses to hourly wages that last although they are not as deep. The sharpest drop in wages is evident two years after job loss when wages loss is at nearly 12%. Notice that these workers experience quite a recovery with wage loss at 6% eight years after job loss. It is also clear that variance in these wage losses are much higher here. Losses become statistically insignificant at the 5% confidence level in year nine. However, scars from this experience are statistically significant in years eighteen and nineteen. Displacement from job closure is an experience that stays with these workers as well although the experience is not nearly as severe.

3.1 Estimation During Recessions

The experience of unemployment may very differ if that displacement occurs during a recession. This will be especially true during a large recession similar to the most recent United States experience. To test this hypothesis we estimate the same equation as our basic regression with additional dummies for whether the displacement took place during the recession of the early 1980s ($R_{t-n} = 1$ if year $t - n$ is a year is 1980-1982).

$$\ln(W_{i,t}) = \alpha X_{i,t} + \beta D_{i,t-n} + \beta r D_{i,t-n} * R_{t-n} + \gamma y_t + \delta I + \epsilon_{i,t}$$

Figure 4 demonstrates our results. Notice that the additional scar for job loss in a recession is positive. This result is immediately statistically significant in the year of job loss and during recovery the result is statistically significant year four and stays significant through year ten. The loss to wages for these workers is about two-thirds the size of the losses for workers outside of this time frame.
4 Model

In this section we construct a model to explore whether informational frictions can account for the permanent earnings losses of fired workers. The important distinction of our model compared to others with the same goal is that our model is dynamic: both firms and workers are long lived. This allows us to critique the usefulness of informational frictions by taking into account the speed of learning. We will evaluate whether results from two period models fall apart when individual fixed effects are considered over a long working life, as in our empirical work.

4.1 Environment

The economy is populated by workers and plants. Time is discrete.
4.1.1 Workers

There exists a measure one of workers. Workers die with probability $\delta$ each period and are replaced by a measure $\delta$ of new labor market entrants. Workers are characterized by time-invariant individual productivity $a_i$ drawn independently across workers from the distribution $F_a$. A worker’s productivity is unknown to all agents, but all agents know the distribution $F_a$. Each period the worker is endowed with a single indivisible unit of labor which they may supply to home production or production in a single plant. The worker is risk neutral and his objective is to maximize the expected future value his wages.

4.1.2 Plants

There are two types of plants: $j \in \{L, H\}$. These plants differ in their production functions. Output in type $j = L$ plant is a function of time-invariant plant productivity $z_L$ and match-specific human capital, $h(\tau)$, a function of worker tenure $\tau$. Output in type $j = H$ plant is a function of time-invariant plant productivity $z_H$, match-specific human capital, $h(\tau)$, and worker ability $a_i$. A plant’s type is public information and $z_L < z_H$. Limiting firms to two types allows us to have directed search while abstracting from issues of adverse selection. Plants die with probability $\rho$ and enter after paying a fixed entry cost $\eta_j$. The firm is risk neutral and the objective of the firm is to maximize expected future profits. The measures of firms of each type $(\psi_j)$ is endogenous and satisfies a zero-profit condition.

4.1.3 Production & Beliefs

A worker-plant match produces output $y_{i,j} = z_j(x_i + h(\tau))$, where $x_i = (a_i + \epsilon)$ and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon)$ is i.i.d across worker-plant matches and over time. Tenure is given by $\tau$ with $h(\tau)$ being accumulated firm-specific human capital. This output is only observ-
able to the worker and plant within the match. Given that $z_j$ is public information and $a_i$ is unobservable to all parties, the matched worker and firm extract the noisy signal $(a_i + \epsilon)$. They update their beliefs on $a_i$ conditional on information pertaining to the entire history of the match, $\Sigma_{i,j,\tau}$ using Bayes’ Rule. Posterior beliefs of $a_i$ depend on tenure $\tau$ and are distributed with mean $m_{i,\tau}$ and variance $s_{i,\tau}$. Matches can be broken by plants or workers when the expected value of continuing the match is less than the expected value of posting a vacancy or searching for a new match or operating home production.

