Wage Scars and Human Capital Theory*

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Abstract

Involuntary job separation causes hourly earnings to fall 15.4% and remain depressed decades later. We clarify a tension common to many theories of scarring: the concavity of the life-cycle wage profile enables rapid recovery if displaced workers restart on the same path. We show that such models can account for, at most, 73% of wage scars if they are forced to accurately match the life-cycle wage profile. Persistent scars instead require displaced workers to follow a different path of lowered wage growth after separation. We quantify the role of wage scarring in empirical wage processes and provide a structural wage process matching both scars and life-cycle dynamics for embedding in structural models.

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1 Introduction

Job loss is a key contributor to differences in earnings paths over the lifecycle across workers. In the US, hourly earnings initially fall by an average of 15.4% following an involuntary job loss and remain substantially lower even 20 years later compared to similar workers who do not experience a job loss.[1] This finding is remarkably robust, with similar large and persistent wage scars documented in various countries and time periods.[2] We estimate that the wage consequences of involuntary separation reduce average life-cycle wage growth by 14.7% and increase cross-sectional wage dispersion by 17.8% in the total workforce compared to the subset of never-separated workers. This underscores the importance of job loss in theories of wage determination and labor income risk. An accurate depiction of job loss is essential in structural frameworks studying policies that address unemployment and income inequality.

The goal of this paper is to investigate and clarify bounds on the roles of human capital loss or job ladder dynamics in accounting for wage scars. Theories positing job loss as a restart along the same earnings process that shapes the life-cycle profile simply cannot produce scars as persistent as observed in the data if the life-cycle earnings process is strongly concave, as is typical empirically. The intuition is straightforward: A strongly concave wage profile implies that most wage growth occurs early in a worker's career. If job loss resets experience along the same path, the worker should rapidly regain lost wages by traversing this steep initial segment.

We illustrate this fundamental tension with a simple example in Figure ??. The base life-cycle path in the top row is the estimated quadratic returns to experience from the PSID sample we study. The left panels show the wage profile for a worker following the base path until job loss at period 5, resetting to zero experience, and

[1] We use hourly earnings and wages interchangeably throughout this paper.

[2] The literature on "scarring" usually uses "displaced" workers to refer to high-tenure male workers with strong labor force attachment. We use the term "separated" to refer to all involuntary separations regardless of tenure and/or experience at the time of separation.

restarting on the same path. The lower panel depicts the wage difference between this worker and one who never separates—a concept akin to wage scar regressions. The worker experiences an initial deep scar, but it fades as they catch up. A persistent scar requires the separated worker to restart on a path with lower wage growth, as shown on the right. Here, post-separation wages grow at 75% of the baseline rate, yielding a persistent scar akin to the data.

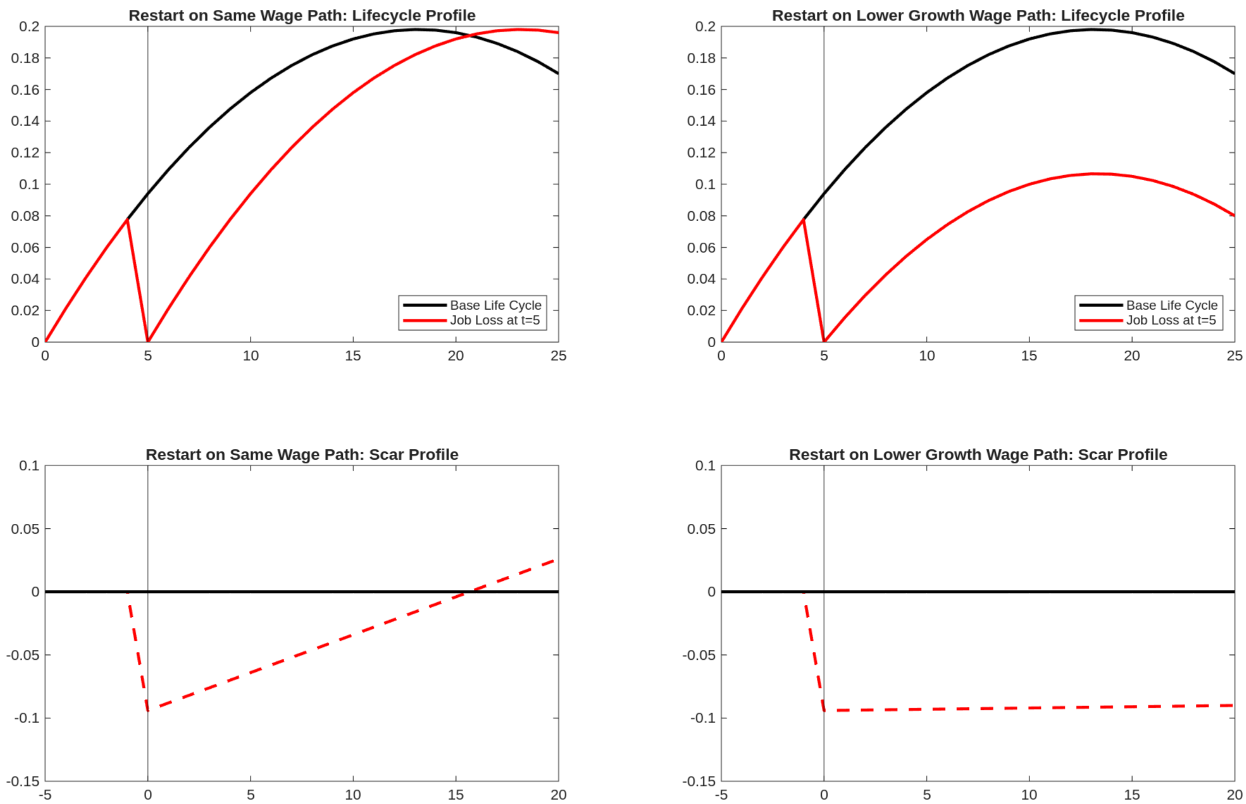

Figure 1: **Why Persistent Wage Scars Require a Different Earnings Process Post versus Pre Separation.** Left: separated workers restart along same wage process. Right: separated workers restart along wage process with lower growth.