4.1.4 Search and Matching

The reason for a worker’s unemployment is public information. Search is divided into three types of markets indexed by reason for unemployment $k \in \{f, q, SD, NE\}$, where $f=$ fired, $q=$ quits, $SD=$ plant shut down, $NE=$ new labor market entrant with no history. Potential employers form beliefs over workers’ productivity given reason for displacement, they do not observe beliefs over ability from prior matches. Unemployed workers in each market choose to search for employment or collect home production $h$. Searching workers choose which type $j$ of firm to direct their search for. Plants posting vacancies search in all markets simultaneously and receive at most one meeting in each period. The total number of meetings between plants of type $j$ and workers displaced by cause $k$ directing applications to plants of type $j$ is given by the function $m(u_{j,k}, v_j)$, where $u_{j,k}$ is the measure of unemployed workers directing search towards plant of type $j$ and $v_j$ is the measure of vacant plants of type $j$. The probability an unemployed worker of type $k$ meets a plant in the current period is $M_{u}^{j,k} \equiv \frac{m(u_{j,k}, v_j)}{u_{j,k}}$. The probability a plant posting a vacancy meets a worker of type $k$ in the current period is $M_{v}^{j,k} \equiv \frac{m(u_{j,k}, v_j)}{v_j}$. Upon meeting the pair observe a noisy signal

\footnote{Where $h$ is sufficiently small such that there are operating plants of each type}
of \( a_i \) and decide whether to form a productive match. We assume the function \( m(\cdot, \cdot) \) is nondecreasing in each argument and the number of firms and workers is sufficiently large such that both take \( u \) and \( v \) as given.

Once a productive match is formed, all agents ignore the reason for the worker’s prior unemployment.

4.2 Timing & Markets

Each period is divided into three phases:

1. **Production**: Production takes place. Wages are paid according to contracts set in the previous period and the plant collects the residual as profits. Worker-Plant matches update beliefs on \( a_i \).

2. **Separations**: The following separations occur sequentially in the following order:
   - **Fired Workers** Workers displaced endogenously by plants.
   - **Quit Workers** Workers who endogenously choose to end match.
   - **Shut Down Workers** A measure \( \rho \) of randomly chosen workers displaced exogenously by firm shut down.
   - **New Labor Market Entrants** A measure \( \delta \) of randomly chosen workers die and are replaced with new labor market entrants with no histories.

3. **Hirings**: In each market, displaced workers or new entrants choose whether to exit the labor force and produce in home production or search in the current market by reason of unemployment. If a worker searches, he also chooses which
type $j$ firm to apply to. When a worker meets a firm, next period’s wages are negotiated by Nash Bargaining. A match is created if both plant and worker agree given beliefs and the bargained wage.

4.3 Value Functions

The relevant state variables are $\Sigma \equiv \{m, s, \tau\}$: mean $m$ and variance $s$ of beliefs over $a_i$, and tenure $\tau$.

4.3.1 Plants

Let the expected value of a plant of type $H$ with match $(m, s, \tau)$ be given by $\Omega^H(m, s, \tau)$ where the wage paid is $\omega(m, s, \tau)$ and plants collect profits $y_{i,j} - \omega(m, s, \tau)$.

\[
\Omega^H(m, s, \tau) = z_H(x_i + h(\tau)) - \omega(m, s, \tau) + \\
(1 - \delta)(1 - \rho)E[\Omega^H(m, s_{\tau+1}, \tau + 1)] + (1 - \rho)\delta E[V^H], \\
(1 - \rho)E[V^H]
\]

The first term in the max operator is the expected value of continuing the match and the second term is the expected value of choosing to post a vacancy in the next period. The plant chooses threshold $m_{i,j,\tau}^f$ below which to fire its current worker in order to maximize the above programming problem.

The expected value of a plant of type $L$ is simply:
\[ \Omega^L(\tau) = z_L(1 + h(\tau)) - \omega_L(\tau) + \max\{(1 - \delta)(1 - \rho)\mathbb{E}[\Omega^L(\tau + 1)] + (1 - \rho)\delta\mathbb{E}[V^L], (1 - \rho)\mathbb{E}[V^L]\} \]  

Let \( \mathbb{E}[V^j_k] \) be the expected value for a plant of type \( j \) of meeting a searching worker unemployed for reason \( k \). Firms posting vacancies receive at most one meeting each period. Then, the expected value of posting a vacancy, \( \mathbb{E}[V^j] \), is defined as:

\[ \mathbb{E}[V^j] = \sum_{k \in \{f, q, SD, NE\}} (M^j_{i,k} \mathbb{E}[V^j_k] + (1 - \rho)(1 - M^j_{i,k})\mathbb{E}[V^j]) \]  

When meeting a worker of unemployment type \( k \), the type \( H \) plant forms an expected distribution of the worker’s ability \( a_i \) consistent with firing and hiring rules of other plants. Let \( F_k \) be the cumulative distribution function over \( a_i \) of worker of unemployment type \( k \). Given expectations, the plant decides whether to form a productive match with the worker or continue posting a vacancy next period:

\[ V^{H,k} = \max\{\int_{-\infty}^{\infty} \Omega^j(m_k, s'_k, 0)\partial F_k(m), (1 - \rho)\mathbb{E}[V^H]\} \]  

Output at plants of type \( L \) is independent of workers’ abilities. These plants face the following problem:

\[ V^{L,k} = \max\{\Omega^L(0), (1 - \rho)\mathbb{E}[V^L]\} \]

Let \( \tilde{m}^{j,k} \in \{0, 1\} \) equal 1 if plant \( j \) will match with a worker of unemployment
Then the expected value of a vacancy becomes:

$$\mathbb{E}[V^j] = \sum_{k \in \{f,q,SD,NE\}} [M^{i,k}_v m^{i,k}] \int_{-\infty}^{\infty} \Omega^j(m, s', 0) \partial F_k(m) + [(1 - M^{i,k}_v)] \mathbb{E}[V^j] \quad (6)$$

Entrants must pay a cost $\eta_j$ to establish a plant of type $j$. New plants are established if expected profits are greater than the entry cost:

$$\mathbb{E}[V^j] \geq \eta_j \quad (7)$$

### 4.3.2 Workers

Let the expected value to a worker of a match $(m, s, \tau)$ with plant of type $j$ be given by $W^j(m, s, \tau)$ where the wage paid is $\omega(m, s, \tau)$.

$$W^j(m, s, \tau) = \omega_j(m, s, \tau) +$$

$$+ \max\{(1 - \delta)(1 - \rho)\mathbb{E}[W^j(m, s_{\tau+1}, \tau + 1)] + (1 - \delta)\rho \mathbb{E}[U^{SD}(m)],$$

$$(1 - \delta)\mathbb{E}[U^q(m)]\} \quad (8)$$

The first term in the max operator is the expected value of continuing the match and the second term is the expected value of choosing to search in the next period. The worker chooses threshold $m^q_{i,j,\tau}$ below which to exit the match in order to maximize the above programming problem.

A worker with unemployment cause $k$ chooses whether to search for a new job or exit the labor force and consume home production $h$ for the remainder of his life. A searching worker additionally chooses whether to direct his applications to firms of
high-type or low in order to solve the following dynamic program.  

\[
U^k(m) = \max\{ \max_{\bar{g}^k \in \{h,l\}} M_{\bar{g}^k, k} \bar{m}^{\bar{g}^k, k} W^{\bar{g}^k}(m, s', 0) + (1 - \bar{m}^{\bar{g}^k, k}) U^k(m), \quad (9) \\
\frac{h}{1 - (1 - \delta)} \}\]  

\[
4.3.3 \text{ Wages and Profits} \\
\]

Output is split between worker and firm by Nash Bargaining with bargaining weight of the worker exogenously given by $\phi$.

\[
(1 - \phi)(\Omega^j[\omega(\Sigma_{i,j,\tau})] - E[V^j]) = \phi(W[\omega(\Sigma_{i,j,\tau})] - E[U[\Sigma_{i,j,\tau}]])) \quad (11) \\
\]

\[
4.4 \text{ Equilibrium} \\
\]

An equilibrium is a set \{ $\Omega^j(m, s, \tau), V^j, U_i^k, W^j(m, s, \tau), m_{i, j, \tau}^f, m_{i, j, \tau}^q, H, G, V, U, \omega_{i, j, \tau} \}$ \}

defined as follows:

\footnote{$m_i = \bar{a}$ for new entrants}
• \( \Omega^j(m,s,\tau) \) Value function of a plant with a match \((m,s,\tau)\)

• \( V^j \) Value to a plant of posting a vacancy

• \( W^j(m,s,\tau) \) Value function of a worker with a match \((m,s,\tau)\)

• \( U^k(m) \) Value to a worker of unemployment in pool \(k\)

• \( m^f_{j,\tau} \) threshold beliefs below which workers are fired by a plant.