Many recent quantitative theories of wage scarring require counterfactual predictions for life-cycle wage growth and dispersion to match the magnitude and persistence of scars.[3] They generate flatter age, tenure, or experience profiles than observed to allow the reference group to pull away and slow separated workers' catch-up. While

[3] We review several specific models in the literature section.

these papers advance understanding of mechanisms like job ladder dynamics, learning-by-doing, and match quality, evaluating their role in empirical scarring is challenging because their wage trajectories for the reference group of never displaced workers diverge from data estimates.

The main contribution of this paper is to provide a transparent, theory-agnostic benchmark that bounds how much a class of human capital theories can account for these wage scars. For our US sample, we find that any theory that posits separated workers restart along the same wage growth profile of new entrants can account for no more than 73% of the present discounted value of wage scarring and will not generate wage scars as ubiquitously persistent as the data. Replicating the data instead requires the wage growth of displaced workers to follow a path of permanently lower growth than was available to the worker as a new entrant. Theories of selection and serial displacement are insufficient.

Our findings have two important implications. First, there is still something left to be explained beyond human capital theory that is generating wage scars. Understanding what this mechanism is could guide policy efforts to aid displaced workers. Second, structural models studying a wide range of topics including household credit, social insurance, and business cycles often use simple skill depreciation or job ladders to generate earnings risk associated with job loss. Our results imply papers using this approach will understate that risk. We provide a simple estimated earnings process requiring one additional state variable, past job loss, that can be used in these models instead to accurately capture the magnitude of earnings risk associated with job loss.

We proceed as follows. First, we review the literature, highlighting how scarring theories often understate life-cycle wage growth and dispersion. Second, we estimate job loss and scarring's role in popular empirical wage processes for structural models. Third, we analyze wage scar variations within structural life-cycle wage dynamics models, viewed through human capital theory à la Ljungqvist and Sargent

(1998) [18], where wages grow with experience and fall post-separation. We calibrate variants to match both life-cycle dynamics and PSID-estimated scars, including serial separations (slippery job ladders) and permanently depressed post-separation growth. Finally, we discuss theories generating such depressed growth, the only variant yielding sufficiently persistent US scars.

Related Literature Davis and von Wachter (2011) [5] conducts an analysis of a similar spirit as this paper, but with a focus on equilibrium search and matching models. They find the frictional wage dispersion provided by such models generates only a couple percentage points of the present discounted value of losses to earnings for separated workers. This is perhaps unsurprising given the findings of Hornstein, Krusell, and Violante (2011) [10] where they show reasonable calibrations of such search models generally imply the average wage in the economy is only 5% above the lowest wage in the economy. Therefore, it would be unexpected to find a subgroup of workers earning 15% less than the average as would be required to match the magnitude of wage scars in the data. Our study instead considers wage processes that do generate life-cycle wage growth and dispersion of similar magnitudes as the data and then tests what would be required of a theory of separation to generate wage scars given these processes. We do not analyze explicitly different micro-foundations of these processes as there are many theories of wage determination one may consider. However, we discuss how some common theories, such as human capital theory, can relate to our result.

Quantitative theory papers attempting to generate these wage scars with learning by doing or job ladders include Jarosch (2023) [12], Krolikowski (2017) [16], Burdett, Carrillo-Tudela, Coles (2020) [1], Jung and Kuhn (2019) [14], and Huckfeldt (2022) [9].[4] While these papers have advanced our understanding of specific mechanisms,

[4] Ljungqvist and Sargent (1998) [18] is related, but with a slightly different objective. They target life-cycle facts and wage losses relative to workers' own past wages, not relative to the reference

the quantitative models face a common challenge: they each generate too little wage growth and dispersion in the reference group when simultaneously matching wage scars[5] Jung and Kuhn (2019) [14] do not report specific statistics related to the model's fit to the life cycle wage profile and instead provide a figure. Visual inspection shows that the model takes until age 35 to achieve wage growth that occurs by age 25 in the data. They target the scar for only five years and display too steep a recovery relative to their sample. Jarosch (2023) [12] understates both wage dispersion and wage growth thus indicating a flatter life-cycle profile than the data, and overstates the rate of job loss by 12%. Huckfeldt (2022) [9] understates average wage growth by about a quarter and overstates the experience premium over five years of experience by 31% which indicates that wage growth is too back-loaded over the life-cycle relative to the data. Burdett, et al. (2020) [1] explicitly highlight that their model "does not generate sufficient curvature as measured by the quadratic experience term in the Mincer wage regression" and instead focus on workers younger than 35.

2 Empirical Wage Scars

To motivate the rest of the paper and to establish the parameters which will be used throughout the paper, we estimate the effect of involuntary job loss at time $t-n$ on the natural log of real hourly earnings (w_t) wage scars using the Panel Study of Income Dynamics (PSID) 1976-2015 wave of data. We use the strategy given in Jacobson, LaLonde, and Sullivan (1993) [13] which develops the standard event study regression framework while incorporating insights from the literature in arriving at the following equation for individuals indexed by i:

comparison group in the empirical literature that provides the permanent scars to which this paper is using for reference.