• \( m^q_{j,\tau} \) threshold beliefs below which workers choose to quit.

• \( H \) set of hiring rules \(\{\tilde{m}^{j,k,\tau}\}\),

• \( G \) set of applying rules \(\{g^k(m)\}\)

• \( V \) set of measures of vacancies \(\{V^k_j\}\)

• \( U \) set of measures of unemployed workers searching \(\{W^k\}\)

• \( \omega_{i,j,\tau} \) set of wage contracts

For continuous index of worker type \(i\), firm types \(j \in \{H, L\}\), tenure possibilities \(\tau \in \mathbb{Z}^{++}\), and search markets \(k \in \{F, SD, NE\}\). Such that, given exogenous parameters \(\Theta\)

• Decision rules solve plant/workers problems

• Beliefs are updated using Bayes’ Rule

• Expectations are consistent with decision rules and beliefs

• Aggregate measures are consistent with decision rules, beliefs, and zero-profit condition.

• Wage contracts determined by Nash Bargaining

Where the zero profit condition for firm of type \(j\) is: \(\eta_j = \mathbb{E}[V^j]\)
5 Equilibrium Characterization

In this section we will solve for the equilibrium objects described above. To do so, we will impose an additional assumption on contracts. We assume contracts specify that workers receive all returns from specific human capital. This allows us to guess a functional form for wages determined by Nash Bargaining and verify these wages are consistent with the definition of an equilibrium.\textsuperscript{5} While the effect of this assumption on wages is unimportant (workers and firms would split the returns according to bargaining weights), we acknowledge this assumption has an important effect on firing decisions of plants.

Conjecture 1: Equilibrium wages $\omega_{i,j,\tau}$ are piecewise-linear in $m_{i,j,\tau}$ and independent of $s$, ie: $\omega_{i,j,\tau} = \lambda^j m_{i,j}$

Conjecture 2: Given that conjecture 1 holds, threshold beliefs for firing/quitting and hiring are independent of $\tau$, ie: $m_{j,\tau}^f = m_j^f$, $m_{j,\tau}^q = m_j^q$, and $\bar{m}_{j,k,\tau}^i = \bar{m}_{j,k}^i \forall j,k$

We now characterize the equilibrium holding the above conjectures as true. Then we verify the conjectures do, indeed, satisfy decision rules.

5.1 Parameter Restrictions

We provide restrictions on parameters to limit our focus to environments relevant to our question.

Restriction 1: $\mathcal{F}_a = \mathcal{N}(\bar{a}, \sigma_a)$

First, we assume $\mathcal{F}_a = \mathcal{N}(\bar{a}, \sigma_a)$ for closed form solution.

\textsuperscript{5}This does not mean there do not exist other functional forms that can yield equilibria under these restricted contracts
Restriction 2: Sufficiently small home production $h$

We impose home production $h$, is sufficiently small such that firms of low type operate.

5.2 Beliefs About Worker Productivity

5.2.1 Evolution of Beliefs over Match Duration

Beliefs about productivity within a plant-worker match evolve according to Bayes’ rule given signal $x_i = (a_i + \epsilon)$ observed each period. The beliefs within the match for a worker with tenure $\tau$ are normally distributed with mean $m_{i,j,\tau}$ and variance $s_{\tau}^2$ defined recursively as follows:

$$m_{i,j,\tau} = \left( \frac{m_{i,j,\tau}}{s_{\tau-1}^2} + \frac{x_{i,j,\tau-1}}{s_{\epsilon}^2} \right) / \left( \frac{1}{s_{\tau-1}^2} + \frac{1}{s_{\epsilon}^2} \right)$$

$$\frac{1}{s_{\tau}^2} = \frac{1}{s_{\tau-1}^2} + \frac{1}{s_{\epsilon}^2} = \frac{\sigma_\epsilon + \sigma_a}{\sigma_\epsilon^2 \sigma_a^2} + \frac{\tau - 1}{\sigma_\epsilon^2}$$