[5]This statement does not apply to Krolikowski (2017) [16]. He does not report wage growth over the lifecycle and his target for wage dispersion comes from a different sample than the one he uses to estimate the wage scar. Therefore we can not evaluate this claim for his model.

$$ln(w_{i,t}) = \Phi\mathbf{X}_{i,t} + \Theta\mathbf{E}_{i,t} + \sum_{n=-2}^{19} \beta_{t-n} D1_{i,t-n} + \gamma_1 D1_{i,20+} + \sum_{j=2}^{5} \gamma_j Dj_i + \delta_t y_t + \zeta_i + \eta_s S + \epsilon_{i,t} \tag{1}$$

The key variables in this estimation are those related to the time since separation and indicator variables on whether the worker has been separated more than once.[6] The dummy variables indicating time from first involuntarily separation $D1_{i,t-n}$ in year $t-n$ closely resemble the strategy put in place by Ruhm (1991) [24] and used elsewhere in the literature (Couch and Placzek (2010) [4], Jacobson, LaLonde, and Sullivan (1993) [13], Stevens (1997) [25]). Note that the separation variable $D1_{i,n}$ includes separate dummies for two years prior to separation, the year of each separation, and each of the first through 19 years following the first separation (ie: $n \in \{-2, -1, 0, 1, ..., 19\}$). Our estimation also includes a dummy indicating that it has been at least 20 years since that first separation. As Stevens (1997) [25] points out, multiple separations are important in understanding the effects of wage scars. Therefore, we control for multiple separations with a dummy for whether the worker has been separated at least twice, at least three times, at least four times or at least five times with Dj_i where j takes the appropriate values two through five.

The independent variables include labor force experience, non-time stationary observable characteristics such as union participation and a vector of dummies related to educational attainment along with fixed effects for the year, state, and individual. The labor force experience variable and its quadratic along with union participation make up the vector ($\mathbf{X}$).[7] Dummies for educational attainment ($\mathbf{E}$) include those indicating less than 12 years of education, more than 12 years of education, a four year college degree, or some graduate school. Year fixed effects (y_t) along with state

[6] See the appendix on the timing of separations as well as more technical details on the construction of variables.

[7] Please see Kambourov and Manovskii (2009) [17] for the algorithm for constructing and cleaning the experience variable.

fixed effects ($\mathbf{S}$) are included to control for macroeconomic conditions. Individual fixed effects are represented with the parameter ζ_i.

We choose 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 run our estimation on log hours and find that separated workers recover to their expected hours worked in the third year after separation. Finally, hourly wages are more likely to be related to human capital dynamics, the focus of this paper.

The lasting scar from job loss is quite clear in Figure 2. This figure depicts the scar from the initial separation. The x-axis accounts for the years since separation and the y-axis depicts the percentage loss in real hourly earnings that will be used in our estimates going forward.[8] The dashed lines represent the 95% confidence intervals on these changes.[9]

These results are similar to those found in the literature. The impacts of separation are documented through ten years, where the loss is still at 7%. [9] Davis and von Wachter (2011) [5] use data from the social security administration and show losses in average earnings to be a little more than 10% upon separation with losses at over 5% twenty years after separation.

[8]These losses are computed as $e^{\beta_{t-n}} - 1$

[9]Please see the appendix for the coefficients estimated from equation 1.

3 Role of Separation in Empirical Models of Wage Processes

Before developing structural theories of wage scarring, we first establish how much separation contributes to key features of the wage distribution.[10] We specifically estimate how much separation and the accompanying wage scars contribute to individuals' wage risk over the life-cycle, cross-sectional wage dispersion, and other statistics. To do this, we estimate a standard empirical wage process incorporating the separation hazards and wage scars documented in Section 2. We then compare this estimated process to a counterfactual with no separations, allowing us to quantify the role of job loss in shaping life-cycle wage growth and cross-sectional inequality. This exercise provides important context for evaluating structural models: any successful theory must not only replicate the wage scars themselves, but also be consistent with how much these scars contribute to overall wage dynamics.

The general empirical process for wages of non-separated workers is specified according to a commonly used form:[11]

$$ln(w_{it}) = \alpha_i + \beta_1 exp + \beta_2 exp^2 + z_{it} + \epsilon_{it} \tag{2}$$

The dependent variable is log wages. The independent variables include individual fixed effects, a quadratic in experience, a persistent shock z_{it}, and a transitory shock ϵ_{it}. Specifically, the persistent shock follows an AR(1) process:

$$z_{it} = \rho z_{i,t-1} + \eta_{it}$$

[10] This exercise complements prior work on sources of life-time income inequality and risk (ex: Low, Meghir, and Pistaferri (2010) [19], Blundell, Pistaferri, and Preston (2008) [2], Hornstein, Krusell, and Violante (2011) [11], Guvenen (2009) [8]). The distinction is that we specify that unemployment has persistent effects on wages independent of realized shocks in the general wage process and thus isolating how much variance is related to these separations.

[11] This income process is widely used in partial equilibrium models concerned with insurance, credit, and inequality, among other applications.

It is assumed that all individuals start with $z_{i0} = 0$ and that the innovations are iid across individuals.

We estimate the parameters of this income process using simulated method of moments closely following Guvenen (2009) [8]. The simulated wage paths of non-separated workers are provided by the empirical wage process in equation 2. Wages of separated workers follow that of the non-separated, except they are reduced by exactly the same magnitudes we estimate in the data: the non-parametric estimates of the 20 years of wage scars following the first loss plus the two extra constant terms following the second and third loss. Separation occurs with a hazard function that we estimate in the data, of the following form for a worker of experience t with at least d past separations $d \in 0, 1, 2, 3$:

$$\xi(d,t) = \lambda_0(e^{\phi t} + \sum_{d=1}^{3}(\lambda_d)D_d)$$

This specification includes a baseline hazard λ_0, plus an estimated negative effect of age ϕ, and positive effect of past separations λ_d, where $D_d = 1$ is the dummy for past separations.

The targeted statistics in the estimation are typical and chosen to be informative about different parameters. The first is a set of regression coefficients from the following regression run in both data sets:

$$ln(w_{it}) = \alpha_i + \beta_1 exp + \beta_2 exp^2 + \epsilon_{it}$$

The values of β_1 and β_2, which describe life-cycle wage growth, as well as the standard deviation of the individual fixed effects α_i are included in the targets.[12] We also include two targets related to the residual wages from this regression: the standard deviation of residual wages for individuals with 5 years and 30 years of

[12] We also add the same constant to wages in the model as calculated in the data regression.

experience. Statistics informative about the AR(1) process deal with higher-order serial correlations of the wage process. Define $Scorr(n)$ to be the n^{th} serial correlation. We target three statistics: $Scorr(1)$, $Scorr(1) - Scorr(2)$, and $\frac{Scorr(2)-Scorr(3)}{Scorr(1)-Scorr(2)}$.[13]

Our resulting parameter estimates are listed in Table 1 and the fit to targeted statistics is shown in Table 2. Our estimates in the first column are comparable to the literature employing other estimation techniques.[14] The second column reports statistics controlling for wage scars incurred from each the first separation as well as additional scarring applied by higher order separations. The difference between the two columns shows that displacements play an important role in the empirical wage process. Notably, the scars account for a more persistent component of wage risk than from other sources shown by the persistence of the AR(1) component decreasing from 0.921 to 0.899 when the scarring effects are explicitly included. The scars also account for a significant share of the variance of the individual fixed effects, increasing them from 0.1334 in the process remaining when scars are removed to 0.2120 when scars are included. Table 2 shows neither specification has a significant advantage in fitting additional moments of the data.

In order to analyze how separation affects wage inequality, we perform a counterfactual simulation. We simulate data from the wage process using the parameters estimated above, but with the separation hazard set to zero. We interpret this counterfactual as a world where we remove the estimated wage effects of separation. We report a comparison of moments with and without separation in Table 3.

We find the presence of wage scarring following separation reduces average 20 year wage growth by 14.7%. It also increases the cross-section dispersion, measured as the standard deviation of estimated individual fixed effects, by 17.8%.

[13]This is a typical estimation strategy as detailed in Guvenen (2009) [8].

[14]For example, Floden & Linde (2001) [6] use GMM on PSID data and find $\rho = 0.9136$ versus our $\rho = 0.9213$, $\sigma_\eta = 0.206$ versus our 0.2709 and $\sigma_\alpha = 0.2052$ versus our 0.2120. Some of the discrepancy is from our inclusion of iid transitory ϵ_{it} shocks and differences in sample construction including the time-span of our data.

4 Testing Candidate Models of Wage Scars

We now turn to structural models to understand what mechanisms can generate the persistent wage scars documented in Section 2. Our strategy is deliberately simple and transparent: rather than embedding wage scars in a rich, fully-specified equilibrium model, we study parsimonious variants of human capital theory to isolate the core mechanisms at work. We directly target the reduced-form regression coefficients from the event-study analysis and evaluate how well these simple models can replicate the empirical patterns. We begin with a baseline learning-by-doing model of human capital accumulation and then consider several intuitive extensions: selection of low-wage workers into unemployment, serially correlated separations, and permanently reduced wage growth following job loss. By studying transparent models where the key mechanisms are easily understood, we can clearly identify which properties are necessary for human capital theory to quantitatively match the data and why more complex models succeed or fail.

4.1 Baseline Learning-by-Doing Model of Human Capital

We build upon a simple life-cycle wage model of learning-by-doing similar to Ljungqvist and Sargent (1998) [18] (LS). Workers differ in human capital $h \in \{h_0, h_1 ... h_N\}$ and their age t. They begin their careers at h_0 and accumulate skills sequentially. Each period they are employed, a worker with human capital h will see his human capital next period increase by step size s: $h' = h + s$ with probability α. Human capital determines each worker's efficiency units of labor. We normalize the consumption paid per efficiency unit to one, implying a worker's total period income is equal to their human capital h.[15] Workers are separated to unemployment with age-dependent

[15]The drop in wages in the full LS model is affected by choices of the worker that we do not explicitly model here. Workers sample one exogenous draw of an additional match specific component of wages each period of unemployment and choose whether to accept it or search again next period. Our estimation serves the purpose of showing how large this drop is in the best fit. It remains

probability $\delta(t)$. Upon separation, workers lose a portion τ of their skills with probability γ. The human capital progression of a worker can then be defined as a function of age t and current human capital h:

$$h' = \begin{cases} h + s, & \text{with probability } (1 - \delta(t)); \\ \tau h, & \text{with probability } \delta(t)\gamma; \\ h, & \text{otherwise.} \end{cases}$$