Note the precision of the signal, $\frac{1}{s_{\tau}^2}$, increases deterministically with tenure. It is well-known that this specification for the evolution of beliefs is unbiased and efficient:

$$\lim_{\tau \to \infty} m_{i,j,\tau} = a_i$$

$$\lim_{\tau \to \infty} s_{i,j,\tau}^2 = 0$$

Furthermore, the posterior mean is a martingale. Expectations about future realizations of $m_{i,j,\tau}$ conditional on the entire history $\Sigma_{i,j,\tau}$ are distributed as follows for any $p > \tau$: 

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\[ m_{i,j,p}\mid \Sigma_{i,j,\tau} \sim \mathcal{N}(m_{i,j,\tau}, \frac{s_4^2(p-\tau)}{s_4^2(p-\tau) + \sigma_e}) \]

### 5.2.2 New Entrants

The expectation of each new entrant’s productivity is distributed as the true productivity distribution: \( \mathcal{F}_a \)

**Theorem 1**: All new entrant workers apply to high type firm.

### 5.2.3 Workers Displaced by Firing

**Theorem 2**: In equilibrium, no worker fired from a high firm will be rehired by a high firm.

*Proof- to be formalized* Intuition: If a high firm fires a worker of type \( \tilde{m} \), then it carries additional information that \( \tilde{m} \) was sufficiently low such that the expected future profits of the match were less than the expected value of searching. Since the expected value of searching is the same for firms with or without matches, outside firms do not need to observe \( \tilde{m} \) to know the expected value of searching is greater than hiring the worker.

Since output from firms of low types does not depend on worker ability, the expectation of hiring a fired worker is simply: \( \Omega^L(0) \).

### 5.2.4 Workers Displaced by Shut Downs

Since the probability of shutdown is the same for all workers, the distribution over ability of shut down workers is equal to the distribution for new entrants. Therefore,
high plants hire shut down workers iff they hire new entrants. Since we restricted parameters such that there is positive employment at high plants, we know $\bar{m}_j^{i,k,\tau} = 1$

5.3 Wages

Wages $\omega(m, s, \tau)$ solve the following Nash Bargaining problem:

$$(1 - \phi)(\Omega^j(\omega_j(m, s, \tau)) - E[V]) = \phi(W^j(\omega_j(m, s, \tau)) - E[U])$$

5.3.1 Firm’s Match Surplus

It will be useful to introduce the following notation: let $G^j_r(m) \equiv Pr(m_{i,j,r} < m | \Sigma_{i,j,\tau})$ for $r > \tau$. A plant’s expect match surplus is defined as:

$$\Omega^j(\omega_j(m, s, \tau)) = E_{\tau}y_{i,j,\tau} - \omega_j(m, s, \tau) +$$

$$+ (1 - \delta)(1 - \rho)[1 - G^j_{r+1}(\bar{m}^j_{\tau + 1})] \int \Omega^j(\omega_j(m, s + 1, \tau + 1)) \partial F(\Sigma_{\tau + 1}^j | \Sigma_{\tau}),$$

$$+(1 - \rho)(G^j_{r+1}(1 - \delta) + \delta)E[V^j]$$

By Conjectures 1 & 2 following our restriction on contracts, a plant’s expected match surplus, for each type, simplify to:

$$\Omega^H(\omega^H(m, s, \tau)) = (z^H(m_{i,j,\tau}) - \omega^H(m, s, \tau)) \left(1 + \sum_{s=\tau+1}^{\infty} ((1 - \delta)(1 - \rho))^{s-\tau} \prod_{r=\tau+1}^{s} [1 - G^j_r(\bar{m}^j_r)] \right)$$

$$+ E[V^H] \sum_{s=\tau+1}^{\infty} \left[ ((1 - \delta)(1 - \rho))^{s-\tau-1}(\delta + (G^j_s)E[V^j]) \right] \prod_{r=\tau+1}^{s-1} [1 - G^j_r(\bar{m}^j)]$$

$$\Omega^L(\omega^L) = (z^L - \omega^L) \left(1 + \sum_{s=\tau+1}^{\infty} ((1 - \delta)(1 - \rho))^{s-\tau} \right)$$

$$+ E[V^L] \sum_{s=\tau+1}^{\infty} \left[ ((1 - \delta)(1 - \rho))^{s-\tau-1}\delta \right]$$
The expected value of posting a vacancy for generic plant \( j \) is:

\[
E[V^j] = \frac{M^j_v}{(1 - \rho)(1 - M^j_v)} \int \Omega(\omega(m, s, 0)) \partial F_a(m)
\]  