4.2 Calibration

We consider a time period of one year. The deterministic career span of our agents is 35 years. For the baseline model, we choose the probability of separation to match the separation hazards to unemployment as a function of labor market experience calculated in our PSID sample. This leaves four parameters to calibrate: s, the value of each human capital step; α, the probability of moving up a step when employed; γ the probability of losing human capital if displaced; and τ, the share of human capital lost at displacement if the shock hits. Our first exercise targets coefficients in the wage scar equation alone: the initial and 15-year value of the scar as well as the present discounted value.[16] In this way, we give the model the best shot at replicating the scars before examining whether ancillary implied life-cycle wage statistics are factual.[17] We calibrate remaining parameters to minimize the weighted distance between these statistics calculated for model simulated data and the analogous statistics in the PSID sample. We choose the set of parameters across s-values that minimizes this distance. These parameters are available in Table 4.

innocuous in relation to this model because the match specific component does not affect wage scars through selection into unemployment as in Mortensen-Pissarides (1994) since all separation is exogenous.

[16]The wage regression in our model includes experience and experience-squared, the first fifteen years of dummies following separation, the dummy for the second separation, the dummy for third separation. The wage regression in the data includes additional demographic controls, and individual and time fixed effects.

[17]The estimation need not be unique. We are only interested in best fit.

The fit of the baseline model to the empirical scar is shown in Figure 3 and to additional statistics are in Table 5. The baseline model cannot produce a persistent scar even when it is allowed to freely choose a wage process that need not replicate other features of reality. Loss of human capital can produce short term wage losses but separated workers have a clear trajectory towards recovery approaching 15 years. The separated workers that are re-employed recover lost human capital through the same process that delivered their initial high pre-separation wages. This provides a tension between the need to have fast enough wage growth to produce a reference group of never displaced to generate a large initial scar and yet slow enough wage growth to produce a persistent scar. In the next subsection we identify three modifications that can break this tension.

4.3 Alternative Specifications

We re-calibrate the model for a series of modifications on the baseline model of ex-ante homogenous agents with random separation. We make two types of modifications. In the first set, we depart from the random separation specification to provide serially correlated separations. We do this because of the finding in Stevens (1997) [25], replicated in this paper, that multiple separations are important for understanding the wage scar. We achieve serially correlated separations in two ways. In the first, we specify that only low-wage workers face a separation hazard. This ties the human capital theory directly to the serial correlation of separations. The next is agnostic and mechanical: we modify the separation hazard to mechanically be serially dependent. The second modification allows a separation to permanently reduce the worker's future wage growth rate (γ) without any implication for the future unemployment hazard.

(a) Baseline (*Red Solid Line labeled "Baseline" in Figures 3 & 4.*) See previous subsection.

(b) Selection of Low Wage Workers (*Solid-diamond line labeled "Selection". Select in Figures 3 & 4.*) We now consider the case where only workers below a given current wage threshold face separation hazards. This specification is related to business cycle theory building on Ljungqvist and Sargent (1998) [18]. The view of this theory is that match destruction is endogenous and occurs when match productivity falls below a certain threshold. Match productivity is a combination of worker, match, aggregate, and firm components, and so low productivity workers are more likely to be in a match that falls below the threshold and face a higher separation probability.

(c) Separation Changes Workers - Correlated Separation (*Solid-square line labeled "Serial Separations" in Figures 3 & 4.*) We modify our baseline such that separated workers are likely to suffer multiple separations. We introduce a new parameter $\lambda \geq 1$ indicating how much each separation a worker experiences increases the hazard of future separation. These probabilities are estimated directly from the data. The first separation increases the probability of a second separation by 2.17 times, the second separation increases the probability of a subsequent separation by 1.15 times, and three or more separations increase the probability of subsequent separation by 1.49 times (see Table 1). This modification is best viewed as human capital theory combined with a job ladder model where the "bottom rung" accessible to unemployed workers is "slippery" or has a higher separation rate.

(d) Separation Changes Workers - Permanently Lowered Wage Growth (*Solid-circle line labeled "Lowered Wage Growth" in Figures 3 & 4.*) We modify our baseline such that separated workers' probability of moving up the skill ladder is permanently lowered to zero. We still calibrate the amount of skills lost (τ)

to best fit our targets, but set the hazard rate of future skill accumulation to be $(\gamma(1-\phi))$, or lowered by ϕ, for workers who are separated. Never separated workers are unaffected.

The bottom-line finding of this exercise is that all three extensions slightly outperform the baseline by producing more consistent scars (Figure 3). The first two modifications provide serial correlation in separations that enables them to generate more persistent scars than completely random iid separations. The last extension starts displaced workers on a fundamentally different human capital accumulation path than never displaced workers. It is successfully produces persistent scars without serial correlation in displacements. These successes, however, result in very different wage processes. The lowered growth specification produces four times more wage dispersion and the fastest wage growth early in life (Table 5). This brings it closer to matching the wage distribution in the PSID. In the next subsection, we explore how much worse these models fare when these wage distribution statistics are added to the set of estimation targets.

4.4 Targeting Life-Cycle Wage Growth and Scars

In the prior section we gave each model the best shot at replicating the wage scars even if counter-factual life-cycle statistics were produced. We now quantitatively explore the tension introduced when attempting to produce factual life-cycle wage growth patterns along-side the permanent scar. To do so, we re-estimate specifications (a)-(d) adding a few key life-cycle statistics as targets. These include the mean wage growth in the first 5 years and the first 30 years of experience. As discussed, these two statistics are important for generating the depth of the initial scar and discipline the speed of the wage recovery. We also display, but do not target, the standard deviation of wages at 30 years experience.