(16)

Following Conjectures 1& 2, restrictions on contracts and directed search, expected value of a vacancy for each type simplify to:

\[
E[V^H] = \frac{M^H_v}{(1 - \rho)(1 - M^H_v)} (z^H - \omega^H(\bar{\omega}, \sigma, 0)) \left( 1 + \sum_{s=\tau+1}^{\infty} ((1 - \delta)(1 - \rho))^{s-\tau} \prod_{r=\tau+1}^{s} [1 - G_r(\bar{m}^f)] \right)
\]

(17)

\[
E[V^L] = \frac{M^L_v}{(1 - \rho)(1 - M^L_v)} (z^L - \omega^L) \left( 1 + \sum_{s=\tau+1}^{\infty} ((1 - \delta)(1 - \rho))^{s-\tau} \right)
\]

(18)

\[
5.3.2 \text{ Worker's Match Surplus}
\]

A worker’s expected match surplus is defined as:

\[
W^j(\omega_j(m, s, \tau)) = \omega_j(m, s, \tau) + (1 - \delta)(1 - \rho)[1 - G_{\tau+1}(\bar{m}^f(\tau + 1))] \int \Omega^j(\omega_j(m, s + 1, \tau + 1)) \partial F(\Sigma_{\tau+1}|\Sigma_r),
\]

\[
(1 - \delta)(G_{\tau+1}(1 - \rho) + \rho)E[U^q]
\]

Given this and Conjectures 1 & 2 following our restriction on contracts, a worker’s expected match surplus, for each type, simplify to:

\[
W^H(\omega_H(m, s, \tau)) = \omega_H(m, s, \tau) \left( 1 + \sum_{s=\tau+1}^{\infty} ((1 - \delta)(1 - \rho))^{s-\tau} \prod_{r=\tau+1}^{s} [1 - G_r(\bar{m}^f)] \right)
\]

(19)

\[
+ E[U^q] \sum_{s=\tau+1}^{\infty} \left( (1 - \delta)(1 - \rho)^{s-\tau-1}(\rho + (G_s)E[V^j]) \prod_{r=\tau+1}^{s-1} [1 - G_r(\bar{m}^f)] \right)
\]
\[ W^L(\omega_L) = \omega_L \left(1 + \sum_{s=\tau+1}^{\infty} ((1-\delta)(1-\rho))^{s-\tau}\right) \]  \hspace{1cm} (20)

\[ + E[U^q] \sum_{s=\tau+1}^{\infty} [(1-\delta)(1-\rho)]^{s-\tau-1}\rho] \]

**Theorem 3** Workers who quit will not be hired by high-type firms

**Proof** Sketch: Workers quit only if the gains from entering with no information are greater than their current wage plus accumulated payments from match-specific human capital. This implies that their belief over their ability must be sufficiently low; in particular lower than the mean ability in the population. High firms will chose not to hire these workers.

By Theorem 3, a worker’s only outside option is employment in a firm of low type.

\[ E[U^q] = \frac{M_u^L}{(1-\delta)M_u^L} \omega_L \] \hspace{1cm} (21)

Following Conjectures 1& 2, restrictions on contracts and directed search, expected value of quitting simplifies to:

\[ E[U^q] = \frac{M_u^L}{(1-\delta)(1-M_u^L)} \omega_L \left(1 + \sum_{s=\tau+1}^{\infty} ((1-\delta)(1-\rho))^{s-\tau}\right) \]

\[ \frac{1}{(1-\delta)(1-M_u^L)E[U^q]} \sum_{s=\tau+1}^{\infty} [(1-\delta)(1-\rho)]^{s-\tau-1}\rho] \]

**6 Results**

Using the value functions defined above, we can estimate the effectiveness of our theoretical model and use it to answer the following questions: How much of the scar is due to lost human capital versus stigma? What does the model suggest to be the change in the rate of human capital accumulation. Finally, we can also use the model to explain why an increase in plant shut downs cause a smaller scar as seen in the
empirical results.

6.1 Parameters

There are several decisions to be made on parameters values and the appropriate functions within the model. We use a simple matching function: \( m(u_{j,k}, v_j) = u_{j,k}v_j \).