Figure shows the models' fit to the wage scar. The baseline specification along with the selection on low wages and the serial separation specification produce less persistent wage scars when they are required to replicate life-cycle moments. The estimation attempts to balance matching the short and long of the wage scar by over stating the short term loss and understating the long term loss. When restricted to produce wage growth moments closer to the data, the largest scar it produces includes an initial wage decline that is about 50% smaller than the data and is 25% smaller than the data in terms of present discounted value. Table 7 shows that these specifications also miss on replicating the general wage distribution. The only specification that successfully produces the permanent scar and a realistic distribution of wages is the lowered wage growth model. Table **??** shows also that human capital acquisition occurs much faster in the general population in the lowered growth specification but loss of skills following displacement is a greater source of wage inequality.

We perform one final exercise on the baseline model in which we require it to match wage growth in the data over five and thirty years of experience. We find that the maximum present discounted value of the scar generated by this model is 73.4% of the empirical estimate. This fit comes at a cost of overstating the initial wage scar by 85.9% and proceeding along a steeper recovery path.

These exercises make it clear that (i) theories of wage scars should be required to also replicate the general wage distribution as the two are fundamentally linked; and (ii) both simple models with random displacement and models with selection struggle to replicate both wage scars and the general wage distribution. An additional point is that the model's ability to replicate the wage scar can best be understood by running the very same regression in the model data as in data like the PSID.

5 Discussion of Results

Relationship to the Results in Ljunqvist and Sargent (LS) (1998) Our notion of wage scarring differs from that studied in LS. We follow the empirical literature and calibrate our models by explicitly targeting wage scar regression coefficients, in addition to life-cycle and cross-sectional statistics. This approach defines the scar by comparing separated workers' future wages to a reference group of similar workers that were not separated. LS instead defines the scar by comparing a worker's future wages to their past, pre-separation wages.[18]

It is intuitive that the baseline LS model requires additional ingredients to produce permanent scars when they are defined relative to a reference group as in the standard regression analysis.[19] This is because the general human capital accumulation process provides a concave life-cycle profile in wages. The quadratic in experience captures this concavity and essentially forms the reference path of never displaced workers to which the earnings of displaced workers is compared to in calculating the scar. This shape generates a larger short-term scar than the basic LS model (our baseline). Even a separated worker with no human capital loss would have some scar due to falling behind on the quadratic life-cycle path. A short-run scar of the magnitude in the data can be achieved with human capital loss but this scar fizzles out as workers complete the steep portion of the life-cycle path. This is because the quadratic representing the reference group becomes flat with higher levels of experience and marginal shortfalls matter less. Additional ingredients are needed to make the scar more persistent.

This intuition holds for other micro-foundations, such as some models of search

[18]This does not imply the results of LS are not useful. The turbulence they describe, the importance of considering how workers' behaviors are affected and the fact that unemployment insurance relates to past wages, which are often higher than future wages for separated workers, are promising margins to consider in analyzing how these scars vary over time and across countries. Our only point is that a modification of this theory on top of the instantaneous human capital loss is necessary to match both the persistent wage scars and life-cycle wage growth patterns in data.

[19]In the LS calibration, it takes an average of less than eight years to move from the lowest wage in the economy to the highest. This implies that wages of the average separated workers should recover in a maximum of eight years.

and matching, that provide concave life-cycle wage growth on average. Although workers suffer an instantaneous reduction in wages upon separation, they should recover as long as they have access to the same wage process as never displaced workers.

Main Results and Promising Theories The main conclusion of our analysis highlights a tension between producing deep, persistent wage scars alongside life-cycle wage statistics. On the one hand, extensions where the wage and employment process changes after first separation improve upon the baseline model in their ability to generate a scar with the high persistence documented in the data. On the other hand, these extensions struggle to produce the correct magnitude of the wage scar when they are required to be consistent with observed pre-separation wage growth and wage growth patterns of the reference group of never separated. We now discuss the implications of these findings for future research.

The takeaway from our study for future research depends on the research objective. If one would simply like to embed a quantitative process for wages that replicates a present value of wage losses following separation, then the baseline Ljungqvist and Sargent type of model can do the job but would miss on the general wage distribution, particularly dispersion. If one would like to understand why the scars are so persistent, then theories where a separation is a restart on the bottom rung of the pre-separation wage process leave something to be desired. Instead, we have shown that theories where separation somehow changes the worker's future prospects by lowering wage growth or raising the incidence of future separation are promising.

The literature has developed a couple classes of theories in which separation changes a worker's future prospects.[20] In the theories of Michaud (2018) and Burdett, et al. (2020) [1], the scars are generated by endogenous selection of a "low-type"

[20] This discussion omits papers that consider only short term losses or limit analysis to high-tenure or full-time workers.

worker. However, in both cases, this selection on type is not captured by the individual fixed effect as in the regression they run on model generated data. In Burdett, et al. (2020) [1], the fixed characteristic has dynamic impact through a heterogeneous wage growth and separation process. In the learning story of Michaud (2018) [22], the fixed heterogeneity is not known to employers at the beginning of a worker's career. This leads to a time-varying impact through the dynamics of an employer learning about the trait through observations of workers' output.

There are also clues about successful theories in the empirical scar literature as to why the wages of displaced workers grow more slowly than new entrants. For example, the canonical work of Jacobson, et al. (1993) [13] specifically studied mass layoffs and found permanent scarring. Loss of a large amount of jobs in a locality could change the future wage growth prospects for workers relative to their prospects as new entrants if they face barriers to moving from the area. Another avenue that could change future prospects is age. The older a worker is, the less incentive they have to invest in training or job search that yields delayed dividends thus making their future earnings prospects more flat.

6 Conclusion

Understanding the long-lasting effects of job loss on wages is important for understanding income risk and how this contributes to income inequality. We estimated that job loss accounts for 17.8% of cross-sectional wage dispersion and is an important contributor to individuals' wage risk over the life-cycle. We then used structural models to highlight quantitative challenges for human capital in replicating the empirical paths of wages after job loss.

Our main contribution is a clear, theory-agnostic benchmark highlighting a tension in structural models: the challenge of delivering a scar that is both as deep and as persistent as scars in the data alongside a life-cycle wage growth with dispersion that is quantitatively in line with the data. This is due to the concave shape of the life-cycle wage profile. It implies that displaced workers should catch up along the steep part of the profile and speedily recover as long as they have access to the same wage process as never displaced workers. This mechanism bites for several intuitive theories. Job ladder type examples where low-wage workers are selected for displacement do not generate scars if those workers get back on the same ladder as never displaced workers. Serial correlation of separations akin to slippery lower rungs on the ladder does not solve the problem if the serial correlation of displacement replicates the data. The successful theory is one where displaced workers can never get on the same ladder as never displaced workers and face permanently lower wage growth.

This paper establishes a benchmark for evaluating theories of wage scarring. Future work should target and make transparent the model fit with regards to both separated workers and the reference group to which their wages are compared: the non-separated workers. This will facilitate synergistic advancements on this topic by allowing for better comparisons of the strengths and weaknesses of different theories and modeling approaches. A separate contribution is that we provide a minimal modification of human capital theory capable of replicating empirical wage scars. The estimated process for the model with reduced human capital growth after separation can be plugged into models interested in studying a breadth of questions in economics. For example, the permanent nature of these wage losses fundamentally alters the optimal design of unemployment insurance, the assessment of credit risk in consumer lending, and even analyses of the balance of risks and objectives for monetary authorities with a dual mandate.

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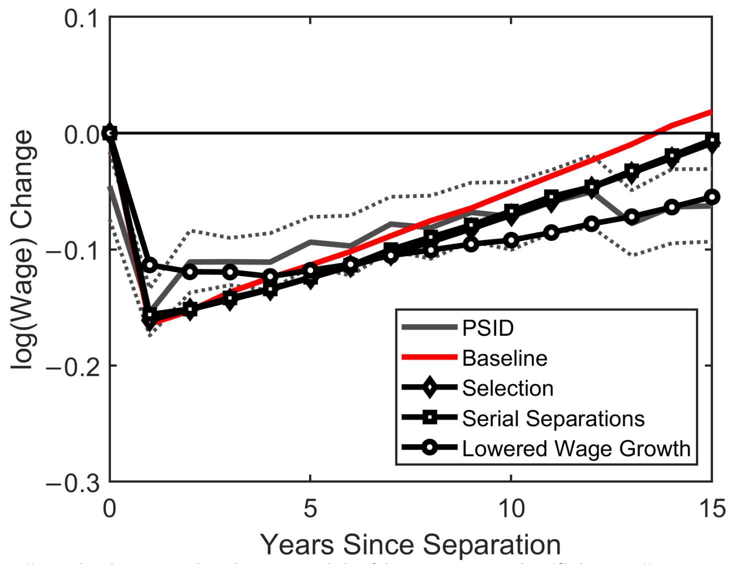
Figure 2: Estimated Wage Effect of Separation

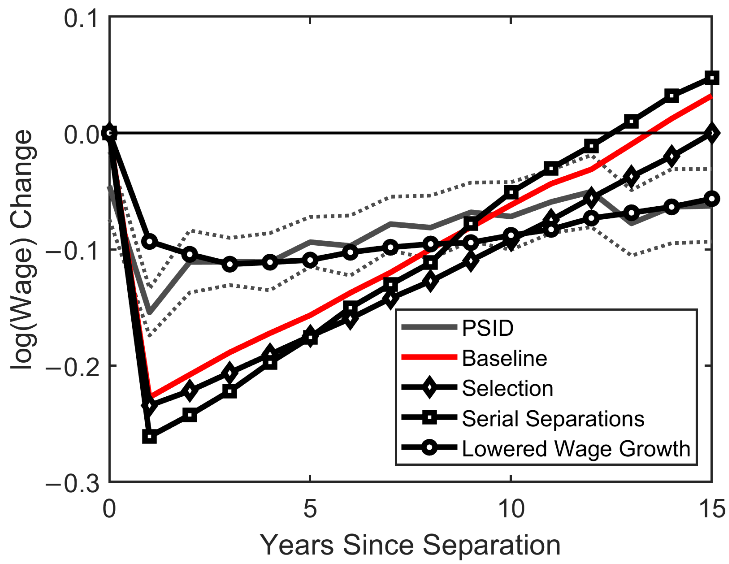
The solid line indicates the values for $\exp(\beta_{t-n})$ from equation 1 with log hourly earnings as the dependant variable. The dashed lines indicate the 95% confidence intervals.

Figure 3: Model Fit- Targeting Scar Coefficients Only



"Baseline" is the learning-by-doing model of human capital. "Selection" is a modification of Baseline with only low-wage workers facing a separation hazard. "Serial Separations" is a modification of Baseline where the probability of future separations increase after each separation. "Lowered Wage Growth" is a modification of Baseline where workers have no wage growth after separation. PSID estimates show the 95% confidence interval.