The probability that a firm finds a match, is simply equal to the proportion of unemployed workers searching for work in that type of firm. The probability that an unemployed worker finds a match is also equal to the proportion of vacant firms willing to hire that type of unemployed worker. We equalize the Nash bargaining weights between workers and plants to abstract from the issue of what the correct weight should be. We set \( \rho \) to be consistent with the frequency of workers displaced due to company closings in the data. Finally, we do not want the results to be driven by the productivity of the firms and therefore choose the productivities to be equal. Notice that what is then driving the differences in wages for the two types of firms is that workers at the high firm are rewarded for their productivity whereas all workers are treated the same at the low firm.

One other important distinction between the two types of firms is related to their human capital accumulation functions. For workers at the high type firm, the human capital accumulation function \( h(\tau) = 0.0774\tau - 0.0013\tau^2 \) is consistent with findings in the literature.\(^6\) The lack of recovery by the displaced workers in the empirical results also suggest that the rates of human capital accumulation differ for workers based on their different reasons for displacement. Based on this numerical experiment, the rate of human capital accumulation must drop by 99% to get these long lasting scars as we see in the data.

---

\(^6\)In this case, we target the results on returns to employer tenure found in Kambourov Manovski 2009.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
<td>0.5</td>
<td>Worker’s Bargaining Weight for Wages</td>
</tr>
<tr>
<td>$(1 - \phi)$</td>
<td>0.5</td>
<td>Firm’s Bargaining Weight for Wages</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.9%</td>
<td>Probability of Firm Closure</td>
</tr>
<tr>
<td>$z_l$</td>
<td>1</td>
<td>Productivity of the Low Firm</td>
</tr>
<tr>
<td>$z_h$</td>
<td>1</td>
<td>Productivity of the High Firm</td>
</tr>
</tbody>
</table>

Using the parameters identified above as well as the functions specified, the model produces data simulating wage and employer history data found in the PSID. We use this data to estimate the scars from displacement in the same fashion as we did with the PSID data. The results of these estimation are below. The thick line is generated with the model and this is plotted on the empirical findings from earlier. As you can see, the model generates the different experiences due to the different types of displacement. The loss in firm specific human capital drives the short-term loss in workers displaced from company closings. However, you can see that these workers recover quickly similar to what we see in the data. Workers displaced via lay-off experience an initial hit to wages that is somewhat deeper than their displaced counterparts while the slow human capital accumulation results in a slow recovery.
Figure 5:

Scar for Laid Off Workers

![Graph showing the estimated change in expected wages over years since displacement for laid off workers.]

Figure 6:

Scar from Company Closing

![Graph showing the estimated change in expected wages over years since displacement for company closing.]

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7 Conclusion

This paper has made an empirical and a theoretical contribution to the literature. The empirical analysis demonstrates that the effects of job loss are long lasting. This is especially true for workers displaced due to lay off; the loss in wages from this type of job loss lasts twenty years on average. This paper also puts an emphasis on the difference in the experiences for the two types of displacement. Contrary to earlier studies, we see that the difference between these two experiences is vast. Workers displaced due to company closings do not experience an initial drop in wages as deep as laid off workers. Furthermore, their drop in wages are not as long lasting. The emphasis on these differences is important as it is quite informative for theoretical purposes.

This paper takes a step in understanding the cause for these scars. We build a theory of wage determination that incorporates human capital accumulation as well as the stigma associated with job loss due to lay off. Our model allows us to measure how much of the scar for laid off workers is due to lost human capital accumulation versus how much is due to information being revealed on the quality of the worker. This information on the quality of the worker has lasting effects through a decrease in the rate of human capital accumulation.

This paper is also important for labor economists and economists concerned with economic growth. The effects of job loss are critical for understanding the labor income process. Our findings suggest that the labor income process may not only be different for the displaced workers versus those that have not been displaced, but that it is important to take into account the reason for displacement. With job loss being such an important determination for future wages, further examination of these workers would provide insight into the nature of economic growth. For example, what kind of jobs are these workers taking that is inhibiting a catch up in wages on average?
What are the properties for the workers who have caught up in wages? What kind of work have these workers taken? A deeper understanding of these questions would provide economists with a deeper understanding of economic growth.

References