Figure 4: Model Fit- Targeting Scar Coefficients & Life/Cross Section Wage Statistics



"Baseline" is the learning-by-doing model of human capital. "Selection" is a modification of Baseline with only low-wage workers facing a separation hazard. "Serial Separations" is a modification of Baseline where the probability of future separations increase after each separation. "Lowered Wage Growth" is a modification of Baseline where workers have no wage growth after separation. PSID estimates show the 95% confidence interval.

Table 1: Empirical Wage Model Parameters- Estimates from PSID

Parameter	**No Separations**	(Std. Err.)	**With Separations**	(Std. Err.)
Return to *Exp*	0.0218	(0.0010)	0.0237	(0.0013)
Return to Exp^2	-0.0006	(0.0000)	-0.0007	(0.0000)
AR(1) persistence (ρ)	0.9213	(0.0112)	0.8996	(0.0333)
std AR(1) innov. (σ_η)	0.2709	(0.0063)	0.3146	(0.0047)
std transitory shock (σ_ϵ)	0.2505	(0.0034)	0.1608	(0.0077)
std permanent level (σ_α)	0.2120	(0.0146)	0.1334	(0.0049)
Initial Separation Hazard (λ_0)	0.0	(n.a.)	0.9582	
Additional Separation Hazards				
After One Separation (λ_1)	0.0	(n.a.)	2.1686	(0.1308)
After Two Separations (λ_2)	0.0	(n.a.)	1.1495	(0.1002)
After 3+ Separations (λ_3)	0.0	(n.a.)	1.4888	(0.1551)

Table 2: Empirical Wage Model:Fit to Additional PSID Statistics

Empirical Wage Model: Estimation Fit			
Moment	**Data**	**No Separations**	**With Separations**
Resid. Wages, 5 yr Exp (std)	0.510	0.510	0.510
Resid. Wages, 30 yr Exp (std)	0.531	0.521	0.529
Wages (Scorr(1))	0.933	0.877	0.869
Wages (Scorr(1)-Scorr(2))	0.039	0.139	0.167
Wages ($\frac{\text{Scorr(2)-Scorr(3)}}{\text{Scorr(1)-Scorr(2)}}$)	0.866	0.872	0.825
Individ. Fixed Effects (std)	0.483	0.462	0.451

Note: Return to experience and experience-squared are coefficients in the regression on model generated data.

Table 3: Role of Separation in the Wage Process

Counterfactual Simulation-Turn off Separation			
Statistic	**No Separation**	**Separation**	**Effect of Sep**
	(Std. Err.)	(Std. Err.)	
20 yr wage growth (mean)	0.395	0.340	-14.7%
	(0.024)	(0.021)	
Resid. Wages, 5 yr Exp (std)	0.483	0.510	+5.6%
	(0.012)	(0.011)	
Resid. Wages, 30 yr Exp (std)	0.496	0.529	+6.7%
	(0.014)	(0.012)	
Wages (Scorr(1))	0.831	0.869	+4.6%
	(0.004)	(0.004)	
Individ. Fixed Effects (std)	0.437	0.515	+17.8%
	(0.011)	(0.012)	

The counterfactual uses the model parameters from the estimation of the model with separation, but then sets separation hazard to zero.

Table 4: Parameter Estimates- Targeting Scar Coefficients Only

Parameter Estimates	Baseline	Selected Separation	Correlated Separation	Lowered Growth
Skill Step Size (s)	0.047	0.028	0.043	0.131
Skill Gain Prob. (α)	0.45	0.45	0.51	0.41
Skill Loss Prob. (γ)	0.59	0.58	0.35	0.77
Percent Skills Lost (τ)	0.02	0.50	0.01	0.96
% Reduction in skill growth (ϕ)				0.35

See Section 4.3 for the specification of each model.

Table 5: Model Fit- Targeting Scar Coefficients

Moment	Data	Baseline	Selected Separation	Correlated Separation	Lowered Growth
5 year wage growth (mean)	0.35	0.12	0.07	0.12	0.23
30 year wage growth (mean)	1.10	0.64	0.38	0.63	0.65
30 year wage dispersion (stdev)	0.40	0.08	0.06	0.08	0.38
Initial wage scar (%)	-0.15	-0.16	-0.16	-0.16	-0.11
10 year wage scar (mean)	-0.09	-0.01	-0.03	-0.03	-0.07

See Section 4.3 for the specification of each model.

Table 6: Parameter Estimates- Targeting Scar Coefficients & Life/Cross Section Wage Statistics

Parameter Estimates	Baseline	Selected Separation	Correlated Separation	Lowered Growth
Skill Step Size (s)	0.063	0.045	0.116	0.199
Skill Gain Prob. (α)	0.49	0.42	0.41	0.43
Skill Loss Prob. (γ)	0.51	0.02	0.77	0.67
Percent Skills Lost (τ)	0.01	0.12	0.54	0.79
% Reduction in skill growth (ϕ)				0.35

See Section 4.3 for the specification of each model.

Table 7: Model Fit- Targeting Scar Coefficients & Life/Cross Section Wage Statistics

Moment	Data	Baseline	Selected Separation	Correlated Separation	Lowered Growth
5 year wage growth (mean)	0.35	0.17	0.11	0.24	0.38
30 year wage growth (mean)	1.10	0.91	0.78	0.99	1.11
30 year wage dispersion (stdev)	0.40	0.09	0.08	0.24	0.47
Initial wage scar (%)	-0.15	-0.23	-0.23	-0.26	-0.11
10 year wage scar (mean)	-0.09	-0.01	-0.03	0.01	-0.07

See Section 4.3 for the specification of each model.